Essays On

The Effects of Risk and Ambiguity Attitudes On Production Choices Of Smallholder Fish Farmers In Southern Ghana

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Dedication

To my mom, Aba Monica,

and

all hardworking fish farmers in Ghana and beyond.

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Abstract

This thesis contains four empirical chapters which together contribute to behavioural economics in the area of fish production in a developing country context. The key thread connecting all the empirical studies is the behavioural characteristic of farmers (risk and ambiguity attitudes) elicited through incentivised field experiments and general survey questions.

The first empirical chapter seeks to answer the questions: *What is the risk attitude of a typical smallholder fish farmer in a developing country? Do risk attitudes of fish farmers remain stable across different elicitation methods and contexts of validation?* Risk attitude measures are known to be sensitive to the method of elicitation and context (Bauermeister and Mushoff, 2016). The purpose of this chapter is three-fold.

1. It elicits and compares the risk attitudes of within-subject sample of smallholder fish farmers in southern Ghana using three of the frontier methods used to elicit risk attitudes in the literature. The risk attitudes elicited from these methods are employed in the subsequent chapters of this thesis to investigate how risk preferences affect production efficiency and technology adoption.
2. It investigates how the risk attitude measures correlate with each other, and how they vary with farmer characteristics.
3. It assesses whether the risk attitude measures can predict farmer responses to questions on hypothetical economic choices.

The results show that a typical smallholder fish farmer is risk preferring in the gains-only lottery experiment, risk averse in the gains-and-losses lottery experiment but is risk neutral from the self-reported risk attitude scale. However, the risk attitude measures from the two lottery experiments are positively correlated, consistent with the assumption that the two experiments capture similar traits of the same farmer. This confirms that risk attitude measures are influenced by the method of elicitation and the context being examined. Some personal characteristics of the farmers influence their risk attitudes. Finally, while risk preferences from the lottery experiments failed to explain hypothetical economic choices, the stated risk preferences were significantly correlated with some hypothetical economic choices, perhaps due to hypothetical bias. These results indicate that care should be taken to tailor the elicitation of risk attitudes to contexts and domains farmers are familiar with.

The second empirical analysis attempts to answer the question: *to what extent does a fish farmer's risk attitude affect his/her level of economic efficiency?* This is predicated on the assumption that the types, levels and frequency of application of inputs could be influenced by the risk attitudes of farmers. Data on the units of inputs, outputs and prices are collated from the farmers in an earlier survey, and their risk attitudes obtained from the previous chapter are then juxtaposed on their production data. The economic efficiency of the farmers is assessed with both the Stochastic Frontier

Analysis (SFA) and the Corrected Ordinary Least Squares (COLS) techniques. While the former assumes that all deviations from the cost frontier are due to farmer-specific factors (including risk attitudes) and stochastic factors, the latter, a deterministic procedure, attributes all deviations from the frontier to farmer-specific factors. The evidence from this chapter suggests that over 80% of the total deviation from the cost frontier results from stochastic factors beyond the control of the farmers. It is also found that risk attitudes play no significant role in the economic efficiency of fish production in the study area. Based on the findings, it is concluded that stochastic factors, such as government policies, may have a greater impact on economic efficiency rather than risk attitudes of farmers.

The third empirical study assesses how risk attitudes of fish farmers affect the speed of technology adoption; adoption decisions are modelled with duration models. This study focuses on the adoption of Floating Cages, Extruded Feed and Akosombo Strain of Tilapia (AST) technologies in the fish farming sector in southern Ghana. Contrary to most existing literature on speed of adoption of technologies (e.g. Liu, 2013), the results from this chapter show that risk averse farmers have a higher proclivity to adopt the AST, Extruded Feed and Floating Cage technologies at a point in time. This novel outcome is due to the nature of the technologies in question, as perceived by the farmers. Liu's (2013) study, for instance, focuses on the adoption of cotton seeds modified genetically with *Bacillus thuringiensis* (Bt) bacteria, which enables cotton plants to produce phytotoxins to kill pests. The subjective risks posed by these phytotoxins to the farmers themselves may be an additional source of uncertainty and a likely reason for the delayed adoption by risk averse farmers. However, in this chapter, even though the AST is also genetically modified, it produces no toxins and yet it is more disease-resistant than the local breeds, therefore it may be perceived by the farmers as risk-reducing and hence it may not be surprising that risk averse farmers adopt this technology earlier.

In the final empirical study, attention is on how ambiguity attitudes affect the farming decisions of smallholder fish farmers, using the speed of adopting the AST technology as an example of such decisions. The speed of technology adoption is analysed with the hazard/survival model. Additionally, this chapter introduces and interacts the number of previous adopters in the same village with ambiguity attitude as a better test of the effect of ambiguity aversion on farmers' decisions. Where a farmer cannot predict with certainty the yield to be obtained from the new technology, an ambiguity averse farmer is expected to adopt the technology late. Ambiguity attitudes are elicited with Ellsberg's (1961) two-colour urn experiment. The results from this chapter show that the average fish farmer is ambiguity averse. However, risk aversion, but not ambiguity aversion, has a significant effect on the speed of adopting the AST technology in the study area, confirming the robustness of the finding in the previous chapter. I also find that the speed of adopting this technology increases with the number of prior adopters in the same village. The lack of any significant impact of ambiguity attitudes in determining the speed of adopting this technology suggests that there are other important determinants of adopting this technology, rather than lack of information about it, that affect other technology adoption decisions.

Overall, this thesis demonstrates and presents the elicitation of risk and ambiguity preferences outside the usual laboratory setting by engaging fish farmers in a field experiment involving real cash incentives, as well as field surveys. The experiments and methods employed are at the frontier of research in the field of development economics. The results of the analysis presented in this thesis indicate that that risk preferences are sensitive to the method of elicitation, as well as the context or domain in which it is elicited. While contrary to findings from other studies, risk averse farmers are more prone to adopt improved fish farming technologies earlier than farmers who are not risk averse. This conclusion is plausible because the technologies may be perceived as risk-reducing by the farmers. This outcome remains robust when ambiguity aversion is introduced into the analysis of the technology adoption decision. Therefore, research on farmer production choices should take their risk attitudes into account, and such risk attitude measures should be elicited in a manner that is compatible with the context of operation of the farmers.

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Chapter 1

Introduction

Smallholder farmers in developing countries are exposed to many and diverse risks, such as floods, droughts, pest attacks, illnesses and price fluctuations. In the absence of well-developed credit and insurance markets, they are not able to shift these risks to a third party. Consequently, they are likely to make farming choices that minimize their risk exposure, often at the expense of productive efficiency (Morduch, 1995).

Most developing countries face food insecurity issues, and achievement of food security has been a developmental concern over the years (Yaro, 2013). These concerns have arisen from the inability of agricultural production systems in developing countries to supply the food necessary to meet demands. This situation is made worse by rapid population growth and to some extent income growth (Ahsanuzzaman, 2014). Evidence also suggests that risks and risk attitudes of farmers negatively impact the production and supply of food (Chavas and Holt, 1996). Farmers may be less willing to undertake activities and investments that may have higher expected outcomes, but which are inherently risky or ambiguous. For instance, in some cases farmers use less production inputs than they should if they were to maximize expected profits, due to risk aversion (Yesuf, et. al., 2007).

When farmers are exposed to similar risks and ambiguities, differences may be observed in the performances of the farmers. These differences in performances may be attributable to the differences in the attitudes of the farmers to these uncertainties (Ullah et. al., 2016). This is because farmers exhibit heterogeneous preferences towards risks and ambiguities. These differences in preferences affect farmers' utility functions as well as their value functions, which subsequently may result in sub-optimal investment and/or production decisions (Ahsanuzzaman, 2014). Thus, to understand economic behaviour of farmers, it is imperative to assess their individual risk and ambiguity preferences (Reynaud and Couture, 2012). However, the challenge faced by researchers investigating unobservable traits such as risk and ambiguity attitudes is the measurement of these traits.

To minimize the effects of climate change on smallholder farmers and to ensure food security, the use of improved agricultural technology is seen as a plausible policy tool not only to enhance productivity but also to meet the excess demand (Ahsanuzzaman, 2014). Therefore, coupled with appropriate institutional and behavioural changes, adoption of improved technologies not only improves the agricultural sector, but also potentially reduces poverty, and improves the livelihoods of farm households through increased productivity (Barrett and Carter, 2010; Bandiera and Rasul, 2006).

Despite the vast expected benefits such as increased yield, pests and disease-resistance from the adoption of improved technologies, it is puzzling that some farmers often fail to adopt or adopt these technologies at a slower rate than may be expected (Suri, 2011). Among the many factors known to influence the decision-making processes of farmers, such as the adoption of technologies, are their attitudes to risk and ambiguity (Binswanger, 1980; Feder et. al., 1985; Liu, 2013; Ward and Singh, 2014)[1].

This thesis is a collection of four empirical studies that measure the risk and ambiguity attitudes and how these behavioural attributes affect farming choices of 120 smallholder fish farmers in Ghana, using both experimental and survey data. The elicitations of risk and ambiguity attitudes are carried out with methods at the frontier of current research.

The first essay, titled *"Risk Attitudes of Smallholder Fish Farmers in Ghana: A Comparison of Multiple Elicitation Methods"*, provides a description of the elicitation and measurement

[1] Other factors include education, information constraints, social networks and social learning, credit constraints etc. (Ahsanuzzaman, 2014).

of the risk attitudes of the smallholder fish farmers. The challenge with the measurement of risk attitudes is that risk attitudes are known to be sensitive to the method of estimation and the context (Bauermeister and Mushoff, 2016; Ihli et. al., 2013; Reynaud and Couture, 2012). Therefore, this study employs three different procedures to investigate the risk attitudes of farmers: lotteries modelled after Brick, Visser and Burns (BVB) (2012); lotteries modelled after Tanaka, Nguyen and Camerer (TCN) (2010) and for comparative purposes, self-reported risk attitude (SRRA) measures on an 11-point scale, following Dohmen et. al., (2011). These methods are at the frontier of modern research in the development economics literature. The BVB is a gains-only lottery, while the TCN is a gains-and-losses lottery. The two lottery experiments are employed to assess whether, and if so how the attitudes of farmers to risks are affected in the presence of gains and losses. Together, the two lottery experiments capture the attributes that influence the choices of the farmers as pertains to their real operations: fish farmers encounter gains and losses in their business. In conducting these experiments, it is also acknowledged that farmers could approach the experiments as mere games and therefore their choices may not reflect their attitudes in real operations. Therefore, farmers were incentivised to reveal their real preferences for risks with real monetary payoffs (Holt and Laury, 2002). After obtaining the risk attitude measures, I assess their correlation with hypothetical economic decisions of the farmers. The study shows that the risk attitude classification of a typical farmer obtained from the three elicitation methods was different. For instance, while the BVB classifies a typical fish farmer as risk preferring, the TCN classifies a typical fish farmer as risk averse, but the two measures are positively and highly correlated, so they may be capturing the same trait of the typical farmer. The SRRA measure places the typical fish farmer about the middle of the scale. These findings confirm the findings of some research in the extant literature that risk attitude classification of an individual may vary subject to the method of elicitation and context (e.g. Bauermeister and Mushoff, 2016).

These varied outcomes from this present study may have resulted from the relatively small number of fish farmers which may not necessarily be representative of the entire population of fish farmers in the study area. Therefore, in the elicitation of risk attitudes, a larger number and representative sample of farmers should be recruited and the context of their operation should be taken into consideration.

The second empirical chapter-*"Effect of Risk Attitudes on Economic Efficiency of Smallholder Fish Farmers in Ghana"*- focuses on the estimation of the economic efficiency of fish production and how this is affected by the risk attitudes of the farmers. This chapter uses data from a collaborative survey carried out by researchers from the University of Ghana. Their data was collected from December, 2013 to January, 2014 through a field survey. This included data on the inputs and output produced by the farmers in the previous fish production season. From their survey sample of 380 fish farmers, this study subsampled 120 and engaged them in the experiments outlined in the previous chapter to elicit their risk attitudes. With the production data obtained from the previous survey, this chapter estimates the economic efficiency of the farmers using both the Stochastic Frontier Analysis (SFA), a parametric procedure, and the Corrected Ordinary Least Squares (COLS), a deterministic procedure. It then assesses if, and to what extent the observed differences among the farmers in terms of their economic efficiencies are explained by the differences in their risk attitudes. As mentioned earlier, the differences in the risk attitudes of farmers affect their utility and value functions, which in turn could lead to production choices that may not be economically optimal. Therefore, it is imperative to include risk attitudes in the analysis of the economic performance of smallholder fish farmers as this may account for some of the differences in the outputs obtained by the farmers. Generally, risk averse farmers are more likely to make suboptimal choices under uncertainty, because of the aversion to risks. For instance, a risk averse farmer may feed his fish more frequently and with more feed to avoid low market sizes, but this decision could also result in higher costs and therefore less profits. The results of this chapter show that risk attitudes play no significant role in the economic efficiency of the farmers in the study area. The reasons for this finding could be due to the relatively small number of farmers interviewed, and also the likelihood of recall bias among some of the farmers. The study suggests that the differences in the economic efficiency of smallholder fish farmers in the study area are influenced more by stochastic factors, such as weather conditions and government policies, rather than the risk attitudes of the farmers.

The third empirical essay is titled *"Effect of Risk Attitudes on the Speed of Adopting Aquaculture Technologies in Ghana".* Technology adoption has been advocated by many researchers and policy makers as an important tool to improve the productivity and livelihood of farmers (Liu, 2013; Barham et. al., 2014). In the analysis of technology adoption decisions, many researchers do not consider the effect of time on the adoption decision and thus reckon the adoption decision as a binary variable, thereby binary model such as probit and logit are normally used in the estimation (e.g. Polson and Spencer, 1991). However, technology adoption decision is dynamic and time-varying, as are some of the determinants (Ahsanuzzaman, 2014; Lapple, 2010). Therefore, static and binary models which do not account for the effect of time on the adoption decision may produce misleading results. The duration/hazard/survival models are alternative models for analysing the adoption of technologies. These models consider the time it takes a farmer to adopt a technology in the estimation of the adoption decision (Burton et. al., 2003). For many studies that employ the survival models, a single technology is normally studied (e.g. Liu, 2013). Farmers generally make decisions regarding multiple technologies at a time and the prior adoption of one technology may enhance or delay the adoption of other technologies. For instance, if technologies are complementary, farmers may adopt the technologies together, while a substitute technology may not be adopted. Therefore, modelling the decision of farmers to adopt multiple technologies may give more accurate results (Byerlee and Hesse de Polanco, 1986). In this study, the duration models are employed to assess the determinants of the speed of adopting three improved technologies by including the risk attitude measures obtained in the second empirical chapter in the estimation[2]. The rationale behind the use of three technologies is that one is able to assess whether there is complementary or substitutability among some technologies, and if these relationships influence the adoption decision. The key hypotheses being tested in this chapter are that risk aversion slows the speed of technology adoption, and some technologies are substitutes. The results of the analysis show that risk attitudes matter significantly in the speed of technology adoption. An interesting finding emerging from this chapter is that risk averse farmers have a higher probability to adopt each of the three technologies at a point in time, *ceteris paribus*. Even though it may seem counterintuitive, the evidence suggests that the three technologies may be risk-reducing; thereby risk averse farmers have the incentive to adopt these technologies earlier as they reduce their exposure to risks. Also, this study indicates substitution between some of the technologies, and therefore by adopting one of the technologies, a farmer may be less likely to adopt the other technology speedily.

The fourth empirical chapter, titled *"Effect of Ambiguity Attitudes on the Adoption of Technology: The Case of Smallholder Fish Farmers in Ghana"* examines the effect of ambiguity attitudes on the decision-making of fish farmers, citing the adoption of technology as an example of such a choice. This chapter explores how ambiguity aversion influences the decision to adapt to climate change, take up index insurance, invest in financial services and adopt a technology. Focussing on the adoption of technology, this chapter is premised on the

[2] [2] These are the Akosombo Strain of Tilapia (AST), extruded feed and Floating Cage technologies.

assertion that newer technologies present more uncertainties regarding the distribution of output as well as prices than existing technologies. Thus, since newer technologies contain an unknown risk (or ambiguity), there is a possibility that ambiguity attitudes may play a role in the decision to adopt technologies (e.g. Ahsanuzzaman, 2014; Barham et. al., 2014). An ambiguity averse farmer is expected to delay the adoption of a new technology. In addition to ambiguity attitudes, the adoption decision of a farmer may be influenced by the behaviour or decisions of other farmers, especially those within the same village. This may be explained by the fact that farmers learn from other farmers (Bandiera and Rasul, 2006), and also the cost of information acquisition is reduced as more farmers adopt the technology. Therefore, for two identical fish farmers, the farmer who has more prior adopters of the technology in the same village is more likely to adopt the technology earlier. Hence in this study, the number of prior adopters in the same village is included as a variable to capture the effect of the influence other farmers have on the speed of adopting the technology. Following Keller et. al., (2007), this study measures ambiguity preferences as the differences in the willingness to pay (WTP) for an ambiguous lottery and the WTP for a risky lottery, using the Ellsberg's (1961) two-colour urn experiment in a field setting. Additionally, this chapter examines how other socio-economic characteristics of farmers affect their ambiguity attitudes. The technology studied in this chapter is the Akosombo Strain of Tilapia, a genetically modified breed that is fast-growing and resistant to diseases. The adoption decision is analysed with the hazard/survival model.

The results from this chapter show that the average fish farmer in the study area is ambiguity averse. Also, some personal characteristics including age, marital status and educational status affect the ambiguity attitude of the farmers. This study finds no significant effect of ambiguity aversion on the speed of technology adoption. This may be due to the fact that for a given farmer, ambiguity is eliminated or diminished if there is at least one prior adopter of the technology in the same village. The number of prior adopters in the same village is also found to be positively and significantly correlated with the speed of technology adoption. Upon inclusion of risk attitudes in the estimation in this chapter, risk aversion, but not ambiguity aversion, is significant in explaining the speed of technology adoption. This finding confirms the robustness of risk attitudes in influencing technology adoption decisions reported in the previous chapter.

Based on the key findings of the four empirical essays discussed above, this thesis makes two contributions to broaden the understanding of how risk and ambiguity attitudes of smallholder fish farmers affect their production choices in a developing country.

The first contribution is the measurement of unobservable behavioural characteristics (risk and ambiguity attitudes) of fish farmers in a developing country setting, obtained with two experimental lotteries and a survey instrument. Evidence from the extant literature suggests that risk attitudes are sensitive to the method of elicitation and context (Reynaud and Couture, 2012; Ihli et. al., 2013, Bauermeister and Mushoff, 2016). This chapter provides the characterisation of the measurements of the risk attitudes of the fish famers. This is achieved by engaging farmers to make choices in multiple price binary lotteries, comprising both gains and losses, in order for the farmers to reveal their risk attitudes. Also, a general survey question is asked for farmers to report their own subjective risk attitudes. Furthermore, I compute the ambiguity preferences of the farmers using a modified version of Ellsberg's two-colour urn experiment. To the best of my knowledge, this is the first study to elicit the risk and ambiguity preferences of smallholder fish farmers in Ghana through incentivised field experiments and surveys. The insights thus gained from this investigation will help policy makers in developing countries in planning interventions in the fish farming sector, such as the introduction of new technologies and insurance facilities, taking into account the risk preferences of the target recipients. This could help improve the rate of technology adoption and fish farming outcomes, improve the wellbeing of smallholder fish farmers and improve food security in the long run.

The second contribution of this thesis relates to further investigation of the field of farmed fish production. While considerable number of studies have been carried out on technology adoption in crop production (Barham et. al., 2014; Liu, 2013, Ahsanuzzaman, 2014), not much has been done specifically in the field of farmed fish production. One study that looks at fisheries in a similar geographical setting to this present study is by Brick et. al. (2012). They study the effect of risk attitudes on the compliance with fishing regulations in South Africa among fishers. Even though their study is conducted in an African setting, it focuses on fishers, but not fish farmers. The present investigation differs from their previous study as it focuses on the decisions of smallholder fish farmers. Fish farming entails higher economic risks than fishing in the sea. Fishers do not invest financial resources to stock the oceans or other wild water bodies with fingerlings and tend them till harvest, like fish farmers, but rather, fishers harvest fish from the wild and therefore do not incur the same level of economic risks. This makes the field of farmed fish production a befitting setting to assess how the attitudes to risks and ambiguity affect the production choices of fish farmers. This investigation is important especially because fish farming has been seen as a vital alternative to the dwindling catch from the marine fisheries (FAO, 2012).

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Chapter 2

Risk attitudes of smallholder fish farmers in Ghana: a comparison of multiple elicitation methods

2.1 Introduction

That risks and risk attitudes influence economic choices and decisions of people is a well-established fact in the economic literature, and many studies have been carried out since Binswanger's (1980) seminal paper to measure risk attitudes. People respond to risks and ambiguities differently, and these differences are attributable to attitudes to risk and ambiguities (Ihli et. al., 2013). Thus, to understand economic behaviour of farmers, it is imperative to assess their individual risk attitudes (Reynaud and Couture, 2012). Such an understanding requires the measurement of risk attitudes.

In recent years much effort has gone into this endeavour; and there is extensive literature especially on the use of experimental methods to elicit risk attitudes across the world (Ihli et. al., 2013). Farmers are generally known to be risk averse (Binswanger, 1980; Liu, 2013). However, the emerging summary from the use of different elicitation methods, such as lottery choice tasks, hypothetical gambles, self-reported assessments, and willingness to pay, and from both the developing and developed world contexts, is that risk attitudes of the same individual may not be consistent across different elicitation methods and contexts (Reynaud and Couture, 2012, Ihli et. al., 2013, Bauermeister and Mushoff, 2016). The differences in risk attitudes observed for the same individual across different elicitation methods is sometimes due to the differences in the complexity of the methods of elicitation and the lack of understanding of tasks by the participants in an experimental setting. Furthermore, the context of the experiments is also known to confound the outcomes of individual risk attitudes.

While this chapter does not attempt to find which method is the best for capturing the risk attitudes of fish farmers in Ghana, it rather provides a characterisation of the measurements of risk preferences of the farmers. This purpose of this chapter is three-fold. First, it elicits and compares the risk attitudes of within-subject sample of smallholder fish farmers in southern Ghana using three of the frontier methods used to elicit risk attitudes in the literature. These are the modified version of the Brick-Visser-Burns (BVB) (2012) multiple price lottery, the Tanaka-Camerer-Nguyen (TCN) (2010) multiple price lottery and a general self-reported risk attitude (SRRA) measure following Dohmen et. al. (2011), on an 11-point scale. The risk attitudes elicited from these methods are employed in the subsequent chapters of this thesis to investigate how risk preferences affect production efficiency and technology adoption.

Secondly, it investigates how the risk attitude measures correlate with each other, and how they vary with farmer characteristics. Finally, it assesses whether the risk attitude measures can predict farmer responses to questions on hypothetical economic choices.

The BVB lottery is modelled after the seminal work by Holt and Laury (2002) (HL) multiple price lotteries where participants make a choice between two lottery pairs. However, the BVB differs from the HL in that instead of varying the probabilities and fixing payoffs, it changes the payoffs but keeps the probabilities fixed. This is premised on the assumption that participants find it relatively easier to comprehend changing payoffs than changing probabilities (Brick et. al., 2012). The BVB lottery is a gains-only lottery and there is no likelihood of losing any amount in the experiment. The TCN lottery is very similar to the BVB but instead of being gains-only, it is a mixed lottery consisting of both gains and losses. Introduction of this lottery in the experiment is meant to capture whether farmers react differently in the context of gains-only and mixed frames, where losses are involved. The final method of eliciting risk attitudes, the SRRA, is a general question meant to capture the subjective willingness to take risk on a scale of 0 to 10, where 0 indicates unwillingness to take risks and 10 indicates full preparedness to take risks (Dohmen et. al, 2011).

It is found that the risk attitudes obtained from the hypothetical general self-reported risk attitude measure is not significantly correlated with the risk attitude measures obtained from the two incentivised lottery experiments. The results also show that the average farmer is risk averse according to the BVB but risk loving in the TCN lotteries. However, the risk attitudes from the two lotteries (BVB and TCN) are positively and highly significantly correlated. The average self-reported risk attitude score is 5.4, which is very close to the middle of the SRRA scale. These varied outcomes show clearly that the risk attitude of a farmer may be different depending on the method of risk attitude elicitation employed and context.

In validating the explanatory powers of the risk attitude measures, two hypothetical economic decisions of the farmers are assessed with their risk attitude measures. The results show that the SRRA is significantly correlated with one of the hypothetical investment choices of the farmers. However, I find no significant correlation between the risk attitude measures from the BVB and TCN lottery experiments and either hypothetical economic choice. This outcome may be explained by the fact that both the SRRA and the investment choices are stated measures and may suffer from hypothetical bias. Thus, this may be a plausible reason why they vary together.

The rest of this chapter is arranged as follows. Section 2.2 provides an overview of the related literature and hypotheses, section 2.3 summarises the experimental design, and section 2.4 describes the estimation of the parameters in the TCN lottery. The data collection process, results, summary and discussion, and the conclusion are discussed in that order in sections 2.6, 2.7 and 2.8.

2.2 Overview of relevant empirical literature and hypotheses

This study attempts to obtain a measure of the risk attitudes of smallholder fish farmers in southern Ghana, and to assess the predictive power of these measures in economic situations. This process begins with the identification of an appropriate method to elicit the risk attitude of the farmers. This section explores two major strands of recent literature on methods of eliciting risk attitudes: using surveys and experimental techniques.

2.2.1 Overview of the use of questionnaires to elicit risk attitudes

Questionnaires have been used as a method to elicit the self-reported risk preferences of subjects in different settings. Normally, subjects are asked a general question or a series of questions and then asked to rate themselves on a predefined scale. This approach assumes that there is a single stable risk preference for each person that underlies their behaviour in all domains of life.

Weber et. al. (2002) used a psychometric scale to study risk preferences of individuals and their decisions in the financial, health/safety, recreational, ethical and social domains. The questionnaire consisted of a total of 101 items in five domains of risk. The subjects in this study were 560 undergraduate students from the Ohio State University (307 women and 253 men), aged between 16 and 46, with a median age of 18. Respondents evaluated the likelihood of engaging in risky behaviours on a five-point rating scale ranging from 1 ('extremely unlikely') to 5 ('extremely likely'). The results from this study showed that the degree of risk taking was highly domain-specific, i.e. respondents were not consistently risk-averse or consistently risk seeking across all content domains. Women appeared to be more risk-averse in all domains except social risk.

Hanoch et. al. (2006) used a German version of the domain-specific risk-taking (DOSPERT) scale (DOSPERT-G) to show that risk taking is domain-specific. They recruited individuals who were known to be risk takers or risk avoiders in one domain, hence they examined not only domain specific behaviours, but also employed ‘‘domain-specific’’ participants, in order to test the validity of the DOSPERT scale (Weber et. al., 2002). The DOSPERT-G contains 8 items each for recreational, health, social, and ethical risks and 4 items each for the gambling and investment domains. Decisions were made on 5-point Likert scales, where higher values indicated greater likelihood of engaging in the behaviour. Their results showed that individuals who exhibit high levels of risk-taking behaviour in one context (e.g., bungee jumpers taking recreational risks) can exhibit moderate levels in other risky domains (e.g., financial).

Dohmen et. al. (2011) examined the association between risk preferences solicited through a general risk attitude question and field experiments and analysed how well they predicted individual behaviour of a large German population. The authors found a significant positive correlation between the general risk attitude question and the risk attitude obtained through the field experiment with real monetary stakes. Although the general risk attitude question had some predictive power across some domains, the best predictor of behaviour in a particular domain was the corresponding domain-specific measure elicited through a method similar to the DOSPERT scale.

The use of questionnaires to elicit risk attitudes has its pros and cons, for instance they are simple to understand, but they are mostly non-incentivised. Therefore it is debatable whether the elicited risk preferences reflect an individual’s true attitudes toward risk, particularly in the domain of financial decision making (Weber et. al.,2002).

2.2.2 Overview of experiments to elicit risk attitudes in developing countries

Some of the earliest studies about risk aversion among farmers in developing country context were by Binswanger (1980). In this study, attitudes to risk were elicited from 140 households in India using an interview method eliciting certainty equivalents and an experimental gambling approach with real payoffs which, at their maximum, exceeded monthly incomes of unskilled labourers. The outcome from this study showed no significant correlation between the risk attitudes obtained with the two measures of risk attitudes. In the experimental set up, outcome probabilities were fixed, but the payoffs of the lotteries were varied. Further analysis from the experimental gambling approach showed that a typical respondent was moderately risk averse at high payoff levels. The study also indicated that risk aversion is positively correlated with certain socio-economic characteristics, such as age, but not significantly affected by wealth.

Tanaka, Camerer and Nguyen (2010) measure risk attitudes and time preferences in Vietnamese villages using a mix of gain-only and gain-and-loss lotteries and also investigated how these attitudes and preferences are influenced by the socio-economic characteristics of respondents. This study used multiple price lotteries (MPL) in which the lottery payoffs are fixed in each choice task, and the outcome probabilities are varied. However, it differs from previous studies by ensuring monotonic switching among respondents during the experiment. They reported that the mean village income is affected by the risk and time preferences of the respondents. Also, they indicated that the rural poor are more averse to losses than to uncertainties.

Most of the previous studies cited measure and sometimes compare the risk attitudes of respondents with different elicitation methods as well as the determinants of the estimated risk attitude measures. However, Brick et. al. (2012) go beyond these assessments and not only assess risk attitudes and their determinants but analyse the compliance of fishers in South Africa, using the estimated risk attitudes as explanatory variable. They found compliance with fisheries regulation to be significantly correlated with risk attitudes.

Furthermore, socio-economic characteristics such as gender and age were found to influence the risk attitudes of the respondents as well as compliance with regulations.

2.2.3 Summary of the literature reviewed

Through the years, risk attitudes have been elicited with hypothetical questions or through experimental procedures, especially multiple price lotteries. There is mixed evidence regarding the validity of either method of risk elicitation in every situation, but there seems to be a general consensus that a typical farmer is risk averse (e.g. Liu, 2013). For instance, Menapace et. al. (2016) test the validity of different mechanisms of eliciting the risk attitudes of farmers, varying the mechanisms in terms of simplicity, context and payoff scales. They assess the relative ability of each mechanism to explain actual economic choices of the farmers and conclude that risk attitudes of the farmers are not consistent across all elicitation methods. Having said this, it is imperative to incorporate the attitudes to risk of fish farmers in the analysis of their economic decisions and choices; because risk attitudes influence the utility and value functions of farmers and therefore their economic decisions. To do this, however, would require an appropriate measure of the risk attitudes of risk attitudes.

This study follows Brick et. al., (2012). They incorporate risk attitudes into the analysis of the choice to comply with fishing regulations in South Africa. This present study adapts their gains-only multiple price lottery experiment, assuming the constant relative risk attitude (CRRA) utility function within the expected utility framework. However, to date this study differs from the Brick et. al., (2012) lottery experiment in some aspects: the respondents and contexts are different. The present investigation focuses on smallholder fish farmers in southern Ghana, not fishers in South Africa. Fish farming is different from fishing from open water bodies in terms of the economic and financial risks involved: fish farmers invest money in constructing ponds or cages, purchase and stock fingerlings, and feed them till they are ready for harvest. The variability in input and output prices of farmed fish puts fish farmers at more economic risks than fishers who only go to fish in the open ocean without investing financially in the stock of fish.

Finally, this current study differs from the previous study by eliciting the risk attitudes of fish farmers not only with the multiple price lottery employed by Brick et. al., (2012) but by also exploring an alternative measure of risk attitudes following Dohmen et. al. (2011) and Tanaka et. al. (2010).

2.2.4 Hypotheses

In recent years there has been a vast increase in the number of studies on risk preferences, as well as the different elicitation methods of risk attitudes; only a few studies compare risk attitudes of the same sample with different elicitation methods. In verity, the number of such studies is even scarcer in the case of smallholder farmers in developing countries, like Ghana.

It is evident from the literature reviewed that the risk attitudes of individuals could vary depending on the method of elicitation and the context. However, no study has been carried out to assess the risk preferences of farmers in the developing world using an adaptation of the BVB lottery which is a gains-only lottery, the TCN lottery which is a gains-and-losses lottery methodology and the general self-reported risk attitude question proposed by Dohmen et. al. (2011). To our knowledge this study is the first to attempt this in Ghana.

Following Ihli et. al., (2013), the consistency of risk attitude measures across the three distinct methods of elicitation are analysed. Thus, the first hypothesis of this study is:

1. BVB vs TCN vs. SRRA*: There are no significant correlations among the risk attitude determined by the self-reported risk score, the BVB and TCN lotteries.*

The extant literature (e.g. Bauermeister and Mushoff, 2016) indicates that risk attitude measures are not consistent across elicitation methods and contexts. Thus, it becomes difficult to make policy recommendations based on general risk attitude measures. Therefore, after obtaining risk attitude measures from the three different risk elicitation methods, this study assesses whether and if so, which of the measures of risk attitudes explains some economic choices of the farmers in real life contexts, although hypothetical in nature.

2. Explanatory power of BVB, TCN and SRRA*: There are no significant differences in the predictive powers of the risk attitude measures in real economic choices.*

2.3 Experimental design

This section presents the designs and implementation of the methods employed in eliciting the risk attitudes of the fish farmers in this study. Farmers were presented with three methods for measuring their individual risk attitudes: the BVB, TCN and SRRA. Each farmer is interviewed in a survey and in addition given the opportunity to indicate on a scale of 0-10 what they believe is their risk attitude is, in a general sense. They are then tasked with the BVB experiment, followed by the TCN lottery.

2.3.1 The self-reported risk attitude measure

This is the first method employed to measure risk preference of the respondents. This method is a self-assessment of the general willingness to take risks on a scale of 0-10. Farmers are asked the following general risk attitude question:

> *"How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please write on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'.*

This method is a "very simple and fast instrument to measure risk attitudes" (Menapace et. al. 2016), and has been used in a large study in Germany by Dohmen et. al. (2011) and also by Reynaud and Couture (2012) among French farmers. The strength of this approach lies in its simplicity and the wide potential for eliciting risk preferences for a large number of people at a relatively low financial cost. Nonetheless, this general question lacks any context and the scale used does not have any quantitative meaning directly, therefore, it is impossible to assign any risk preference coefficient to each individual. Furthermore, because it does not involve the use of monetary incentives or probabilities, it is potentially possible that not all the variation in the responses of farmers could be attributable solely to risk preferences.

2.3.2 The modified Brick-Visser-Burns (BVB) lottery-choice task

The current study adapts the original BVB lottery design in three ways: first, there are ten rows in this study instead of the eight in the BVB set up. The second adaptation is in the payoffs: in this study, there is constant decrease of GHC1.00 from the first row in the less risky lottery option (A), unlike the nonlinear decreases in the original BVB set up[3]. The final difference lies in the presentation of the lottery matrix to the farmers. In this investigation, the payoffs and probabilities are represented with coloured bingo balls; different colours have different monetary values (Ihli et. al., 2013). However, I maintain the probabilities (50%) and the payoffs in the more risky lottery option, B. I proceed to provide some more details on the BVB lottery and its implementation as employed in this study.

The design of the modified BVB in this study asks participants to choose from two options (A or B) in ten rows. The probability of getting the value indicated on the balls in option A is 100% and 50% in option B. In option A, the payoffs decreased from GHC10.00 in the first row to GHC1.00 in the last row, and each row presents a secure alternative. In option B, blue and green balls respectively with a value of GHC10.00 or GHC0.00 each with a 50% probability is presented consistently in all rows. In the visual presentation used, there are ten red coloured bingo balls in each row, which change in their values as one goes down from the first to the tenth row. In option B, there are five blue balls valued at GHC10.00 each and five green balls each valued at GHC0.00. Given the payoffs and probabilities, the expected values of lottery A reduce from GHC10.00 in the first row to GHC1.00 in the last row; for option B, the expected values remain at GHC5.00.

[3] GHC is Ghana Cedis, the official currency of Ghana.

From the first to the fifth row, the expected value of lottery option A is greater than that of B; but this changes from the 6th row in favour of lottery option B. Thus, participants who switch from the safe lottery A, to the risky option B, at the fifth row (would choose the safer option four times) are classified as risk neutral; participants who switch to the risky lottery option before and after fifth row are classified as risk-preferring and risk averse respectively.

I assume that the farmers' utility function for the lottery prizes is characterized by constant relative risk aversion (CRRA) (e.g. Holt and Laury (2002), Brick et. al. (2012)). Given this assumption, an individual's utility has the form $u(x) = \frac{x^r}{r}$, which is a function of the payoff (x) from the Brick et. al. lottery[4].

The CRRA parameter, r, describes the degree of relative risk aversion for an individual: in this case a farmer is risk averse if $r < 1$, risk neutral if $r = 1$, and risk loving if $r > 1$.

Using a farmer's switching point in the lottery, and the payoffs in that row, it is possible to compute an individual's CRRA parameter. Generally, the payoff in the switching row suggests that the expected utility from this option must be greater than or equal to the utility derived from any other option, in particular the next largest and next smallest possible investment choice. Expressing these two conditions in terms of the individual's utility function, and substituting the payoff as an argument, it is possible to solve for upper and lower bound values for r (Holt and Laury, 2002).

In order to avoid inferring extreme parameter values from the lottery choices, I assume an initial wealth level of zero (Dohmen et al, 2011). This assumption is not trivial but could instead capture the real notion that farmers do not take their current wealth into consideration when making their decisions.

[4] Here I use the power (r) instead of $(1 - r)$ to conform to the utility functional form in the TCN utility function for gains.

