Small-scale raspberry producers' risk and ambiguity preferences, and technology adoption: empirical evidence from rural Maule, Chile

Dissertation

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Tal como lo dijo Johann Wolfgang von Goethe (1808) *"La indecisión conlleva retrasos, lo que sea que puedas hacer o soñar, comienza hacerlo ya. La valentía tiene ingenio, poder y magía en sí"*. Hoy, después de 16 años persiguiendo mi sueño lo he obtenido. Familia y amigos, este logro es también de todos ustedes.

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1 Introduction

1.1 General background

In economic environments, decision-makers' actions are bound to many possible outcomes. Since not all of these outcomes are beneficial to decision-makers, they must take economic decisions while facing some level of uncertainty (Ihli & Musshoff, 2013; Moschini & Henessy, 2001). Since producers could not control with certainty their production outcomes, then it is implied that uncertainty is an element intrinsically bound to production (Moschini & Henessy, 2001). The agricultural sector as an economic environment is not exempt from this reality. Daily producers must take decisions about their production systems under uncertain situations: future market prices, cost fluctuation of production inputs, climate variation, technological uncertainty, and financial constraints are just a few examples of these uncertain situations (Charness & Viceisza, 2012; Liu, 2012; Moschini & Henessy, 2001).

Therefore, as a way to help producers cope with uncertainty in their production systems, it is relevant to analyze producers' behavior and decision-making under uncertainty. Many agricultural researchers have studied producers' behavior under uncertainty and the characteristics that trigger differences in this behavior (Bocqueho et al., 2013; Harrison et al., 2010; Tanaka et al., 2010; Warnick et al., 2011). These researchers provide empirical evidence about producers' behavior under uncertainty that serve as inputs for designing efficient policies (Barham et al., 2014; Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015).

In addition, as a complement for producers' behavior under uncertainty, researchers also focus on finding alternative methods for producers to cope with this production uncertainty (Elabed & Carter, 2015; Liu, 2012; Ward & Singh, 2015). Hence, one of the most studied methods in current literature to cope with production uncertainty is producer's adoption of new and improved technologies (Adesina & Chianu, 2002; Lewis et al., 2011; Love et al., 2014). In addition to help producers cope with uncertainty, technology adoption could also improve producer's living conditions (Liu, 2012; Love et al., 2014). Also other benefits of technology adoption are that is relatively easy for producers to test technologies, also agricultural technologies are usually accessible and easy to introduce in different countries (Cavatassi et al., 2011; Ward & Singh, 2015). All of these benefits make adoption of some agricultural technologies a convenient alternative for producers to cope with uncertainty, or to increase their current production in developing countries.

As of today, most studies in the current literature that analyze producers' behavior under uncertainty and technology adoption focus on small-scale producers in developing countries, because these producers face harder constraints to adapt and cope with production uncertainty (Handschuch et al., 2013; Morton, 2007). However, studies that analyze producers' behavior under uncertainty are scarce in Latin America. Moreover, I am not aware of previous studies in Chile that analyze the role of producers' behavior under uncertainty on technology adoption. To fill this gap, in this dissertation I focus on small-scale raspberry producers in Maule region of Chile. I decide to focus on these raspberry producers because the analysis of producers' behavior and technology adoption of soft fruits producer have not been much explored in developing countries. Also, the current situation of small-scale raspberry producers is not much different from other soft fruits producers in Chilean central regions (Domínguez, 2012). The Maule region alone accounts for more than sixteen thousand small-scale raspberry producers (Domínguez, 2012; Jara-Rojas et al., 2016).

This doctoral dissertation consists of two studies, which represent the main chapters of this dissertation. In these chapters, I combine experimental procedures and spatial methods to address producers' behavior under uncertainty, and technology adoption in developing countries. In the following sections, I briefly discuss these two chapters.

1.2 Producers' risk and ambiguity preferences and policy-making design

In past decades, researchers considered that uncertainty was composed by risk alone, as a consequence producers' preferences under risk scenarios are widely studied in the current literature (Binswanger, 1980; Moschini & Henessy, 2001; Nguyen, 2011; Tanaka et al., 2010). In this regard, risk scenarios in agriculture occur when producers must face a decision with complete information about outcomes and probabilities involved (Binswanger, 1980; Chavas & Holt, 1996; Moschini & Henessy, 2001). However, recent studies explore ambiguity as a complement to risk to characterize uncertainty (Barham et al., 2014; Klibanoff et al., 2005). Ambiguity scenarios in agriculture arise when producers face a decision with incomplete information about the outcomes and probabilities involved (Takahashi, 2013; Ward & Singh, 2015).

Many studies have demonstrated that producers are averse to risk and ambiguity (Barham et al., 2014; Binswanger, 1980; Tanaka et al., 2010). This finding has encouraged many researchers to study the role of producers' aversion on producer's decision-making process (Liu, 2012; Warnick et al., 2011). Most of these studies confirm a link between producers' risk and ambiguity aversion and producer's decision-making process. Some examples of the link between producer's decision-making process and their risk and ambiguity preferences are: agricultural insurance uptake (Elabed & Carter, 2015; McIntosh et al., 2015), crop diversification (Bezabih & Sarr, 2012; Warnick et al., 2011), technology adoption (Liu, 2012; Ward & Singh, 2015), and producers coordination (Alpizar et al., 2011). Hence, identifying producers' risk and ambiguity preferences, and producer's characteristics that influence these preferences is crucial for policy-makers, as these preferences could provide meaningful elements to create efficient agricultural policies.

I use the experiments developed by Tanaka et al. (2010) and further modified by Ward & Singh (2015) to identify small-scale Chilean raspberry producers' risk and ambiguity preferences. But, in current literature there are two common methods to identify producers' risk preferences from Tanaka's field experiment: the midpoint method (Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015) and the structural method (Andersen et al., 2010; Bocqueho et al., 2013; Harrison et al., 2010). As of today, Only Bocqueho et al. (2013) identify and compare producers' preferences by using both methods in a developed country context. Therefore, there is not much empirical evidence regarding whether the method used to estimate producers' risk preferences could deliver different results, especially in a developing country context.

Most of the current literature that analyzes producers' risk preferences focuses on small-scale producers and in developing countries. This is because these producers are more vulnerable and face stiffer constraints to cope with uncertainty (Elabed & Carter, 2015; Handschuch et al., 2013; Ward & Singh, 2015; Warnick et al., 2011). However, one of the main issues that agricultural researchers usually encounter in developing countries, is the lack of information to determine producers' preferences from existent data. Therefore, this situation forced many researchers to develop methods to determine such preferences by direct interaction with producers (Andersen et al., 2006; Holt & Laury, 2002; Tanaka et al., 2010). Among the methods to estimate producers' preferences, many researchers prefer direct elicitation using incentivized field economic experiments, because they are simple to use and to comprehend by producers (Charness et al., 2013; Harrison & Rutström, 2008; Holt & Laury, 2002). In these experiments, producers decide between binary lotteries in controlled scenarios, these lotteries have known outcomes, but different known and, in some cases, unknown probabilities associated with these outcomes. In this way, risk and ambiguity are present into the experiments (Andersen et al., 2006; Ward & Singh, 2015).

The influence of producers' risk preferences on many agricultural decision-making processes is widely explored in the current literature (Barham et al., 2015; Liu, 2012; Takeshima & Yamauchi, 2012). However, the analysis of producers' risk and ambiguity preferences jointly, as components to characterize producers' behavior under uncertainty, and the socioeconomic and farm characteristics that determine these preferences are scarcely explored in developing countries, and particularly in Latin American countries (Cardenas & Carpenter, 2013; Nielsen et al., 2013; Warnick et al., 2011).

In light of the above, in my second chapter I study producers' risk and ambiguity preferences under uncertainty. I use field experiments to elicit small-scale Chilean raspberry producers' risk and ambiguity preferences. In addition, I identify and compare producers' preferences by using the two most common methods in the literature to estimate producers' preferences from the field experiment developed by Tanaka et al. (2010). Furthermore, I estimate probit and OLS models to distinguish determinants of producers' risk and ambiguity preferences (Harrison et al., 2010; Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015).

With this research, I provide inputs for a better characterization of producers' decision-making process under uncertainty. First, I compare the most common methods in the literature to estimate producers' risk preferences from field experiments, and highlight the differences in the results by using both methods. Second, I distinguish producers' characteristics that are determinants of producers' risk and ambiguity preferences. I pursue both of these objectives using data from field experiments carried out with smallholder raspberry producers in Chile. I am aware of no studies to date that analyze producers' risk and ambiguity preferences jointly in Chile or any other Latin American countries.

1.3 Agricultural technology adoption and small-scale producers' production uncertainty

Small-scale producers must deal with a wide range of production uncertainty sources, including financial limitations, future product prices, and climate variability and climate change. As a response, agricultural researchers focus on study methods that could help producers to cope with production uncertainty (Cavatassi et al., 2011; Handschuch et al., 2013; Warnick et al., 2011). One of these methods is the adoption of improved technologies. Technology adoption can not only help producers cope with production uncertainty, but it also correlates with economic development and with better living conditions (Liu, 2012). Therefore, many researchers focus on adoption of improved technologies as a key component in agricultural policy-making design, and ultimately help producers to cope with production uncertainty (Liu, 2012; Ward & Singh, 2015).

