The Effects of Risk and Ambiguity Aversion on Technology Adoption: Evidence from Aquaculture in Ghana

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Abstract

We study how aversion to risk and ambiguity affects the adoption of new technologies by Ghanaian smallholder aquafarmers. We conduct a set of field experiments designed to elicit farmers' risk and ambiguity preferences and combine it with survey-based information on their technology adoption decisions. We find that aquafarmers who are more risk-averse were quicker to adopt the new technologies: a fast-growing breed of tilapia fish, extruded feed and floating cages. By contrast, ambiguity aversion has no effect on the adoption of the new tilapia breed and extruded feed. Furthermore, it slows down the adoption of floating cages - a technology which entails higher fixed costs than the others - and the effect is diminishing in the number of other adopters in the village. We argue that these differential effects are due to the fact that the technologies are risk-reducing, with potential ambiguity about their payoff distributions at the early stages of adoption. The findings highlight the importance of distinguishing between risk and ambiguity in investigating technology adoption decisions of small-holder farmers in developing countries.

JEL classification: C93, D81, O33, Q12, Q16

Keywords: Risk aversion, Ambiguity Aversion, Technology Adoption, Aquaculture, Extruded Feed, Floating Cages, Akosombo strain of Tilapia (AST)

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1 Introduction

Small-scale farmers in developing countries frequently make production decisions in a situation of uncertainty because of the prospect of weather-related shocks, crop failure, price fluctuations, etc. In the absence of well-functioning systems of credit and insurance, they are compelled to make choices that reduce consumption risk at the cost of future expected profits (Rosenzweig and Binswanger 1993; Morduch 1995; Dercon and Christiaensen 2011). The adoption of productivity-enhancing technologies is a domain where these trade-offs can become particularly important. New technologies may be inherently more risky, require additional investments that increase the risk exposure of farmers, or generate uncertainty because of the imperfect knowledge of early adopters (Foster and Rosenzweig 2010; Feder, Just and Zilberman 1985). Recent evidence supports this hypothesis. Dercon and Christiaensen (2011) find, for Ethiopian farmers, that consumption risk due to rainfall variability has a negative impact on the adoption and application of fertilizers. Liu (2013) studies Chinese farmers' decision whether or not to adopt genetically modified Bt cotton, and finds that more risk averse farmers adopt the technology later. Nevertheless, the relation between uncertainty and technology adoption is not a settled question. Uncertainty may stem not only from risk – i.e. the future state of the world is unknown – but also ambiguity – i.e. the probabilities associated with these different states may themselves be unknown (Klibanoff, Marinacci, Mukerji 2005). Barham et al.(2014) find evidence that farmers in the US Midwest with a higher aversion to ambiguity adopt new GM corn seeds *sooner*, suggesting that the GM crop's insect-resistance trait reduces ambiguity. More generally, a new technology may reduce risk or ambiguity and, thus, provide farmers with limited access to credit and insurance a means to negotiate an uncertain environment.

In this paper, we study how aversion to risk and ambiguity affects the adoption of new technologies by Ghanaian smallholder aquafarmers. We consider in this paper the adoption of three distinct technologies: (i) Akosombo strain of Tilapia (AST), a fast-growing breed of tilapia fish that offers farmers the potential to harvest twice a year compared to once only for the existing local breed; and the use of (ii) floating cages; and (iii) extruded feed for the fish under cultivation. We combine data from a survey of farmers with information on production choices and technology adoption, and field experiments with the same farmers designed to elicit their risk and ambiguity preferences. In the experimental design, we follow Tanaka, Camerer and Nguyen (2010) and Liu (2013) so that risk aversion may be represented both within an Expected Utility (EU) and Prospect Theory (PT) framework. To measure ambiguity preferences, we replicate the classic experiments conducted by Ellsberg (1961) with our sample of aquafarmers.

The experiments indicate that our sample of farmers are, on average, averse to both risk and ambiguity. We use duration/survival models to study determinants of the speed of adoption of the new technologies and find, contrary to most of the existing literature, that farmers that exhibit greater risk-aversion adopt the AST, extruded feed and floating cages sooner. We argue that this is due to the risk-reducing nature of each of these technologies. The AST is more disease-resistant than existing local breeds of tilapia, the extruded feed reduces the risk of water pollution and contamination associated with the conventional sinking feed which can pose a threat to the health of the fish, while floating cages protect the cultivated fish from their natural predators in the environment. We find no difference in adoption behaviour according to our measure of ambiguity aversion with regard to AST and extruded feed but we find that ambiguity slows down the adoption of floating cages. We hypothesise that this is due to the significantly higher cost of this technology. However, we also find that the speed of adoption increases strongly with the number of prior adopters within one's own village. Given that prior adoption of the technology within one's locality may reduce ambiguity about the risks and potential returns, we argue that this is suggestive evidence of technology adoption speeding up as ambiguity declines.

Fish production and exports in developing countries are extremely important in terms of development and growth prospects. The annual fish consumption in Ghana is about 20-25 kg which is above the world average of 18kg and 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: how long it takes before farmers adopt the technologies and the factors driving such adoption decisions. The present paper contributes by adding evidence towards the fact that risk and ambiguity aversion can have different effects upon technology adoption and that actually some technologies can be risk-reducing and risk aversion can speed up their adoption.

The paper is organized as follows. Section 2 lays out the conceptual framework and shows that the effects of risk and ambiguity on adoption can be positive and negative depending on the specificities of the technology. Section 3 provides a description of the three technologies considered. Section 4 describes the data collection and Section 5 provides summary statistics. Section 6 presents the econometric specification and the results and Section 7 concludes.

2 Theoretical Framework

In this section, we provide a simple framework for considering how aversion to risk and ambiguity affects a farmer's technology adoption decisions. For this purpose, we use the formulation of ambiguity aversion introduced by Klibanoff et al. (2005) and follow Barham et al.(2014) in our modelling and choice of notation.

We represent a farmer's technology adoption decision as a choice $x \in \mathbf{X}$ with payoff $\pi(x, e)$ where e is a stochastic vector. The vector e captures factors that affect the returns to different technologies, unknown to the farmer when making the technology adoption decision. The distribution of e is described by the cumulative distribution function $F(e|v)$, where v is a parameter that may also be unknown to the farmer when making the technology adoption decision. If v is unknown, its distribution is described by the cumulative distribution function $G(v)$ (the distribution being known to the farmer).

