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

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Abstract

Small-scale farmers in developing countries frequently make production decisions in situations of uncertainty. There is growing evidence that ambiguity - and not just risk - affects farming decisions, limiting the adoption of new farming practices and technologies. We study the adoption of three new technologies, designed to be risk-reducing, among smallholder aquafarmers in Ghana. 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, as expected, that aquafarmers who are more risk-averse are quicker to adopt the new technologies but ambiguity aversion has no effect on the adoption of two out of the three technologies (a fast-growing breed of tilapia fish, and extruded feed). Ambiguity-averse farmers are slower to adopt the third technology which entail large fixed costs (floating cages), but its effect is diminishing in the number of prior adopters in the village. We argue that the evidence highlights the specific situations in which ambiguity is an impediment to technology adoption: when large fixed costs prevent small-scale experimentation, and there are limited sources of information available to potential adopters.

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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, understanding whether and how ambiguity affects technology adoption decisions by farmers is important as it may have policy implications distinct from those implied by risk. While improving access to insurance – or services that facilitate risk-sharing – can speed up adoption of risky new technologies, access to information about the *distribution of returns* from adoption – or services that facilitate information-sharing among farmers – may play an equally important role if ambiguity impedes technology adoption.

To isolate and understand better the effects of ambiguity – as opposed to risk – on the adoption of new technologies, we study adoption decisions, among smallholder aquafarmers in Ghana, of three distinct technologies that are all designed to be risk-reducing: (i) the Akosombo strain of Tilapia (AST), a fast-growing breed of tilapia fish; and the use of (ii) floating cages; and (iii) extruded feed for the fish under cultivation. 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 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, as expected for these technologies – but contrary to most of the existing literature – that farmers that exhibit greater risk-aversion adopt the AST, extruded feed and floating cages sooner. 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 aversion *slows down* the adoption of floating cages. We argue that this is because floating cages require a substantial initial investment (while the AST and extruded feed do not) and, thus, precludes small-scale experimentation by the farmer that would enable learning and reduce ambiguity.

We hypothesize that prior use of the technology by one's neighbours may reduce ambiguity about the distribution of returns. Therefore, the negative effects of ambiguity aversion on the adoption of floating cages should decline as adoption of the technology increases in the locality. To test this hypothesis, we interact our measure of ambiguity aversion with the number of prior adopters of the technology within one's own village. Consistent with the prediction, we find that the estimated effects of ambiguity aversion on floating cages declines as the number of prior adopters increases. By contrast, the interaction term has no effect on the adopton of the AST and extruded feed. The evidence highlights the specific situations in which ambiguity is an impediment to technology adoption: when large fixed costs prevent small-scale experimentation, and there are limited sources of information available to potential adopters.[1]

Our findings add to the growing evidence of the effects of risk and ambiguity preferences on farming choices in developing countries. Warnick, Escobal and Laszlo (2011) find that, while risk aversion among Peruvian farmers increases crop diversification, ambiguity aversion reduces crop and varietal diversification. Ross, Santos and Capon (2012) find that ambiguity aversion among Laotian farmers limits the adoption of a new crop even though risk aversion does not affect adoption decisions. Bryan (2019) shows that index insurance (with basis risk) and access to credit (with limited liability) has a negative effect on the adoption of new crops by ambiguity-averse farmers in Malawi and Kenya respectively. Compared to this literature, the present study is distinctive in that it focuses on three new technologies that, by design, are intended to reduce the risk exposure of farmers. Our finding that risk-aversion among farmers *accelarates* adoption for all three technologies confirms this feature. We find, for these farming technologies, that ambiguity aversion does not hinder technology adoption except in the case where large fixed costs are involved and that prior adoption in one's locality mitigates the problem.

Thus, our findings suggest that, in a developing country setting, the adverse effects of ambiguity aversion on risk-reducing technologies may be mitigated if resources are made available for experimentation and knowledge-transmission. This reasoning is supported by Barham et al.'s (2014) finding that ambiguity aversion among grain farmers in the United States – who have 'greater access to information regarding new technologies from exten-

[1] These findings echo a literature in industrial organisation which shows, using theoretical models of dynamic competition, that entry (and exit) are lower in industries characterized by high fixed/sunk costs (Dixit, 1989; Lambson, 1991 & 1992; Hopenhayn, 1992; Lambson and Jensen, 1998) and hence there may be less opportunity for experimentation. At the same time, empirical studies have shown that profitability in these industries are more volatile (Gschwandtner and Lambson 2006), potentially making experimentation financially less feasible.

sion agents, field trials, and seed dealers' than farmers in developing countries – *speeds up* adoption of new ambiguity-reducing GM crops. This interpretation of the results also implies a coordination failure: if farmers were able to pool resources to experiment with – and collectively learn about the distribution of returns from – a new technology, this could potentially increase the pace of adoption, but existing institutions may not be equipped to solve the coordination problem. Such a coordination failure may justify government support for the purpose of experimentation and knowledge transmission for agricultural technologies characterised by sizeable fixed costs and ambiguity in potential returns.

It is important to note that there are potentially multiple explanations that are consistent with our findings. This is due to the fact that our main results make use of the variation in risk and ambiguity aversion among farmers (elicited using lottery choice field experiments) that may be correlated with other farmer characteristics important for the adoption decision. In the discussion above, we highlight one possible interpretation, consistent with our empirical results, as it has important policy implications for technology adoption among farmers in developing countries. Validating the hypothesis will require further investigation, a task we leave to future work. In Section 8.3 of the paper, we discuss alternative explanations and explore whether and to what extent they can account for the empirical findings.

The rest of the article is organised 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 (see Section 3) . 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 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 increases.

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 play 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. The product is considered to be more hygienic than the conventional feed because of the sterilisation of pathogens in the extrusion process. As the fish need to float near the surface to access the extruded feed, this facilitates monitoring their growth and health and adjust feeding amounts as necessary. Fish raised on extruded feed grow to nearly twice the size achieved with conventional feed (Ansah et al. 2014). 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). Commercial extruded feed became available in Ghana in 2005 when it was imported via an Israeli firm, Ranaan (Kassam 2014). However, Ghanaian farmers also manufacture extruded feed on-farm (Frimpong and Anane-Taabeah 2017).