However, despite of the benefits of adopting improved technologies, producers are not always keen to do so. Much research has been carried out to explain this (Liu, 2012; Maertens & Barrett, 2012; Wossen et al., 2015). Many authors report empirical evidence that suggests that many producer's characteristics could assist or constraint producers' decision to adopt technology. Some examples of these characteristics are: producer's risk and ambiguity preferences (Liu, 2012; Love et al., 2014; Ward & Singh, 2015; Warnick et al., 2011); and, their socioeconomic and farm attributes: education, farm size, experience and age, among others (Adesina & Chianu, 2002; Krishnan & Patnam, 2013; Mendola, 2007; Nkegbe &

Shankar, 2014). In addition to these characteristics there is an additional factor that is being explored in recent literature, which is the influence of spatial patterns among producers on technology adoption. These spatial patterns are composed by a spatial dependence component and spatial spill-over effects (Läpple & Kelley, 2014; Roe et al., 2002). Spatial dependence refers to whether a producer's attitude towards a technology could influence neighboring producers' attitudes, and their decisions to adopt the same technology (Bhargava et al., 2015; Läpple & Kelley, 2014; Roe et al., 2002; Wollni & Andersson, 2014). Spatial spill-over effects refer to whether a change in a producer's characteristics could influence neighboring producers' decisions to adopt (Lacombe & LeSage, 2015; Läpple & Kelley, 2014; Wollni & Andersson, 2014).

Chilean policy-makers are aware of the importance of producer's technology adoption, as a way to cope with production uncertainty. Technology adoption is a key component in the National Plan to Adapt Forestry, Farming and Livestock Development to Climate Change and Climate Variability (Gobierno de Chile, 2013; Universidad de Chile, 2006). Therefore, producer's adoption of improved varieties, water-saving irrigation techniques, and other soil and water conservation practices play a relevant role for producers to cope with production uncertainty in Chile. Although producer's adoption of these practices is relevant for Chilean policy-makers, I am not aware of previous studies that analyze technology adoption in Chile. Consequently, analyzing producer's decisions to adopt a technology, their characteristics, and the preferences that influence these decisions, could contribute to strengthening the National Plan (Gobierno de Chile, 2013).

Considering the explanation above, in the third chapter I analyze small-scale raspberry producer's decision to adopt improved raspberry varieties and drip irrigation in the Maule region of Chile. I use a spatial Durbin probit model to identify the influence of producer's socioeconomic and farm characteristics, risk and ambiguity preferences, and spatial patterns on their decision to adopt technology. This spatial Durbin probit model combines the advantages of a non-spatial probit model which casts light on the role of producer's characteristics on their decision to adopt, with the ability to reveal spatial patterns in technology adoption (Lacombe & LeSage, 2015; Läpple & Kelley, 2014; Roe et al., 2002).

This second paper contributes to the literature in three ways. First, I am not aware of previous studies that combine producers' risk and ambiguity preferences that stem from direct elicitation with field experiments, and spatial methods to analyze producer's decision to adopt technology. Second, the role of spatial patterns among producers is a scarcely explored field in developing countries, hence I contribute with empirical evidence about whether producer's decisions and characteristics influence their neighboring producers' decision to adopt technology. Third, since many studies report mixed evidence about the influence of producers' risk and ambiguity preferences on technology adoption, I contribute with empirical evidence about the role of these preferences on producer's decision to adopt technology (Alpizar et al., 2011; Love et al., 2014; Ray et al., 2016; Ward & Singh, 2015; Warnick et al., 2011). My findings have a direct link to the National Plan to Adapt Forestry, Farming and Livestock Development to Climate Change and Climate Variability, by revealing insights about small-scale producers and their decisions to adopt improved raspberry varieties and drip irrigation.

1.4 Following chapters

This dissertation presents two studies in the field of producers' behavior under uncertainty and technology adoption. Following this introductory chapter, I present in chapter 2 a paper entitled *"Assessing small-scale raspberry producers' risk and ambiguity preferences: evidence from field-experiments data in rural Chile"*. As outlined above, in this paper I conduct incentivized field experiments to elicit producers' risk and ambiguity preferences. In addition, I use probit and OLS models to identify producer's characteristics as determinants of these preferences. This research has been published as a Discussion Paper in the Department of Agricultural Economics and Rural Development of the University of Göttingen[1].

In chapter 3 I present a second paper entitled *"The role of spatial patterns and producers' risk and ambiguity preferences on small-scale agricultural technology adoption"*. In this paper, I use producers' risk and ambiguity preferences that were elicited in chapter 2, and combine these preferences with producer's characteristics, using spatial methods to analyze producers' decisions to adopt technology. As a result, I am able to identify how producers' preferences, their socioeconomic and farm characteristics and whether spatial patterns influence producer's decision to adopt drip irrigation and improved raspberry varieties.

Finally, chapter 4 presents the concluding remarks of the two studies, key findings and limitations of my research, and briefly describes prospects for future research.

Contributions

The paper entitled *"Assessing small-scale raspberry producers' risk and ambiguity preferences: evidence from field-experiments data in rural Chile"* is coauthored by Prof. Dr.

[1] Available at DARE Discussion papers: http://www.uni-goettingen.de/en/working-papers-of-the-department-starting-issue-4-2007/72592.html

Stephan von Cramon-Taubadel[2]. My contributions to this paper are: first, I designed the experiments and questionnaire that used during the field work. Second, I trained the field enumerators and supervise their work. And third, I wrote the code to estimate producers' risk and ambiguity preferences from the results of the field work. In close cooperation with Prof. Dr. Stephan von Cramon-Taubadel analyzed the results from the field experiments and questionnaire. Also, writing and the structure of the paper was conducted with many valuable comments and suggestions from Prof. Dr. Stephan von Cramon-Taubadel.

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2 Assessing small-scale raspberry producers' risk and ambiguity preferences: evidence from field-experiment data in rural Chile

Abstract

Most researchers who analyze producers' preferences under uncertainty report that producers are averse towards risk and ambiguity scenarios. This aversion has an influence on producers' decision-making processes; hence the relevance of determining and analyzing these preferences as a key factor to design agricultural policies that help producers to cope with production uncertainty. In this study we elicit small-scale raspberry producers' preferences through field experiments in rural Maule (Chile). In addition, we identify producers' socioeconomic and farm characteristics that influence these preferences. Finally, we compare the two standard methods in the current literature to estimate producers' risk preferences from field experiments, and analyze if the estimation method influences these preferences.

Our results show an asymmetry in producers' risk preferences; producers are twice as sensitive to losses as to gains. Additionally, we find that producers get smaller lottery utilities in scenarios where ambiguity is present, which implies ambiguity aversion. We also show that the method used to estimate risk preferences can influence the results, with obvious implications for policy design.

Keywords: Risk Preferences, Ambiguity Preferences, Small-scale Producers, Raspberry Producers, Producers' Preferences Elicitation.

2.1 Introduction

Understanding risk and ambiguity preferences is important because these preferences influence producers' decision-making processes (Barham et al., 2014; Binswanger, 1980; Cardenas & Carpenter, 2013; Holt & Laury, 2002; Liu, 2012; Tanaka et al., 2010). In addition, small-scale producers face stiffer constraints to adapt their crops to uncertainty. Hence, researchers are increasingly conducting field experiments with small-scale producers, mostly in developing countries, to determine their risk and ambiguity preferences and to analyze the influence of these preferences on many aspects of farm decision-making, for instance: technology adoption (Barham et al., 2014; Liu, 2012), agricultural insurance demand (Elabed & Carter, 2015; McIntosh et al., 2015) and climate change adaptation (Alpizar et al., 2011).

Initially, researchers analyzed production uncertainty as composed of risk preferences alone. However, many researchers have found that producers behave differently when dealing with risk and ambiguity, and that risk and ambiguity correspondingly have different implications for producers' decision-making (Alpizar et al., 2011; Barham et al., 2014; Ross et al., 2010; Warnick et al., 2011). Hence, we consider uncertainty as being composed of two components: risk and ambiguity. Ihli & Musshoff (2013) show that uncertainty aversion can lead to sub-optimal decisions by producers.

Most of the studies that analyze producers' risk and ambiguity preferences focus on developing countries. However, in such countries it is uncommon to have access to data that allows to measure risk and ambiguity from pre-existing information. Consequently, researchers have developed experimental methods to elicit risk and ambiguity preferences from binary choice experiments under controlled conditions (Holt & Laury, 2002; Tanaka et al., 2010; Ward & Singh, 2015; Warnick et al., 2011). Although, the majority of empirical literature on risk and ambiguity preferences focuses on developing countries, the elicitation of these preferences is a field scarcely explored in Latin America.