The farmer's preferences over payoffs are given by the von Neumann-Morgentern utility function $U(.)$. If v is known, then the farmer's welfare from choice x is defined as the expected utility:

$$W(x|v) \equiv \mathbf{E}_{e|v} U(\pi(x, e))$$

where $\mathbf{E}_{e|v}$ is the expectations operator using the conditional distribution $F(e|v)$ [Under

Prospect Theory, we simply replace $\mathbf{E}_{e|v}U(\pi(x,e))$ by the PT equivalent]. If v is unknown, then the farmer's welfare from choice x is as follows:

$$W(x) \equiv \mathbf{E}_v h\left(\mathbf{E}_{e|v}U(\pi(x,e))\right)$$

where $h(.)$ is a strictly increasing function. If the function $h(.)$ is linear, then the farmer's welfare is unaffected by the presence of ambiguity; but if $h(.)$ is concave, then the farmer achieves lower welfare when v is uncertain.

Barham et al.(2014) show that the welfare function can be written as follows:

$$W(x) \equiv U(M(x) - R_r(x) - R_a(x))$$

where $M(x)$ is the ex-ante mean payoff from choice x, $R_r(x)$ is the standard Arrow-Pratt risk premium, and $R_a(x)$ is the 'ambiguity premium' – the maximum the farmer is willing to pay for the uncertainty associated with v to be replaced by $\mathbf{E}v$. From the last equation above, it is evident that the welfare-maximising choice of x also maximises the expression $M(x) - R_r(x) - R_a(x)$. It follows that a higher expected return (thus, higher $M(x)$) makes a technology more attractive; increased risk (higher $R_r(x)$) or increased ambiguity (higher $R_a(x)$) makes a technology less attractive; for technologies that introduce risk and ambiguity, higher risk aversion (leading to higher $R_r(x)$) or higher ambiguity aversion (leading to higher $R_a(x)$) also makes the technology less attractive.

The three acquaculture technologies we consider in this study – extruded feed, the Akosombo strain of the Tilapia fish, and floating cages – are all, arguably, risk-reducing, as we will discuss in the next section. On the other hand, the farmers may not have known – when they first heard about these technologies – the values of all the parameters relevant for determining the distribution of payoffs associated with each one (represented by v above), in which case adopting these technologies may involve increased ambiguity.

If technology adoption involves a low fixed cost, it may be possible to experiment with it on a small scale to determine the value of v without suffering a significant loss. If this is the case, then the farmer's ambiguity aversion should not be a significant determinant of technology adoption. On the other hand, if introducing the technology involves a substantial fixed cost, then small scale experimentation is infeasible and, therefore, ambiguity aversion should be a more important factor. In describing the acquaculture technologies in more detail in the next section, we show that the adoption of floating cages involved high fixed costs while the extruded feed and the Akosombo strain of Tilapia did not.

We can also hypothesize that the level of ambiguity associated with a particular technology is not constant over time but declines as adoption by neighbours reveals information about the relevant parameters. In particular, if a new technology introduces ambiguity then, ceteris paribus, it would be adopted first by farmers who have the lowest levels of ambiguity aversion. Their experience with the technology would reveal information about the relevant parameters, which reduces the perceived ambiguity of the technology for farmers considering adoption at a later date, and so on.

We can summarise this discussion in terms of the following observations:

1. If a technology is risk-reducing, then risk-averse farmers will be more likely to adopt it.

2. If a technology introduces ambiguity, then farmers who are more ambiguity-averse will be less likely to adopt it.

3. For technologies that introduce ambiguity, ambiguity-aversion is a determinant of adoption if the technology involves a high fixed cost but not if it allows small-scale experimentation.

4. If a technology introduces ambiguity, then the adoption rate should increase with the number of prior adopters in the neighbourhood.

5. If a technology introduces ambiguity, then the adoption rate becomes less sensitive to ambiguity-aversion as the number of prior adopters in the neighbourhood increase.

Observations 1 and 2 have previously been noted in the literature (see, for example, Barham et al., 2014) and provide a useful way of assessing how a new technology affects risk and ambiguity. While Observation 4 may be important in the context of ambiguity, we acknowledge that alternative models of technology adoption would generate similar predictions, such as learning spillovers (Foster and Rosenzweig 1995) and network effects (Bandiera and Rasul 2006). However, the predictions in Observations 3 and 5 would be difficult to account for under alternative models. Hence, we argue that they provide an important test to investigate whether ambiguity and ambiguity aversion plays a role in technology adoption.

3 Description of Technologies

In this section, we describe the three technologies for which we analyse adoption practices among Ghanaian aquafarmers: extruded or floating feed, the Akosombo strain of Tilapia (AST), and floating cages. Extruded or floating feed is an alternative to the conventional feed used in aquafarming. The latter is usually prepared as a mixture of agricultural and food industry waste (e.g. corn meal, peanut husks and wheat or rich bran) that is milled into powder. The powder sinks to the bottom of the pond quickly making it difficult for fish to find the feed. The feed accumulates at the bottom of the pond, where it decomposes to set off physio-chemical reactions and increase the risk of disease outbreaks. Extruded feed is prepared with a balance of macro- and micro-nutrients considered essential for fish growth (Bell and Waagbo, 2008). The commercial processing of this feed removes anti-nutritional factors, thus making it more suitable for consumption by fish (Drew et. al, 2007; Hardy, 2010). The feed is extruded (pressed) and palletized, allowing it to float on the water surface and remain available to fish for long periods. This helps to reduce food waste and save costs (Engle and Valderrama, 2004) but the product is also considered to be more hygienic than the conventional feed. Fish raised on extruded feed grow to nearly twice the size achieved with conventional feed. However, the extruded feed is also more expensive, with a unit cost that is nearly six times higher than that of conventional feed (Frimpong et. al, 2014).

AST is a relatively new and improved strain of tilapia (Oreochromis niloticus) developed by the Aquaculture Research and Development Centre (ARDEC). The growth rate of the AST is about 30-50% higher than that of the conventional tilapia in the region (Lind et.

al., 2012). AST requires just 6 months to reach the size at which it is ready for the market, compared to 8 months for the conventional breed. As a result, farmers who cultivate the new breed can harvest it twice a year on average as opposed to just once a year for the conventional breed. Apart from its fast-growing properties, the AST also enjoys higher survival rates and is more disease-resistant. Despite of this, the cost of AST fingerlings are only about one-and-half times that of the conventional fingerlings.

Floating cages have a number of advantages over conventional rearing systems: protection of fish from potential predators, better hygienic conditions than traditional ponds and use of already existing water bodies (Beveridge 2004). They also provide a quick way to relocate fish in response to unfavourable weather or other environmental conditions (Pillay and Kutty, 2005). The cage system is typically used in combination with extruded feed, and the combination presently accounts for about 90% of Ghana's aquaculture production (Ainoo-Ansah, 2013; Awity, 2013). However, this technology has also significantly higher cost than AST or extruded feed.

All three technologies – extruded feed, AST, and floating cages – are, arguably, risk-reducing: extruded feed because it lowers the risk of disease outbreaks; AST because it is disease-resistant; and floating cages because it allows the farmer to respond quickly to changes in environmental conditions. If the farmer is unfamiliar with the probabilities of these mishaps using conventional technology, then the adoption of the new technologies also, arguably, reduces uncertainty. However, all three technologies involve also higher costs, which can translate into higher variability in profits, with floating cages having the highest cost among them. Therefore, we expect a different behavior with respect to the floating cages as compared with the other two technologies.