AST is a relatively new and improved strain of tilapia (*Oreochromis niloticus*) developed in 2003 by the Aquaculture Research and Development Centre (ARDEC) in Ghana. 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 (Ansah et al. 2014). Apart from its fast-growing properties, the AST can tolerate a wide range of environmental conditions, is resistant to stress, disease and poor water quality and, as a result, enjoys higher survival rates than the conventional breed. AST fingerlings cost about one-and-half times that of 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 also involves substantial costs. Ofori et al. (2010) reports a typical size of 48 cubic meters for floating cages in the Volta Lake, and a cost of USD 1000 per cage, nearly half the average cost of production over a six month cycle. The first cage farm was established in Ghana in 2000 (Kassam 2014). But the technology has been in use in other parts of the world for a much longer period. For example, in neighbouring Côte d'Ivoire the technology has been used since the 1980s (Hem 1982).

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 they enable farmers to maintain better hygiene than in traditional ponds and to respond quickly to changes in environmental conditions. Among the type of information that aquafarmers most commonly seek from agricultural extension officers relate to water quality assessment and management, and the identification and control of diseases (Ayisi et al 2016), which suggests that there is a demand for risk-reducing technologies among aquafarmers.

The existing literature also indicate that these technologies are substantially more profitable than their conventional alternatives, but these studies are typically conducted under ideal conditions that do not take into account resource constraints of small-holder farmers along other dimensions. Small-holder farmers in Ghana typically have limited access to agricultural extension officers, and therefore may lack knowledge about the distribution of returns from the adoption of the new technology, especially under local farming conditions and resource constraints (Frimpong and Anane-Taabeah, 2017). Therefore, technology adoption may initially lead to increased ambiguity.

Engaging in small-scale experimentation with the new technology may provide farmers with better knowledge about the distribution of potential returns under local conditions and resource constraints. There is evidence that at the early stages of adoption of the three aquaculture technologies in Ghana, small-holder farmers were engaged in such small-scale experimentation with aquaculture, while allocating the major part of their land to other farming activities. For example, in a survey of fish farms in southern Ghana in 2006, fewer than 10% of the farmers named aquaculture as their main economic activity; and the median size of fish farm was about 0.06 hectares, compared to median farmer land ownership of 1 hectare (Asmah, 2008). But the three aquaculture technologies under consideration all involve higher costs – with floating cages having the highest cost among them – which may limit the ability of small-holder farmers to experiment with them. As such, ambiguity aversion may be an important constraint to the adoption of the new 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 representative sample of 320 aquafarms (80 from each of the four regions), included in an earlier agricultural survey conducted by the University of Ghana (see Onumah et al. 2018). The sampling design ensured that each aquafarmer in any village in these four regions of southern Ghana had the same ex-ante probability of being selected into the sample. The final sample of 120 aquafarmers were located in 34 different villages, thus an average of about 3.5 farmers per village. 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 respectively). 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 A1. 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.[2] 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.[3] 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

[2]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).

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

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. For each lottery series, all the lottery pairs were presented to the participant simultaneously, and the participant was instructed to indicate his or her "switching point" from the safer to the riskier lottery.

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 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.

We used the same ordering of the experiments for all participants as follows. Participants were presented with the BVB lottery series first, followed by the TCN lottery series 1, 2 and

3. The BVB lottery series is similar in appearance to the three TCN lottery series, but the average stakes are easier to calculate. The rationale for presenting participants with the BVB lottery series first was to give them the opportunity to work with a relatively easy set of figures before being presented with a more complex set of alternatives. The TCN lottery series have been presented in the same order in previous experiments reported in the literature (see, for example, Tanaka, Camerer and Nguyen 2010, and Liu 2013), and our aim was to make our risk preference measures comparable to these to the extent possible. The experiment to elicit ambiguity preferences was conducted after the participants were presented with the BVB and TCN lottery series. We opted for this ordering to ensure that participants had already had some experience reflecting on such choices (with real financial stakes) before answering a question on willingness to pay on a similar hypothetical game.

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 for the different technologies as follows. In the case of AST, we measure time to adoption from the year 2003, when it was developed in Ghana. The extruded feed and floating cage technologies have been available for much longer periods and it is difficult to identify a specific date when the technologies became accessible to farmers in Ghana. For these technologies, we measure time to adoption from the year 1994, which is the earliest year – in both instances – that any farmer in our sample reported learning about the technology.[4] A large fraction of the farmers adopt at least one of three aquaculture technologies in the same year that they start aquaculture (52.5%) or within a year of starting (18.3%). These figures suggest that it is often the availability of

[4]In Section 7, we discuss robustness checks using alternative start dates for these two technologies.

the technology that induces a farmer to start aquaculture production.[5] 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.

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, Bricks, Visser and Burns (2012) finds, for a sample of South African fishers, that average farmer is moderately risk-averse. The median farmer in our sample has a value of r in the range $(0.756, 1.000)$, which is identical to that obtained for the South African fishers. The average self-reported risk attitude value in our survey is 5.4 (on an 11 point scale), which suggests neither a strong aversion to risk nor a strong preference for it.[6]

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 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-

[5] Given the potential endogeneity of the start date of aquaculture, we do not consider the time to adoption from starting aquaculture as a dependent variable.

[6] 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.

reported risk measure is based on a hypothetical question, it may be subject to hypothetical bias.[7] Therefore, to estimate the effects of risk preferences on technology adoption, we make use of the experimental measures only.

The fact that the average farmer is risk-loving according to the BVB experiments but risk-averse according to the TCN experiments requires some comment. Unlike the TCN experiments, in the BVB experiments the farmer had no possibility of suffering a loss. As such, the BVB experiments may have been somewhat removed from decisions faced by smallholder farmers in a developing country setting where potentially profitable investments would typically carry a risk of financial loss. If some of the participants perceived these experiments to be a game designed for their entertainment, they may have been more willing to take gambles than they would have otherwise. However, as the CRRA parameter r and the PT parameter σ are strongly, positively correlated (Table 2), the two sets of experiments generate roughly the same *ordering* of farmers in terms of risk preferences.

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

In response to a survey question about the reasons for technology adoption, the response given by the farmers most frequently was 'because everyone uses it' for each of the aquaculture technologies (47.83% for floating cages, 26.32% for extruded feed and 56.04% for the AST). This suggests that prior adoption by other farmers in the locality was an important driver of technology adoption. This may be because farmers were encouraged by high re-

[7] Previous studies have found that survey-based measures of risk preferences correlate well with measures based on incentivised lottery experiments. However, our respondents are drawn from a sample (smallholder farmers in a developing country) that differs substantially from those typically used in these studies; e.g. the general population in a developed country (Dohmen et al. 2011), university students (Vieider et al. 2015).

turns achieved with the new technologies by their neighbours but also, arguably, because prior adoption by others provided better information about the *distribution* of returns and thus lowered ambiguity.

