# RISK AVERSION AND CERTIFICATION: EVIDENCE FROM THE NEPALI TEA FIELDS[1]

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November 2017

[1]This paper has been prepared in partial fulfillment of a PhD in Economics. I would like to thank Alisha Magar Barton, Somnath Acharya, Bhushit Dahal, Lashang Lama, Sunita Phago, and Ganesh Raisili for their diligent help with field research. I would also like to thank the following individuals for their assistance during fieldwork: Sanjeev, Takemaya, Susma and Sanju Pradhan (Daragoun), John Taylor (HIMCOOP), RC Nepal (Himalayan Shangri-La), Dilip Rai (Nestprol), Madhab Niroula (Eco Coop Kolbung), Rabin Rai (Central Tea Cooperative Federation), Patrick Ward (IFPRI), Robin Banerjee (Itabari), Bachan Gyanwali (Jun Chiyabari), Arun Rana (SP-UK Nepal), Udaya Chapagain (Gorkha), Deepak and Nischal Banskota (Kanchenjenga), Kamal Raj Mainali (Himalayan Shangri-La), and the South Asian Network for Development and Environmental Economics (SANDEE). Assistance with research design and analysis was generously offered by Frances Woolley, Radovan Vadovic (Carleton University), Emmanuel Benhin (Statistics Canada), Matt Webb (Carleton University), Marcel Voia (Carleton University), Santosh Upadhyaya (Carleton University), Edgard Rodriguez (International Development Research Centre, IDRC), and Ana Dammert (Carleton University). Detailed and helpful comments from the University of Ottawa Department of Economics lunchtime seminar were greatly appreciated. The standard disclaimer applies.

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**Abstract**

This paper examines the role of individual risk attitudes in the decision to get certified to an agricultural standard. I conducted a survey and a field experiment to elicit the risk preferences of Nepali small-scale tea farmers who faced the decision of whether to get certified to the organic standard. The analysis uses an expected utility framework to investigate the relationship between risk preferences and certification decisions. Results indicate that farmers who are more risk averse have a higher propensity to get certified. How certification is governed influences its risk profile and whether risk averse farmers see it as attractive. These findings provide concrete evidence against previous assumptions that only risk lovers get certified. Instead, they suggest that certification schemes may provide a benefit not yet considered in the literature: that of providing risk-reduction opportunities to risk averse farmers in developing countries.

KEYWORDS: Standards, Certification, Risk Aversion, Small-scale farming, Nepal

# 1 Introduction

Agricultural standards have the potential to connect farmers to market requirements, improving livelihoods and sparking rural development. Yet certification to these standards has been far from universal. This paper examines the case of Nepali tea farmers who were offered the opportunity to get certified to the organic standard. On its introduction, organic certification was backed by dramatic assertions that it would improve prices and market access. Given such promising claims, this begs the question: why did some tea farmers refuse to get certified?

A burgeoning literature sheds light on this question. Analysis indicates that land owned (Maertens and Swinnen 2009; Karki et al 2011; Olabisi et al 2015**???**), age (Ayuya et al 2015; Karki et al 2011), access to credit (Ihli et al 2016), education (Ayuya et al 2015), and household labour endowments (Maertens and Swinnen 2009; Kersting and Wollni 2012**?**) might influence whether a farmer decides to adopt the crop production rules in a certification scheme. Yet when a group of Nepali tea farmers were asked about their decision whether to get certified to the organic standard, many of them cited the risk of productivity changes as a major factor. They feared that organic methods could reduce their output somewhat, but also thought that help from the factory could mitigate some of this risk (Mohan, 2013; 2014; 2016**???**). The farmers' perceived risk regarding organic certification

made their individual risk preferences important in their certification decision, which is the main focus of this paper.

There are several reasons to be interested in the role of risk preferences in farmers' decisions to get certified to an agricultural standard[1]. One is that the literature on certification has largely ignored the role of risk preferences, despite extensive evidence that they affect farmers' economic decisions (Feder et al 1985; Rosenzweig 1988; Morduch 1994**???**). Ignoring risk aversion in first stage selection regressions of treatment effects models of certification could bias the estimation of the impact of certification on welfare. Second, the direction of the relationship between risk aversion and certification is not immediately obvious. While the technology adoption literature finds that risk averse farmers tend to avoid adopting risky new technologies (Liu 2013; Knight et al 2003; Vargas Hill 2009**???**), and would therefore predict a negative relationship between risk aversion and certification with more risk averse farmers having a lower propensity to adopt, the contract farming literature predicts the opposite. The contract literature suggests that when certification occurs as part of an agricultural contract, adoption can provide access to risk protection that is relatively more appealing to more risk averse farmers (Abebe et al 2013; Cahyadi and Waibel 2016; Ramaswami et al 2009; Simmons 2002**????**). This implies a positive relationship between risk aversion and certification, with more risk averse farmers having a higher propensity to adopt. Lastly, methodological issues have plagued the little empirical research that has been carried out to date that might enable us to evaluate the relative importance of the technology adoption and contract mechanisms in the certification-risk re-

[1]The terms "standard" and "certification scheme" refer to slightly different phenomenon. "Standard" is a general term referring to a set of rules on how to produce something (Busch 2011**?**). A producer can adopt a standard of his/her own volition and without any external recognition. In other cases, compliance with a standard is verified by an external actor, and then we speak of "certification" to the standard in question, which in turn can also be known as the "certification scheme". The terminological schism roughly follows disciplinary lines: "standard" is used in the trade policy, theoretical economics, and business study literature, and "certification" in the anthropology, development studies, applied economics, political science and non-governmental sector. There are also prolific bodies of work that discuss similar phenomenon using the terms "labeling", "public regulation", "intermediation", and "private sector governance". "Certification" is the preferred term in this paper because it is more specific and captures the fact that the schemes of interest – such as organic, fair trade, HACCP, Rainforest Alliance and ISO standards – are adopted for marketing reasons, that is, to sell produce differently. Obviously, certification also has implications for production functions since it requires adoption of new production practices. Despite the focus on certification, this paper uses the more general "standard" term when referring to the set of production requirements themselves.

lationship (Ruben and Fort 2008; Lapple and Van Rensberg 2011; Kisaka-Lwayo and Obi 2014; Ihli et al 2016**???**). This paper aims to address this research gap through an empirical investigation of the relationship between risk aversion and certification.

Both the technology adoption mechanism, wherein the risk averse would avoid the new certification technology, and the contract mechanism, wherein the risk averse would seek it out to protect themselves from risk, could be present and relevant. Notwithstanding their different predictions, the two conceptual frameworks share a set of three assumptions. First, farmers perceive ex ante that certification is more risky, and higher return, than conventional methods. Second, farmers' risk aversion does not change over time. Third, farmers have free choice whether to certify. Each of these assumptions is discussed in more depth later in this paper. If they hold, then the technology adoption hypothesis can be tested against contract theory's opposing prediction through an empirical investigation into which effect dominates the relationship between measured risk aversion and certification status in a population of farmers.

This paper conducts such an investigation using data obtained through primary field research. That is, it seeks to test whether evidence supports the prediction of technology adoption theory – of a negative relationship wherein more risk averse farmers have a lower propensity to get certified – against contract farming theory's opposing hypothesis of a positive relationship, with a higher certification propensity amongst the risk averse. This paper is the first to our knowledge to focus on a rigorous empirical estimation of the relationship between risk aversion and certification.

This paper uses the introduction of organic certification into the orthodox tea sector in Nepal as a means to study how risk aversion affects certification decisions. This certification scheme is well suited for our study since its adoption was proposed to risk averse (Dhungana et al 2004) small-scale farmers (NTCDB 2016**?**) and was adopted by some, but not all of them (Mohan 2013; 2014; 2016; Karki et al 2011**?**). The certification scheme was presented to farmers as an opportunity to change production technologies – notably replacing chemical inputs with organic materials – to obtain higher prices[2]. Factory owners, cooperatives, and non-governmental organizations also promised that technical assistance would be provided to converting farmers and suggested that there would be better market

[2]Interview, Jyoti Adhikari, TEASEC NGO, Fikkal, 12 May 2010.

access. Yet these actors admitted that conversion could decrease farm output, and estimates of the extent of the productivity drop varied from as low as 5% to as high as 75%. As a result, although farmers perceived that certification would lead to higher returns than the conventional farming status quo, it was also perceived as a relatively risky endeavor. In this context, some of the farmers chose to adopt the organic certification scheme, while others chose to abstain. Their choice provides an ideal setting for the examination of how poor risk averse small-scale cash crop farmers choose whether to get certified to a high-return high-risk standard.

In 2016 I hired a Nepali research team to conduct a household survey and field experiment. The research instrument covered information on household characteristics, tea livelihoods, certification status and attitudes, and included experiments designed to elicit individual risk preferences. It was conducted with 270 orthodox tea farmers in four villages in two Nepali districts.

A field experiment modeled on Binswanger (1980; 1981**??**) and Eckel and Grossman (2008**?**) was used to elicit risk attitudes and respondent choices are converted into a coefficient of relative risk aversion using an Expected Utility (EU) framework. A simple theoretical framework conceptualizes actual certification status as an indicator of the latent propensity to be certified, which is in turn a measure of the utility differential between certified and uncertified production. I used the risk preference parameters derived from the experiments to predict whether farmers decided to get certified. A reduced form econometric model regresses observed certification status on the coefficient of relative risk aversion to obtain an estimate of the effect of risk aversion on certification status.

I find that farmers who made more risk averse choices during the experiment were more likely to be certified organic. That is, the study finds a significant and positive relationship between risk aversion and organic certification amongst small-scale Nepali orthodox tea farmers who faced the option of going organic. This result suggests that the contract farming mechanism dominates the technology adoption mechanism in the risk-certification relationship. It implies that certification may be different from other agricultural technologies insofar as it can be relatively appealing to the risk averse. This is the case notwithstanding its perceived riskiness. Previous research on contract farming, and some supporting evidence in this case study, suggests that this difference stems from the risk protection that can accompany certification. Analysis suggests that the governance of the scheme – and particularly whether it is adopted at the behest of trustworthy downstream

buyers who promise to provide accompanying risk reduction services – affects how it is perceived by risk averse farmers, and indeed whether they choose to get certified.

It should be noted that nothing in these findings contradicts the existence of social learning effects that may help or hinder the certification process. In the case study region, as elsewhere in the rural developing world, those who adopt first are leaders who the more reluctant learn from and follow. This herding process may amplify the small differences in risk aversion between early adopters and non-adopters, thus leading to big differences in adoption outcomes across risk aversion categories. The role of social learning processes are examined in more detail in the robustness section.

The remainder of the paper proceeds as follows. The next section reviews the relevant literature, while section 4.3 presents background on the case study. Section 4.4 presents the data, empirical methodology and econometric approach. Section 4.5 shows the regression and robustness results and section 4.6 discusses them. Finally, section 4.7 offers concluding comments.

## 2 Related Literature

A farmer's decision to get certified can be thought of either as a decision to adopt a particular form of technology, or a decision to enter into a particular type of contract. The rest of this section discusses why risk is important to certification decisions, presents the literature on technology adoption and contracting in a developing country agricultural context, considers the predictions of these literatures for the certification and risk relationship, and concludes with a brief presentation of empirical work to date on risk and certification.

The conventional approach to understanding the certification decision assumes that risk aversion is irrelevant and excludes it from models of selection into certification schemes. Yet empirical studies of certification highlight that farmers, ex ante, can perceive certification to a standard as more risky than the status quo because of the upfront investment that is often required, higher yield variation, and higher production costs (Bolwig et al 2009; Simmons 2002**?**). At the same time, there is preliminary evidence that farmers who get certified to agricultural standards experience lower ex post price volatility (Bolwig et al 2009; Minten et al 2009; Handschuch et al 2013**??**). The distinct risk profile of certified farming is particularly important for farming households living close to subsistence.

Certification may be appealing to them as a marketing strategy to access higher prices. But the rural development literature tells us that poor households craft their livelihoods in part to protect themselves from the risk of drops in income that might push them below subsistence (Chambers 1983; Fafchamps 2003**??**). Farming households in the developing world reduce their exposure to risk in part through decisions about what to produce[3]. As such, one could expect that they consider the relative riskiness of certified farming when making their certification decision.