If we assume a wealth level of zero (e.g. Holt and Laury, 2002), indifference between the lottery of winning GhC10 or GhC0 with equal probability $p = 0.5$ and a safe option in say row 3 in Table A.3 implies the expected utility of lottery A equals the expected utility of lottery B i.e. $0.5\left(\frac{10^r}{r}\right) + 0.5\left(\frac{0^r}{r}\right) = \frac{8^r}{r}$. This simplifies to $0.5(10^r) = 8^r$ and hence $r = \frac{\ln 0.5}{\ln 8 - \ln 10} = 3.106$. The value of r in the next row is 1.943, the value of r in row 3 lies between 3.106 and 1.943. However, in my estimation I used the upper limit of r in each switching row.

2.3.3 The modified Tanaka-Camerer-Nguyen (TCN) lottery-choice task

Unlike the BVB lottery experiment which characterizes risk preferences by one parameter (r), the concavity of the utility function, the TCN lottery argues that concavity of the utility function is not the only parameter affecting risk preferences, but rather nonlinear weighting of probabilities and aversion to loss also influence risk preferences. Thus, the TCN design measures all three parameters in a prospect theory framework. In the original set up, there are three complementary lotteries[5]; the first and second series consist of fourteen rows of gains-only lottery options and the third consists of seven rows of lottery pairs involving gains and losses. In the modified version of this lottery, I employ the same probabilities and payoffs as used by TCN (2010) but I enhance the visual appeal for ease of comprehension by using coloured bingo balls; the number of balls in each bag represents the respective probabilities, and the values of each ball is indicated by the colour of the balls. Take row 25 of this lottery for instance: bag A contains one red ball (10%) (lower payoff) and nine (90%) yellow balls (higher payoff); while bag B contains three blue (30%) (lower payoff) and seven (70%) green balls (higher payoff)[6].

[5] See appendix A
[6] More in-depth explanations are given in Tanaka et al. 2010.

A major difference between the TCN lotteries and the BVB lies in the variation in the probabilities and payoffs. While there was a 100% probability of obtaining the amounts in lottery A, and 50% chance of obtaining the higher payoff consistently in the BVB design, the TCN lotteries vary in both payoffs and probabilities in every series. The parameters in this study are obtained via the prospect theory framework following Tanaka et. al., (2010).

2.4 Measurement of TCN parameters

Estimation of σ and α

The first parameter (σ) dictates the curvature of the prospect value function, and can be thought of as a measure of risk aversion. The higher the sigma, the higher the degree of risk aversion; and individual is risk loving if σ < 1, risk neutral if σ = 1 and risk averse if σ > 1 (Tanaka et. al. 2010). The second parameter (α) captures the degree to which low probability outcomes are disproportionately weighted when valuing risky prospects. The third parameter (λ) characterizes loss aversion. Together, these three parameters jointly characterize the valuation of risky prospects.

Consider the case of a risky prospect with two outcomes, x and y, occurring with probabilities p and $q = 1 - p$, respectively. The value of the prospect can be written as:

$$v(y) + w(p)(v(x) - v(y)); \text{ for (for } xy > 0 \; and \; |x| > |y|) \quad (1)$$

Or

$$v(y) + w(p)v(x) + w(q)v(y) \quad (2)$$

Following Tanaka et. al., (2010), I assume a piecewise power function for value,

$$v(x) = x^{\sigma} \text{ for gains } x > 0 \quad (3)$$

$$\text{and } v(x) = -\lambda(-x)^{\sigma} \text{ for losses } x < 0. \quad (4)$$

where $v(x)$ is the value function and the functional form would depend on whether x is below zero or not; λ measures the sensitivity to loss versus gain. Bigger values of λ would indicate one is more sensitive to loss over gain. The parameter σ is the standard measure of risk aversion. The higher the sigma, the higher the degree of risk aversion; $w(p)$ is the probability weighting function adapted from Prelec (1998). Following Tanaka et. al. (2010) and Liu (2013) the probability weighting function is

$$w(p) = exp\ [-(-\ ln\ p)\alpha] \tag{5}$$

The values of σ and α for all possible combinations of switching points in series 1 and 2 are summarized in the appendix of Tanaka et. al. (2010), but can be derived manually as demonstrated by Liu (2013).

Estimation of λ

As already stated, the λ parameter elicits the loss aversion. It is obtained from the switching point in the third series of the TCN lottery and the σ from the first two series[7]. For example, suppose a farmer switched from Option A to option B in the second row in series 3 of the lottery. I assume that the utility derived from option B in row 2 is the same as the utility from option A in the same row, i.e. farmers are indifferent between the two. From the series 3 Table in Appendix A, the winning payoff in lotteries A and B are GhC1 and GhC30 respectively, and the corresponding losses are -4 and -21.

Thus utilities of the prospects in option A are set equal to that of option B as $w(0.5)v(0.4) + w(0.5)v(-4) = w(0.5)v(30) + w(0.5)v(-21)$ (6)

This then becomes $w(0.5)[v(4) + v(-4)] = w(0.5)[v(30) + v(-21)]$

Which reduces to $v(4) + v(-4) = v(30) + v(-21)$

This becomes $4^{\sigma} - \lambda\big(-(-4)\big)^{\sigma} = (30)^{\sigma} - \lambda\big(-(-21)\big)^{\sigma}$

[7] See Appendix A.

$$(21^{\sigma} - 4^{\sigma})\lambda = (30)^{\sigma} - (4)^{\sigma} = \lambda = \frac{(30)^{\sigma} - (4)^{\sigma}}{21^{\sigma} - 4^{\sigma}}$$

Hence, if it is assumed the σ associated with this farmer's switching points in the two previous lotteries is 0.20, it implies the upper bound of λ that satisfies this equation is

$$\lambda = \frac{(30)^{0.2} - (4)^{0.2}}{(21)^{0.2} - (4)^{0.2}} = 1.26. \quad (7)$$

The lower limit is obtained from the value of λ in the preceding row, which in this case is 0.14. Therefore the interval of values which could satisfy this relation is $0.14 < \lambda < 1.26$. Hence, following Tanaka et. al., (2010) and Liu (2013), I use the midpoint of this interval, 0.70, in the estimations.

2.5 Data Collection

In this section I provide a description of the sampling technique, the implementation of the lottery design in the field and the survey to collect data from the smallholder farmers.

2.5.1 Sampling procedure

The data for this study are derived from two main sources: the first is the household survey to gather socio-economic and demographic data from the farmers with a structured questionnaire, as well as the SRRA in a face-to-face setting. The second source is the field lottery experiment, where farmers made choices from both the BVB and TCN multiple price lotteries. The current research was conducted in four regions in southern Ghana (Greater Accra, Volta, Ashanti and Western regions), from April to May, 2014. The farmers in this study were part of a larger group of about 380 smallholder fish farmers who were interviewed in an earlier study conducted by researchers from the University of Ghana to collect data on the use of inputs, production figures and the sale of fish. The list of the fish farmers interviewed in the previous survey which took place from December, 2013 to February, 2014 were obtained. Since the objective was to relate the productivity of the farmers to their risk attitudes, it was prudent for us to follow up these same farmers whose production data had been gathered already to provide the vital link between risk attitudes and output from them. Furthermore, by using a sub sample of this sample, time was saved as well as other resources that would otherwise had been spent trying to find the farmers for the present study.

In sum, 120 fish farmers were selected because of logistical reasons and time constraints. Thirty farmers were selected from each region through a simple random sampling technique. After selecting the farmers randomly, this information was passed on to the researchers in the University of Ghana who had conducted the previous survey, and they in turn contacted the leaders of the fish farmers in the various areas within the regions via telephone conversations to inform them of the intended field experiment to follow up shortly. This invitation was made at least a month before the experiment took place in any region. Prior to the field experiment and survey for this study, four of the researchers who had participated in the previous survey were trained for the field experiment. These researchers were graduates from the University of Ghana and very experienced in research surveys, especially among the farmers in this study. In terms of communicating effectively to the farmers in each region, each research assistant was very fluent in at least two of the major local dialects used in all four regions, but English was used where necessary during the field experiment. The farmers were either the owners or the main decision makers for each fish farm.

2.5.2 Field experiment and survey procedures

Research assistants were briefed and trained for a day in the protocol and procedure of the field experiments and a pilot study was carried out in a village in the Greater Accra Region to assess the feasibility of conducting the study among the fish farmers, and to address any possible challenges that may be encountered in the main experiment. This pilot enabled us to make some changes to the original design of the questionnaire and the design of the final visual layout of the coloured diagrams I used in the study. On the day of each experiment, farmers showed up to predesignated areas, which included church premises, under trees, and in open places and got registered and checked against the names I had collated. These places were selected based on recommendations from the contact person from each area, and places which farmers were fairly familiar with. The venues were also meant to be within walking distances for most of the respondents[8]. The contact person in each area introduced us to the farmers and then each group of farmers was briefed regarding the purpose of the experiments, the protocol for each lottery, and the incentives available. Farmers who consented to participate in the experiment were informed of the participation reward of GhC10.00 after the experiment[9]. Farmers were given the opportunity to seek clarification about any aspect of the experiment and their queries were duly addressed. After questions asked by the farmers were addressed and consent given by all farmers the sessions took off starting with the survey questions.

Each session was composed of five farmers, who were individually interviewed by an enumerator and their responses recorded accordingly on the structured questionnaires. At the start of each experiment, every farmer randomly picked a ball out of five balls placed in a bag, and the number on the ball was the identification of the farmer throughout the session. After the interviews which lasted about 20-25 minutes on average, each farmer was presented with an A3 poster with the lotteries depicted as coloured bingo balls, each colour of ball representing a payoff.

In all, every farmer was shown four posters: the first was the ten row-gains-only BVB lotteries, the TCN lotteries comprised posters which showed fourteen pairs of lotteries in the

[8] There were a few cases where farmers were asked to travel down to the venues and the cost of travel was duly refunded when they turned up. In other cases, we drove them from their farms and homes to the venue where necessary.
[9] This was equivalent to 2.5 times the minimum wage rate per day in the regions at the time of the experiments.

second and third posters, and the last poster comprised seven rows of choices (mixed lotteries). When a poster was shown to a farmer, he/she chose between bag A or B in each row of the lottery, and the enumerator duly recorded the choice of the farmer in each row. Monotonic switching was maintained throughout the experiments to avoid the possibility of losing some data due to the likelihood of multiple switches (Tanaka et. al., 2010). Therefore, once a farmer switches from the safer lottery A, to lottery B, the enumerator records the row of switch and moved on to the next poster. After all the choices had been made by all the farmers, they all came together to play the lottery for real cash. This is explained further in the next section.

2.5.3 The real monetary-incentive game design

Farmers were informed at the start of each session that in addition to their participation reward, one of them would be randomly selected to play the lottery for real cash. They were also informed that one task will be selected at random for the game. The design of this incentive system introduces chance at two levels: each farmer had an equal chance to be selected out of five to play the game for real cash or loss of cash in the case of the TCN lottery. Secondly, one of the tasks, totalling 45 rows, is randomly selected to be played. This design was adopted instead of allowing every participant to play for real cash because research has shown that using high monetary incentives for a proportion of participants improves performance during the experiments (Camerer and Hogarth, 1999).

The amount of money a farmer won was based on the choice of the farmer between lotteries A and B in each of the 45 rows of all the lotteries together. The probability of a row being picked for the real payment was equal for each row. It must be noted that some of the rows (the last seven) involved negative payoffs.[10] This real incentive design is implemented in the

[10] Even though farmers were informed that in the event of winning a negative payoff he/she would lose that much money, we did not enforce this at the end of the experiment; only four farmers had a negative outcome.

following manner. First, five balls are placed in a bag, numbered according to the number of farmers in each session of the experiment. An enumerator draws one ball from the bag, and the farmer whose number was picked was a winner of one of the prizes. The row which was relevant for payment was determined by drawing a ball from a bag containing forty five balls; this draw was done by the farmer. A final draw decided whether the low or high payoff of Bag A or Bag B would be the final prize. This third draw was not necessary if the second draw was a ball numbered 1-10, and the farmer indicated option A in that row. This is because these rows presented a sure sum, with a 100% probability. However, if the farmer chose option B, a number of blue and green balls according to the respective probabilities in each row are placed in the sack and the farmer draws out a ball, and the colour of he picks determines the final payoff.

2.6 Results

In the sections below I present the summary of the measures of risk attitudes as well as the distribution of farmers according to the elicitation methods described earlier. In addition, the correlation among the elicitation methods is also discussed.

2.6.1 Summary of the measures of risk attitudes

Assuming that the preferences of the farmers is characterised by the CRRA utility function, the risk aversion coefficients obtained from the BVB and TCN lotteries are calculated and the means are summarized in Table 2.1. In addition, the average score from the responses of the farmers in the SRRA question is stated. However, because the scale of the SRRA cannot be converted to values of relative risk aversion, it is not directly comparable to the TCN and BVB lotteries. The averages of the risk aversion coefficients from the BVB and TCN are respectively 2.35 and 0.89, which indicates that the average fish farmer is respectively risk preferring in the gains-only lottery and risk averse in the gains-and-losses lottery. The mean

SRRA value was 5.39, which is similar to the findings of Menapace et. al. (2016), who found the mean SRRA of 5.64 among farmers in Northern Italy.

Table 2.1: Summary of risk attitude measures

Risk Attitude Measure	Mean	Standard Deviation
BVB (CRRA)	2.35	2.45
TCN (σ)	0.89	0.52
SRRA	5.39	3.22

2.6.2 Distribution of fish farmers by elicitation method

In Figures 2.1-2.4, the distributions of farmers according to their switch point in the lottery and their self-reported risk attitudes are summarised. While a smaller number (earlier switch) indicates risk preferring attitude in the lotteries, it indicates less willingness to take risks on the self-reported risk attitude scale. Therefore, for clarity and ease of comparison, the self-reported risk attitude scores have been arranged in a reverse order to align with the switch points in the lotteries. It may be seen that the distributions for all elicitation methods are not normally distributed. Furthermore, I see no similarity in the distribution of the farmers according to the different elicitation methods. One observation is that majority of the farmers in the BVB and the TCN (gains-only) do not switch from the safe lottery (A) at all, but the reverse is true for the TCN which involved gains-and-losses. For the TCN which involved losses, farmers visibly behaved differently than in the gains-only lotteries. For instance, about 9% of the farmers switched from the safe to the risky lottery in row 1, indicative of very highly risk loving attitude, while some 11% stated 10 as their risk attitude on the SRRA scale, indicative of high willingness to take risks. The distributions get more dissimilar in the middle section. While about 14.2% of farmers switched at the 6th row, indicative of risk neutrality, 26.6% stated 5 or 6 as their risk attitude score (relatively risk neutral). Finally, 16.7% of the respondents did not switch from the safe to the risky lottery at all, a very risk averse behaviour; on the self-reported scale however, 14.2% of farmers stated 0 as their risk attitude score (not willing at all to take risks). However, the distribution of the farmers according to their risk attitudes contrasts the findings of Dohmen et al (2011); they find 78% of their subjects to be risk-averse, 13% arguably risk-neutral and 9% as risk loving.

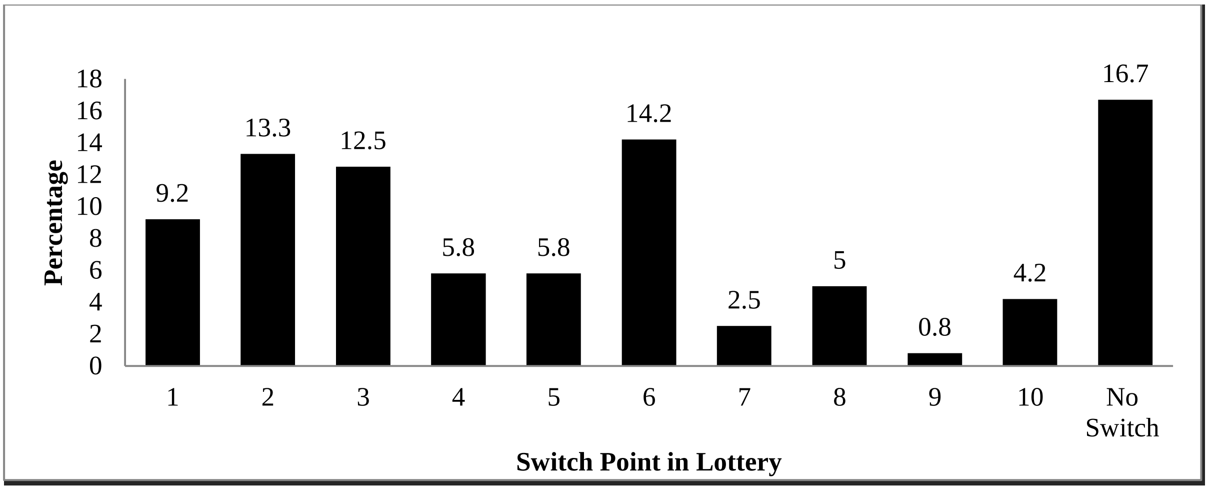

Figure 2.1: Distribution of farmers according to switch point in the BVB lottery

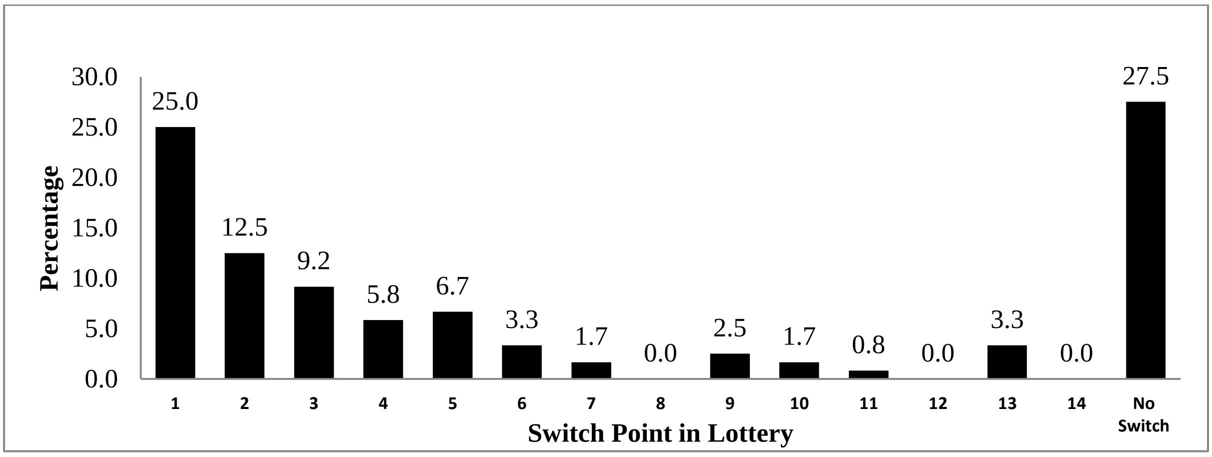

Figure 2.2: Distribution of farmers according to TCN (Gains-Only)

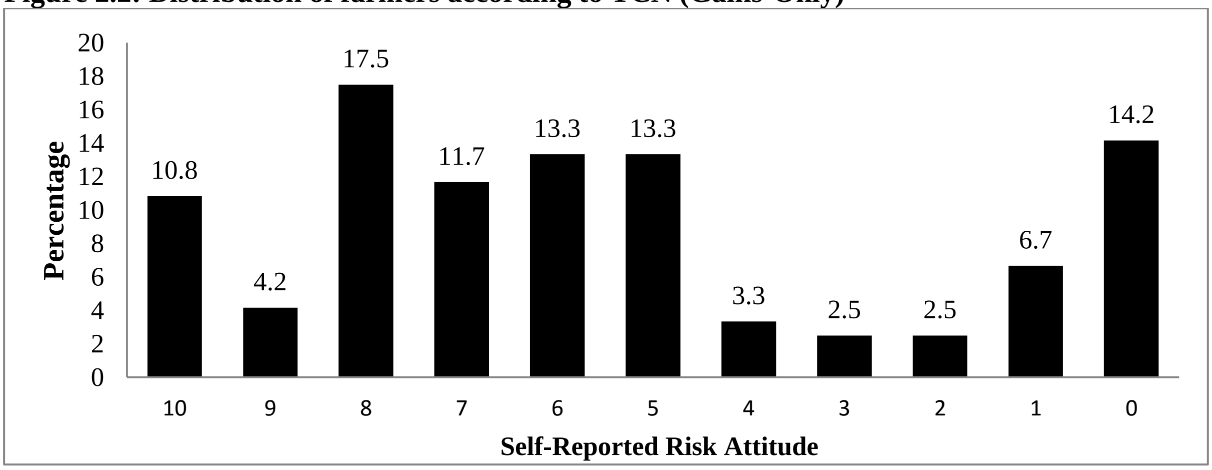

Figure 2.3: Distribution of farmers according to SRRA

2.6.3 Correlations among risk attitude measures

Beyond the row of switch, I consider how the risk attitude scores obtained from the utility function correlate with the SRRA measure, using the simple Spearman Correlation test of independence. The results for this correlation tests are summarised in Table 2.2. The SRRA measure is not correlated to any significant level with any of the other measures of risk attitudes; the BVB lottery and the σ (value function curvature) from the TCN lottery experiments are highly and positively correlated. Furthermore, the BVB is found to be negatively and significantly related to the α (probability weighting) parameter from the TCN lottery. Finally, σ and λ, both parameters from the TCN lottery are also positively correlated. The significant correlations among some of the risk attitude measures may suggest that those risk attitude measures may be capturing similar traits or characteristics of the farmers in relation to how the farmers respond to risk. This may be because they are both obtained from incentivised lotteries played by the same respondents in the same experimental setting. The findings thus far suggest that risk attitudes obtained with incentivised multiple price lotteries capture similar risk attitudes from the same sample[11]. Thus, contrary to the findings of Dohmen et. al., (2011), this study finds a disparity in the stated risk preferences (SRRA) of the farmers and their observed/revealed risk preferences (BVB and TCN). These results confirm the findings of Anderson and Mellor (2009) and Lönnqvist et. al., (2015) that the measures of individual risk attitudes obtained from the experiments and survey are not correlated.

Table 2.2: Correlation among the elicitation methods

	SRRA	BVB	σ	α	λ
SRRA	1				

[11] Even though the average values from Table 2.1 show that the risk attitudes of the average farmer is different from the two lotteries, the two measures are significantly and highly correlated (Table 2.2).

BVB	0.053 (0.569)	1			
σ	-0.012 (0.897)	0.520*** (0.000)	1		
α	0.016 (0.864)	-0.212** (0.020)	-0.045 (0.624)	1	
λ	-0.010 (0.916)	0.000 (0.999)	0.241*** (0.008)	-0.115 (0.213)	1

Note: Coefficients are Spearman rho coefficients, and p-values are in parenthesis; ** and *** show significance at 5% and 1% respectively.

2.6.4 Demographic characteristics and attitudes to risk

One of the purposes of this study was to investigate the farmer/farm specific characteristics that affect the attitudes to uncertainty of the farmers. To accomplish this objective, a simple linear regression model relating each measure of risk attitude and specified characteristics of each farmer is estimated as follows:

$$R_i = \alpha + \gamma X + \mathcal{E}_i \qquad (3)$$

Where R_i is the risk attitude of the *i*th farmer; γ is a vector of parameters to be estimated; X is the set of the farmer's characteristics such as age, marital status etc.; $\mathcal{E}_i$ is the error term of the linear regression**.**

This investigates whether and if so which, of the socio-economic characteristics of the farmers collected as part of the field survey has any effects on their risk attitude measures. The characteristics of the farmers include personal information (e.g. age, educational status, marital status, past experiences etc.), household information (e.g. household size, ownership of house), farm data (regional location), and social network characteristics (e.g. membership in fish farmer associations, religious affiliation etc.). The results from these regressions are summarized in Table 2.3. To ensure consistency, the same characteristics of famers are used in all regressions. A positive coefficient implies increasing risk aversion. The results from these regressions show that none of the specified characteristics is significantly correlated with the risk attitude measure from the BVB lottery. This may imply that this risk attitude measure is a distinct trait of the farmers, just as age or gender.

The results also show that the TCN utility curvature parameter, σ (risk aversion), is negatively correlated with gender and freehold tenure. However, there is a negative significant correlation (at 10% level of significance) of experience in fish farm-related activities and number of rooms and the SRRA risk attitude measure. In other words, the more experienced farmers and farmers who owned more rooms self-reported themselves as not willing to take risks in general. From this section, it is found that only a few personal characteristics affect the risk attitude measures, therefore it appears that there may not be much concern with multicollinearity arising from the inclusion of these socio-demographic characteristics and the measures of risk attitudes in subsequent chapters in investigating production efficiency and technology adoption decisions.

Table 2.3: Regression Analysis for determinants of risk attitudes among fish farmers in Ghana

Explanatory Variable	**Risk Attitude (BVB)**	**Risk Attitude (SRRA)**	**Risk Attitude (TCN σ)**
Age	-0.198	-0.006	-0.002
	(0.022)	(0.028)	(0.005)
Male	-0.105	-1.141	-0.442**
	(0.877)	(1.127)	(0.181)
Married	0.677	0.443	-0.168
	(0.602)	(0.774)	(0.124)
Household Size	-0.085	0.000	-0.014
	(0.094)	(0.121)	(0.019)
Education	-0.016	-0.037	-0.006
	(0.059)	(0.075)	(0.012)
Experience	-0.050	-0.118*	-0.004
	(0.048)	(0.062)	(0.010)
Experienced Past Weather Shock	0.323	0.090	0.055
	(0.566)	(0.727)	(0.117)
Main Occupation	-0.179	-0.242	0.028
	(0.562)	(0.722)	(0.116)
Owns house	0.189	-0.776	0.102
	(0.521)	(0.670)	(0.108)
Number of Rooms	0.134	-0.248*	0.003
	(0.097)	(0.125)	(0.201)

Membership in FFA	-0.530	0.331	0.001
	(0.630)	(0.810)	(0.130)
Freehold Tenure	-0.876	0.573	-0.214*
	(0.571)	(0.734)	(0.118)
Volta	0.233	0.955	-0.018
	(0.797)	(1.025)	(0.165)
Ashanti	0.876	1.469	0.115
	(0.848)	(1.090)	(0.175)
Western	0.561	0.790	0.122
	(0.706)	(0.908)	(0.146)
Constant	3.283**	8.067***	1.582***
	(1.393)	(1.791)	(0.288)
R-Squared	0.095	0.132	0.151

Notes: The dependent variable in each column is the risk attitude measure. The number of farmers in each regression is 120. Simple linear regressions are employed for the reported results in each column. Numbers in parentheses are *p*-values; *, ** and *** show significance at 5% and 1% respectively.

2.6.5 Validation of risk attitudes with economic choices

It has been demonstrated that while there is a significant correlation between the risk attitude measures obtained from the BVB and TCN lotteries, neither lottery is significantly correlated with the SRRA. Thus, the critical query that remains is *which of the three measures of risk attitudes is able to proffer plausible explanations for the economic decisions of the farmers?* I attempt to answer this query by assessing how risk attitudes explain two hypothetical economic choices made by the farmers. The next section explains this further.

Investment

Tables 2.4-2.6 summarise the outcomes for two economic decisions of farmers and how these are influenced by the risk attitude measures. The first economic decision has to do with investment in a hypothetical bank. The following scenario was presented to the farmers:

Imagine you had won GhC5000. A reputable bank makes you an investment offer: you give them a part of the money for two years, and there is a 50% chance to double the money, and a 50% chance that you lose half of the money you gave to the bank. What share of the GhC5000 would you invest in this offer?

This scenario encapsulates the elements of risk and loss, and therefore a risk or loss averse farmer is expected to invest less amount in the bank, while a risk loving farmer is expected to invest relatively larger amount because of the likelihood of doubling the invested amount.

In Table 2.4, the amount each farmer would like to invest in the bank is regressed on farmer-specific socio-economic characteristics such as age and risk attitudes in a simple linear regression. Each column in the table bears the name of the risk attitude measure included in that linear regression. The results in the table show that only the coefficients of SRRA and the α (probability weighting) are significant. The positive sign of the coefficient of the SRRA indicates that a farmer with a higher SRRA value (more prepared to take risks) is more likely to invest higher sums in the bank, and the negative sign of the coefficient of the α (probability weighting) shows that a farmer who overweights small probabilities is less likely to invest larger sums in the bank. Also, it is found that religion influences the amount invested in the bank. This could be explained by the social network effect Christians have from being members of church communities, and hence are more likely to invest more money in the bank, as they observe others do same. They may learn from others whether or not it is safe to invest in any venture more easily than those who are not associated in a similar fashion.

Having carried out the linear regression with the amount of money to invest as dependent variable, I proceeded to create a dichotomous variable which takes a value of 1 if a farmer is willing to invest at least GhC2500 (half of the amount) in the bank, and 0 otherwise. This new variable was used in place of the raw amount stated by the farmer as the dependent variable, in a probit regression and the results are summarised in Table 2.5. Only the coefficient of the SRRA variable is significant in explaining the probability of investing at least half of the amount in the bank: farmers with higher SRRA values are more likely to invest higher sums in the bank. This is consistent with expectations and similar to the outcome in the previous regression.

Additionally, in the presence of the SRRA variable, males, Christians and members of fish farmer associations (FFA) are more likely to invest at least half of the amount with the bank; however, farmers who own their houses are less likely to do so. In the case of the BVB model, farmers who own their houses and have more rooms are less likely to invest GhC2500 or more in the bank, while Christians and members of fish farmer associations are more likely to invest larger sums in the bank.

When all three TCN parameters are included in the estimation it is found that farmers with more experience and those who own their houses will be less likely to invest larger sums in the bank, whereas Christians and members of fish farmer associations are found to be more likely to invest at least GhC2500 in the hypothetical bank.

Table 2.4: Linear Regression of Investment in a hypothetical bank

VARIABLES	Model with SRRA	Model with BVB	Model with TCN σ	Model with TCN α	Model with TCN λ	Model with all TCN parameters
SRRA	169.1***					
	(41.12)					
Age	5.294	6.024	5.467	6.076	4.275	6.194
	(11.97)	(12.86)	(12.93)	(12.70)	(12.91)	(12.86)
Male	338.2	159.9	256.3	145.6	186.5	226.5
	(477.9)	(509.9)	(529.4)	(504.6)	(514.2)	(525.3)
Married	71.03	95.48	179.6	129.4	167.5	165.6
	(324.6)	(349.4)	(352.4)	(343.7)	(350.6)	(350.3)
Experience	-24.73	-41.01	-43.92	-45.76	-43.97	-44.87
	(26.62)	(28.18)	(28.22)	(27.75)	(28.22)	(27.99)
Education	-35.60	-40.74	-40.86	-38.08	-39.91	-36.21
	(31.91)	(34.16)	(34.38)	(33.84)	(34.48)	(34.23)
Past_Weather_Shock	-484.9	-494.5	-483.1	-379.8	-527.5	-423.9
	(304.6)	(326.8)	(328.6)	(326.1)	(337.1)	(339.0)
Main Occupation	179.0	153.3	139.7	92.17	127.6	85.24
	(307.9)	(329.8)	(331.6)	(327.1)	(332.2)	(330.0)
Household Size	-5.442	0.876	-2.879	-1.832	-7.378	-1.311
	(50.63)	(54.47)	(54.68)	(53.71)	(54.63)	(54.33)
Own_house	-278.4	-391.0	-416.5	-410.3	-399.3	-420.7
	(285.0)	(303.8)	(306.3)	(300.5)	(305.5)	(303.7)
Number of rooms	11.09	-41.22	-32.87	-37.03	-27.03	-34.84
	(53.57)	(56.76)	(56.65)	(55.77)	(57.01)	(56.66)
Credit_Access	-1,071*	-1,127*	-1,214*	-1,242**	-1,167*	-1,238**
	(576.1)	(618.6)	(620.7)	(610.4)	(621.2)	(617.2)
Ashanti	-152.7	36.03	87.47	89.61	112.1	79.44
	(463.4)	(494.9)	(495.5)	(486.7)	(494.8)	(491.3)
Western	403.2	508.4	550.5	582.4	612.0	597.5
	(400.7)	(429.4)	(430.2)	(422.7)	(434.4)	(431.7)
Volta	-296.1	-149.6	-123.7	-168.4	-112.7	-152.8
	(431.7)	(460.7)	(463.2)	(456.0)	(463.7)	(460.2)
Christian	801.0*	831.9*	909.0*	851.3*	849.5*	873.4*
	(460.6)	(493.9)	(499.8)	(488.0)	(496.6)	(496.4)
Freehold	-221.3	-62.04	-88.33	-51.57	-112.9	-17.00
	(309.3)	(334.6)	(337.4)	(329.4)	(333.3)	(336.4)
FFA	452.1	551.7	518.7	522.6	525.4	527.7
	(342.3)	(367.3)	(368.5)	(362.4)	(368.6)	(365.4)
CRRA		74.39				
		(56.76)				
σ (value function curvature)			204.0			138.4
			(278.3)			(280.4)
α(probability weighting)				-892.9**		-848.6*
				(449.6)		(457.9)
λ (loss aversion)					43.80	24.63
					(60.12)	(60.82)
Constant	909.7	1,985*	1,802	2,755**	2,085**	2,414**
	(1,011)	(1,042)	(1,159)	(1,060)	(1,046)	(1,201)
Observations	120	120	120	120	120	120
R-squared	0.265	0.156	0.146	0.174	0.146	0.178

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Probit Analysis of Investment in Hypothetical Bank

Variable	Model with SRRA	Model with BVB	Model with TCN σ	Model with TCN α	Model with TCN λ	Model with all TCN parameters
SRRA	0.114**					
	(0.0455)					
Age	0.00995	0.0131	0.0122	0.0136	0.0120	0.0134
	(0.0132)	(0.0127)	(0.0126)	(0.0129)	(0.0127)	(0.0130)
Male	0.915*	0.826	0.786	0.809	0.832*	0.816
	(0.496)	(0.505)	(0.509)	(0.498)	(0.501)	(0.520)
Married	-0.342	-0.301	-0.267	-0.292	-0.255	-0.297
	(0.338)	(0.333)	(0.334)	(0.333)	(0.330)	(0.341)
Experience	-0.0419	-0.0492	-0.0519*	-0.0543*	-0.0522*	-0.0545*
	(0.0315)	(0.0309)	(0.0312)	(0.0319)	(0.0314)	(0.0320)
Education	-0.0240	-0.0311	-0.0318	-0.0283	-0.0303	-0.0276
	(0.0333)	(0.0324)	(0.0323)	(0.0324)	(0.0323)	(0.0326)
Past_Weather_Shock	-0.471	-0.422	-0.401	-0.343	-0.448	-0.378
	(0.321)	(0.311)	(0.309)	(0.312)	(0.319)	(0.324)
Main Occupation	-0.116	-0.131	-0.129	-0.208	-0.143	-0.219
	(0.315)	(0.313)	(0.310)	(0.316)	(0.312)	(0.317)
Household Size	0.0215	0.0120	0.00789	0.0137	0.00588	0.0114
	(0.0548)	(0.0531)	(0.0525)	(0.0535)	(0.0528)	(0.0538)
Own_house	-0.514*	-0.582**	-0.588**	-0.602**	-0.589**	-0.596**
	(0.285)	(0.280)	(0.281)	(0.282)	(0.280)	(0.284)
Number of rooms	-0.0638	-0.0909*	-0.0815	-0.0879	-0.0778	-0.0844
	(0.0555)	(0.0547)	(0.0532)	(0.0538)	(0.0535)	(0.0543)
Credit_Access	-0.705	-0.683	-0.705	-0.775	-0.694	-0.750
	(0.679)	(0.653)	(0.653)	(0.656)	(0.654)	(0.661)
Ashanti	-0.568	-0.390	-0.332	-0.370	-0.335	-0.364
	(0.507)	(0.483)	(0.475)	(0.483)	(0.473)	(0.484)
western	-0.252	-0.171	-0.140	-0.125	-0.113	-0.103
	(0.409)	(0.400)	(0.398)	(0.397)	(0.401)	(0.399)
Volta	-0.519	-0.385	-0.377	-0.462	-0.373	-0.463
	(0.454)	(0.439)	(0.439)	(0.451)	(0.440)	(0.453)
Christian	0.992*	0.936*	0.950*	0.978*	0.932*	0.947*
	(0.538)	(0.521)	(0.526)	(0.526)	(0.520)	(0.531)
Freehold	-0.130	-0.0286	-0.0625	-0.0330	-0.0509	-0.0404
	(0.325)	(0.321)	(0.323)	(0.322)	(0.318)	(0.328)
FFA	0.656*	0.631*	0.611	0.655*	0.635*	0.674*
	(0.389)	(0.374)	(0.374)	(0.382)	(0.380)	(0.387)
CRRA		0.0440				
		(0.0531)				
σ (value function curvature)			-0.00304			-0.0620
			(0.264)			(0.270)
α(probability weighting)				-0.687		-0.678
				(0.438)		(0.443)
λ(loss aversion)					0.0333	0.0265
					(0.0562)	(0.0577)
Constant	-1.251	-0.558	-0.413	-0.0102	-0.497	0.0375
	(1.077)	(1.020)	(1.114)	(1.029)	(1.004)	(1.160)
Observations	120	120	120	120	120	120

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Willingness to pay for hypothetical rainfall index insurance

Since all but five farmers in the sample indicated that they will be willing to pay for hypothetical rainfall index insurance, the analysis of willingness to pay is based on the highest amount each farmer is willing to pay for this insurance (this provides some variation). The description of the insurance package is as follows:

Given the risks you experience and are exposed to, imagine that a new insurance company is going to be set up to help manage some of these risks.