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. Thus, the variable is farmer-technology-year specific and equals the number of other farmers from the same village (in the sample) who have adopted that technology in a previous year. This count measure serves as a proxy for the number of distinct, independent sources of information about the technology in question within a specific village in a specific year.[8]

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.

In Figure 1, we plot the total number of prior adopters in the sample for each technology, 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.

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,

[8]We do not adjust for the size of the village as we lack this information in the dataset. Therefore, interpreting our measure as the availability of information about the technology in question is based on the assumption that the villages in the sample are of similar size. This is a plausible assumption given that the villages are all located in four closely situated regions in southern Ghana.

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).

A concern about including these farm and farmer characteristics in the econometric model is that they are potentially endogenous to the technology adoption decision and we lack historical information on these variables. We address this issue after presenting the results from our base specification in Section 7.

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 potentially undermines the representativeness of the final sample of aquafarmers included in the survey and experiments.

However, we can check the representativeness of our sample by comparing it to other studies which use random samples drawn from the population of all registered aquafarmers in Ghana. The proportion of smallholder aquafarmers that are male is 91% in the sample used by Onumah and Acquah (2010); 95% in Asmah (2008) and 88% in Asamoah et al. (2012). By comparison, 92% of the farmers in our sample are male. Asmah (2008) and Asamoah et al. (2012) report averages of 10 years and 9.1 years of formal education for the farmers in their respective samples. By comparison, the average farmer in our sample has 9.8 years of formal education.

No data on income or wealth was 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).[9] These comparisons suggest that the present sample is not very different from other, representative, samples of aquafarmers in Ghana.

6 Econometric Specification

To investigate how the risk and ambiguity preferences of aquafarmers affect their technology adoption decisions, we employ 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: $h_0(t) = pt^{p-1}\exp(\beta_0)$. 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 ($p = 1$).

[9] 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.

The term $\mathbf{X}_i'(t)\beta$ is the empirical equivalent of the expression $W(1) - W(0)$ where the function $W(\theta)$ is as defined in Section 2 and θ indicates the adoption status of the new technology (1=adoption, 0=non-adoption). 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, 5 and 7 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 3 and Table 5), but slows down adoption of floating cages. Specifically, in the case of floating cages, we obtain a hazard ratio smaller than one (Table 7). 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 5). 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, 5 and 7. 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. In the case of all three technologies, we reject the hypothesis that the hazard ratio is equal to one 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 5). Thus, the two the two technologies are, arguably, substitutes.[10]

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. 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 (the

[10]The results do not show that floating cages and extruded feed are complements because, even when the hazard ratio is greater than 1, it is statistically insignificant. In other words, we donâ€t find evidence that having adopted one technology accelerates the adoption of the other. The reason for this could be that while the two technologies are technological complements (i.e. adopting one technology raises the marginal product of the other), they may be substitutes in peopleâ€s choices because of credit constraints.

excluded, reference region is Greater Accra). 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.[11] Farmers in the Western Region have a higher probability of adopting the AST, but 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).

A potential concern with the estimates reported in tables 3, 5 and 7 is that the farm and farmer characteristics are endogenous to the technology adoption decisions. In tables 4, 6 and 8, we report on alternative specifications where these farmer and farm characteristics are removed from the model. The estimated effects of the risk and ambiguity preferences are broadly similar – in terms of magnitude and statistical significance – to those obtained with our base specifications. The one exception to this pattern is that, for the Akosombo Strain of Tilapia, the hazard ratio of the risk aversion parameters are no longer statistically different from 1 when farmer and farm characteristics are removed from the hazard model but the ratio is below 1 as in the base specifications. This suggests that the estimated effects of risk and ambiguity preferences on the technology adoption are not substantially affected by the potential endogeneity of the farm and farmer characteristics.

A potential concern with the estimates obtained for the adoption of extruded feed and floating cages is that the start date used in the hazard model – i.e. the date from which there is positive hazard of adoption – is incorrect. For this reason, we provide alternative estimates for these technologies with alternative start dates in the time period 1995-2000 in Tables A4 and A5. As these tables show, the estimated effects of risk and ambiguity aversion do not change substantially when we use a later start date.

[11] 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.

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 costs. 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 a technology increases with the number of prior adopters of that technology.

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.

8.3 Alternative Explanations

In this section we consider whether and to what extent alternative explanations can account for our empirical results.[12]

Trust in Strangers: There is, potentially, heterogeneity among farmers in terms of their level of trust in strangers. If farmers were uncertain about whether the experimenter would make payment for large winnings in the lottery choice experiments, then they would undervalue large winnings and, thus, appear more risk-averse than they are. If so, the risk aversion measures elicited using the lottery choice experiments may be proxying for lack of trust in strangers. The same lack of trust in strangers may lead farmers to discount information provided by agricultural extension officers and thus slow down the pace of adoption

[12] We thank an anonymous referee for proposing some of these alternative explanations.

of new agricultural technologies. Under these assumptions, our measures of risk preferences would be correlated with technology adoption decisions even if, in reality, risk aversion did not matter for technology adoption. Prior adoption by other farmers within the village would increase the rate of adoption as they would provide more trustworthy sources of information. However, under these assumptions, farmers with high measured risk aversion should be *slower* to adopt a new technology while our hazard model estimates imply the opposite for all three technologies under consideration.

Prudence: Prudence, by definition, can induce farmers to save for the future rather than make costly investments in the present. Thus, prudent farmers may be slower to adopt new technologies. Prudence may also induce farmers to prefer sure payments (that can be saved for the future) over risky gambles. If so, the risk aversion measures elicited using the lottery choice experiments may be proxying, at least in part, for prudence. Under these assumptions, our measures of risk preferences would, again, be correlated with technology adoption decisions even if, in reality, risk aversion does not matter for technology adoption. However, under these assumptions, farmers with high measured risk aversion would be slower to adopt a new technology while we obtain the opposite result for all three technologies.

Unobserved Wealth: Poorer farmers are likely to be more risk-averse. If there is unobserved heterogeneity in wealth among farmers, then the experimental measures of risk aversion may be proxying for wealth. These farmers are also more likely to be credit-constrained, which may slow down their adoption of new agricultural technologies compared to richer farmers. This would lead to a negative relationship between measured risk aversion and technology adoption. However, this explanation based on ubobserved wealth heterogeity and credit constraints cannot account for our results as the hazard model estimates imply that risk aversion accelerates technology adoption for all three technologies.