Understanding risk and ambiguity preferences is a key ingredient in designing effective policies. For example, the Chilean government has a special interest in helping farmers cope with the uncertainty that arises from climate change and climate variability. According to Universidad de Chile (2006), central and southern areas of the country show a decreasing trend in rainfall since the 1970s. This increases the probability of droughts, and creates shocks that can have negative effects on agricultural production. These shocks especially affect small-scale producers, who usually face stiffer constraints to adapt their production systems (Handschuch et al., 2013; Morton, 2007). The Chilean government has implemented a National Forestry, Farming and Livestock Development Adaptation to Climate Change plan to help producers cope with this situation. One of the key components of this plan refers to producers' adoption of agricultural insurance and agricultural innovations such as improved varieties, drip irrigation, and other practices to cope with production uncertainty (Gobierno de Chile, 2013). However, as of today there are no studies that measure producers' risk and ambiguity preferences in Chile as an input into improving the design of such policies.

In this study we focus on small-scale raspberry producers in Chile. Raspberry production is attractive for small-scale producers, because of its low investment and mechanization requirements, and its labor intensity (Jara-Rojas et al., 2016; Toledo & Engler, 2008). Consequently, most of the raspberry production in Chile is in the hands of small-scale producers. Currently, more than twenty thousand households in Chile depend on raspberry production for at least part of their income (Domínguez, 2012). Due to soil and climate conditions raspberry production is concentrated in central regions of Chile. The Maule region alone accounts for more than 16 thousand small-scale Chilean raspberry producers (Domínguez, 2012; Jara-Rojas et al., 2016).

Our objectives are first to elicit small-scale raspberry producers' risk and ambiguity preferences using economic field experiments in rural areas of Maule region, and second to identify the socioeconomic and farm level determinants of these preferences. To elicit producers' risk and ambiguity preferences, we use the experimental procedure proposed by Tanaka et al. (2010) and Ward & Singh (2015). In addition, we use probit and OLS models to identify factors that influence producers' risk and ambiguity preferences respectively (Galarza & Carter, 2011; Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015). As a third objective, we analyze whether producers' risk preferences vary according to the estimation method. We do this by comparing the two standard methods that are used to analyze risk preferences from field experiments: the midpoint method (Liu, 2012; Nguyen, 2011; Tanaka et al., 2010; Ward & Singh, 2015) and the structural method (Andersen et al., 2014; Bocqueho et al., 2013; Harrison et al., 2010).

Our findings generate insights into producers' decision-making processes under uncertainty in three ways. First, we do not use results based on experiments with students, instead, we generate results using field experiments with actual producers. Second, we contribute to current literature by distinguishing between the possibly different determinants of producers' risk and ambiguity preferences. Third, we are not aware of other studies that elicit producers' risk and ambiguity preferences specifically in Chile, neither are we aware of other studies that analyze preferences conjointly in any other Latin American countries.

In Section 2 we review the current literature on raspberry production in Chile and on the elicitation of producers' risk and ambiguity preferences using experimental procedures. In Section 3 we describe our sample and data collection process, respectively. In section 4 we detail our structural specification, and we describe our results and concluding remarks in sections 5 and 6, respectively.

2.2 Raspberry production and producers' preferences for risk and ambiguity aversion in Chile

2.2.1 Chilean raspberry production and small-scale producers

During the 1980s Yugoslavia was the largest raspberry producer in the world. However, when the Yugoslav War started, raspberry production was interrupted. This created a shortage on international markets, and corresponding opportunities for producers in other countries. As a result, raspberry production in Chile increased from nearly nothing in 1980s to thirty thousand tons in 1990s (Domínguez, 2012). Following the cessation of hostilities, raspberry production in Yugoslavia began to recover in the early 2000s, ending the raspberry shortage on international markets. This reduced the profit of many large and medium Chilean raspberry producers, who then decided to switch their production towards more profitable crops, thus creating an opportunity for small-scale raspberry producers to expand (Domínguez, 2012; Jara-Rojas et al. 2016). The labor intensity and low investments that raspberry production requires make it attractive for small-scale producers (Toledo & Engler, 2008).

Today Chile is one of the largest raspberry producers and exporters worldwide. It has roughly 16·000 ha of raspberry and more than 21·100 producers, most of who are located in central regions of Chile. Maule region alone has more than 16·300 raspberry producers and 10·800 ha dedicated to this crop. Consequently, in the central regions of Chile raspberry production represents an important source of income for many small-scale producers (Domínguez, 2012; Jara-Rojas et al., 2016).

Producing raspberries is a risky business. High international price volatility, financial constraints, climate change and climate variability are some of the sources of uncertainty that small-scale raspberry producers must face (Challies & Murray, 2011). Consequently, understanding producers' risk and ambiguity preferences can assist policy makers in designing policies that help producers cope with uncertainty in their production systems (Bocqueho et al., 2013). Nevertheless, to date there are no studies that elicit risk and ambiguity preferences in Chile, and, none that elicit fruit producers' risk and ambiguity preferences in Latin America.

2.2.2 The influence of producers' risk and ambiguity preferences on their decision-making

Following Barham et al. (2014) and Klibanoff et al. (2005), we consider uncertainty as made up of two components: risk and ambiguity. Risk aversion occurs when decision-makers know the probability distribution associated with different possible outcomes and try to avoid risk even at the cost of a reduction in income. For example, producers who are risk averse will be reluctant to adopt improved technologies even if they know the probabilities of the possible outcomes during the adoption process; hence, they prefer to keep their current technology, even if that means reduced earnings (Ward & Singh, 2015).

Ambiguity aversion arises when producers are unsure about the probability distribution associated with different possible outcomes. For example, small-scale producers generally have incomplete information about the price and yield distributions of the various crops that they can plant. A producer who is ambiguity averse will be unwilling to change his/her current crop, even when others might offer more benefits (Warnick et al., 2011).

Even though policy-makers could have informed guesses about the nature of producers' risk and ambiguity preferences, to assume the effect of these preferences on producers decision-making processes can lead to misperceptions and inefficiencies in policy-making process (Johansson-Stenman, 2008). This is also stated by Barham et al. (2014) who report that different agricultural decisions have different degrees of uncertainty for producers. Accordingly, the effect and/or magnitude of producers' risk and ambiguity preferences can vary according to the decision that producers are facing. Hence, producers' risk preferences have different implications for different decisions: adoption of improved farm management practices (Wossen et al., 2015), improved varieties adoption (Liu, 2012; Ward & Singh, 2015) and agricultural insurances uptake (Elabed & Carter, 2015; McIntosh et al., 2015).

As a result, numerous authors have conducted research with experimental methods to study producers' risk preferences in developing countries (Alpizar et al., 2011; Barham et al., 2014; Bocqueho et al., 2013; Cardenas & Carpenter, 2013; Galarza & Carter, 2011; Harrison et al., 2010; Liu, 2012; Nguyen, 2011; Tanaka et al., 2010; Ward & Singh, 2015). Of these studies only Liu (2012) and Nguyen (2011) deal with small-scale producers; Alpizar et al. (2011), Warnick et al. (2011), Galarza & Carter (2011) and Cardenas & Carpenter (2013) work in Latin America. In addition, Toledo & Engler (2008) measure risk aversion in a setting close to ours; however they do not use elicitation methods to measure producers' risk preferences.

However, there is comparatively less research on producers' ambiguity preferences in developing countries (Alpizar et al., 2011; Cardenas & Carpenter, 2013; Ross et al., 2010; Takahashi, 2013; Ward & Singh, 2015; Warnick et al., 2011). Among these studies; Alpizar et al. (2011), Cardenas & Carpenter (2013), Ward & Singh (2015) and Warnick et al. (2011) distinguish between producers' risk and ambiguity preferences. These studies produce mixed results. For instance, Alpizar et al. (2011), Ross et al. (2010) and Warnick et al. (2011) report significant evidence about producers' ambiguity aversion on Costa Rica, Lao PDR and Peru, respectively. Yet Cardenas & Carpenter (2013), Takahashi (2013) and Ward & Singh (2015) do not find significant evidence of producers' ambiguity preferences in studies covering Colombia, Argentina, Venezuela, Peru, Uruguay and Costa Rica, Indonesia and India.

Most studies that analyze producers' risk and ambiguity preferences focus on the influence of these preferences on farm-related decisions such as technology adoption, agricultural insurance uptake, and crop diversification (Liu, 2012; Love et al., 2014; McIntosh et al., 2015; Nguyen, 2011; Tanaka et al., 2010; Ward & Singh, 2015). However, the factors that influence a producer's risk and ambiguity preferences have scarcely been explored in developing countries. The few exceptions include Elabed & Carter (2015), Galarza & Carter (2011) and Harrison et al. (2010). In this paper we elicit risk and ambiguity preferences and we also study the socioeconomic and farm-level factors that explain variation in these preferences across individual smallholders.

Two standard methods have been used to analyze producers' risk preferences from field experiments: the midpoint method (Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015) and the structural method (Andersen et al., 2006; Bocqueho et al., 2013; Harrison et al., 2010). The structural method uses a maximum likelihood approach to create latent variables to estimate producers' risk preferences (Bocqueho et al., 2013; Harrison & Rutström, 2008). According to Harrison & Rutström (2008) and Andersen et al. (2010), the structural method is preferred because it has advantages for multi parameter estimation, such as risk preferences which parameters are estimated jointly.

