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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: Uncertainty Aversion, Aquafarming, Technology Adoption, Extruded Feed, Floating Cages, Akosombo strain of Tilapia (AST)

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Non-Technical Abstract

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. They are often compelled to make choices that reduce consumption risk at the cost of future expected profits. The adoption of productivity-enhancing technologies is a domain where these trade-offs can become particularly important. New technologies may be inherently more risky, or require additional investments that increase the risk exposure of farmers.

In this paper, we study how aversion to risk and ambiguity affects the adoption of new technologies by smallholder aquafarmers in Ghana where, over the years, the government and other development agencies have introduced improved technologies to enhance productivity and profitability in fish production.

In the present study we consider 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.

Our results show that, for all three technologies, risk aversion accelerates their adoption. This is in contrast with most of the literature which finds that risk aversion delays the adoption of new technologies. We explain this result by arguing that all three technologies under consideration are risk reducing. On the other hand, we find differential effects of ambiguity aversion on the adoption of the three technologies: ambiguity aversion among farmers slows down the adoption of floating cages but has no effect on the rate of adoption of the two other technologies. We attribute this finding to the significantly higher cost of adopting floating cages, which prevents farmers from small-scale experimentation with the technology. Additionally, we find that the presence of other adopters in the locality attenuates the negative effect of ambiguity aversion on the adoption of floating cages.

The results suggest that the implementation of these technologies might provide fish farmers in Ghana with limited access to credit and insurance a means to negotiate an uncertain environment. Moreover, providing practical information about new agricultural technologies with the help of extension agents and existing farmers in neighbouring villages may mitigate the effects of ambiguity and ambiguity aversion on technology adoption. Our findings also suggest that informing farmers about technologies that mitigate the effects of adverse shocks may accelerate the adoption of new agricultural technologies.

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 aversion on adoption can be positive or negative depending on the specificities of the technology. Section 3 provides a description of the three technologies considered. We describe the survey and field experiments in Section 4, and discuss descriptive statistics and the construction of variables in Section 5. In Section 6, we present the econometric specification. We present the results in Section 7 and and discuss our findings in Section 8. Conclusions are provided in Section 9.

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 $\theta \in \mathbf{\Theta}$ with payoff $\pi(\theta, e)$ 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-Morgenstern utility function $U(.)$. If v is known, then the farmer's welfare from choice x is defined as the expected utility:

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

where $\mathbf{E}_{e|v}$ is the expectations operator using the conditional distribution $F(e|v)$. If v is unknown, then the farmer's welfare from choice x is as follows:

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

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:

$$W(\theta) \equiv U(M(\theta) - R_r(\theta) - R_a(\theta)) \tag{1}$$

where $M(\theta)$ is the ex-ante mean payoff from choice θ, $R_r(\theta)$ is the standard Arrow-Pratt risk premium, and $R_a(\theta)$ 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 θ also maximises the expression $M(\theta) - R_r(\theta) - R_a(\theta)$. It follows that a higher expected return (thus, higher $M(\theta)$) makes a technology more attractive; increased risk (higher $R_r(\theta)$) or increased ambiguity (higher $R_a(\theta)$) makes a technology less attractive; for technologies that introduce risk and ambiguity, higher risk aversion (leading to higher $R_r(\theta)$) or higher ambiguity aversion (leading to higher $R_a(\theta)$) also makes the technology less attractive.

It is possible to show the same decomposition using a Prospect Theory (PT) framework, rather than an Expected Utility framework. For this purpose, we would replace the von Neumann-Morgenstern utility function $U(.)$ by a value-function $V(.)$ that allows for loss-aversion, and the expectations operators $\mathbf{E}_{e|v}$ and $\mathbf{E}_v$ by $\mathbf{E}^p_{e|v}$ and $\mathbf{E}^p_{e|v}$ that incorporate probability weights, potentially varying with the size of the probability. In Section 6, we indicate the specific functional forms used for $U(.)$, $V(.)$ and the probability weighting function in our empirical analysis.