The technology adoption and contract farming literatures present competing conceptualizations of how risk aversion affects the certification decision. Scholarly interest in technology adoption arose in response to puzzlingly low rates of technology adoption amongst developing country farmers. Following on early theoretical work showing that risk aversion could affect production decisions and outcomes (Sandmo 1971; Feldstein 1971; Ratti and Ullah 1976**???**), it was hypothesized that risk aversion could affect technology adoption decisions. The vast empirical literature testing this hypothesis has shown that relatively more risk averse farmers tend to be less likely to adopt risky new technologies (Feder et al 1985; Knight et al 2003; Liu 2013**?**)[4]. Certification scholars have followed this line of reasoning on the rare occasions that they have looked at risk, assuming that risk averse farmers will see certification as a risky new technology and will shy away from getting certified. For example, one study found that young farmers tend to adopt standards more often than older ones and argued this was because the young tend to be more amenable to risk and thus more willing to try the standard (Ayuya et al 2015)).

Recent papers on technology adoption have shed light on the nature of the relationship between risk attitudes and adoption decisions. Liu (2013) suggests, drawing on the insights of Prospect Theory (Kahneman and Tversky 1979**?**), that the timing of technology adoption can be influenced not only by risk aversion but

[3]Other risk management techniques may be used – notably crop and livelihood diversification and saving and borrowing over time – but research indicates that market failures in rural areas of the developing world, including structural and financial constraints, has made them less prevalent strategies amongst farmers there compared to their developed world compatriots (Morduch 1994; Morduch 1995; Kurosaki and Fafchamps 2002**???**).

[4]A good survey of this literature can be found in Hurley (2010**?**). More broadly, research has shown that risk aversion affects farmers' production decisions, including crop diversification (Hellerstein et al 2013**?**), labour demand (Vargas Hill 2009**?**), contract type (Bezabih 2009**?**), and efficiency (Dhungana et al 2004).

also by farmers' disproportionate sensitivity to loss compared to gains. She found that farmers who were more risk averse or loss averse tended to adopt the new technology later. Ward and Singh (2015**?**) hypothesize that farmers may not have full information on a production option, realize that this is the case, and avoid options that expose them to such (Knightian) uncertainty. However, evidence on this subject is mixed (Engle-Warnick et al 2006; Ross et al 2012; Barham et al 2014; Ward and Singh 2015**??**). This literature has not, however, considered how risk aversion affects the adoption of marketing technologies. By examining how risk aversion affects the certification decision, this paper aims to address this research gap.

The literature on contract farming takes a different approach by placing certification within the broader institutional context of agricultural economies. This literature notes that standards are often adopted as part of a contract between farmers and buyers. Certification to such tied standards entails buyer-supplier cooperation during the compliance process that brings the two actors closer together. Economic theory shows that close contractual ties may reduce the suppliers' exposure to risk if the less risk averse principal (the buyer) insures a relatively more risk averse agent (the supplier). Buyers do appear to offer a set of complementary services alongside contract and certification scheme adoption that can reduce the risk faced by adopting farmers. These services can include subsidies for the initial investment in certification to reduce risk from setup; assistance with operating costs; extension and management input to reduce yield risk; hedging price risk including through price guarantees; and income diversification through access to markets whose price movements are independent of conventional products (Simmons 2002**?**). These services can serve to reduce price, quantity, and income volatility. The fact that adoption of standards within agricultural contracts reduces farmers' exposure to volatility has been found in a variety of settings, including amongst poultry farmers in India (Ramaswami et al 2009), oil palm farmers in Indonesia (Cahyadi and Waibel 2016**?**), and potato farmers in Ethiopia (Abebe 2013)[5].

This contract farming literature highlights that adopting a certification scheme whose new production requirements could increase variability in yields in the short-term could actually be, when adopted as part of a contract, risk-reducing in

[5] A good but early survey of the empirical literature can be found in Simmons (2002), which notes that evidence on reduced exposure to volatility, and higher contract adoption by the risk averse, is mixed: see, for example, Wang et al (2011**?**) and Vassalos et al (2016**?**).

the long run, provided the contract is offered alongside buyer services that reduce exposure to risk. In such a scenario, farmers who are relatively risk-averse could have a higher propensity to opt into standard-governed contract farming schemes.

In sum, although the technology adoption school argues that risk averse farmers will not adopt risky standards through certification, research on contract farming suggests that when such schemes are tied to risk-reducing contracts, risk averse farmers may have a higher propensity to adopt. Unfortunately, there is little research that could help us investigate which framework best explains the relationship between risk aversion and certification. Those studies that do exist have serious methodological flaws, including failing to provide real payoffs in risk experiments (which the experimental economics literature suggests may introduce bias into the results) and ignoring the role of cooperatives (Kisaka-Lwayo and Obi 2014; Ruben and Fort 2008; Lapple and Van Rensberg 2011; Ihli et al 2016**???**). The findings from these studies are mixed: the evidence leans towards finding that more risk averse individuals are less likely to get certified, but the relationship is not clear-cut: there is no difference in risk aversion between early adopters and non-adopters (Lapple and Van Rensberg 2011), and there is heterogeneity in the relationship across certification categories (Kisaka-Lwayo and Obi 2014) and risk aversion categories (Ihli et al 2016).

The aim of this paper is to begin to fill this gap in the literature through a rigorous empirical investigation of the relationship between risk aversion and certification. A negative relationship between risk aversion and certification would be consistent with the finding of the technology adoption literature that people with higher risk tolerance are more likely to adopt new technologies. A positive relationship between risk aversion and certification would suggest that the agricultural contracting mechanism dominates this effect: that despite their risk aversion, farmers seek out certification to obtain accompanying risk reducing services.

This chapter focuses on the relationship between the propensity to get certified and risk aversion, and pays particular attention to addressing potential sources of measurement bias. Analysis of the data sheds light on whether the technology adoption or contracting mechanisms dominates the certification adoption decision. Before methodological and conceptual questions are studied, however, a little background on the case study context is in order.

## 3 Background on the Institutional Setting of Tea in Nepal

[6]

Nepal is a small mountainous landlocked least developed country (LDC) in South Asia, positioned between China and India. Although it ranks just 19th in global tea production, the Nepali tea sector is important to the country's growth and development prospects (Rana 2007; Warakaulle et al 2007; NTCDB 2016; USAID 2011**????**). Thousands of small-scale farmers grow high quality labour-intensive orthodox tea in the foothills of the Himalayan mountains, just across the border from the Indian Darjeeling tea gardens (see map in Figure 4.1[7]). Their tea is processed and exported by private factories.

### *3.1 The Introduction of Organic Certification*

To improve the quality and reputation of Nepali tea, several of these factories adopted a domestic standard called the Code of Conduct (CoC) in 2004. Marketing and implementation difficulties with the CoC led the first factory to seek organic certification in 2004, and by 2006 several other factories had also sought organic certification for their suppliers. Certification to the organic scheme was conferred by an independent agency such as NASAA (National Association for Sustainable Agriculture Australia) or the IMO (Institute of Marketecology). In order to obtain organic certification farmers have to abstain from using chemical pesticides or fertilizers for at least three years. During those first three years without agrochemical use, they are considered to be "in conversion", and their produce is treated separately from conventional and from non-organic produce. There is a significant up front certification cost that was borne in part by the factory and in part by farmers (via their cooperatives).

The decision to get certified began at the factory level, where the factory owner in consultation with the factory manager decided to seek organic certification. There are approximately 20 orthodox tea factories in Nepal, but only four[8] of them decided to offer the certified organic option to their supplying small-scale tea farm-

[6] This section draws heavily on Mohan (2013, 2014, 2016, and forthcoming**????**).

[7] All figures and tables can be found in Appendix 1.

[8] Two additional estates and their associated factories were certified organic, but did not have any certified small-scale farmers. Several factories were in the process of converting to organic at the time of the survey, but these four factories were alone in selling certified organic tea from Nepali smallholders.

ers[9]. Since the farmers who supplied to these four factories were the only ones who faced the option of going organic, they make up our population of interest and are worth mapping out in more detail. The Gorkha factory sources certified and non-certified tea from farmers in Sundarepani and Kolbung villages (see Figure 4.1). The small Green Tea Factory sources certified tea from a handful of farmers in Pashupati Nagar, near Sundarepani. Himalayan Shangri-La is a factory sourcing tea from small-scale farmers in the Sankhejung region. The Kanchenjenga Tea Estate sources tea from farmers from Phakphok and other villages: I call this the "Phidim region", which adjoins Sankhejung. Each factory has a local monopsony: since tea degrades quickly, and has to be delivered to the factory within hours of being plucked from the bush, all the farmers in each area deliver to the closest factory. Each farmer has only one factory it can supply to. Each factory accepts certified, conversion, and uncertified goods. Each factory accepts all the tea that it receives.

### *3.2 Farmer Perception of the Organic Scheme*

Interviews with farmers, factory owners and managers, and other stakeholders[10] indicate that organic certification was presented to farmers as means to earn higher prices. Once they decided to pursue organic certification, the factory owner or manager made presentations to gatherings of (mostly male) representatives of tea farming households[11]. During these presentations, the owner explained what the organic standard was, promised that farmers who adopted it would access higher and more stable prices, and urged the farmers to get certified[12]. The owner often made a specific price promise at this time, e.g. that organically certified farmers would get double the conventional per-kilogram tea price. Certification was described as a way to get access to lucrative markets overseas that would pay high

[9]Factory characteristics – notably a history of exporting overseas and the personality, entrepreneurial spirit and contacts of the factory owner – affected the decision to convert to organic. They facilitated the identification of the organic opportunity; promoted planning to take advantage of it; and helped to muster the finance, buyers, and suppliers to make certification happen.

[10]A set of 85 field interviews conducted in Spring 2010 inform the discussion here as well as analysis in Mohan (2013, 2014, 2016). The 2010 field research included 55 in-depth qualitative interviews and 30 quantitative surveys of farmers, informants, and labourers in the Nepali orthodox tea sector.

[11]Interview, Udaya Chapagain, Owner, Gorkha Tea Estate, Sundarepani, 12 February 2016.

[12]Interview, NN Acharya, Manager, Kanchenjenga Tea Estate and Factory, Phidim, 10 February 2016.

prices for tea that would be fed back to farmers[13]. Factories promised to provide services to certified farmers, which could include training sessions, organic inputs, record-keeping assistance, subsidies for initial certification costs, factory-hired field extension officer advice, and visits from overseas buyers (Mohan 2013, 2014, 2016). In some locations additional information sessions were run by local NGOs and cooperatives in which the high returns from certification, and its sustainability dividends, were underscored[14].

On the basis of all this information, members of tea farming households began forming an ex ante prior about certification in a process that continued when they went home and discussed the prospect of certification with other family members[15]. Although in reality returns from tea farming are influenced by the price received for tea leaf as well as costs and productivity, in practice, farmers consider returns largely in terms of per kilogram prices (Mohan 2013). Factory owner promises of higher prices were thus taken very seriously. These expectations proved crucial in the decision to get certified: as one respondent put it, "there is a rumour that if you go organic you will get a good price. So we're converting."[16] At the time of making the certification decision, households clearly considered certification to be the high return option, particularly because of the high price promises and long-term improved market access, and that was a key reason many of them chose to go organic (Karki et al 2011; Mohan 2013). Quantitative analysis reaffirms that certified farmers in 2010 received a significantly higher price for the tea leaf they sold to the factory, and were more hopeful about their future market prospects than conventional farmers (Mohan 2013).

Yet there was a great deal of uncertainty concerning the impact of organic methods on farm productivity. Factory owners and sector experts acknowledged that organic conversion reduced productivity, particularly in the short term, but farmers heard mixed messages about the degree and duration of the output drop. While some factories said the output only decreased by 5% in the first year or two of organic production and quickly went back to normal, there were also stories of output being cut to a quarter of previous levels and/or never recovering to previous levels (Mohan 2013). Rumours circulating amongst farmers about the extent

[13]Interview, Lila Mukhiya, Farmer, Sundarepani, 10 May 2010.

[14]Interview, Jyoti Adhikari, TEASEC NGO, Fikkal, 12 May 2010.

[15]Interview, Ganesh Kumar Rai, Coordinator, Sundarepani Tea Farmers' Cooperative, 25 February 2016.

