The Role of Spatial Dependence in Risky Decision Making: Evidence from a Developing Country

Abstract

Farmers’ attitudes toward risk taking have been identified as one of the factors affecting their investment decisions and wealth accumulation. However, while existing studies identified the socio-economic factors determining farmers’ risk attitudes, climatic, environmental and spatial variables that correlate with decisions are often ignored in the risk models because of the difficulty in measurement. Therefore, we provide insight into the role of spatial dependence in risky decision making among rice farmers in Nigeria using experimental data. Due to the potential endogenous problem, we estimated spatial autoregressive model using instrumental variable method. It was revealed that farm and farmers’ specific factors such as age, marital status and gender significantly explain farmers’ risk attitudes. More importantly, decision makers’ risk attitudes are spatially correlated while farmers living in the bad road network areas avoid taking risky decisions relative to those who live in more accessible road locations. The policy implications of the findings are discussed. The study suggests the need to pay specific attention to heterogeneity in risky decision making as some important latent factors correlate with farmers’ risky decision making processes.

Key words: decision making, instrumental variable, neighbourhood effects, risk preferences, spatial dependence

JEL Classifications: D1, D7, D8, D9, O1, O2, Q1

1.0 Introduction

The risk associated with farm decisions could be viewed from two perspectives. The first relates to the weather shocks faced by farmers during production activities (World Bank, 2008). Farmers, especially in the developing countries often face varying degrees of background risks ranging from vagaries of weather (which cause flood, drought, pest and disease infestation) to fluctuation in prices of inputs and outputs. These background risks usually impact directly on farm output, yield and consequently the food security and livelihood of farmers. Second, the risk preference which reflects the extent to which a decision maker (DM thereafter) is willing to take risky decisions (Charness, et al., 2013). The latter which examines the sensitivity of individuals to risk (Bocqueho, et al., 2014), is the focus of this article, with a specific attention to the correlation between farmers’ neighbours in decision making processes. Understanding farmers’ risk attitudes may aid gaining insights into their economic activities as well as the factors affecting preferences.

Many factors including access to infrastructural facilities such as schools as well as spatial attributes like socio-economic, agro-climatic and topographic conditions may
correlate with farmers’ risk behaviour (Reardon and Taylor, 1996; Humphrey and Verschoor, 2004; Nguyen and Leung, 2009; Nguyen, 2011; Tanaka and Munro, 2014). In other words, risk preferences reflect the climatic and economic environment of individuals. For example, using large experimental data from Uganda, Tanaka and Munro (2014) reveal farmers located in low rainfall areas show higher aversion to risk. Individuals who faced income uncertainty are reported to be highly averse to risk (Guiso and Paiella, 2008). While Bezabih and Sarr (2012) report more risk averse farmers have high tendency to diversify crops, Gollier and Pratt (1996) contend variation in income increases risk aversion. Notwithstanding, modelling spatial correlation in risky decision making has never attracted attention in the literature. In brief, understanding the heterogeneity in farmers’ risk preference may guide policy on risk management and investment decisions in developing countries.

Tobler (1970) posits closer observations or individuals may be more related relative to distant ones. It is well acknowledged agricultural data are spatially related and non-controlling for the spatial aspects of such data may result in a misleading inference (Benirschka and Binkley, 1994; Bockstael, 1996; Weiss, 1996; Roe, et al., 2002; Kim, et al., 2003). Spatial dependence in risky behaviour may be a consequence of variation in soil types, weather and climate, topographic and farmers’ socio-economic conditions. Farmers may influence one another due to geographical proximity, availability or otherwise of infrastructural or institutional facilities such as roads, schools and markets (Areal, et al., 2012). In the agricultural technology adoption literature, for example, farmers’ adoption patterns were found to reflect the spatial variability or neighbourhood effects (Case, 1992; Holloway, et al., 2002; Krishnan and Patnam, 2014; Läpple and Kelley, 2015; Tessema, et al., 2016). Indeed, spatial dependence may reflect in risky decision making because culturally, farmers living closely often rely on their friends and neighbours to acquire and share information on farm practices. In other words, social interaction effects could be used to disseminate technological innovation. However, despite advances in the spatial econometrics (Anselin, 2002; LeSage and Pace, 2009), there is no attempt to examine the role of spatial dependence in decisions relating to experimental risk. This leaves a gap in the literature which this study filled by testing the hypothesis that farmers living closely have similar risk attitudes relative to distant ones.
Many behavioural studies sought to examine the determinants of risk attitudes in developing countries (Binswanger, 1980; Binswanger, 1981; Wik, et al., 2004; Yesuf, 2004; Harrison, et al., 2005; Yesuf and Bluffstone, 2009; Harrison, et al., 2010; Tanaka, et al., 2010; Brick, et al., 2012). However, only few studies attempted to examine heterogeneity in risk attitudes. For example, farmers working in riverine areas were reportedly less risk averse in Vietnam (Nguyen and Leung, 2009; Nguyen and Leung, 2010; Nguyen, 2011) while those in the climatically least favourable regions such as low rainfall areas are more averse to risk, loss and highly impatient in Uganda (Tanaka and Munro, 2014). This current study differs in terms of elicitation and estimation methods, and setting. For instance, Tanaka and Munro (2014) only control for some environmental factors in their study while we estimate spatial autoregressive model which incorporate spatial weights of the risk variable.