The three acquaculture technologies we consider in this study – extruded feed, the AST, 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 AST 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 adop-

tion 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 were incentivised to reveal 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 (see Table A1). 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 gain in the lotteries was much smaller, approximately GhC 6.68 (or US$3.07) which is roughly equivalent to 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 A3 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 A3.

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

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

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

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 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

In this section, we describe the variables we construct using the survey and experimental data to study technology adoption decisions by aquafarmers. Summary statistics for these variables 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. It is notable that the average time to adoption for floating cages is the longest, at 17.8 years (even though this figure excludes the 42% of farmers who were yet to adopt the technology at the time of the survey).

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.[3]

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 only a weak 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. We argue that, 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,

[3]Note that values near the middle of the scale need not correspond to risk neutrality as the farmers were not explicitly instructed to interpret the 11 point scale in this manner.

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 having used the technology in a previous year. Given that the sample consistents of, approximately, the same number of of aquafarmers from each village (about 30), the variable is a proxy for the proportion of aquafarmers in a village who have adopted the technology by a given date. For example, if in a specific year, in a specific village, the number of prior adopters is equal to 1 (which is, roughly, the mean value of the variable in our sample), this is equivalent to an adoption rate of 1/30 or 3.3% (given that there are roughly 30 farmers from each village). In Figure 1, we plot the mean number of prior adopters by village, by year. We note that the number of prior adopters in the village is consistently lower for floating cages – the technology with the largest fixed costs – compared to AST and extruded feed.

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 other explanatory variables used in our analysis can be divided, broadly, into three categories as follows: demographic characteristics (age, gender, years of schooling, marital status, household size); farm-related characteristics (farmer's main occupation, farming experience, property rights over farmland, farm size, contact with extension agents, access to credit, membership of fish farmers' association, previous experience of weather-related shocks), and wealth indicators (home ownership, number of rooms in the house).

The summary statistics for these variables are provided in Table 1. The demographic characteristics all relate to the farmer who is responsible for the technology adoption decision. The majority of farmers in our sample are male (92%), married (75%), and engaged in aquafarming as his primary occupation (71%). On the other hand, only a minority own the land on which they are farming (33%), and belongs to a fish farming association (32%). On average, the farmers have completed nearly 10 years of schooling, and have been engaged in aquafarming for more than 5 years.

In our econometric model (presented in the next section), we control for the farmer's age, gender, education and marital status as the existing literature shows that these factors can influence stated or measured preferences regarding uncertainty. We use an indicator for home ownership and the number of rooms in the house as proxies for household wealth. We control for farm size and property rights as these factors can affect the farmer's incentives to invest in the farm, including the adoption of new technologies. An indicator for prior experience of weather-related shocks is included in the model as it can affect the farmer's beliefs regarding the probability of future shocks and, therefore, affect technology adoption decisions.

We also include in the model indicators for membership in a fish farming association, and access to an extension agent, as these are potential sources for obtaining information about new aquafarming technologies. The inclusion of these variables is motivated by a large literature which shows that the farmer's social network can affect technology adoption decisions (Burton et al. 2003; Bandiera and Rasul 2006; Di Falco and Bulte 2011; Beyene and Kassie 2015; Nazli and Smale 2016).

5.5 Representativeness of the Data

In this section, we provide a discussion of the representativeness of our sample of farmers. At the start of the the survey, 30 farmers were randomly selected from four regions in Ghana, from a representative sample of 320 aquafarmers included in an earlier agricultural survey conducted by the University of Ghana. However, there was some attrition and replacement from this original list. In the Volta Region, three of the farmers opted not to participate in the survey and experiment, citing religious reasons (prohibition against gambling). In the Western Region, four farmers could not participate due to other obligations. In the Ashanti Region, ten farmers on the original list could not be surveyed as they were participating in a training programme conducted by the Ministry of Fisheries at the same time. In order to maintain a sample of 120 aquafarmers, 17 additional farmers were randomly selected and subsequently surveyed in the Greater Accra Region. This undermines the representativeness of the final sample of aquafarmers included in the survey and experiments.