Effect of Technology Adoption on Risk and Ambiguity Preferences: It is important to note that the experiments for eliciting the risk and ambiguity preferences of farmers were conducted in 2014, while the analysis focuses on technology adoption decisions at previous points in time. If risk and ambiguity preferences change over time, then the hazard model estimates may be affected by reverse causality. In particular, if farmers who adopt new farming technologies subsequently become less risk-averse, then this would account for the estimated 'effects' of the risk-aversion parameters. However, other studies using the same the experimental measures of risk aversion and recall data on technology adoption have found that risk aversion slows down the adoption of certain new agricultural technologies (e.g. Liu 2013). If this method was simply revealing a causal relationship from technology adoption to risk preferences, it would be difficult to explain why the risk aversion measures have a positive relationship with certain technologies and a negative relationship with others.

Geographical Variation in Returns: There is potentially geographical variation in the returns from the adoption of a new technology. Where the expected returns are higher, there may also be less ambiguity regarding the distribution of returns. In these areas, farmers will adopt the technology more quickly. This would lead to a positive relationship between prior adoption and adoption probability. Also, ambiguity aversion would not have a "dampening effect" on adoption probability in areas where prior adoption is high, consistent with the effects we obtain for the adoption of floating cages. However, the hazard model estimates indicate a correlation between probability of adoption and prior adoption of the technology in the area (with a larger effect for ambiguity-averse individuals) not just in the cross-section but also *over time*. For example, our estimates imply that the effect of ambiguity aversion on the adoption of floating cages in the Volta region (where the technology is likely to be more beneficial) is negative and large at the early stages of adoption and dampened only after the use of the technology in the region has become widespread. A negative relation between the benefits of the technology and its ambiguity across areas cannot, on its own, account for such a pattern.

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. Compared to traditional aquaculture ponds, floating cages allow better hygiene practice and, as the fish are placed in enclosed nets, better protection from their natural predators. Moreover, these cages can be moved relatively easily if the weather or environmental conditions deteriorate. Thus, they provide 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 for small-scale experimentation by farmers. Therefore, initial adopters are faced with ambiguity in the distribution of payoffs from floating cages, which may slow down the rate of 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 argue 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.

Our findings add to the growing evidence of the effects of risk and ambiguity preferences on farming choices in developing countries. The present study is distinctive in that it focuses on three distinct technologies that, by design, are all intended to reduce the risk exposure of farmers. Our finding that risk-aversion among farmers *accelarates* adoption for all three technologies confirms this feature. It suggests that, in an environment where farmers have limited access to credit and insurance, informing them about new technologies that *reduce* the risk of adverse shocks may help to accelarate the adoption of new agricultural technologies.

Our findings on ambiguity aversion suggest that, in a developing country setting, the adverse effects of ambiguity aversion on risk-reducing technologies may be mitigated if resources are made available for experimentation and knowledge-transmission. In particular, providing practical information about new agricultural technologies and information about the distribution of returns from adoption – with the help of extension agents and existing farmers in neighbouring villages – may mitigate the effects of ambiguity and ambiguity aversion on technology adoption. Additionally, government support that enables potential adopters to coordinate expermentation with new technologies under local conditions, and thus share experimentation costs, can accelerate adoption. This reasoning is supported by Barham et al.'s (2014) finding that ambiguity aversion among grain farmers in the United States – who have greater access to information regarding new technologies than farmers in developing countries – *speeds up* adoption of new ambiguity-reducing GM crops.

It is important to note that there are potentially multiple explanations that are consistent with our findings. Validating the hypothesis we propose will require further investigation. Future work may examine how interventions that deal specifically with the problem of ambiguity in new agricultural technologies – for example by providing farmers information about the distribution of returns from adoption – affect the speed of adoption for technologies with low versus high fixed costs.

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	9.33	1.46
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 at adoption of technology	Age of respondent at the time of adopting technology	38.55	13.15
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
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 Aversion Variables

	SRRA	CRRA (r)	TCN (σ)	TCN (α)	TCN (λ)
SRRA	1.000				
CRRA (r)	0.053	1.000			
TCN (σ)	-0.012	0.524***	1.000		
TCN (α)	0.016	-0.212	-0.045	1.000	
TCN (λ)	-0.010	0.000	0.241***	-0.115	1.000

Notes: Statistical significance is denoted by *** (1% level), ** (5% level) and * (10% level).

Table 3: Hazard Model Estimates for Adoption of the Akosombo Strain Tilapia (AST)

VARIABLE	Ambiguity	CRRA and Ambiguity	Ambiguity and TCN Parameters
σ (value function curvature)			0.588*
			(0.164)
α (probability weighting)			0.997
			(0.437)
λ (loss aversion)			1.055
			(0.066)
CRRA		0.818***	
		(0.050)	
#Adopters in village	2.860***	3.037***	2.802***
	(0.704)	(0.751)	(0.687)
#Adopters2	0.863***	0.854***	0.866***
	(0.040)	(0.040)	(0.040)
#Adopters*Ambiguity	1.004	1.005	1.004
	(0.005)	(0.005)	(0.005)
Ambiguity Aversion	1.024	1.007	1.018
	(0.030)	(0.034)	(0.031)
Age	1.013	1.006	1.014
	(0.013)	(0.013)	(0.013)
Male	0.758	0.597	0.613
	(0.344)	(0.270)	(0.294)
Education	1.104**	1.125***	1.113***
	(0.044)	(0.045)	(0.046)
Married	1.534	1.810	1.392
	(0.538)	(0.663)	(0.505)
Experience	1.116***	1.114***	1.112***
	(0.021)	(0.020)	(0.026)
Experienced Past Weather Shock	1.398	1.939**	1.337
	(0.438)	(0.644)	(0.432)
Main Occupation	1.030	1.079	1.110
	(0.343)	(0.370)	(0.379)
Household Size	1.070	1.071	1.078
	(0.051)	(0.051)	(0.054)
Owns house	1.520	1.830**	1.693*
	(0.426)	(0.528)	(0.481)
Number of Rooms	1.105*	1.107*	1.092
	(0.061)	(0.059)	(0.063)
Farm Size	2.065**	2.570***	2.325**
	(0.746)	(0.923)	(0.850)
Freehold	0.959	0.856	0.875
	(0.312)	(0.270)	(0.294)
Extension Contact	0.553	0.446**	0.394**
	(0.204)	(0.167)	(0.1708)
Access to Credit	2.237**	1.873*	2.169**
	(0.788)	(0.663)	(0.775)
Floating Cages	1.081	1.031	0.970
	(0.670)	(0.621)	(0.592)
Extruded Feed Technology	0.046***	0.039***	0.046***
	(0.026)	(0.022)	(0.025)
FFA	0.374**	0.288***	0.425*
	(0.177)	(0.133)	(0.200)
Ashanti	1.774	2.759	2.728
	(1.174)	(1.844)	(1.909)
Western	1.670	1.794	1.787
	(0.689)	(0.757)	(0.764)
Volta	0.984	1.477	1.142
	(0.540)	(0.785)	(0.605)
P	9.323***	9.818***	9.433***
	(0.915)	(0.959)	(0.920)
Constant	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Observations	984	984	984