4 Data Sources and Experimental Procedures

The data for this study come from two sources: a survey of households engaged in aquafarming, in four regions in southern Ghana (Greater Accra, Volta, Ashanti and Western regions); and a set of field experiments involving lottery choices with the survey respondents designed to elicit their risk and ambiguity preferences. The survey and field experiments were conducted between March and April 2014, and included 120 participants with thirty farmers from each of the four regions. The respondents were randomly selected from a sample of 320 aquafarmers included in an earlier agricultural survey conducted by the University of Ghana. The selected farmers were all either the owner or main decision-maker on their respective aquafarms. The interviews and experiments were conducted on the same day, when the selected farmers were instructed to gather in predesignated areas, such as a church, under a tree, or an open area within the village within easy access of their homes.

4.1 Survey Data

Prior to the start of the experiments, the farmers were interviewed individually to obtain information on their demographic and socio-economic characteristics, experience of adverse shocks and risk management strategies, use of financial services and adoption of aquafarming technologies. In particular, they were asked about whether they had ever used any of the three aquafarming technologies considered in this study. Farmers were also asked to recall the year they first heard about each technology, and the year they started using it, as well as the reasons for doing so. The interviews lasted between 20 and 25 minutes each. Following Dohmen et al.(2011), the farmers were also asked to assess their own risk preferences using an 11-point scale, based on the following 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 rank on a scale where the value 0 means unwilling to take risks and the value 10 means willing to take risks." We use the farmers responses to construct a self-reported risk attitude (SRRA) measure.

4.2 Experimental Design

Each experiment session involved five farmers, which took place immediately after these farmers had concluded their interviews. The design of the field experiments for eliciting risk preferences were modelled after Brick, Visser and Burns (2012), and Tanaka, Camerer and Nguyen (2010) (henceforth abbreviated as BVB and TCN). Ambiguity preferences were elicited using a version of Ellsberg's (1961) two-colour urn experiment. Both the BVB and TCN experiments involved giving participants a series of choices between lottery pairs, designed to elicit their risk-related preference parameters. As advocated by Holt and Laury (2002), real stakes were used in the experiments – discussed in more detail below – to ensure that the participants took the choices seriously and revealed their true preferences. In addition, each participant received GhC 10 (Ghanaian cedis) at the end of the experiment as a reward for participation, which was two-and-half times the daily minimum wage in the study areas at the time of the experiment. In the BVB design, participants make a lottery choice from each of 10 different lottery pairs. In each pair, lottery B involved a 50% probability of winning GhC 10, and a 50% probability of winning nothing; while in lottery A, the participant receives GhC X with certainty, with X varying from 10 to 1 monetary units across the different pairs. Thus, the expected payoff is fixed at 5 in lottery B and varies between 10 and 1 in lottery A. The lottery pairs were arranged in rows, in decreasing order according to the potential winnings in lottery A. The field-workers recorded the row in which a participant switched from lottery A to B, with only one switch permitted in choosing among the 10 pairs. Within the expected utility framework, for each participant, the switching row provides a range of possible values of the risk-aversion parameter, as shown in Table A3. Participants who switch before the fifth row would be classified as risk-loving and those who do not switch till after the fifth row would be classified as risk-averse. In the TCN design, participants make a lottery choice from each of 35 different lottery pairs, arranged into three series as shown in Table A2. Series 1 and 2 involve positive winnings only with a maximum possible payoff of GhC 1700.[1] However, the average gains in the lotteries

[1]This was equivalent to $782 which was about half of Ghana's average annual income per capita of $1,605 in 2012 according to Kassam(2014).

were only GhC 6.68 ($\approx$ \$3.07) which was approximately the daily minimum wage.[2] Series 3 involves possible losses, but these are restricted to be smaller than the participation fee that the farmers received for taking part in the experiments. Following Tanaka, Camerer and Nguyen (2010), the winnings and probabilities were carefully chosen to elicit three preference parameters within a Prospect Theory framework: σ (curvature of the value function), λ (loss aversion) and α (parameter for the probability weighting function). In stating their preferences for each lottery pair, participants were able to indicate at most one switching row in each series. The switching rows in Series 1 & 2 together provide a range of possible values for σ and α. This is illustrated in Table A1 which shows the switching row implied by different combinations of values for σ and α. For a given value of σ, the switching row in Series 3 determines a range of possible values for λ as shown in Table A1. At the start of the session, the participants were informed that one of them (out of the five participating in the session) would be randomly selected to play the lottery for cash. This real incentive design was implemented in the following manner. After all the session participants had indicated their lottery preferences, five balls were placed in a bag, numbered according to identification numbers assigned to each farmer at the beginning of the session. The field-worker picked a ball at random from the bag, and the farmer with the identification number imprinted on the ball was selected for the cash lottery. Next, the farmer was asked to pick a ball at random from another bag of 45 balls numbered one through forty-five. Finally, the lottery corresponding to the row indicated by the ball and the participant's stated preference for lottery A or B in that row was implemented using a bag with 10 balls.

As mentioned above, we used a version of Ellsberg's (1961) two-colour urn experiment to elicit farmers' ambiguity aversion. Participants in the experiment were presented with two bags, each consisting of 20 balls. Participants were told the total number of balls in each bag, and that each ball was either black and white. In the case of one bag, they were also told the number of balls of each colour while, in the case of the other bag, they were not informed about the colour composition of the balls. Next a lottery was described to the participant whereby he/she would be asked to pick a colour – black or white – and receive

[2] Farmers also got the participation fee which was about 2.5 the daily minimum wage.

GhC 100 if a ball picked at random from one of the bags matched that colour. Finally, the participant was asked how much he/she would be willing to pay to play such a lottery using (i) the bag with the known colour composition, and (ii) the bag with the unknown colour composition. As explained by Keller et al. (2007), the difference in willingness to pay in the two instances provides us with a measure of the participant's aversion to ambiguity.

5 Description of Variables and Summary Statistics

Firstly, we discuss the technology adoption variables. Secondly, we explain how the risk and ambiguity aversion variables were calculated from the results of the experiments and present summary statistics for them. Thirdly, we discuss other survey data including explanatory variables. Statistics are presented in Table 1.

5.1 Technology Adoption Variables

We define time for technology adoption as the number of years from the date that a farmer first learnt about a specific technology till the date of its first use. The earliest date that a farmer indicated having knowledge of the availability of any of the three technologies was 1994, i.e. 20 years prior to the date of data collection. There is significant variation in adoption rate across the three technologies: at the time of the survey, about 96% of the farmers had adopted extruded feed, 75% had adopted the AST and only about 58% had adopted floating cages. Among adopters, the mean time to adoption was in the range 16-17 years for all three technologies. Even though differences are not very large, it can be observed that the longest average time of adoption is for floating cages (17.8 years).