There are, however, other studies that have representative data on all registered fish farmers in Ghana that can be compared to our sample. Onumah and Acquah (2010) report that 91% of smallholder fish farmers are male, compared to 92% in our sample. Similarly, Asmah (2008) and Asamoah et al. (2012) report that 95% and 88% respectively of smallholder fish farmers in Ghana are male. In terms of formal educational attainment, Asmah (2008) reports that the average aquafarmer in Ghana attained 10 years of formal education. Asamoah et al. (2012) report that the average aquafarmer in Ghana has attained 9.1 years of formal education. By comparison, in our sample, the average farmer has 9.8 years of formal education.

No data on income or wealth was not collected during our survey and the proxy variables (such as land ownership, plot/pond size, number of rooms in the house) are measured differently or were not included in previous studies, thus preventing a meaningful comparison. However, we are able to provide comparions on the basis of farm output. The average output for our sample of farmers was 1557 kilograms of fish per annum, similar to the figure of 1518 kg/annum reported in Asmah (2008) 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).[4] These comparisons suggest that the present sample is not be very different from other, representative, samples of aquafarmers in Ghana.

[4]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.

6 Econometric Specification

To investigate how the risk and ambiguity preferences of aquafarmers affect their technology adoption decisions, we make sure of survival/duration models. In each model, the outcome of interest is the timing of adoption of a particular technology. There is a long tradition of using duration models to investigate determinants of unemployment spells (Kiefer 1988; Devine and Kiefer 1991); and has also been adopted in the macroeconomics literature to study business cycles (Diebold and Redbush 1990) and in the marketing literature to investigate the timing of household purchases (Jain and Vilcassim 1991; Boizot, Robin and Visser 2001). More closely related to our work is a growing literature that employs duration models to investigate technology adoption in agriculture (Fuglie and Kascak 2001; Burton et al. 2003; Abdulai and Huffman 2005; Liu 2013; Barham et al. 2014).

We denote by $\mathbf{X}_i(t)$ a vector of observable, potentially time-varying, characteristics of farmer i at time t that are relevant for the technology adoption decision. We define the hazard function – the probability of adopting the technology in question for the first time in period t, conditional upon no adoption up to period $t-1$ – as follows:

$$h_i(t|\mathbf{X}(t), \beta) = h_0(t) \exp\left[\mathbf{X}_i'(t)\beta\right] \tag{2}$$

where β is a vector of parameters to be estimated and $h_0(t)$ is the baseline hazard rate. Following Liu (2013) and Barham et al. (2014), we use a Weibull baseline hazard specification: $h_0\left(t\right) = pt^{p-1}\exp\left(\beta_0\right)$. This specification allows the baseline hazard rate to be time-dependent and nests the exponential model as a special case. The shape parameter p determines whether the hazard rate is decreasing ($p < 1$), increasing ($p > 1$) or constant ($p = 1$).

The term $\mathbf{X}_i'(t)\beta$ is the empirical equivalent of the expression $W\left(1\right) - W\left(0\right)$ where the function $W\left(.\right)$ is as defined in Section 2. Thus, the hazard model defined in (2) posits that the technology adoption decision depends on the gain in expected utility or prospect value, with larger gains being associated with higher probabilities of adoption. In our empirical analysis, we estimate two versions of the hazard model. In the first version, we adopt the

Expected Utility framework and assume a von Neumann-Morgenstern utility function with constant relative risk aversion: $U(x) = \frac{1}{r}x^r$. In the second version, we adopt the Prospect Theory framework and, following Tanaka, Camerer and Nguyen (2010), assume a value function of the form $V(x) = x^\sigma$ for gains $x > 0$ and $V(x) = -\lambda(-x)^\sigma$ for losses $x < 0$; and a probability weighting function $\pi(\rho) = [\exp\{\ln(1/\rho)\}^\alpha]^{-1}$ where probability $\rho \in (0, 1]$. In these expressions, r, σ, λ and α are parameters to be estimated.

Following the reasoning provided in Section 5, we also include in vector $\mathbf{X}_i(t)$ farmer i's demographic characteristics (age, gender, years of schooling, marital status, household size), farm-related characteristics (main occupation, farming experience, land rights, farm size, extension contact, access to credit, membership of fish farmers' association, previous experience of weather shocks), and wealth indicators (home ownership, number of rooms in the house). In each specification, we also include region fixed-effects.