Notes: The dependent variable is the time to adoption in years since 2003 when the technology was first developed. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

Table 4: Alternative Estimations for Akosombo Strain of Tilapia

VARIABLE	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
σ (value function curvature)				0.585*	0.971	0.917
				(0.162)	(0.208)	(0.198)
α (probability weighting)				1.034	0.820	0.777
				(0.450)	(0.303)	(0.290)
λ (loss aversion)				1.089	1.006	0.976
				(0.061)	(0.044)	(0.047)
CRRA	0.812***	0.921*	0.926			
	(0.048)	(0.044)	(0.045)			
Adopters in village	3.163***	3.460***	3.386***	2.899***	3.415***	3.355***
	(0.772)	(0.773)	(0.763)	(0.696)	(0.768)	(0.764)
$\#Adopters^2$	0.850***	0.837***	0.840***	0.862***	0.839***	0.841***
	(0.039)	(0.037)	(0.037)	(0.039)	(0.037)	(0.038)
Ambiguity Preference			1.013			1.021
			(0.021)			(0.024)
#Adopters*Ambiguity Preference			1.002			1.003
			(0.004)			(0.004)
Other Farm/Farmer Characteristics	Yes	No	No	Yes	No	No
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
P	9.824***	6.900***	6.923***	9.414***	6.873***	6.905***
	(0.957)	(0.690)	(0.690)	(0.914)	(0.688)	(0.691)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	984	984	984	984	984	984

Notes: The dependent variable is the time to adoption in years since 2003 when the technology was first developed. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

Table 5: Hazard Model Estimates for Adoption of 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 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 Aversion	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

Notes: The dependent variable is the time to adoption in years since 1994, the earliest date in our sample that a farmer reports learning about the technology. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

Table 6: Alternative Estimations for Extruded Feed Technology

VARIABLE	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
σ (value function curvature)				0.636*	0.679**	0.659**
				(0.151)	(0.118)	(0.116)
α (probability weighting)				1.916*	1.730*	1.658*
				(0.659)	(0.515)	(0.500)
λ (loss aversion)				0.998	1.033	1.010
				(0.048)	(0.042)	(0.044)
CRRA Parameter	0.884***	0.871***	0.872***			
	(0.042)	(0.035)	(0.036)			
# Prior Adopters in Village	3.377***	3.898***	4.048***	3.200***	3.832***	3.933***
	(0.626)	(0.640)	(0.678)	(0.588)	(0.628)	(0.655)
# Prior Adopters Squared	0.836***	0.828***	0.825***	0.845***	0.832***	0.831***
	(0.031)	(0.029)	(0.029)	(0.031)	(0.029)	(0.029)
# Adopters × Ambiguity Aversion		0.988			0.989	
			(0.008)			(0.008)
Ambiguity Aversion			1.029			1.043**
			(0.019)			(0.020)
Other Farm/Farmer Characteristics	Yes	No	No	Yes	No	No
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
P	13.405***	10.240***	10.216***	13.236***	10.099***	10.093***
	(1.014)	(0.769)	(0.768)	(1.004)	(0.760)	(0.759)
Observations	1,989	1,989	1,989	1,989	1,989	1,989

Notes: The dependent variable is the time to adoption in years since 1994, the earliest date in our sample that a farmer reports learning about the technology. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

Table 7: Hazard Model Estimates for Adoption of 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 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 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

Notes: The dependent variable is the time to adoption in years since 1994, the earliest date in our sample that a farmer reports learning about the technology. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

Table 8: Alternative Specifications for Adoption of Floating Cage Technology

VARIABLE	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
σ (value function curvature)				0.493*	0.678*	0.675*
				(0.178)	(0.144)	(0.146)
α (probability weighting)				0.655	0.747	0.712
				(0.313)	(0.286)	(0.279)
λ (loss aversion)				1.000	0.997	1.000
				(0.014)	(0.041)	(0.047)
CRRA Parameter	0.826***	0.902*	0.897*			
	(0.055)	(0.049)	(0.005)			
# Prior Adopters in Village	3.412***	3.800***	3.809***	3.111***	3.625***	3.607***
	(0.663)	(0.649)	(0.656)	(0.603)	(0.618)	(0.620)
# Prior Adopters Squared	0.864***	0.859***	0.854***	0.878***	0.865***	0.6863***
	(0.029)	(0.025)	(0.025)	(0.029)	(0.026)	(0.026)
# Adopters × Ambiguity Aversion			1.018*			1.021**
			(0.009)			(0.010)
Ambiguity Aversion			0.930**			0.931**
			(0.028)			(0.031)
Other Farm/Farmer Characteristics	Yes	No	No	Yes	No	No
Regional Controls	Yes	Yes	Yes	Yes	Yes	Yes
P	7.997***	6.002***	6.045***	7.883***	5.995***	6.039***
	(0.819)	(0.601)	(0.600)	(0.815)	(0.600)	(0.600)
Observations	2,070	2,070	2,070	2,070	2,070	2,070

Notes: The dependent variable is the time to adoption in years since 1994, the earliest date in our sample that a farmer reports learning about the technology. 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), and * (10% level). P is the shape parameter. If P<1, the hazard decreases monotonically with time, P>1 implies hazard increases monotonically with time and P = 1 implies the hazard is independent of time.