Social composition of farmers may reveal neighbourhood effects (Holloway, et al., 2007). Such influence may extend beyond the current agricultural zones or farm divisions in Nigeria. For instance, the degree of heterogeneity in risk preference may reflect the existing economic reality of farmers within and across agricultural zones in Nigeria since spatial dependence captures the geographical influence of the presence or absence of infrastructure like markets (insurance and financial). The climatic requirements for rice production points this peculiarity. Uncertainty may affect the livelihood of rice farmers, especially the rural ones who rely mainly on the traditional farming methods and lack access to information and other resources. Furthermore, rice farmers tend to reflect their income status and status quo bias in their decisions. Thus, insight into spatial dependence effects and heterogeneity in risky decision making is \textit{sine qua non} for policy formulation.

The remainder of this paper is organised as follows. The review of literature on the risk elicitation methods and determinants of risk attitudes is presented in the next section. The theoretical models and source of data are the focus in section 3. The results and discussion are reported in section 4 while section 5 concludes the findings with policy implications.
2.0  Elicitation Methods and Factors Affecting Risk Attitudes

2.1  Risk Attitudes’ Elicitation Methods
Risk elicitation methods are generally classified into laboratory or field based (Charness, et al., 2013; Harrison & Rutstrom, 2008). Most laboratory-based methods require computer skill and expertise which are lacking among most farmers in the developing countries yet some methods place too much information on the probabilities. The risk elicitation methods applied mostly in the developing countries are summarized below. Binswanger (1980) is one of the foremost researchers to examine the risk attitudes of farmers in the developing countries. The elicitation method enforces making a choice from an ordered set of eight lotteries. A risk averse subject is expected to choice from the top six rows, a risk neutral subject chooses row seven, while a risk loving subject chooses the last row. This method is simple but suffers from the anomaly of certainty effects. One popular variant to Binswanger’s approach is the Holt and Laury’s (2002) (HL thereafter). HL elicits risk attitudes from ten binary choices ordered by probabilities. Similarly, Brick, et al., (2012) varied the payoffs and fixed the probabilities on the assumption that subjects get confused with varied probabilities. The above methods impose monotonic switching.

Mixed lotteries was used to examine the heterogeneity in risk attitudes (Tanaka, et al., 2010). Subjects’ risk attitudes are elicited using 3 series binary lotteries. This method has been applied in different contexts, yet it may not be easily comprehended among low educated farmers. Dohmen et al., (2011) argue that risk attitudes self-reported by individuals may produce an accurate prediction of risky behaviour. While this method may reveal preferences, it casts doubt on the possibility of capturing the diversity in risk attitudes.

The panel lotteries proposed by Sabater-Grande and Georgantzis (2002) (SGG thereafter) provide alternative to the one-dimensional, parameter-based lotteries. SGG elicit risk attitudes with a choice between positive outcome and null outcome. The lotteries are designed in a way that the topmost option is safest (100 per cent probability) while the last option is riskiest (10 per cent probability). The original SGG with four panels has been extended to four treatments with sixteen panels (García

---

1Charness et al. (2013) provide a comprehensive review on the risk preferences elicitation methods including the advantages and disadvantages of each method. Harrison and Rutstrom (2008) equally acknowledge the different ways of eliciting risk attitudes especially in the laboratory setting.
Gallego, et al., 2012). Thus, sixteen panels result in sixteen observations unlike the HL
where one observation comes from the switching row. The panel lotteries have many
advantages. It is easy to comprehend and 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). In addition, it does not
require parameter estimation and does not impose monotonic switching. Lastly, it’s bi-
dimensional in nature.

2.2 Determinants of Risk Attitudes
Risk aversion has been identified as one of the important economic factors affecting
financial and investment decisions and consequently the wealth accumulation of
individuals (Harrison, et al., 2002; Holt and Laury, 2002). Many attempts have been
made to examine the socio-economic factors affecting the risk attitudes of individuals in
both the developed and developing countries (Bocqueho, et al., 2014; Liebenehm and
Waibel, 2014). Research also indicates risk preference may reflect the climatic and
economic environment of individuals (Reardon and Taylor, 1996; Tanaka and Munro,
2014). Individuals who faced income uncertainty are highly averse to risk (Guiso and
Paiella, 2008). Bezabih and Sarr (2012) report the more risk averse a farmer is, the
higher the tendency to diversify his crops while Gollier and Pratt (1996) show variation
in income increases risk aversion. Furthermore, Tanaka and Munro (2014) reveal
farmers located in low rainfall areas show higher aversion to risk in Uganda.
Notwithstanding, no attempt has been made to examine the spatial dependence effects
in risk preferences. In brief, farmers living in the rural areas or remote villages may
show less willingness to risk taking or spatially related in decisions.

The results on the correlation between wealth/income and risk aversion have been
mixed. For example, a negative correlation is reported in Africa (Wik et al., 2004;
Yesuf, 2004; Yesuf and Bluffstone, 2009; Liebenehm and Waibel, 2014), and Asia
(Tanaka et al., 2010; Liu, 2013); although studies found no significant correlation in
India (Binswanger, 1980; Binswanger, 1981). Farm size may serve as proxy for income
in developing countries where most population’s livelihood largely depends on farming.
Farm size and risk aversion are found to be negatively correlated (Yesuf and Bluffstone,
2009) and positively related (Wik et al., 2004) in Ethiopia. However, some studies
found no significant relationship between these variables (Tanaka et al., 2010; Liu,
2013). Since farm size may serve as proxy for wealth or income in rural communities;
as small holder rice farmers may be less willing to take risky decisions, farm size and risk aversion may be negatively related.