The midpoint method is an analytical approach that uses a series of equations to calculate a producer's risk preferences (Harrison & Rutström, 2008). This method uses information from risk experiments around the producer's switching choice during risk experiment's series to jointly create producer's risk preferences' upper and lower bounds (Bocqueho et al., 2013; Liu, 2012).

According to Andersen et al. (2008), the structural method is a flexible way to estimate producers' risk preferences from field experiments. We agree with that statement, considering that this method uses maximum likelihood to maximize producers' risk preferences' parameters, while using first and second derivatives to achieve the maximization process and minimizing parameter's variance.

Even though that midpoint and structural methods are standard to estimate risk preferences from field experiments, as of today only Bocqueho et al. (2013) compare the results of producers' risk preferences by using both methods in a developed country context. Therefore, we contribute to current literature with empirical evidence about producers' risk preferences estimated by using both methods in an emerging economy.

2.3 Survey and experimental setting

2.3.1 Survey

The data were collected in a survey carried out from June to September 2015 in nine rural communes of Maule region: Molina, Romeral, Longaví, Parral, Retiro, Yerbas Buenas, Río Claro, Curicó and San Clemente. These communes are known in Maule for their raspberry production (Instituto de Desarrollo Agropecuario, 2007). One the most relevant actors that work with small-scale berry producers in Maule region is the National Institute for Agricultural Development (INDAP, official acronym in Spanish), a state department that focuses its work on small-scale producers in Chile. We selected households for our survey based on INDAP's 2011 national dataset of raspberry producers (Instituto de Desarrollo Agropecuario, 2011). From this dataset, we randomly selected 250 small-scale raspberry producers who live in rural Maule. We contacted these producers by phone to make appointments, and conducted field experiments and questionnaires. Of the 250 producers selected from INDAP's list, 148 were excluded because they no longer produce raspberries, their contact information was incorrect, or they were not willing to participate. Ultimately, we conduct our field experiments and questionnaire with 102 producers (Figure 2-1).

During the initial phone call, we informed producers that the session would last about ninety minutes, but we did not inform them about the experiment or the incentive for participating. As a result, a potential participants' decision to take part in the survey was not affected by his/her risk and ambiguity preferences, which reduces the likelihood of selection bias.

In addition to the experiment, we also interviewed producers according to a survey to collect information on their socioeconomic characteristics and the characteristics of their farm operations that could influence their risk and ambiguity preferences.

Table 2-*1* shows descriptive statistics of our sample. On average, producers are just over 51 years of age, their households are composed of three to four members, and the household head has eight years of education. The average total farm size is 3.6 hectares, of which 0.5 hectares are used to grow raspberries. In addition, fifty percent of the surveyed households have access to saving accounts, and 54 percent have access to agricultural loans. Also, producers have more than ten years of experience working with raspberries, and 19 percent of them are members of a farmers' association. Finally, one-third of the producers earn off-farm income, and their mean monthly household expenditure is 226·657 Chilean pesos (approximately € 325)[3].

[3] When the fieldwork was conducted the exchange rate was just under 700 Chilean pesos per Euro.

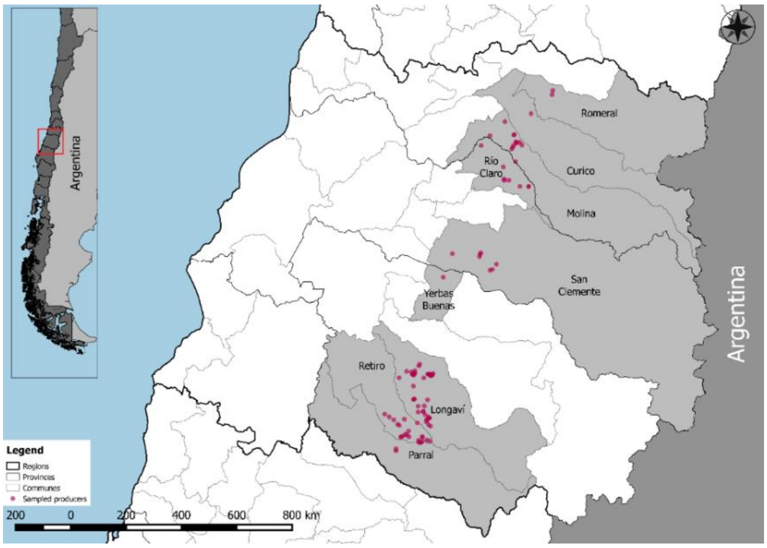

Figure 2-1. Location of sampled producers in rural Maule, Chile
*Source**: Authors' own calculations based on Sistema Integrado de Información Territorial (SIIT) (2014)***

Table 2-1. Descriptive statistics

Variable description	**Mean**	**Standard error**
Producer's age	51.25	1.30
Household size	3.39	0.11
Years of education	7.96	0.32
Total raspberry area (ha)	0.50	0.05
Total farm size (ha)	3.60	0.63
Proportion of producers who have off-farm income	0.33	0.05
Proportion of producers with access to saving accounts	0.50	0.05
Proportion of producers with access to agricultural loans	0.54	0.05
Years working with raspberry	10.65	0.64
Proportion of producers who are members of farmers' association	0.19	0.04
Monthly household expenditure (Chilean pesos)	226·657	10·613
Total observations	**102**	

Source: own calculations

2.3.2 Structure of the experimental session

We describe the data collection process in two sub-sections. The first sub-section describes the field experiments used to elicit producers' risk and ambiguity preferences, and the second sub-section describes the questionnaire that we used to collect information on producers' socioeconomic and farm characteristics.

To elicit producers' risk preferences, we followed Ward & Singh's (2015) modification of Tanaka et al.'s (2010) MPL experiment. This experiment has a well-defined structure, calibrated payouts and it is simple to use. We used another modification proposed by Ward and Singh to determine producers' ambiguity preference. By combining these modified experiments, we were able to maintain the same general structure and rules during the experimental sessions, which increased producers' comprehension and reduced errors and inconsistencies.

The experimental session was divided into risk and ambiguity experiments; during both experiments, producers faced a series of binary choices (rounds) to elicit their risk and ambiguity preferences. The ambiguity experiment consisted of two series, each of 11 rounds, and the risk experiment consisted of three series, two of 14 rounds and one of seven. In total, producers were presented with 57 rounds. Each round was composed of a safe lottery (lottery A) and a risk lottery (lottery B). Whenever lottery A was selected, producers won a certain amount of money; however, when lottery B was selected then producers faced two possible outcomes, winning and losing. Compared with the safe lottery A, the winning outcome in lottery B involved a larger payment, and the losing outcome involved a smaller payment.

Each producer's task during the experimental session was to decide which lottery he/she would choose for every one of the 57 rounds. To minimize errors during both experiments, we followed Tanaka et al. (2010) and Andersen et al. (2006) and asked producers to select from each series the round at which they would like to switch lotteries. However, we did not force them to switch; in this way, we assured that producers' answers capture their true preferences under risk and ambiguity scenarios.

During the experimental session we encountered four types of behavior: producers who never switched, whom we consider to be strongly risk averse; producers who switched at the beginning, whom we consider to be strong risk seekers; farmers who switched from one lottery to the other according to the expected value, whom we consider to be risk neutral; and producers who switched back and forth among lotteries, whom we consider to be inconsistent[4] (Bocqueho et al., 2013; Tanaka et al., 2010; Ward & Singh, 2015).

2.3.3 Experiment's incentive

To capture producers' true risk and ambiguity preferences, we provided participants with two monetary incentives. First, we gave an incentive at the beginning of the experiment. This incentive had two goals: to convince producers that they would earn money during this session, and to create an endowment effect in their minds (Liu, 2012; Tanaka et al., 2010). This endowment effect has crucial implications for producers' risk preferences in losses domain elicitation.

[4] One of the assumptions of risk experiments is that producers switch from lottery A to lottery B according to the lottery outcome. Lottery A's outcome remains constant in all rounds, while the outcome of lottery B increases monotonically from round to round. It is expected that producers will eventually switch to lottery B to earn a larger outcome, however we do not expect producers to switch back to lottery A to earn a smaller outcome. Hence, we consider producers who switch back and forth between lotteries to be inconsistent (Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015).

Second, immediately after we gave the first part of the incentive to producers, we explained that they would earn more money according to their decisions during the session. We clarified that one of the ensuing rounds would be selected randomly, and we that would pay more money according to their decision in that round. The goal of this incentive was to encourage them to consider all of their decision carefully. On average, producers earned roughly 14·000 Chilean pesos (roughly € 20) altogether.

To randomly select the round that determined the final pay-off, we used two black opaque bags. The first bag contained numbered chips that corresponded to each round of the experimental session. Producers selected one chip and the number selected determined the pay-off round. If a producer chose the safe lottery in this round, then he/she received the riskless amount of money declared in the series; if the producers chose the risky lottery in this round, then he/she was asked to draw from the second bag. This bag contained ten balls, some blue (winning) and some green (losing). The proportion of blue and green balls varied according to the probabilities stated in each series, and the color of the ball selected determined the amount of the final pay-off.