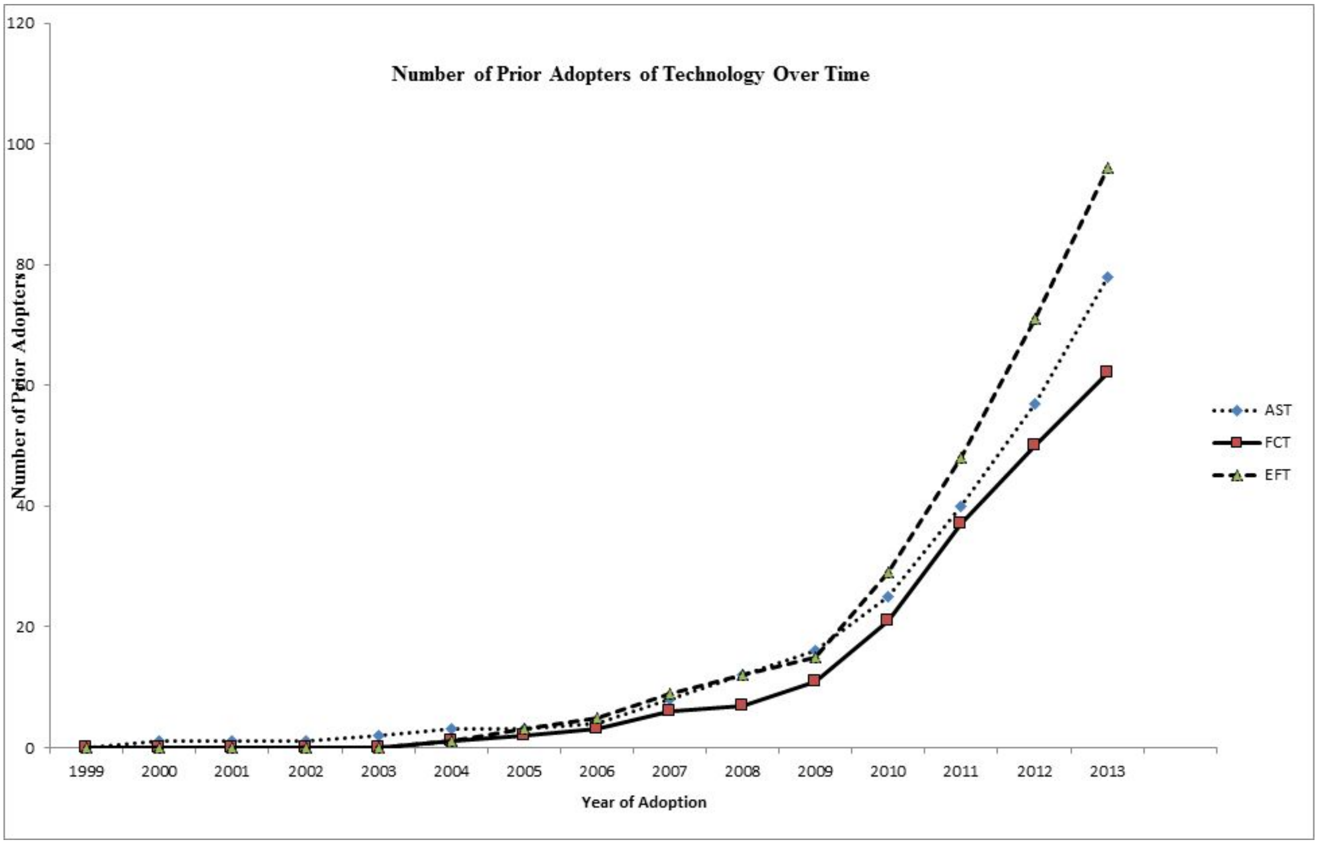

Figure 1: Prior Adopters for extruded feed (EFT), Akosombo strain of Tilapia (AST) and floating cages (FCT)

References

- Abdulai, A., Huffman, W.E. 2005. The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. *American Journal of Agricultural Economics, 87(3)*, pp. 645-659. DOI: 10.1111/j.1467-8276.2005.00753.x

- Ainoo-Ansah, J. 2013. Tilapia farming in Ghana: Breeding, feed advances support rising output. *Global Aquaculture Advocate, 16*, pp. 24-26.

- Ansah, Y. 2014. Enhancing Profitability of Pond Aquaculture in Ghana through Resource Management and Environmental Best Management Practices. DPhil. Thesis. Virginia Polytechnic Institute and State University.

- Ansah, Y., Frimpong, E., and Hallerman, E. 2014. Genetically-Improved Tilapia Strains in Africa: Potential Benefits and Negative Impacts. *Sustainability, 6,* 3697-3721.

- Asamoah, E. K., F. K. K. Nunoo, Y.B. Osei-Asare, S. Addo, and U. R. Sumaila. 2012. A production function analysis of pond aquaculture in southern Ghana. *Aquaculture Economics and Management, 16 (3),* 183–201. DOI: 10.1080/13657305.2012.704616

- Asmah, R., 2008. Development potential and financial viability of fish farming in Ghana.

- Awity, L.K., 2013. On-farm feed management practices for Nile tilapia (Oreochromis niloticus) in Ghana. On-farm feeding and feed management in aquaculture, pp. 191-211. http://www.fao.org/tempref/FI/CDrom/T583/root/07.pdf

- Ayisi, C.L., E.H. Alhassan, D. Addo, B. O. Agyei, A. Apraku (2016). "Aquaculture Extension Services: A Case Study of Fish Farms in the Eastern Region of Ghana", *International Journal of Fisheries and Aquatic Studies*, Vol. 4(4), pp. 24-30.

- Bandiera, O. and Rasul, I., 2006. Social networks and technology adoption in northern Mozambique. *The Economic Journal, 116(514)*, pp. 869-902. doi.org/10.1111/j.1468-0297.2006.01115.x

- Barham, B.L., Chavas, J.P., Fitz, D., Salas, V.R. and Schechter, L., 2014. The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior & Organization, 97*, pp. 204-218. doi.org/10.1016/j.jebo.2013.06.014
- Bell, J.G. and Waagbo, R., 2008. Safe and nutritious aquaculture produce: benefits and risks of alternative sustainable aquafeeds. In *Aquaculture in the Ecosystem* (pp. 185-225). Springer, Dordrecht.
- Beveridge, M.C.M. 2004. Cage aquaculture, 3rd edition. Blackwell Press, Oxford.
- Beyene, A.D. and Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: An application of duration analysis. *Technological Forecasting and Social Change, 96*, pp. 298-307. DOI: 10.1016/j.techfore.2015.04.007
- Boizot, C., Robin, J.M. and Visser, M., 2001. The demand for food products: an analysis of interpurchase times and purchased quantities. *The Economic Journal, 111(470)*, pp. 391-419. doi.org/10.1111/1468-0297.00613
- Brick, K., Visser, M., and Burns, J. 2012. Risk Aversion: Experimental Evidence from South African Fishing Communities. *American Journal of Agricultural Economics, 94(1)*, pp. 133-152. https://www.jstor.org/stable/41331233
- Bryan, G., 2019. Ambiguity Aversion decreases the Impact of Partial Insurance: Evidence from African Farmers. *Journal of the European Economic Association.*DOI: 10.1093/jeea/jvy056
- Burton, M., Rigby, D. and Young, T., 2003. Modelling the adoption of organic horticultural technology in the UK using duration analysis. *Australian Journal of Agricultural and Resource Economics, 47(1)*, pp. 29-54. DOI: 10.1111/1467-8489.00202
- Butler, J.S. and Moser, C.M., 2010, July. Complementarities and differences in adoption: an application of hazard models to two technologies in Madagascar. In 2010 Annual Meeting, July 25-27, 2010, Denver, Colorado (No. 61381). Agricultural and Applied Economics Association.