We account for other socio-economic variables including education, age and gender. The direction of the relationship between education and risk aversion has been mixed. For instance, educated farmers are reportedly highly averse to risk taking in some developing countries (Tanaka et al., 2010; Nguyen, 2011; Ihli, Chiputwa, and Musshoff, 2013). Positive relationship is also reported between risk aversion and education in Southern Peru (Galarza, 2009); West Africa (Liebenehm and Waibel, 2014). 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. Research shows that younger farmers are less risk averse (Harrison et al., 2010; Nguyen, 2011) while others indicate older farmers are more risk averse (Tanaka et al., 2010; Liebenehm and Waibel, 2014). Age is expected to be positively related with experience in farming. Thus, older farmers may be more risk averse; show negative attitudes to risky decisions.

The debate on whether women are more risk averse relative to men is inconclusive in the literature. While some studies provide strong statistical evidence in support of males being less averse to risk, others reported otherwise. Specifically, the gender variation in risk attitude is highly debatable (Schubert, 2006). In finance and investment, for instance, women have been reported to be less financially tolerant and more financially risk averse relative to men (Charness and Gneezy, 2012; Bannier and Neubert, 2016; Fisher and Yao, 2017). On the other hand, Harris et al., (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 and Zawojska, 2015). In agricultural setting, women have been reported to be more risk averse than men (Liu, 2013; Ward and Singh, 2014; Tanaka and Munro, 2014). On the other hand, Harrison et al. (2010) indicate females are marginally less risk averse than men while Tanaka et al. (2010) did not find significant gender difference in risk attitudes. Males students have also been
reported as risk takers (García Gallego et al., 2012). The departing statement is that results on gender differences in risk attitudes have been mixed.

The marital status is not often controlled for in empirical studies. It is however 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 received less attention 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 and thus risk preference. Notwithstanding, there is no expectation on the direction of this variable. Like other variables, mixed results have been reported between risk aversion and family size. For example, Liebenehm and Waibel (2014) reported positive correlation in West Africa. Indeed, 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.

3.0 Methodology

This section covers the theoretical basis for the application of spatial autoregressive model (SAR). First, we define the spatial weights matrix, followed by SAR model. In addition, the source of data is presented.

3.1 The Spatial Autoregressive Model

This study adopts spatial autoregressive model (SAR) to account for spatial heterogeneity in decision making following the argument on the potential spatial correlation in agricultural variables (Benirschka and Binkley, 1994; Bockstael, 1996; Weiss, 1996). The nature of data and theoretical motivation are central to the application of spatial models (Anselin, 2002; LeSage and Pace, 2009). Spatial dependence is a tendency for random variables to correlate with one another due to geographical proximity. Therefore, in this study, spatial dependence is assumed proxies to latent variables such as climatic, geographical, ecological conditions and socio-economic characteristics. Put differently, the observed variation in DM risk preferences may be associated with infrastructure, cultural values, climatic conditions, etc. These
unobserved variables are accounted for through the neighbouring values of the decision makers’ willingness to risk taking index assuming the utility a DM derived from the risk lotteries in location \( i \) may be related with the utility derived by his neighbours in location \( j \).

Assuming a DM maximizes the payoff or expected payoff in the panel risk lotteries\(^2\), Equation (1) applies.

\[
\text{Max } U(y_i, y_j; X)
\]

Where \( U \) is a utility function, \( y_i \) represents the utility derived by a DM from the lottery in location \( i \); \( y_j \) implies the utility derived by the DM from the lottery in location \( j \); and \( X \) is the vector of farmers’ exogenous (and endogenous) socio-economic variables. Put differently, Equation (1) suggests utility derived by a DM in location \( i \) may be related with that derived by his neighbours in location \( j \), given farmers’ socio-economic factors (\( X \)). The maximization objective produces a spatial reaction function, \( y_i = F(y_{ij}, X) \) which forms the SAR (Equation 3) which captures the dependency between observational units (Anselin, 1988). The resulting data generating process (DGP) of Equation (4) reveals a global spill over because \((I - \rho W)^{-1}\) links \( y_i \) to all \( X \) through a multiplier, the spatial weights matrix (\( W \)). Power weights matrix is adopted in this study (Equation 2) following Areal \textit{et al.}, 2012\(^3\).

\[
W_{ij} = \exp\left(-d_{ij}^2/s^2\right)
\]

Where \( d_{ij} \) is the distance between DM in locations \( i \) and \( j \), estimated from the recorded GPS coordinates (latitude and longitude), \( s \) is the cut-off distance that tests the dependency limit between DM. Different cut-off distances were tested to determine the limit of spatial dependence in line with past studies (Roe \textit{et al.}, 2002; Kim \textit{et al.}, 2003; Areal \textit{et al.}, 2012).

In most cited studies, the weights matrix, \( W \) is row-standardized in which the sum of each row of the matrix equals one for easy interpretation (Case, 1992; Holloway \textit{et al.}, 2002; Läpple and Kelley, 2015). This is achieved by first converting the diagonal

\(^2\)Panel lotteries with four treatments are applied in this study. Detailed formulations are presented in the data sub-section. The treatments are defined as small gain one (\( SG_1 \)), small gain two (\( SG_2 \)), large gain one (\( LG_1 \)) and large gain two (\( LG_2 \)) to capture heterogeneity in risk preferences.