We estimate the hazard model using Maximum Likelihood as follows. Using (2), the probability density function of the time to adoption can be written as follows:

$$f(t|\mathbf{X}(t), \beta) = \exp(\beta_0 + \mathbf{X}_i'(t)\beta)\, t^p$$

If we denote by D_i a censoring dummy, taking a value of 1 if a farmer has adopted the technology in question by the end of the period of observation and 0 otherwise, then the likelihood contribution of a farmer who has adopted the technology at time t_i can be written as

$$L_i = f(t_i|\mathbf{X}(t_i), \beta)^{D_i} [1 - F(T|\mathbf{X}, \beta)]^{1-D_i}$$

where $F_i(T|\mathbf{X}, \beta)$ is the corresponding cumulative distribution funciton and T is the final period observed in the data. Then the Maximum Likelihood Function is given by $L(\beta, p) = \prod_{i=1}^{N} L_i$.

In estimating the hazard model for each technology, we include among the explanatory variables the adoption status of the other two technologies. Specifically, we include time-varying dummy variables indicating whether the farmer had adopted the two other technologies prior to the date in question (for a similar approach, see Butler and Moser 2010; Colombo and Mosconi 1995; Stoneman and Kwon 1994). We also include regional dummies to capture region-specific characteristics not captured by the other variables, with Greater Accra as the reference region.

Where possible, we include farmer characteristics in the model as time-varying characteristics, including age and experience. We introduce education as a time-invariant characteristic – equal to years of formal education at the time of the survey in 2014 – given that most farmers would have completed their formal schooling before becoming responsible for key farming decisions such as technology adoption.

7 Results

The estimates from our regression models on the adoption of AST, extruded feed and floating cages are reported in Tables 3, 4 and 5 respectively. For each variable, we report hazard ratios, with values greater (smaller) than 1 indicating that larger values of the variable in question speeds up (slows down) adoption. For each technology, we estimate three models: a model with the farmer's ambiguity aversion, demographic characteristics, farm-related characteristics and region dummies (column 1); a model where we add the farmer's risk aversion, based on a CRRA utility function (column 2); a model where we add the farmer's risk aversion based on a PT utility function (column 3).

First, we note that the farmer's ambiguity aversion has no effect on the adoption of AST and extruded feed (Table 1 and Table 2), but slows down adoption of floating cages. Specifically, in the case of floating cages, we obtain a hazard ratio smaller than one (Table 5). A test of the null hypothesis that the coefficient is equal to one is rejected in all three specifications used for floating cages at the 5% level. By contrast, for AST the corresponding hazard ratio is larger than one across all three models and we cannot reject the null hypothesis that it is equal to one at standard levels of statistical significance (Table 3). Similarly, for extruded feed, the hazard ratio is larger than one (Table 4). While the estimate is statistically significant at the 10% in column (1), it is no longer so when we introduce risk aversion into the specification.

Second, we note that the number of prior adopters in the village has a strong, positive effect on the speed of adoption for all three technologies, across all three models (statistically significant at the 1% level). The estimated coefficient of the corresponding squared term is also significantly different from one for all three technologies, implying that the relation between the number of prior adopters and the speed of adoption is non-linear. For AST, the estimated coefficient is larger than one, implying a convex relationship between prior adoption in the village and the current speed of adoption, while it is smaller than one for extruded feed and floating cages, implying a concave relationship between the same variables.

In each specification, we interact ambiguity aversion with the number of prior adopters in the village, to investigate whether the effect of ambiguity aversion on technology adoption evolves as others in the village adopt the same technology. We find that the hazard ratio for the interaction term is close to one (and statistically insignificant) in the case of AST and extruded feed, implying that the effect of ambiguity aversion on the adoption of these technologies does not depend on prior adoption in the village. By contrast, the hazard ratio is larger than one and statistically significant (at the 10% level) in the case of floating cages across all three specifications. Thus, while ambiguity averse farmers are less inclined to adopt floating cages, this reluctance is diminished if other farmers in the village have already adopted the technology.