5.2 Measures of Risk and Ambiguity Aversion

In the BVB experiments, as shown in Table A1, switching from lottery A to lottery B in any particular row is consistent with a range of values of r, the coefficient of relative risk-aversion. To each farmer, we assign a value of r corresponding to the mid-point of the range corresponding to his or her switching row. This procedure yields a mean value of r equal to 2.4, implying that the average farmer is risk-loving. For the purpose of comparison, the average self-reported risk attitude value is 5.4 (on an 11 point scale), which suggests neither a strong aversion to risk nor a strong preference for it. However, it does not suggest risk neutrality either as a farmer would not know what risk-neutral means. In the case of the TCN experiments, we use Table A3 (for series 1, 2 and 3) to obtain, for each farmer, values of the parameters σ, α and λ. We obtain mean values of 0.9, 0.7 and 1.9 respectively, implying the average farmer has a concave value function, overweighs small probabilities and is loss averse. Table 2 reports the correlation coefficients between all possible pairs of the risk-preference parameters. We find a strong correlation between r and σ (coefficient of 0.524). This is expected and reassuring as both parameters affect an individual's willingness to take risk (in the EU and PT frameworks respectively). On the other hand, there is little correlation between the self-reported risk aversion measure and either r or σ, implying that there was little relation between how farmers assessed their own risk preferences and how they behaved in an experimental setting. As the self-reported risk measure is based on a hypothetical question, it may be subject to hypothetical bias.

We measure ambiguity aversion using the difference between a farmer's willingness to pay to play the risky lottery and the corresponding amount for the ambiguous lottery. On average, farmers have a higher willingness to pay for the former compared to the latter (GhC 7.07 versus GhC 5.87), and the difference is statistically significant (p-value = 0.013). Thus, on average, farmers are more averse to the ambiguous gamble than the lottery with known probabilities.

5.3 Prior Adopters in the Village

Using data on the year of adoption of the different technologies by farmer, we construct a measure of prior adoption of the technology as follows. For each technology, village and year, we count the number of farmers in our sample in that village who reported have used the technology in a previous year. Given that there is approximatively an equal number of aquafarmers in the sample from each village, the variable is a proxy for the proportion of aquafarmers in a village who have adopted the technology by a given date. The average number of prior adopters in the same village of a typical farmer is about one (1), which suggests that 1/30 or 3.3% of aquafarmers in the village have previously adopted the technology. As can be seen from figure 1, at any point in time, the number of prior adopters in the village is lowest for floating cages, the technology with the largest fixed costs.

From the perspective of any farmer, prior adoption of a technology within one's own village may yield information about its yield distribution that, over time, lowers or eliminates ambiguity about the returns to the technology. Therefore, if ambiguity is a limiting factor, the extent of prior adoption may affect an individual farmer's own decision whether or not to adopt.

5.4 Other Explanatory Variables

The age of the respondent responsible for adoption decisions was measured in years; this is a time-varying covariate so it is used in the period of observation for each farmer. Human capital is measured by the number of years of formal education attained. We 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 are 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. Furthermore, Beyene and Kassie, (2015) using data from Ethiopia show that kinship networks crowd out incentives for adopting strategies that reduce exposure to weather shocks. Equally, the existence of an 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). 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 farmers may not have changed their asset ownership through adoption within the period. We 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. The values of the coefficients of the three remaining regions compare to this region. 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. This is achieved 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). For example, 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 cages is included in the equation for extruded feed in the same manner. Conversely, in the estimation of AST, extruded feed and floating cages each take a value of 1 if adopted at least a year prior to the adoption of AST, and 0 otherwise. Table 1 shows that many farmers (39%) adopt the extruded feed, for example, before floating cages, possibly because of the differences in costs.

The average farmer in the present study is a male around 40 years old, married, having around 10 years of education and around 5 years of experience with fish farming. Around 70% of the farmers have experienced past weather shocks and for most of the farmers fish farming is their main occupation. The average number of people living in a household is around 6 and 63% of the farmers own their own house. However, only 33% own their own farm land. The average number of rooms per household is around 4 and 48% of the farmers have access to an extension service but only 32% are members of fish farmer's association. A significant percentage have access to credit (78%). Most farmers come from the reference region (Greater Accra).

5.5 Brief on the Representativeness of Data

Thirty (30) farmers were originally randomly selected from a list of farmers used in a previous survey from each region. However, the number of farmers in the Greater Accra Region increased by seventeen (17), while the numbers in the other regions decreased by at most ten (10). Two main reasons accounted for the changes in the number of farmers surveyed. The primary reason was attrition. For instance in the Volta Region, three of the farmers opted not to participate in the survey and experiment, citing religious reasons (no gambling), while in the Western Region, four farmers could not participate due to other obligations. In the Ashanti Region ten farmers could not be surveyed, because the Ministry of Fisheries was conducting training programme for a session of the farmers at the same time. In order to make up for the intended number, an emergency list of the remaining farmers in the Greater Accra Region was consulted and seventeen farmers were then randomly selected and subsequently surveyed. This undermines the representativeness of the final number of farmers in this study. There are however, other studies that have representative data on all registered fish farmers in Ghana to allow a significant comparison. Onumah and Acquah (2010) indicate that 91% of smallholder fish farmers are males, while 92% from our sample are males. Similarly, Asmah (2008) and Asamoah et al.(2012) report that 95% and 88% respectively of smallholder fish farmers in Ghana are males. This suggests that the present sample is not too different in terms of distribution by gender from the one used in other studies. In terms of formal educational attainment, Asmah (2008) reports that the average fish farmer in Ghana attained ten (10) years of formal education. Asamoah et al.(2012) report that the average fish farmer in Ghana has attained 9.1 years of formal education. If these data shall be representative of the average fish farmer in Ghana, the present data is not too different, as the average farmer has 9.8 years of formal education. Unfortunately, data on income was not collected and the proxies that we have (such as land ownership, plot/pond size, number of rooms in the house) are measured differently or are not included in previous studies in order to allow comparison. However, similarly to Barham et al. (2014) we could compare a measure of output. The average output of the farmers in our sample is 1556.7 kg fish/annum is similar to the one in Asmah (2008), approx. 1518 kg/annum for farms with an average size of 0.25 ha (farm type 5) which is similar to the average pond/plot size in our sample (0.16 ha).[3] Unfortunately, we were not able to make more comparisons but the comparisons we could make, give us some confidence that the present sample might not be very different from more representative samples of fish farmers in Ghana.