\(^3\)The distance based power weights function has many advantages. First, unlike the binary contiguity method, neighbours may be assigned with 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 distance (\( d \)) is less than the cut-off distance (\( s \)) but tend towards zero when the distance is greater than the cut-off distance. In addition, assuming equal number of neighbours may be inappropriate since the number of sampled farmers is not equal across all locations or agricultural zones.
elements of the weights matrix to zero, and secondly, the matrix with zero diagonal elements is divided by the vector matrix, the sum of each row. Thus, the final weights matrix, $W$ corresponds to averaging the neighbouring values. Row standardization may increase the influence of association 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 himself.

$$y_r = \rho W y_r + X\beta + \varepsilon \quad (3)$$

$$y_r = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \quad (4)$$

In Equations (3) and (4), $y_r$ is a column vector of willingness to risk taking (risk avoidance$^4$). This is a probability index corresponding to farmers’ choices in the panel lotteries. This ranges between 0.1 and 1 with an index of 1 indicating highly unwilling to risk taking. The $\rho$ measures the strength of spatial dependence or spatial correlation between risk preference of a DM and the adjusted-by-distance mean risk preference of his neighbours. $W$ is the $N \times N$ weights matrix (Equation 2). $X$ is $N \times K$ vector of exogenous explanatory variables. $\beta$ is a $K \times 1$ vectors of estimated parameters. $Wy_r$ is a spatial lag which is the weighted average of risk willingness in the neighbourhood locations. Lastly, $\rho Wy_r$ relates the utility derived by DM from the risk experiment with that derived by his neighbours. The disturbance term is assumed to be independently and identically distributed, $\varepsilon \sim N(0, I\sigma^2)$.

Expansion of $(I - \rho W)^{-1}$ as an infinite series results in Equation 5. The substitution of 5 into 3 gives Equation 6.

$$(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots \quad (5)$$

$$y_r = X\beta + \rho W X\beta + \rho^2 W^2 X\beta + \cdots + \varepsilon + \rho W \varepsilon + \rho^2 W^2 \varepsilon + \rho^3 W^3 \varepsilon + \cdots \quad (6)$$

The rho ($\rho$) is not restricted between -1 and 1 (LeSage, 2008); suggesting it cannot be linearly interpreted as a conventional correlation between decision makers’ willingness to risk taking ($y_r$) and the adjusted by distance willingness to risk taking ($Wy_r$). Since the DGP reflects the simultaneity of the spatial autoregressive process, it follows that from Equation 6, the expected value of DM willingness to risk taking, $y_r$ depends on

$^4$ Risk avoidance is used interchangeably with willingness to risk taking to refer to risk aversion because the parameter of the curvature of the utility function is not estimated. This is because risk preference has been previously defined as the extent to which individual is willing to take risky decisions (Charness et al., 2013).
$X\beta$ plus the neighbouring values of DM scaled by the dependence parameter, $\rho$. In other words, following Case (1992), DM willingness to risk taking is a function of his socio-economic characteristics, $X$, neighbours’ characteristics, $WX$, neighbours’, neighbours’ characteristics, $W^2X$ as so on, with the neighbourhood effects reducing with distance.

The potential endogenous problem of spatially lag variables (the correlation between the spatial lag ($Wy_r$) and the disturbance error, $\varepsilon$) is addressed using instrumental variable (IV) method. Application of IV requires a choice of an instrument which must satisfy two conditions. First, an instrument, $Z$ must be exogenous; not correlated with the error, $\varepsilon$. Mathematically, $Cov(Z, \varepsilon) = 0$. Second, an instrument, $Z$ must correlate with the endogenous explanatory variable, $Wy_r$ (an instrument must be relevant). That is, $Cov(Z, Wy_r) \neq 0$. According to Anselin (2001), the choice of an instrument for a spatial lag model depends on the conditional expectation of Equation 3. Thus, $X$ are exogenous variables and instruments while their spatial lags, $WX$ are useful set of instruments. If $Z$ represents set of instruments $(X, WX)$ and $P$ represents the endogenous variable (spatial lag or $Wy_r$) plus other exogenous variables ($X$), it follows that $Z$ may not correlate with the disturbance term, $\varepsilon$ but may correlate with the spatial lag. The order condition for identification is $Z \geq P$. Here, $P$ has the same column rank as $Z$ resulting in the IV estimator: $IV_2 = (Z'P)^{-1}Z'y_r$. In other words, it is assumed that other variables in our model, apart from the spatial lag are exogenous and therefore used as instruments plus the lag of education variable to identify the model. The descriptive statistics of the variables are presented in Table 1.