Coverage*: This is the risk-management product that covers the* **destruction of fish stock** *during excess rainfall (above 70 mm/month) measured at the district meteorological officer for a fixed term of three (3) years.*

Benefit: *In the case of the destruction of fish stock during the selected period the policyholder will receive a fixed benefit of GHC5, 000.*

Claim Processing: *Within one month of the event, the benefit will be transferred by cash to the policyholder.*

Provider: *The service will be provided by a Fish Farmer Association that will act as an "agent" for a Ghanaian insurance company.*

Proximity*: The service is available in the district where the respondent resides.*

Price*: Initial bid price per period of premium payment is GHC 15*

Frequency of Premium Payment: *To be paid every quarter (that is every 3 months)*

Q1: Will you be willing to take up such an insurance package? *Yes [ ] No [ ]*

If Yes, go to question 2, otherwise go to question 3.

Q2: How much money will you be willing to pay per quarter as premium for this insurance package? GHC[ ]

***For interviewer: Ask if he/she is willing to increase this amount by another GHC 1; if the answer is Yes, keep bidding it up till respondent says no. Write this value as the HIGHEST BID. Highest bid** in GhC [ ]*

Q3: Why will you not be willing to take up this insurance package?

01 = I don't need insurance for my fish farm [ ] 02 = I don't trust insurance companies [ ]

03 = I don't have the money to pay quarterly premium [ ] 04 = Other [ ]. Please specify…………

Table 2.6 provides a summary of the outcomes when the highest amount a farmer is willing to pay for the insurance is used as the dependent variable and regressed on farmer and farm-specific characteristics including the risk attitudes discussed earlier.

The results show that there is no significant correlation between the willingness to pay for the hypothetical insurance and any of the risk attitude measures used. However, Christians have lower willingness to pay for the hypothetical insurance across all models. In the case of the model in which SRRA was included as an explanatory variable, farmers in the Volta Region, relative to farmers in the base region, Greater Accra, have lower willingness to pay for the rainfall index insurance.

Table 2.6: Willingness to pay for a hypothetical rainfall index insurance

Variable	Model with SRRA	Model with BVB	Model with TCN σ	Model with TCN α	Model with TCN λ	Model with all TCN parameters
SRRA	1.935					
	(1.275)					
Age	0.0668	0.0475	0.0755	0.0608	0.0572	0.0718
	(0.371)	(0.376)	(0.376)	(0.376)	(0.376)	(0.381)
Male	0.772	-1.263	0.776	-1.264	-1.070	0.858
	(14.82)	(14.91)	(15.39)	(14.93)	(14.96)	(15.56)
Married	-0.0414	1.354	1.533	0.813	0.973	1.626
	(10.07)	(10.22)	(10.24)	(10.17)	(10.20)	(10.37)
Experience	0.600	0.333	0.387	0.372	0.377	0.390
	(0.826)	(0.824)	(0.820)	(0.821)	(0.821)	(0.829)
Education	-0.0389	-0.128	-0.0870	-0.114	-0.0971	-0.0822
	(0.990)	(0.999)	(0.999)	(1.001)	(1.003)	(1.014)
Past_Weather_Shock	9.233	9.638	9.140	9.381	8.974	8.817
	(9.447)	(9.556)	(9.551)	(9.650)	(9.811)	(10.04)
Main Occupation	-5.503	-6.054	-5.974	-5.926	-6.034	-5.985
	(9.548)	(9.644)	(9.639)	(9.680)	(9.667)	(9.775)
Household Size	1.418	1.349	1.473	1.417	1.404	1.460
	(1.570)	(1.593)	(1.589)	(1.589)	(1.590)	(1.609)
Own_house	-3.930	-5.415	-5.674	-5.319	-5.315	-5.653
	(8.840)	(8.884)	(8.904)	(8.893)	(8.890)	(8.994)
Number of rooms	0.426	0.0378	-0.0874	-0.0639	-0.0293	-0.0616
	(1.662)	(1.660)	(1.647)	(1.650)	(1.659)	(1.678)
Credit_Access	-11.84	-13.97	-13.67	-13.24	-13.04	-13.50
	(17.87)	(18.09)	(18.04)	(18.06)	(18.08)	(18.28)
Ashanti	-13.70	-9.951	-11.15	-10.72	-10.69	-11.10
	(14.37)	(14.47)	(14.40)	(14.40)	(14.40)	(14.55)
Western	-12.36	-9.888	-10.82	-10.51	-10.16	-10.64
	(12.43)	(12.56)	(12.50)	(12.51)	(12.64)	(12.79)
Volta	-23.55*	-21.43	-21.52	-21.64	-21.52	-21.41
	(13.39)	(13.47)	(13.46)	(13.49)	(13.49)	(13.63)
Christian	-40.00***	-38.91***	-38.33***	-39.27***	-39.38***	-38.40**
	(14.29)	(14.44)	(14.53)	(14.44)	(14.45)	(14.70)
Freehold	8.629	8.927	10.56	9.662	9.797	10.54
	(9.592)	(9.784)	(9.806)	(9.747)	(9.699)	(9.963)
FFA	16.73	17.11	17.51	17.48	17.54	17.53
	(10.62)	(10.74)	(10.71)	(10.72)	(10.73)	(10.82)
CRRA		-0.804				
		(1.660)				
σ (value function curvature)			4.329			4.234
			(8.090)			(8.306)
α(probability weighting)				0.0705		0.879
				(13.30)		(13.56)
λ(loss aversion)					0.323	0.186
					(1.749)	(1.801)
Constant	51.71	68.38**	58.21*	66.21**	65.54**	57.41
	(31.35)	(30.47)	(33.69)	(31.37)	(30.43)	(35.57)
Observations	120	120	120	120	120	120
R-squared	0.155	0.138	0.138	0.136	0.136	0.139

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

2.7 Discussion, summary and conclusion

Smallholder fish farmers in a developing country face risky decisions in their daily operations, and the choices made by farmers are influenced by their individual risk attitudes. In order to better understand the behaviour of these farmers in different economic situations, it is imperative to measure their risk attitudes. However, the measurement of risk preferences is not a straightforward task. While recent advances in experimental and behavioural economics have developed many methods to elicit risk preference, a common drawback is the lack of consistency of risk attitude measures across different elicitation methods and contexts. This chapter elicits risk attitudes of smallholder fish farmers in southern Ghana using three different methods (BVB, TCN and SRRA) in a field survey; two of the methods involved lottery choices and the last method is a general self-reported risk attitude question. The evidence from this study suggests that the average fish farmer in this study may be risk averse (BVB), risk loving (TCN) or risk neutral (SRRA), depending on the elicitation method employed. Perhaps, this could be due to the differences in the nature of the two lotteries: the BVB is a gains-only lottery, while the TCN is mixed, involving both gains and losses. In spite of this, I find a significant correlation between the risk preferences in the two lottery experiments, implying that they are both capturing the same attribute of the fish farmers, but the two measures are significantly distinct from the SRRA. The objective of this chapter was to describe these methods used to elicit risk preferences of the farmers which are employed in the subsequent chapters of this thesis to investigate how risk attitudes affect production efficiency and technology adoption. The chapter also investigates how the risk attitude measures correlate with each other, how they vary with farmer characteristics, and whether they can predict farmer responses to questions on hypothetical economic choices.

From the analysis carried out, it is found that the risk attitudes obtained from the two experiments could not provide sufficient explanation of the two hypothetical economic choices of the farmers in the context of investment and willingness to pay for a rainfall index insurance. However, the SRRA showed some significant correlation with the choice of investment in the hypothetical bank: farmers with greater SRRA values are more likely to invest larger sums in the bank, an expected outcome. It is possible that the SRRA and WTP for the rainfall insurance are both subject to hypothetical bias derived by the hypothetical nature of the questions. Hypothetical bias is said to occur when responses that are elicited in a hypothetical context, such as a survey, deviate from those elicited in a real world context (Loomis, 2011).

The results indicate that experimentally-elicited risk attitude measures do not sufficiently offer explanation for the two specific hypothetical economic decisions in the specific context presented. This could be explained by the nature of risk attitudes in general: they are domain/context-sensitive, and may well be able to explain real-life economic decision directly related to fish production. Evidence of this assertion is seen in Chapters 4 and 5 of this thesis, where significant correlation between the timing of technology adoption and the risk attitude measures is reported. Further evidence is found in the literature; risk attitudes from different lottery experiments have been used to predict a number of important risky agricultural decisions in developing country contexts. These studies include crop diversification in Peru (Engle-Warnick et. al. 2011), labour share in coffee production in Uganda (Hill, 2009), technology adoption among Vietnamese farmers (Nielsen et. al., 2013), and Bt technology adoption among cotton farmers in China (Liu, 2013). Specific to the use of hypothetical rainfall index insurance, there are suggestions that farmers may not adopt this insurance due to factors other than risk aversion. For example, better-off farmers who can afford insurance do not purchase the index insurance because they insure themselves through income diversification, their assets and networks. Poorer farmers, who are posited to benefit immensely from these insurance packages, do not use them because of credit constraints (Binswanger-Mkhize, 2012). Furthermore, it is recommended that farmers need better understanding of insurance packages and the benefits they promise to farmers. Thus, it is clear that perhaps credit constraints, lack of understanding and other motivations, rather than risk attitudes influence the uptake of rainfall index insurance among smallholder farmers. This could explain why the risk attitude measures were not significantly correlated with the uptake of rainfall index insurance in this study.

In summary, this study has attempted to provide some insight into the effectiveness of different elicitation methods in measuring the risk preferences of smallholder farmers in a developing nation context. It has been demonstrated that risk preferences are sensitive to the method of elicitation and that the risk preferences revealed in the lottery experiments do not offer significant explanation for two specific hypothetical economic choices made by fish farmers, at least in our context. These findings, however, do not imply that risk attitudes elicited with incentivised lottery experiments can never explain risky economic decisions of farmers. Given that an attempt was made to enhance comprehension of the farmers using coloured bingo balls in the field experiment, this study claims that risk attitudes elicited from smallholder farmers in the developing world context do not provide sufficient explanatory power for hypothetical economic decisions, possibly due to hypothetical bias. Nonetheless, there is overwhelming evidence that the elicited risk attitudes provide very good prediction of real domain-specific risky economic choices, such as the adoption of technologies. Therefore, it is imperative that when designing experiments to elicit risk preferences in developing world, participants should be engaged in appropriate and relatable risk domains and contexts specific to their field of operation. Perhaps, more farmers should be included in future studies to gain more explanatory power from the analyses.

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Appendix A

TCN Lotteries

SERIES 1

Table A1: TCN Lottery Series

ROW	Option A	Option B	Expected Payoff Difference (A-B)
1	3/10 of 40 and 7/10 of 10	1/10 of 68 and 9/10 of 5	7.7
2	3/10 of 40 and 7/10 of 10	1/10 of 75 and 9/10 of 5	7
3	3/10 of 40 and 7/10 of 10	1/10 of 83 and 9/10 of 5	6.2
4	3/10 of 40 and 7/10 of 10	1/10 of 93 and 9/10 of 5	5.2
5	3/10 of 40 and 7/10 of 10	1/10 of 106 and 9/10 of 5	3.9
6	3/10 of 40 and 7/10 of 10	1/10 of 125 and 9/10 of 5	2
7	3/10 of 40 and 7/10 of 10	1/10 of 150 and 9/10 of 5	-0.5
8	3/10 of 40 and 7/10 of 10	1/10 of 185 and 9/10 of 5	-4
9	3/10 of 40 and 7/10 of 10	1/10 of 220 and 9/10 of 5	-7.5
10	3/10 of 40 and 7/10 of 10	1/10 of 300 and 9/10 of 5	-15.5
11	3/10 of 40 and 7/10 of 10	1/10 of 400 and 9/10 of 5	-25.5
12	3/10 of 40 and 7/10 of 10	1/10 of 600 and 9/10 of 5	-45.5
13	3/10 of 40 and 7/10 of 10	1/10 of 1000 and 9/10 of 5	-85.5
14	3/10 of 40 and 7/10 of 10	1/10 of 1700 and 9/10 of 5	-155.5

SERIES 2

ROW	Option A	Option B	Expected Payoff Difference (A-B)
15	9/10 of 40 and 1/10 of 30	7/10 of 54 and 3/10 of 5	-0.3
16	9/10 of 40 and 1/10 of 30	7/10 of 56 and 3/10 of 5	-1.7
17	9/10 of 40 and 1/10 of 30	7/10 of 58 and 3/10 of 5	-3.1
18	9/10 of 40 and 1/10 of 30	7/10 of 60 and 3/10 of 5	-4.5
19	9/10 of 40 and 1/10 of 30	7/10 of 62 and 3/10 of 5	-5.9
20	9/10 of 40 and 1/10 of 30	7/10 of 65 and 3/10 of 5	-8
21	9/10 of 40 and 1/10 of 30	7/10 of 68 and 3/10 of 5	-10.1
22	9/10 of 40 and 1/10 of 30	7/10 of 72 and 3/10 of 5	-12.9
23	9/10 of 40 and 1/10 of 30	7/10 of 77 and 3/10 of 5	-16.4
24	9/10 of 40 and 1/10 of 30	7/10 of 83 and 3/10 of 5	-20.6
25	9/10 of 40 and 1/10 of 30	7/10 of 90 and 3/10 of 5	-25.5
26	9/10 of 40 and 1/10 of 30	7/10 of 100 and 3/10 of 5	-32.5
27	9/10 of 40 and 1/10 of 30	7/10 of 110 and 3/10 of 5	-39.5
28	9/10 of 40 and 1/10 of 30	7/10 of 130 and 3/10 of 5	-53.5

SERIES 3

ROW	Option A	Option B	Expected Payoff Difference (A-B)
29	5/10 of 25 and 5/10 of -4	5/10 of 30 and 5/10 of -21	6
30	5/10 of 4 and 5/10 of -4	5/10 of 30 and 5/10 of -21	-4.5
31	5/10 of 1 and 5/10 of -4	5/10 of 30 and 5/10 of -21	-6
32	5/10 of 1 and 5/10 of -4	5/10 of 30 and 5/10 of -16	-8.5
33	5/10 of 1 and 5/10 of -8	5/10 of 30 and 5/10 of -16	-10.5
34	5/10 of 1 and 5/10 of -8	5/10 of 30 and 5/10 of -14	-11.5
35	5/10 of 1 and 5/10 of -8	5/10 of 30 and 5/10 of -11	-13

Table A2: Approximate ranges of loss aversion coefficient (λ) for different switching rounds under different values of risk aversion σ

Row	σ=0.05	0.10	0.20	0.25	0.35	0.40
1	infinity<λ<0.12	infinity<λ<0.13	infinity<λ<0.14	infinity<λ<0.14	infinity<λ<0.16	infinity<λ<0.17
2	0.12<λ<1.23	0.13<λ<1.24	0.14<λ<1.26	0.14<λ<1.27	0.16<λ<1.30	0.17<λ<1.32
3	0.23<λ<2.00	1.24<λ<1.96	1.26<λ<1.88	1.27<λ<1.84	1.30<λ<1.79	1.32<λ<1.77
4	2.00<λ<2.41	1.96<λ<2.37	1.88<λ<2.31	1.84<λ<2.29	1.79<λ<2.26	1.77<λ<2.25
5	2.41<λ<4.74	2.37<λ<4.58	2.31<λ<4.32	2.29<λ<4.21	2.26<λ<4.03	2.25<λ<3.95
6	4.74<λ<5.89	4.58<λ<5.72	4.32<λ<5.43	4.21<λ<5.31	4.03<λ<5.11	3.95<λ<5.03
7	5.89<λ<10.41	5.72<λ<10.17	5.43<λ<9.78	5.31<λ<9.62	5.11<λ<9.37	5.03<λ<9.29
NS	10.41<λ<infinity	10.17<λ<infinity	9.78<λ<infinity	9.62<λ<infinity	9.37<λ<infinity	9.29<λ<infinity

Table A3: BVB lottery

Row	Option A	Option B	Expected Payoff Difference (A-B)	Range of CRRA
1	10/10 of 10	5/10 of 10 and 5/10 of 0	5	Infinity<r<6.579
2	10/10 of 9	5/10 of 10 and 5/10 of 0	4	6.579<r<3.106
3	10/10 of 8	5/10 of 10 and 5/10 of 0	3	3.106<r<1.943
4	10/10 of 7	5/10 of 10 and 5/10 of 0	2	1.943<r<1.357
5	10/10 of 6	5/10 of 10 and 5/10 of 0	1	1.357<r<1.000
6	10/10 of 5	5/10 of 10 and 5/10 of 0	0	1.000<r<0.756
7	10/10 of 4	5/10 of 10 and 5/10 of 0	-1	0. 756<r<0.576
8	10/10 of 3	5/10 of 10 and 5/10 of 0	-2	0. 576<r<0.431
9	10/10 of 2	5/10 of 10 and 5/10 of 0	-3	0. 431<r<0.301
10 and no Switch	10/10 of 1	5/10 of 10 and 5/10 of 0	-4	0.301<r<infinity

Table A4: Distribution of farmers by risk attitudes under the two lottery experiments

Risk attitude	Percentage in Brick et. al. lottery	Percentage in TCN lottery
Risk Averse	53.33	48.33
Risk-Preferring	46.67	51.67
Total	**100**	**100**

Chapter 3

Effect of risk attitudes on economic efficiency of smallholder fish farmers in Ghana

3.1 Introduction

Many of the poor in developing countries depend primarily on agriculture and aquaculture for their livelihoods. However, farming as a primary source of livelihood is inherently risky. Extreme and unpredictable changes in weather conditions, as well as the adoption of new and improved agricultural technologies and the presence of diseases have the potential to cause fluctuations in yield. Fluctuations in yield could lead to dramatic changes in income of smallholder farmers (Key, 2005). In developing countries, where the markets for insurance and credits are absent, farmers are not able to transfer these risks to third party entities. Therefore, they are more likely to make production choices that are suboptimal in order to reduce their risk exposure, often at the expense of economic efficiency (Morduch, 1995). For example, evidence from the extant literature suggests that more risk averse farmers have a higher proclivity to plant conventional but less productive crops, and also use suboptimal levels of inputs in production. Owing to these suboptimal production choices risk averse farmers are more likely to be trapped in poverty (see review article by Hurley, 2010).

Many factors affect the production decisions of farmers; prominent among these are output risk and risk attitudes of farmers (Chavas et. al., 2010). Therefore, for effective policy intervention to help farmers overcome poverty, and to make them more productive and food secure, it is important to understand the empirical correlation between their risk attitudes and production decisions (Hellerstein et. al., 2013). However, the investigation of how risk attitudes affect the production choices of farmers is not easy, because of modelling complexity and noise in observed production data (Just and Pope, 2003; Hellerstein et. al., 2013).

Over the years, technology adoption has been recognized by policy makers as an essential tool for increasing agricultural productivity, premised on the assumption that productivity increases with the adoption of a new technology. Thus, in many instances the main focus of governments and other agencies has centred on identifying and removing the constraints to technology adoption among resource-poor farmers (Obwona, 2006). Dhungana et. al., (2004) suggest that in order to attain productivity growth one of two steps must be taken. New and improved technologies must be adopted or existing technologies available to farmers must be used more efficiently, or a combination of these two must be pursued. In less developed countries, introduction of new technologies has often failed to achieve desired improvement in productivity (Xu and Jeffrey, 1998). This results from farmer-specific attributes (e.g. risk aversion) or institutional, cultural and environmental constraints, which prevent the adjustment of input levels to achieve optimal outputs (Ghatak and Ingerset, 1984). Therefore, if farmers are not improving productivity because they are using existing technologies inefficiently, it will be more cost effective to find ways to improve their efficient use of the technology than introducing newer technologies that farmers are less familiar with (Shapiro, 1983; Belbase and Grabowski, 1985).

Based on these recommendations, the purpose of this chapter is to investigate whether the economic efficiencies of smallholder fish farmers are consistent with their risk attitudes measured in a field experiment involving incentivised multiple price lotteries. This investigation is carried out among 120 smallholder fish farmers in southern Ghana. The economic efficiency analysis is carried out within the stochastic frontier framework. The stochastic frontier analysis posits that the deviation of farmers from the least possible cost of producing a given output is due to farmer inefficiency and stochastic or random factors, outside the control of the farmer. In addition, I also employ the deterministic corrected ordinary least squares (COLS) methodology. By using both deterministic and stochastic approaches, the results of this study could provide relatively more precise measures of efficiency scores, which could lead to more accurate policy recommendations.

The fish farming sector in Ghana faces risks in terms of price and yield variability, and therefore it serves as an appropriate testing ground to assess the overall economic efficiencies and how these are affected by the attitudes to risk of the farmers. The technical efficiency scores of smallholder fish farmers as well as socio-economic characteristics that drive observed variability in the efficiencies have been studied empirically in Ghana (e.g. Onumah and Acquah, 2010; Crentsil and Essilfie, 2014 etc.). Outcomes from these studies show that fish farmers are not 100% technically efficient. A shortcoming of these studies is that they do not conduct a necessary diagnostic test on the appropriateness of the stochastic frontier methodology on the dataset before carrying out the analysis. Also, most of these studies focus only on the technical efficiency of the farmers and not the overall economic efficiency. Bravo-Ureta and Pinheiro (1993) suggest that it is by improving overall economic efficiency that major gains in output could be achieved. Furthermore, they ignore the influence of risk attitudes on the efficiency outcomes presented. This present study is an attempt to fill this gap, by testing whether, and if so how, the risk attitudes of farmers explain farm inefficiency.

The results show that risk attitudes of farmers play no significant role in explaining inefficiency of fish production in the study area. Furthermore, some of the input prices and the output are positively related to the total cost of production of fish and that economies of scale prevails in the study area. Lastly, stochastic factors, beyond the control of the farmers (e.g. weather shocks, price shocks, government policies affecting fish farming and measurement errors) rather than inefficiency of farmers explain most of the observed differences in the economic efficiency of farmers. Based on these outcomes, the study recommends policies that would enable farmers to scale up their current production levels, as well as keep accurate records for future research data. This is because there is economies of scale in the study area, and expanding the current scale of production will result in a decrease in per unit cost of output (Amewu and Onumah, 2015). Also, keeping accurate records will help reduce 'noise' in the data for future analysis and more accurate outcomes and policy recommendations.

After this introduction, the next section reviews the literature. This is followed by the hypotheses, skewness tests on residuals, theoretical framework of the study and empirical application. The data and data collection, empirical results, summary and conclusion follow in that order.

3.2 Review of literature on efficiency

3.2.1 Concepts of efficiency and frontier models

The literature credits the commencement of the study of efficiency of production units to the early works of Koopmans (1951) and Debreu (1951); the former provided the definition of technical efficiency while the latter introduced the distance functions as a way to model inefficiency[12]. However, these two studies were theoretical, but Farrell (1957) extended these two studies by providing an empirical decomposition of economic efficiency into technical and allocative efficiencies.

While the aim of this chapter is not to provide detailed discussion of efficiency, a brief discussion of technical inefficiency, allocative inefficiency and economic inefficiency are discussed here[13]. In terms of costs, a farmer is technically inefficient when, given the chosen inputs the output produced is less than the maximum possible, with a given technology. In other words, a farmer is technically inefficient if that farmer in unable to operate on the production frontier due to the less than optimal application of inputs and wrong timing of applying inputs. This inefficiency may arise from lack of appropriate information regarding

[12] A distance function is a function that defines a distance between each pair of elements of a set.
[13] Greene (1993) provides a detailed discussion of the concepts.

the relevant skills necessary in the use of a technology or the untimely supply of inputs. On the other hand, a farmer is allocative inefficient when suboptimal input combinations are adopted given prices and outputs. In another sense, it is the inability of a farmer to use the input mix that maximises profits, given the output and prices. This inefficiency results from farmer-specific characteristics such as risk aversion and capital constraints. Other constraining factors include the interdependence of production and consumption decisions in farm households, and failures in input supply markets (Alene, 2003; Ellis, 1988; Ali and Byerlee, 1991). Economic inefficiency arises from both technical and allocative inefficiencies (Greene, 1993). Conversely, an economically efficient firm has the ability to produce a given output at minimum cost.

Many theories have been propounded to explain why farmers may be inefficient in their operations. Among these is the efficiency hypothesis, advanced by Schultz (1964). This hypothesis essentially assumes that farmers are 'poor but efficient'. It also relates production of farmers to a static and steady state, where external factors do not create any uncertainty in the production process. But in reality, the environments within which farmers in developing countries operate is constantly changing, sometimes such changes are not predictable. This introduces risk into the production system, and the attitudes of the farmers to these risks determine their outcome. This is largely not taken into account in the efficiency hypothesis. Ali and Chaudry (1990) contend that disequilibrium in the production process arises from variabilities in input and output prices. Thus, it is not surprising that the 'poor but efficient' hypothesis is rejected by many economists, including Shapiro (1983). Shapiro (1983) carried out an empirical investigation of the production of cotton by farmers in Tanzania. He showed that output could increase by 51% if all farmers attained the levels of output obtained by the most efficient farmer in the same geographical area, using the same inputs and technologies.

Alternative models to Schultz hypothesis include the risk-averse peasant model (Ellis, 1988). This posits that smallholder farmers are risk averse and therefore have as their main objective the food security needs of their families rather than profit maximization. Another theory put forth to explain the economic behaviour of peasant farmers is the theory of utility maximization (Chayanov, 1966). This theory adduces that smallholder farmers have profit maximization as their key objective, and therefore are efficient producers. This theory considers the smallholder farm household as being producers and consumers, hinged on the assumptions that labour market is non-existent and that there is free access to agricultural land. In a similar fashion, Morduch (1995) considers farm households as entities that try to smooth their consumption over time, using their outputs and sales of produce.[14]

Another theory advanced by Singh et. al., (1986) and later by Bardhan and Udry (1999) is the household model. This model, like the Chayanov model, couples production and consumption decisions of the household, but differs from the former model by relaxing the absence of the labour market and unlimited supply of land assumptions.

While no single theory or model can proffer sufficient explanation of the production decisions of smallholder farmers under every circumstance, Ellis (1988) concludes that farmers are not homogenous in terms of resource allocation. Therefore, there is no justification for assuming that all smallholder farmers are efficient in their production choices. If all production units were fully efficient, there would be no need to study the relative inefficiencies of firms, but evidence from the extant literature suggests that some producers are not 100% efficient (Coelli et. al., 2005), justifying the study of efficiency of production units.

[14] Evidence in support of the hypothesis of profit maximization in traditional agriculture may be found in Hopper (1965), Welsch (1965)

The challenge with efficiency measurements is the fact that is almost impossible to know the absolute efficiency position of any farmer. This necessitates the measurement of the efficiency of each farmer relative to other farmers, usually, using the same technology (Dhungana et. al., 2004). Measurements of relative efficiencies of farm units have been carried out based on the original study of Farrell (1957). These studies broadly adopt parametric or non-parametric approaches, depending on whether or not a functional form is assumed. Studies that adopt the parametric approach (e.g. Stochastic Frontier Analysis (SFA)) assume a functional relationship (such as the Cobb Douglas or Translog) between output and inputs. Studies that adopt the non-parametric approach (e.g. Data Envelopment Analysis (DEA)) do not impose any functional relationship between output and inputs *a priori*. A common drawback of the parametric approach is the fact that there is no *a priori* justification for choosing a particular function form (Thiam et. al., 2001). Nevertheless, Koop and Smith (1980) conclude that the functional form of the production function chosen has a negligible effect on the estimated efficiency.

Parametric frontier models are further distinguished into two categories depending on assumptions about the cause of deviation from the frontier: deterministic and stochastic frontiers. The former assumes that any deviation from the frontier is due to inefficiency related to the decision making unit, while the latter assumes that deviation from the frontier is not only due to inefficiency, but also statistical or measurement errors (outside the control of the decision maker). By attributing all deviations from the frontier to inefficiency, the deterministic models are sensitive to measurement errors or any other noise, and inefficiency scores would be overestimated in the presence of these errors which are not accounted for (Greene, 1993). The stochastic frontier methodology addresses some of the shortfalls in the deterministic models by making it possible to estimate standard errors and to make inferences (Schmidt, 1976). It also disaggregates the deviation from the frontier into inefficiency and stochastic factors. A drawback of the stochastic frontier approach is that it provides only average, but not firm-specific efficiency measures for a sample, which may not be very useful from a policy perspective. This drawback was addressed by Jondrow et. al. (1982), with tools for estimating the firm-specific efficiency scores.

The parameters in the parametric production or cost function are estimated with many econometric or non-econometric techniques, such as corrected ordinary least squares (COLS) or maximum likelihood (ML) methods (Ouattara, 2012). The Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA) are the two main analysis tools in the non-parametric and parametric domains, respectively. The COLS is a parametric procedure but it is similar in concept to the DEA, because they are both deterministic, they attribute all deviations from the frontier to farmer inefficiency. They are also different, in that the former imposes a functional form while the latter does not. In this study the COLS is employed in addition to the relatively more complex SFA, since it is easier to run the linear regression for the COLS.

The literature on risks and risk attitudes and how these affect efficiency measures, as intimated, is scanty.

3.2.2 Risk, risk attitudes and efficiency of production

Risk may be defined as the state of imperfect knowledge, where the probabilities of the possible outcomes are known (Hardaker, 2000). Furthermore, Hardaker (2000) suggests three common meanings of risk: “the chance of bad outcome”, “the variability of outcomes” and “the uncertainty of outcomes”[15]. Farmers face a myriad of risks ranging from weather-related risks to diseases; from price fluctuations to policy and regulatory risks. The primary source of risks in most cases is production or yield variability. These risks come from stochastic factors

[15] See Hardaker, 2000 for in-depth discussion.

that affect the amount and quality of farm output, such as unpredictable weather, drought, diseases and insects (Dillon and Anderson, 1990; Hardaker, et. al., 2004). While risks may differ in terms of sources and impacts on farm households, they may not be independent, and may be linked to each other (Aimin, 2010). This necessitates the need for a holistic approach in addressing the risks faced by farmers, especially in developing countries where formal coping mechanisms may be lacking.

The effects of risk attitudes on the production choices of farmers under uncertainty have long been recognized in the literature (e.g. Binswanger, 1980). Importance of this consideration stems from the fact that the variability and expected values of returns from production choices may be affected by the attitudes of farmers to uncertainty. Wolgin (1975) concludes that risk aversion plays a key role in the production choices of farmers. For instance, he finds that farmers are willing to adopt high risk cops only if they get a higher payoff in expected return. Furthermore, Tobin (1985) also adduces that risk aversion may explain why some farmers may choose to diversify their production. This, he explains, is due to the fact that farmers can obtain similar expected returns at lower risk from growing multiple crops, just as much as they can get from specializing in monocropping, which may entail higher risks. In assessing the impact of rainfall variability as a source of risk on the decision to invest in farming portfolios, Rosenzweig and Binswanger (1993) show that risk averse farmers in riskier environments select portfolios that are less risky but also less profitable. Morduch (1993) also reports that subsistence farmers in India have a higher proclivity to use low-risk conventional seed varieties rather than high-yielding but risky varieties.

These outcomes provide some evidence that farmers' risk attitudes affect their production choices, and thus could lead to efficiency losses when safety is the objective of the farmer (Mendola, 2007). This may explain why risk averse farmers may choose a low-risk conventional input mix which would result in low return rather than one with potential higher returns, but with a higher risk (Mendola, 2007). Thus, risk averse farmers are expected to be less economically efficient under uncertainty.

This present study is not the first to assess the effect of risk attitudes on the production choices of farmers. The consideration of production risks and estimation of a heteroskedastic model of production began with the seminal work by Just and Pope (1978). The authors assert that commonly used formulations of production functions are restrictive and lead to inefficient and biased outcomes. They also provide a production function formulation under risk. However, their model does not account for the effect of farmers' own risk attitudes on efficiency outcomes (Kumbhakar, 2002).

Since inputs and outputs are both chosen by farmers, their attitudes to risk can affect these choices, hence a model that incorporates not only production risks but also farmers' own risk attitudes in the estimation of efficiency of farm outcomes is very important (Kumbhakar, 2002). The shortfall in Just and Pope's (1978) analysis is addressed by Love and Buccola (1999): they consider producers' risk preferences in a joint estimation of input allocation and output supply decisions.[16]

3.2.3 Estimating efficiency of production in agriculture in developing countries

Tan et. al. (2011) assess the technical efficiency with which cage culture operators operate in four locations in the Philippines. They apply the stochastic frontier analysis in their estimation of the technical efficiency of the Genetically Improved Farmed Tilapia (GIFT) and GIFT-derived strains relative to conventional strains in the four locations. In all, four strain groupings are used in the analysis and their results showed that the average technical efficiencies ranged from 18.3% to 46.4% across all four locations. The variance parameter, gamma (γ) from their estimation was 1.000, and significant at 1%, implying that all the

[16] For more literature on risk and efficiency, the reader is referred to Kumbhakar (2002).

deviation from the frontier output was due to technical inefficiency. The study fails to assess the technical efficiencies of the different strains of tilapia. This is because the performance of tilapia could be affected in different environments differently.

Onumah and Acquah (2011) employ a single-stage Translog stochastic frontier to assess the technical efficiency of fish producers in southern Ghana. Their study focuses on the effects of family and hired labour on fish production. They show that the two labour types are not much different in terms of productivity and also found that the mean technical efficiency of the smallholder fish farmers in the study area was 78% and this was influenced negatively and significantly by age, experience and level of formal education. They conclude that smallholder operators were more technically efficient than farmers with large farms.

Onumah and Acquah (2010) also apply the single stage stochastic frontier approach to study the technical efficiency and its determinants among fish farmers in 15 districts in southern Ghana. The interesting fact about this study is that is it explores the interactive effects of farm-specific variables on the technical efficiency of fish production. They find that the production technology of fish production in Ghana exhibits increasing returns to scale, and average technical efficiency is found to be about 81%. The study finds significant correlations between farm and farmer-specific characteristics such as age, gender, education and the interaction of age and experience; but finds no conclusive significant effect of regional location on efficiency of production. This study focuses only on the technical efficiency, and not the overall efficiency.

To fill this gap Asamoah et. al. (2012) attempt to assess allocative efficiency of 74 smallholder fish farmers in four regions in southern Ghana, in addition to a production function analysis, linking the output of fish to inputs such as feed, fingerlings, fertilizer and labour. They find stocking rate as the most significant physical determinant of the output of fish in the study area[17]. Furthermore, they find that the technology used by the farmers exhibits increasing returns to scale. The study uses marginal physical productivity as proxy for allocative efficiency, and concludes that stocking rate should increase, while feed and labour should be decreased to increase productivity. They, however, do not provide estimates for individual farm-level allocative efficiency scores, which are very important from policy perspective in determining the overall economic efficiency.

Thus, from the brief review of existing literature on fish production in Ghana it is evident that no single study addresses the overall cost/economic efficiencies of the same farmers, nor is there a study that considers the risk attitudes of farmers in their analysis of efficiency; this chapter is an attempt to fill the gap, using data from a sample of 120 smallholder fish farmers from southern Ghana.

3.3 Hypothesis

The key hypothesis tested in this study is *Risk aversion has negative effect on economic efficiency.*

Risk preferences affect production decisions and need to be accounted for in efficiency analysis. Risk averse producers may choose to produce less than risk neutral or risk preferring individuals and be incorrectly deemed inefficient when it is only the risk preferences that differ (Robison and Barry 1987; Mester, 1996).

3.4 A skewness test on OLS Residuals

For economic efficiency estimation, it is expected that the residuals have a positive skewness; in other words, farmers are expected to operate above the frontier (i.e. they are operating at higher costs than the frontier firm) otherwise there is no justification for applying the stochastic frontier estimation.

[17] The stocking rate refers to the number of fishes stocked per unit area of pond.

Several distributions are assumed for the error terms in the composed error term, ε, including normal/half-normal, truncated normal, gamma, among others in the literature (see Kumbhakar et. al., 2015 for a review). However, as noted by Kumbhakar et. al. (2015), regardless of the choice of distribution, the likelihood function of a stochastic frontier model is highly nonlinear and estimation can be challenging. Given this potential challenge, it is recommended to perform a simple test on the validity of the stochastic frontier specification before attempting maximum likelihood (ML) estimation (Kumbhakar, 2015).

This test on OLS residuals was proposed by Schmidt and Lin (1984). The intuition for this test is straightforward: for a production stochastic frontier model with the composed error, $v_i - u_i$, where $u_i > 0$ and v_i distributed symmetrically around zero, the residuals from the corresponding OLS estimation should have negative skewness (skew to the left)[18]. According to Kumbhakar et. al., (2015), this is true regardless of the distribution function chosen for u_i in the model estimation after the pretesting. This argument is also applicable to the cost frontier, where the composed error, is $v_i + u_i$. The distribution of the OLS residuals should skew to the right (positive skewness). Given that the slope coefficients of the OLS estimation are consistent estimates of those of the corresponding stochastic frontier model (Kumbhakar et. al., 2015), a test of the null hypothesis of no skewness as opposed to the alternative hypothesis can be constructed using the OLS residuals.

Decision:

If the estimated skewness has the expected sign, rejection of the H_0 provides support for the existence of the one-sided error, u_i.

[18] This is composed of the two components, v_i and u_i , where v_i is the stochastic production/noise effect, and u_i; is the inefficiency component.

The Test Statistic:

Schmidt and Lin (1984) proposed a simple sample-moment based static, commonly referred to as $\sqrt{b_1}$ test and it is stated as $\sqrt{b_1} = \frac{m3}{m2\sqrt{m2}}$, Where m_2 and m_3 are respectively, the second and third moments of the OLS residuals[19]. The second and third sample moments of a random variable x are $\frac{\sum(x-\bar{x})^2}{n}$ and $\frac{\sum(x-\bar{x})^3}{n}$ respectively. When the estimated value of the statistic above is less than 0 (at any significant level), it indicates that the residuals are skewed to the left, and if it is greater than 0, it shows the residuals are positively skewed. One may not be able to reject the null hypothesis of no skewness if the *p*-value is not significant at any level of significance.