6 Econometric Specification and Results

This section describes the survival/duration model used to estimate the effects of risk and ambiguity aversion on the probability to adopt the three technologies discussed. We are especially interested to see whether the ambiguity and risk aversion associated with fish farming, which all three technologies should help to reduce, will lead to an earlier or later adoption of these technologies. Therefore, the variable of interest is the timing of adoption of the three technologies. Duration analysis was commonly used to analyse unemployment (Kiefer 1988;Devine and Kiefer 1991), and has been since used in macroeconomics to study business cycles (Diebold and Redbush 1990) and in marketing to analyse the timing of household purchases (Jain and Vilcassim 1991, Boizot, Robin and Visser 2001). It has been also used to analyse technology adoption in agriculture (Fuglie and Kascak 2001, Burton et al 2003, Abdulai and Huffman 2005, Barham et al.2014) however, to our knowledge it has not been applied to fish farming before. Let t be the time elapsed from the time of first exposure to the technology until adoption. Let $X_i(t)$ be a vector of relevant explanatory variables, and β be a vector of coefficients. Denoting the cumulative density function as $F_i(t|X,\beta) = Prob(T|X,\beta)$ and the density function as $f_i(t|X,\beta)$ the hazard function which indicates the probability of adopting the specific technology at period t, conditional upon no adoption at time $t-1$, is defined as $h_i(t|X,\beta) = f_i(t)[1-F_i(t)]$. The general form of the

[3] 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.

proportional hazard function is as follows:

$$h_i(t|X(t), \beta) = h_0(t) exp \{X_i'(t)\beta\} \tag{1}$$

where $h_o(t)$ is the baseline hazard. To test whether hazard is time dependent, we use a Weibull baseline hazard specification similarly to Liu (2013) and Barham et al.(2014).

In the present study, hazard rates are reported for the regression outcomes, with a higher rate associated with earlier adoption. For any two variables, the one with a hazard ratio greater than unity speeds up adoption, while the other slows adoption. The outcomes from our regressions for the Akosombo strain of Tilapia, extruded feed and floating cages technologies are reported in Tables 3, 4 and 5 respectively. The results reported in the tables compare the speed of adoption of the three technologies as influenced by the measures of risk and ambiguity aversion.

The results for each technology are organized in each table into four columns, with the first column listing the variables in the regressions; the second column showing the outcome of the regression when only ambiguity aversion is included, the third column combines risk aversion according to CRRA and ambiguity aversion, and the last column presents results when additionally risk aversion according to the TCN parameters is included.

For all three technologies, we find that risk aversion plays a significant role in the speed of technology adoption. Specifically, given that higher values of CRRA and σ (from TCN) are associated with less risk aversion, we find that the hazard ratios of CRRA and σ are less than one, showing that less risk averse smallholder fish farmers are likely to adopt the technologies later. Conversely, these hazard ratios mean that risk averse farmers have a higher proclivity to adopting the technologies earlier.

For the Akosombo strain the hazard ratio of ambiguity aversion is not significant at any level. This outcome does not change when risk aversion is introduced in the regression (Table 3). For extruded feed the ratio of ambiguity aversion is significant at 10% but the significance disappears when risk aversion is introduced (Table 4). However, for the floating cages, the hazard ratio of ambiguity aversion is significant (at 5%) and less than one and it stays significant after including the risk aversion measures (Table 5). This shows that ambiguity aversion slows the adoption of the floating cages, but it has no significant effect on the adoption of the other two technologies.

Farmers in rural areas learn from other farmers, as well as through experience. We tested how the number of prior adopters of a technology could influence the speed of adoption by a given farmer. For all three technologies the hazard ratios for the number of prior adopters in a farmer's village is greater than one, implying that as the number of prior adopters in a farmer's village increased, the rate of technology adoption increased too. The hazard ratio for the squared number of prior adopters is also significant in the regressions for all three technologies. While the coefficient of this variable is less than one for floating cages and the extruded feed, it is greater than one for the the Akosombo strain. These suggest a possible quadratic (concave) relationship between the speed of technology adoption and the squared number of prior adopters in the village for floating cages and extruded feed and a convex curvature for AST. A convex curvature would suggest that farmers get additional information from the last 10% of farmers adopting the technology while a concave curvature would mean that this information is not relevant.

One interesting result in Table 5 is that ambiguity aversion slows the adoption of floating cages (hazard ratio is less than one). However, we find that the interaction between ambiguity aversion and number of prior adopters speeds up the adoption of this technology. This means that an ambiguity averse farmer is more likely to be reluctant to adopt the technology, but when other farmers in his/her village adopt the technology in earlier years, the ambiguity averse farmer will be more likely to also adopt the technology. This outcome lends support to the conjecture that in the presence of other adopters the ambiguity about the technology is reduced, therefore enabling an ambiguity averse farmer to decide whether or not to adopt the technology given the known risks.

We also explored possible complementarity among the technologies. While we find no relationship among the adoption of floating cages and the other two technologies, we find a possible substitution effect between the extruded feed and the Akosombo strain. It may be seen in Table 3 that the coefficient of extruded feed is less than one and highly significant, which implies that the prior adoption of extruded feed delays the adoption of Akosombo Strain. From Table 4, we also find the hazard ratio of Akosombo strain to be less than one and significant, confirming that the prior adoption of Akosombo strain also slows the adoption of extruded feed. This may be explained by the fact that both technologies help fish grow faster.

While controlling for regional effects, we find some evidence of regional effects on the speed of adopting some technologies among the smallholder fish farmers in southern Ghana. For instance, the hazard ratio for the Volta Region is significant for both the extruded feed and the floating cages: it is less than one in the former and greater than one for the latter technology. This results show that while farmers in the Volta Region have a higher proclivity to adopt the floating cages, they are also less likely to adopt the extruded feed, than farmers in the reference region, Greater Accra. Maybe the higher probability to adopt floating cages is supported by the fact that there are more and larger rivers and lakes in this region than in the others where the cages could be kept. The Volta River is the main river system in Ghana and the Volta Lake is one of the largest man made reservoirs in the world.[4] Farmers in the Western Region have a higher probability of adopting the Akosombo strain, but there is no significant difference in the adoption rate of the other two technologies between farmers in this region and the reference region (Greater Accra).

6.1 Discussion

6.1.1 Risk aversion and speed of technology adoption

Risk aversion, in the presence of ambiguity aversion, influences the speed of technology adoption. Specifically, we find that in general risk averse farmers are more likely to adopt all three technologies sooner. This is quite remarkable because it confirms the hypothesis that the technologies in this study are risk-reducing. This novel outcome is due to the nature of the technologies in question, as may be perceived by the farmers. Liu (2013) 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

[4]'Lake Volta, Ghana'. Visible Earth. NASA. Retrieved 7 March 2018.

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 the present study, even though the Akosombo strain 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. 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.