[16]Interview, anonymous Farmer, Fikkal, 20 May 2010.

and duration of productivity drops influenced expectations[17]. For those who were not amongst the first wave of early adopters, demonstration effects from neighbours who adopted organics also influenced expectations about output variation[18]. Experts, the data and experience elsewhere suggests that on average, in the first year of conversion, production drops by 50%, but generally increases again, and within three to four years is 75 to 90 percent of the output of conventional farms[19]. Risk in tea farming comes from several sources – including variation in prices, productivity, the proportion of output sold at full price, costs, and access to technical assistance. The proportion of farmers' output categorized as "A" grade tea could differ between certified and conventional methods, including because organic farmers could have better training and incentives to pluck the two leafs and a bud needed for high quality tea, and the two varieties could similarly have different levels of variation in the proportion of produce that earned "A"-grade top prices. The cost structure of conventional and certified farming differs: certified farmers incur a fixed cost for the initial certification, and although they do not incur the agrochemical variable costs of conventional farming, they do face higher labour variable costs since organic farming is more labour-intensive than conventional farming. Yet the cost of both agrochemicals and labour were quite stable over time, and both modes of production offer little scope for adjusting costs. However, interviews with farmers in 2010 and 2016 underscored widespread concern regarding the risk from productivity variation. Variation in cost and other factors were scarcely mentioned during interviews (Mohan 2013). Ex ante, conversion to organic methods was perceived as risky, particularly in the short run, because of wide variation in the productivity of tea farming using these methods.

At the same time, the factory promised to provide accompanying services that would have ramifications for the risk faced by certified farmers. The promise of better prices suggested a reduction in price volatility, while the factory pledge to provide technical assistance could be expected to reduce output volatility. Finally, the provision of subsidies could reduce income volatility.

In sum, farmers perceived that conversion to organic methods would increase prices and reduce yields, and hoped that prices would increase such that net income would on average be higher. However, they expected yields to be more

[17]Interview, Uma Kanta Aryal, Farmer, Kolbung, 17 May 2010.

[18]Interviews, Madhab Niroula, Coordinator, Eco Tea Cooperative, Kolbung, 20 February 2016; Bandana Shrestha, Farmer, Itabari, 2 May 2010.

[19]Interviews: Pasang Mukhiya, Farmer, Sundarepani, 10 May 2010; Thir Bahadur Raud, Farmer, Sankhejung, Uma Kanta Aryal, Farmer, Kolbung, 17 May 2010.

variable under organic methods, so much so that net income would be more variable. As such, certification itself was seen as a high-return, but high-risk, option. However, services accompanying certification offered the potential to reduce risk through lower price, yield and income volatility.

### *3.3 Institutions*

Fourteen tea farmers' cooperatives supported the households in this study. Each was made up of anywhere from ten to fifty farmer-members and was a participatory, local body supporting its members through training sessions, administrative assistance, and liaison with authorities. At the time of fieldwork, 82% of tea farming households in the sample belonged to an organically certified cooperative, 5% belonged to a cooperative in conversion, and 11% did not belong to a cooperative[20]. The popularity of cooperatives in the tea sector in Nepal is typical of their pervasiveness amongst small-scale farmers in the developing world: in fact, since organic and other certification is only conferred on farmer cooperatives, they form an important part of farmers' choice environment. Despite this, cooperatives have to date been ignored by the literature on certification (Ayuya et al 2015; Maertens and Swinnen 2009; Kersting and Wollni 2012; Hansen and Trifkovic 2014; Ihli et al 2016; Karki et al 2011**????**). This paper, and particularly the rest of this section, strives to correct this neglect through an analysis of the role of cooperatives in the Nepali case.

In some study villages the cooperative was formed expressly for the purpose of organic certification after the factory announced it would accept organic tea. Farmers who wanted to get certified joined the new coop, while those who didn't stayed independent[21]. Other villages had cooperatives already in place when the factory announced the introduction of the organic option, and these groups voted on whether to get certified[22]. In this case, farmers who did not want to get certified exited cooperatives that voted to be certified and either joined a non-organic cooperative or went independent. A farmer who wanted to get certified, but did not yet belong to a cooperative, entered a cooperative which had decided to get certi-

[20]There were also 4 individuals, or 1.5% of the sample, which supplied to the Green Tea Factory and obtained organic certification through the factory yet did not belong to a cooperative.

[21]Interview, Ganesh Kumar Rai, Coordinator, Sundarepani Tea Farmers' Cooperative, 25 February 2016.

[22]Interview, Rabin Rai, General Secretary, Central Tea Coop.Fed. (CTCF), Ilam Town, 7 February 2016.

fied[23]. Comments from farmers and informants suggest that there was free entry and exit into the cooperatives[24]. However, there could have been transaction costs of entering or exiting a certified cooperative, for example if incumbents of an organic cooperative charged a prohibitively expensive entry fee[25] or if a member decided it was too much work to de-register from a cooperative that has voted to get certified[26]. Unfortunately, respondents in the survey had very poor recall and cooperative records were sparse, making it impossible to measure the presence and extent of such transaction costs.

If those transaction costs are important, then the decision to belong to the cooperative is important in its own right. It would entail a sequential decision-making process with two components – the decision to belong to the cooperative and the decision to get certified – wherein actual certification status is influenced by cooperative membership. It would then be difficult to ascertain whether the measured relationship between actual certification status and risk aversion reflects innate certification propensity or rather cooperative processes. Yet there are good reasons to believe that the cooperative and certification decision was singular. The bulk of the case study evidence, as well as expert testimony, suggest that farmers decided on certification, and the cooperative decision followed by implication. Interviews with farmers and cooperative representatives indicate that farmers freely entered and exited the cooperatives according to their interest in certification, suggesting that cooperatives were passive actors[27]. This is supported by analysis in the robustness section of this paper, where I show that the use of data on inherent propensity to get certified – obtained independently of cooperative membership through a discrete choice experiment – yields the same measured relationship between certification and risk as when real certification status data is used. Finally, even if cooperatives have an active role in a minority of cases, it is not clear how one would model all the complexities of sequential decision-making. For all these reasons, it is a good first-shot approximation to model farmers' choice as a simultaneous certification and cooperative-membership decision. In this conceptualization, farmers' certification choice in 2006 was between option one, which

[23]Interview, Rabin Rai, Ilam Town, 7 February 2016.

[24]pers. comm., Rabin Rai, 3 September 2016; pers. comm., Miriam Wenner, 5 February 2017; Miriam Wenner, 16 February 2017; Mohan 2013.

[25]Interview, Deo Kumar Rai, Farmer, Pashupati Nagar (Sundarepani), 30 May 2010

[26]Indeed, the decision to leave the coop may be endogenous since relatively more risk-averse people may be more reluctant to leave the cooperative.

[27]pers. comm., Rabin Rai, 3 September 2016; pers. comm., Miriam Wenner, 5 February 2017; Miriam Wenner, 16 February 2017; Mohan 2013.

consisted of getting certified and belonging to a certified cooperative, or option two, to remain uncertified as an independent farmer or member of an uncertified cooperative[28]. This simultaneous choice is the subject of this study and is reflected in Figure 4.2. The next section discusses the methods we use to study how farmers' risk aversion influences this choice.

## 4 Data and Empirical Methodology

This chapter is based on the analysis of data gathered during fieldwork conducted in February-April 2016 in Ilam and Panchthar districts of Nepal. Since I am only interested in farmers who had the option of getting certified, the farmers who supply to the four factories[29] who buy organic tea are our population of interest. The factories shared lists with the name, location, certification status, land size, and tea sales of their suppliers in 2015. As noted in more detail in the discussion of the sampling strategy in the third chapter of this thesis, a sample of 311 households was drawn from these lists, of whom 270 were successfully interviewed. The sample households are representative of all orthodox tea farming households in Nepal who had the option of getting certified. The sample was stratified into the four village-regions with farms meeting that description: Kolbung, Sundarepani, Sankhejung, and Phidim. A team of five locally hired interviewers collected data by going directly to the households in the sample. A household survey (see Appendix to Chapter 3) was carried out which generated data on household characteristics, farming livelihoods, certification, tea economics, and labour. Games administered during the interview generated data on risk preferences. Since illiteracy is common in the region, both the survey and game were administered verbally, in Nepali. Within each household, we interviewed the self-declared household head or the individual whom the household head designated as most knowledgeable about the tea farm[30]. Survey participants were paid according to the payoffs

[28]The cooperatives that were uncertified in 2006 decided many years later (eg. in 2014) to get certified, and were as such in conversion during fieldwork in 2016. However, their members' initial choice to remain uncertified shows their low interest in certification, and this coupled with the fact they were not fully certified at the time of fieldwork led the study to consider them as uncertified.

[29]The supplier lists of these factories (Himalayan Shangri-La, Gorkha, Green Tea, and Kanchenjenga) make up our sample frame. Only farmers who, according to those lists, supplied a positive non-zero amount of tea leaf to the factory in 2015 are included in the sample frame.

[30]The preponderance of male respondents in our sample reflects cultural norms in Nepal wherein men are more likely to be identified as the household head and thus be the designated survey household respondent.

from the games administered during the survey, receiving on average 438 Nepali Rupees (CA$5.23), or approximately two days' wage as a tea labourer.

### *4.1 Survey and Factory Data*

More than 15,000 farming households grow tea on small-scale plots in Nepal (NTCDB, 2017). The households in our sample had a diversified livelihood strategy, with some 34% of income coming from tea and the rest coming from other occupations such as other agriculture, running a shop, teaching, or working in a business. The median land size in tea was 0.46 hectares, but farmers also had land in other crops such as potato, vegetables, cardamom and corn, and raised livestock. Average annual individual income in the region was US$1260 and the Human Development Index was 0.526[31].

Table 4.1 shows summary statistics for the key variables of interest. Column 1, which has the sample means and standard errors for the whole sample, is discussed here. The average interviewee in the sample is 44 years old and has completed slightly more than the equivalent of an elementary school diploma. However, 12 percent of the sample is illiterate. Of the total sample of 270 respondents, 65% are from the Sankhejung region, 14% are from Kolbung, 11% are from Sundarepani, and 10% are from Phidim. One individual without data on risk aversion was dropped from the sample.

Table 4.2 provides detailed breakdowns of the sample by certification status. In our case study, all farmers who were interested in organic certification adopted it soon after it was introduced, and by the time of this survey, ten years after its introduction, were fully certified. Those with a low level of interest in certification, on the other hand, remained uncertified at the time of the survey. The uncertified either continued to practice conventional methods, or they had decided to follow the trend and began conversion to organic methods a year or two before the survey. This study follows others in the technology adoption literature (Liu 2013) in characterizing the early adopters, who had obtained full certification by the time of the survey, as having a higher propensity to adopt than the uncertified, reluctant farmers. That is, I measure latent certification propensity using a simple binary indicator of whether the household has actually already obtained full organic certification. This coarse classification reflects that households with a high propensity to adopt certification are more likely to have already obtained it by now, whereas

[31] 2011 figures, GDP per capita PPP (UNDP 2014: 23,99**?**).

those with a low propensity have not. The first row of Table 4.2 separates respondents simply into the 226 individuals who have obtained full organic certification and the 43 who have not. 84% of the population and our sample are fully certified organic, while 16% is not.

The second row of Table 4.2 shows a more refined 3-way categorization that separates the uncertified farmers out into those who have decided to adopt but are in conversion, and conventional farmers who still refuse to pursue certification. This categorization of conventional, conversion and certified farmers is used in the regression shown in Table 4.6 Column 1. Finally, the last row also distinguishes between early and late adopters of the scheme. This categorization of conventional, conversion, late certifiers and early certifiers is used in the regression of Table 4.6 Column 2.

Section 4.3.3 considered the possibility that institutional factors, and specifically the influence of cooperatives, could make actual certification status data diverge from the latent propensity to get certified. The discrete choice experiment method provides a way to assess respondents' latent preferences when real data on choices is not available or is biased[32]. It describes a scenario to the survey respondent and asks what they would choose if they were in the situation. In our context, discrete choice experiments enable us to capture a pure measure of the respondents' latent attitudes to certification. Although data obtained through choice experiments is known to suffer from hypothetical bias, the time-saving and other reasons cited for this bias apply less to the production-choice context, where just one choice is made and the choice made does not affect the time taken in the experiment. Furthermore, this bias works similarly across individuals (Harrison and Rutstrom 2008**?**), which implies that hypothetical bias would appropriately sort our population, albeit with a shift factor.