3.5 Stochastic frontier analysis and economic efficiency

In deterministic models (e.g. DEA) all variation in farm outputs and performance is attributed to farmer inefficiencies, but this assertion is difficult to prove empirically (Forsund et. al., 1980). However, it is plausible that a farm's performance is affected by factors totally outside the control of the farmer (e.g. bad weather condition, government policies etc.) and factors under the farmer's control (inefficiency). Therefore, it is questionable to put the effects of external/exogenous shocks together with the effects of measurement errors and inefficiency into a single one-sided error term, inefficiency. The main strength of the stochastic frontier model is that the error term is composed of two elements: the symmetric component allows us to capture the random variation of the frontier across farms, as well as the effects of measurement error and other statistic or stochastic 'noise' beyond the control of the farmer. In addition, a one-sided error term captures inefficiency among the farmers below the stochastic frontier (production function) or above the frontier (cost function).

[19] The second moment is the variance and the third moment is the kurtosis.

The cross-sectional stochastic frontier production function as originally proposed by Aigner et. al. (1997) and Meeusen and Van den Broeck (1997) is specified as

$$Y_i = f(x_i;\beta)\exp(\epsilon_i) = f(x_i;\beta)\exp(v_i - u_i) \tag{1}$$

Where Y_i is the level of output for farmer i, f is a suitable functional form (Cobb-Douglas, for example), $f(x_i;\beta)$ is the deterministic component, v_i is the stochastic production/noise effect, and u_i; is the inefficiency component, x_i is a vector of inputs, β is a vector of unknown parameters, ϵ_i is the composed error term, made up of two independent parts: v_i and u_i; the former accounts for random and stochastic factors outside the control of the farmer (e.g. measurement errors, weather conditions etc.) and the latter captures the inefficiency relative to the stochastic frontier, associated with farm/farmer-specific characteristics; the error terms are generally related as $\epsilon_i = v_i - u_i$ (in a production function) or $\epsilon_i = v_i + u_i$ (for a cost function). It must be noted that v_i and u_i are assumed to be distributed independently of each other and of the regressors.

Estimation of the parameters of the stochastic frontier is influenced significantly by assumptions underlying the distribution of the two elements of the composed error term described earlier. The error terms, v_i and u_i are assumed to be independently, identically and normally distributed *(iid)* with zero mean and constant variance, $\sigma_v^2[v_i \sim N(0, \sigma^2\ v]\ and\ \sigma_u^2[v_i \sim N(0, \sigma^2\ u],$ respectively (Kumbhakar, 2000).

The parameters may be obtained directly by either the maximum likelihood (ML) or corrected ordinary least square (COLS) methods, but the former is known to give more consistent estimates (Kumbhakar et. al., 2015) . An estimation of the stochastic frontier is accomplished following Battese and Corra (1977) as

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \tag{2}$$

Where σ^2 is the total deviation from the frontier; σ_v^2 is the variance arising from stochastic/noise factors; σ_u^2 is the variance due to farmer inefficiency.

An alternative measure of this parameter is obtained by expressing the deviation from the frontier due to inefficiency, σ_u^2, as a fraction of the total deviation from the frontier as follows:

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \tag{3}$$

The value of the parameter, γ, shows the share of the total deviation from the frontier due to inefficiency and stochastic noise. If the value of γ is close to one, it means the deviation from the frontier is mostly due to technical inefficiency; otherwise the stochastic random error dominates. Specifically, if $\gamma = 1$, the one-sided error component of the composed error term dominates the symmetric error component and the model is deterministic with no stochastic noise; conversely, if $\gamma = 0$, it implies that all the variation observed in the performance of farmers is attributable entirely to stochastic factors and measurement errors outside the control of the farmer. Where this is the case, then the ordinary least squares (OLS) is an adequate representation of the data. Furthermore, if $0 < \gamma < 1$, the observed variation in output is due to both inefficiency and stochastic/random errors (Battese and Corra, 1977).

The Cobb-Douglas production function is known to demonstrate self-dual properties (Thabethe, 2013; Amewu and Onumah, 2015), which means that it is easier to understand the nature of an alternative form of that function. Assuming duality, the corresponding dual cost frontier is expressed as:

$$C_i = g(P_i; Y_i, \alpha)\exp(v_i + u_i) \tag{4}$$

Where C_i is the level of total cost of the ith farm, P_i is a vector of input prices for the ith farm, Y_i, is the total output for the ith farm, and α is a vector of parameters to be estimated. In equation (4), u_i is indicative of cost inefficiency, and it shows how far above the cost frontier the farm operates, and v_i captures stochastic or random errors, outside the control of the farmer. The u_i is assumed to be independently distributed as truncation (at zero) of the normal distribution with mean $z_i\delta$ and variance $\sigma^2 u$.

The economic efficiency of the *i*th farm, EE, is obtained as the ratio of the observed cost of production of a given farm to the minimum/frontier cost, as

$$EE = \frac{E\left(\frac{C_i}{P_i,u_i}\right)}{E\left(\frac{C_i}{P_i,u_i}\right)} = \exp((u_i|c_i,p_i)) \qquad (5)$$

3.6 The corrected ordinary least squares approach to measuring economic efficiency

In examining the economic efficiency of production units within the parametric framework, one may use the maximum likelihood procedure (for example SFA) or the COLS method. While the SFA is stochastic, the COLS is deterministic, therefore when both are estimated for the same dataset, they serve as a robustness check for each other.

Two potential difficulties are noted with the use of the maximum likelihood (ML) procedures (Coelli et.al, 2005): the outcomes are affected by the size of the sample, and also there is no *a priori* justification for the assumptions underlying the distribution of the composed error terms[20]. The COLS, like the ML, is also sensitive to small sample size and outliers but it is easier to estimate and does not assume any distributional forms for the residuals, and also it is described as a consistent and efficient estimator for a frontier model (Kumbhakar et. al., 2015). This study employs both the COLS and ML procedures to estimate the farm-specific economic efficiency. Before proceeding any further, a brief explanation for the COLS procedure is presented.

[20] They may not be well behaved in small to medium-sized samples.

Theoretically, with the exception of the constant/intercept term, one can obtain consistent and reliable estimates for all the parameters of the model using the ordinary least squares (OLS) procedure (Kumbhakar et. al., 2015). The OLS procedure yields an average function, therefore the estimates obtained would include outputs that are greater or less than the reference average output from the model. The COLS procedure for a production function is explained in greater depth in Greene (1993), and Kumbhakar et. al., (2015), but a brief summary for cost minimization using the COLS is provided here.

For a cost minimization model, first, OLS is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimated of the intercept parameter. Next, the entire function is shifted downwards to ensure that the adjusted function bounds observations above (Kumbhakar et. al., 2015). A step by step explanation of the procedure is provided below:

1. At the first stage, ordinary least squares (OLS) regression of the standard cost function is run following Aigner et al., (1977) as

$$lnC_i = ln\hat{C}^*(Y_i, w_i) + \hat{e} \tag{6}$$

Where ln is natural logarithm; C_i is the total cost of production of the ith farm; Y_i represents the output of fish (kg), w_i represent the vector of input prices, and $\hat{e}$ is the error term, which captures the departure of the cost of the ith farm from the frontier cost; $e = (v_i + u_i)$

From this estimation, one obtains consistent slope coefficients but biased intercept.

2. One can obtain zero-mean OLS regression residual, as

$$\hat{e} = lnC_i - ln\hat{C}^*(Y_i, w_i) \tag{7}$$

3. The OLS intercept is adjusted downwards by the amount of the residual, $min\{\hat{e}\}$, so that the adjusted function now bounds observations from below. The residual therefore becomes

$$\hat{e}_i - \ min\{\hat{e}\}, = lnC_i - [ln\hat{C}^*(Y_i, w_i) + \ min\{\ \hat{e}\ \}] \ \geq 0 \quad (8)$$

4. An estimate of the inefficiency of the ith farmer is obtained as

$$\hat{e}_i^{\ *} \equiv \hat{e}_i - min\{\hat{e}\} \geq 0 \quad (9)$$

5. Economic efficiency, EE, of the ith farmer is thus

$$\widehat{EE}_i = exp(-\hat{e}_i^{\ *}\ ) \quad (10)$$

This value ranges from 0 to 1, where 0 indicates 100% cost inefficiency and 1 shows 100% cost efficiency.

3.7 Explaining efficiency

After estimating the cost efficiency, interest of researchers lies in finding and explaining the factors responsible for the differences in the predicted efficiencies of the farmers. Two main methods are used in this regard: the one-stage and two-stage approaches; the former assumes that the inefficiencies of farmers affect the production function outcome and therefore employs the stochastic frontier production function with composed error term in a single regression (Battese and Coelli, 1992).

The latter method occurs in two stages:

1. Inefficiency scores are predicted from production frontier estimation (without explanatory variables)
2. The scores from (1) are regressed on explanatory variables posited to influence inefficiency.

The two-stage method presumes that the explanatory variables influencing inefficiency are related to farmer-specific characteristics, but not the production function directly. The two-stage approach has been criticized by Kumbhakar et. al. (1991) and Reifschneider and Stevenson (1991) on grounds that it gives statistically inconsistent outcomes and some of the assumptions of the error term, such as independent distribution are violated in the second stage, and hence it is biased (Wang and Schmidt, 2002) and not as efficient as the single-stage procedure (Reifschneider and Stevenson, 1991). In spite of these criticisms, other more recent studies find similar or equivalent results with both methods (e.g. Kalirajan, 1991; Murillo-Zamorano, 2004). This study employs the two-stage approach predicated on the fact that we are able to prevent any possible measurement errors associated with the second stage from affecting the frontier coefficients (Ouattara, 2012). One important advantage of the two-stage procedure is that is can be used for both the parametric and non-parametric models (Kumbhakar and Lovell, 2000). Therefore, this study employs the one-stage approach in the SFA procedure and the two-stage in the COLS procedure.

Following Battese and Coelli (1995) I assess the influence of farm and farmer-specific characteristics on economic efficiency with the following inefficiency model:

$$u_i = \delta_0 + \sum_{w=1}^{n} \delta_w Z_{iw} + e_i \qquad (11)$$

Where δ_0 and δ_w are parameters to be estimated, Z_{iw} is a set of farmer-specific and farm-specific variables explaining inefficiency; e is the ‘error term’ in the inefficiency model, with zero mean and finite variance, σ_ϵ^2. The mean of u_i,

$$\mu_i = \delta_0 + \sum_{w=1}^{n} \delta_w Z_{iw} \qquad (12)$$

is farm-specific and the variances are assumed to be equal ($\sigma_u^2 = \sigma_\epsilon^2$) (Bukenya et. al., 2013).

3.8 Empirical application

Choosing an appropriate functional form that fits the data collected from the smallholder fish farmers in southern Ghana is difficult, but guided by literature (e.g. Karagiannis et. al., 2000; Onumah et. al., 2010) I employ the Cobb-Douglas functional form because of its duality property (Kumbhakar, 2000), and because it has also been used by other researchers (Amewu and Onumah, 2015; Coelli, 1996; Ogundari and Ojo, 2007) in similar settings.

The Stochastic cost function

The empirical cost frontier is as shown below:

$$lnC_i = \alpha_0 + \alpha_1 lnY_i + \alpha_2 lnPArea_i + \alpha_3 lnPFingerlings_i + \alpha_4 lnPlabour_i + (v_i + u_i) \quad (13)$$

Where ln is the natural logarithm; C_i is total cost of production of ith farm; Y_i is observed fish output (kg), $PArea_i$ is the opportunity cost of pond area (GhC); $PFingerlings_i$ is the price of fingerlings (GhC); $Plabour_i$ is the wage of labour per day (GhC), u_i is the measure of cost inefficiency; v_i captures stochastic/random errors.

Determinants of cost inefficiency

Following Lundvall and Battese (2000), the inefficiency scores, u_i, are explained by farm and farmer-specific factors as:

$$u_i = \delta_0 + \sum_{w=1}^{12} \delta_w Z_{iw} + e_i \quad (14)$$

Where δ and w are parameters to be estimated; e_i are the error terms of the regression; the farmer/farm-specific characteristics, $Z_1 - Z_{12}$ are respectively age, gender, marital status, household size, formal education, fish farming experience, main occupation, freehold tenure, risk attitude, and region[21]. These characteristics are described in some detail in Table 3.1 (under empirical results section)

All the parameters of the stochastic frontier cost function along with the inefficiency parameters are estimated simultaneously in single-stage maximum likelihood estimation.

Economies of scale

Since this study focuses on cost efficiency, the economies of scale becomes an important concept to explore. Economies of scale is the proportionate saving in cost gained by an increase in level of output or production. This generally results from the inverse relationship

[21] This is composed of the Western, Ashanti and Volta Regions. The risk attitude is as described in Chapter 2 of this thesis.

between output and fixed costs per unit of output. The overall economies of scale is computed as the reciprocal of the total cost elasticity with respect to output as

$$SCALE = \frac{1}{\frac{\partial lnC}{\partial lnY}} \tag{15}$$

Where $\partial lnC/\partial lnY$ is the partial derivative of the natural logarithm of the total cost function with respect to the natural logarithm of output, Y.

Three possible scale economies are notable:

1. If the computed value of scale is greater than 1, it implies economies of scale (increasing returns to scale) exists, and that an equal proportionate increase in all outputs leads to a less than proportionate increase in total costs.
2. If the computed value of scale is less than 1, it implies diseconomies of scale (decreasing returns to scale) exists: total costs increase more than proportionately with the increase in output.
3. If the computed value of scale is equal to 1, it shows that neither economies nor diseconomies of scale (i.e. constant returns to scale) exists and that the farm operates at the optimal production level.

3.9 Description of the data

The data for this present study are obtained from two main sources:

1. The data on input prices and quantities, as well as fish output are obtained from a survey of farmers, using face-to-face interviews involving structured questionnaires.
2. The risk attitudes are obtained from choices of farmers in a field experiment with incentivised multiple price lotteries[22].

[22] Details of this are in Chapter 2 of this thesis

The sampling procedure and survey techniques employed in gathering the data for this study are as described in Chapter 2 of this thesis.

3.9.1 Definition of variables

Fish output in this study is the dependent variable in the stochastic frontier production function. It is the quantity of fish harvested by the fish farmers in kg.

Production inputs[23]

Pond Area: represents the total area of fish ponds operated by each farmer in hectares (ha). It is assumed that all ponds have identical depths (Onumah et. al., 2010).

Fingerlings: The average number of fingerlings stocked in all ponds and/or cages for the 2012/2013 season, measured as counts.

Labour: The amount of hired and family labour employed during the production season, from stocking to harvesting. This is measured in man-hours.

Input prices

Price of land: This is the average opportunity cost of land for fish farming/ha (GhC/ha)

Price of fingerlings: Average price of fingerlings per kg (GhC/ha)

Wage rate of labour: Average wage rate for a day of working on a fish farm (GhC)

Some **explanatory variables** for inefficiency model:

Age is reckoned as the numerical age of the farmer in years, and it is included in the model to assess whether older farmer are more or less efficient.

Education in this current study is the number of years of formal education attained by the farmer as of the 2012/2013 production season. The attainment of formal education of the fish

[23] Feed is an essential input in the production of fish, but it is excluded from here because it is not significant from previous regressions.

farmers is very important for many reasons, for instance it is positively correlated with the knowledge level and adoption level of improved technology (Singh, 2003). Technical efficiency of farmers in Ghana has also been known to positively correlate with the level of formal education (e.g. Onumah and Acquah, 2010), and therefore knowing the level of education makes it easier for appropriate programmes to be designed to improve the efficiency of fish farmers and subsequently the industry at large.

Fish farming experience is the number of years a farmer has engaged in fish farming related activities. Like any other endeavour, the more years a farmer spends in fish production, the better he is expected to become and therefore more efficient.

Household size in this study refers to the number of people who are related by family ties to the farmer and eat from the same pot. The size of households serves as proxy for source of labour for farmers.

Fish production is main work is a dichotomous variable, taking on the value 1 if fish farming is the primary occupation of the respondent. Farmers may engage in other economic activities as a survival strategy or as a means of spreading risks.

Access to credit is measured as a binary variable and was obtained by asking farmers if they had access to credit for the 2012/2013 production season; it does not distinguish between farmers who eventually accessed credit and those who did not. Lack of credit access has been linked to the inability of smallholder farmers to attain the efficient level of outcomes in their operations.

Experienced past weather shocks is measured as a binary variable, taking on the value 1, if farmer experienced negative weather shocks in the past five years of their existence, especially floods. Past experiences could influence the decisions and choices made by farmers, such as the levels and timings of input use, and these could affect the final outcomes of the farm. It is pertinent to assess how this attribute affects the efficiency of production among farmers in this study.

Attitudes to risk is calculated based on the row of switch from the safe to the risky lottery, based on an adapted version of the CRRA utility function modelled after Tanaka et. al., (2010) and Brick et. al., (2012). The full elicitation and calculation are explained in Chapter 2 of this thesis. In this chapter, I employ the calculated risk attitude measures as an explanatory variable for cost efficiency. Theoretically, risk attitudes could influence efficiency of production as it could affect the decisions farmers make in the choice of input/output mixes, therefore I included this variable to assess if and how it influences the cost efficiencies of the farmers in a developing country setting.

3.10 Empirical results

3.10.1 Descriptive statistics

A summary of the data is presented in Tables 3.1 and 3.2 below. The first table shows the variables that are posited to influence the efficiency of production, while the second table provides a summary of the production output, factors of production and factor prices. As may be seen in Table 3.1, the average age of farmers in the sample is about 41 years, about 73% of the farmers had experienced some weather shocks in the past five years, and the average farmer is risk averse (CRRA=2.35). About 92% of the fish farmers are males, marginally lower than 93% reported by Crentsil and Essilfie (2014), but slightly higher than 91% observed by Onumah and Acquah (2010) for fish farmers in Ghana. Fish farming in Ghana is a male-dominated enterprise, mostly because it is labour-intensive, however, it is observed that women participate significantly in this enterprise by selling the fish to the rural community and in markets on market days (Crentsil and Essilfie, 2014). The average farmer has 5.47 years of fish farming experience, which is lower than 8.31 years of experience reported by Asamoah et. al. (2012). In terms of main occupation, fish production is the main work of 71% of the farmers.

Shifting attention to production elements, the average output of fish for the sample was 155kg, produced with an average of 0.16 ha of pond area, and 614 pieces of fingerlings. The average opportunity cost of land, fingerlings and labour wage were GhC3854.17/ha, GhC33.63/kg, and GhC26.50/day respectively.

Table 3.1: Summary of determinants of technical efficiency and allocative efficiency

Variable	**Description**	**Mean**	**Std.Dev.**	**Min**	**Max**
Age	Years	41.93	13.19	19	72
Married	1=Married	0.74	0.44	0	1
Years of formal education	Years	9.83	4.61	0	21
Household size	Number	6.08	3.02	1	15
Fish farming experience	Years	5.47	5.35	1	30
Male	1= Male	0.92	0.28	0	1
Christian	1= Christian	0.91	0.29	0	1
Own House	1= Owns house	0.63	0.48	0	1
Number of Rooms	Number	4.23	2.67	1	15
Credit Access	1= Had access	0.78	0.41	0	1
Membership in FFA	1 = Member	0.29	0.45	0	1
Freehold	1 = Freehold	0.33	0.47	0	1
Fish Production is main work	1= Fish farming is main work	0.71	0.45	0	1
Greater Accra Region	1=Operates in Greater Accra	0.39	0.49	0	1
Volta Region	1=Operates in Volta	0.23	0.42	0	1
Ashanti Region	1 = Operates in Ashanti	0.17	0.37	0	1
Western	1= Operates in Western	0.22	0.41	0	1
Experienced past weather shock	1= Experienced shock	0.73	0.44	0	1
Risk attitude Measures					
CRRA	Coefficient of relative risk aversion	2.35	2.45	0.30	6.58
SRRA	Self-Reported Risk Attitude	5.39	3.22	0.00	10.00
TCN Parameters					
σ	Risk Aversion (Utility curvature)	0.89	0.52	0.05	1.50
α	Probability Weighting function	0.53	0.23	0.05	1.10
λ	Loss Aversion Parameter	1.98	2.61	0.12	11.98

Source: Survey results, 2014

Table 3.2: Description and summary of variables used in the efficiency analysis

Variable	**Unit**	**Description**	**Min**	**Max**	**Mean**	**Std Deviation**
Output of fish	kg	The total weight of fish harvested at the end of the 2012/2013 fish farming season. This included the fish sold, consumed, and given as gift to family and friends.	65	13170	1556.69	2113.95
Pond area	ha	This is the total size of all active ponds and/or cages, originally in m^2 but converted to ha by dividing by 10,000	0.01	2.88	0.16	0.32
Fingerlings	Count	The average number of fingerlings stocked in all ponds and/or cages for the 2012/2013 season	23	4320	614.86	716.42
Labour	Man-hours	The amount of hired and family labour employed during the production season, from stocking to harvesting	576	188894	5490.38	4239.53
Price of land[24]	GhC[25]	This is the average opportunity cost of land for fish farming	3300.00	4700.00	3854.17	585.09
Price of fingerlings	GhC	Average price of fingerlings per kg	30.00	40.00	33.63	3.66
Wage rate of labour	GhC	Average wage rate for a day of working on a fish farm	17.50	32.50	26.50	5.01

Source: Survey results, 2014

[24] This is similar to values obtained from Nunoo et al., 2012.
[25] This is Ghana cedis, the official currency of Ghana, and the exchange rate to the dollar as of 1st January, 2013 was 1.19.

3.10.2 Hypothesis testing

1. OLS regression outcome:

The first step in the skewness test is to run an OLS regression. The results from the OLS regression are as shown below. It shows that all but the price of fingerlings were significant in the cost of production. These results are discussed in more depth in the results section.

Table 3.3: OLS regression results of the estimation of the cost function

Variable	**Coefficient (Standard Error)**
ln Price of Labour	2.623*
	(1.406)
ln Price of Fingerlings	2.557
	(2.739)
ln Price of Land	-1.223**
	(0.470)
ln Fish Output	0.228***
	(0.063)
Constant	2.764
	(16.093)
R-squared	0.301
Prob>F	0.000

Notes: *, **, *** represent significance at 10%, 5% and 1% respectively. There are 120 farmers in the analyses. Here, the Cobb-Douglas cost function is linearized with natural logarithm. The dependent variable is the natural log of total cost of production. Numbers in parentheses are standard errors.

2. Skewness test outcome

The point estimate of the statistic, $\sqrt{b_1}$ is obtained from the summary statistic of the OLS residuals, e. The test statistic,$\sqrt{b_1}$, labelled as 'skewness' in the outcome below has a value of -0.139. The negative sign shows that the distribution of the residuals skews to the left, which is contrary to expectation for a stochastic frontier cost specification.

Table 3.4: Results from Skewness Test

Variable	Value
Mean	-4.81×10^{-10}
Standard deviation	0.680
Variance	0.462
Skewness	-0.139
Kurtosis	2.592
Number of Observations	120

Notes: This table summarises the outcome of the skewness test on the residuals from the OLS regression

3. Statistical test:

The test returns a p-value (0.515) that is greater than 0.10, therefore I am not able to reject the null hypothesis of no skewness at any level of significance. This means the data is normally distributed. This may affect the results obtained, as explained later in this chapter.

Table 3.5: Skewness/Kurtosis tests for Normality

Variable	Value
Pr (Skewness)	0.515
Pr (Kurtosis)	0.373
Chi Square (df=2)	1.22
Prob>Chi Square	0.544

4. Graph for showing skewness

The graph below gives some visual evidence to the absence of skewness in the residuals of the error term in the data. It may be seen that the distribution of the residuals is not skewed to the right as was expected.

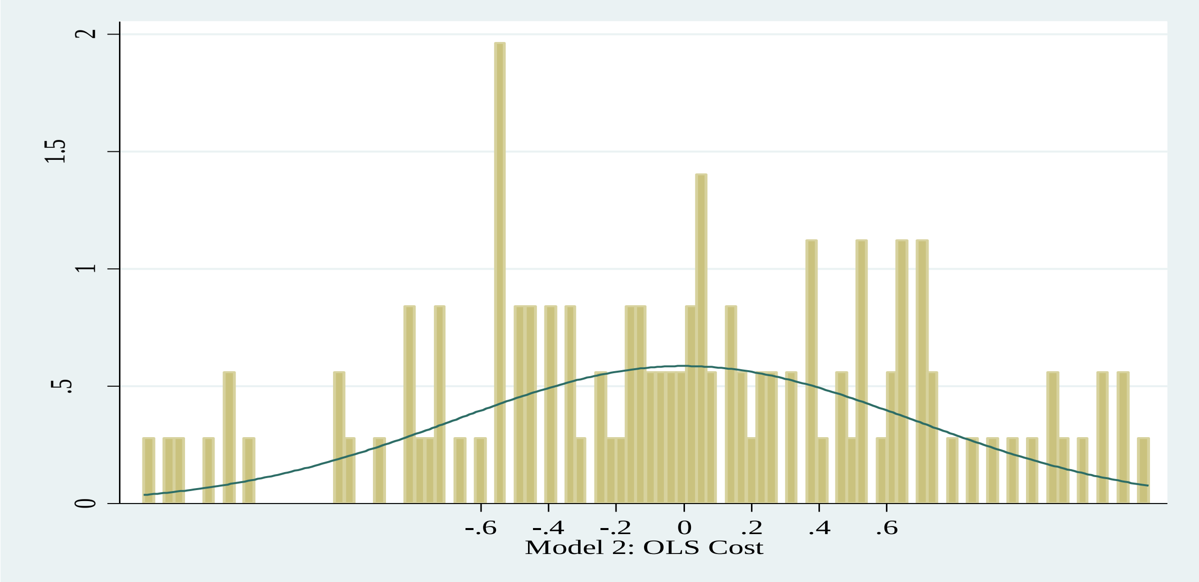

Figure 3.1: Distribution of OLS residuals from cost estimation

3.10.3 SFA and COLS model estimates of economic efficiency

The sign of the 'skewness' shows that the residuals are negatively skewed, contrary to expectation for a stochastic frontier cost model. This wrong skewness is not unique to this dataset. Hafner et. al. (2016) indicates that this is a common phenomenon with the classic stochastic frontier model, and especially magnified for smaller samples, such as in this study. Hafner et. al. (2016) posit that the wrong skewness may persist even when the model is accurately specified[26]. This current study focuses on finding out if any variation in the cost of production can be explained by the risk attitudes of the farmers, and the correction of the skewness of the data is beyond the scope of this study. However, it is acknowledged that the wrong skewness in the data could affect the results; therefore the results should be interpreted taking this into account. The justification for using the SFA in spite of the above concerns stated is that "stochastic models are more reliable than deterministic models because the former accounts for statistical noise" (Bravo-Ureta and Pinheiro, 1993).

[26] For alternative tests and solutions suggested in the literature the reader is referred to Ahmad and Li (1997), Kuosmanen and Fosgerau (2009) and Hafner et al. (2016).

Table 3.6 presents a summary of the maximum likelihood estimation of the parameters of the cost functions for both the SFA and COLS. All the variables in the cost frontier for the SFA model have positive and significant effects on the total cost of production, except opportunity cost of pond area, which has a negative coefficient. The positive coefficients show that total costs increase monotonically with an increase in the prices of the inputs, as well as the output. The negative coefficient of price of pond area suggests that an increase in the opportunity cost of pond area leads to a reduction in the total costs of fish production.

Notable of mention is the coefficient of the lnY variable: the positive coefficient shows that as output of fish increases, the total cost of fish production also increases, which is as expected.

The estimate of the variance parameter, γ, shows that only about 19.30% of the variation in the total cost of production of fish farmers is due to cost inefficiency[27], hence the deviation from the frontier cost frontier is dominated by noise or stochastic factors, outside the control of the farmers. The low value of γ means that most of the differences observed in the cost of production of the farmers in this current study are attributable to potential measurement errors, and other factors not under the control of the farmer.

The resultant estimated Cobb-Douglas cost function is:

$$lnC_i = 3.185 - 1.853LnPArea_i + 3.714PFingerlings_i + 2.809lnPLabour_i + 0.219lnY_i \qquad (16)$$

The outcome from the COLS estimation is as seen in the fourth column of Table 3.6. This outcome is reported as a 'check' on the SFA. For the average function, similar results to the SFA are observed: the variables have the same signs as reported for the SFA, except that the values are smaller in magnitude, and the coefficient of the price of fingerlings is not

[27] This implies that 80.7% of the variation is due to stochastic factors

significant. In general, the results from the COLS are very similar to those obtained with SFA.

Economic efficiency arises from optimizing behaviour relating to both outputs and inputs where a farmer's objective is to minimize the cost of a unit of fish output (Dong et. al., 2014). Economies of scale exist in fish production in the study area; the value 4.56 (i.e. $\frac{1}{0.219}$) is greater than one (1). This means that on average, the farmers can save operating costs by scaling up their current production.

3.10.4 Economic efficiency analysis

To better understand the factors driving the differences in the economic efficiency among the fish farmers, this study explores the determinants of economic efficiency. The outcome of this exploration is found in the lower section of Table 3.6 below.

For the COLS model, Age and Married (marital status) have significant positive and negative effects respectively on the economic efficiency of the farmers[28]. These show that while economic efficiency improves with age (possibly to experience over time), it decreases with marital status, that is, married people are less cost efficient in fish production.

Before discussing the inefficiency outcomes for the SFA, it is pertinent to point out that the diagnostic tests show that most of the observed variation (over 80%) in the cost of production of the farmers is due to stochastic errors, rather than farmer inefficiency[29]. Furthermore, the residual test indicates that this data exhibits the wrong skewness, and therefore the implication is that stochastic/random errors dominate the composed error term. The efficiency model outcome from the SFA shows that none of the variables hypothesized to influence efficiency has any significant coefficients.

[28] As previously indicated, this model is deterministic and assumes that all deviations from the frontier are due to farmer inefficiencies, and therefore may be sensitive to outliers and measurement errors.

[29] This is derived from the γ value of 0.193, i.e. 1-0.193=0.807

Table 3.6: Estimates of the SFA and COLS cost frontier function and inefficiency model

Variable	Parameter	Stochastic Frontier	COLS
	Average Function		
Constant	β_0	3.185 (1.031)	2.764 (16.093)
lnPArea	β_1	-1.853*** (0.506)	-1.223** (0.470)
lnPFingerlings	β_2	3.714*** (0.874)	2.557 (2.739)
lnPLabour	β_3	2.809*** (0.465)	2.623* (1.406)
lnY	β_4	0.219*** (0.062)	0.228*** (0.063)
Inefficiency Model			
Constant	δ_0	0.864 (0.842)	0.126 (0.103)
Age	δ_1	-0.040 (0.018)	0.003* (0.002)
Male	δ_2	0.472 (0.659)	-0.019 (0.068)
Married	δ_3	-0.317 (0.527)	-0.084* (0.046)
Household size	δ_4	0.037 (0.055)	0.003 (0.007)
Edu	δ_5	-0.038 (0.079)	0.002 (0.004)
Experience	δ_6	0.004 (0.04)	0.004 (0.004)
Main Work	δ_7	-0.612 (0.417)	0.014 (0.043)
Freehold	δ_8	-0.556 (0.417)	-0.024 (0.045)
Risk attitude	δ_9	-0.127 (0.085)	0.007 (0.008)
Volta	δ_{10}	1.152 (0.690)	-0.022 (0.054)
Ashanti	δ_{11}	1.409 (0.953)	-0.018 (0.066)
Western	δ_{12}	1.681 (0.705)	0.036 (0.052)
Variance Parameters			
Sigma-Squared (σ^2)	σ^2	0.483 (0.143)	
Gamma	γ	0.193 (0.212)	
R-Squared (R^2)	R^2		0.079

*, **, *** represent significance at 10%, 5% and 1% respectively. There are 120 farmers in the analyses. The dependent variable in the single-stage SFA is the total cost of production; for the COLS the dependent variable in the average function is also the total cost but the efficiency in the second-stage (inefficiency).

The efficiency model outcome from the SFA shows that none of the variables hypothesized to influence efficiency has any significant coefficients. The hypothesis of interest, as far as this chapter is concerned, is the effect of risk attitudes on the efficiency of fish production. As confirmed by the outcome of the hypothesis testing, there is no significant effect (coefficient=-0.127, t-ratio=-1.437) of risk attitudes on economic efficiency from the maximum likelihood estimation. This outcome suggests that the variation in the total cost of production among the fish farmers in the sample is not significantly affected by the differences in the risk attitudes of the farmers at any significant level. This means that farmers' objective of cost minimisation is affected by factors other than risk attitudes. However, this must be explained with caution, as most of the variance in the observed total costs is due to stochastic factors outside the control of the farmers, rather than famer-specific inefficiency. While none of the explanatory variables was significant in explaining in(efficiency) in the SFA, Age and Married (marital status) are significant in the COLS estimation. In both models, the coefficient of risk attitudes has no significant effect on the cost of production among farmers in this study. In other words, the fact that similar outcomes are obtained for risk attitudes from both the SFA and COLS may suggest that the effect of risk attitudes on cost of production is not sensitive to the method of analysis.

3.10.5 Summary and conclusion

This chapter investigates the effect of risk attitudes on the economic efficiency of 120 smallholder fish farmers in southern Ghana using both SFA and COLS estimation procedures. Both the single-stage and two-stage maximum likelihood estimation procedures are employed in this study. The risk attitudes of the fish farmers are elicited through a field experiment, composed of incentivised multiple price lotteries.

Before analysing the data using the stochastic frontier cost procedure, the skewness of the error terms is assessed, since this gives an indication as to the appropriateness of the estimation procedure, given the data. The outcome of this assessment reveals that the residuals are normally distributed, contrary to the expectation of a positive skewness for cost frontier estimation. This may have resulted from the small sample size as well as possible measurement errors arising from data collection.

The variable of interest is the risk attitude; but there is no significant effect of this variable on economic efficiency of the fish farmers. If this outcome was sensitive to the method of analysis, then it is expected that the SFA outcome will be different from that from the COLS. This is because while the COLS is deterministic and attributes all deviations from the cost frontier to the inefficiency of farmers, the SFA disaggregates the deviation into inefficiency (farmer-specific) and stochastic factors (outside the control of the farmers). The results show that risk attitudes provide no significant explanation for the differences in economic efficiency among the fish farmers; therefore it is possible to conclude that this outcome is not sensitive to the method of estimation.

In terms of the elasticity of total cost of production with respect to total output of fish, the result shows that economies of scale exists in the production of fish in the study area. This result suggests that regardless of their farm sizes, farmers experience on average, a decrease in total operating costs given the available technology and the underlying functional form assumed for the cost function (Cobb-Douglas). Furthermore, the derived scale outcome shows that there is increasing returns to scale in the production of fish in the study area, and thus scaling all inputs of production will result in more than proportionate increase in the output of fish. From a policy perspective, if the government aims to improve the production of fish in the study area, efforts should be geared towards equipping the farmers with the necessary assistance to scale up their current levels of production to benefit from the increasing returns to scale.

Most of the farmers did not have written down and up-to-date records of all their expenditures, outputs and even prices, therefore they relied on their memories to recall some of the vital information (recall bias). Recall bias, usually resulting from faulty memory, has been cited in the literature as a potential source of reporting error that leads survey estimates to deviate from actual values (Beegle et. al., 2012). It is possible that some of the data given by the farmers were either overstated or understated and these could impact the outcome of the analysis. The evidence of this assertion is seen in the economic efficiency estimation, where none of the farmer/farm-specific characteristics significantly affects the estimated efficiencies of the farmers.

Furthermore, the value of γ (see Table 3.6), which shows the proportion of the total variance in the cost of production attributable to inefficiency of the farmers, shows that less than 20% of the observed variance is due to inefficiency. The implication is that most of the variation observed in the total cost of production is due to stochastic factors, beyond the control of the farmer, rather than inefficiencies of the farmers.

Overall, the findings of the study indicate that stochastic factors, for instance weather shocks, input price shocks and measurement errors account for greater proportion of the variation observed among farmers in terms of cost efficiency; farmer-specific characteristics have on average no significant impact on the performance of the farmers. Therefore, improvement in the overall economic efficiency of fish production in the study area may depend more on government policies and interventions rather than farmer-specific characteristics, such as risk attitudes. Also, to improve outcomes of future research in the study area, there is a need to educate and equip fish farmers on proper records keeping to ensure that more accurate records are obtained from them for analysis. This may be facilitated by extension outreach efforts through practical demonstration and providing incentives to ensure farmers keep record of all transactions and production outcomes in log books that would be inspected and tracked by extension agents. Another recommendation will be to increase the number of farmers surveyed, as this may enhance the outcome of the analysis.

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Chapter 4

Effect of Risk Attitudes on the Speed of Adopting Aquaculture Technologies in Ghana

4.1 Introduction

This chapter combines experimental data and survey information to investigate how risk attitudes affect the speed of technology adoption among smallholder fish farmers in a developing country context. Policy makers and development agencies are often confronted with the objective of speeding up the growth of the agricultural sector in order to ensure food security (Dadi et al., 2004). Speeding up technology adoption is important because when adopted at the right time, an improved technology could lead to improvements not only in the productivity of farms, but also the livelihoods of farmers and their families (Fuglie and Kascak, 2001; Batz et al., 2003). Furthermore, policy makers may choose to invest in a technology that is more readily adopted because production increases in the early years of adoption have a much greater impact on the rate of return on capital investment than increases in later years (Hazell and Anderson, 1986). Also, the speed of adopting a technology may have a bearing on the survival of farms: if more farmers adopt the technology early, it is likely to result in lower output prices and conversely lead to increases in input prices. Where this is the case, marginal farmers who delay their adoption may be adversely affected (Fuglie and Kascak, 2001).