For all three technologies, we find that the farmer's risk aversion plays a significant role in the speed of technology adoption. The hazard ratio for the CRRA parameter is shown in column (2) in tables 3, 4 and 5. In each instance, we find that the hazard ratio is less than one, implying that higher values of the CRRA parameter are associated with slower adoption. As higher values of the CRRA parameter imply lower risk aversion, these estimates imply that more risk-averse farmers adopt these technologies more quickly. In column (3), where we replace the CRRA parameter with the PT parameters σ, α and λ, the results are less clear-cut but broadly consistent. In particular, the estimated hazard ratio of σ – which determines the curvature of the value function – is smaller than one, suggesting that the farmer is less likely to adopt the technology when the value function is more concave, i.e. when the farmer is more risk-averse. But the standard errors for the estimated coefficient are large, such that we cannot reject the hypothesis that the hazard ratio is equal to one in the case of AST; in the case of extruded feed and floating cages, we can reject the corresponding hypothesis at the 10% level. For none of the three technologies do we find any evidence that loss aversion affects the speed of adoption (the estimated hazard ratio for λ is statistically indistinguishable from one).

In each specification, we include time-varying binary variables indicating whether the farmer had adopted the other two technologies by that date. The inclusion of these variables allows us to explore for the presence of complementarity and substitutability between technologies. We find that the hazard ratios are consistently below one, suggesting substitutability between technologies. However, the coefficients are imprecisely estimated, with large standard errors such that, in most instances, we cannot reject the null hypothesis that the hazard ratio is equal to one. The effect of prior adoption of extruded feed on the likelihood of AST adoption is the exception: the hazard ratio is close to zero and significantly different from one (at the 1% level) across all three specifications (Table 3) implying that a farmer who has adopted extruded feed is subsequently very unlikely to adopt AST. We also find that the estimated hazard ratios for AST in the adoption equation for extruded feed are below one and statistically significant (at the 10% level), implying that the adoption of AST slows down the adoption of extruded feed (Table 4). Thus, the two the two technologies are, arguably, substitutes.

The hazard ratios for the region dummies show significant variation in the speed of adoption of the three aquafarming technologies in different parts of Ghana. The excluded (reference) region is Greater Accra. 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. Thus, while farmers in the Volta Region have a higher proclivity to adopt floating cages, they are less likely to adopt the extruded feed, than farmers in Greater Accra. These patterns may be explained by the fact that the Volta region is characterised by a large river system and and lakes, suitable for the use of floating cages.[5] Farmers in the Western Region have a higher probability of adopting the AST, but

[5]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.

there is no significant difference in the adoption rates of the other two technologies between farmers in this region and the reference region (Greater Accra).

8 Discussion

8.1 Risk Aversion and Technology Adoption

We find that, in general, risk averse farmers are more likely to adopt all three technologies sooner. This finding is consistent with the hypothesis that these technologies are risk-reducing, as discussed in Section 3 or, at least, perceived as such by the farmers. This finding contrasts with Liu (2013), a study which finds that risk averse farmers in China are slower to adopt genetically modified cotton seeds. More precisely, the cotton seeds are modified genetically with the 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.

In the present study, the AST is also genetically modified and it is more disease-resistant than local breeds. But it does not produce any toxins. Therefore, it is plausible that farmers perceive it as a risk-reducing technology. In the same vein, extruded feed reduces the risk of water pollution and contamination associated with the conventional sinking feed, which could pose a threat to the health of the fish and the environment; and floating cages provide an enclosure for the farmed fish, and thus reduce the threat posed by natural predators to fish in conventional ponds.

8.2 Ambiguity Aversion and Technology Adoption

We find that ambiguity aversion has no effect on the adoption rate of AST and extruded feed but slows down the adoption rate of floating cages (estimated coefficient is below one and statistically significant at the 1% level). In Section 2, we argued that ambiguity aversion would slow down adoption of a new technology if it entails large fixed efforts. If not, small scale experimentation enable farmers to reduce ambiguity associated with new technologies.