6.1.2 Ambiguity Aversion and Technology Adoption

For both the Akosombo strain and extruded feed regressions, the hazard ratio of ambiguity aversion, in the presence of risk, is mostly not significant at any level. However, for the floating cage technology, the hazard ratio of ambiguity aversion is significant (at 5%) and less than one. This shows that ambiguity aversion slows the speed of adopting the floating cages, but it has no significant effect on the adoption of the other two technologies. This may be attributable to the differences in the costs of the technologies. The Akosombo strain and extruded feed do not require as much initial cost outlay as the floating cages, and therefore an ambiguity averse farmer may be more reluctant in adopting the floating cages than the other two technologies. Furthermore, the other two technologies can be adopted in small portions for trial before adopting them fully, unlike the floating cages which is indivisible and cannot be adopted in batches for trial.

7 Conclusion

The present study examines how risk and ambiguity influence the adoption of three fish-farming technologies in rural Ghana using data from experimental games. Two of the technologies are relatively inexpensive and contribute to a rapid fish growth (extruded feed and Akosombo strain of Tilapia) and one is relatively more expensive but helps protecting fish from predators (floating cages). The results show that for all three technologies risk aversion accelerates their adoption. This is in contrast with most of the literature which finds that aversion to risk rather delays than hastens adoption. We explain this result by the risk reducing nature of the three technologies. The analysis suggests however, that the role of ambiguity is different and varies with the nature of the technology under consideration.

Floating cages offer farmers a reduced risk of mortality of fish as they are in enclosed nets into the river and herewith protected from predators. Moreover, cages can be relatively easily moved if the weather or environmental conditions shall deteriorate. Therefore, they offer strong protection against weather and other forms of risk. However, they are also significantly more expensive than a conventional pond and therefore offer a higher ambiguity with respect to their overall profitability. We therefore hypothesized that ambiguity might play a larger role in their case relative to the other two technologies. We tested this hypothesis using a survival model including the experimental measures of risk and ambiguity aversion.

The results show that while ambiguity aversion does not play a role for extruded feed and the Akosombo strain of Tilapia (AST), it does play a significant role for floating cages. As opposed to risk it rather delays than hastens adoption especially in the development country context (Barham et al., 2014). This is in accordance with the literature that shows that in general risk and ambiguity delay adoption. We explain the difference between the technologies by the significantly higher costs of floating cages in comparison with extruded feed and AST.

One important contribution of the present paper is that it analyzes the impact of prior adopters in the village on the probability that a specific technology is adopted. We expect that prior adoption of the technology within one's locality may reduce ambiguity about the risks and potential returns. The results show that, as expected, the interaction between adopters and ambiguity aversion is attenuating the effect of ambiguity for floating cages but has no impact on AST and extruded feed. The more adopters are in the village, the more attenuate is the ambiguity aversion effect for floating cages.

The impact of the number of adopters is always positive and significant and suggests that the more adopters there are in the village the higher the adoption rate for all three technologies. The squared term of the number of adopters shows the curvature of the impact and is concave for floating cages and extruded feed (as the coeff < 1) but convex for AST. This suggests that the information from the last 10% of farmers adopting the technology is especially important for this technology. Moreover, we obtain different results per region.

The present article has several implications for understanding the adoption of the three technologies under consideration and for technology adoption in general. First the results show that it is important to distinguish between risk and ambiguity of technology adoption. The results between aversion to risk and ambiguity are different and this shows the importance of exploring new ways to distinguish between the two both in theoretical and empirical analysis. Second, we obtain different result for ambiguity between the three technologies and show herewith that the role of ambiguity varies with the characteristic of the technology. Therefore, the analysis shows the importance in determining empirically the effect for each specific technology under consideration. Third, similarly to Barham et al.(2014) our results show that new technologies can sometimes help reduce farmer's exposure to risk and uncertainty contrary to what might be usually expected. Therefore, the specific technologies might provide farmers with limited access to credit and insurance a means to negotiate an uncertain environment. Finally, one of the main contributions of the paper is that it considers the role of prior adopters in the village on the probability of adoption. The results show that not only the number of adopters increase the probability of adoption of all three technologies but it also reduces the ambiguity related to the technology bearing higher costs (floating cages). This might have important policy implications: since ambiguity aversion slows the adoption of the floating cage technology, in the introduction of this technology to new farmers in new areas, it may be essential to demonstrate the outcome of the technology in practical ways to reduce ambiguity. For instance, the floating cages of existing farmers in neighbouring villages could be used as practical demonstration sites by extension agents. Furthermore, as risk averse farmers adopt all technologies earlier, therefore to ensure even further adoption, there is need to educate the farmers about the risk-reducing aspects of the technologies.

Table 1: Descriptive Statistics of variables used in the analysis (N=120)

Variable	Definition	Mean	Standard deviation
Time Adoption			
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 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
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
Risk and ambiguity aversion			
Risk aversion (r) (CRRA)	Risk attitude obtained from Brick et al lottery	2.35	2.45
Risk aversion (σ) from TCN	Risk attitude obtained from TCN lottery experiment	0.89	0.52
Loss aversion (λ) from TCN	Loss aversion from TCN lottery experiment	1.92	2.40
Probability weighting (α) from TCN	Probability weighting from TCN lottery experiment	0.74	0.30
Self-reported risk attitude (SRRA)	Self-reported risk attitude on a scale from 0-10 similar to Dohmen et. Al. (2010)	5.39	3.22
Ambiguity Attitude (AA)	Ambiguity preference measured as difference in the WTP between risky and ambiguous prospects	1.20	5.86
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
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[1] 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

[1] Fish Farmer Association

Table 2: Correlations among TCN parameters, SRRA and CRRA

	SRRA	CRRA (r)	TCN (σ)	TCN (α)	TCN (λ)
SRRA	1.000				
CRRA (r)	0.053	1.000			
TCN (σ)	-0.016	0.524***	1.000		
TCN (α)	0.020	0.102	0.285***	1.000)	
TCN (λ)	0.010	-0.125	0.075	0.046	1.000

*** - 1%, ** - 5%, * - 10% level of significance

Table 3: Akosombo Strain Tilapia (AST)