Given the documented vast benefits of adopting new and improved technologies speedily, it is puzzling that there is slow and sometimes incomplete adoption of agricultural technologies. This may be explained by differences in farm and farmer-specific characteristics, such as risk attitudes (Ward and Singh, 2015). This chapter therefore seeks to answer the question *how do risk attitudes affect the speed with which smallholder fish farmers adopt technologies*? To address this question, risk attitude measures of 120 farmers are elicited with multiple price lottery experiments in the field. This is then combined with information on the actual technology adoption choices of the same farmers obtained through a field survey. The speed of technology adoption is then analysed using duration models.

Generally, new farming technologies present more uncertainty than do conventional technologies (Engle-Warnick et. al., 2011; Liu, 2013); therefore risk-averse farmers would be less likely to adopt new technologies or may adopt technologies later. As to whether this assertion holds true for all technologies requires empirical exploration (Barham et. al., 2014). Furthermore, some previous studies of technology adoption consider the adoption decision as a static binary choice, without considering time (e.g. Feder et. al., 1985). However, the decision to adopt a technology is a dynamic process, which may change with time; therefore, the static analyses, usually carried out with probit or logit models have limitations in terms of inferences that are drawn from the outcomes. Thus, to overcome this limitation, this present study uses duration/survival models, which acknowledge the length of time it takes to adopt a technology and the factors that drive these choices. A key advantage of the duration models over static binary model (such as logit and probit) is that they account for the influence of time in the uptake of new technologies and therefore they provide better information for policy promulgation (Burton et. al., 2003).

Contextually, this study focuses on the adoption of Floating Cages, Extruded Feed and Akosombo Strain of Tilapia (AST) technologies in southern Ghana. For the past two decades, aquaculture has gained much attention, because it is perceived as a way to bridge the gap between the demand and supply of fish (Onumah and Acquah, 2011). In Ghana, fish production is a significant contributor to the economy; the sector contributes about 5% to the gross domestic product (GDP), and annual per capita fish consumption is about 20-25 kg, which is higher than the world average of 18 kg. Additionally, 60% of animal protein in the diets of Ghanaians is from fish (Food and Agriculture Organization, 2012). Over the years, the government of Ghana and other development agencies have introduced improved technologies to enhance the productivity and profitability of the sector, but not much is known about the adoption of these technologies and how long it takes before farmers adopt the technologies and the factors driving such adoption decisions.

A novel result from this chapter is that contrary to most existing literature on speed of technology adoption (e.g. Liu, 2013), I find that risk averse farmers are more likely to adopt the AST, Extruded Feed and Floating Cage technologies earlier. The findings are also consistent with the assumption that the Extruded Feed and the AST are substitutes in the production process in the study area. There is no significant correlation between the decision to adopt Floating Cages and any of the other two technologies.

One possible reason the main result from this study differs from other adoption studies (e.g. Liu, 2013) may be the nature of the technologies in question, as perceived by the farmers. For instance, Liu (2013) focuses on the adoption of cotton modified genetically with *Bacillus thuringiensis* (Bt) bacteria, which enables the cotton plants to produce phytotoxins to kill pests. The subjective risks posed by these phytotoxins to the farmers themselves may be a source of uncertainty and a likely reason for the delayed adoption by risk averse farmers. However, in this present study, the AST is also genetically modified, but it produces no toxins and yet it is more disease-resistant than the local breeds, therefore it may be perceived by the farmers as risk-reducing and hence it may not be surprising that risk averse farmers adopt this technology earlier. A possible explanation for why the Extruded Feed is also adopted earlier by risk averse farmers may be because it reduces the risk of water pollution and contamination associated with the sinking conventional feed, which could pose a threat to the health of the fish and the environment. In like manner, the Floating Cage technology reduces the risk of fish mortality in conventional ponds since they are enclosed in nets and therefore not easily accessible to possible natural predators in other water bodies. Thus, I believe this may explain why risk averse farmers are likely to adopt these technologies earlier.

The rest of the chapter is organized as follows. The next section is a review of the literature, followed by a discussion of the duration model of technology adoption. The next main section presents the empirical application of the duration model in technology adoption. After that, the data and variables are described, followed by the results, summary and conclusion.

4.2 Review of literature

In this section, I examine the literature on technology adoption, and I present some general definition of adoption, determinants of the speed of adoption, empirical application of duration analysis in the adoption of technology and conclude with a summary of the section.

4.2.1 **Definition and concept of technology adoption**

Technology refers to some knowledge, information acquired or applied to accomplish a given objective, such as a service or product (Enos and Park, 1988). The decision to use such knowledge or information or the outcome of accepting such a decision is generally termed adoption (Haillu Beyene, 2008). A more synthesised definition of the term adoption is as provided in the review by Feder et. al. (1985) as "*a mental process an individual passes from first hearing about an innovation to final utilization*". This definition shows that adoption is not a one-point-in time event, but a series of thought processes that yield the final decision to use or not use a given innovation, after the innovation has become available and accessible to the farmer. Technology use begins with an individual or a group of individuals (adoption) and then spreads within a region or population (diffusion or aggregate adoption) (Haillu Beyene, 2008).

For policy considerations, a distinction is often made between rate/speed of adoption and intensity of adoption. The former relates to the relative speed with which farmers adopt a technology and therefore has a temporal element embedded, while the latter refers to the level of use of a given technology in any period. The only justification for the introduction of or the adoption of a new technology is when it does or is perceived to have an advantage over the conventional practices (Rogers, 1995). For instance, in this present study, Extruded Feed is posited to result in relatively faster rate of fish growth (up to 100%) because of its bioavailable protein content.

Final adoption decision may be seen as an outcome of many preceding decisions, beginning with awareness of the technology (Rogers, 1983), followed by interest, evaluation, acceptance, trial, and eventual adoption (Lionberger, 1960). These stages are not mutually exclusive events, but rather occur concurrently; however, it is difficult to distinguish one stage from another, and in some cases not all stages actually occur before adoption. Diffusion of a technology on the other hand involves learning (by observing or doing) over time (Rogers, 1995), and the average time lapse from awareness to adoption is influenced negatively or positively by heterogeneity arising from person, place or practice.

4.2.2 **Measurement of technology adoption**

The measurement of adoption is essentially a measurement of choices of people at a given point or over a period of time. Adoption can be measured by estimating the rate or the intensity of use of the technology, depending on the nature of the data. The technology adoption decision also involves the choice of how resources, like land, should be allocated to the new improved and old technologies if the technology is not divisible (e.g. mechanization, irrigation) (Feder et. al., 1985). Conversely, if the technology is divisible (e.g. improved seed, feed, fertilizer, agronomic practices and herbicide), the decision process involves area allocations as well as levels of use or rate of application. Therefore, the adoption decision includes the simultaneous choice of whether to adopt a technology or not, and the rate and intensity of its use. The current study focuses on the rate of adoption or the length of time it takes before a farmer uses a technology, given that the technology is available.

4.2.3 **The roles of risk and risk aversion in technology adoption**

Farm households face many risks, which are even greater in developing countries where risks are either production-related (mostly environment and weather-related variability) or price-related (input and output prices) (Newbery and Stiglitz, 1981). These risks influence many economic decisions of farmers, including technology adoption. This is because the livelihoods of farmers, from consumption and sales of their outputs, depend on the yields from their farms. When farmers adopt a new technology, they are exposed to uncertain returns on their investment in that technology. Therefore, switching from a conventional to an improved technology (mostly more expensive) is an inherently risky decision, especially where the new technology entails greater risks. In developing countries where the markets for insurance, credits and savings are absent or inefficient, a bad farming outcome can potentially have very serious and sometimes long-term impacts on the welfare of the farmers and their families. Thus, under such circumstances, farmers are more likely to make suboptimal farming choices that reduce their risk exposure at the expense of productive efficiency (Morduch, 1995). This may explain why risk averse farmers are more likely to continue to use conventional technologies with low profitability rather than risk adopting new and improved technologies. But this could thrust them into permanent food insecurity conditions (Rosenzweig and Binswanger 1993; Dercon and Christiaensen, 2011).

A number of studies have found significant correlation between risk attitudes and technology adoption (Binswanger, 1980; Feder, 1980, Feder et. al, 1985; Engle-Warnick et. al., 2007; Liu, 2013; Holden, 2015). Vast empirical evidence suggests that farmers are risk averse (Binswanger, 1980; Saha et al, 1994; Kim and Chavas, 2003). Risk aversion is the aversion to a set of outcomes with a known probability distribution (Pratt, 1964).

Despite the vast number of articles published in this field, there seems to be different outcomes in the measurement of risk attitudes, and how they influence technology adoption decisions. The reason for this lack of consensus could be due to the ‘complex dynamics of technology adoption process’ (Moser and Barrett, 2006 *in* Mukasa, 2016), as well as the structural differences in agriculture around the globe. Another reason stems from different methodological approaches adopted by the researchers (Mukasa, 2016).

4.2.4 **Speed and determinants of technology adoption**

The speed of adoption is usually measured by the length of time required for a farmer to use a given technology, from the time the farmer learns about the existence of the technology (Dadi et. al., 2004). Since the decision to adopt or not adopt a technology is subjective, the perception of prospective farmers regarding the attributes of the new technology influences the speed with which adoption takes place (Haillu Beyene, 2008). If a technology is perceived as being risk-reducing (such as drought-resistant varieties in a drought-prone area), it is likely that that the speed of adoption will be faster. Thus, a key determinant of the rate of adoption is the technology itself. As noted by Rogers (1983), for instance, five characteristics of technology that can influence the rate of adoption include relative advantage, compatibility, complexity, divisibility, and observability. In addition, Supe (1983) identifies two other characteristics, which are variations in the cost of adoption and group action requirements of the technology. Supe (1983) explained further that technologies which require group actions for adoption (e.g., drainage and watershed management) are adopted slowly compared to technologies that are taken up entirely on individual basis (e.g. feed, fertilizer).

The speed of technology adoption is also affected by the interaction of factors inherent in the technology and external factors. For instance, the speed of adopting more profitable or less risky technologies is expected to be faster, but profitability could be a function of other factors such as commodity prices and agro-climatic conditions, thus rainfall and prices may have indirect influences on the speed of adoption of a given technology (Bulti, 2013).

4.2.5 **Explaining the trend of adoption of technologies**

Researchers have tried to explain the process of technology adoption and diffusion by propounding many theories. One of these strands of theory in the literature is the epidemic theory of diffusion. This theory suggests that diffusion is the disequilibrium/epidemic process resulting from asymmetry of information between potential users (e.g. Mansfield, 1968). Another strand of theory contrary to the epidemic theories is the equilibrium theory, which assumes perfect information regarding the existence and nature of new technologies. A farmer’s decision to (or not to) adopt a new technology depends on the perceived costs and benefits from using or not using the technology; in other words a farmer will adopt a technology if the perceived net benefit from adopting the technology is positive (Abdulai and Huffman, 2005).

Karshenas and Stoneman (1995) group these equilibrium theories into three main categories, namely rank or probit, stock or game theoretic, and order effects. In the rank models, firm-level heterogeneity among potential users of a new technology means that some firms can achieve greater profits from using the new technology than others, and as such, they will adopt earlier (Ireland and Stoneman, 1986).

The stock (game theoretic) effect posits that the benefits from a technology adoption by a marginal firm is negatively related to the cumulative number of previous adopters; when the technology is novel, early adopters have a competitive advantage, but as the technology becomes more commonly used by other firms, no firm has an advantage, because as the number of adopters increases the overall industry output increases affecting the process and profitability (Abdulai and Huffman, 2005). In the order effects, a firm's position in the succession of adopters (later or early) determines its net return: earlier adopters obtain a greater return than later adopters do.

In addition to the above, the general literature on technology adoption is moving in three identifiable directions: one strand focuses on the econometric and modelling techniques (e.g. Besley and Case (1993), Staal et. al. (2002)). Another strand looks at learning and social networks in adoption choices (e.g. Conley and Udry, 2010), and the last strand is mainly based on context-specific micro-level studies with special emphasis on local data for policy reasons (Doss, 2006).

The adoption of technology is multi-faceted, and not just a single point in time decision. To adopt a technology a farmer goes through three simultaneous choices: to adopt components of the technology or the full package, the allocation of different technologies across his farm and how much of complementary inputs to apply (Smale, 1995).

Technology adoption decisions are generally dynamic in nature, and therefore panel data is best suited for such studies; however, cross-sectional analysis at the micro-level can answer important questions about technology use (Doss et. al., 2003); for instance these studies help us to know what crops farmers are actually growing in their fields, farmers' decision-making processes, farmers' preferences, prevailing weather conditions in specific areas as well as farmers' perceptions of the constraints they face in their specific locations. In other words, these studies explain 'what farmers are currently doing' and the factors influencing such decisions.

4.2.6 **Modelling technology adoption**

Generally, empirical models used in adoption studies that examine farm-level behaviour are logit or probit; these explain the probability of a farm adopting a new technology at a given time. These models do not explicitly address the effects of explanatory variables on the time-path of adoption, which is an important aspect of the adoption process, especially for technologies for fish production. Furthermore, most adoption studies (e.g. Bandiera and Rasul, 2006; Teklewold et. al., 2013) in developing countries fail to consider the timing to adoption. However, including the time it takes to adopt a technology in adoption analysis furnishes us with very important information (Beyene and Kassie, 2015) such as how risk attitude affects the decision to adopt technologies.

By employing a hazard/survival model to examine the factors affecting the timing of adoption of technologies in fish production this study bridges the gap between empirical studies that analyse adoption with discrete choice models (logit/probit models), and the time-path of diffusion (Abdulai and Huffman, 2005) as well as the factors that influence the choices of the farmers (Matuschke and Qaim, 2008). How soon farmers adopt technologies is crucial from the perspective of productivity and survival of farms (Fuglie and Kascak, 2001). This is because greater impact on the rate of return on capital results from earlier adoption of technology, thereby justifying policy intervention.

Thus, by using duration analysis to explore the determinants of the length of time required for smallholder fish farmers to adopt improved technologies this present study contributes to the existing literature in three ways. First, most empirical studies on the adoption and diffusion of high-yielding technologies in developing countries focus on the crop sector (e.g. Liu, 2013, cotton, China; Suzuki, 2014, pineapple, Ghana). Therefore the study of the timing of adoption of technologies related to fish farming is essential to the profitability and sustainability of the industry. Secondly, unlike many others, this study focuses on three improved technologies posited to enhance productivity of fish farmers[30]. These technologies are the AST, floating/Extruded Feed and Floating Cages. By focussing on three technologies, one is able to assess whether different factors influence the adoption of different technologies differently; as well as the complementarity or substitutability among technologies.

Finally, in addition to the many factors usually considered in the analysis of adoption decisions I include risk attitudes of fish farmers. These risk attitude measures are obtained from incentivised field experiments involving multiple price lotteries. Risk and risk attitudes influence decisions of farmers, and farmers are generally thought to be risk averse (Binswanger, 1980), and that risk averse farmers adopt technologies later (Liu, 2013). Therefore, by including risk attitude measures in the duration analysis it is possible to determine the possible channels through which risk attitudes influence the time to adoption of the three technologies. Here, the risk attitude of farmers is posited to influence the timing to adopt three technologies in the production of fish.

4.2.7 **Related empirical literature**

Since the review of the technology adoption literature by Feder et. al. (1985) many studies have been carried out to study adoption decisions; the literature in this area is vast. However, the literature on technology adoption decisions of fish farmers, particularly in developing countries is scanty (Ansah et. al., 2014). In this section, I will focus on three studies that are of most significance to my current study. The first two papers were selected because they measure risk attitudes of farmers and use these measures to explain various technology adoption decisions, in developing countries. The third paper was selected because it

[30] Fuglie and Kascak (2001) also study the duration of adoption of three technologies-conservation tillage, integrated pest management and testing for nutrient levels, but they do not focus on fish farming

characterises the adoption of environmental best management practices in pond aquaculture in Ghana, the study area for this present chapter.

Liu (2013) elicits the risk attitudes, as well as the loss aversion and probability weighting parameters from a utility function, and examines how these traits affect the speed of adoption of cotton genetically modified with *Bacillus thuringiensis* (Bt) among cotton farmers in China. Unlike most prior studies which mostly measure adoption as a dichotomous variable at a point in time (e.g. Knight et. al., 2003), Liu (2013) models adoption as the time lapse from knowing about the technology and actually using the technology. This study also expands the measurement of risk preferences beyond expected utility to incorporate prospect theory. She finds that farmers who are more risk averse or more loss averse adopt Bt cotton later. Farmers who overweight small probabilities adopt Bt cotton earlier.

Ward et. al. (2014) conduct a series of field experiments in rural India in order to measure preferences related to risk, potential loss, and ambiguity. They find that on average women are significantly more risk averse and loss averse than men, though the higher average risk aversion arises due to a greater share of women who are extremely risk averse. Coupling these behavioural parameters with a discrete choice experiment designed to study preferences for drought-tolerant (DT) rice, they observe that farmers' risk and loss aversion interact with their perceptions about the potential risks and losses associated with the new seeds. They find that both risk aversion and loss aversion significantly increase the probability that farmers will choose the newer seeds: farmers are more likely to experiment with new seeds that provide some form of yield benefit, whether it is a reduction in variability or protection against low-probability, high-impact extreme droughts. They find no evidence that ambiguity aversion affects farmers' preferences for the new DT rice variety.

Ansah et. al. (2014) employ ordered logistic framework to assess the determinants of the simultaneous adoption of two environmental best management practices (BMP): water reuse and commercial Extruded Feed on pond fish farms in Ghana. In addition, they determine the rate of adoption and effectiveness of three techniques for diffusing the BMP to nonusers. They show that awareness, perceived relative profitability of the water reuse technology and years of experience have the strongest influence on the simultaneous adoption of the BMPs, and that the most effective channels for disseminating the technologies are workshops, demonstrations and peer influence. Furthermore, they find that the maximum adoption rate of the Extruded Feed is higher (58.2%) than the water reuse technology (27.4%).

The first two studies are similar to the present study in terms of the measurement of risk preferences. They both elicit risk preferences within the prospect theory framework; they also measure the loss aversion and probability weighting parameters of the same sample. The two studies differ in their key findings: while risk averse farmers delay adoption of Bt cotton in China (Liu, 2013), they are more likely to adopt drought-tolerant rice early in India (Ward and Singh, 2014).

Of the first two studies, Liu (2013) is the closer to the present study in terms of the methodology: it employs duration analysis rather than modelling adoption as a discrete choice. However, the present study differs from the previous studies in a number of ways. Instead of analysing the adoption of a single technology, this study studies the adoption decision of three technologies. Additionally, the other studies focus on crops, but this present study focusses on technologies in fish farming. Fish farming differs from crop farming in terms of the challenges and risks farmers face in their operations, therefore applying the techniques used in the previous studies in this present study is an attempt to bridge this gap in the literature and to provide an empirical evidence of the effect of risk attitudes on the adoption of fish farming technologies in a developing country context.

The last paper reviewed in this chapter is by Ansah et. al. (2014). This study is conducted in the same study area as this present study, and it focuses on some aspects of fish farming, as well. Just like this present study, their study models the adoption of Extruded Feed technology among the fish farmers, but their study differs from the present study in terms of analysis. They assume that the two technologies are adopted together, or are complementary, and therefore model them as bundled technologies. Furthermore, they model the adoption decision as a binary static choice, within a logistic framework. The present study, however, employs duration/survival analysis, taking into account the effect of time on the decision to adopt a technology. Lastly, while not imposing complementarity on the technologies, this chapter assesses possible relationships among the technologies (complementarity and substitutability) via the model outcome.

This present chapter investigates some potential determinants of the speed of technology adoption by incorporating a wide range of variables, including an experimentally obtained measure of risk aversion, using duration analysis. It is an attempt to fill the void in the literature regarding the length of time fish farmers take to adopt AST, Extruded Feed and Floating Cages.

4.2.8 Complementarity and substitutability among technologies and hypotheses

Complementarity or substitutability among technologies could also influence the rate of adopting a given technology. The benefits of using improved seed (hybrid),for instance, are enhanced by fertilizer application under favourable environmental conditions in high potential areas measured by rainfall potential, soil fertility and other agro-ecological factors, such as altitude, etc. (Byerlee and Hesse de Polanco, 1986). However, one would expect that the prior adoption of pest-resistant crop varieties would lead to a reduction in the adoption of pesticides. Therefore, in examining the rate of adoption of a given technology it is imperative to consider how the adoption of other technologies could influence the decision to adopt a given technology.

The three technologies described above (AST, Extruded/Floating Feed and Floating Cages) are distinct, can, and have been used in different mixes by different farmers for different reasons. There is no predefined sequence of adopting one technology before or after another. However, there is potential complementarity or substitutability among the technologies. For instance, Floating Cages rely on extruded/floating feed for the optimum output from the fish stocked in it. This means that farmers who own Floating Cages are also more likely to use floating feed, and vice versa. Thus, Extruded Feed and Floating Cages are expected to be complementary, in other words, adoption of Floating Cages increases the likelihood of adopting extruded feed. This leads to the first hypothesis:

1. ***Floating Cages and Extruded Feed are complementary technologies: prior adoption of Floating Cages speeds up the adoption of extruded/floating feed***

Extruded Feed and AST serve similar purposes. AST is a fast-growing breed of tilapia which offers farmers the economic potential of harvesting twice a year compared to the locally available breed. Extruded Feed also enhances the growth of stocked fish and offers farmers the chance of early harvest of their fish. However, this feed is the most expensive input used by farmers in the industry. While the joint use of Extruded Feed and the AST is recommended, some farmers adopt either, only a few adopt both. This suggests a possible substitutability between the Extruded Feed and the AST; in the presence of credit constraints a farmer may adopt one or the other. If this is the case, then it is expected that the adoption of AST could lead to a delay in the adoption of extruded feed. Thus, the second hypothesis to be tested is:

2. ***AST and Extruded Feed are substitute technologies: prior adoption of extruded/floating feed delays the adoption of AST.***

There is no direct relationship between use of the Floating Cage technology and the AST. The Floating Cage can be used to stock any species of fish, including, but not limited to the AST. Farmers have the flexibility of moving the cages to a new body of water if the need arises. Thus, the decision to adopt a Floating Cage may not necessarily have any direct bearing on the decision to stock AST or vice versa, in the absence of credit constraints. However, AST stocked in Floating Cages yield higher outputs and mature faster than if stocked in conventional ponds, thus they could be regarded as complementary. Nevertheless, the initial high cost of the Floating Cages could mean that its acquisition could lead to the delay in the adoption of the AST, since conventional tilapia stocked in Floating Cages yield greater outputs than in other fishponds. Thus the third hypothesis is:

3. ***The relationship between Floating Cages and AST is indeterminate: prior adoption of Floating Cages may or may not speed up the adoption of AST and vice versa.***

However, in spite of the above, it is possible that there is no correlation between the adoption of one technology and another and that adoption choices might simply be because certain farmers are more likely to adopt new techniques in general and the complementarities may not be significant.

4.3 Duration model of technology adoption

Survival analysis or commonly, duration analysis, has been applied in the medical and engineering fields for a long time but in recent years, it has been applied in the social sciences. For instance in labour economics, duration analysis is applied to analyse the duration of unemployment and jobs (see the survey article by Devine and Kiefer, 1991). Duration analysis has also been used in macroeconomics to study business cycles (e.g.

Diebold and Redebusch, 1990); it has also been applied in marketing to analyse the timing of household purchases (e.g. Vilcassim and Jain, 1991) and in consumer economics to assess how long it takes for individuals to buy a durable item (Robin and Visser, 1997). A few studies have applied this technique in the study of technology adoption decisions in agriculture, including Fuglie and Kascak (2001) (natural resource conserving agricultural technology), Burton et. al., (2003) (organic horticulture), Abdulai and Huffman (2005) (crossbred cows), but not in fish farming.

The purpose of duration analysis is to identify the factors that influence the length of time to a spell, where a spell in this chapter is adoption of technology. A spell starts at the time when a farmer becomes aware of the existence of a technology for the first time and ends when adoption takes place. Probability is a fundamental component of duration analysis; therefore, one can focus on the probability of a spell ending rather than the length of the spell itself. I seek to address the question: *what is the probability of a smallholder fish farmer adopting a given technology at time t, given that s/he has not adopted by that time*?

The dependent variable, Duration, is denoted by T, which is a random variable, assumed to have a continuous probability distribution, f (t). The probability that the duration will be less than t is

$$F(t) = Prob(T \leq t); t \geq 0 \tag{1}$$

Equivalently, the distribution of T can be expressed in terms of the survival function, $S(t)$, which is the probability that the spell will be at least t, implying the probability of surviving beyond time t. Therefore, the $S(t)$ can be expressed as

$$S(t) = 1 - F(t) = Prob\ (T\ > t) \tag{2}$$

The ***hazard function/rate*** is the probability that the duration will end after time t, given that it has lasted until time t. In other words, it is the probability that a farmer will adopt the technology at time t while the individual is at risk of adopting the technology. The hazard function is specified as

$$h(t, X) = \lim_{\Delta \to 0} \frac{\Pr(t \le T \le t + \Delta t | T \ge t, X)}{\Delta t}, t \ge 0 \qquad (3)$$

The hazard function provides the instantaneous rate of failure at time t and it is the continuous time version of sequence of conditional probabilities of adoption, in this context. A higher hazard rate indicates the likelihood of an earlier adoption.

Thus from the above, one may see that a clearly defined relationship between the hazard and survival functions is

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \qquad (4)$$

The three functions, $f(t)$, $S(t)$ and $h(t)$ are mathematically equivalent specifications of the distributions of the survival time,T, therefore knowing any one of them could lead to the deduction of the others (Ahsanuzzaman, 2014). Thus, duration models estimate one of these functions as the basis for statistical analysis. Even though they have similar properties, the survival function is most suited for comparing the survival progress of two groups, whilst the hazard function describes the risk (likelihood) of failure (adoption) at any point in time (Ahsanuzzaman, 2014).

The underlying data-generating process determines the shape of the hazard function. Since non-parametric models do not assume any generating process, it is important to specify a functional form, either parametrically or semi-parametrically before estimation. However, the choice of a specific model is usually based on theoretical and empirical evidence, especially regarding the distribution of the data (Allison, 1984; Lapple, 2010).

There are many functional forms used in the parametric estimation of the distribution of T, including exponential, Weibull, Gompertz and Log-logistic; however, for ease of comparison to Liu (2013), and to incorporate time dependent variables, this study adopts the Weibull baseline hazard specification. The exponential model in duration model is the baseline model as it has a constant hazard rate, which is independent of time (Lapple, 2010). Where the hazard function is assumed or known to have duration/time dependence, the Weibull model can be used to represent the effect of time. In the Weibull model, the hazard is expressed as

$$h_0(t) = pt^{p-1}\exp(\beta_0) \tag{5}$$

Where $h_0(t)$ is the baseline hazard and depends only on time (t), β is the vector of parameters to be estimated. This is a more flexible model than the exponential model and it allows for hazard rates that are non-constant but monotonic. The parameter, p, is the shape parameter because it determines whether the hazard is increasing, decreasing or constant over time. The shape parameter shows the following possibilities:

1. If $\hat{p} < 1$, then the hazard is monotonically decreasing with time
2. If $\hat{p} > 1$, then the hazard is monotonically increasing with time
3. If $\hat{p} = 1$, then the hazard is flat or is independent of time, and this would be the same as the exponential model. This means that the Weibull model actually nests the exponential.

In specifying duration models, the proportional hazard (PH) model is often adopted (Ahsanuzzaman, 2014), as it is suitable in cases of exponential, Weibull, and Gompertz distributions (e.g. Lapple, 2010; Addison and Portugal, 1998). In the PH specification, covariates are related multiplicatively with the baseline hazard and the hazards are independent of time:

$$h(t|X,\beta) = h_0(t)p(X,\beta) \tag{6}$$

where $h_0(t)$ is the baseline hazard and depends only on time, t, and $p(X,\beta)$ is the hazard that depends on covariates determined by economic theory, and β is the vector of parameters to be estimated.

Equation (6) can be estimated using two approaches: semi-parametric and fully parametric. The Cox PH specification estimates equation (6) without any parametric specification of the baseline hazard $h_0(t)$, while the alternative, PH model, which uses any of the distributions, such as exponential, Weibull or Gompertz etc. specifies the baseline hazard function.

The sign of the parameter of the model or the magnitude of the hazard ratio (greater than or less than unity) implies the direction of the effect and each parameter summarizes the proportional effect on the hazard of absolute changes in the corresponding covariates (Jenkins, 2005). Moreover, this effect is independent of survival time (Ahsanuzzaman, 2014).

Estimation of the parametric models in duration analysis follows the maximum likelihood procedure, although the estimation is complicated because of right censoring.

Focusing on the Weibull distribution in (6), the density function can be expressed as

$$\exp(\beta_0 + X_i\beta_i)t^p \tag{7}$$

If we let D_i be the censoring dummy, taking a value of 1 indicating that the farmer has adopted the technology and 0 otherwise, then the likelihood contribution is written as:

$$L_{i=}[f(t)]^{D_i}[S(t)]^{1-D_i} \tag{8}$$

The likelihood function L is then given by

$$L(\beta, p) = \prod_{i=1}^{N} L_i \tag{9}$$

The values of β and p that maximize the likelihood function are the estimators of the Weibull hazard model.

4.4 Empirical application of duration analysis

The time to adoption or survival model discussed above is employed to assess how long it takes for smallholder fish farmers to adopt Extruded Feed, Floating Cages and AST in Ghana. I model these adoption decisions premised on the availability of these technologies and household, farmer and location-specific characteristics. Thus the hazard rate for adoption is defined as the probability that a farmer will adopt a given technology at time *t* conditional on him not having adopted the technology before t.

For this study, the hazard function of adopting a technology for an individual farmer at time t is $h(t|X, \beta) = h_0(t)p(X, \beta)$, where the parameters are as described in (6).

Where the dependent variable, t, is the time to adoption (adoption spell, t) and is defined as the length of time (in years) the farmer took from the initial exposure to the possibility of adoption of the technologies to the actual time when the farmer started using a particular technology; X is a vector of farmer characteristics such as $\boldsymbol{age}$ (the age in the period of observation), $\boldsymbol{male}$ (is the male gender), $\boldsymbol{edu}$ is years of formal education, $\boldsymbol{exp}$ is years of experience in fish farm-related activities, $\boldsymbol{weather}$ (dummy) is experience of past weather shocks, $\boldsymbol{mainoccu}$ is the main occupation of farmer (=1 if fish farming), $\boldsymbol{hhs}$ is the household size, $\boldsymbol{ownhouse}$ (dummy) is ownership of a house, $\boldsymbol{rooms}$ is number of rooms owned, $\boldsymbol{freehold}$ is freehold tenure (dummy), $\boldsymbol{extension}$ is access to extension contact (dummy), $\boldsymbol{credit}$ is access to credit (dummy), $\boldsymbol{ffa}$ is membership in fish farmer association (dummy), $\boldsymbol{ash}$ is Ashanti Region, $\boldsymbol{west}$ is Western Region (dummy), $\boldsymbol{volta}$ is Volta Region (dummy), and **married** is marital status (dummy, =1 if married).

4.5 Data and description of variables

The data used in this chapter come from a field survey, which gathered information about the adoption of technologies by the fish farmers. Additionally, the risk attitudes of the farmers were elicited through the use of incentivised lottery experiments conducted in the field. Full details of the elicitation and measures of risk attitudes are described in Chapter Two of this thesis.

The actual future outcome of a new technology is not known with certainty, and due to these associated uncertainties, farmers are expected to exhibit different behaviour to adoption because of their different levels of risk aversion (Ansah et. al., 2014). The differences in attitudes and characteristics of farmers are likely to influence the length of time it takes to adopt a technology. In this empirical study, I analyse a number of potential determinants of the adoption decision, which are broadly categorized as farmer characteristics, household characteristics, access to services and regional characteristics. It must be noted that the characteristics of farmers described here were gathered from the survey conducted in 2014, but I assume that these characteristics were potentially time-invariant and were comparable to the characteristics of the farmers prior to the adoption of the technologies. While this may hold for some farm characteristics such as number of ponds, especially given the short duration, some other features may vary over time. For instance, the membership in fish farmer associations, access to extension services, marital status could change over time; a farmer may have been single prior to adoption but could be married at the time of the survey. However, since in this survey I did not ask for information on the long-term history of each farm it is not possible to assess potential impact of this assumption. Perhaps a better approach to assess the influence of these variables is with a panel survey of the farms (Fuglie and

Kascak, 2001). I acknowledge that time-variant variables such as input and output price changes, as well as the cost of the technologies could affect the adoption decision, but I am not able to include these in the model due to lack of data. Table 4.1 presents a summary of the variables included in the empirical model.

4.5.1 **The dependent variable**

The dependent variable in this study is the time to adoption of technology, hence for each farmer there is a different value for the time to adoption for each of the three technologies, since some of them do not adopt the technologies at the same time. The three technologies are described in detail in an earlier section. Farmers were asked to recall the year they first learnt/heard about each technology, and the year they started using each technology, as well as the reasons for doing so. The obvious challenge with such data is the likelihood of measurement errors, since farmers may state these dates incorrectly. If this is the case it will imply that variance of the parameters are biased, however coefficients of the variables remain unbiased if the errors in responses are not correlated with farmer characteristics (Matuschke and Qaim, 2008; Fuglie and Kascak, 2001). The earliest time a farmer indicated having knowledge of the availability of any of the three technologies was 1994, and the year of data collection was 2014, implying a time lapse of 20 years[31]. However, from Figures 4.1 to 4.3 most of the adoption of the three technologies occurred from 2009 onwards, therefore since most adoption occurred fairly recently, I am fairly confident about the relative accuracy of the recall data. This minimizes possible errors that could result from recalling historic events, in this case year of adoption.

[31] Not aware of the actual years the technologies were available to the farmers; therefore I used the earliest time mentioned by the farmers as the first year of analysis.

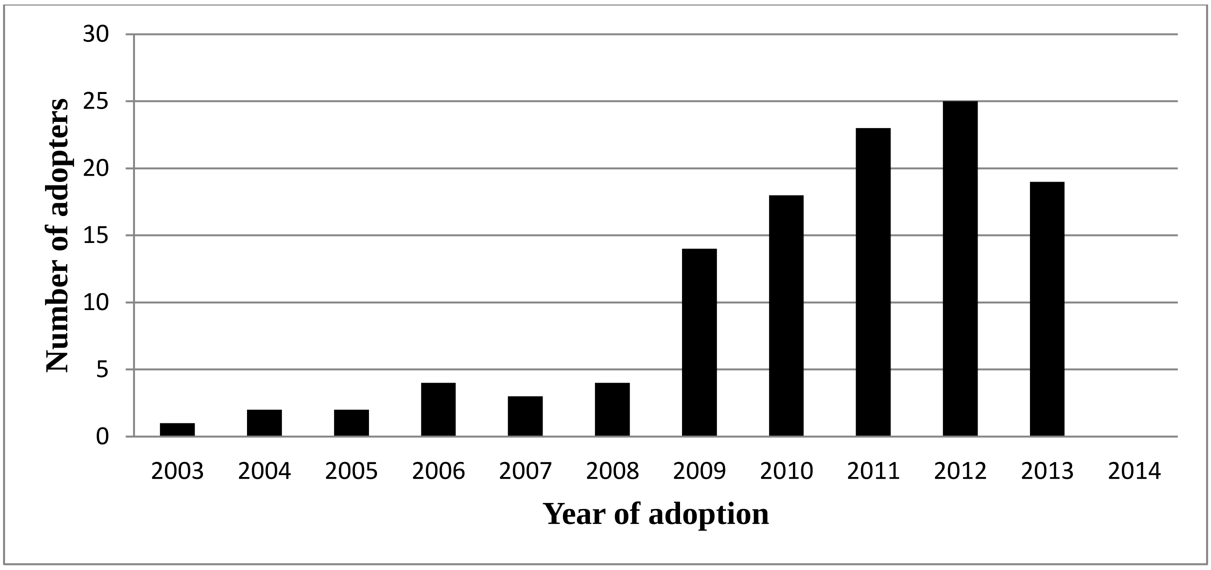

Figure 4.1: Distribution of farmers by year of adoption of Extruded Feed

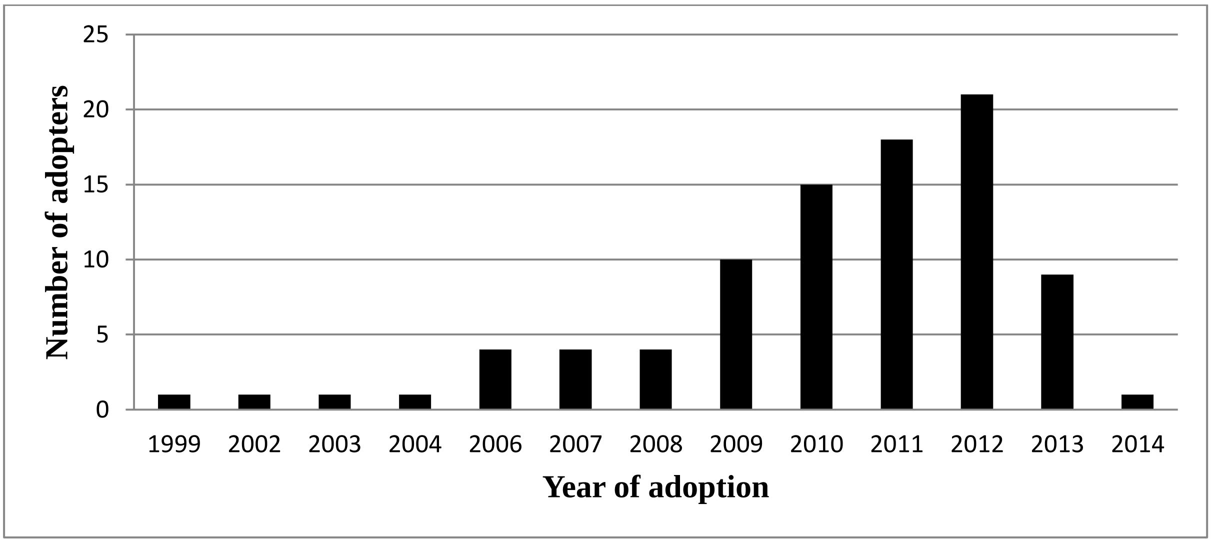

Figure 4.2: Distribution of farmers by year of adoption of Akosombo Strain

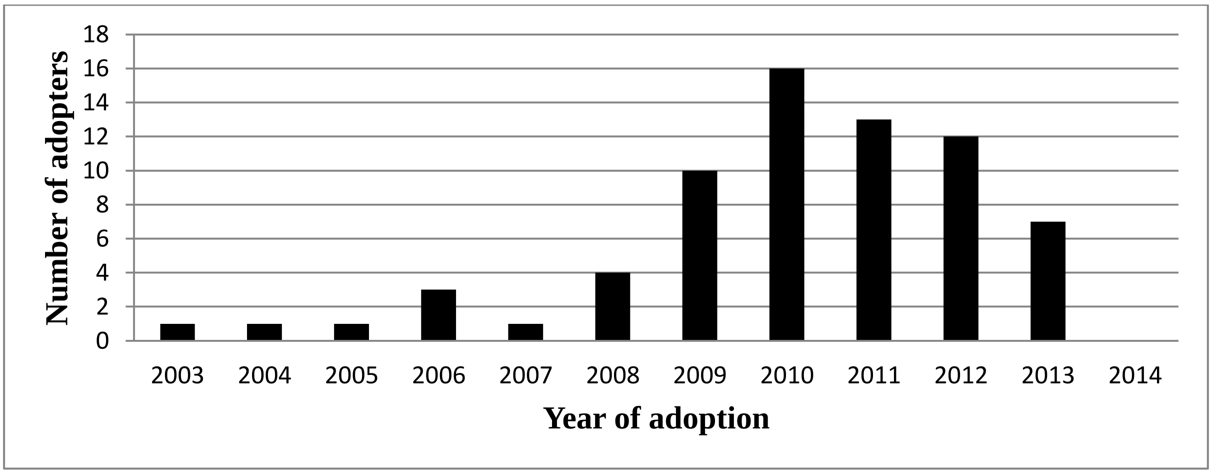

Figure 4.3: Distribution of farmers by year of adoption of Floating Cages

4.5.2 **Explanatory variables**

Explanatory variables included in this study were chosen based on existing duration adoption literature and economic theory (e.g. Fuglie and Kascak, 2001, Burton et. al., 2003, Dadi et al, 2004, Beyene and Kassie, 2015, Nazli and Smale, 2016), and are summarised in Table 4.1. This section describes a few of the variables as they relate to this study.