2.3.4 Ambiguity experiment

In both series of the ambiguity experiment, lottery A had a constant payment across all rounds. Similarly, the winning outcome in lottery B was also constant, but it involved a larger payment than lottery A, while the losing outcome in lottery B was smaller and decreased as the rounds progressed (Table A-1). To integrate the ambiguity specification into the experiment, during the first series of this experiment we intentionally did not reveal probabilities of winning and losing outcomes in lottery B. Therefore, producers needed to decide whether and when to switch based on a comparison of lottery A with known information and probabilities, and lottery B with incomplete information.

One of the assumptions of this experiment is that producers subjectively assign probabilities to winning and losing outcomes in lottery B. Hence, to capture this information, after the first series we asked them to reveal what they thought were the probabilities associated with the outcomes in lottery B. This is the only series in the experimental session in which we kept information from producers, and to avoid that their assessments be biased by the information that they received in other series, we began the experimental session with this series.

In the second series of this experiment, producers faced the same outcomes as in the first; however, this time we revealed the probabilities associated with winning and losing outcomes in lottery B. Since producers were provided with complete information in both lotteries, there was only risk and no ambiguity specification in this series.

2.3.5 Risk experiment

In the first two series of risk experiment, the outcome in lottery A was constant across all rounds. Similar to lottery A, the losing outcome in lottery B was also constant. However, in the risk experiment the winning outcome in lottery B increased as the rounds progressed (Table A-2).

The third series of the risk experiment differed from the previous series in two ways. First, there was no certain outcome in lottery A, as both lotteries A and B involved winning and losing outcomes. Second, the losing outcome in both lotteries involved real losses (Table A-3). However, these losses were designed so that given the initial incentive provided to all producers, no one could lose money overall. In addition, the endowment effect created with the first part of the incentive was necessary for this experiment to reveal producers' risk preferences in the loss domain. Producers realized that they could lose at least part of the initially provided incentive and, hence, had an incentive to reveal their true preferences.

2.4 Structural specification and experimental derivation of risk and ambiguity preferences

To address producers' risk and ambiguity preferences we estimate four parameters. First, the curvature of the prospect value function (σ) reflects how a producer behaves when confronted with risk in the gains domain. Second, the loss aversion parameter (λ) captures how a producer behaves when facing risk in the losses domain. Third, the probability weighing parameter (γ) characterizes whether producers disproportionately give more importance to low probability events when facing risk. Fourth, the augmented utility parameter (θ) dictates how a producer's utility that results from lotteries varies when he/she faces both risk and ambiguity scenarios. The interaction of the σ, λ and γ parameters reflects producers' risk preferences, and θ captures their ambiguity preferences (Harrison et al., 2010; Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015).

We follow Ward & Singh's (2015) method to assess producers' risk and ambiguity preferences, but deviate from their study in three ways. First, Ward & Singh only use the midpoint estimation method to assess producers' risk and ambiguity preferences, whereas we also use the structural method to assess their risk preferences (Bocqueho et al., 2013; Harrison et al., 2010). Second, Ward and Singh (2015) calculate two versions of ambiguity preferences: naïve and subjective. In naïve estimation, the producers' subjective probabilities are assumed to be $\hat{p} = 1 - \hat{p} = 0.5$, during the first series of the ambiguity experiment. In subjective estimation subjective probabilities provided by producers following the first series of the experimental session are used. We consider that the probability assumption underlying the naïve estimation is unrealistic and consequently we only carry out the subjective estimation. Third, Ward and Singh (2015) analyze the influence of producers' risk and ambiguity preferences on the adoption of improved varieties. We focus instead on analyzing the socioeconomic and farm factors that influence a producer's ambiguity and risk preference, and not on the effect of these preferences on a specific decision.

2.4.1 Producers' risk preferences estimation with the structural method

During risk experiment, producers face scenarios with two possible outcomes, x and y in the gains and losses domains. Hence, the CPT first establishes two coefficients to differentiate among these domains (Bocqueho et al., 2013; Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015):

$$v(x) = \begin{cases} x^{\sigma} & if\ x > 0 \\ -\lambda(-x)^{\sigma} & if\ x < 0 \end{cases} \tag{2.1}$$

In (1) σ represents the curvature of the prospect value function in the gains domain. This preference should be greater than zero. $\sigma < 0.5$ denotes a strong concavity in the curvature of the prospect value function, which correlates with a strong risk aversion; $0.5 < \sigma < 0.9$ implies moderate risk aversion; $\sigma = 1$ implies risk neutrality; and $\sigma > 1$ implies risk seeking behavior.

Furthermore, λ represents producers' sensitivity to losses. If $\lambda > 1$, then producers are more sensitive to losses than gains; if $\lambda < 1$, then they are less sensitive to losses; and $\lambda = 1$ suggests that producers are indifferent.

We follow Tanaka et al. (2010) and calculate the decision weights based on cumulative probabilities, this equation is written as:

$$u(x, y, p) = \begin{cases} v(y) + \omega(p) \cdot (v(x) - v(y)) & if\ x \geq y \geq 0\ or\ x \leq y \leq 0 \\ \omega(p) \cdot v(x) + \omega(1-p) \cdot v(y) & if\ x < 0 < y \end{cases} \tag{2.2}$$

where $u(x, y, p)$ represents producers' lottery utility with outcomes x and y, and probabilities p and $1 - p$, respectively, and $\omega(\cdot)$ is a probability weighting function that measures whether a producer distorts probabilities of unlikely events. To be consistent with recent literature, we follow Tanaka et al. (2010), Liu (2012), Bocqueho et al. (2013) and Prelec's (1998) to define this function as:

$$\omega(p) = \exp[-(-\ln p)^{\gamma}] \tag{2.3}$$

where γ captures whether producers distort the probabilities of events when facing risk situations. If $\gamma < 1$, this function has an inverse s-shape form, which means that producers over-weigh low probability outcomes and under-weigh high probability results. When $\gamma = 1$, there is no probability distortion and the function is a straight line. When $\gamma > 1$ the function takes a s-shape form and producers tend to under-weigh extreme events (Nguyen, 2011; Tanaka et al., 2010).

We consider Δ_{RP} to be the producers' utility difference between both lotteries. We use Δ_{RP} as an input variable in the following likelihood function, which is conditional to the structural specification:

$$\ln L^{RP}(\delta, X;\ \sigma, \gamma, \lambda) = \sum_k \left[ln\Phi(\Delta_{RP}) \times I(\delta_j = A) + \ln(1 - \Phi(\Delta_{RP})) \times I(\delta_j = B)\right] \quad (2.4)$$

In equation (4), Φ represents the cumulative distribution function of the standard normal distribution and the δ_j are the producers' lottery choices. The maximum likelihood function for $(\sigma, \gamma, \lambda)$ is:

$$(\hat{\sigma}, \hat{\gamma}, \hat{\lambda}) = \arg\max \ln L^{RP}(\delta, X;\ \sigma, \gamma, \lambda) \quad (2.5)$$

To calculate $(\hat{\sigma}, \hat{\gamma}, \hat{\lambda})$, we implement the maximum likelihood probit method[5] in STATA, following structural method by Harrison (2008) and Bocqueho et al. (2013). This method allows us to estimate producers risk preferences by using all producers' decisions during the experiment. Since, decisions from the same producer could be correlated, we cluster the standard errors in our estimation (Andersen et al., 2010; Bocqueho et al., 2013; Harrison, 2008)[6].

2.4.2 Producers' risk preferences estimation with the midpoint method

We also estimate γ and σ jointly using the midpoint method (Tanaka et al., 2010; Liu, 2012). This method applies equations (2.1) through (2.3) to information generated by the switching choices between lotteries A and B of the risk experiment. Applying these equations produces a set of inequalities for each series; solving for γ and σ in these inequalities, we estimate parameters' upper and lower bounds.

Since there are many values of γ and σ that satisfy these inequalities, we use the combination of these parameters that maximizes producers' expected utility from both lotteries. For example, consider, a producer who in the risk section switches at choice five in series one and at choice six in series two; in this case we must solve the following inequalities:

$$Series\ 1 \begin{cases} 0^\sigma + \exp[-(-\ln 1)^\gamma] * (1200^\sigma - 0^\sigma) > 600^\sigma + \exp[-(-\ln 0.1)^\gamma] * (4900^\sigma - 600^\sigma) \ \ if\ \delta_j = A \\ 0^\sigma + \exp[-(-\ln 1)^\gamma] * (1200^\sigma - 0^\sigma) < 600^\sigma + \exp[-(-\ln 0.1)^\gamma] * (5650^\sigma - 600^\sigma) \ \ if\ \delta_j = B \end{cases}$$

[5] To be consistent with recent literature, we used a probit model for our calculations. The results of a logit estimation (available from the authors) are similar.