Three different tests are usually carried out to ascertain the relevance of the instruments, endogenous of an explanatory variable (spatial lag) and the validity of the instrument. The test of instrument relevance involves examining the significant of the Wald statistic. The Wu-Hausman test, a test of restriction is adopted to test the endogenous nature of the spatial lag variables. This test is important since IV may produce estimates with larger standard errors relative to OLS if the spatial lag variable is not endogenous. Thus, it is referred to as test of consistency of OLS. Third, the test of validity of instrument, often called Sargan test tests over-identification restriction. It is not usually reported for exactly identified model.
Table 1: Definition of the Variables used in the SAR Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
<th>Mean (SD)</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>SG1</td>
<td>Small gain one probability index</td>
<td>0.80 (0.15)</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>SG2</td>
<td>Small gain two probability index</td>
<td>0.60 (0.13)</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>LG1</td>
<td>Large gain one probability index</td>
<td>0.70 (0.15)</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>LG2</td>
<td>Large gain two probability index</td>
<td>0.60 (0.16)</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>Age</td>
<td>Age of farmers in years</td>
<td>47.00 (12.50)</td>
<td>20.00</td>
<td>80.00</td>
</tr>
<tr>
<td>Education</td>
<td>Years of formal schooling</td>
<td>4.60 (4.50)</td>
<td>0.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Male</td>
<td>1 if male, 0 if female</td>
<td>0.68</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Christians</td>
<td>1 if Christian, 0 otherwise</td>
<td>0.56</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Married</td>
<td>1 if married, 0 otherwise</td>
<td>0.94</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Household size</td>
<td>Numbers of household</td>
<td>6.00 (3.00)</td>
<td>1.00</td>
<td>21.00</td>
</tr>
<tr>
<td>Farm size</td>
<td>Rice farm area in hectare</td>
<td>1.90 (1.50)</td>
<td>0.20</td>
<td>16.00</td>
</tr>
<tr>
<td>Bad road</td>
<td>1 if farmers live in untarred, bad poorly accessible road areas, 0 otherwise</td>
<td>0.37</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Source: Authors’ Compilation, 2017

3.2 The Data

This study uses experimental and survey data collected from Ogun State Nigeria. The DM risk preferences were elicited using panel lotteries, Sabater-Grande and Georgantzis (2002) (SGG hereafter). The SGG has been applied in different context but we follow García Gallego et al., (2012) specifications with modifications to the nomenclatures. The panel lotteries have four treatments with four panels each (see Table 2 for the summary of the payoffs). One unique feature of the panel lottery is that each panel has ten separate lotteries from which DM chooses one option. The lotteries also allow the examination of the sensitivity of individual DM to the varied payoffs. The original SGG lottery is presented in Euro but this study presented the lotteries in Naira with an exchange rate of 1 Euro equals 225 Nigerian Naira.

For $SG_1$ (and other stakes), DM is faced with a probability ($P$) to win a payoff ($X$), or nothing otherwise. Both the payoffs and the probabilities vary across the rows in each panel. 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 we move from row (option) one to row (option) ten.

---

5 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 and Rutstrom, 2008; Charness et al., 2013). Our risk experiment belongs to lab experiment on the field. As earlier stressed, the term risk avoidance is introduced in place of risk aversion to refer to an individual farmer who is strongly less willing to take risky decision since the parameter of the curvature of the utility function is not estimated.
Panel Lotteries for Four Treatments (currency in Nigerian naira)

<table>
<thead>
<tr>
<th>Panel</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
<th>0.4</th>
<th>0.3</th>
<th>0.2</th>
<th>0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel 1</td>
<td>225</td>
<td>251</td>
<td>282</td>
<td>322</td>
<td>376</td>
<td>451</td>
<td>563</td>
<td>751</td>
<td>1,126</td>
</tr>
<tr>
<td>Panel 2</td>
<td>225</td>
<td>251</td>
<td>282</td>
<td>322</td>
<td>376</td>
<td>451</td>
<td>564</td>
<td>753</td>
<td>1,129</td>
</tr>
<tr>
<td>Panel 3</td>
<td>225</td>
<td>251</td>
<td>283</td>
<td>324</td>
<td>379</td>
<td>455</td>
<td>570</td>
<td>762</td>
<td>1,145</td>
</tr>
<tr>
<td>Panel 4</td>
<td>225</td>
<td>252</td>
<td>284</td>
<td>326</td>
<td>382</td>
<td>460</td>
<td>578</td>
<td>774</td>
<td>1,165</td>
</tr>
</tbody>
</table>

Decision makers who avoid taking 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). Thus avoidance of zero earning by not picking higher rewards implies risk aversion. In other words, a DM with a uniformly concave utility function may choose extreme options; sure choices (100 percent probability) while those with uniformly convex utility functions may choose the last or risky option (when the probability is 10 per cent). In addition, the lotteries expose subjects to the entire range of the probabilities and monetary rewards. In fact, a DM who avoid taking 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. The choice of one (1) out of the ten (10) options in each panel results in sixteen (16) observations per subject. The payoff associated with each probability in the SG1 treatment is constructed using Equation 7.

$$EV_{ij}(SG1) = P_{ij}X_{ij} = C + (1 - P_{ij})t_j, \quad X_{ij}(SG1) = \frac{c+(1 - P_{ij})t_j}{P_{ij}}$$ (7)
Where $EV_{ij}(SG1)$ is the expected value of $SG1$. $X_{ij}(SG1)$ is the payoff associated with ($SG1$). $i$ varies from 1 to 10 corresponding to the lottery rows; $j$ 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 fixed at $225$ for each of the panel in the $SG1$. This is the Naira equivalent of the 1 Euro used in the original SGG lottery. Therefore, all the four panels under $SG1$ begin with a sure amount (225) which is responsible for a linear large increment in the expected values down the vertical rows. $t_j = 0.1, 1, 5, 10$ is a panelspecific 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. Other treatments are calculated from the $SG_1$. $SG2$ is $SG1$ less 225 ($SG2 = SG1 – 225$) as defined in Equation 8. On the other hand, $LG1$ is a product of $SG1$ and a constant, $LG1 = SG1 * 100$ as defined in Equation 9. This is done to bring about large increment in the small gain one, to examine variation in subjects’ risk attitudes. Lastly, $LG2$ is expressed as $LG1$ less 22,500, $(LG2 = LG1 – 22,500)$ as illustrated in Equation 10.