The age of the respondent responsible for adoption decisions was measured in years; this is a time-varying covariate so I use the age in the period of observation for each farmer.

Human capital is measured by the number of years of formal education attained. I assume the farmers concluded their formal education before learning about the technologies, hence this variable is considered as time-invariant. Farmers who were more formally educated were expected to adopt technologies earlier since they are able to comprehend information regarding the pros and cons of each technology, and therefore would adopt if they perceived the technologies to be more beneficial than the existing technologies.

Capital and social networks have been shown to be important determinants of adoption decisions (Burton et. al., 2003, Bandiera and Rasul, 2006, Beyene and Kassie, 2015, Nazli and Smale, 2016). Access to adequate sources of information and functional markets is limited and therefore social networks such as membership in fish farmer associations and extension services could potentially facilitate exchange of information and overcome credit constraints, leading to earlier adoption. However, Di Falco and Bulte (2011) note that social capital can, to some degree, discourage investment or adoption, therefore the influence of social capital is indeterminate *a priori* (Beyene and Kassie, 2015). Less than 50% of the farmers had access to extension services in the year of the survey, but it was impossible to verify if this was the same situation prior to the adoption of the technologies, this is because it is possible that extension access could be a result of adoption, and not always the cause. For instance extension contact is reported to enhance adoption (Cavane and Donovan, 2011), but in some cases there was no significant effect of extension contacts (Krishnan and Patnam, 2014). Extension contact alone may not lead to adoption of technology, but the trust farmers have in the extension agent could tilt the decision in favour of adopting a new technology or otherwise (Beyene and Kassie, 2015).

A variable of key interest to this study is risk aversion[32]. In a developing country like Ghana and in the fish farming sector risks abound due to a number of factors such as extreme weather shocks such as floods and drought, diseases and fluctuating input and output prices as well as yield variability. Thus, farmers are generally expected to delay adoption of new technologies owing to such uncertainties and risks. However, if technologies are risk-reducing farmers may be incentivised to adopt these improved technologies that promise higher and more assured returns, even if these are perceived to be risky (Beyene and Kassie, 2015).

Ownership of house and number of rooms are used as proxies for wealth of the household. The inclusion of asset ownership and household size in duration analysis is inferred from the poverty trap hypothesis, which posits that poor households remain low-income households for a long time (Matushcke and Qaim, 2008; Beyene and Kassie, 2015). Since most farmers adopted the three technologies from 2009 onwards, it is likely that they may not have changed their asset ownership simply through adoption within the period.

I include dummy variables to capture region-specific characteristics not captured by the other variables. The Greater Accra Region is the reference region, so it is left out of the regression and the values of the coefficients of the three remaining regions compare to that of the left

[32] The elicitation and estimation the risk attitudes variable is explained in Chapter 2 of this thesis. In this chapter I employ the calculated risk attitude measures obtained from Chapter 2 here as an explanatory variable.

out region[33]. For example, if the hazard ratio of the dummy variable Ashanti Region is greater than one (1), it implies that farmers in the Ashanti Region adopt more quickly than farmers in the reference region, Greater Accra; similar interpretation apply to the other dummy variables.

Separate hazard models are estimated for each technology but adoption information of the other two technologies is included in the adoption of a given technology. I achieve this by including among the explanatory variables a time varying dummy variable, which captures the effect of the adoption of other technologies in previous periods on the adoption of a technology in a given period (Butler and Moser, 2010; Colombo and Mosconi, 1995; Stoneman and Kwon, 1994). As an illustration, in the estimation of the hazard model for extruded feed, AST is included as a dummy, which takes a value of 1 if AST was adopted at least a year before the adoption of extruded feed, and equals 0 otherwise; Floating Cage is included in the equation for Extruded Feed in the same manner. Conversely, in the estimation of AST, Extruded Feed and Floating Cage each take a value of 1 if adopted at least a year prior to the adoption of AST, and 0 otherwise. Table 4.1 shows that many farmers (39%) adopt the extruded feed, for example, before Floating Cages, possibly because of the differences in costs. Risk attitude measures and how they influence the speed of technology adoption are discussed later in section 4.8.

Table 4.1: Descriptive Statistics of variables used in the analysis (N=120)

Variable	**Definition**	**Mean**	**Standard deviation**
Dependent Variables			
Time to adoption of Extruded Feed	Number of years from date of knowing about to date of first use of extruded feed	16.62	2.28
Time to adoption of Floating Cages	Number of years from date of knowing about to date of first use of Floating Cages	17.76	2.53
Time to adoption of Akosombo strain of tilapia	Number of years from date of knowing about to date of first use of Akosombo strain of tilapia	17.11	2.79

[33] Hazard ratios are the exponentiated coefficients (βi)

Independent Variables ***Farmer characteristics***			
Age of farmer at adoption of technology	Age of respondent at the time of adopting technology	38.55	13.15
Gender of farmer	=1 if farmer is male	0.92	0.28
Education	Years of formal education attained by farmer	9.83	4.62
Marital Status	= 1 if farmer is married	0.75	0.44
Risk aversion (σ) from TCN	Risk attitude obtained from TCN lottery experiment	0.89	0.52
Risk aversion (CRRA)	Risk attitude obtained from Brick et. al. lottery	2.35	2.45
Loss aversion (λ)	Loss aversion from TCN lottery experiment	1.92	2.40
Probability weighting (α)	Probability weighting from TCN lottery experiment	0.74	0.30
Experience	Number of years a farmer has engaged in fish production	5.47	5.37
Past weather shocks	= 1 if farmer experienced flooding in the past	0.73	0.44
Main occupation	= 1 if fish farming is main occupation	0.71	0.46
Prior adoption dummies			
Akosombo before extruded	=1 if Akosombo strain is adopted prior	0.1	0.30
Akosombo before Floating Cage	=1 if Akosombo strain is adopted prior	0.28	0.45
Extruded before Akosombo	=1 if Extruded Feed is adopted prior	0.28	0.45
Extruded before Floating Cages	=1 if Extruded Feed is adopted prior	0.39	0.49
Floating Cage before extruded	=1 if Floating Cage is adopted prior	0.04	0.20
Floating Cage before Akosombo	=1 if Floating Cage is adopted prior	0.13	0.33
Household characteristics			
Household size	Number of people with whom farmer eats from the same pot	6.08	3.03
Own House	= 1 if farmer owns his house	0.63	0.48
Number of rooms	Number of rooms in famers' household	4.23	2.68
Freehold tenure	=1 if farmer owns the farm land	0.33	0.47
Access to services			
Access to extension services	=1 if farmer has access to extension services	0.48	0.50
Access to credit	= if farmer has access to credit	0.78	0.42
FFA[34] membership	= 1 if farmer is a member of fish farmers' association	0.32	0.47
Region level variables			
Western	= 1 if farmer is resident in the Western Region	0.22	0.41
Ashanti	= 1 if farmer is resident in the Ashanti Region	0.17	0.37
Volta	= 1 if farmer is resident in the Volta Region	0.23	0.41

4.5.3 Description of the technologies

Most forms of conventional aquaculture practices are perceived to have adverse effects on the environment, including eutrophication of water bodies, through the deposition of remnant nutrient-rich feeds from the feeding of farmed fish. The traditional feed and feeding regime among resource-poor farmers in the farmed-fish industry involves the use of left-over foods from homes and harvests from farms, which do not provide balanced feed to the fish and therefore fish do not reach marketable sizes in time and harvests are generally carried out

[34] FFA= Fish Farmer Association.

once in a year on average. Thus, apart from negative environmental impacts, most existing conventional technologies do not provide enough economic returns for farmers in time. However, as previously mentioned, the aquaculture sector has seen much improvement in recent years with the introduction of more improved and modern technologies, which are considered as practical solutions to reducing negative effects of farmed fish production on the environment and to improve the economic wellbeing of farmers. Therefore, voluntary of adoption of these technologies in time could ensure the profitability and sustainability of the industry, especially in a developing country like Ghana.

Many improved aquaculture technologies exist; and they may be broadly categorised into two types: nutrient management and effluent management (Louisiana State University, AgCenter, 2003). The former type includes technologies that are related to feeding and fertilizer applications, which minimize waste and prevent deterioration of water quality (Tucker et. al. 1996). The latter refer to cage culture and other pond types that minimize the leaching of chemicals and nutrients into the environment. This present study focusses on the adoption of three technologies from each of the two broad categories: the use of extruded/floating feed and AST (nutrient management) and Floating Cages (effluent management)[35]. These will enable the assessment of whether the decision to adopt a given technology is influenced by or influences the adoption of other technologies, and how the speed of adoption of different technologies is affected by farmer/farm-specific characteristics; which cannot be achieved by studying a single technology in isolation.

The Extruded/Floating Feed is a commercial feed formulated with essential nutrients for fish growth and development. It is prepared with a good balance of macro and micronutrients needed by fish for growth (Bell and Waagbo, 2008). The commercial processing of this feed

[35] This is considered in contrast to conventional sinking feed.

removes anti-nutritional factors and makes Extruded Feed more utilizable to fish (Drew et. al., 2007; Hardy, 2010). It is extruded and palletized, allowing it to float on the water surface for long periods and remain available to feeding fish. This helps to reduce food waste and save costs (Engle and Valderrama, 2004). For best outcome from farmed fish, the appropriate feeding regime in terms of frequency and quantity must be adhered to. This is only achieved with the use of pelleted or extruded feed, unlike the conventional feed, which is usually prepared with mixture of agricultural and food industry waste, such as corn meal, wheat or rice bran, and peanut husks. The mixture is milled into powder, which quickly sinks to the bottom of the pond when administered. Fish growth is hampered by not only the unavailable feed and nutrients, but sinking feed accumulates on the pond bottom, where it decomposes to set off physico-chemical reactions that degrade the quality of the pond and could result in disease outbreaks. The use of Extruded Feed results in relatively faster rate of fish growth resulting from the bioavailable protein contents. Even though it is relatively more expensive costing almost seven times the unit cost of the local alternative, it results in fish twice the size of fish fed the conventional sinking feed (Frimpong et. al., 2014)[36]. Furthermore, from an enterprise budget analysis, Ansah et. al (2014) find that the use of the Extruded Feed result in about seven times higher net returns than the conventional feed. The rate of adoption of the Extruded Feed between 2011 and 2013 was 58.2 % among fish farmers in Ghana (Ansah, et. al., 2014).

The AST is a relatively newer and improved strain of tilapia (*Oreochromis niloticus*) developed by the Aquaculture Research and Development Centre (ARDEC), and has about 30-50% higher growth rates than tilapia in the region (Lind et. al., 2012). On average, it takes six months for this strain to reach a weight of 420g from an initial stocking weight of 15g.

[36] The extruded feed costs GhC40/20kg bag and the local (sinking) feed costs on average GHC 13/50 kg/bag. In terms of feed conversion ratios, the extruded feed is on average 2.06; while the local alternative is about 4.18 (total feed/ total weight gain) Analysis of profits indicated that extruded feed results in up to 45% profitability of fish production (Frimpong et al., 2014).

The implication of the situation means that instead of eight months for the traditional breed to reach market size, a farmer who cultivates the new breed is sure to harvest twice in the year, *ceteris paribus*. Apart from its fast-growing properties the AST also has a higher survival rate and disease-resistance. Most hatcheries have adopted the AST as their brood stock and are producing fingerlings for the whole industry. The cons of this technology lie mostly in institutional factors, such as inadequate access to urban and ready markets due to poor road networks and unreliable electricity supply leading to absence of cold storage in the rural tilapia value-chain and therefore inefficient and risky post-harvest handling.

The third technology is the Floating Cage. These cages are used mostly on the Volta Lake, and rely on commercial Extruded Feed and these systems account for about 90% of Ghana's aquaculture production (Ainoo-Ansah, 2013; Awity, 2013). Tilapia are stocked at an average rate of 103 fish per cubic metre and fed locally with available pelleted feed for approximately six months. Advantages of cages over other rearing systems include low capital costs, relatively simple management, better quality of fish, and use of existing water bodies (Beveridge, 2004). They can also be relocated if unfavourable weather or other environmental conditions occur (Pillay and Kutty, 2005) and also reduces mortality as the fish are protected in an enclosure from predators that may exist in the wild. The cage system operates best on extruded feed, which is more expensive and in the absence of credit, this may be a challenge for the resource-poor farmer to adopt this technology.

For all the three technologies described above, there exist elements of uncertainty regarding actual yields and prices, both of inputs and outputs. Nonetheless, given the compelling advantages of the three technologies it is still puzzling as to why it takes a long time for farmers to adopt some of the technologies. Also, existing adoption studies have focused on either a single new technology (improved water and irrigation system, modern fertilizer, or improved seeds) or a set of modern technologies treated as a unique bundle. In other words, the adoption decision may be described more like a multivariate adoption than a univariate process; this is why this investigation focuses on the decision of the farmers to adopt these three technologies.

Estimation consideration

To ascertain whether the risk attitude measures used in this study capture real economic choices of the farmers this study employs two multiple price lotteries: the BVB lottery which is a gains-only lottery, and the TCN lottery which involves both gains and losses[37]. It is possible that farmers treated the gains-only lottery experiment as 'just a game' without much thought since they had nothing to lose in the process. Thus, it may seem this lottery may not capture the real economic risky choices fish farmers face in their operations which involve losses and gains. If this intuition is true, then the introduction of losses should make farmers take the lottery experiment more seriously and the second lottery experiment should capture this real risk attitude[38]. The results show that more farmers (53.3%) are risk averse under the former lottery than the latter (48.3%), but the difference is only marginal. To ascertain that both lottery experiments actually captured the same attributes (risk attitudes) of the farmers, I conducted a Spearman rank correlation test between the two risk attitude measures (CRRA and σ) for each farmer. I find that the two measures of risk attitudes are not independent, in other words the null hypothesis that the two measures of risk preferences are independent is rejected, in favour of the alternative hypothesis that they are both capturing the same attribute (risk attitudes) of the farmers (see results in Table 4.2). This gives credence to the measures of risk attitudes used in modelling the speed of adoption of the technologies.

[37] The lotteries have been described in greater detail in Chapter 2 of this thesis.

[38] It was explained to the farmers that the losses from the lottery experiment would only be from the payment they were given for showing up.

4.6 Results

4.6.1 Outcomes from lottery experiments

A summary of the risk attitude measures used in this investigation is provided in Table 4.2. Based on the mean values of the BVB risk attitude measure (2.4), the average farmer is classified as risk loving. The values of the TCN parameters (σ, α, λ) are 0.9, 0.7, 1.9 and they respectively imply that the average farmer is risk averse, overweights small probabilities and is loss verse. The value of 5.4 obtained from the self-reported risk attitude (SRRA) shows that the average famer's risk attitude is somewhat in the middle of the Dohmen et. al. (2010) scale[39].

Table 4.2: Summary of Risk Attitude Measures

Risk Attitude Measure	Mean	Standard Deviation
BVB (CRRA)	2.4	2.5
TCN (σ)	0.9	0.5
TCN (α)	0.7	0.3
TCN (λ)	1.9	2.4
SRRA	5.4	3.2

4.6.2 Correlation among risk aversion measures

A Spearman correlation test was performed among the three parameters from the TCN lottery and the CRRA parameter from the BVB lottery (Table 4.3). It is not possible to reject the null hypothesis that α and σ are independent measures, as are α and λ. For the purpose of the study it is reassuring to find that the two measures of risk aversion are positively correlated, in other words the two measures of risk aversion (CRRA and σ) are measuring the same attribute of the farmers.

[39] This is explained in more detail in Chapter 2 of this thesis

Table 4.3: Correlations among TCN parameters, SRRA and CRRA

	SRRA	CRRA	Sigma	Alpha	Lambda
SRRA	1.000				
CRRA	0.053	1.000			
Sigma	-0.016	0.524***	1.000		
Alpha	0.020	0.102	0.285***	1.000	
Lambda	0.010	-0.125	0.075	0.046	1.000

4.7 Duration analysis: empirical results

4.7.1 **Nonparametric results**

In duration analysis, prior to rigorous parametric analysis, it is usual to perform some summary of the survival times or the lengths of time to adoption of all the individuals in the sample. These summaries help us to choose appropriate functional forms for parametric analysis (Kiefer, 1988); the Kaplan-Meir estimate of the survival function is employed here because some of the observations are censored (Burton et. al., 2003). The Kaplan-Meir estimation is a non-parametric approach, making no assumptions about the distribution of the length of time it took to adopt a given technology. This estimation process is carried out by dividing the period of observation into a series of intervals, each containing one or more adoptions at its beginning. The function can only be identified at times when adoption occurs. The estimated survivor function between time periods t_1 and t_2 is calculated as the number of farmers who have not adopted a given technology at time t_1, divided by the number of farmers 'at risk' of adopting at time t_1. This estimate changes only when in the next time period a farmer adopts the technology, otherwise it is a constant horizontal line.

The Kaplan-Meier estimate of the survivor functions for the three technologies are plotted in Figures 4.5 and 4.6. In each figure the horizontal axis is scaled in 'artificial time' (Burton et.

al., 2003), from 0 to 20, representing the 20 years or periods since the technologies became known or available to the fish farmers (1994) and the year of data collection (2014). It must be noted that for ease of analysis and following other researchers (e.g. Burton et. al., 2003) all cases enter at $t = 0$, regardless of which point in calendar time they begin to be observed. Therefore, a farmer who starts using a given technology in April of a particular year is reckoned as entering the analysis at the same time as a farmer who adopts that technology in December of the same year. In 1994 (t = 0), the value of the function is 1, since none of the farmers in our sample had adopted any of the technologies prior to this year.

Figures 4.5 and 4.6 are the graphs for the Kaplan Meier survival functions for the three technologies, using the categories of fish farmers according to the BVB and TCN lotteries respectively. It may be seen that there is a general lag between the first period of the Extruded Feed technology being available and the 9th period when the first adoption takes place. The rate of adoption of this technology is not uniform over time. This shows that the hazard rate increases over time. The value of the function falls steadily after the 9th period since only one farmer adopted the Extruded Feed in the 9th period. The function falls sharply after the 14th period when 7 (5.8%) farmers adopt the technology and subsequently the number of adopters increases over the rest of the period. Comparing the survival rates of the risk averse and risk preferring farmers shows that risk averse farmers adopt Extruded Feed earlier than risk preferring farmers in all figures. Where there are no adopters in a given period the function does not change. As of the time of data collection, five farmers had not adopted Extruded Feed and they were all risk preferring. Similar interpretations hold for the survival functions for AST and Floating Cages, as depicted in the remaining figures.

In Table 4.4, the technology that has been adopted by the largest number of farmers in our sample is the Extruded Feed technology.

Table 4.4: Technologies and adoption

Technology adopted	Yes	No
Floating Cage	69	51
Akosombo Strain	90	30
Extruded Feed	115	5

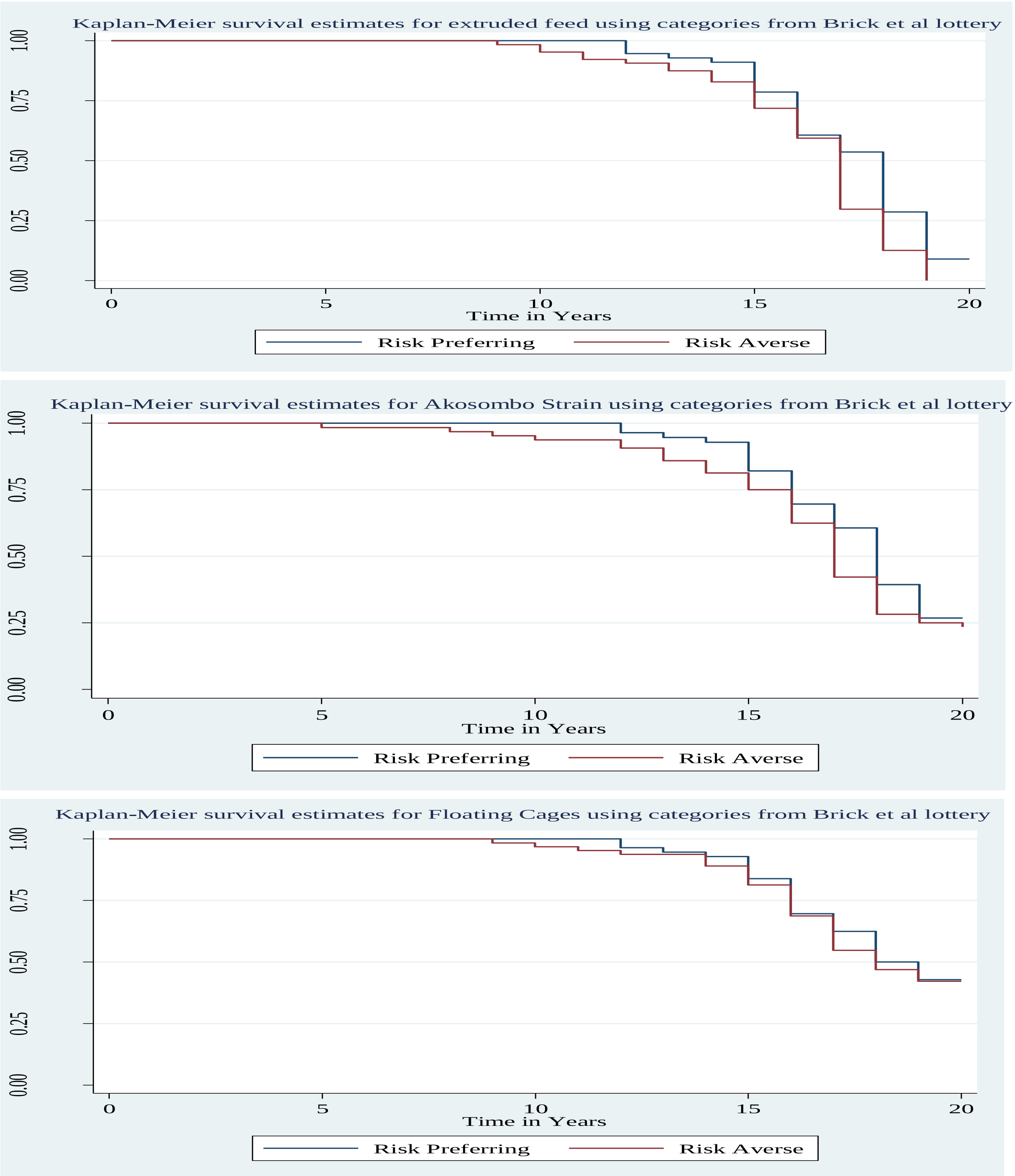

Figure 4.4: Length of time to adoption of technologies for risk averse and risk preferring farmers with BVB lotteries

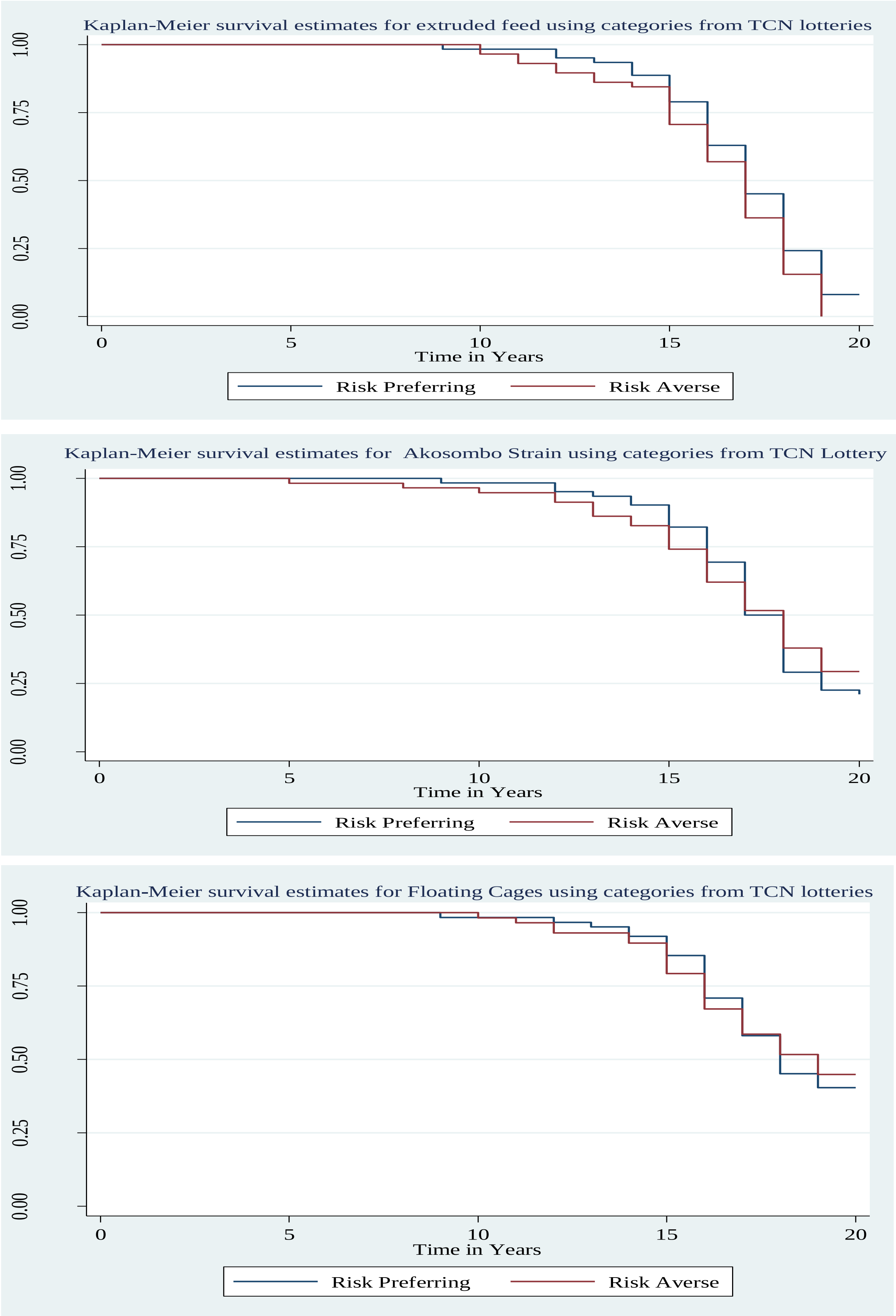

Figure 4.5: Length of time to adoption of technologies for risk averse and risk preferring farmers with TCN lotteries

4.7.2 **Parametric results**

The hazard ratios for the estimation of the three technologies are summarized in Tables 4.5 - 4.7. The first column in each table shows the outcome when no risk attitude variable is included, the remaining columns are labelled according to the key variable that is added in the regression, with parameters reported as hazard ratios in each case, except for the shape parameter, P. The standard errors of the hazard ratios are reported in parentheses, where the significance level is with respect to the null of no effect, i.e., the hazard ratio equals one (Burton et. al., 2003). A hazard ratio greater than one (1) indicates that the variable in question accelerates the adoption of the technology. A hazard ratio less than one (1) denotes that the variable slows the adoption of technology. For each technology I report the hazard ratios for six regressions, assuming a Weibull distribution.

Based on the results in Tables 4.5- 4.7, I reject the hypotheses that the shape parameter, P=1 (or ln p=0) for all three technologies. This is because in these cases the values of P for AST, Floating Cages and Extruded Feed are respectively 8.49, 7.77, and 12.05 and highly significant (p-value=0.000), implying that there is a positive duration dependence and therefore the baseline hazard is monotonically increasing and not constant over time.

4.7.3 **Adoption of technologies in the absence of risk attitudes**

In the absence of risk attitudes, very similar results are obtained in terms of the factors that influence the speed of adoption for all three technologies. For instance, age (in the year of observation), experience, and access to credit are significant and accelerate the adoption of all three technologies. Education and experience of past adverse weather conditions (particularly flooding) are used as measures of human capital. Experience of past weather shocks is not significant in the decision to adopt AST, but it significantly accelerates the adoption of Extruded Feed and Floating Cages. Conversely, access to extension services delays the adoption of Floating Cages and Extruded Feed but has no significant effect on the speed of adoption the AST technology. The results also show that where significant, region of operation has very little effect on the speed of adoption. For instance, all things being equal, a farmer in the Volta Region has a lower probability of adopting the Extruded Feed and AST technologies at a point in time than their colleagues in the Greater Accra Region (reference region). However, there is no significant relationship between the region of operation and the speed of adopting Floating Cages.

In terms of the effect of the prior adoption of one technology on the speed of adopting another technology, the results in Tables 4.5-4.7 show that a farmer who adopts the Extruded Feed technology in a prior period has a lower probability of adopting the AST in a given time (hazard ratio =0.034, significant at 1%). This suggests a substitutionary relationship between these two technologies, and this may be attributable to the cost of the extruded feed. It may be adduced from the description of the technologies that Extruded Feed and AST give similar outcomes: increased and faster yields of fish. The cost of feed is the highest cost (up to 70%) faced by farmers in their production (Ainoo-Ansah, 2013), therefore in the absence of adequate liquidity, farmers, upon having adopted one technology may be constrained to adopt another technology like the AST. Though not a directly related study, Butler and Moser (2010) find a positive influence on the adoption of system of rice intensification (SRI) on the adoption of off-season crops (OSC) in Madagascar. The prior adoption of Floating Cages also shows a negative effect on the speed of adoption of AST, but this is not significant at any level of significance.

Differences in regional characteristics are found to play some role in the length of time to adoption of AST: farmers in the Volta Region, compared to those in the Greater Accra Region are likely to adopt this technology; no significant effect of Ashanti and Western Regions on the speed of adoption of this technology is observed. This shows that the speed of adopting the Akosombo strain of tilapia may not be influenced to any significant extent by the regional location of the farmers.

4.7.4 Effects of risk attitudes on speed of technology adoption

For all the three technologies investigated in this study, the hazard ratios show that risk averse farmers have a higher probability of adopting the AST, Extruded Feed and Floating Cage technologies at a point in time, *ceteris paribus*. For instance in columns 3, 5 and 6 of Table 4.5, the hazard ratios of risk attitude variables, σ (0.578 and 0.510) and CRRA (0.875), are less than and significantly different from one (1), respectively. These hazard ratios show that farmers who are risk averse have a higher proclivity to adopt the AST technology.

The results showing the effect of risk attitudes on the speed of adopting Extruded Feed technology are presented in Table 4.6. The hazard ratios of the value function curvature (σ) (0.488 and 0.502) and the CRRA (0.883) show that all things equal, a risk averse farmer has a higher probability of adopting the Extruded Feed technology at a point in time.

The hazard ratios for the Floating Cage technology are summarized in Table 4.7.The inclusion of risk attitudes in the model for Floating Cage technology show similar results to the other two technologies: the hazard ratios show that *ceteris paribus*, a risk averse farmer has a higher probability of adopting this technology at a point in time.

These findings corroborate the findings of Koundouri et. al. (2006). They find that risk aversion plays a significant role in the time to adoption of modern irrigation technology in Crete, Greece and conclude that farmers who are more sensitive to the risk of extreme events have a higher probability of adopting a modern irrigation technology. Other studies have shown that risk aversion will increase the probability of adopting a technology if the technology is risk-reducing (Isik and Khanna, 2003; Koundouri et al, 2006). In their study on the dynamic modelling of innovation process adoption with risk and learning, Tsur et. al., (1990), find that risk aversion positively affects adoption of technology. They argue that as a result of learning which, in turn, depends on present adoption decisions, higher risk aversion increases the appreciation of future declines in risk. This is because risk averse agents do not want to take the risk of not trying the innovation in time. However, some studies also find negative correlations between risk aversion and technology adoption. Knight et. al., (2003) study the influence of risk attitudes on technology adoption among Ethiopian farmers. They use a general hypothetical question to obtain the risk attitudes of the farmers and based on farmers' responses they were categorized into risk-averse and non-risk-averse groups. They find that risk aversion is associated with lower probabilities of technology adoption. Liu (2013) also finds that risk aversion significantly affects the speed of adoption of a new biotechnology among cotton farmers in China, and concludes that risk and loss averse farmers are more likely to delay the adoption of the Bt cotton.

Table 4.5: Estimates of Duration Model of the adoption of AST (Weibull Model)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	No Risk	**σ**	**α**	**λ**	**σ,α,λ**	**CRRA**
CRRA	_	_	_	_	_	0.875** (0.0471)
σ (value function curvature)	_	0.578** (0.138)	_	_	0.510*** (0.128)	_
α (probability weighting)	_	_	0.840 (0.376)	_	0.857 (0.356)	_
λ (loss aversion)	_	_	_	1.071 (0.054)	1.106* (0.059)	_
Age[40]	1.057*** (0.012)	1.058*** (0.012)	1.057*** (0.012)	1.056*** (0.011)	1.057*** (0.012)	1.052*** (0.012)
Male	1.292 (0.559)	1.065 (0.481)	1.321 (0.578)	1.282 (0.563)	1.068 (0.498)	1.010 (0.435)
Education	1.056 (0.039)	1.059 (0.040)	1.056 (0.039)	1.071* (0.040)	1.078* (0.042)	1.068* (0.040)
Married	0.988 (0.301)	0.897 (0.280)	0.989 (0.301)	1.053 (0.327)	0.959 (0.305)	1.095 (0.336)
Experience	1.068*** (0.023)	1.065*** (0.022)	1.065*** (0.024)	1.065*** (0.023)	1.058** (0.024)	1.063*** (0.023)
Experience of past weather shocks	1.302 (0.373)	1.369 (0.399)	1.302 (0.374)	1.215 (0.355)	1.254 (0.376)	1.519 (0.446)

[40] This is the age in the period of observation.