[6] Since during the risk experiment, each producer faces a total of 35 decisions to make (rounds) and we cluster by producers. Altogether we have a total of 3255 observations in 93 clusters.

$$Series\ 2 \begin{cases} 0^{\sigma} + \exp[-(-\ln 1)^{\gamma}] * (4000^{\sigma} - 0^{\sigma}) > 500^{\sigma} + \exp[-(-\ln 0.7)^{\gamma}] * (6900^{\sigma} - 500^{\sigma})\ if\ \delta_k = A \\ 0^{\sigma} + \exp[-(-\ln 1)^{\gamma}] * (4000^{\sigma} - 0^{\sigma}) < 500^{\sigma} + \exp[-(-\ln 0.7)^{\gamma}] * (7300^{\sigma} - 500^{\sigma})\ if\ \delta_k = B \end{cases}$$

In these inequalities, γ and σ are the arguments that we jointly maximize to quantify the producer's risk preferences. δ_j and δ_k represent a producers' lottery choice regarding the switching round in series one and two of the risk experiment, respectively. In this example, the values for γ and σ that maximize utility are 1 and 0.91 for series one, and 1 and 0.77 for series two; hence, the mean values are 1 and 0.84 for σ and γ, respectively.

We calculate λ from the third series of the risk section. Since we know producers' switching choice, and equations (2.1) and (2.2), solving for λ produces the loss aversion parameter equation (2.6) (Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015). Since the probability for every outcome in lottery B is the same ($p = 1 - p = 0.5$), γ does not play a role in this estimation and is dropped from λ parameter calculation.

$$\lambda_j(\sigma) = \frac{x_{j,A}^{\sigma} - x_{j,B}^{\sigma}}{(-y_{j,A})^{\sigma} - (-y_{j,B})^{\sigma}} \tag{2.6}$$

2.4.3 Producers' ambiguity preference estimation

Following Ward & Singh (2015), we also use the midpoint method to determine producers' ambiguity preference. Therefore, we assume that a producer's utilities at the switching choices of both lotteries are equal; in other words:

$$U(x_A) = [U(x_{j,B}, y_{j,B}; \hat{p}, 1 - \hat{p}; \gamma, \sigma)]^{\theta} \tag{2.7}$$

where x and y are winning and losing outcomes, respectively, and j represents switching choice during series one, in which we did not inform producers about the probabilities of outcomes in lottery B. Hence, to reveal a producer's subjective probability after the first series we asked him/her what he/she thinks are the probabilities associated with winning ($\hat{p}$) and losing ($1 - \hat{p}$) in lottery B, and we use these probabilities in equation (2.7). Consequently, θ captures a producer's ambiguity preference based on his/her choice of an ambiguity lottery with incomplete information over a safe lottery with complete information. λ only arises when analyzing risk preferences in the loss domain; since we analyze producers' ambiguity preference on gains domain, we do not calculate a loss aversion parameter.

To calculate producers' utility based on the second series of the ambiguity experiment, we also use equation (2.7). Since we reveal the probabilities associated with winning and losing outcomes to the producers, θ does not play a role in this series. Furthermore, since outcomes for lotteries A and B are equal in both series, we can compare a producer's utility in both series at switching choices j and k for the first and second series, respectively. Then, solving for θ we find the equation that captures the producer's ambiguity preference:

$$\theta = \frac{\ln U(x_{k,B}, y_{k,B}; p, 1-p; \gamma, \sigma)}{\ln U(x_{j,B}, y_{j,B}; \hat{p}, 1-\hat{p}; \gamma, \sigma)} \tag{2.8}$$

$\theta > 1$ implies that the utility that results from the lottery is larger when ambiguity is absent, i.e. that the producer is ambiguity averse. If $\theta = 1$ then the producer derives the same utility from both series, i.e. he/she is ambiguity neutral. If $\theta < 1$ then the utility from the lottery is larger when ambiguity is present, i.e. the producer is an ambiguity seeker.

To identify the factors that influence producers' risk and ambiguity preferences, we follow Harrison & Rutström (2008) and Ward & Singh (2015) and conduct probit and OLS models to regress these preferences on a set of producers' socioeconomic and farm characteristics. According to the current literature, we expect that producer's assets decrease producer's risk aversion. Hence, we include available land to produce and off-farm income as covariates (Liu, 2012; Tanaka et al., 2010; Ward & Singh, 2015). Also, we expect that producers who are more risk averse tend to look for risk-sharing institutions, such as farmers' associations (Mobarak & Rosenzweig, 2013). In addition, we include other producer's characteristics that could decrease producers' risk and ambiguity aversion, such as years of education, access to agricultural loans, producer's experience working with raspberry, and household expenditure as a proxy for producers' household income (Cardenas & Carpenter, 2013; Warnick et al., 2011). Furthermore, we include producer's gender to identify if there are differences of producers' risk and ambiguity preferences between male and female producers (Ward & Singh, 2015). Finally, we include additional characteristics that we expect them to increase producers' risk and ambiguity aversion, such as the producer's age and household size (Alpizar et al., 2011; Harrison et al., 2010; Ross et al., 2010; Warnick et al., 2011). Although many studies find no evidence that household expenditure, household size, and available land influence producers' risk and ambiguity preferences, we believe that they might have an influence in the Chilean context (Liu, 2012; Ward & Singh, 2015; Warnick et al., 2011).

2.5 Results

Following Hirschauer et al. (2014), inconsistent producers can bias the mean and variance of producers' risk and ambiguity preferences estimates. In our data, nine producers show inconsistent behavior and are excluded from the analysis.

In the following we first present the results of the estimation of producers' risk preferences. Then we show how these estimates differ depending on whether they are produced using the midpoint or the structural method. Later we present the results for the regression of producers' risk preferences on a set of producers' characteristics. Finally, we present the results for producers' ambiguity preference and the regression of producers' ambiguity preference on producer specific socioeconomic and farm characteristics.

2.5.1 Producers' risk preferences estimation method comparison

Our estimates for producers' risk preferences parameters (γ, λ and σ) are shown in Table 2-2. We find with the structural method that producers' risk preferences are significantly different from zero ($p < 0.001$), and that $\lambda > 1$ and $\sigma < 1$, both at 99 percent significance level ($p < 0.001$). This implies that producers are risk and loss averse.

We find that $\gamma = 0.952$, with a 95 percent confidence interval of 0.791 – 1.111. Since this estimate is not different from one ($p = 0.56$), we conclude that on average, producers do not distort the probabilities of unlikely extreme events. This behavior is consistent with other theories in the literature that assume linear probability weighing among producers (Galarza, 2009; Harrison et al., 2010)[7]. Regarding loss aversion, we find that $\lambda = 2.06$, with a 95 percent confidence interval of 1.607 – 2.517. This suggests that producers are roughly twice as sensitive to losses as they are to gains. This result is consistent with those of Liu (2012) ($\lambda = 3.47$) and Nguyen (2011) ($\lambda = 3.255$). We also find that $\sigma = 0.214$, with a 95 percent confidence interval of 0.199 – 0.228. This points to a strong risk aversion among producers (Andersen et al., 2010), and is similar to findings by Harrison et al. (2010) ($\sigma = 0.464$), Tanaka et al. (2010) ($\sigma = 0.59$) and Liu (2012) ($\sigma = 0.48$).

Table 2-2. Comparison of producers' risk preferences estimates

	Structural method					Midpoint method				
	Coefficient	Std. Err.	95 percent confidence interval		$\beta_0 = 1$	Coefficient	Std. Err.	95 percent confidence interval		$\beta_0 = 1$
γ	0.952***	(0.082)	0.791	1.111	0.56	0.849***	(0.03)	0.787	0.910	0.00
λ	2.062***	(0.232)	1.607	2.517	0.00	3.543***	(0.28)	2.986	4.100	0.00
σ	0.214***	(0.007)	0.199	0.228	0.00	0.659***	(0.04)	0.583	0.734	0.00
θ						1.497***	(0.24)	1.020	1.973	0.04

Source: own calculations; Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Furthermore, like Bocqueho et al. (2013) we find that producers' risk preferences estimates from both methods are similar. However, there are three important differences. First, that the estimate of σ from the structural method ($\sigma = 0.214$) is lower than that from the midpoint method ($\sigma = 0.659$). Hence, while our result for σ with the structural method suggests strong risk aversion, our result with the midpoint method suggests only moderate risk aversion. Second, λ increases from 2.062 with the structural method to 3.543 with the midpoint method. Hence, according to the midpoint method producers are on average three and a half times more sensitive to losses as they are to gains. Further, both changes on σ and λ increase the asymmetry between producers' risk preferences in gains and loses domains.

[7] Expected Utility Theory (EUT) is one of the most prominent theories used to address producers' risk preferences, and it assumes linear probability weighing among producers (Bocqueho et al., 2013; Harrison & Rutström, 2008; Tanaka et al., 2010).

Third, the estimate of γ is similar for both estimation methods. However, according to the results of the structural method γ does not differ from one ($p = 0.56$), while with the midpoint method it is statistically smaller than one ($p < 0.01$). Hence, the structural estimate indicates that producers do not disproportionately distort the probabilities of unlikely events but the midpoint method estimate indicates that they over-weigh unlikely events (Bocqueho et al., 2013; Liu, 2012; Ward & Singh, 2015). Our estimate of γ with the midpoint method is similar to estimates by Liu (2012), Tanaka et al. (2010) and Ward & Singh (2015), who find that $\gamma = 0.69$, 0.74 and 0.736, respectively.