The survey thus included the following question, which following the literature was framed in a context that paralleled how in practice factory owners tend to describe standards to their suppliers. Respondents were asked to "Pretend the factory tells you about a certification scheme. This scheme will take more time for training and your output may decrease somewhat. In return they say that the

[32]It has been used extensively in the willingness to pay literature (Murphy et al 2005; Harrison and Rutstrom 2008**??**), in transportation and ecological valuation, and in economic research on the determinants of production choices when real data is unavailable (Scarpa et al 2003; Ward and Singh 2015; Wale and Yalew 2007; Birol et al 2015; Christensen et al 2011; Vassalos et al 2016; Hudson and Lusk 2004; Saenger et al 2013**???????**).

prices you receive will be more stable from year to year. Do you agree to adopt now?" I define a measure of certification propensity based on this discrete choice experiment which is equal to 1 if respondents replied "yes" to this question, and zero otherwise.

## *4.2 Field Experiment*

### *4.2.1 Design*

Empirical researchers have deployed several different experimental designs to elicit risk preferences (Binswanger 1980; Binswanger 1981; Eckel and Grossman 2008; Gneezy and Potters 1997; Holt and Laury 2002; Brick et al 2012; Tanaka et al 2009**???????**). The Holt and Laury (2002) experiment (hereafter referred to as the "HL" approach), which presents respondents with a list of paired lotteries, has emerged as the most popular method to elicit risk attitudes in developed countries. However, several studies have shown that in populations with low numeracy, the structure of the Holt-Laury game can be difficult to understand. Indeed, it has been accompanied by confusion with noisy and inconsistent choices (Dave et al 2010; Ihli et al 2016; Engle-Warnick et al 2006). When working with low-literacy populations, including in rural areas of the developing world, simpler games (Binswanger 1980; Binswanger 1981; Eckel and Grossman 2008; Brick et al 2012; Gneezy and Potters 1997) generate behaviour that is significantly more consistent and less noisy than behaviour in more complex risk elucidation tasks (Dave et al 2010; Ihli et al 2016; Charness and Viceisza 2016**?**). This is particularly relevant for the present study given evidence of the limited numeracy and literacy of rural Nepali farmers (UNDP 2009; Mohan 2013; Mohan 2014; Mohan 2015**?**).

This paper thus relies on data from a relatively simple experiment developed by Binswanger (1980, 1981) and refined by Eckel and Grossman (2008) (hereafter referred to as the "EGB" approach). The EGB approach is relatively easy to understand and has become a popular risk elicitation experiment for use with rural populations in the developing world (Engle-Warnick et al 2006; Ruben and Fort 2009; Yesuf and Bluffstone 2009; Dhungana et al 2004; Vargas Hill 2009; Bezabih 2009; Kisaka-Lwayo and Obi 2014**??**)[33]. The EGB game offers decision-makers a

[33]Other experimental methods that have been deployed amongst rural populations in the developing world are more complicated and less commonly used than the EGB method, and were thus eschewed here. The methods of Tanaka et al (2009) and Gneezy and Potters (1997) involve the use

single choice among 6 gambles, each of which has a 50% probability of winning a higher prize. Since the gambles differ in their riskiness, and subjects choose which of the 6 gambles they wish to play, each respondent can be attributed to one of six risk categories. In order to measure ambiguity aversion, the research instrument also included Holt-Laury modified Price List games following Barham et al (2014) and Ward and Singh (2015)[34]. In order to measure loss aversion, and given the limited time available in interviews, the research instrument included a blunt measure of loss aversion through a question offering a hypothetical choice between two ways of tea farming: a stable, low-return way, and a high-return way with a risk of loss.

There is evidence that cognitive ability affects the choices an individual makes in risk games (Huck and Weizsacker 1999; Burks et al 2009; Dave et al 2010**??**). As such, the survey included a digit span exercise as a proxy for respondent's cognitive ability. Digit span is a measure of short-term or working memory. It is a sign of sequential processing ability that measures how able a person is to take in and process information in an orderly fashion (Dempster 1981**?**), and is widely accepted as a proxy of cognitive ability (Barham et al 2014).

of the concept of probability, which respondents in the study would have difficulty understanding. Tanaka et al (2009) has varying probabilities which can generate confusion amongst developing world farmers (Brick et al 2012); the game proposed by Gneezy and Potters (1997) requires explanation of the concept of an investment in which the principal could be won or lost; and the Brick et al (2012) method still requires multiple rounds of choices and probabilities that differ between lotteries.

[34]Unfortunately the EGB game only measures risk aversion, and it is not apparent how to modify it to measure ambiguity aversion while retaining its simplicity. The method of EEL requires the respondent to understand the idea of paying varying amounts of money to have information revealed, which would be very difficult for our respondents to comprehend. The experimental method of Barham et al (2014), which was also used in Ward and Singh (2015) and is similar to the approach of Brick et al (2012), was instead deployed for this study to elicit ambiguity aversion attitudes and is discussed in more detail in the second chapter of this thesis. Ongoing work by the author shows that while this experiment is simpler than Engle-Warnick et al (2006) and traditional ambiguity aversion elicitation methods, the choices made by respondents in our study during this game exhibit significantly higher rates of confusion and noise compared to the EGB game. For this reason, this study uses the EGB data for its risk aversion measure. For lack of a better measure of ambiguity aversion, I use the choices from the game derived from Barham et al (2014), as well as the parameter calculation method presented in that paper, for measuring ambiguity aversion.

### *4.2.2 Procedures*

Participants were told that the game they were about to play could be randomly chosen for a real payoff at the end, so they should make each choice as if it were for a real payoff, and asked them if they understood they would be getting real cash as a result of their choices. The participant was shown a board divided into six different coloured squares. On each square were two photographs, one of which showed Nepali Rupee bills amounting to a winning payoff, one of which showed the losing payoff. Participants were told that each coloured paper on the board showed a lottery where there was a 50/50 chance of each outcome. A practice game was demonstrated and discussed to ensure the participant understood the game. Then the participant was asked to choose one of the six lotteries. The interviewer recorded which colour the respondent chose on the interview paper.

The payoff matrix to the game is shown in Table 4.3. Extremely risk averse subjects chose lottery 1 (Green), which had no risk whatsoever: subjects were guaranteed a payoff of 200. The least risk averse subjects chose lottery 6 (purple), which offered both the highest expected value and highest standard deviation in payoffs.

At the end of the interview, the respondent was asked to draw two chips from a bag containing numbered chips corresponding to each of the games in the research instrument. The two games thereby chosen were actually played. If the chip with the game number corresponding to the EGB game was chosen, the interviewer consulted the written record to see which colour lottery the respondent chose. A coin was then taken out and the respondent was asked which side would represent a “win”. The coin was tossed: if the winning side came up, the respondent would be paid in cash for the larger amount on the lottery they chose. If the losing side faced up, the respondent was paid in cash the lower amount shown on the coloured square they chose.

The digit span exercise was modeled on that used by Barham et al (2014). The interviewer read out a number and respondents were asked to repeat the number. This exercise started with one-digit numbers and continued up to a maximum of 9 digits. If a farmer made a mistake at a certain level, the exercise ended. The last level successfully completed was that farmer’s score for the exercise.

### *4.2.3 Game Results*

The distribution of lottery choices is shown in the 6th column of Table 4.3. In our sample, almost forty percent of farmers chose the lowest-risk, lowest expected value lottery, indicating a high degree of risk aversion. Nonetheless, there was a wide dispersion of respondents across the different risk choices. Table 4.4 reports shows the number of people in each certification category who are in each risk choice category: 8 conventional farmers, for example, chose the no-risk lottery option one. Respondents performed poorly on the digit test exercise, indicating lower average cognitive ability relative to international norms. The average digit span for an average adult in the USA was seven plus or minus two (Miller 1956**?**): in our sample, it is 4.5 plus or minus 1.4. Approximately 6% of the sample was unable to recall three digits, indicating very low cognitive ability.

### *4.2.4 Choice of Risk Variable*

The actual numbered choice made by the respondents in the game is the least transformed and most disaggregated measure of risk aversion available, and is closer to the actual decisions made by respondents. Several scholars thus choose to use it as their measure of risk aversion (Engle-Warnick et al 2006; Mosley and Verschoor 2012; Ruben and Fort 2009). The inclusion of the full set of choice dummies may, however, include too much detail, obscuring the forest for the trees. It may also be that people who are not most nor least risk averse choose amongst the interior risk options (neither the most nor least risky ones) using non-economic criteria, such as how many bills are shown or randomly. Including each choice dummy can capture this noise, throwing into stark relief bumps from measurement error and thereby obscuring the big picture structure of responses.

Instead, several scholars group responses into high, medium and low risk choice categories (Bezabih 2009; Kisaka-Lwayo and Obi 2014; Ihli et al 2016). In Bezabih (2009), for example, choices in the risk game generated six categories of farmers, ranging from most to least risk averse, and the author grouped these into three categories of risk preference as severe, moderate, and slight.

Still others object to the ordered nature of the choice data and transform it into a risk aversion parameter using an assumed utility function and choice of midpoints (Vargas-Hill 2009; Mosley and Verschoor 2012). Transformation of risk choices into a continuous risk aversion parameter can be criticized, including because it

introduces artificial gaps into the data which could skew the results; suggests unrealistic levels of risk aversion in transactions involving larger amounts of money; treats discrete experimental data as continuous; is based on an assumption about the functional form of utility; and is contingent on the choice of midpoints. In practice, most scholars show their results both in terms of untransformed risk choices/categories, and in terms of a transformed risk parameter, choosing one measure as their baseline and the other as a robustness check.

We follow this practice and – in light of the well-founded critiques of a parameter measure – present our baseline estimates in terms of categories of risk choice, using the other measures as a robustness check. Following Bezabih (2009), Kisaka-Lwayo and Obi (2014), and Ihli et al (2016), we create a new Risk Category variable that assigns each respondent to low, medium, and high risk aversion categories. The least risk averse chose option 6 in the Binswanger game, and as per the practice in previous papers, are default category 0. The moderately risk averse, who chose options 2-5 in the game, belong to risk category 1. The extremely risk averse, who chose option 1 in the game (which had no risk), belong to risk category 2. The baseline risk categories measure enables us to minimize bias introduced from transformation of the risk choices into a risk aversion parameter, and grouping all those who chose an interior choice within a medium risk aversion category allows us to avoid the noise. It also follows the literature on the relationship between risk and certification, which found that the nature of the relationship varies across risk aversion categories (Kisaka-Lwayo and Obi 2014).

#### *4.2.5 Estimation of Risk Parameter*

The common approach to estimating risk preferences assumes that individuals maximize their Expected Utility (EU) given the risk parameter in their constant relative risk aversion (CRRA) utility function. In this framework, an agent's CRRA parameter summarizes his or her risk aversion and entirely explains the curvature of the utility function[35]. Following Eckel-Grossman (2008**?**) and the

[35]Prospect theory has critiqued this analytical framework, arguing contrary to EU theory that the curvature of a utility function is jointly determined by risk aversion, loss aversion, and nonlinear probability weighting (Liu 2013). Furthermore, scholarship in behavioural and development economics has shown that even if we accept EU as a framework, the assumption of constant relative risk aversion is unlikely to hold in practice. De Brauw and Eozenou (2011**?**), for example, reject the hypothesis of CRRA behaviour amongst a population of Mozambican farmers, finding instead evidence of power risk aversion preferences and rank dependent utility. Notwithstanding these critiques, we adopt the conventional EU-CRRA framework since it is the standard approach

applied literature on risk aversion, I use the iso-elastic utility function that displays constant relative risk aversion (CRRA) and decreasing absolute risk aversion (DARA)[36]:

$$U = \frac{x^{1-\sigma}}{1-\sigma} \tag{1}$$

Where $\sigma$ corresponds to the coefficient of relative risk aversion and $x$ corresponds to wealth. Individuals with $\sigma > 0$ can be classified as risk averse, $\sigma < 0$ as risk loving and $\sigma = 0$ as risk neutral. Table 4.3, column 7 contains intervals for the risk coefficient corresponding to each chosen gamble. The intervals are determined by calculating the value of $\sigma$ that would make the individual indifferent between the gamble she chose and the two adjacent gambles. For example, a choice of Lottery 3 implies a risk coefficient in the interval of (0.81, 1.32): indifference between Gambles 2 and 3 corresponds to $\sigma$=1.32, and indifference between 3 and 4 to $\sigma$=0.81.