Main occupation	1.255	1.317	1.268	1.262	1.326	1.309
	(0.380)	(0.404)	(0.385)	(0.381)	(0.406)	(0.400)
Household size	1.045	1.048	1.046	1.040	1.043	1.043
	(0.044)	(0.045)	(0.044)	(0.044)	(0.046)	(0.044)
Own House	1.393	1.503	1.390	1.480	1.663*	1.500
	(0.372)	(0.395)	(0.372)	(0.406)	(0.455)	(0.407)
Number of rooms	1.067	1.057	1.065	1.080	1.068	1.072
	(0.056)	(0.057)	(0.056)	(0.057)	(0.057)	(0.055)
Freehold Tenure	1.002	0.894	0.999	1.036	0.908	0.95
	(0.300)	(0.271)	(0.300)	(0.307)	(0.273)	(0.278)
Access to extension services	0.641	0.493*	0.632	0.572	0.389**	0.551*
	(0.225)	(0.189)	(0.223)	(0.206)	(0.156)	(0.199)
Access to credit	4.154***	3.840***	4.290***	4.264***	4.105***	3.742***
	(1.483)	(1.368)	(1.578)	(1.518)	(1.501)	(1.360)
Extruded Feed	0.034***	0.030***	0.034***	0.035***	0.032***	0.031***
	(0.018)	(0.016)	(0.019)	(0.019)	(0.017)	(0.016)
Floating Cages	0.829	0.849	0.817	0.769	0.717	0.846
	(0.507)	(0.501)	(0.500)	(0.467)	(0.421)	(0.512)
FFA	0.634	0.656	0.647	0.640	0.686	0.580
	(0.259)	(0.257)	(0.268)	(0.265)	(0.275)	(0.234)
Ashanti	0.742	1.082	0.755	0.774	1.268	0.993
	(0.408)	(0.625)	(0.419)	(0.422)	(0.735)	(0.550)
Western	0.650	0.724	0.646	0.627	0.707	0.624
	(0.239)	(0.276)	(0.238)	(0.231)	(0.271)	(0.231)
Volta	0.370*	0.448	0.378*	0.405*	0.544	0.472
	(0.202)	(0.243)	(0.206)	(0.222)	(0.294)	(0.258)
P	8.490***	8.678***	8.483***	8.555***	8.815***	8.802***
	(0.785)	(0.802)	(0.785)	(0.788)	(0.812)	(0.817)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,064	2,064	2,064	2,064	2,064	2,064

Notes: ***, **, and * denote significance at 1%, 5% and 10% respectively; standard errors are in parentheses. Each column presents the hazard ratios from the inclusion of the variable of interest, using the Weibull model in each case.

Table 4.6: Estimates of Duration Model of the adoption of Extruded Feed (Weibull Model)

	Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
	No Risk	**σ**	**α**	**λ**	**σ,α,λ**	**CRRA**
CRRA	_	_	_	_	_	0.883***
						(0.042)
(value function curvature)	_	0.488***	_	_	0.502***	_
		(0.110)			(0.115)	
α (probability weighting)	_	_	1.670	_	1.397	_
			(0.606)		(0.486)	
λ (loss aversion)	_	_	_	1.002	1.012	_
				(0.045)	(0.046)	
Age	1.075***	1.074***	1.074***	1.075***	1.074***	1.070***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Male	0.448***	0.376***	0.442***	0.448***	0.377***	0.394***
	(0.124)	(0.110)	(0.123)	(0.125)	(0.110)	(0.113)
Education	1.087***	1.079**	1.090***	1.088***	1.084**	1.090***

	(0.032)	(0.033)	(0.032)	(0.033)	(0.034)	(0.032)
Married	0.616**	0.585**	0.593**	0.617**	0.575**	0.650*
	(0.140)	(0.136)	(0.136)	(0.142)	(0.136)	(0.150)
Experience	1.096***	1.094***	1.104***	1.096***	1.100***	1.090***
	(0.0219)	(0.0216)	(0.0229)	(0.0219)	(0.0227)	(0.0220)
Experience of past weather shocks	2.538***	2.431***	2.419***	2.536***	2.333***	2.903***
	(0.683)	(0.668)	(0.651)	(0.685)	(0.647)	(0.801)
Main occupation	1.010	1.183	1.037	1.009	1.192	1.024
	(0.231)	(0.280)	(0.237)	(0.231)	(0.280)	(0.234)
Household size	0.976	0.980	0.975	0.975	0.978	0.980
	(0.042)	(0.043)	(0.042)	(0.042)	(0.043)	(0.042)
Own House	2.107***	2.102***	2.016***	2.110***	2.055***	2.104***
	(0.470)	(0.458)	(0.457)	(0.474)	(0.455)	(0.465)
Number of rooms	1.067	1.042	1.077	1.067	1.053	1.076
	(0.051)	(0.051)	(0.052)	(0.052)	(0.054)	(0.051)
Freehold Tenure	1.152	0.961	1.084	1.153	0.941	1.024
	(0.295)	(0.258)	(0.283)	(0.296)	(0.252)	(0.263)
Access to extension services	0.353***	0.247***	0.374***	0.351***	0.256***	0.324***
	(0.104)	(0.080)	(0.113)	(0.108)	(0.088)	(0.096)
Access to credit	2.432***	2.588***	2.351***	2.433***	2.515***	2.209***
	(0.682)	(0.742)	(0.654)	(0.683)	(0.718)	(0.628)
Floating Cages	0.912	0.730	0.803	0.915	0.707	0.742
	(0.503)	(0.402)	(0.457)	(0.507)	(0.393)	(0.417)
Akosombo Strain	0.559	0.535	0.577	0.561	0.556	0.578
	(0.215)	(0.209)	(0.223)	(0.218)	(0.220)	(0.222)
FFA	0.800	0.792	0.778	0.802	0.779	0.721
	(0.225)	(0.218)	(0.221)	(0.228)	(0.219)	(0.202)
Ashanti	0.526	1.047	0.523	0.527	1.008	0.660
	(0.230)	(0.511)	(0.228)	(0.231)	(0.492)	(0.287)
Western	0.596	0.650	0.588*	0.596	0.643	0.596
	(0.190)	(0.217)	(0.189)	(0.190)	(0.216)	(0.190)
Volta	0.209***	0.300***	0.202***	0.210***	0.296***	0.275***
	(0.079)	(0.116)	(0.078)	(0.080)	(0.117)	(0.105)
P	12.05***	12.32***	12.13***	12.05***	12.38***	12.47***
	(0.903)	(0.925)	(0.907)	(0.904)	(0.930)	(0.937)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,994	1,994	1,994	1,994	1,994	1,994

Notes: ***, **, and * denote significance at 1%, 5% and 10% respectively; standard errors are in parentheses. Each column presents the hazard ratios from the inclusion of the variable of interest, using the Weibull model in each case.

Table 4.7: Estimates of Duration Model of the adopting Floating Cages (Weibull Model)

	Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
	No Risk	**σ**	**α**	**λ**	**σ, α, λ**	**CRRA**
CRRA	_	_	_	_	_	0.874**
						(0.0550)
σ (value function curvature)	_	0.447**	_	_	0.393***	_
		(0.144)			(0.132)	
α (probability weighting)	_	_	0.653	_	0.716	_
			(0.296)		(0.351)	
λ (loss aversion)	_	_	_	1.073	1.078	_
				(0.0525)	(0.0619)	
Age	1.056***	1.059***	1.058***	1.062***	1.067***	1.052***
	(0.0130)	(0.0136)	(0.0133)	(0.0141)	(0.0148)	(0.0128)
Male	3.620**	2.389	3.900**	4.026**	2.822	2.227
	(2.094)	(1.514)	(2.273)	(2.401)	(1.839)	(1.322)
Education	1.098***	1.091**	1.105***	1.103***	1.101***	1.089**
	(0.0371)	(0.0385)	(0.0379)	(0.0385)	(0.0401)	(0.0377)
Married	0.788	0.560	0.742	0.823	0.537	1.044
	(0.299)	(0.232)	(0.283)	(0.317)	(0.234)	(0.424)
Experience	1.084***	1.082***	1.079***	1.083***	1.076***	1.080***
	(0.0230)	(0.0231)	(0.0238)	(0.0233)	(0.0243)	(0.0237)
Experience of past weather shocks	2.585***	2.801***	2.792***	2.439**	2.913***	2.657***
	(0.947)	(1.058)	(1.040)	(0.910)	(1.186)	(0.986)
Main occupation	1.878	1.829	2.088*	1.952*	2.098*	1.876
	(0.723)	(0.708)	(0.836)	(0.758)	(0.851)	(0.745)
Household size	0.947	0.922	0.939	0.932	0.897*	0.923
	(0.0516)	(0.0531)	(0.0522)	(0.0526)	(0.0544)	(0.0505)
Own House	0.472**	0.601	0.435**	0.425***	0.514*	0.503**
	(0.150)	(0.202)	(0.143)	(0.141)	(0.179)	(0.164)
Number of rooms	1.088	1.083	1.103*	1.113*	1.125*	1.110*
	(0.0603)	(0.0641)	(0.0627)	(0.0644)	(0.0708)	(0.0636)
Freehold Tenure	0.897	0.807	0.975	0.883	0.810	0.742
	(0.321)	(0.292)	(0.356)	(0.315)	(0.298)	(0.271)
Access to extension services	0.449**	0.346***	0.426***	0.401***	0.274***	0.379***
	(0.146)	(0.121)	(0.139)	(0.135)	(0.103)	(0.128)
Access to credit	2.258**	2.574***	2.374***	2.445***	3.015***	2.345**
	(0.737)	(0.902)	(0.788)	(0.811)	(1.107)	(0.797)
Extruded Feed	0.206	0.220	0.196	0.153	0.197	0.209
	(0.238)	(0.244)	(0.228)	(0.192)	(0.227)	(0.237)
Akosombo Strain	0.688	0.500	0.860	0.772	0.635	0.591
	(0.549)	(0.417)	(0.720)	(0.648)	(0.560)	(0.490)
FFA	0.231***	0.348**	0.258***	0.263***	0.464*	0.251***
	(0.0903)	(0.144)	(0.105)	(0.106)	(0.204)	(0.0974)
Ashanti	1.97e-08	2.83e-08	1.70e-08	2.35e-08	2.92e-08	3.03e-08
	(3.13e-05)	(4.50e-05)	(2.67e-05)	(3.65e-05)	(4.57e-05)	(4.87e-05)
Western	1.91e-08	1.88e-08	1.58e-08	2.27e-08	1.54e-08	2.16e-08
	(2.63e-05)	(2.54e-05)	(2.14e-05)	(3.06e-05)	(2.00e-05)	(2.97e-05)
Volta	1.367	1.120	1.235	1.203	0.885	1.331
	(0.605)	(0.509)	(0.554)	(0.549)	(0.416)	(0.594)
P	7.772***	7.824***	7.784***	7.721***	7.819***	7.912***
	(0.797)	(0.801)	(0.797)	(0.791)	(0.799)	(0.809)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)
Observations	2,120	2,120	2,120	2,120	2,120	2,120

Notes: ***, **, and * denote significance at 1%, 5% and 10% respectively; standard errors are in parentheses. Each column presents the hazard ratios from the inclusion of the variable of interest, using the Weibull Model in each case.

4.7.5 Robustness check on the functional form of the hazard

To check the robustness of the findings of this study to allowing for a hazard model that is not Weibull, Table 4.8 shows the outcome with the Cox Model. It may be seen that the hazard ratios of the main variable of interest, risk aversion (CRRA, and σ) remain stable, for all three technologies. Therefore, this confirms the robustness of the findings reported earlier. Also, it shows that the results are stable, regardless of the hazard model adopted in the estimation.

Table 4.8: Robustness check with Cox Hazard Model

	Extruded Feed			Akosombo Strain			Floating Cage		
	CRRA	σ	σ, α, λ	CRRA	σ	σ, α, λ	CRRA	σ	σ, α, λ
CRRA	0.909**			0.889**			0.880**		
	(0.042)			(0.047)			(0.055)		
σ (value function		0.559**	0.580**		0.619**	0.557**		0.496**	0.447**
curvature)		(0.125)	(0.132)		(0.148)	(0.140)		(0.158)	(0.147)
α (probability			1.416			0.829			0.731
weighting)			(0.496)			(0.348)			(0.360)
λ (loss aversion)			0.984			1.083			1.065
			(0.046)			(0.058)			(0.062)
Age	1.071***	1.074***	1.073***	1.053***	1.057***	1.057***	1.055***	1.061***	1.067***
	(0.100)	(0.010)	(0.010)	(0.011)	(0.012)	(0.011)	(0.013)	(0.014)	(0.015)
Male	0.393***	0.372***	0.372***	0.963	1.003	1.0128	2.012	2.186	2.527
	(0.113)	(0.109)	(0.109)	(0.418)	(0.453)	(0.470)	(1.199)	(1.385)	(1.639)
Education	1.085***	1.078**	1.077**	1.073*	1.065*	1.080**	1.096***	1.096***	1.104***
	(0.032)	(0.032)	(0.034)	(0.040)	(0.040)	(0.041)	(0.038)	(0.039)	(0.040)
Married	0.679*	0.623**	0.599**	1.074	0.896	0.943	1.017	0.583	0.564
	(0.158)	(0.145)	(0.142)	(0.330)	(0.279)	(0.299)	(0.411)	(0.241)	(0.246)
Experience in fish	1.086	1.088***	1.096***	1.060***	1.062***	1.054**	1.078***	1.079***	1.073***
farming	(0.022)	(0.022)	(0.023)	(0.023)	(0.022)	(0.024)	(0.024)	(0.023)	(0.024)
Experience of	2.541***	2.269***	1.096***	1.461	1.348	1.256	2.829	2.893***	2.994***
past weather shocks	(0.700)	(0.621)	(0.023)	(0.431)	(0.394)	(0.430)	(1.070)	(1.107)	(1.244)
Main occupation	1.016	1.134	1.143	1.356	1.368	1.378	2.049*	1.975*	2.222*
	(0.233)	(0.268)	(0.269)	(0.411)	(0.416)	(0.420)	(0.827)	(0.778)	(0.919)
Akosombo Strain	0.630	0.583	0.579				0.749	0.655	0.804
	(0.240)	(0.227)	(0.230)				(0.631)	(0.542)	(0.702)
Extruded Feed				0.045***	0.045***	0.048***	0.192	0.230	0.193
				(0.024)	(0.023)	(0.025)	(0.225)	(0.259)	(0.228)

Floating Cages	0.701	0.699	0.656	0.851	0.853	0.745			
	(0.395)	(0.385)	(0.365)	(0.513)	(0.503)	(0.438)			
Household size	0.965	0.964	0.966	1.034	1.036	1.033	0.931	0.931	0.911
	(0.041)	(0.042)	(0.041)	(0.044)	(0.045)	(0.046)	(0.051)	(0.054)	(0.055)
Own house	1.928***	1.930***	1.865***	1.437	1.444	1.566	0.508**	0.601	0.529*
	(0.424)	(0.419)	(0.417)	(0.389)	(0.381)	(0.429)	(0.1677)	(0.204)	(0.185)
Number of rooms	1.069	1.044	1.048	1.074	1.060	1.068	1.118*	1.087	1.121*
	(0.049)	(0.050)	(0.053)	(0.055)	(0.056)	(0.057)	(0.065)	(0.065)	(0.070)
Freehold Tenure	1.013	0.942	0.905	0.936	0.885	0.895	0.770	0.838	0.849
	(0.252)	(0.245)	(0.239)	(0.273)	(0.266)	(0.269)	(0.283)	(0.306)	(0.317)
Access to extension	0.376***	0.302***	0.333***	0.581	0.530*	0.437**	0.404***	0.377***	0.312***
services	(0.107)	(0.094)	(0.110)	(0.206)	(0.199)	(0.171)	(0.134)	(0.130)	(0.114)
Access to Credit	2.244***	2.513***	2.417***	3.598***	3.655***	3.870***	2.228**	2.374**	2.709***
	(0.645)	(0.724)	(0.692)	(1.292)	(1.289)	(1.401)	(0.763)	(0.829)	(0.990)
FFA membership	0.777	0.831	0.795	0.603	0.673	0.702	0.271***	3.607**	0.463
	(0.214)	(0.225)	(0.220)	(0.235)	(0.256)	(0.272)	(0.106)	(0.150)	(0.205)
Ashanti	0.658	0.958	0.908	0.935	1.014	1.154	0.000	0.000	0.000
	(0.278)	(0.452)	(0.427)	(0.502)	(0.569)	(0.653)	(0.000)	(0.000)	(0.000)
Western	0.617	0.653	0.651	0.614	0.696	0.687	0.000	0.000	0.000
	(0.196)	(0.215)	(0.216)	(0.228)	(0.265)	(0.262)	(0.000)	(0.000)	(0.000)
Volta	0.285***	0.313***	0.3003***	0.496	0.479	0.565	1.200	1.063	0.860
	(0.110)	(0.123)	(0.121)	(0.265)	(0.265)	(0.300)	(0.528)	(0.475)	(0.398)
Observations	1,994	1,994	1,994	2,064	2,064	2,064	2,120	2,120	2,120

Notes: ***, **, and * denote significance at 1%, 5% and 10% respectively; standard errors are in parentheses. Each column presents the hazard ratios from the inclusion of the variable of interest, and for the designated technology using the Cox Model in each case.

4.8 Summary and conclusion

This chapter models the effect of risk attitudes on the time it takes for smallholder fish farmers in Ghana to adopt (with duration models) three improved technologies believed to enhance the productivity of fish production. These technologies also present uncertainties-mainly variabilities in outputs and prices. The study also investigates the effects of other farmer-specific, household, farm-specific, access to services and location-specific factors on the timing of adoption of the technologies. A number of findings emerge from this study.

First, the path of adoption is similar for all the three technologies. From Figures 4.4 and 4.5 initially, there is a slow rate of adoption, followed by a rapid increase in the rate and then a decline: rate of technology adoption changes over time. This is confirmed by the value of the *P*- parameter in the parametric regressions which is greater than unity, implying that rate adoption of the technologies changes over time.

Secondly, risk aversion has a positive effect on the timing of adopting the AST, Extruded Feed and Floating Cage technologies: risk averse farmers have a higher probability of adoption. The AST is a genetically modified breed of tilapia and disease-resistant and Extruded Feed poses no known disease-threat to fish, less risky than the existing conventional technologies, therefore the earlier adoption by risk averse farmers is as expected. Extruded Feed reduces the risk of water pollution and contamination associated with the sinking conventional feed, which could pose a threat to the health of the fish and the environment. In like manner, the Floating Cage technology reduces the risk of fish mortality in conventional ponds since they are enclosed in nets and therefore not easily accessible to possible natural predators in other water bodies. Thus, I believe this explains why risk averse farmers are likely to adopt these technologies earlier.

Another find from this study is that the two risk attitude measures obtained from different incentivized multiple price lottery field experiments were positively correlated, and had similar effects on the speed of adoption of all three technologies. This is may be an important outcome because there are mixed outcomes in the literature regarding the measurement and influence of different measures of risk attitudes on the adoption of technologies. So this empirical finding gives support to the main findings in this study.

Furthermore, similar conclusions are drawn from both the nonparametric and parametric results from the analysis in this chapter. The Kaplan Meir Survival curves in Figures 4.4 and 4.5 and the results in Tables 4.4-4.6 show that risk averse farmers adopt all the technologies earlier.

Finally, the results from this empirical chapter show that the prior adoption of Extruded Feed delays the adoption of the AST but this has no significant effect on the speed of adopting the Floating Cages. The prior adoption of the other two technologies has no significant effect on the speed of adopting extruded feed. This suggests a possible substitutability particularly between the AST and extruded feed. This is also seen from the Kaplan Meir survival curves in Figures 4.4 and 4.5 above, where the graphs of Extruded Feed and AST are very similar. This shows that even though the best outcome is obtained when technologies are adopted as a bundle, it seems rare for the farmers to adopt all the three technologies simultaneously.

These findings have policy implications. Since risk aversion matters in the adoption of the three technologies, it is necessary for policy makers in the study area to promulgate *ex-post* policies, like making credit accessible to enhance adoption of the technologies. This is evidenced from the fact that access to credit is the variable with the highest hazard ratio in all estimations. This means that if credit is accessible to the farmers it could accelerate the adoption of the technologies.

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Chapter 5

Effect of ambiguity attitudes on the adoption of technology: the case of smallholder fish farmers in Ghana

5.1 Introduction

This chapter seeks to unravel how ambiguity attitudes influence the production choices of smallholder fish farmers in a developing country context, citing the adoption of technology as an example of such a choice. Understanding ambiguity preferences is crucial because ambiguity preferences influence the decision-making process of farmers (Barham et. al., 2014). Seasonally, and on daily basis, fish farmers make decisions and the decisions they make under uncertainty result in different outcomes at the end of the production season. For instance, the yields and prices from the use of a technology - low or high - may not be known with absolute certainty at the beginning of the production season. In some instances, the realization of the payoffs and the probability with which the payoffs occur may be unknown or ambiguous. Ambiguity averse farmers dislike being uncertain about the probability with which events will take place (Ellsberg, 1961), hence the presence of ambiguity may affect the decisions they make. Particularly, when the likelihoods of good and bad outcomes from a choice are not known with certainty, ambiguity averse farmers are more likely to evaluate such choices assuming the worst possible outcome and therefore this could lead to suboptimal production choices. This may explain in part, why ambiguity aversion may limit the take up of insurance (Bryan, 2010), the investment in stocks (Zhang, 2015), diversification of crops (Engle-Warnick et. al., 2009), and the adoption of new technologies (Barham et. al., 2014). The problem is that development economists have often observed that such suboptimal choices contribute to the persistence of rural poverty in developing countries (Barham et. al., 2014).

While it is generally expected that an ambiguity averse farmer will not adopt a new technology, insurance, or investment as readily as an ambiguity neutral agent, it remains unclear whether attitudes toward ambiguity work in every context (Barham et. al., 2014). Empirically, it is essential to understand the ambiguity attitudes of farmers, to enable policy makers promulgate appropriate policies to reduce or eliminate any negative effects of ambiguity on the economic welfare of rural smallholder fish farmers. Farmers' ambiguity attitudes influence their utility function, and therefore may result in suboptimal economic decisions. When ambiguity preferences result in suboptimal choices, policy makers can employ *ex-ante* schemes, such as education or agricultural extension services, to reduce farmers' ambiguity (Engle-Warnick et. al., 2011).

Farmers learn from other farmers by observing the practices, experiences and outcomes from their neighbours (Engle-Warnick et. al., 2014), and the behaviour of farmers in the same village can influence or be influenced by the decisions of others. In terms of technology adoption, for instance, interaction with other farmers reduces the ambiguity associated with a new technology and this may accelerate adoption. In view of this, I introduce "*Number of prior adopters in the same village*" as a variable that captures the influence of the presence of other adopters in the same village on the decision of neighbours to use the technology. In a village setting, proximity between farmers ensures that as more farmers adopt a given technology, more information about the technology is made available to other farmers. If ambiguity is a limiting factor to the use of the technology, the presence of prior adopters should eliminate or at least diminish the ambiguity associated with the technology and therefore reduce the cost associated with information gathering (Alpizar et. al., 2011) and this can potentially accelerate the adoption of the technology.

This chapter addresses three main issues. First, it measures the ambiguity aversion of fish farmers through a field experiment, and a survey in a developing country context. It also seeks to assess how demographic or socio-economic characteristics affect the ambiguity measures of the farmers. The second issue is the investigation of whether ambiguity attitudes matter in explaining fish farming choices, particularly their technology adoption decisions. The third issue addressed is the study of the effect of the number of prior adopters of a technology on the speed with which a farmer adopts a technology.

Contextually, this chapter enhances our understanding of the effect of ambiguity preferences on the decision-making processes of fish farmers in a developing country setting. It combines experimental data on ambiguity attitudes, as well as survey data to answer the question: *how do ambiguity attitudes affect the production choices of smallholder fish farmers*? This chapter is an attempt to answer this question by focusing on the effect of ambiguity attitudes on the decision to adopt a genetically modified strain of fish, the Akosombo Strain of Tilapia (AST) technology in southern Ghana[41]. This technology offers a fitting platform to assess the effect of ambiguity attitudes on technology adoption: it is a genetically modified strain of tilapia, which promises faster growth, disease-resistance and larger-sized fish for the market. However, the genetic modification presents some uncertainty, as farmers do not know with certainty what the distribution of yields of fish would be season after season. Additionally, this chapter also highlights how the presence of prior adopters in the same village could influence the adoption of this technology. I obtain measures of ambiguity attitudes from incentivised experiments conducted in the field, following Ellsberg (1961).

The results of the analysis show that ambiguity preferences differ from risk preferences among the farmers in this study[42]. Furthermore, the results show that ambiguity preferences

[41] This technology is described in greater detail later in Chapter 4.
[42] Risk preferences are described in greater detail in Chapter 2 of this thesis.

do not matter in the speed of adopting the AST technology among smallholder fish farmers in Ghana, even though other behavioural parameters, such as risk attitudes, are found to play significant roles in this respect. In addition, the number of prior adopters in the same village has a positive effect on the speed of adopting the technology. The lack of any significant impact of ambiguity attitudes in determining the speed of adopting this technology suggests that there are other important determinants of adopting this technology, rather than lack of information about it, that affect other technology adoption decisions.

The reset of this chapter is arranged as follows. After this brief introduction, section 5.2 summarises the role of ambiguity attitudes in farming choices, especially technology adoption. Related empirical literature is discussed in section 5.3, followed by the statements of hypotheses in section 5.4, description of the AST technology in section 5.5, and explanation of technology adoption in section 5.6. The data collected and the process of obtaining the data to unravel the influence of ambiguity attitudes on the decision to adopt the technology is the subject of section 5.7. How the ambiguity preferences are elicited is discussed in section 5.7.1. The results, summary and conclusion follow in sections 5.8, 5.9 and 5.10 respectively.

5.2 The role of ambiguity attitudes in farming decisions

While new technologies and innovations promise increases in outputs, productivity, and profit, many new technologies only perform optimally under certain conditions (which may not be easily replicated by farmers in their respective farmlands), such as with precise additions of complementary inputs (Ward and Singh, 2015). Deviations from these conditions may result in not only lower yields than from existing technologies, but also increased variation in yields. Ambiguity in this scenario is due to the fact that the new technologies are unknown and unproven by farmers who generally do not know the yield distribution of the new technology. Therefore, in the presence of ambiguity, farmers may make suboptimal production choices, depending on the farmers' attitudes to ambiguity.

Fish farmers in developing countries face various uncertainties, and the absence or limited access to functioning coping mechanisms such as insurance and credit facilities could hamper the productivity of farmers. However, it has been shown that even where insurance facilities, such as rainfall index insurance, are present, the uptake is usually low. This low uptake is generally attributable to factors including ambiguity aversion (Platteau et. al., 2017, Elabed and Carter, 2015; Bryan, 2013). While farmers know what to expect if they do *not* buy an insurance package, they have to grapple with ambiguity if they decide to purchase insurance; for instance can they trust the insurance provider? What is the exact coverage of the insurance contract? Index insurance is most likely to be affected by ambiguity aversion since this type of insurance is prone to suffer from basis risk (Elabed and Carter, 2015)[43]. For instance, rainfall index insurance will not pay out if there is drought and the farmer loses fish due to the drought, and not a flood, for example. Thus, when deciding whether to buy the insurance package, a farmer faces two levels of uncertainty: having losses from unpredictable extreme weather conditions and not receiving a pay out in the event of losses (Platteau et. al., 2017). Therefore, the presence of these uncertainties will most likely discourage an ambiguity averse fish farmer from taking up this insurance.

Climate change is known to affect agriculture (e.g Schlenker et. al., 2005; Alpizar et. al., 2011). Changes in weather patterns, such as rainfall, relative humidity, winds and temperature, among others, have direct and indirect effects on ecosystems that support fish production (Asiedu et. al., 2017). Directly, drastic changes in climatic conditions in an area affect the growth, reproduction and mortality of fish (IFAD, 2014). In Ghana, a large number

[43] This is the risk that insurer does not pay out, even though there are losses.

of fish farmers depend on rainfall for their operations, but erratic changes in rainfall patterns result in extreme floods or drought in some cases, leading to mortality of the fish in ponds (Asiedu et. al., 2017). With the effects of climate change expected to continue, adaptation is critical to the survival of the small scale fish farms. However, farmers and policy makers alike do not know the probability that risks associated with changes in climate will happen with certainty (Alpizar et. al., 2011). The decision to adapt to climate change may be influenced by the ambiguity attitudes of farmers. If farmers are ambiguity averse they will more likely adapt to climate change when the risk of disaster is unknown to them, compared to a similar situation with known risk (Alpizar et. al., 2011). Fish farmers in a village may know the pattern of weather conditions from experience but extreme weather conditions such as extreme flooding which could destroy fish farms is unpredictable, therefore ambiguity averse farmers may invest in adaptations such as planting of trees to control strong wind and also to provide shade as well as the creation of dykes to protect ponds from flooding and constructing bore hole to supply water during dry season. Sometimes, this might lead to too much investment in avoiding ambiguous situations (Alpizar, et. al., 2011), which may be economically inefficient.

In terms of technology adoption, the literature extensively cites risk aversion as a factor that influences the decision to adopt a new technology (e.g. Liu, 2013, Ward et. al., 2014); however, ambiguity aversion may also play a role in the decision to adopt new and relatively less familiar technologies. Prior to adopting a new technology, farmers, especially in developing countries have limited knowledge about the distribution of outputs as well as the prices that would be received for the produce post-harvest. Therefore, following Ross et. al., (2010), this chapter seeks to find out whether farmers' ambiguity and risk aversion are sufficiently different so that their effects on farming decisions can both be estimated.

Contextually, this investigation examines the effect of ambiguity attitudes in the field of aquaculture in a developing country setting. Traditional/conventional and new technologies present differing levels of both risk and ambiguity to the farmer. In fish farming, ambiguity is present when probability assessments prove more difficult, due to say, lack of information (Barham et. al., 2014). Since ambiguity is likely to exist in the field of aquaculture, ambiguity attitudes may influence the choices of fish farmers in technology adoption. If the new technology presents greater level of uncertainty to the farmer, aversion to risk or ambiguity could deter adoption. Conversely, if the technology is ambiguity-reducing, for instance, by reducing mortality or diseases, I anticipate that more ambiguity averse farmers may be incentivised to adopt the technology early (Barham et. al., 2014). This is plausible, for instance in a situation where fish mortality in the study area is difficult to predict. If the new technology could reduce ambiguity exposure by making the outcomes more predictable, then more ambiguity averse farmers would have a higher proclivity to adopt the new technology.

Engle-Warnick et. al., (2011) study the influence of ambiguity aversion as well as risk aversion on the choice of portfolio of crops and diversification in rural Peru among small scale farmers. They elicit ambiguity aversion from the choices farmers made in an experiment involving multiple gambles and a single certain price. The authors' choice of this measure was based on the ease of derivation and the similarity between this measure and their risk preference measure. They used the calculated risk and ambiguity aversion measures in the assessment of the adoption of farming technology portfolios. They find a high and significant correlation between risk aversion and ambiguity aversion. The results of their study also show that ambiguity aversion, but not risk aversion, significantly influence the choice of diversification among varieties of crops by Peruvian farmers. This study does not focus on any specific technology, but a farmer is classified as an adopter if he plants any modern crop in the production season. In this present chapter, I focus on a specific technology, the AST.

Akay et. al., (2012) investigate and compare the risk and ambiguity preferences of Western University students and Ethiopian farmers with the same decision task. They find that both groups are risk and ambiguity averse; but farmers are more risk and ambiguity averse than students. They conclude that risk and ambiguity aversion could influence agricultural decisions. This study justifies the use of field experiments to elicit their ambiguity and risk attitudes among fish farmers in a developing country context.

In another study, Barham et. al. (2014) study the impacts of risk and ambiguity aversion on the speed of adoption of genetically modified (GM) corn and soy seeds among Midwestern grain farmers in America. They elicit the risk and ambiguity preferences of the farmers through experiments with the farmers. The outcome of their study suggests that risk aversion has only a small impact on the timing of adoption of GM soy, while ambiguity aversion has a large impact speeding up farmer adoption of GM corn. Their study highlights the importance of considering both risk and ambiguity when studying the effects of behavioural parameters on the adoption of new technologies.

Ward and Singh (2015) measure preferences related to risk, loss, and ambiguity through a series of experiments among farmers in rural India. With these measures, they investigate how the decisions to adopt new technologies are influenced by farmers' attitudes to risk and ambiguity. Specifically, they focus on a discrete choice experiment over new and familiar rice seeds, and show that these behavioural parameters affect decisions to adopt the technologies, especially when the new technologies are risk-reducing. They find that risk averse and loss averse individuals are more likely to adopt the new seeds (risk-reducing), but contrary to expectations, ambiguity averse individuals seemed indifferent between the new seeds and the traditional varieties. The current study differs from Ward and Singh's (2015) study because I model adoption as a continuous variable-time lapse before adoption-not a discrete choice variable.

The varied outcomes from previous studies clearly demonstrate that there is no consensus outcome regarding the effect of ambiguity attitudes on adoption choices. This present empirical study contributes to the existing debate by focusing on ambiguity attitudes in fish production. First, fish farming differs from crop farming in terms of the challenges and risks farmers face in their operations, therefore applying some of the techniques used in the previous studies in this present study is an attempt to bridge the gap in the literature and to provide an empirical evidence of the effect of ambiguity attitudes on the speed of adopting fish farming technologies in a developing country context. Secondly, unlike most studies on adoption (except Barham et. al., 2014) the adoption decision in this chapter is modelled as a time-varying variable, using the hazard models [44].

5.3 Hypotheses

Guided by the findings in the literature and the available data, two main hypotheses are tested in this chapter:

1. Ambiguity attitudes and technology adoption: *More ambiguity averse farmers adopt the AST later*.

The AST is a relatively new technology, it is a genetically modified strain and is relatively less known and therefore farmers may not be able to assign accurate probabilities to the yield distribution from adopting the technology. For instance, they may not be certain if they will always produce lower or higher yield from adopting the relatively more expensive new technology. Furthermore, this technology is optimal in the presence of complementary

[44] The hazard model used in this chapter is as described in Chapter 4 of this thesis; therefore it is not described here.

technologies such as the Extruded Feed technology. What will happen to the yield if a farmer is not able to afford the Extruded Feed throughout the season? Will the yield be less than that from the traditional breed of fish? This uncertainty could cause farmers who are averse to ambiguous situations to be less likely to adopt the technology or may adopt it late. Therefore, one might expect ambiguity aversion to be important in determining the speed of technology adoption.

2. Ambiguity aversion, number of prior adopters in the same village and technology adoption: *In the presence of ambiguity aversion and the number of prior adopters in the same village, ambiguity aversion will become less important in the adoption of technology.*

For a given farmer, ambiguity about a technology may be eliminated or minimized when at least one other farmer in the same village adopts the technology. This is because the farmer may be able to gain information about the yield distribution from the adopter in the course of time, and therefore this may enhance adoption of the technology, if ambiguity is a limiting factor. The number of prior adopters in the same village is generated for a farmer as follows.

Consider a farmer who lives in Atasvanya, a village in the Greater Accra Region, who learnt about the technology in 2005 but started using it in 2009. For every year the farmer could have adopted the technology, I count how many other farmers in the same village adopted the technology. However, for the first year, 2005, the adoption of the other farmers will not have any effect on the adoption decision of the farmer in the same year, until the next season, 2006, when the farmer could have observed the distribution of yield from the farmers in 2005. The number of adopters whose adoption decisions could have an effect on the choice of the farmer in 2007 will be the number of adopters in 2005 as well as those who adopted in 2006. Thus for every year from 2006, the number of adopters whose yield distribution could provide information to the farmer is a cumulative number (as illustrated in Table 5.1 below).

Table 5.1: Cumulative Number of adopters from the same village

Farmer ID	Period of Observation	Adoption status of farmer	Number of adopters from same village	Cumulative number of adopters
1	2005	0	2	0
1	2006	0	5	2
1	2007	0	4	7 (2+5)
1	2008	0	1	11 (7+4)
1	2009	1	2	12 (11+1)

5.4 Data sources and experimental procedures

The data for this chapter is cross-sectional, drawn from a field experiment involving incentivised multiple lotteries (for risk attitudes)[45], a version of Ellsberg's (1961) two-colour urn[46] experiment (for ambiguity attitudes) and survey data on technology adoption decisions[47]. The data is part of a larger random survey data, and since only a subsample was interviewed for their adoption choices, I do not have full information about the adoption of the AST technology among all the farmers in the study area. Furthermore, since the data is cross-sectional and collected post-adoption, I acknowledge the likelihood of endogeneity arising from the ex-post measurement of the explanatory variables (Besly and Case, 1993; Ahsanuzzaman, 2014), especially ambiguity attitudes. However, it may be unlikely that the adoption of the AST would affect ambiguity attitudes of farmers to any significant level (Barham et. al., 2014). There is evidence in the literature that suggests that risk preferences among some farmers could be stable over a two (2)-year period of time (e.g. Love and Robinson, 1984); therefore I assume same for ambiguity preferences. Another likely concern with the present data is multicollinearity, arising from the possible correlation between risk

[45] A detailed description of this experiment and the measurement of risk attitudes used in this chapter are summarized in Chapter 2 of this thesis. In this chapter I focus on the measurement of ambiguity attitudes.
[46] In the field, I used bags of coloured bingo balls instead of urns. The bags were more visually appealing to the farmers and something they could easily identify with.
[47] The survey and field experiments to elicit risk attitudes are explained in detail in Chapter 2 of this thesis.

and ambiguity preferences of the farmers, or some other explanatory variables. To address this concern, I perform a test of correlation (Spearman correlation) among the risk attitude measures and ambiguity attitudes.

5.4.1 **Eliciting ambiguity attitudes**

Ellsberg's (1961) experiment on ambiguity attitudes has been studied over the years, especially in laboratory settings (for example Kahn and Sarin, 1988; Bowen and Zi-lei, 1994), but elicitation of ambiguity attitudes with field experiments in developing country settings is scarce (Ross et. al., 2010). This study obtains the ambiguity preferences of the farmers through the use of Ellsberg's two-colour urn experiment. Ellsberg (1961) showed that a paradox exists when two choices, which should be indifferent according to expected utility, will often not be indifferent if one of them is perceived to have unambiguous probabilities and the other ambiguous probabilities (Keller et. al., 2007). In Ellsberg's demonstration of ambiguity, ambiguity is created by the uncertainty regarding the number of balls of each colour there were in an urn. In practical decisions, a probability can be ambiguous due to vagueness, imprecision, conflicting or lack of information (Keller et. al., 2007). In this experiment, farmers were presented with two-colour balls in two different bags; one bag with a known number of balls of each colour and the other with the same number of balls, but an unknown composition of each colour of balls. It is expected that this present research will be able to unravel the ambiguity aversion of the farmers based on their willingness to pay to play either the unambiguous (risky) or ambiguous lottery. Ambiguity averse farmers are expected to pay higher amounts to play the lottery with known number of balls of each colour. Empirically, I elicited the ambiguity aversion of the farmers by presenting them with the following two scenarios and their responses were recorded:

Imagine the following game and tell us what your response is:

a) Risky Gamble

A sack is filled with 10 white balls and 10 black balls. I will ask you to pick a colour-black or white- and then let you pick one ball out of the sack without looking. If the ball turns out to be the colour you picked earlier, then I will give you GHC100. However, if the colour is different from what you picked earlier, you get nothing.