2.5.2 Producers' risk preferences determinants

In Table 2-3 we present the results of the probit and OLS regressions estimations of producers' risk and ambiguity preferences on their socioeconomic and farm characteristics respectively. First, we find that γ increases with producers' age, education and available land to produce. Hence, older, more educated producers who farm more land are more likely to under-weigh unlikely events. In addition, producers who are members of a farmers' association and have larger household expenditures are more likely to over-weigh unlikely events. These results are similar to those of Galarza (2009) who finds that education has a significant influence on the size of the probability weighing parameter. We are not aware of any other studies that analyze the influence of membership in a farmers' association on risk preferences, but one possible explanation is that producers who over-weigh unlikely events consider farmers' associations as an informal means of risk sharing. Moreover, we are not aware of previous studies that find significant effects of household expenditure, household size, available land to produce, and producer's age on γ.

Second, as expected we find that producers' available land correlates with less loss aversion. In addition, λ is positively correlated with producer's age. However, the size of this effect is small. These results are similar to those of Liu (2012) who also reports that available land correlates with less loss aversion among producers, and Tanaka et al. (2010) who also show that producer's age is correlated with λ.

Third, our results show that producers' age and agricultural loans are associated with stronger risk aversion σ. Also, producers with larger household expenditure are less risk averse. Our results for this parameter are similar to Harrison et al. (2010) and Alpizar et al. (2011), who find that σ increases with age, and to Ward & Singh (2015), who report similar effects for expenditure.

Table 2-3. Regression estimates of producers' risk and ambiguity preferences on their socioeconomic and farm characteristics

	Variable description	Coefficient		Std. Err.
Producer's risk preferences				
γ	Constant	0.554		(0.692)
	Producer's age	0.021	*	(0.012)
	Female	-0.129		(0.148)
	Household size	-0.091		(0.103)
	Agricultural loans (1 = yes)	0.331		(0.341)
	Years studied	0.056	*	(0.031)
	Total available land	0.024	**	(0.010)
	Farmers' association member	-0.359	**	(0.177)
	Off farm income	0.013		(0.243)
	Monthly household expenditure (CLP 100·000)	-0.302	**	(0.149)
λ	Constant	0.884		(2.985)
	Producer's age	0.059	*	(0.032)
	Female	-0.560		(0.672)
	Household size	-0.135		(0.336)
	Agricultural loans (1 = yes)	-0.470		(1.207)
	Years studied	0.091		(0.161)
	Total available land	-0.125	***	(0.040)
	Farmers' association member	1.887		(1.209)
	Off farm income	-0.971		(0.740)
	Monthly household expenditure (CLP 100·000)	-0.309		(0.389)
σ	Constant	0.178	*	(0.102)
	Producer's age	-0.002	*	(0.001)
	Female	-0.012		(0.023)
	Household size	0.013		(0.012)
	Agricultural loans (1 = yes)	-0.060	*	(0.032)
	Years studied	0.008		(0.007)
	Total available land	0.002		(0.001)
	Farmers' association member	-0.028		(0.031)
	Off farm income	-0.045		(0.038)
	Monthly household expenditure (CLP 100·000)	0.029	***	(0.010)
	Model p-value	0.002		
Producer's ambiguity preferences				
θ	Constant	0.096		(1.531)
	Age	-0.016		(0.019)
	Female	-1.130	*	(0.560)
	Household size	0.373	*	(0.218)
	Agricultural loans (1 = yes)	-0.966		(0.614)
	Total land available	-0.052		(0.043)
	Farmers' association member	-0.773		(0.627)
	Monthly household expenditure (CLP 100·000)	0.480	**	(0.237)
	Years working with raspberry	0.099	**	(0.042)
	Model p-value	0.080		
	r^2	0.068		

Source: own calculations; Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

2.5.3 Producers' ambiguity preferences

Our estimate of θ is 1.497, with a 95 percent confidence interval of 1.02 – 1.97 (Table 2). Since θ is significantly larger than one ($p = 0.041$), producers are, on average, ambiguity averse. This confirms findings by Alpizar et al. (2011) and Warnick et al. (2011), who report ambiguity aversion among small-scale producers in Costa Rica and Peru, respectively.

In Table 2-3 we report the results of regressing θ on a set of producers' socioeconomic and farm characteristics. Our results show that on average female producers are less ambiguity averse than male producers. Contrary to our expectations, household expenditure and years of experience working with raspberry are positively correlated with ambiguity aversion, as is household size. Cardenas & Carpenter (2013) also find a significant effect of gender on ambiguity preferences, however they report the opposite effect. This might be due to the fact that Cardenas & Carpenter study urban individuals from the capital cities of six countries in Latin America, while we study small producers in rural Chile.

In addition, we find that producers from larger households are more ambiguity averse. Warnick et al. (2011) also find a significant effect for household size on producers' ambiguity preference. Cardenas & Carpenter (2013) analyze the effect of producers' income, and Warnick et al. (2011) consider the influence of producers' experience on their ambiguity preference; however they do not find that these variables have significant effects. Furthermore, their studies are carried out in developed countries. To the best of our knowledge we are the first to analyze factors that influence ambiguity aversion in a developing country.

2.6 Conclusions

Our research contributes to the understanding of small raspberry producers' decision-making process by analyzing their risk and ambiguity preferences in rural Maule. We highlight three main findings. First, producers are strongly risk averse, and there is an asymmetry between the gains and losses domains, implying that on average producers do not behave in the same way for rewards and for penalizations. Producers put more effort into avoiding losses than into realizing gains (Bocqueho et al., 2013). In addition, we find that producers derive less utility from the experiments in which ambiguity is present, which implies that producers are on average ambiguity averse.

Second, our results show that the midpoint and structural methods produce different estimates of producers' risk preferences. The results from the midpoint method suggest that producers are less risk averse, and that the asymmetry between risk aversion in gains and losses domains is larger, than the results from the structural method. These different estimates have obvious connotations for agricultural policies and strategies design.

Third, we find that many producers' socioeconomic and farm characteristics are correlated with their risk and ambiguity preferences. According to our estimates, age, membership in a farmers' association membership, and current agricultural loans are positively correlated with a producer's risk and loss aversion. Years of education, total available land, and monthly household expenditure are negatively correlated with risk and loss aversion. We also find that male producers, household size, monthly household expenditure, and years of experience working with raspberry are positively correlated with ambiguity aversion.

Possible venues for future research are to apply different methods to measure producers' risk and ambiguity preferences, such as Harrison et al.'s (2010) mixture method to estimate risk preferences, and Cardenas & Carpenter's (2013) method to estimate ambiguity preference. Applying Tanaka et al.'s (2010) method for measuring time preferences could generate further insights into producers' behavior under uncertainty. Ultimately, research such as this can help public and private stakeholders design and improve policies and products that help smallholders in Chile deal with risk and uncertainty.

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Appendix

Table A-1. Payoff schedule for ambiguity experiment (in Chilean pesos)

Round	**Lottery A**	**Lottery B**[+]		**Expected payoff difference**[*]
Series 1 and 2	*Probability = 1*	*Probability = 0.5*[+]	*Probability = 0.5*[+]	
1	2200	4400	2200	-1100
2	2200	4400	1800	-900
3	2200	4400	1400	-700
4	2200	4400	1100	-550
5	2200	4400	850	-425
6	2200	4400	750	-375
7	2200	4400	650	-325
8	2200	4400	550	-275
9	2200	4400	400	-200
10	2200	4400	200	-100
11	2200	4400	0	0

Source: own calculations
* Expected payoff difference (expected utility of lottery A – expected utility of lottery B) is not shown to producers.
\+ The producers were not informed about these probabilities during the first series of the ambiguity section.

Table A-2. Payoff schedule for the first two series of risk experiment (in Chilean pesos)

Round	**Lottery A**	**Lottery B**		**Expected payoff difference***
Series 1	*Probability = 1*	*Probability = 0.1*	*Probability = 0.9*	
1	1200	3100	600	350
2	1200	3400	600	320
3	1200	3850	600	275
4	1200	4300	600	230
5	1200	4900	600	170
6	1200	5650	600	95
7	1200	6700	600	-10
8	1200	7600	600	-100
9	1200	8650	600	-205
10	1200	10200	600	-360
11	1200	12500	600	-590
12	1200	16000	600	-940
13	1200	21750	600	-1515
14	1200	33600	600	-2700
Series 2	*Probability = 1*	*Probability = 0.7*	*Probability = 0.3*	
1	4000	5600	500	-70
2	4000	5700	500	-140
3	4000	6000	500	-350
4	4000	6200	500	-490
5	4000	6500	500	-700
6	4000	6900	500	-980
7	4000	7300	500	-1260
8	4000	7700	500	-1540
9	4000	8200	500	-1890
10	4000	8700	500	-2240
11	4000	9500	500	-2800
12	4000	10500	500	-3500
13	4000	11900	500	-4480
14	4000	13700	500	-5740

Source: Own calculations
* Expected payoff difference (expected utility of lottery A – expected utility of lottery B) is not shown to producers.