- Colombo, M.G. and Mosconi, R., 1995. Complementarity and cumulative learning effects in the early diffusion of multiple technologies. *The Journal of Industrial Economics, (1)*, pp. 13-48. DOI: 10.2307/2950423

- Dercon, S., and L. Christiaensen. 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics, 96 (2)*, pp. 159-173. doi.org/10.1016/j.jdeveco.2010.08.003

- Devine, T.J. and N.M. Kiefer.1991. *Empirical Labour Economics*, Oxford University Press, Oxford.

- Diebold, F. X. and G.D. Rudebusch. 1990. A nonparametric investigation of duration dependence in the American business cycle, *Journal of Political Economy, 98*, pp. 596-616. dx.doi.org/10.1086/261696

- Di Falco, S. and Bulte, E., 2011. A dark side of social capital? Kinship, consumption, and savings. *Journal of Development Studies, 47(8)*, pp. 1128-1151. doi.org/10.1080/00220388.2010.514328

- Dixit, A., 1989. Entry and Exit Decisions under Uncertainty. *Journal of Political Economy, 97(3)*, 1989, pp. 620-638.

- Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G.G. Wagner. 2011. Individual Risk Attitudes: Measurement, Determinants and Behavioural Consequences, *Journal of the European Economic Association, 9(3)*, pp. 522-550. doi.org/10.1111/j.1542-4774.2011.01015.x

- Drew, M. D.; Borgeson, T. L.; Thiessen, D. L., 2007. A review of processing of feed ingredients to enhance diet digestibility in finfish. *Animal Feed Science Technology. 138 (2)*, pp. 118-136. DOI: 10.1016/j.anifeedsci.2007.06.019

- Ellsberg, D., 1961. Risk, ambiguity and the Savage axioms. *Quarterly Journal of Economics, 75*, pp. 643-669.

- Feder, G., E. R. Just and D. Zilberman. 1985. Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change, 33*, pp. 255-298. doi/abs/10.1086/451461

- Frimpong, E.A. & Anane-Taabeah, G. 2017. Social and economic performance of tilapia farming in Ghana. In J. Cai, K.K. Quagrainie & N. Hishamunda, eds. *Social and economic performance of tilapia farming in Africa*, pp. 49–90. FAO Fisheries and Aquaculture Circular No. 1130. Rome, Italy.

- Frimpong, E.A., Ansah, Y.B., Amisah, S., Adjei-Boateng, D., Agbo, N.W. and Egna, H., 2014. Effects of two environmental best management practices on pond water and effluent quality and growth of Nile Tilapia, Oreochromis niloticus. *Sustainability*, 6(2), pp. 652-675. DOI: 10.3390/su6020652

- Foster, A.D. and Rosenzweig, M.R. 2010. Microeconomics of technology adoption. *Annu. Rev. Econ.*, 2(1), pp. 395-424. https://doi.org/10.1146/annurev.economics.102308.124433

- Fuglie, K.O.; Kascak, C.A. 2001. Adoption and diffusion of natural-resource-conserving agricultural technology. *Review of Agricultural Economics, (23)*, pp. 386-403. DOI: 10.2307/1349955

- Gschwandtner, A. and Lambson V. E. 2006. Sunk Costs, Profit Variability, and Turnover. *Economic Inquiry, 44(2)*, pp. 367-73. doi:10.1093/ei/cbj021

- Hardy, R.W., 2010. Utilization of plant proteins in fish diets: effects of global demand and supplies of fishmeal. *Aquaculture Research, 41(5)*, pp. 770-776. doi.org/10.1111/j.1365-2109.2009.02349.x

- Hem, S., 1982. L'aquaculture en enclos: adaptation au milieu lagunaire ivoirien. *Aquaculture*, 27(3), pp. 261-272.

- Hopenhayn, H. 1992. Entry, Exit and Frim Dynamics in Long Run Equilibrium. *Econometrica, 60*, pp. 1127-50.

- Holt, C. A. and S. K. Laury. 2002. Risk Aversion and Incentive Effects. *The American Economic Review, 92(5)*, pp. 1644-1655. DOI: 10.1257/000282802762024700
- Jain, D.C. and Vilcassim, N.J. 1991. Investigating household purchase timing decisions: A conditional hazard function approach. *Marketing Science, 10(1)*, pp. 1-23. doi.org/10.1287/mksc.10.1.1
- Kassam, L.2014. Aquaculture and food security, poverty alleviation and nutrition in Ghana: Case study prepared for the Aquaculture for Food Security, Povertry Alleviation and Nutrition project. WorldFish.
- Keller, L. R., R. K. Sarin, and J. Sounderpandian. 2007. An examination of ambiguity aversion: Are two heads better than one? *Judgment and Decision Making, 2*, pp. 390-397. http://journal.sjdm.org/jdm7619.pdf
- Kiefer, N.M. 1988. Economic Duration Data and Hazard Functions. *Journal of Economic Literature, (26)*, pp. 646-679.
- Klibanoff, P., Marinacci, M. and Mukerji, S., 2005. A smooth model of decision making under ambiguity. *Econometrica, 73(6)*, pp. 1849-1892. doi.org/10.1111/j.1468-0262.2005.00640.x
- Lambson, V., 1991. Industry Evolution with Sunk Costs and Uncertain Market Conditions. *International Journal of Industrial Organization, 9(2)*, pp. 171-196.
- Lambson, V., 1992. Competitive Profits in the Long Run. *Review of Economics Studies, 59(1),*, 125-142.
- Lambson, V., and F. Jensen, 1998. Sunk Costs and Firm Value Variability: Theory and Evidence. *American Economic Review, 88(1)*, pp. 307-13.
- Lind, C.E., Ponzoni, R.W., Nguyen, N.H. and Khaw, H.L., 2012. Selective breeding in fish and conservation of genetic resources for aquaculture. *Reproduction in domestic animals, 47*, pp. 255-263. doi.org/10.1162/REST_a_00295

- Liu, Elaine M. 2013. Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics, 95(4)*, pp. 1386-1403.