\[
X_{ij}(SG2) = X_{ij}(SG1) - 225 \quad (8)
\]

\[
X_{ij}(LG1) = (X_{ij}(SG1)) \times 100 \quad (9)
\]

\[
X_{ij}(LG2) = (X_{ij}(LG1)) - 22,500 \quad (10)
\]

The average payoffs associated with $SG_1$ are 659.8, 661.2, 668.9 and 678.6 respectively for panels 1, 2, 3 and 4. The $SG_2$ have average payoffs of 434.8, 436.2, 443.9 and 453.6 for panels 1, 2, 3 and 4, respectively. On the other hand, the $LG_1$ are associated with the average payoffs of 65,980, 66,120, 66,890 and 67,860 respectively for panels 1, 2, 3 and 4 while $LG_2$ have average payoffs of 43,421, 43,595, 44,367 and 45,331 respectively for panels 1, 2, 3 and 4.

As at the time the experiment was conducted, the average rewards associated with $SG_1$ and $SG_2$ are below the average minimum farm labour wage rate of 1,500 (Nigerian naira). On the other hand, the rewards associated with the $LG_1$ and $LG_2$ are above the wage rate. Both rewards (small and large) reflect farmers’ 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). At another time, they make profit at margin or at equilibrium. More importantly, DM did not only show understanding about the payoffs
but also the consequences on farm investment decisions as well as day-to-day farm earnings. In short, the variation in average rewards aids the examination of the farmers’ risk attitudes as well as sensitivity to change in rewards.

Order of Presentation
A total number of 329 rice farmers were interviewed during the survey period from the main rice growing towns and villages in Ogun State Nigeria, with 328 fully completed questionnaires. All data were electronically collected using open data kit (ODK collect) with the aid of two smart android phones. This technology was used to record the GPS coordinates (latitude and longitude) of individual rice farmers. Prior to the commencement of the survey, 3 post-graduate students were trained as research assistants on the use of the technology for data collection. The training which lasted for approximately two hours was done in late February, 2016. The enumerators were also illustrated on how to fill the record sheets.

Rice farmers were individually interviewed by contacting them at different locations including homes and farms. The risk experiment was conducted first and lastly questions were asked on the socio-economic factors. Respondent’s mind was equally prepared on the need to use smart phones since most farmers were never familiar with such technology for data collection. Subjects were presented first with the panel lotteries starting from panel 1 to panel 4 of $SG_1$, then $SG_2$, $LG_1$ and $LG_2$, respectively. In addition, each DM was shown a bag containing 10 mixed blue and red balls which represent the winning and losing probability. Overall, no respondent indicated interest in withdrawing from the experiments and survey. For the payment, only one of the panels in each treatment determines the earnings. 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.

Instruction for small gain one and large gain one treatments
After welcoming rice farmers with brief explanation on the importance of the survey, experiments and the likely impact of the study, instructions for $SG_1$ are read to farmers as follows. “The following 4 panels have 10 options each, the winning prize in each panel is the amount of Naira shown under the heading “amount”. The blue balls represent the chances of winning; 10 blue balls imply hundred per cent chances (sure)
while 1 blue ball means ten per cent chance of winning a payoff. Conversely, the red balls imply loss. You earn nothing if you do not win the lottery. Your earning would be determined by tossing a four-sided die. That is, any of the number 1, 2, 3 or 4 occurring from a toss of four-sided die determines the payment panel. For instance, if you choose option 7 and one appears during die toss, you win ₦563 if any of the blue balls 1, 2, 3 or 4 is drawn from the bag and nothing otherwise”. Lastly, the record sheet was shown to the DM to make his choice. Similar instructions were given for $LG_1$.

**Instruction for small gain two and large gain two treatments**

The instructions for $SG_2$ are read as follow. “The following 4 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; 10 blue balls imply hundred per cent chance (sure) while 1 blue ball means ten per cent chance. Conversely, the red balls imply loss. If you do not win the lottery, you will earn nothing or lose the sure amount. Your earning would be determined by tossing a die; any of the number 1, 2, 3 or 4 occurring 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. Kindly choose one option from each panel”. Then, the record sheet is given to the DM to make a choice. Similar instruction applies for $LG_2$.

### 4.0 Results and Discussion

The results of the IV model are presented in Table 3 respectively for $SG_1$, $SG_2$, $LG_1$ and $LG_2$. The average values for each treatment are used in the analyses due to high correlation between the panels within each treatment. The results across treatments are highly comparable. The null hypotheses of weak instruments are rejected suggesting the instrumental variables used are strong enough to obtain consistent estimates. The null hypotheses of the consistency of OLS are equally rejected for all the risk models implying OLS may not yield consistent estimates (see Table 4; Appendix 2). In addition, the Wald statistic which is significantly different from zero for all the treatment models attest to the overall goodness of fit of the models. The results corresponding to the 60 km (limit of spatial dependence) are reported for $SG_1$, $SG_2$, $LG_1$ and $LG_2$, respectively in line with Roe et al., (2002) and Kim et al., (2003) who reported spatial dependence limit in their studies.

---

8 In addition to the smart phones, record sheets were shown to farmers to visualize the lotteries. An example of the record sheet is presented in Appendix 1.
Factors that significantly explain rice farmers' risk attitudes ($SG_1$) 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 $SG_2$. Similarly, age, farm size, gender, marital status, bad road and spatial dependence are the determining factors for attitudes toward $LG_1$ while attitudes toward $LG_2$ are significantly explained by age, gender, marital status, bad road and spatial dependence. Note that positive coefficients imply less willingness to risk taking (risk avoidance). The significant variables are presented next, with the main finding presented first.