Following Vargas Hill (2009), a unique value of $\sigma$ was calculated for each alternative as the geometric mean of the two endpoints, except for the most risky alternative that has an endpoint of 0 (assuming no farmer was risk loving) where the arithmetic mean was used. For the no risk option, the value of the lowest endpoint was used as the unique value of $\sigma$. Column 8 has these point estimates of the coefficient of relative risk aversion. The last row of Table 4.4 shows the average relative risk aversion coefficient for respondents, grouped by certification category. Conventional farmers have the lowest average risk aversion coefficient, at 1.825, and the average risk aversion increases by certification status, with the group of farmers who were the first to be certified having the highest average risk aversion level.

### *4.3 Empirical methodology*

The propensity to get certified can be modeled as a latent variable in a utility maximization framework (see Appendix B). This framework is operationalized using the observed data in a reduced-form model of the effect of risk aversion on observed certification choice:

$$Y_i = \beta_0 + \beta_1 R_m + \beta_2 R_h + \beta_3 D + \beta_4 W_i + \beta_5 X_i + \epsilon_i \tag{2}$$

and generates a good first baseline analysis of the risk-certification relationship.

[36]When $\sigma = 1$, this expression is undefined; instead, at this point, $U = \ln(x)$.

The binary dependent variable $Y$ reflects the respondent household's actual organic certification status: it is equal to 1 if the factory database indicates the household is fully organically certified, and 0 otherwise. Alternative specifications of the model are presented in the robustness section that disaggregates certification status. Coefficients $\beta_1$ and $\beta_2$ measure the impact of risk aversion on certification status $Y$. Recalling that respondents who chose the least risk averse lottery are the default group, $\beta_1$ measures how moving from the least to moderately risk aversion choice affects the probability of being certified while $\beta_2$ measures the impact of moving from the least to extreme risk aversion choice affects the probability of being certified.

Place-based social and geographical factors may influence risk attitudes: lest such factors bias our measure of $\beta_1$, the model includes village fixed effects in vector $D$[37].

Risk theory suggests that individuals make production choices taking into account not only their innate risk preferences, but also their perception of their exposure to risk and the risk management strategies they have available to them. Risk management capacity should thus be controlled for in studies with risk choices. We follow Liu (2013) in emphasizing wealth as a major determinant of risk management capacity. In the eastern Nepali mountains, size of landholdings is the main sign of wealth, and land can be leased or used as collateral when cash is needed to cope with shocks. The total land owned in hectares is thus included here as proxy of wealth and risk management capacity $W$.

Previous studies on certification and development have indicated that propensity to get certified depends on a gamut of demographic and economic characteristics, including the education of the household head, sale quantities[38], land size, migration, household size, gender, cognitive ability, and age. However, analysis presented later in the chapter suggests that education and migration are statistically

[37] Although the farmers living in what we've defined as Sankhejung and Phidim villages supply to different factories, there is geographical overlap amongst them, and they are similar socio-economically and agro-ecologically. Sankhejung and Phidim are thus grouped together in one baseline region and dummies are included for the other two regions, namely Kolbung and Sundarepani.

[38] Previous literature has included quantity of sales, citing it as a measure of size of the farm business and risk measurement capacity, and so it is included as a covariate here. However, it is likely to be endogenous since organic methods reduce yield. The estimates for this variable are thus tentative.

significant drivers of risk aversion but do not affect certification, which suggests that including these control variables could lead to misspecification bias. As such, they are excluded from the regression model[39]. Gender, age, land size, household size, cognitive ability and sale quantities are included in the vector of household characteristics $X$. Finally, based on the argument in section 4.2.1, and following other similar studies that make inclusion in the analysis conditional on satisfaction of a basic cognitive ability test (Liu 2013) or include it as a control (Barham et al 2014), this paper makes inclusion in the regressions conditional on ability to recall and repeat three numbers.

One potential concern regarding the analytical strategy of this paper is that it assumes the direction of causation runs from risk aversion to certification choices. If a farmer's ex ante certification status affected their ex post risk aversion, however, reverse causality could bias a regression based on real certification data that ignored this effect. An extensive literature on technology adoption and risk aversion takes as a given that risk aversion is an inherent characteristic whose influence on production decisions does not change significantly over time (e.g. Knight et al 2003; Wale and Yalew 2007; Bezabih 2009; Engle-Warnick et al 2006; Liu 2013; Barham et al 2014**?**)[40]. This approach is borne out for the Nepali tea farmers in this study, amongst whom entrepreneurial attitudes (and by extension interest in risk) are closely tied to individual personality, which is unlikely to vary in the short time frame between obtaining full certification and the survey. Following this evidence and the literature, this paper assumes risk aversion is an innate and exogenous characteristic of the respondents, and so it cannot be affected by past certification choices.

## 5 Risk and Certification: Empirical Results

I begin by estimating equation (1) with a linear probability model (LPM) using 2016 data for orthodox tea farmers in Nepal who have the opportunity to get certified[41]. The dependent variable is binary and equal to one if factory records

[39]Note that neither education nor having a family member who has emigrated overseas are significant in any specification of the model, nor does their inclusion significantly change the results.

[40]Evidence in support of the commonly made assumption that risk aversion is an inherent characteristic that does not vary over time is found in Jaeger et al (2010**?**), Harrison et al (2005**?**), and Love and Robinson (1984**?**).

[41]Inclusion in the regression is made conditional on a result of 3 or greater on the cognitive test exercise, which excludes 16 people, or 6% of the sample. Findings do not change substantially if

indicated the household was fully organically certified. The main independent variables are two dummy variables indicating moderate and extreme risk aversion choices in risk experiments conducted during fieldwork, where low risk aversion is the default category. As extensively discussed by Wooldridge (2003**?**) and Cameron and Miller (2015**?**), standard errors should be clustered when the errors could be correlated within groups of observations, such as cooperatives or villages in our case. Since coops are entirely nested within villages in our data set, any intra-coop error correlation will be picked up by within-village error correlation[42]. Therefore, all the regression results presented in this paper are clustered at the village level. To compute the correct p-values using the adjusted standard errors, and given that there are relatively few clusters, I use the Wild Cluster Bootstrap of Cameron et al (2008**?**) implemented in Stata using the "cgmwildboot" command.

The first column of Table 4.5 features a simple regression of certification status on risk. It suggests that there is a positive and statistically significant relationship, with relatively more risk averse tea farmers more likely to be certified organic[43]. Column 2, which includes village fixed effects, shows similar results, but the difference in likelihood of certification between the low and moderately risk averse groups is no longer significant. In Column 3, a wide range of demographic and economic variables are included that can affect the propensity to get certified, as well as the proxy for risk management capacity. The coefficient on extreme risk aversion remains positive and statistically significant.

Finally, column 4 shows the final baseline regression, where the gender and land ownership covariates have been retained since they were significant in the previous specification of the model. The coefficient on extreme risk aversion is positive and significant at a 5% level of significance, suggesting that individuals with a higher degree of risk aversion had a higher propensity to choose certification[44]. This indicates that if an individual went from the least to the most risk averse attitude, this would lead to a statistically significant 14% increase in the probability that

these individuals are included, as shown in the next subsection.

[42]Pers. Comm., Prof. Matt Webb, Carleton University, 29 September 2016.

[43]A complete interpretation of coefficients is presented for the baseline regression in column 4.

[44]$R^2 = 0.07$ in this regression. While $R^2$s in the regressions in this chapter are rather low, they are consistent with those found in the literature on the determinants of certification, where the $R^2$ figures run from $0.02$ to $0.6$ (Kersting and Wollni 2012; Bolwig et al 2009; Handschuch et al 2013)

the individual is certified[45]. The economic effect is not negligible: in our sample, if all the risk lovers become risk haters it would lead to a 2.6% increase in the proportion of the population which is certified.

### *5.1 Robustness Analysis*

This subsection investigates whether the empirical results are robust to different specifications of the empirical and conceptual model. First, it investigates whether results are simply the result of stark differences between the certified and uncertified farmers. The role of confounding factors, including wealth, gender and education, is then analyzed. Next, alternative measures of certification status and risk aversion are used in regression analysis. An additional set of robustness checks examines how alternative models of risk behaviour, econometrics, and social learning affect the result. A final robustness check uses data from the discrete choice experiment to measure latent certification attitudes.

#### *5.1.1 Comparing Certified & Uncertified Farmers*

Are those who adopt certification schemes so different from those who refuse as to defy comparison? Table 4.1 columns 2-4 compare those who are certified to those who are not. A larger share of certified farm households are male-headed and the household head is older as compared to non-certified households. Emigration is less prevalent amongst certified households, who also own more land in total than non-certified households. This evidence suggests that certification could be an agriculturally focused livelihood strategy alternative to outmigration of the male household head. This hypothesis is supported by the fact that the inherent characteristics of households belonging to the two groups are similar in several key dimensions. Estimates suggest that we cannot statistically reject the hypothesis that the two groups have similar household size, education, area of land in tea and quantity of tea sold at conventional levels of statistical significance[46].

[45]Note that results in all columns of this table are robust to sample size changes and that multicollinearity tests were negative

[46]The t-test comparing risk aversion between certified and non-certified groups finds that the difference is not significantly different from zero, likely because factors that influence both risk aversion and certification status are not controlled for here and are confounding the comparison. When such factors are included in the regression analysis above to separate their effect from that of risk aversion, there is a significant difference

### 5.1.2 *Potential Confounding Factors: Gender, Wealth, Education & Migration*

This latter result implies that there are significant gender differences in certification: female respondents were significantly less likely to be certified organic than male respondents. Furthermore, t-tests on gender differences in risk choices indicate that consistent with previous research, female respondents were significantly more risk averse. Given these results, one would think that the relationship between risk and certification is even stronger for a male-only group. However, regressions of risk on gender as well as certification on gender find that gender does not have a significant independent effect on either risk attitudes or certification status, suggesting that women tend to have different average levels of risk aversion than men, and different propensities to be certified, because of other aspects of households which happen to be led by women.

To verify that our certification-risk estimates are independent of gender, the baseline regression was re-run separately for only the male respondents in our sample. Risk aversion once again had a positive and statistically significant impact on certification status. When the sample was constrained to just the female respondents, similar results were obtained, although the estimates were no longer significant[47]. Taken together, these results indicate that the core finding of a positive and significant relationship between risk aversion and certification status is independent of gender.

Risk is measured here through a measure of risk aversion that is assumed to be constant across absolute money amounts. Yet this assumption is questionable. Indeed, if risk attitudes are affected by wealth, and wealthier people are more likely to get certified, then the estimates of risk aversion will be biased: the risk aversion of wealthy households will tend to be underestimated and that of poor households overestimated. Econometric analysis of our conditional sample shows that wealth, as measured by the land owned by the household, is not correlated with the household relative risk aversion (RRA) coefficient: the correlation between the two is a very small 0.0656. Regressions of risk on wealth in our conditional sample show that the latter is not a large nor statistically significant driver of risk attitudes in linear nor nonlinear frameworks. Finally, a simple regression of certification status on wealth yields an estimate that is virtually identical to the multinomial

[47] It appears that the size of the effect of risk aversion on certification is stronger for men than women: the coefficient is 0.014 in the regression with the full sample, 0.017 in the men-only sample, and 0.012 in the women-only sample. Similar results were obtained when risk aversion was interacted with gender in regressions with the full sample.

context. In sum, these findings suggest that wealth and risk attitudes are independent in our sample. These findings allow us to be confident that our RRA measure is not simply picking up wealth effects, and rather reflects stable underlying risk preferences.