- Morduch, J. 1995. Income smoothing and consumption smoothing. *The Journal of Economic Perspectives, 9(3)*, pp. 103-114.

- Nazli, H. and Smale, M., 2016. Dynamics of variety change on wheat farms in Pakistan: A duration analysis. *Food Policy, 59*, pp. 24-33.DOI 10.1016/j.foodpol.2015.12.009

- Ofori, J. K., E. K. Abban , A. Y. Karikari & R. E. Brummett (2010) Production Parameters and Economics of Small-Scale Tilapia Cage Aquaculture in the Volta Lake, Ghana, *Journal of Applied Aquaculture*, 22(4), pp. 337-351. doi.org/10.1080/10454438.2010.527591

- Onumah, E. E., Acquah, H. D. 2010. Frontier Analysis of Aquaculture Farms in Southern Sector of Ghana. *World Applied Sciences Journal, 9(7)*, pp. 826-835.

- Onumah, E.E., Onumah, J.A. and Onumah, G.E. 2018. Production Risk and Technical Efficiency of Fish Farms in Ghana. *Aquaculture 495*, pp. 55-61. doi.org/10.1016/j.aquaculture.2018.05.033

- Pillay, T.V.R.; Kutty, M. 2005. Aquaculture: Principles and Practices; Blackwell Publishing: Oxford, UK.

- Rosenzweig, M.R., and Binswanger H.P, 1993. Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. *Economic Journal, 103*, pp. 56-78. doi.org/10.2307/2234337

- Ross, N., Santos, P. and Capon, T., 2012. Risk, Ambiguity and the Adoption of New Technologies: Experimental Evidence from a Developing Economy. 2012 Conference, August 18–24, 2012, Foz do Iguacu, Brazil 126492, International Association of Agricultural Economists.

- Stoneman, P. and Kwon, M. J., 1994. The diffusion of multiple process technologies. *The Economic Journal*, pp. 420-431.DOI: 10.2307/2234761

- Tanaka, T., Camerer, C. F., and Nguyen, Q. 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review, 100(1)*, pp. 557-571. DOI: 10.1257/aer.100.1.557

- Vieider, F.M., Lefebvre, M., Bouchouicha, R., Chmura, T., Hakimov, R., Krawczyk, M. and Martinsson, P., 2015. Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries. *Journal of the European Economic Association*, 13(3), pp.421-452. DOI: doi.org/10.1111/jeea.12102

- Warnick, J.C.E., J. Escobal, and S.C. Laszlo, 2011. Ambiguity aversion and portfolio choice in small-scale Peruvian farming. *The BE Journal of Economic Analysis & Policy*, 11(1). DOI: 10.2202/1935-1682.2331

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

Notes: The table, adapted from Brick, Visser and Burns (2012), describes the lottery choices in the BVB experiments and, for each row, the range of values of the CRRA parameter *r* consistent with switching from option A to option B in that row.

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

Notes: The table, adapted from Tanaka, Nguyen and Camerer (2010), describes the lottery choices in the TCN experiments.

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 (Switching Point in Series 2)	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 TCN Lottery Pairs

	Switching Point in Series 1														
α (Switching Point in Series 2)	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

Notes: The table has been adapted from Tanaka, Nguyen and Camerer (2010). The first two panels show values of the preference parameters σ and α, approximated to the nearest increment of 0.05, consistent with each possible combination of switching points in Series 1 and Series 2 shown in Table A2. The third panel shows, for each row in Series 3, and specific σ values, the range of values of the preference parameter λ consistent with switching from option A to option B in that row

Table A4: Hazard Model Estimates for Extruded Feed Technology with Alternative Starting Dates

Starting Year	**1995**		**1996**		**1997**		**1998**		**1999**		**2000**	
CRRA Parameter	0.893**		0.893**		0.892**		0.893**		0.891**		0.893**	
	(0.043)		(0.043)		(0.043)		(0.043)		(0.042)		(0.043)	
σ (value function curvature)		0.640*		0.639*		0.641*		0.635*		0.637		0.651*
		(0.151)		(0.151)		(0.151)		(0.150)		(0.150)		(0.153)
Ambiguity Aversion	1.032	1.040	1.029	1.037	1.026	1.033	1.035	1.043	1.018	1.026	1.012	1.019
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.035)	(0.034)	(0.035)
# Prior Adopters x Ambiguity Aversion	0.997	1.001	0.997	1.001	0.998	1.001	0.997	1.001	0.998	1.002	1.000	1.003
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Notes: The table shows hazard ratios and standard errors (in parentheses) using alternative starting dates. All regressions assume a Weibull survival distribution. Statistical significance is denoted by *** (1% level), ** (5% level), and * (10% level). The specifications include the same controls as those listed in Table 5.

Table A5: Hazard Model Estimates for Floating Cage Technology with Alternative Starting Dates

Starting Year	1995		1996		1997		1998		1999		2000	
CRRA Parameter	0.832**		0.840***		0.847**		0.854**		0.860**		0.866**	
	(0.055)		(0.054)		(0.056)		(0.056)		(0.057)		(0.057)	
σ (value function curvature)		0.563		0.606		0.648		0.689		0.729		0.772
		(0.208)		(0.221)		(0.234)		(0.247)		(0.260)		(0.274)
Ambiguity Aversion	0.930**	0.938**	0.930**	0.937**	0.930**	0.936**	0.930**	0.935**	0.929**	0.933**	0.927**	0.931**
	(0.028)	(0.029)	(0.028)	(0.029)	(0.028)	(0.030)	(0.029)	(0.030)	(0.029)	(0.030)	(0.030)	(0.031)
# Prior Adopters x Ambiguity Aversion	1.017*	1.019*	1.017*	1.019*	1.017*	1.018*	1.017*	1.018*	1.017*	1.018*	1.017*	1.018*
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)

Notes: The table shows hazard ratios and standard errors (in parentheses) using alternative starting dates. All regressions assume a Weibull survival distribution. Statistical significance is denoted by *** (1% level), ** (5% level), and * (10% level). The specifications include the same controls as those listed in Table 7.