**Table 3: The Effect of Spatial Dependence on Rice Farmers’ Risk Preferences**

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

Source: Data Analysis, 2017

N = 328
Diagnosis Statistics:
Weak instruments: $SG_1 = 30562.80$ (p < 2E-16), $SG_2 = 23621.55$ (p < 2E-16), $LG_1 = 25382.5$ (p < 2E-16), $LL = 18951.71$ (p < 2E-16)
OLS consistency: $SG_1 = 29.15$ (p = 1.31E-07), $SG_2 = 57.88$ (p = 3.16E-13), $LG_1 = 71.4$ (p = 1.05E-15), $LL = 36.59$ (p = 4.08E-09)
Wald Tests: $SG_1 = 787.9$ (p < 2.2E-16), $SG_2 = 753.4$ (p < 2.2E-16), $LG_1 = 738$ (< 2.2E-16), $LG_2 = 92.9$ (< 2.2E-16)

**Main Finding: Evidence of spatial dependency in risk preferences**

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 (Table 3). The spatial variables measure the correlation between the risk preferences of a farmer and adjusted by distance risk preference of his neighbours. Similar studies observed the spatial parameter, rho increases up to a particular distance and later decreases (Bell and
Bockstael, 2000; Areal et al., 2012). Similar pattern is observed with 60 km constituting the limit of spatial dependency in risk taking.

Recall that the expectation of willingness to risk taking (Equation 6) is a function of rice farmers’ 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, 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 and farm. Specifically, with respect to $SG_1$, willingness to risk taking is expected to decrease by 23 per cent ((average $Wy_r \cdot \text{coefficient})$, i.e $(144.09\times0.0016)$) as the distance increases from the centre of radius to 60 km. For $SG_2$, $LG_1$ and $LG_2$ the percentage decreases in willingness to risk taking associated with increasing distance are 22 per cent $(115.90\times0.0019)$, 26 per cent $(133.66\times0.0019)$ and 21 per cent $(137.13\times0.0019)$, respectively. Put differently, the farther the distance among the farmers the less likely they would behave in similar manner. This is a plausible finding as it reflects the geographical relationship among individual farmers. 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 and other geographical features.

The results are compared to related studies. Specifically, the finding agrees with Ward and Pede (2015) who found evidence of positive neighbourhood influence in hybrid rice adoption in Bangladesh. It is also in agreement 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 and Patnam, 2014; Wollni and Andersson, 2014; Ward and Pede, 2015; Tessema et al., 2016). As stressed by Läpple and Kelley (2015), similar patterns of adoption suggests may aid the diffusion of improved agricultural innovation. Indeed, farmers living closely to one another may share some degree of heterogeneity, have similar patterns of adoption or fall in the same income categories.

Informal communication and interaction are common phenomenon in both the urban and rural areas of most developing countries due largely to clustering. The revelation here shows rice farmers are related climatically, geographically, socially, culturally and
ecologically. In line with Tobler (1970), farmers living closely may behave similarly relative to distant ones. In this study, DM 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 as well as decisions relating to other investment opportunities. In short, risky behaviour of a farmer is positively and significantly related to her neighbours’ indicating a significant positive impact of neighbourhood influence in risky decision among sampled farmers.

The results also revealed 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 some empirical studies which reported a negative correlation between age and risk aversion (Tanaka et al., 2010; Liebenehm and Waibel, 2014). It is however contrary to some 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 old age. They may have strong desire and expectation for enjoyment, more willing to enjoy life goodies because death is inevitable. On the contrary, 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.

The results presented in Table 3 reveal farmers practising Christianity are less willing to take risky decisions or tend to avoid taking risky decisions with respect to small stakes compared to their counterparts practising other religions especially Islam. Past studies reported religious farmers as being risk averse (Liu, 2013; Liebenehm and Waibel, 2014). Although it may be difficult to infer how religious an individual is, the results indicate Christian farmers statistically and significantly behave differently to other farmers. Religion may drive farmers’ belief as well as influencing their level of gambling, day to day activities including investment decisions. Again, there is no clear distinction between the socio-economic attributes of Muslim and Christian farm households in most parts of Western Nigeria. Notwithstanding, the politics may contribute to the preferences revealed by the subjects and subsequently farm decisions.

The findings also indicate 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 the decision makers. This result is
consistent with the expectation and previously reported findings including Yesuf and Bluffstone (2009). There are two possible reasons for this finding. On one hand, small-scale farmers may require significant amount of 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 may be the case in the developing countries), it is safe to conclude the result agrees with previous findings reporting the tendency of less risk aversion among wealthier farmers (Wik et al., 2004; Yesuf, 2004; Yesuf and Bluffstone, 2009; Tanaka et al., 2010; Liu, 2013; Liebenehm and Waibel, 2014). In short, risk aversion is correlated with small farm size reflecting low income and poverty with negative effects on loan access.