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.680
			(0.192)
α (probability weighting)			0.837
			(0.383)
λ (loss aversion)			1.042
			(0.068)
CRRA		0.874**	
		(0.050)	
Adopters in Village (Cumulative)	1.265***	1.268***	1.258***
	(0.038)	(0.038)	(0.039)
#Adopters^2	1.038**	1.038**	1.039***
	(0.015)	(0.015)	(0.015)
#Adopters*Ambiguity Aversion	1.004	1.004	1.005
	(0.005)	(0.005)	(0.005)
Ambiguity Aversion	1.032	1.027	1.029
	(0.034)	(0.037)	(0.034)
Age	1.031**	1.027**	1.032**
	(0.013)	(0.013)	(0.013)
Male	0.693	0.548	0.577
	(0.318)	(0.252)	(0.283)
Education	1.109**	1.126***	1.123***
	(0.046)	(0.048)	(0.049)
Married	1.696	1.902*	1.626
	(0.589)	(0.687)	(0.591)
Experience	1.147***	1.146***	1.141***
	(0.022)	(0.021)	(0.023)
Experienced Past Weather Shock	1.313	1.611	1.309
	(0.406)	(0.526)	(0.414)
Main Occupation	1.230	1.336	1.357
	(0.404)	(0.456)	(0.457)
Household Size	1.071	1.068	1.074
	(0.053)	(0.053)	(0.056)
Owns house	1.050	1.152	1.138
	(0.296)	(0.330)	(0.324)
Number of Rooms	1.159**	1.163***	1.147**
	(0.067)	(0.066)	(0.070)
Farm Size	1.904*	2.166**	2.146**
	(0.667)	(0.769)	(0.778)
Freehold	1.198	1.129	1.133
	(0.390)	(0.359)	(0.381)
Extension Contact	0.800	0.711	0.591
	(0.310)	(0.281)	(0.270)
Access to Credit	3.909***	3.485***	3.921***
	(1.487)	(1.359)	(1.605)
Extruded Feed	0.032***	0.030***	0.032***
	(0.019)	(0.017)	(0.018)
Floating Cages	0.637	0.638	0.631
	(0.406)	(0.399)	(0.396)
FFA	0.326**	0.296***	0.358**
	(0.156)	(0.138)	(0.171)
Ashanti	1.354	1.797	1.885
	(0.862)	(1.158)	(1.284)
Western	2.228*	2.188*	2.309*
	(0.960)	(0.959)	(1.022)
Volta	0.651	0.820	0.788
	(0.380)	(0.472)	(0.455)
P	9.071***	9.300**	9.187
	(0.869)	(0.889)	(0.878)
Observations	2,033	2,033	2,033

All regressions assume a Weibull survival distribution; the dependent variable is years from knowing about and using the technology; hazard ratios are reported here; *** - 1%, ** - 5%, * - 10% level of significance, P = shape parameter, P<1 hazard decreases monotonically with time, P = 1 hazard is independent of time, P>1 hazard increases monotonically with time.

Table 4: EXTRUDED FEED

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.628*
			(0.150)
α (probability weighting)			1.833*
			(0.633)
λ (loss aversion)			0.979
			(0.050)
CRRA		0.893**	
		(0.043)	
Adopters in village (Cumulative)	3.173***	3.343***	3.120***
	(0.599)	(0.640)	(0.590)
#Adopters^2	0.846***	0.838***	0.849***
	(0.031)	(0.031)	(0.031)
#Adopters*Ambiguity	0.997	0.996	1.000
	(0.011)	(0.011)	(0.012)
Ambiguity Aversion	1.054*	1.045	1.053
	(0.032)	(0.032)	(0.034)
Age	1.056***	1.052***	1.055***
	(0.011)	(0.011)	(0.011)
Male	0.307***	0.272***	0.263***
	(0.089)	(0.081)	(0.081)
Education	1.101***	1.101***	1.095***
	(0.036)	(0.035)	(0.037)
Married	0.717	0.759	0.666
	(0.179)	(0.193)	(0.170)
Experience	1.166***	1.161***	1.174***
	(0.020)	(0.020)	(0.021)
Experienced Past Weather Shock	2.032**	2.322***	1.874**
	(0.571)	(0.672)	(0.535)
Main Occupation	0.757	0.762	0.849
	(0.180)	(0.182)	(0.208)
Household Size	0.987	0.995	0.996
	(0.048)	(0.047)	(0.049)
Owns house	2.117***	2.192***	2.014***
	(0.475)	(0.495)	(0.458)
Number of Rooms	1.096*	1.018**	1.082
	(0.052)	(0.051)	(0.056)
Farm Size	1.063	1.097	1.078
	(0.386)	(0.396)	(0.405)
Freehold	1.158	1.018	0.991
	(0.308)	(0.276)	(0.273)
Extension Contact	0.515**	0.457**	0.482*
	(0.162)	(0.145)	(0.180)
Access to Credit	2.463***	2.268***	2.295***
	(0.760)	(0.696)	(0.695)
Akosombo Strain	0.454*	0.459*	0.466*
	(0.201)	(0.203)	(0.209)
Floating Cages	0.585	0.483	0.424
	(0.354)	(0.298)	(0.263)
FFA	0.475**	0.431***	0.440**
	(0.148)	(0.132)	(0.145)
Ashanti	0.799	1.076	1.154
	(0.396)	(0.546)	(0.625)
Western	1.061	1.135	1.106
	(0.343)	(0.372)	(0.375)
Volta	0.282***	0.362***	0.349**
	(0.110)	(0.142)	(0.144)
P	13.329***	13.536***	13.428
	(1.013)	(1.024)	(1.018)
Observations	1,989	1,989	1,989

All regressions assume a Weibull survival distribution; the dependent variable is years from knowing about and using the technology; hazard ratios are reported here; *** - 1%, ** - 5%, * - 10% level of significance, P = shape parameter, P<1 hazard decreases monotonically with time, P = 1 hazard is independent of time, P>1 hazard increases monotonically with time.

Table 5: FLOATING CAGES

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.520*
			(0.195)
α (probability weighting)			0.612
			(0.296)
λ (loss aversion)			0.988
			(0.063)
CRRA		0.824***	
		(0.055)	
Adopters in village (Cumulative)	3.136***	3.493***	3.153***
	(0.599)	(0.691)	(0.617)
#Adopters^2	0.877***	0.859***	0.874***
	(0.028)	(0.029)	(0.029)
#Adopters*Ambiguity Aversion	1.019*	1.018*	1.020*
	(0.010)	(0.010)	(0.011)
Ambiguity Aversion	0.931**	0.929**	0.938**
	(0.028)	(0.027)	(0.029)
Age	1.002	0.991	1.004
	(0.014)	(0.015)	(0.015)
Male	1.989	1.181	1.428
	(1.213)	(0.706)	(0.969)
Education	1.059	1.039	1.064*
	(0.038)	(0.039)	(0.039)
Married	1.362	2.054*	1.007
	(0.545)	(0.896)	(0.445)
Experience	1.119***	1.127***	1.115***
	(0.024)	(0.025)	(0.024)
Experienced Past Weather Shock	1.910*	1.980*	2.299**
	(0.688)	(0.751)	(0.962)
Main Occupation	1.016	0.843	1.073
	(0.376)	(0.335)	(0.419)
Household Size	0.990	0.948	0.970
	(0.063)	(0.060)	(0.066)
Owns house	0.642	0.663	0.685
	(0.205)	(0.224)	(0.235)
Number of Rooms	1.077	1.116*	1.082
	(0.062)	(0.068)	(0.068)
Farm Size	0.521	0.459	0.518
	(0.709)	(0.677)	(0.741)
Freehold	0.796	0.623	0.857
	(0.291)	(0.232)	(0.313)
Extension Contact	0.427**	0.335***	0.325***
	(0.151)	(0.122)	(0.130)
Access to Credit	1.935**	1.913*	2.342**
	(0.650)	(0.666)	(0.861)
Akosombo Strain	0.335	0.195*	0.308
	(0.263)	(0.172)	(0.262)
Extruded Feed	0.651	0.673	0.667
	(0.786)	(0.825)	(0.808)
FFA	0.107***	0.101***	0.160***
	(0.045)	(0.045)	(0.076)
Ashanti	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Western	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Volta	4.212***	4.813***	3.095**
	(2.114)	(2.561)	(1.634)
P	8.036***	8.217***	8.077***
	(0.827)	(0.841)	(0.835)