Could the risk aversion and certification relationship be confounded by education and migration status? There are very low levels of correlation between education and risk attitudes, and between education and certification. A household's emigrant status – namely whether it has an emigrant overseas – similarly has low correlation with both risk attitude and certification. However, a regression of risk on wealth, education, gender, age and migrants does find that households with more education or someone living overseas are less risk averse, and it is a statistically significant difference. Although education and migrant status appear to affect risk aversion, neither are significant explanatory variables in a regression for certification status without risk aversion in the equation. As such, it is best to exclude them from regressions of certification on risk to avoid misspecification bias.

#### *5.1.3 Disaggregated Measures of Certification Status and Risk Aversion*

Our finding that more risk averse individuals have a higher propensity to be certified is robust to the choice of measure of the independent variable of interest, risk aversion. An alternative specification of the model was run in which the simple choice of lotteries was the measure of risk aversion. The regression shown in table 4.6 column 1 uses this risk aversion measure, where the default category is the least risk averse choice (6), and the top row shows the most risk averse choice (1). The positive coefficients on this variable reinforce the result found earlier: more risk averse people are more likely to get certified. Furthermore, when risk choices are transformed into a continuous coefficient of relative risk aversion $\sigma$ using the procedure outlined in section 4.4.2.5, and that $\sigma$ is used as the measure of risk aversion in the regression shown in Column 2, results once again indicate that relatively more risk averse farmers are significantly more likely to be certified organic.

This categorical risk measure can be used alongside a disaggregated certification measure to shed light on possible non-monotonicities in the relationship between risk aversion and certification. Table 4.7 shows the results of multinomial logit regressions of certification status on risk categories. Although I would like to deploy a clustering method appropriate for my sample (which includes few clusters,

some of which are small), unfortunately there is no econometric method that fits the situation[48]. Despite this, we would like to know more about how the relationship varies across a disaggregated certification categorical variable. As such, we use a standard clustering approach within a multinomial logit regression, cognizant that the p-values resulting from applying this approach to our data will be flawed since the standard approach assumes many clusters, while we have only few. Specifically, we would expect that the p-values are over-estimated here.

Table 4.7 Column 1 shows the results of a multinomial logit regression where the dependent variable is separated out into conventional, conversion, and certified farmers, and the main independent variable is separated into low, moderate, and extremely risk averse farmers. The coefficients in the table reflect the marginal effect (of going from the default low risk aversion category to the higher-risk category specified in that row) on the probability of moving from the default uncertified status to the certification status described in that column. The coefficient on extreme risk aversion in column 1b of Table 4.7, for example, suggests that the probability of an extremely risk averse person being certified instead of uncertified is 115% higher than the corresponding probability of her low risk aversion neighbour. The insignificance of estimates in Column 1a, which compares the risk aversion of uncertified and conversion farmers, reflects more the low sample sizes of these two groups than any economic difference.

The size of the estimates in this table are much larger than in the baseline and column 2 of Table 4.6, suggesting that there are important differences between each of the two uncertified categories of farmers, on the one hand, and certified farmers, on the other. This finding is affirmed in Table 4.7 Column 2, which features an even more disaggregated measure of certification status. The dependent variable separates certified households into those that were amongst the first wave to be certified and those that were not (see Table 4.2, last row). The default category of farmer in this column is once again uncertified low risk averse farmers. Once again, I find large, positive and significant effects of risk aversion on certification[49]. As a further robustness check, an alternative specification set the default

[48]The Cameron et al (2008) methodology used elsewhere in this paper and the Webb (2014) method can not be used for non-linear models besides the simple binary LPM. Furthermore, the standard clustering modules are compatible with non-linear models but require high numbers of clusters. Finally, the work of Esarey and Menger (2016**?**) to extend the method of Ibragimov and Muller (2010**?**) to multinomial contexts with few clusters depends on large numbers of individuals being in each cluster.

[49]Could the inclusion of farmers in conversion be distorting the estimation of differences be-

category as the certified and moderately risk averse farmers, who are the largest group in the sample. The results from a multinomial logit regression with this default, shown in Table 4.8, are consistent with other findings: the significant and positive coefficient on low risk aversion in column 1a of Table 4.8, for example, suggests that a low risk averse person was much more likely to be a conventional farmer than her moderately risk averse neighbour. The significant and negative coefficient on extreme risk aversion in column 1b highlights that an extremely risk averse person was much less likely to be in conversion than his moderately risk averse neighbour – instead, this very risk averse person was more likely to be part of the default organic group. Unfortunately, the small sample sizes of a number of the subcategories in this table render several of the coefficients insignificant.

#### *5.1.4 Alternative Risk, Econometric, and Social Learning Models*

Results appear to be sensitive to the model of risk behaviour, as regressions using uncertainty-based and Prospect Theory-based frameworks show. Analysis of the data on ambiguity aversion and loss aversion does not yield statistically significant findings. In Table 4.6 Column 3, I find that the respondent's ambiguity aversion has a small and statistically insignificant impact on the probability of being certified[50]. This result is unsurprising given the poor quality of the data (see footnote 36). Similarly, the results of a regression using our data on loss aversion, shown in column 4, indicate that the influence of this measure on certification is not statistically different from zero.

The findings are robust to a variety of different econometric models. Column 5 of Table 4.6 uses an alternative method for clustering with few clusters proposed by Webb (2014**?**) and once again finds a positive relationship, although it is only significant at a 10% level. Column 6 includes individuals with low cognitive ability, and shows that there continues to be a positive and significant relationship.

In the presence of social learning, early certification leaders may be followed by others who join up to the scheme because of their tendency to imitate the leaders rather than their risk attitudes. While the adoption choice of leaders would in

tween conventional and organic farmers? I investigated this by dropping conventional farmers and re-running the baseline specification of the model. The results (not shown here) are virtually identical to the baseline specification, indicating that the inclusion of conventional farmers is not distorting the results.

[50]Following evidence that ambiguity aversion is a compound gamble (Klibanoff et al 2005**?**), risk aversion is included in this regression and is not collinear with the ambiguity measure.

this situation reflect the influence of their risk aversion on their decision, the measure of risk aversion's influence on subsequent adoption would be biased by herd behaviour. Specifically, farmers who got certified early on could have low risk aversion, while farmers who certified later on could have had high risk aversion but a high tendency to follow leaders. Unfortunately, data on herding propensity is not available, making it difficult to explicitly disentangle herding and risk attitudes. However, analysis of the evidence at hand sheds light on the matter. The last line of Table 4.4 indicates the average coefficient of relative risk aversion for respondents classified by certification status. Respondents who were the first to be certified in each village were assigned to a group entitled "early certifiers": as the table shows, they have the highest level of risk aversion in the sample. Late certifiers are the followers, who are less risk averse, with the level of risk aversion decreasing monotonically in the conversion and conventional groups. The fact that risk aversion is increasing monotonically in certification propensity is also supported in a regression context, where for example the multinomial logit regressions in Table 4.7 column 2c second row indicates that early certifiers were more likely to be extremely risk averse than late certifiers[51]. The weakness of the quadratic specification of the model (not shown here), where the squared risk score was included but was insignificant, is additional proof of the monotonic relationship between risk aversion and certification propensity. Furthermore, farmers may well have learned about standards through social networks[52], which seem to have extended fairly evenly amongst farming households. In rural Nepal, individuals with more extensive social networks tend to be more entrepreneurial, interested in new schemes, less risk averse and more interested in certification. As such, the results presented here may in fact be conservative.

### *5.1.5 Discrete Choice Experiment*

The last robustness check, shown in Table 4.6 column 7, replaces the measure of latent certification propensity. Thus far this propensity has been measured by

[51] Unfortunately the small subsample of early adoptors in the regression Table 4.8 Column 2c, and the disaggregated risk categories, makes it difficult to accurately and significantly measure the difference between early and late adopters. A multinomial logit regression was run with the setup as Table 4.8 column 2 modified to measure risk aversion with a singular relative risk aversion coefficient. That regression, not shown here, finds that the first certifiers were more risk averse than late adopters (p=0.13).

[52] Although the research instrument included a question designed to measure the extent of the respondent's social network, the quality of responses was poor and the variation low and so this data was not used.

actual certification status, but as noted in section 3.3, institutional factors can make this measure diverge from latent propensity. Section 4.1 discusses in more detail the discrete choice experiment used to measure respondents' underlying interest in adopting a hypothetical certification scheme. Column 7 of Table 4.6 shows a regression in which the dependent variable is equal to 1 if respondents chose to immediately adopt the certification scheme proposed to them in the discrete choice experiment. I control for actual certification status since this affects interest in new certification schemes[53]. We find that more risk averse individuals have a higher probability of adopting the certification scheme, as before. While the estimate was statistically significant at a 5% level prior to clustering, once clustered it becomes not significant, indicating that there are important village-level influences on the error term. Interestingly, results indicate that men were more likely to adopt the scheme immediately.

# 6 Discussion

Analysis of the evidence in this case study consistently indicates that farmers who made more risk averse choices during an experiment were significantly more likely to be certified organic. Recall that there are two competing explanations of the certification-risk relationship: on the one hand, the literature on technology adoption predicted that risk averse farmers will see certification as a risky investment and refuse to adopt it. On the other hand, the contract farming school argued that even if the standard is perceived as risky, if it is part of a contract package that provides access to risk protection, it may be relatively more appealing to the risk averse. The positive relationship between certification and risk aversion found here supports the hypothesis that the contract farming mechanism is dominant. It suggests that in the case study data, the positive relationship induced by the contract farming mechanism is more important than the negative relationship induced by the technology adoption mechanism, which had predicted the risk averse would avoid certification.

Although these are reduced form results, they establish that there is indeed a relationship between risk aversion and certification, albeit in the reverse direction that is commonly supposed. Why would farmers who are more afraid of risk find certification more appealing? The contract farming literature suggests that it may

[53] Excluding the actual certification control generates regression estimates that are virtually identical to those with the control.

be because farmers perceive certification as going hand-in-hand with contracts that reduce exposure to risk. There is some evidence of this phenomenon in the case study. As described in section 3.2 above, Nepali factory owners promised that farmers who were certified to the organic standard would get training, input subsidies, and improved access to markets in the long run.

These results, and the contract school's explanation of them, underscore the importance of the governance of the standard in determining its attractiveness to farmers. Tied standards, where farmers get certified to a standard at the urging of downstream buyers, are a quite different strategy than certification to an untied standard, which farmers adopt of their own volition. In the latter case, farmers choose to get certified independently, as a brand differentiation strategy that can liberate them from dependence on existing buyers and open access to alternative markets. In Morocco, for example, female olive oil producers sought Fair Trade certification to bypass local wholesale buyers in favour of direct sale to Fair Trade retailers in Europe (Chohin-Kuper and Kemmoun 2010**?**). The choice to invest in certification to an independent standard may be a leap into the unknown that is relatively similar to the decisions studied in the technology adoption literature.

When a farmer gets certified to a standard that ties them to a buyer via a contract, on the other hand, it can be a means to get closer to the buyer and obtain associated risk protection. This vision echoes the value chain literature approach, which sees standards as a tool for economic governance across chain nodes (Mohan 2014). In this framework, standards reduce the transaction costs of sharing information and monitoring compliance across nodes that may be organizationally and geographically dispersed.

At the same time, research on contract farming has highlighted that it can entrench monopsony power. A single buyer could use its market power to force contract farmers to accept disadvantageous conditions, including low prices or costly changes in production practices, without benefits to the farmers themselves (Sivramkrisna and Jyotishi 2008**?**). While the existence of monopsonistic exploitation is ultimately an empirical matter in each case, the fact that farmers' consent is required for participation in an externally-validated certification scheme indicates that the buyer must take steps to make the scheme appealing to its farmers and viable in the long run. Marketing of produce from successful certified farmers can generate lucrative rents for their buyers, which gives buyers extra incentives to support their farmers. This suggests that certification could actually

increase the leverage of farmers in the farmer-buyer relationship by putting a premium on farmer-supplied quality that is contingent on buyer support of farmers. The existence of cooperatives as mediators of the certification process may also mitigate the exercise of monopsony power (Sivramkrisna and Jyotishi 2008**?**). Taken from the perspective of these literatures on value chains and monopsony, the findings here suggest that farmers may implement the demanding production practices associated with the standard in the hopes that it will enable them to join a well-coordinated, lower-risk global value chain thread which is better supported by buyers.