The results as shown in Table 3 equally revealed 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 risk takers (García Gallego et al., 2012). It is also opposed to the previously expressed findings in the developing countries that female farmers are more averse to risk taking than their male counterparts (Liu, 2013; Ward and Singh, 2014; Tanaka and Munro, 2014). It is however in agreement with Harrison et al. (2010) who found a marginal difference between the risk aversion of male and female. More so, it disagrees with previously expressed view on the financial risk behaviour between male and female; women are less financially tolerant and more financially risk averse relative to men (Charness and Gneezy, 2012; Bannier and Neubert, 2016; Fisher and Yao, 2017). It also disagrees with Harris et al. (2006) who attributed the gender differences in perceptions about outcomes and risky decision making to low propensity to enjoyment 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 dive their desire and willingness towards taking risk irrespective of the size of the stake. Farmers’ attitudes
may also be viewed from the fact that male decision makers may have strong attachment to status quo or endowment effect. In other words, male farmers which constitute the larger proportion of the sample may not be willing to lose the ‘certain’ yield from the traditional technology or be less willing to pay a price for the ‘uncertain’ yet higher yield from the improved technology.

Furthermore, married farmers show less willingness to risk taking (avoid risky decisions) relative to single farmers. As noted earlier, 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 more family responsibility and financial commitments. Indeed, 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 residing in rural areas. It can therefore influence farmers’ behaviour or attitudes during the decision making processes. The results (all treatments) show farmers living in the un-tarred bad road network areas are less willing to take risky decisions compared to those living in more accessible road areas. This suggests 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 account for road variable in risk models as proxy for infrastructure. Furthermore, rural areas are often associated with poverty attributable to lack of access to social amenities and infrastructural facilities. This finding therefore aligns with past studies which found poor farmers more averse to risk taking (Lawrance, 1991; Wik et al., 2004; Yesuf and Bluffstone, 2009). Since roads are important development infrastructure, it may be safe to conclude that the current finding agrees Tanaka and Munro (2014) whose finding reveals farmers living in low rain areas show higher aversion to risk.
Access to good road may aid economic activities such as transportation of farm inputs and outputs. Thus, this finding aligns with those reported on the potential of higher risk aversion in income variability (Guiso and Paiella, 2008; Bezabih and 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. In summary, access to good road network significantly explains farmers’ risk aversion behaviour in the study area.

5.0 Concluding Remarks

This study provides insights into the role of spatial dependence in risky decision making among rice farmers (decision makers) in developing country using experimental and survey data from Nigeria. The results indicate some socio-economic factors including age, religion, gender and bad road networks significantly determine farmers’ risk avoidance attitudes. More importantly, decision makers’ risk attitudes is spatially dependent while farmers’ locations were found to significantly influence risk taking with farmers living in bad road network or remote areas avoid risky decisions relative to others living in more accessible road areas.

Emanating from the findings, the following policy options are recommended. First, heterogeneity in risky decision making should be given special consideration and attention in the design and formulation of policies and programmes that would improve the living conditions of farmers living in the 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 attitudes of farmers is important in persuading them to change their attitudes to undertaking risky investment decisions which may have significant and positive income effects. Second, improvement in the road networks in the rural areas is recommended. Rehabilitation of existing roads and construction of new roads are possibility in most rural areas. Good and accessible roads will not only increase farmers’ level of awareness or information on improved agricultural technology but also increase the chances of transporting and marketing farm produce. Furthermore, evidence of spatial dependency in risky decision making is a revelation of the existence of social interactions and learning effects among farmers. It shows the likelihood of similar behaviour among farmers living closely.
Such spatial dependency suggests geographical, ecological, climatic and socio-economic conditions may reflect in farmers’ risky decision making processes. It follows that policy makers, government and development partners alike should not only consider individual socio-demographic variables as the sole determining factors in risky decision making while formulating policy relating to risk management but also include the spatial aspects. Further research should focus on the identification of the unobserved drivers of farmers’ risky decisions.

6.0 Acknowledgement

This article is extracted from the PhD research studies conducted at the University of Reading, UK under the sponsorship of Olabisi Onabanjo University, Nigeria. The authors wish to express their sincere appreciation to these two Universities and more importantly, the Tertiary Education Trust Fund (TETFUND) of Nigeria for funding the project.

7.0 Conflict of Interest

There is no conflict of interest.

References


### Appendix 1: Record Sheet: SG1 Panel 1

<table>
<thead>
<tr>
<th>Row</th>
<th>Blue Balls = WIN, Red Balls = LOSE</th>
<th>Amount (£)</th>
<th>Choose 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10 blue balls win</td>
<td>225</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>9 blue balls win</td>
<td>251</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>8 blue balls win</td>
<td>282</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>7 blue balls win</td>
<td>322</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>6 blue balls win</td>
<td>376</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>5 blue balls win</td>
<td>451</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>4 blue balls win</td>
<td>563</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>3 blue balls win</td>
<td>751</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2 blue balls win</td>
<td>1,126</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1 blue ball win</td>
<td>2,251</td>
<td></td>
</tr>
</tbody>
</table>
Appendix 2: OLS Estimates

Table 4: Effects of Spatial Dependence on Risk attitudes (OLS estimates)

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

Diagnostic statistics:
SG1: \( R^2 = 0.95 \), Adjusted \( R^2 = 0.95 \), F-value = 700 (DF=9, 319) (\( p < 2.2E-16 \))
SG2: \( R^2 = 0.94 \), Adjusted \( R^2 = 0.94 \), F-value = 595 (DF=9,319) (\( p < 2.2E-16 \))
LG1: \( R^2 = 0.95 \), Adjusted \( R^2 = 0.94 \), F-value = 635 (DF = 9, 319) (\( p < 2.2E-16 \))
LG2: \( R^2 = 0.93 \), Adjusted \( R^2 = 0.92 \), F-value = 448 (DF = 9, 319) (\( p < 2.2E-16 \))

Number of observation (\( N = 328 \))

Source: Data Analysis, 2017