Observations	2,070	2,070	2,070

All regressions assume a Weibull survival distribution; the dependent variable is years from knowing about and using the technology; hazard ratios are reported here; All regressions assume a Weibull survival distribution; *** - 1%, ** - 5%, * - 10% level of significance, P = shape parameter, P<1 hazard decreases monotonically with time, P = 1 hazard is independent of time, P>1 hazard increases monotonically with time.

Appendix

Table A 1: Pair of lottery choices and expected values in the BVB experiment

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 A 2: Three Series of Pairwise Lottery Choices and expected values from Tanaka et al. (2010)

SERIES 1			
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			
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			
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 A 3: Switching Point from Option A to Option B and approximations of σ, α and λ
Approximations of σ from Series 1 and 2 from Tanaka et al (2010) lottery pairs

		Switching Point in Series 1														
Switching Point in Series 2	σ	1	2	3	4	5	6	7	8	9	10	11	12	13	14	NS
	1	1.50	1.40	1.35	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.55	0.50
	2	1.40	1.30	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.55	0.50
	3	1.30	1.20	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45
	4	1.20	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.50	0.45	0.40
	5	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.40	0.35
	6	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
	7	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
	8	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25
	9	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
	10	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20
	11	0.80	0.75	0.65	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15
	12	0.75	0.65	0.60	0.55	0.50	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.15	0.10
	13	0.65	0.60	0.50	0.50	0.45	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15	0.10	0.10
	14	0.60	0.50	0.45	0.45	0.40	0.35	0.35	0.30	0.25	0.20	0.15	0.10	0.10	0.10	0.05
	NS	0.50	0.45	0.40	0.40	0.35	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05	0.05

Approximations of α from Series 1 and 2 from Tanaka et al (2010) lottery pairs

		Switching Point in Series 1														
Switching Point in Series 1	α	1	2	3	4	5	6	7	8	9	10	11	12	13	14	NS
	1	0.60	0.75	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.40	1.45
	2	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.35	1.40
	3	0.55	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30
	4	0.50	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
	5	0.45	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20
	6	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15
	7	0.40	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
	8	0.35	0.40	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05
	9	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00
	10	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90	0.95
	11	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.60	0.70	0.75	0.80	0.85	0.90
	12	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
	13	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
	14	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
	NS	0.05	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.65	0.60

Approximations of λ from approximated values of 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

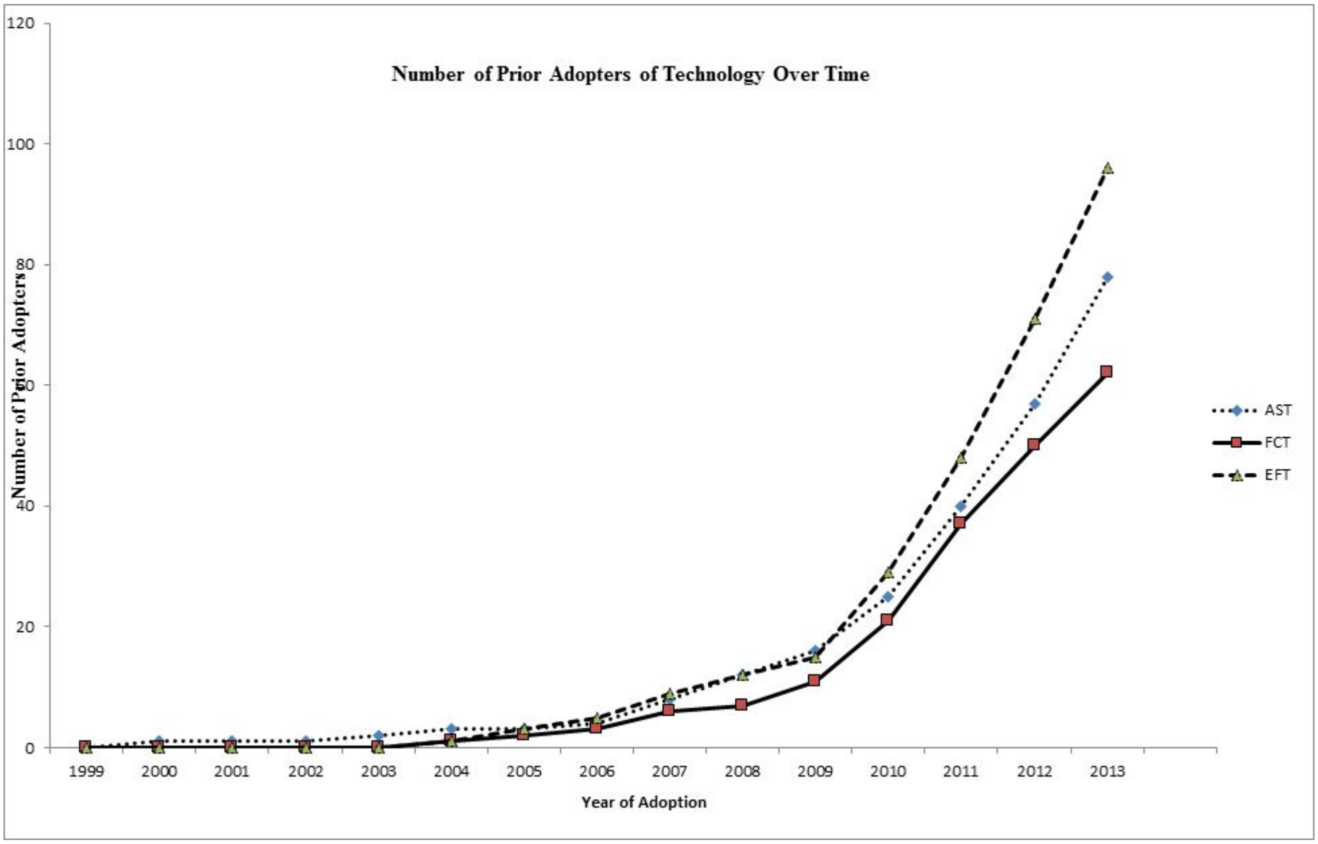

Figure 1: Prior Adopters for extruded feed (EFT), Akosombo strain of Tilapia (AST) and floating cages (FCT)

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