By implication, the relationship between risk aversion and certification truly depends on how the standard is presented to and perceived by farmers. A certification scheme that seems risky will, in the absence of accompanying risk reduction services, tend to deter the risk averse. More interestingly, the analysis of this paper highlights that the content and credibility of the presentation accompanying the scheme is crucial to its adoption. In the case study, the standard was perceived[54] as a relatively high-risk and high-return strategy but was presented alongside promises about future prices and the sustainability of production. The content of this promise affected farmers' expectations regarding the risk-reduction services that could accompany the standards and ultimately encouraged the risk averse to adopt. They only took the promises seriously, however, because they trusted the actor making them and took his utterances to be credible statements (Mohan 2013). Liu (2013) notes that even if agricultural extension officers share the truth about the benefits of adoption, farmers may not trust the officers and thus refuse to accept their statements. This, in turn, can lead to a subjective expectation about the technology that diverges from the objective reality. Amongst Nepali tea farmers trust in tea experts and factory owners is not a given (Mohan 2013), but in the case of promises concerning the organic standard, farmers generally made

[54]It should be noted that how the scheme is portrayed and understood ex ante by farmers may not be borne out in reality. In our case study, although conversion to organic was seen ex ante as relatively high return and high risk, ex post it appeared to lead to relatively low returns and low risk, at least in the short run. Analysis of 2009 data indicates that organic farmers had significantly lower revenues than conventional farmers because of lower productivity, and high costs may have further hurt them, although they experienced lower price volatility (Mohan 2013). A similar analysis of 2015 data indicates that organic farmers had slightly higher revenues than conventional farmers, although the difference was not significant. Organic farmers had significantly lower price volatility. The finding of an ex post lower risk exposure bears out the hypothesis that contract attributes associated with the standard reduce risk. It also underscores the importance of portrayal and perception, rather than reality, in decision making.

a leap of faith and decided to trust them and take their promises about the impacts of certification as credible.

On a different note, the high estimated levels of risk aversion in this study seem to pose a problem since they would suggest unrealistic levels of risk aversion in transactions involving larger amounts of money. This problem is well known: indeed, theoretical (Rabin 2000**?**) and empirical work, including in the developing world (Cox et al 2013; De Brauw and Eozenou 2011**?**), has shown that when the expected utility framework is used to analyze experiments involving modest stakes, it generates estimates of risk aversion that imply absurdly high aversion to risk in higher stakes situations. This critique of the EU framework implies that the scale of the risk aversion estimates in this paper is provisory. However, so long as the ordering of risk aversion generated by the estimates is correct, this critique does not necessarily undermine the findings in this study for the following reason. This paper is interested in a relative ordering of individuals by risk aversion to large stakes payoffs, but obtains the closest proxy: an ordering by aversion to small stake payoffs. According to the above critique, the small-stakes EU risk aversion estimates will consistently over-estimate the scale of large-stakes risk aversion, but this distortion applies equally to all individuals, so the ordering of individuals will be the same from our small-stakes experiment as it would be in the large-stakes real world. That is, so long as the ordering we obtain from small stakes is the same as the actual ordering of individuals by aversion to large stakes, then our conclusions are robust to the small-scale measures critique[55].

[55]If, however, individuals differ in the extent to which their small-scale stakes EU risk aversion differs from their large-scale stakes attitudes to real business decisions, then individuals' small-stakes risk aversion will be distorted from the large stakes risk aversion to different degrees, and thus the ordering at a small scale could be different from the large scale. There is some evidence on this from Fehr-Duda et al (2010**?**), who find that choice behaviour with small stakes differs from large stakes not only because of the way that individuals value different amounts of money, but also because probability weighting is sensitive to stake size. Specifically, they find that a majority of respondents in their Beijing experiments assign a lower probability of winning when the stakes are higher than when the stakes are low. A minority, on the other hand, do not change their probabilities regardless of the stakes and operate as expected-utility maximizers. Other studies affirm that probability weights vary by stakes (Krawczyk 2015**?**) and that behaviour is heterogeneous, with for example half of respondents in one study acting as EU maximizers (Santos-Pinto et al 2015**?**). If there are in this manner multiple types of decision-makers in our data set, and each type has a different manner in which their real large-stakes preferences are distorted by small-stakes symmetric-preference EU games and analysis, then the ordering could indeed be different between our small-stakes risk aversion measures and respondent's large stake risk preferences. This study follows others in the technology adoption literature in abstracting away from this phe-

More fundamentally, the weak empirical foundation for several other EU assumptions – including the assumption of symmetry of preferences and perfect knowledge of risk – suggest that other frameworks, including the loss and ambiguity perspectives analyzed briefly here, can be usefully deployed to complement an EU-based analysis of risk behaviour[56].

## 7 Summary and Conclusions

This study examined a population of small-scale tea farmers in Nepal with a view to understanding the relationship between their risk aversion and the decision whether to be certified organic. Results suggest that in the case study, more risk averse farmers had a higher likelihood of choosing certification. The robustness of the finding of a positive and significant relationship between risk aversion and certification across a variety of specifications at the very least questions the assumption of a negative or nonexistent relationship found in the certification literature to date.

The positive relationship between certification and risk aversion found here suggests that farmers may see certification as a risk-reducing technology. Since other technologies (e.g. new crops, GM cotton, or pesticides) do not appear to be perceived in this manner, this begs the question of what is different about certification. Is it how the scheme is presented to farmers, or its direct link to marketing opportunities, or indeed the fact that certification is undertaken for cash rather than subsistence crops? It may be that certification schemes whose adoption is tied to buyers through contract could actually provide insurance to farmers, but

nomenon here. In general, empirical risk research methods that captures a more finely-grained nonparametric measure of risk attitudes – which could include games with small and large stakes, giving respondents a chance to behave differently towards wins and losses, and to express their probability weightings – are more likely to accurately represent true risk preferences in the population (Dickhaut et al 2013; Santos-Pinto et al 2015**?**).

[56]Studies have shown that in practice, individuals are more sensitive to losses than they are to gains, respond more to changes in income than to wealth, and that they are averse to bets where the probabilities of outcomes are uncertain. The EU framework deployed in this study fails to accurately model these phenomenon. Empirical studies have shown that other models of risk attitudes, including rank dependent utility theory (Quiggin 1993**?**) and prospect theory (Kahneman and Tversky 1979), are a better empirical fit with actual decision-making behaviour (De Brauw and Eozenou 2011; Liu 2013). Future research could examine the relationship between certification decisions and risk behaviour using these models, but would need to pay particular attention to simple experimental procedures when working with low-literacy populations in developing countries.

more research is needed to evaluate this possibility.In this case, the contracting mechanism may be relatively more important in determining the nature of the risk-certification relationship, while the choice to get certified independently may be dominated by the traditional technology adoption mechanism. Additional research is warranted into the actual and perceived impact of certification on volatility and how that impact varies depending on the governance of the scheme.

One policy implication of this work is that certification schemes could be advantageous even if the short-term impact on prices and profits are ambiguous or even negative. If they give risk-averse farmers more stable long-term prices or quantities, then they provide these farmers with a less risky option whose adoption improves their welfare. Unlike other interventions, certification is (according to the findings here) particularly appealing to the risk averse, who may view certification as reducing their exposure to risk. As such, encouraging factories to adopt certification schemes, development agencies to support them, and consumers to buy from them, can improve the welfare of small-scale farmers in developing countries.

# 8 Appendix A: Figures and Tables

Figure 1: Map of Nepali Tea Factories & their Cooperatives

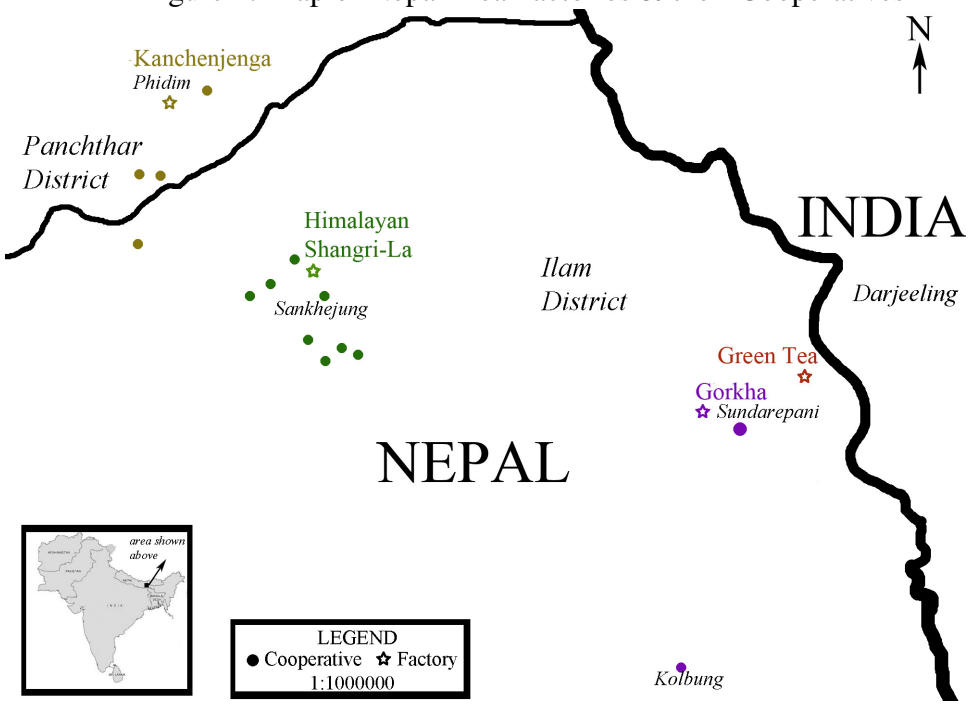

Figure 2: The Organic Certification and Cooperative Choice

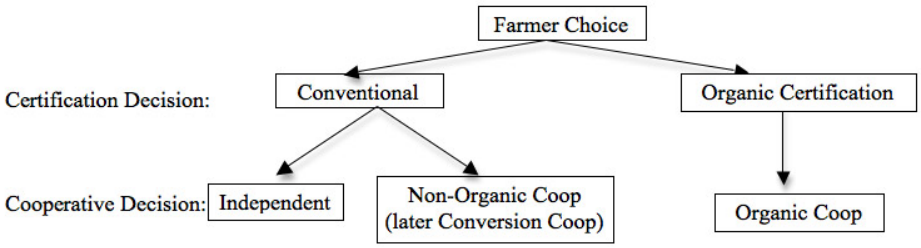

Table 1: Summary Characteristics

| | (1) Sample | (2) Certified# | (3) Uncertified# | (4) Difference |
|---|---|---|---|---|
| Age | 44.17 | 44.88 | 40.40 | 4.49** |
| | (0.82) | (0.89) | (2.10) | (2.24) |
| Male | 0.70 | 0.72 | 0.58 | 0.14** |
| | (0.03) | (0.03) | (0.08) | (0.07) |
| Education (Years) | 7.06 | 7.07 | 7.02 | 0.04 |
| | (0.27) | (0.30) | (0.68) | (0.75) |
| Literacy | 0.88 | 0.88 | 0.88 | 0.01 |
| | (0.02) | (0.02) | (0.05) | (0.05) |
| Household size | 4.38 | 4.35 | 4.58 | -0.23 |
| | (0.11) | (0.13) | (0.27) | (0.31) |
| Emigration | 0.32 | 0.29 | 0.46 | -0.17** |
| | (0.03) | (0.03) | (0.08) | (0.08) |
| Total land owned (hectares) | 1.79 | 1.86 | 1.39 | 0.47** |
| | (0.08) | (0.08) | (0.19) | (0.21) |
| Tea Land operated (hectares) | 0.63 | 0.65 | 0.52 | 0.13 |
| | (0.04) | (0.05) | (0.08) | (0.11) |
| Quantity Tea Sold 2015 (kg) | 1158.67 | 1117.45 | 1370.50 | -253.05 |
| | (139.92) | (146.96) | (412.28) | (379.32) |
| % household income from tea | 34.62 | 34.59 | 34.76 | -0.17 |
| | (1.53) | (1.66) | (4.02) | (4.20) |
| Coefficient of Relative Risk Aversion | 2.05 | 2.08 | 1.90 | 0.19 |
| | (0.10) | (0.10) | (0.24) | (0.26) |
| Cooperative Member | 0.87 | 0.98 | 0.33 | 0.65*** |
| | (0.02) | (0.01) | (0.07) | (0.04) |
| Proportion of food from own farm | 43.66 | 44.17 | 40.96 | 3.22 |
| | (1.42) | (1.59) | (3.00) | (3.89) |
| Number of observations | 269 | 226 | 43 | |

Note: Standard errors are in parentheses. # certified is defined as those respondents who were fully certified organic in factory records at the time of the survey. ** significant at the 5% level. *** significant at the 1% level.