In Section 3, we highlighted that while the adoption of floating cages require aquafarmers to make substantial investments, the AST and the extruded feed do not. Therefore, farmers can learn about the AST and extruded feed, and their respective payoff distributions, through small-scale trials but the same approach is not practical in the case of floating cages. Therefore, the estimated effects of ambiguity aversion on the adoption of the three technologies are consistent with the theoretical predictions.

As discussed in Section 2 the adoption of a new technology by other farmers in the locality also provide a means of learning about a new technology and, in particular, resolve ambiguities in the payoff distribution of the technology. Therefore, the prior adoption of a technology by other farmers in the locality should accelerate the rate of adoption. Consistent with this reasoning, we find that the rate of adoption of all three technologies increase with the number of prior adopters of that technologies.

But more importantly, we find that the negative effect of ambiguity aversion on the adoption of floating cages declines as the number of other adopters in the village increases (interaction term statistically significant at the 10% level). This is consistent with our theoretical reasoning that ambiguity aversion should not matter for technology adoption if the farmer has access to sufficient information – from other adopters – to resolve the ambiguity in the distribution of payments. For the other two technologies, the estimated effect of ambiguity aversion on technology adoption does not vary with the number of other adopters.

9 Conclusion

The present study examines how risk and ambiguity aversion influence the adoption of three aquafarming technologies in rural Ghana using data from a survey of farmers and field experiments. Two of the technologies are relatively inexpensive and contribute to a rapid growth in fish production (extruded feed and the Akosombo strain of Tilapia) while the third one is relatively expensive but helps protect fish from natural 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 risk aversion delays the adoption of new technologies. We explain this result by arguing that all three technologies under consideration are risk reducing.

On the other hand, we find differential effects of ambiguity aversion on the adoption of the three technologies: ambiguity aversion among farmers slows down the adoption of floating cages but has no effect on the rate of adoption of the two other technologies. Additionally, we find that the presence of other adopters in the locality attenuates the negative effect of ambuity aversion on the adoption of floating cages. Floating cages offer farmers a reduced risk of fish mortality as they are placed in enclosed nets in the river and, thus, protected from natural predators. Moreover, these cages can be moved relatively easily if the weather or environmental conditions deteriorate. Therefore, they offer strong protection against a variety of adverse shocks. On the other hand, as they are significantly more expensive than farming in a conventional pond, they provide little scope of small-scale experimentation by farmers. Therefore, initial adopters are faced with ambiguity in the distribution of payoffs from floating cages, implying that ambiguity adoption would retard adoption. By contrast, farmers can experiment with the Akosombo strain of Tilapia and extruded feed and consequently learn about their payoff distributions. Based on this reasoning, we argued that, at the early stages of the adoption process, ambiguity aversion should play a larger role in the adoption of floating cages compared to the two other technologies.

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 aversion in the context of technology adoption. Second, similar to Barham et al. (2014), our results show that new technologies can sometimes help reduce farmers' exposure to risk. These technologies might provide farmers with limited access to credit and insurance a means to negotiate an uncertain environment. Third, we provide evidence that the impact of ambiguity aversion on technology adoption may evolve as others in the locality adopt the technology.

Therefore, providing practical information about new agricultural technologies – with the help of extension agents and existing farmers in neighbouring villages – may mitigate the effects of ambiguity and ambiguity aversion on technology adoption. Furthermore, our findings suggest that informing farmers about new technologies that lower the risk of adverse shocks may also accelerate the adoption of new agricultural technologies.