Would you be willing to pay some money in advance to play this game? Yes [ ] No [ ]

If yes, how much would you be willing to pay to play this game? GHC [ ]

If no, why not? ……………………………………………………………………………………

Now imagine another game**:**

b) **Ambiguous Gamble**

A sack is filled with 20 balls, a mix of white and black balls. You don't know the exact number of each colour of ball in the sack. I will ask you to pick a colour-black or white- and then let you pick one ball out of the sack without looking. If the ball turns out to be the colour you picked earlier, then I will give you GHC100. However, if the colour is different from what you picked earlier, you get nothing.

Would you be willing to pay some money in advance to play this game? Yes [ ] No [ ]

If yes, how much would you be willing to pay to play this game? GHC [ ]

If no, why not?…………………………………………………………………………………

5.4.2 Ambiguity aversion measure

Generally, the most standard and the simplest way to measure ambiguity aversion in the laboratory is to elicit subjects' willingness to pay (WTP) for the ambiguous gamble and the WTP for the unambiguous gamble separately, then the difference between the two valuations is reckoned as the measure for ambiguity aversion (Keller et. al., 2007). This study measures ambiguity aversion as the difference between the willingness to pay for the risky (unambiguous) gamble and the willingness to pay for the ambiguous gamble (Keller et. al., 2007). For instance, if a farmer indicates the willingness to pay for the risky lottery and the ambiguous lottery as GHC10 and GHC5 respectively, the ambiguity aversion of this farmer is reckoned as 5 ($i.e. 10 - 5 = 5$)[48].

There are a few points to note regarding the measure of ambiguity attitudes employed in this study compared to other measures of ambiguity attitudes in the literature. Most of the few studies that measure ambiguity attitudes in an experimental setting use multiple rows of binary lottery, and the participant's ambiguity preference is measured at the point/row at which a participant switches from the unambiguous to the ambiguous prospect (Lauriola and Levin, 2001, Barham et. al., 2014; Akay et. al., 2012). Specifically, these approaches make subjects reveal their certainty equivalents for the lotteries. The certainty equivalent is the certain amount that makes subjects indifferent between receiving the prospect or the sure amount (Ahsanuzzaman, 2014). Eggert and Lokina (2007) and Akay et. al., (2012), calculate the certainty equivalent as the midpoint between the lowest certain payoffs for which the agent chooses the sure amount and the highest certain payment for which the agent chooses to play the lottery. The relative location of the switch-over in the ambiguous lottery compared to the unambiguous lottery reveals the agent's ambiguity preferences.

Particularly, Akay et. al., (2012) calculate ambiguity aversion (θ) as

$$\frac{CE_R - CE_A}{CE_R + CE_A} \tag{2}$$

Where CE_R is the certainty equivalent amount of money for the risky prospect, CE_A is the certainty equivalent for the ambiguous prospect. Their measure of ambiguity preference ranges from -1 (ambiguity loving) to 0 (risk neutral) to 1 (ambiguity averse).

[48] GHC is Ghana Cedis, and it is the official currency of Ghana.

The measure of ambiguity preferences used in this chapter is more simplistic than the above, but the classification of the outcomes is the same as those of Akay et. al. (2012). The data in this study does not permit the elicitation of certainty equivalent. This is because instead of rows of lotteries and a sure amount in the experiment, the farmers were presented with two scenarios, one describing a risky gamble and the other an ambiguous gamble (Ellsberg, 1961). However, it is still possible to measure ambiguity preference as the difference in willingness to pay to play the unambiguous lottery and the ambiguous lottery. This procedure is more appealing in the field setting as it is easier for the farmers to comprehend, and easily reveals the relative preference of the farmers for the unambiguous and ambiguous lottery. This survey was carried out immediately after the risk attitude elicitation with incentivised multiple price lottery, therefore it is most probable that the farmers understood the process to elicit their ambiguity attitudes through prior experience.

5.5 Results

5.5.1 **Summary of data**

Table 5.2 provides the descriptive statistics of the farmers surveyed for this chapter[49]. About 75% of the farmers had adopted the AST technology at the time of this survey. On average, it takes 17.55 years from the time of knowing about the technology till a farmer adopts the technology. The average age of the participants is about 41 years, with about 9.8 years of formal education, and household size of 6 persons. In terms of experience in fish farming, the average farmer had been in fish-farming related activities for about 5.5 years. When asked if they had encountered any negative weather shocks (especially flooding) in the past five years, 73% of the famers responded in the affirmative. The average number of prior adopters in the same village of a typical farmer is about one (1), which may suggest that most farmers had at least one other farmer adopting the technology in the same village before adopting the

[49] Most of the variables are described in the previous chapter, only a few are discussed here.

technology. In terms of the primary occupation of the farmers, about 71% indicated fish farming as their primary occupation. This suggests that they are involved in diversified enterprises or are involved in other ventures aside fish farming. I find that only 48% of the farmers had had some extension contact in the past production season, while 78% had access to credit.

Table 5.2: Descriptive Statistics of smallholder fish farmers in Ghana

Variable	Definition	Mean	Standard deviation
Dependent Variables			
Adoption of AST	=1 if farmer had used the AST	0.75	0.435
Time to adoption	Time lapse to adoption	17.55	2.39
Independent Variables			
Farmer characteristics			
Age of farmer	Age of respondent in the period of observation, in years	41.93	13.24
Gender of farmer	=1 if farmer is male	0.92	0.28
Education	Years of formal education attained by farmer	9.83	4.62
Marital Status	= 1 if farmer is married	0.75	0.44
Ambiguity Attitude	Ambiguity preference measures as difference in the WTP between a risky and an ambiguous prospect	1.20	5.86
Risk attitude (σ) from TCN	Risk attitude obtained from TCN lottery experiment	0.89	0.52
Risk attitude (CRRA)	Risk attitude obtained from Brick et. al. lottery	2.35	2.45
Loss aversion (λ)	Loss aversion from TCN lottery experiment	1.92	2.40
Probability weighting (α)	Probability weighting from TCN lottery experiment	0.74	0.30
Experience	Number of years a farmer has engaged in fish production	5.47	5.37
Past weather shocks	= 1 if farmer experienced flooding in the past	0.73	0.44
Main occupation	= 1 if fish farming is main occupation	0.71	0.46
Household characteristics			
Household size	Number of people with whom farmer eats from the same pot	6.08	3.03

Own House	= 1 if farmer owns his house	0.63	0.48
Number of rooms	Number of rooms in famers' household	4.23	2.68
Freehold tenure	=1 if farmer owns the farm land	0.33	0.47
Adopters in same village	Number of farmers from the same village who adopted the AST up each year up to the year of adoption by a given farmer	0.85	2.74
Access to services			
Access to extension services	=1 if farmer has access to extension services	0.48	0.50
Access to credit	= if farmer has access to credit	0.78	0.42
FFA[50] membership	= 1 if farmer is a member of fish farmers' association	0.32	0.47
Region level variables			
Western	= 1 if farmer is resident in the Western Region	0.22	0.41
Ashanti	= 1 if farmer is resident in the Ashanti Region	0.17	0.37
Volta	= 1 if farmer is resident in the Volta Region	0.23	0.41

5.5.2 **Ambiguity attitudes**

A summary of the ambiguity attitudes of the farmers is presented in Table 5.3. As expected, there is evidence that farmers have a higher willingness to pay for the risky lottery (GhC 7.07) than for the ambiguous lottery (GhC 5.87), therefore the calculated average ambiguity attitude measure is 1.20. This difference is statistically significant (p-value=0.013). This outcome shows that the farmers are more averse to the ambiguous gamble and were therefore willing to pay less to participate in this gamble than the other lottery with known probabilities. This positive value indicates that the average farmer is generally ambiguity averse. This outcome is corroborated by Keller et. al., (2007), who indicated that people pay less under ambiguous situations relative to a corresponding unambiguous situation, and the more ambiguous the gamble, the less people were willing to pay for it. From a technology adoption point of reference, if the outcome from the experiment could be extrapolated to their technology adoption decisions, it may be inferred that they would be more likely to invest in the relatively familiar technologies than newer technologies with ambiguous outcomes.

[50] FFA= Fish Farmer Association

Figure 5.1 shows the distribution of the farmers according to their ambiguity attitude classifications. Even though the average farmer is ambiguity averse, it may be seen from the figure that majority (59%) of the farmers are ambiguity neutral. This means many of them are generally indifferent between the risky and ambiguous lottery choices.

Table 5.3: Willingness to Pay (WTP) for gambles and ambiguity aversion

Variable	Mean	Std Deviation	Min	Max
WTP for risky (unambiguous) gamble	7.07	9.87	0	50
WTP for ambiguous gamble	5.87	9.29	0	50
Ambiguity Measure	1.20	5.86	-40	30

5.5.3 Correlation among risk aversion and ambiguity aversion measures

Table 5.4 summarizes the test of correlations among the ambiguity measure and the risk attitude scores of the farmers. The Spearman correlation test was performed among the three parameters from the TCN[51] lottery, the CRRA[52] parameter from the Brick et. al. (2012) lottery, and the ambiguity aversion measure. The Spearman correlation procedure tests the null hypothesis of no association between variables. The main interest in this aspect of the study is to answer the question: *is a risk averse farmer also ambiguity averse?* The null is rejected in favour of the alternative hypothesis that ambiguity aversion and utility curvature (Sigma) are related measures. In other words, a typical risk averse farmer (at least according to the TCN measure) may also be ambiguity averse. However, apart from correlation with the sigma parameter, the ambiguity aversion measure is not correlated with any of the other risk aversion parameters. Since the ambiguity measure is not correlated with CRRA at any level

[51] This is the Tanaka, Camerer and Nguyen (2010) lottery from which three parameters (σ, α, and λ) are obtained, and described in detail in Chapter 4.
[52] This is the Constant Relative Risk Aversion utility function

of significance, it indicates that the ambiguity and risk attitude measures may be measuring different attributes of the farmers. This outcome contradicts the findings of Ahsanuzzaman (2014). He finds positive, high and statistically significant correlation between risk and ambiguity attitudes. This could be due to the fact that they obtain both the risk and ambiguity measures from the same lottery experiment and calculated the certainty equivalent for both the risk and ambiguity attitudes from the row the participants switched in the lottery, which is quite different from the procedure in this study. In this study, risk and ambiguity attitudes are obtained from two separate experiments, and therefore that may account for the differences in the observed attitudes of the farmers. It is essential to highlight the fact that if risk and ambiguity attitudes are found to be significantly correlated, it is possible that if only ambiguity attitudes are used in the hazard model, the ambiguity attitude variable could pick up the effect of the risk attitude measure. However, ambiguity could be eliminated or at least minimized in the presence of at least one prior adopter in the same village, but risk aversion will persist in the presence or absence of other adopters. Therefore, interacting ambiguity attitudes with number of prior adopters provides a better test of whether ambiguity aversion is affecting farming decisions.

Table 5.4: Correlations among Risk and Ambiguity Aversion Measures

	Ambiguity Aversion	**CRRA**	**Sigma**	**Alpha**	**Lambda**
Ambiguity Aversion	1.000				
CRRA	-0.024	1.000			
Sigma	0.219**	0.524***	1.000		
Alpha	0.201**	0.102	0.285***	1.000	
Lambda	0.070	-0.125	0.075	0.046	1.000

Note: *, **, *** represent significance at 10, 5, and 1 percent levels respectively.

5.5.4 **Demographic characteristics and attitudes towards ambiguity**

One objective of this study was to investigate the farmer/farm specific characteristics that affect the attitudes to ambiguity[53] of the farmers. To accomplish this objective, I estimate a simple linear regression model relating each specified measure of ambiguity attitude to specified characteristics of each farmer as follows:

$$A_i = \alpha + \gamma X + \mathcal{E}_i \qquad (3)$$

Where A_i is the ambiguity of the *i*th farmer; γ is a vector of parameters to be estimated; X is the set of the farmer's characteristics such as age, marital status etc.; $\mathcal{E}_i$ is the error term of the linear regression**.**

The results from these regressions are summarized in Table 5.5 below. The results from these estimations show that some socio-economic characteristics of the farmers are significantly correlated with the measures of ambiguity attitudes. For instance, characteristics such as age, household size, freehold tenure and the Ashanti Region relative to the base region, Greater Accra, are significant at the 5% level of significance. While age and freehold tenure have negative effects on ambiguity aversion, household size and Ashanti Region have positive effects. The negative coefficient of age suggests that older farmers are less ambiguity averse. This assertion confirms a similar finding by Sanou (2015), among farmers in Niger. Owning the farmland provides a sense of security to the farmer, compared to renting a piece of land, where uncertainties about the future of the farmland exists: land owners could evict a farmer from the land with little or no prior notice. Thus, farmers with freehold tenure may be less ambiguity averse. Larger household sizes could mean that outcome from any bad decision on the part of the farmers would affect not only the farmer but many other people. Therefore, this could mean that a farmer with a larger household size would be more cautious in making

[53] The discussion of the other attributes of farmers and how they are correlated with risk attitudes is detailed in Chapter 2 of this thesis.

economic choices which may result in delays. This is consistent with findings in the extant literature (e.g. Ahsanuzzaman, 2014).

From this section, it has been demonstrated that only a few personal characteristics affect the ambiguity attitude measure and therefore multicollinearity arising from the inclusion of these socio-demographic characteristics and the measures of ambiguity attitudes in the technology adoption estimation may not be an issue of concern at this point. The result of technology adoption and how it is affected by attitudes towards ambiguity is discussed next.

Table 5.5: Regressions of factors affecting attitudes to ambiguity

Explanatory Variable	**Coefficient (Standard error)**
Age	-0.106** (0.049)
Male	-0.867 (1.967)
Married	-0.909 (1.351)
Household Size	0.544** (0.211)
Education	-0.168 (0.132)
Experience	-0.147 (0.108)
Experienced Past Weather Shock	1.674 (1.269)
Main Occupation	0.990 (1.260)
Owns house	0.661 (1.169)
Number of Rooms	-0.305 (0.218)
Membership in FFA	0.136 (1.414)
Freehold Tenure	-3.097** (1.281)
Volta	1.381 (1.789)
Ashanti	3.772** (1.903)
Western	2.188 (1.585)
Constant	4.794 (3.126)
R-Squared	0.203

Note: *, **, *** represent significance at 10, 5, and 1 percent levels respectively.

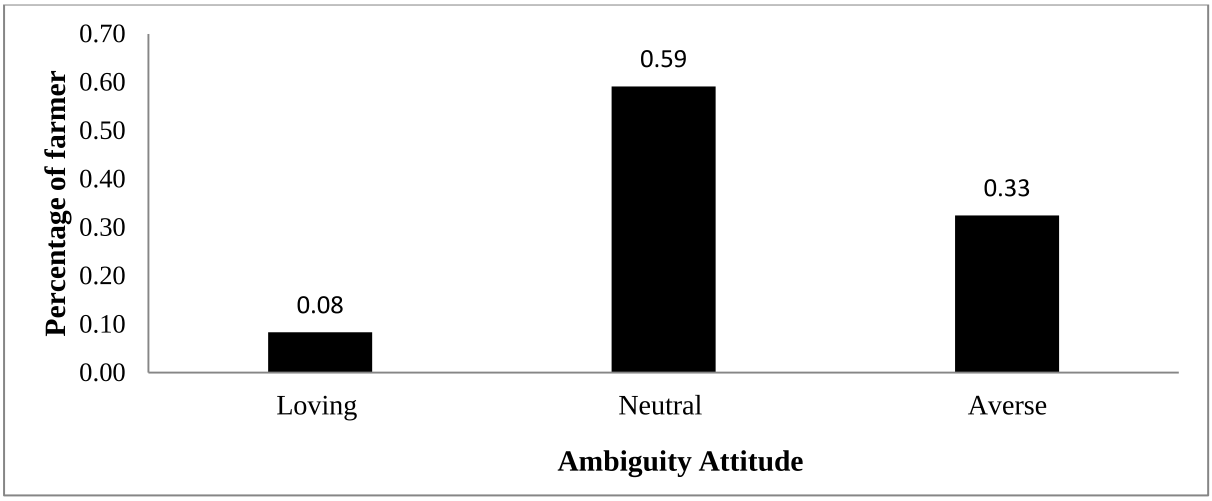

Figure 5.1: Distribution of farmers according to their ambiguity attitudes

5.5.5 Effect of ambiguity attitudes and other variables on the speed of adopting the AST technology

The hazard ratios from the estimation of the hazard model are presented in Table 5.6. For each variable, a hazard ratio greater than one (1) speeds up adoption, while a hazard ratio of less than one (1) is associated with slower rate of adoption. Overall, the value of the shape parameter, *P*, greater than one (1) implies that the probability of adopting the AST increases over time. When risk attitudes are not included in the hazard model, it is found that ambiguity attitude alone, is not significant in explaining the speed of adopting the AST. When interacted with the number of prior adopters, ambiguity attitudes are still not significantly correlated with the speed of adopting the AST technology among the farmers in the study area. On the other hand, risk attitudes (BVB and TCN (σ)), are found to have statistically significant effect on the adoption of the technology, and remain significant when ambiguity attitudes are included in the same regression.

The results obtained in this chapter are similar to Ward and Singh (2014).They find that risk, but not ambiguity aversion, has a significant effect on the adoption of new rice seeds among Indian farmers. A possible explanation for the finding in this study could stem from the fact that 75% of the farmers in this study had adopted the AST technology. Perhaps, some farmers had had the opportunity of observing other farmers use the technology and therefore may have learnt about the probability distribution associated with the use of the AST technology (Sanou, 2015), and hence ambiguity may have been reduced or eliminated and therefore plays no significant role in their choice. These outcomes, however, are contrary to the findings of Ross et. al., (2010). They find that ambiguity aversion decreases the likelihood of technology adoption but risk aversion plays no significant role in the adoption decision.

If it is true that ambiguity may be eliminated by the number of adopters in same village, then it may be inferred that the speed of adopting the AST will increase when more farmers adopt the technology in previous seasons. There is evidence of this in the results: the hazard ratio for Adopters in Village (cumulative) is greater than one (1) and highly significant in all estimations. This suggests that for two identical farmers who have not adopted the AST in this season, the farmer who has more adopters in his village is more likely to adopt it in the next season. Interaction between ambiguity attitudes and the number of prior adopters of the technology, however, is found to have no significant effect on the speed of adoption. In other words, even though the number of adopters may influence adoption decisions independently of ambiguity attitudes, ambiguity attitudes interacting with the number of adopters has no effect on adoption. In addition to the number of prior adopters, ambiguity and risk attitudes, some other factors have significant effects on the speed of technology adoption. Age, Education, Experience, Number of rooms and Access to credit have hazard ratios greater than one (1), implying that these attributes of the farmers accelerate the adoption of the technology[54].

Table 5.6: Hazard Ratios for Ambiguity And Risk Attitudes with Weibull Model

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.630*
			(0.167)
α (probability weighting)			0.591
			(0.258)
λ (loss aversion)			1.071

[54] Age here is a time-varying variable depicting the age of the farmer in each period under observation.

			(0.063)
CRRA		0.850***	
		(0.049)	
Adopters in village (Cumulative)	1.282***	1.289***	1.278***
	(0.034)	(0.034)	(0.035)
#Adopters*Ambiguity	1.006	1.005	1.006
	(0.005)	(0.005)	(0.005)
Ambiguity	1.029	1.032	1.029
	(0.031)	(0.034)	(0.032)
Age	1.034***	1.030**	1.035***
	(0.012)	(0.012)	(0.013)
Male	1.080	0.781	0.906
	(0.467)	(0.333)	(0.423)
Education	1.073*	1.086**	1.086**
	(0.040)	(0.041)	(0.042)
Married	1.594	1.819*	1.610
	(0.513)	(0.599)	(0.541)
Experience	1.084***	1.080***	1.069***
	(0.029)	(0.024)	(0.024)
Experienced Past Weather Shock	1.313	1.607	1.268
	(0.376)	(0.476)	(0.376)
Main Occupation	1.150	1.275	1.324
	(0.356)	(0.405)	(0.417)
Household Size	1.072	1.067	1.068
	(0.049)	(0.049)	(0.052)
Owns house	1.317	1.446	1.493
	(0.357)	(0.396)	(0.412)
Number of Rooms	1.120**	1.124**	1.113*
	(0.062)	(0.060)	(0.063)
Freehold	1.122	1.042	1.029
	(0.346)	(0.312)	(0.329)
Extension Contact	0.617	0.540*	0.396**
	(0.226)	(0.201)	(0.168)
Access to Credit	4.728***	4.325***	5.543***
	(1.723)	(1.609)	(2.203)
Extruded Feed	0.022***	0.020***	0.020***
	(0.012)	(0.011)	(0.011)
Floating Cages	0.569	0.557	0.510
	(0.349)	(0.335)	(0.309)
FFA	0.459*	0.439*	0.535
	(0.208)	(0.194)	(0.241)
Ashanti	1.629	2.473	2.722
	(0.970)	(1.482)	(1.769)
Western	1.608	1.547	1.690
	(0.640)	(0.623)	(0.688)
Volta	0.606	0.756	0.813
	(0.349)	(0.429)	(0.457)
P	8.184***	8.498***	8.431***
	(0.769)	(0.797)	(0.793)
Constant	0.000***	0.000***	0.000***
	(0)	(0)	(0)
Observations	2,064	2,064	2,064

Note: *, **, *** represent significance at 10, 5, and 1 percent levels respectively

Robustness Check

It may be argued that perhaps the results obtained were influenced by the functional form of the hazard model employed. In this study, the preferred model was the Weibull model, because it allows the influence of time-varying variables to be assessed. However, as a robustness check on the key outcomes of this present chapter, the speed of adoption is assessed using the Cox model; the results are shown in Table 5.7. The hazard ratios of the key variables of interest, ambiguity aversion and risk aversion (CRRA) remain unchanged in terms of direction: risk aversion (CRRA) but not ambiguity aversion, plays a significant role in the speed of adopting the AST technology. Furthermore, the number of prior adopters also has a positive and significant effect on the adoption decision of the farmers. These suggest that the findings from the analysis are not simply because of the functional form of the hazard model employed.

Table 5.7: Hazard Ratios for Ambiguity and Risk Attitudes with Cox Model

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.691
			(0.182)
α (probability weighting)			0.582
			(0.253)
λ (loss aversion)			1.047
			(0.062)
CRRA		0.867***	
		(0.048)	
Adopters in village (Cumulative)	1.287***	1.293***	1.284***
	(0.034)	(0.034)	(0.035)
#Adopters*Ambiguity	1.006	1.005	1.006
	(0.005)	(0.005)	(0.005)
Ambiguity	1.033	1.035	1.033
	(0.032)	(0.034)	(0.033)
Age	1.034***	1.031**	1.035***
	(0.012)	(0.012)	(0.013)
Male	0.960	0.728	0.850
	(0.411)	(0.310)	(0.392)
Education	1.081**	1.093**	1.089**
	(0.039)	(0.040)	(0.041)
Married	1.597	1.816*	1.610
	(0.512)	(0.598)	(0.538)
Experience	1.080***	1.076***	1.066***
	(0.024)	(0.024)	(0.024)
Experienced Past Weather Shock	1.308	1.553	1.287
	(0.376)	(0.462)	(0.383)
Main Occupation	1.232	1.346	1.381
	(0.377)	(0.422)	(0.431)
Household Size	1.056	1.055	1.054
	(0.049)	(0.048)	(0.051)

Owns house	1.297 (0.350)	1.405 (0.384)	1.428 (0.393)
Number of Rooms	1.121** (0.062)	1.126** (0.060)	1.113* (0.063)
Freehold	1.095 (0.334)	1.031 (0.306)	1.007 (0.321)
Extension Contact	0.641 (0.232)	0.568 (0.209)	0.452* (0.189)
Access to Credit	4.421*** (1.588)	4.115*** (1.504)	5.135*** (2.005)
Extruded Feed	0.032*** (0.018)	0.030*** (0.016)	0.031*** (0.017)
Floating Cages	0.576 (0.351)	0.561 (0.336)	0.515 (0.313)
FFA	0.464* (0.203)	0.450* (0.192)	0.531 (0.231)
Ashanti	1.708 (0.998)	2.399 (1.407)	2.538 (1.613)
Western	1.629 (0.648)	1.553 (0.626)	1.681 (0.680)
Volta	0.709 (0.400)	0.836 (0.465)	0.882 (0.489)
Observations	2,064	2,064	2,064

Note: *, **, *** represent significance at 10, 5, and 1 percent levels respectively.

5.6 Summary and Conclusion

Research has shown that technology adoption, especially in developing countries, is slow and incomplete, at best (Ahsanuzzaman, 2014). This has been attributed to many factors; prominent among them is risk aversion. However, prior to the adoption of a new technology, the distribution of the possible outcomes of the technology may not be known with certainty by the farmers. This introduces ambiguity into the adoption decision, but the literature investigating ambiguity attitude and fish production in developing context is scarce. This chapter attempts to fill the gap by investigating how ambiguity attitudes influence the decisions of a fish farmer in a developing country context; by focussing on the adoption of the AST technology, as an example of such decisions. Two main questions are answered in this chapter:

"What are the determinants of ambiguity attitudes among smallholder fish farmers?"

"How do ambiguity attitudes affect the decision to adopt the AST technology?"

The results from this analysis show that ambiguity preferences of the farmers are affected by some personal and socio-economic characteristics of the farmers, including age and educational status. For Hypothesis One, the null hypothesis (that ambiguity aversion slows adoption) is rejected, in favour of the alternative that ambiguity aversion plays no significant role in determining the speed of adopting the AST technology. The second Hypothesis (Number of prior adopters and adoption) could not be rejected. This demonstrates that the number of prior adopters in a village accelerates the adoption of the AST technology. Furthermore, the results indicate that a typical smallholder fish farmer in the study area is ambiguity averse; however, this is not correlated with the risk attitude measures.

It must be highlighted that the results of this chapter regarding risk aversion and adoption decisions confirm that the findings in the previous chapter are robust to the inclusion of measures of ambiguity aversion. Risk averse farmers are found to have a higher proclivity of adopting the AST technology earlier, perhaps because this technology is risk-reducing[55].

This chapter advances and contributes to our comprehension of how behavioural characteristics (ambiguity preferences and risk preferences) affect the decision-making processes of smallholder fish farmers in a developing country context by combining data from a lab experiment in the field, and a survey data on actual farm technology adoption as well as demographic characteristics of farmers, all collected in the same experimental session.

The findings from this investigation have policy implications. Though ambiguity attitudes have no significant effect on the speed of adopting this technology, it is still possible that in villages where this technology is not prevalent, ambiguity aversion could slow the rate of adoption, therefore when introducing this technology to new farmers extension agents may

[55] This is also confirmed in Chapter 4 of this thesis.

need to provide practical demonstration of the use of the technology and the resultant outcome from such demonstration to reduce ambiguity associated with the technology. Furthermore, access to credit[56] accelerates adoption; therefore it is imperative that if the government or policy makers want to enhance the adoption of the AST, measures should be put in place to make credit more accessible to smallholder fish farmers.

Like any other research work, there is still more to learn about the effect of ambiguity attitudes on farming decisions in developing countries. This chapter has contributed to the knowledge in this respect, but for future research purposes one area to consider is to increase the number of farmers recruited for the field experiment. This may enhance the power of predicting their economic decisions with their ambiguity attitude measures.

[56] This is shown by the fact that access to credit is the variable with the highest hazard ratio in all estimations

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Chapter 6

Conclusion and Recommendations

6.1 **Conclusion**

The overarching objective of this thesis was to elicit and compare the risk attitudes of within-subject sample of smallholder fish farmers in southern Ghana using three of the frontier methods used to elicit risk attitudes in the literature. The risk attitudes elicited from these methods are employed in subsequent chapters of this thesis to investigate how risk preferences affect production efficiency and technology adoption.

To achieve this objective, this study employed incentivised field experiments involving multiple price lotteries to elicit risk preferences as well as the use of Ellsberg's (1961) two-colour urn experiment to elicit ambiguity preferences of the same sample of farmers. The average farmer is ambiguity averse. There is sufficient evidence from the findings of this study that suggests that risk, but not ambiguity preferences influence actual production choices of the fish farmers. It is also shown, as in some previous studies, that the method of elicitation of risk preferences does have an influence on the measures of risk attitudes, and that risk preferences of farmers could be context or domain-specific, rather than constant across all domains. A summary of the key findings from each chapter of this thesis is provided below.

Chapter 2 reports the findings of the incentivised multiple price lottery, modelled after Brick et. al., (2012) and Tanaka et. al., (2010), employed in eliciting the risk preferences of the farmers. Also reported in this chapter are the subjective self-reported risk attitude scores of the farmers on an 11-point scale, following Dohmen et. al., (2011). The aim of this chapter was to find out if the experimentally elicited risk preferences correlated with the self-reported risk attitudes, and whether they both could explain some observed production choices of the farmers. Results show that a typical farmer in our study is risk preferring (from the Brick et. al. lottery), or risk averse (from the Tanaka et. al. lottery) depending on the method of elicitation, but the two measures of risk attitudes are highly correlated. It is possible that the two experiments capture similar attributes of the farmers. Additionally, from the Tanaka et. al. (2012) lottery experiment, it was found that the average fish farmer overweights small probabilities and is loss averse. Furthermore, the experimental measure of risk preferences and the self-reported risk attitude measure provide significant explanation of some but not all observed and hypothetical economic and production choices made by the farmers. Thus, it is may be concluded that risk preferences of farmers may not be constant in every domain/context and elicitation method. Also, hypothetical bias may help explain why the stated risk attitude measure (SRRA) is correlated with the hypothetical investment decision of the farmers.

Chapter 3 focusses on the measurement of economic efficiency, and how this measure is affected by the risk preferences of the farmers. The risk attitude measures obtained from the field experiment conducted in Chapter 2 are used as explanatory variables in this third chapter. The economic efficiency is estimated using a deterministic procedure (COLS), where all deviation from the economic frontier are attributed to farmer inefficiency, and a stochastic (SFA) procedure, which disaggregates deviation from the frontier into farmer inefficiency and stochastic factors (outside the farmers' control). Before the stochastic frontier estimation, a skewness test is conducted on the residuals to justify the use of SFA, instead of the COLS. The result showed that our data is not significantly skewed in the right direction to warrant the use of SFA, however, I report findings from both the SFA and COLS. This is because the SFA incorporates stochastic noise, such as measurement errors in the analysis of efficiency. From the SFA analysis, less than 20% of the variation in costs of production among the farmers is due to farmer inefficiency. It was expected that more risk averse farmers would be less economic efficient, however, no statistically significant effect of risk attitudes on the economic efficiency is evidenced. This could be due to the fact that the data did not have the expected skewness, and also because most (about 80%) of the variation in the observed economic efficiency is due to stochastic factor factors much more than farmer-specific attributes, such risk attitudes.

Chapter 4 highlights the effect of risk attitudes on the speed of adopting Floating Cages, Extruded Feed and Akosombo Strain of Tilapia (AST) technologies in the fish farming sector in southern Ghana. The adoption decisions are modelled with the hazard/survival models. Contrary to most existing literature on speed of adoption of technologies (e.g. Liu, 2013), the analysis shows that risk averse farmers are more likely to adopt AST, extruded/floating feed and Floating Cage technologies earlier. This novel outcome is due to the nature of the technologies in question, as perceived by the farmers. Liu's (2013) study, for instance, focuses on the adoption of cotton seeds modified genetically with *Bacillus thuringiensis* (Bt) bacteria, which enables cotton plants to produce phytotoxins to kill pests; the subjective risks posed by these phytotoxins to the farmers themselves may be an additional source of uncertainty and a likely reason for the delayed adoption by risk averse farmers. However, in this study, even though the AST is also genetically modified, it produces no toxins and yet it is more disease-resistant than the local breeds, therefore it may be perceived by the farmers as risk-reducing and hence it is not surprising that risk averse farmers adopt this technology earlier.[57] The outcome from this chapter confirms the need to incorporate risk attitudes in the analysis of technology adoption decisions of fish farmers in developing countries.

Chapter 5 assesses the effects of ambiguity attitudes on the decision to adopt the Akosombo Strain of Tilapia technology among smallholder fish farmers using the hazard model. The risk

[57] Similar reasons explain the earlier adoption of the extruded feed and the Floating Cage technologies by risk averse farmers

attitude measures used in this chapter were obtained from the field experiment described in Chapter 2 of this thesis. The ambiguity attitude is elicited following Keller et. al., (2007), as the difference in the willingness to pay to play a lottery with risky prospects and a lottery with ambiguous prospects. Since the focus of this chapter is how ambiguity attitudes influence farming choices, using speed of technology adoption as an example, the hazard model is employed. The results from this analysis show that risk aversion, but not ambiguity aversion, significantly affects the decision to adopt the AST technology. This outcome is robust when each of the behavioural parameters is included independently of each other and when they are used together in the hazard model. This suggests that perhaps, risk aversion has a more consistent and significant influence on the adoption of technologies in the study area than ambiguity aversion. I argue that ambiguity is resolved or at least reduced when there is one other adopter in the village of a prospective adopter, but risk is unaffected by the presence or absence of other adopters. Therefore, with over 75% farmers having adopted the AST in the study area, ambiguity about the technology is diminished, but risk will still persist. The finding of this chapter confirms that the result of the previous chapter remains robust after the inclusion of ambiguity attitudes. Thus, in the analysis of the adoption of technologies, perhaps risk attitudes should be taken into consideration, since they may affect the decision and speed of adoption of technology significantly.

Overall, there is no consensus conclusion among researchers about the best all-round method of eliciting risk and ambiguity attitudes and how these behavioural parameters affect economic decisions. However, the general understanding is that risk and ambiguity attitudes are sensitive to the method of elicitation and context. This study is an attempt to provide some insight into the effectiveness of different elicitation methods in measuring the risk preferences of smallholder farmers in a developing nation context. This study has shown that risk preferences are sensitive to the method of elicitation and that the risk preferences revealed in the lottery experiments do not offer significant explanation for two specific hypothetical economic choices made by fish farmers, at least in a developing world context. This finding, however, does not imply that risk attitudes elicited with incentivised lottery experiments may never explain risky economic decisions of farmers. Given the enhanced comprehension of the farmers using visual aids, such as coloured bingo balls in the field experiment, this study claims that risk attitudes elicited from smallholder farmers in the developing world context could provide a good prediction of real life, domain-specific risky and ambiguous economic choices, such as the actual adoption of technologies. Therefore, it is imperative that when designing experiments to elicit risk and ambiguity preferences in developing world, participants should be engaged in appropriate and relatable domains and contexts specific to their field of operation. Furthermore, more farmers should be recruited in future experiments to provide more explanatory power in the regressions.

6.2 **Limitations of the thesis**

The cross-sectional data used in this study came from two main primary sources. The data used in Chapter 2 was obtained from a field experiment, involving incentivised multiple price lotteries, modelled after Brick et. al. (2012) and Tanaka et. al. (2010). The sample of 120 farmers, from whom data was obtained were from a larger sample of about 380 farmers who were surveyed in an earlier research work carried out by researchers from the University of Ghana. This was necessitated by time and financial concerns at the time of the survey, and also the relative ease of reaching farmers who had been previously interviewed. The challenge with this ‘sample from a sample’ is that even though our sample of 120 was representative of the 380, I could not verify whether or not the original sample of 380 was truly representative of the population of fish farmers in the study area. This was because it was not possible to access the list of farmers from which the 380 were sampled. If the original sample was not representative of the population, it could potentially affect the conclusions drawn in this study.

Another possible limitation of this study is the dataset used in Chapters 3, 4 and 5 is recall. In the survey to collect data on production and output values and technology adoption, farmers were asked to recall quantities and prices of inputs used, as well as the output produced in the previous season. Since there was no record of these values, I had to take the values provided by the farmers as accurate or close to accurate. Thus, the results reported in these chapters should be considered with this in mind.

It is important to note that in spite of the seeming limitations discussed above, the data and procedures used in this study are relevant in addressing the research questions in the thesis. This is evidenced by the fact that most of the conclusions reached in this study remained fairly the same after the inclusion of some variables and alternative estimation procedures. Though some of the findings seemed contrary to expectation, there is consistent and robust empirical support for the novel outcomes in this study. Nonetheless, given these results and the limitations outlined, it is acknowledged that there is scope for future improvement in this line of enquiry.

6.3 **Future considerations**

Regarding future research, it will be worthwhile to consider the measurement of the risk and ambiguity aversion of the farmers over time to ascertain if the preferences of the farmers change over time and if so, to investigate which factors are responsible for this. Also, in the measurement of economic efficiency, it would be useful to provide farmers with the necessary training to enable them keep up-to-date records for their next season of fish farming and to collect these data from season to season to have a panel data. This may enable researchers to check for changes in economic efficiencies over time. This would be necessary from a policy perspective as it could provide policy makers with the tools to adjust policies to meet changing needs of the farmers over time.

In eliciting ambiguity attitudes, future research may consider the use of multiple rows of lotteries, like in Keller and Sarin (2007). This will enable the elicitation of the certainty equivalent measures which are normally employed in the calculation of ambiguity aversion. Additionally, future studies may use larger and more representative samples to give a better understanding of the choices of the farmers in the study area.

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