Table 2: Certification in the sample

| | uncertified | | certified | |
|---|---|---|---|---|
| | conventional | conversion | late certified | early certified |
| Binary categorization | 43 | | 226 | |
| 3-way categorization | 29 | 14 | 226 | |
| 4-way categorization | 29 | 14 | 133 | 93 |

Table 3: Binswanger-EG game choices, values, CRRA, and distribution

| 1. Choice | 2. low payoff | 3. high payoff | 4. expected value | 5. standard deviation | 6. fraction subjects | 7. Implied CRRA range | 8. CRRA, point |
|---|---|---|---|---|---|---|---|
| 1. GREEN | 200 | 200 | 200 | 0 | 37% | $3.94 < r$ | 3.94 |
| 2. PINK | 175 | 250 | 212.5 | 37.5 | 14% | 1.32<r<3.94 | 2.28 |
| 3. BLUE | 150 | 300 | 225 | 75 | 15% | 0.81<r<1.32 | 1.03 |
| 4.YELLOW | 125 | 350 | 237.5 | 112.5 | 5% | 0.57<r<0.81 | 0.68 |
| 5.WHITE | 100 | 400 | 250 | 150 | 12% | 0.44<r<0.57 | 0.50 |
| 6.PURPLE | 75 | 450 | 262.5 | 187.5 | 17% | 0<r<0.44 | 0.22 |

Table 4: Risk Choices By Certification Category of Respondent

| | conventional | conversion | late certified | early certified | total |
|---|---|---|---|---|---|
| Lottery 1 (most risk averse choice) | 8 | 4 | 44 | 34 | 90 |
| Lottery 2 | 6 | 3 | 12 | 11 | 32 |
| Lottery 3 | 2 | 2 | 21 | 14 | 39 |
| Lottery 4 | 2 | 1 | 8 | 4 | 15 |
| Lottery 5 (least risk averse choice) | 9 | 3 | 19 | 15 | 46 |
| Total | 28 | 14 | 123 | 88 | 253 |
| Average Relative Risk Aversion Coefficient | 1.83 | 1.89 | 1.96 | 2.10 | 1.99 |

Table 5: The Effect of Risk Aversion on the Probability of Nepali Tea Farmers' Organic Certification, Linear Probability Model, Low Risk Aversion Default

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Moderate Risk Aversion | 0.11** | 0.10 | 0.10 | 0.10 |
| | (0.05) | (0.17) | (0.17) | (0.17) |
| Extreme Risk Aversion | 0.13** | 0.12** | 0.12** | 0.14** |
| | (0.05) | (0.05) | (0.05) | (0.05) |
| Male | | | 0.06** | 0.06 |
| | | | (0.05) | (0.17) |
| Total land owned (hectares) | | | 0.003** | 0.002 |
| | | | (0.05) | (0.17) |
| Age | | | 0.001 | |
| | | | (0.79) | |
| Household Size | | | -0.02 | |
| | | | (0.43) | |
| Quantity Tea Sold 2015 | | | -0.00001 | |
| | | | (0.18) | |
| Digit Test Score | | | 0.006 | |
| | | | (0.55) | |
| Village Fixed Effects | No | Yes | Yes | Yes |
| $R^2$ | 0.0151 | 0.0354 | 0.0901 | 0.0664 |
| Number of observations | 253 | 253 | 242 | 248 |

Note: The dependent variable in these regressions is equal to one if the respondent has obtained full organic certification, and is zero otherwise. p values are in parentheses, calculated using standard errors clustered at the village level. Note that one individual failed to complete the EGB risk game, and as such is excluded from these regressions, and 16 people were excluded who had a score lower than 3 in the cognitive ability test, resulting in a working sample of 253 of the original 270 individuals interviewed. * significant at the 10% level ** significant at the 5% level.

Table 6: Alternative Regression Specifications to Evaluate the Robustness of the Effect of Risk Aversion on the Probability of Nepali Tea Farmers' Organic Certification

| | (1) Risk Choices# | (2) Risk Coefficient | (3) Ambiguity | (4) Loss | (5) Webb | (6) Uncondtnl | (7) Hypothetical |
|---|---|---|---|---|---|---|---|
| Lottery 1 (Green) | 0.140** | | | | | | |
| (most risk averse choice) | (0.05) | | | | | | |
| Lottery 2 (Pink) | -0.005 | | | | | | |
| | (0.96) | | | | | | |
| Lottery 3 (Blue) | 0.156 | | | | | | |
| | (0.17) | | | | | | |
| Lottery 4 (Yellow) | 0.003 | | | | | | |
| | (0.90) | | | | | | |
| Lottery 5 (White) | 0.201** | | | | | | |
| | (0.05) | | | | | | |
| Relative Risk Aversion Coefficient | | 0.014** | 0.016** | | 0.014* | | |
| | | (0.05) | (0.05) | | (0.07) | | |
| Ambiguity Aversion | | | 0.017 | | | | |
| | | | (0.17) | | | | |
| Loss Aversion | | | | 0.016 | | | |
| | | | | (0.33) | | | |
| Moderate Risk Aversion | | | | | | 0.114 | -0.13 |
| | | | | | | (0.17) | (0.55) |
| Extreme Risk Aversion | | | | | | 0.146* | 0.050 |
| | | | | | | (0.06) | (0.17) |
| Male | 0.06 | 0.05 | 0.06 | 0.05 | 0.05 | 0.056 | 0.15** |
| | (0.17) | (0.17) | (0.17) | (0.17) | (0.12) | (0.17) | (0.05) |
| Total land owned | 0.002* | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | -0.0001 |
| | (0.06) | (0.17) | (0.17) | (0.17) | (0.07) | (0.17) | (0.92) |
| Real Certification Status | | | | | | | 0.004** |
| | | | | | | | (0.05) |
| Village Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.0949 | 0.0528 | 0.0597 | 0.0492 | 0.0528 | 0.0610 | 0.0806 |
| Number of observations | 248 | 248 | 230 | 248 | 248 | 264 | 247 |

Note: The dependent variable in these regressions is equal to one if the respondent has obtained full organic certification. The main independent variable is risk aversion. All regressions, except for column 6, include only those who could recall 3 numbers on the digit test exercise. Column 6 includes the full sample for which we have data on both risk, certification, gender and land ownership (264). # The rows in this regression correspond to dummies for each choice in the EGB game (see Table 3 for the cash amounts and implied RRA coefficient for each choice). The top row is for individuals who chose the least risky lottery, and each successive line below indicates less and less risk averse choices. Farmers who chose lottery 6, the least risk averse choice, are the default category. Coefficients thus indicate the effect of higher risk aversion. p values are in parentheses, calculated using standard errors clustered at the village level. *significant at the 10% level ** significant at the 5% level. *** significant at the 1% level.

Table 7: Multinomial Logit Robustness Regressions, Low Risk Aversion Conventional Default Group

| | (1) (Multinomial) | | (2) (Multinomial+) | | |
|---|---|---|---|---|---|
| | (a) conversion | (b) certified | (a) conversion | (b) late certified | (c) early certified |
| Moderate Risk Aversion | 0.911<br>(0.70) | 0.957**<br>(0.31) | 0.874<br>(0.70) | 1.030***<br>(0.28) | 0.812*<br>(0.47) |
| Extreme Risk Aversion | 0.412<br>(0.30) | 1.15**<br>(0.43) | 0.417<br>(0.26) | 1.129**<br>(0.47) | 1.216***<br>(0.43) |
| Male | -0.91<br>(0.68) | 0.403**<br>(0.07) | -0.12<br>(0.72) | 0.478***<br>(0.03) | 0.254<br>(0.19) |
| Total land owned | -0.002<br>(0.01) | 0.021**<br>(0.00) | -0.003<br>(0.01) | 0.022***<br>(0.00) | 0.018***<br>(0.00) |
| Village Fixed Effects | (Yes) | | (Yes) | | |
| Pseudo R2 | (0.0902) | | (0.1889) | | |
| Number of observations | (248) | | (248) | | |

Note: The dependent variable in these multinomial logit regressions is certification status, and the default category is uncertified. The main independent variable is risk categories, where the default value is low risk aversion. The sample is limited to those who could recall 3 numbers on the digit test exercise. p values are in parentheses, calculated using standard errors clustered at the village level. *significant at the 10% level ** significant at the 5% level. *** significant at the 1% level

Table 8: Alternative Multinomial Logit Robustness Regressions, Moderate Risk Aversion Organic Default Group

| | (1) (Multinomial) (default: certified, middle risk) | | (2) (Multinomial+) (default: late certified, middle risk) | | |
|---|---|---|---|---|---|
| | (a) conventional | (b) conversion | (a) uncertified | (b) conversion | (c) early certified |
| Low Risk Aversion | 0.957*** | 0.047 | 1.030*** | 0.157 | 0.219 |
| | (0.31) | (0.98) | (0.28) | (0.94) | (0.22) |
| Extreme Risk Aversion | -0.195 | -0.694** | -0.098 | -0.555* | 0.307 |
| | (0.18) | (0.32) | (0.25) | (0.34) | (0.29) |
| Male | -0.403*** | -0.494 | -0.478*** | -0.597 | -0.224 |
| | (0.07) | (0.64) | (0.03) | (0.70) | (0.20) |
| Total land owned | -0.021*** | -0.023*** | -0.022*** | -0.025*** | -0.004 |
| | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) |
| Village Fixed Effects | (Yes) | | (Yes) | | |
| Pseudo R2 | (0.0902) | | (0.1889) | | |
| Number of observations | (248) | | (248) | | |

Note: The sample is limited to those who could recall 3 numbers on the digit test exercise. p values are in parentheses, calculated using standard errors clustered at the village level. *significant at the 10% level ** significant at the 5% level. *** significant at the 1% level

## 9 Appendix B: Theoretical Framework

I model farmers' participation in a certification scheme using a random utility framework. Utility, $U$, is determined by a set of socioeconomic variables and contextual factors, $X$, which also influence the farmers' ability and propensity to get certified. I assume farmers maximize utility:

$$\max U = f(X) \tag{3}$$

I postulate that farming household $i$ ($i = 1, 2, 3, ..., n$ ) will choose to participate in a certification scheme $j$ if and only if the utility associated with the certified market, $U_{ij}$, is greater than the utility $U_{im}$ obtained via the status quo conventional market $m$. This relationship can be represented by the farmers' latent propensity to get certified, $y_i*$, defined as the difference in utility derived by individual $i$ from participation in the certification scheme compared to the status quo:

$$y_i* = U_{ij} - U_{im} \tag{4}$$

where $y_i*$ reflects the benefit of participating in the certification scheme. The extent of those benefits, and thus the latent propensity to get certified, will vary with personal characteristics, as the following latent equation indicates:

$$y_i* = X_i\alpha + \epsilon_i \tag{5}$$

Where $\alpha$ is a conformable parameter vector and the error term $\epsilon$ is independent and identically distributed as standard normal. Although $y_i*$ itself is unobserved, we can observe the type of marketing channel the farmer chooses. The observed variable ($Y_i$) relates to the latent variable ($y_i*$) such that:

$$Y_i = \begin{cases} 1 & \text{if } y_i* > 0, \\ 0 & \text{if} y_i* \leq 0. \end{cases} \tag{6}$$

Where $Y_i = 1$ if the farmer chooses to get certified and $Y_i = 0$ if they do not. Consequently, the probability of adoption is given by:

$$Pr\left\{Y_i = 1|X_i\right\} = Pr\left\{y_i* > 0|X_i\right\} = 1 - \Phi(-X_i\alpha) \tag{7}$$

Where $\Phi$ is the cumulative distribution function of the standard normal. Estimation is based upon a binary choice maximum likelihood model where these probabilities enter the likelihood function. The interpretation of the regression coefficients can thus be made in terms of the underlying latent variable model.