Table 1: Summary Statistics

Variable	Definition	Mean	Standard deviation
Technology Adoption			
Time to adoption for Extruded Feed	Years between learning about technology and first use	16.62	2.28
Time to adoption for AST	Years between learning about technology and first use	17.11	2.79
Time to adoption of Floating cages	Years between learning about technology and first use	17.76	2.53
Risk and Ambiguity Aversion			
Risk aversion (r)	Constant Relative Risk Aversion Coefficient	2.35	2.45
Risk aversion (σ)	Value Function Curvature (Prospect Theory)	0.89	0.52
Loss aversion (λ)	Loss aversion Parameter (Prospect Theory)	1.92	2.40
Probability weighting (α)	Probability weighting Parameter (Prospect Theory)	0.74	0.30
Self-reported risk attitude (SRRA)	Self-reported risk attitude on a scale from 0-10 (0 = unwilling to take risks, 10 = very willing to take risks)	5.39	3.22
Ambiguity Aversion	Ambiguity Aversion measured as difference in the WTP between risky and ambiguous prospects	1.20	5.86
Farmer Characteristics			
Age of farmer	Age of fish farmer at the time of data collection	41.93	13.19
Gender	= 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
Household Characteristics			
Household Size	Farmer + number of people who eat 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 the famers' house	4.23	2.68
Freehold tenure	= 1 if farmer owns the farm land	0.33	0.47
Farm size	The total size of all active ponds and/or cages (ha)	0.16	0.32
Access to Services			
Extension Services	= 1 if farmer has access to extension services	0.48	0.50
Access to Credit	= 1 if farmer has access to credit	0.78	0.42
FFA	= 1 if farmer is a member of a fish farmers' association	0.32	0.47
Regional 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

Table 2: Correlation Matrix for Risk and Ambiguity Aversion Variables

	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: Hazard Model Estimates for Adoption of the Akosombo Strain Tilapia (AST)

Variable	(1)	(2)	(3)
σ (value function curvature)			0.680
			(0.192)
α (probability weighting)			0.837
			(0.383)
λ (loss aversion)			1.042
			(0.068)
CRRA parameter		0.874**	
		(0.050)	
# Prior Adopters in Village	1.265***	1.268***	1.258***
	(0.038)	(0.038)	(0.039)
# Prior Adopters Squared	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

The dependent variable is the number of years between learning about the technology and its first use by the farmer. Hazard ratios and standard errors (in parentheses) are reported in the table. All regressions assume a Weibull survival distribution. Statistical significance is denoted by *** (1% level) ** (5% level) * (10% level). P is the 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: Hazard Model Estimates for Adoption of Extruded Feed

Variable	(1)	(2)	(3)
σ (value function curvature)			0.628*
			(0.150)
α (probability weighting)			1.833*
			(0.633)
λ (loss aversion)			0.979
			(0.050)
CRRA Parameter		0.893**	
		(0.043)	
# Prior Adopters in Village	3.173***	3.343***	3.120***
	(0.599)	(0.640)	(0.590)
# Prior Adopters Squared	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

The dependent variable is the number of years between learning about the technology and its first use by the farmer. Hazard ratios and standard errors (in parentheses) are reported in the table. All regressions assume a Weibull survival distribution. Statistical significance is denoted by *** (1% level) ** (5% level) * (10% level). P is the 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 Technology (FCT)

Variable	(1)	(2)	(3)
σ (value function curvature)			0.520*
			(0.195)
α (probability weighting)			0.612
			(0.296)
λ (loss aversion)			0.988
			(0.063)
CRRA Parameter		0.824***	
		(0.055)	
# Prior Adopters in Village	3.136***	3.493***	3.153***
	(0.599)	(0.691)	(0.617)
# Prior Adopters Squared	0.877***	0.859***	0.874***
	(0.028)	(0.029)	(0.029)
# Adopters × Ambiguity	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

The dependent variable is the number of years between learning about the technology and its first use by the farmer. Hazard ratios and standard errors (in parentheses) are reported in the table. All regressions assume a Weibull survival distribution. Statistical significance is denoted by *** (1% level) ** (5% level) * (10% level). P is the 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 A1: Pairs of Lottery Choices and Expected Values in the BVB Experiments

Row	Option A	Option B	Expected Payoff Difference (A-B)	Range of CRRA Parameter
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 A2: Pairwise Lottery Choices and Expected Values in the TCN Experiments

Row	Option A	Option B	Expected Payoff Difference (A-B)
SERIES 1			
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 A3: Switching Point from Option A to Option B and Approximations of σ, α and λ

Approximations of σ from Series 1 and 2 from TCN Lottery Pairs

		Switching Point in Series 1														
	σ	1	2	3	4	5	6	7	8	9	10	11	12	13	14	NS
Switching Point in Series 2	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 TCN Lottery Pairs

		Switching Point in Series 1														
	α	1	2	3	4	5	6	7	8	9	10	11	12	13	14	NS
Switching Point in Series 1	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

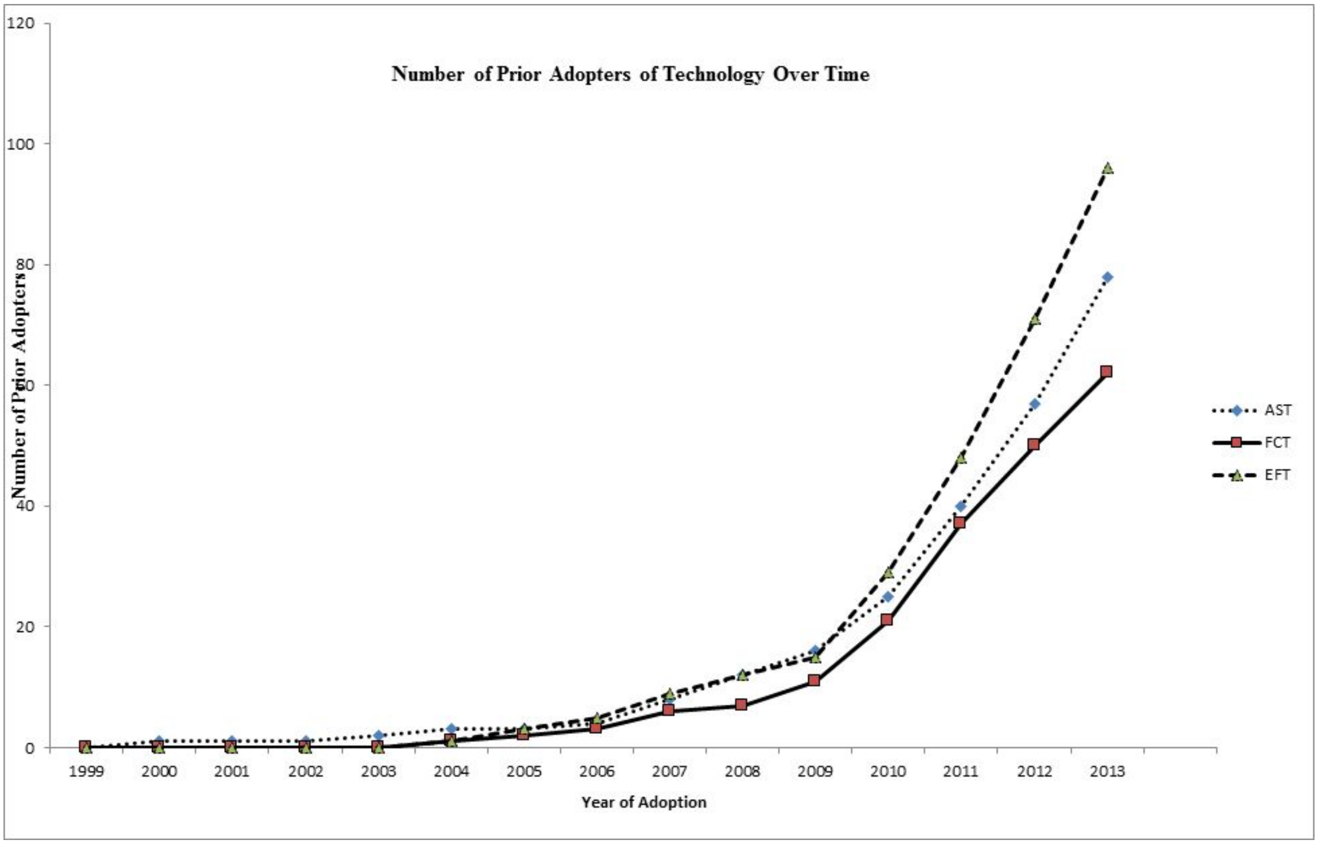

Figure 1: Prior Adopters for extruded feed (EFT), Akosombo strain of Tilapia (AST) and floating cages (FCT)

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