Table A-3. Payoff schedule for third series of risk experiment (in Chilean pesos)

Round	**Lottery A** *Probability = 0.5*	*Probability = 0.5*	**Lottery B** *Probability = 0.5*	*Probability = 0.5*	**Expected payoff difference***
1	10000	- 2000	12000	- 8500	2250
2	2000	- 2000	12000	- 8500	-1750
3	500	- 2000	12000	- 8500	-2500
4	500	- 4000	12000	- 6800	-4350
5	500	- 4000	12000	- 6800	-4350
6	500	- 4000	12000	- 5900	-4800
7	500	- 4000	12000	- 4650	-5425

Source: Own calculations
* Expected payoff difference (expected utility of lottery A – expected utility of lottery B) is not shown to the producers.

3 The role of spatial patterns and producers' risk and ambiguity preferences on small-scale agricultural technology adoption

Abstract

Raspberry production is the main source of income for more than twenty thousand Chilean small-scale producers. Daily, these producers face market, financial, and climate constraints; they must cope with uncertainty in their production system. The Maule region, where most of Chilean raspberry production is located, is vulnerable to climate variability and climate change effects. To help producers cope with this vulnerability, the Chilean government developed a plan to adapt agriculture to climate change and climate variability. In this plan, producers' technology adoption plays a key role in mitigating climate effects on agriculture. However, there are no previous studies in Chile that analyze technology adoption decisions of small-scale raspberry producers. Hence, our research focuses on adoption of drip irrigation and improved varieties as technologies that could help producers to cope with climate effects.

We use a spatial Durbin probit model to identify how producers' socioeconomic and farm characteristics, risk and ambiguity preferences, and spatial patterns influence their decisions to adoption technology. Our findings confirm that risk and ambiguity averse producers are less likely to adopt improved technologies. Also, a producer's decision to adopt, his/her socioeconomic characteristics and risk and ambiguity preferences generate spatial spill-over effects that influence neighboring producers' adoption decisions.

3.1 Introduction

Technology adoption is a key component for producers to cope with uncertainty in their production systems. Moreover, technology adoption is also of particular relevance for small-scale producers to face and adapt to uncertain situations (Alpizar et al., 2011; Bhargava et al., 2015; Ross et al., 2010; Tambo & Abdoulaye, 2011). According to previous studies, a producer's socioeconomic and farm characteristics, and his/her risk and ambiguity preferences influence a producer's decision to adopt (Barham et al., 2014; Liu, 2012; Ward & Singh, 2015; Wossen et al., 2015). In addition, some authors demonstrate that a producer's farm-related decisions are not random within a territory, but rather there are spatial patterns that influence a producer's decision to adopt. This means that a producer's attitude towards a technology, and his/her characteristics generate spatial spill-over effects that influence neighboring producers' decisions to adopt the same technology (Bhargava et al., 2015; Bichler et al., 2005; Edirisinghe et al., 2013; Wollni & Andersson, 2014).

Kane (1999), Minetti et al. (2003) and Universidad de Chile (2006) discuss Chilean vulnerability towards climate variability and climate change, and report that the Chilean northern and central regions show a decreasing rainfall trend based on historic rainfall records. This rainfall reduction, in combination with the variability caused by El Niño Southern Oscillation (ENSO), increases producers' uncertainty in their production systems. The Chilean government is aware of this situation and created a national plan to adapt forestry, farming and livestock development to climate change and climate variability (Gobierno de Chile, 2013). In this plan, the Chilean government details strategies to adapt agriculture to climate change and climate variability for the oncoming years. Producers' adoption of improved varieties to resist drought and diseases, water saving irrigation technology and other related practices are key components of these strategies. Consequently, understanding a producer's decision to adopt these technologies is relevant for the Chilean government and other policy-makers to adapt agriculture to climate change and climate variability.

Since small-scale producers face stiffer constraints to adapt to changes and shocks, compared with medium and large-scale producers, we focus on small-scale raspberry producers in the rural areas of the Maule region, in central Chile (Handschuch et al., 2013; Morton, 2007). In addition, we focus on raspberry production because as of today, Chile is one of the largest raspberry producers worldwide; in this country raspberry exports represent three percent of the total fruit exports (Jara-Rojas et al., 2016). Furthermore, the Chilean raspberry market is mostly composed of small-scale producers. Currently there are more than twenty thousand producers to whom raspberry production represents an important portion of their income. The Maule region alone agglomerates more than sixteen thousand producers (Domínguez, 2012). Despite the relevance of raspberry production for small-scale producers and their families in central regions of Chile, as of today, there have been no previous studies that analyze these producers' decision to adopt technology.

In our study, we use a spatial Durbin probit model to understand raspberry a producer's decision to adopt drip irrigation and improved raspberry varieties in rural Maule. To analyze a producer's decision to adopt, we consider that his/her decision is influenced by three components: producer's socioeconomic and farm characteristics, risk and ambiguity preferences and spatial patterns. Ultimately, this research provides inputs that could help to support and/or redefine current agricultural policies, and help producers to cope with uncertainty in their production systems.

Our results confirm that a producer's risk and ambiguity preferences, except for the probability weighing parameter, constraint a producer's decisions to adopt technology. In addition, a producer's socioeconomic and farm characteristics, and his/her risk and ambiguity preferences generate spatial spill-over effects, which also influence neighboring producers' adoption decisions. Finally, contrary to what the current literature suggests, we find that a producer's decision to adopt can constraint neighboring producers' technology adoption decisions.

We contribute to the current literature in three ways. First, we are not aware of previous studies that combine spatial methods and a producer's risk and ambiguity preferences that stem from a direct elicitation with field experiments to analyze a producer's decision to adopt. Second, since there is mixed evidence about the effect of a producer's risk and ambiguity preferences on technology adoption in developing countries, we contribute with empirical evidence about how these preferences influence a producers' adoption decisions. And third, we explore spatial dependence among producers, and whether a producer's socioeconomic and farm characteristics, and his/her risk and ambiguity preferences generate spatial spill-over effects that influence neighboring producers' adoption decisions.

Our study is structured as follows: in the next section, we conduct a literature review on raspberry production in Chile, the role of spatial patterns, and a producers' risk and ambiguity preferences on agricultural technology adoption. In section three, we describe our sample and dataset, continuing with our econometric results in section four. Finally, our concluding remarks are detailed in section five.

3.2 Raspberry production, producer's risk and ambiguity preferences, and spatial patterns influence on technology adoption

3.2.1 Raspberry production in Chile

Raspberry production due to its low investment and production costs, and high labor intensity is an attractive alternative for small-scale producers (Toledo & Engler, 2008). As of today, in Chile there are more than 16·000 hectares dedicated to raspberry, this area is in hands of more than 21·100 producers, to who raspberry production represents an important part of their income (Domínguez, 2012; Jara-Rojas et al. 2016). Also, due to the current favorable soils and climatic conditions, the raspberry production in Chile is concentrated in the central regions. The Maule region alone has 10·800 ha dedicated to produce raspberry, distributed among approximately 16·300 producers (Domínguez, 2012; Jara-Rojas et al., 2016).

However, producing raspberry is not an easy task. Small-scale producers face many sources of uncertainty in their production systems: credit and financial constraints, national and international market price volatility, and climate variability and climate change effects, among others (Challies & Murray, 2011). Consequently, to cope with production uncertainty, we analyze a producer's decision to adopt two technologies: adoption of improved raspberry varieties and drip irrigation. Regarding adoption of improved raspberry varieties, these varieties have enhanced resistance to diseases and are adapted to other adverse situations, which are desirable features for producers (Jennings & McGregor, 1988). In addition, we analyze the adoption of drip irrigation as a water saving irrigation technique that could help producers cope with climate variability effects. Furthermore, the adoption and combination of both technologies would boost production. As Morales et al. (2013) show, the use of Heritage as an improved raspberry variety in combination with drip irrigation systems in Chile could increase yields 106.1 percent, compared to non-irrigated raspberry crops.

Nevertheless, adopting drip irrigation is not an easy process for small-scale producers. According to Lavín & Matsuya (2004), in Chile to install a drip irrigation system on a half hectare of fruit crops requires an investment of approximately 2·225 Euros. Therefore, given the credit and financial constraints that many small-scale producers face, it is hard for them to invest this amount of money without adequate incentives, subsidies or assistance (Handschuch et al., 2013).

Lastly, a producer's adoption of drip irrigation and improved varieties is in line with the Chilean government priority strategic plan to adapt agriculture to climate variability and climate change (Gobierno de Chile, 2013). This plan remarks on the importance of producers' technology adoption for local and regional governments and other policy-makers. However, despite the benefits of adopting these technologies, and even though both are part of a national strategic priority, as of today there are no previous studies that analyze a producer's adoption of these technologies with Chilean small-scale producers.

Therefore, in this research we base our analysis of understanding a producer's decision to adopt on three components. First, we consider a producer's socioeconomic and farm characteristics, such as: age, education, years of experience and farm size, among others influence on his/her decision to adopt improved varieties and drip irrigation (Adesina & Chianu, 2002; Green et al., 1996; Katengeza et al., 2012; Maertens & Barrett, 2012). Second, we look at a producer's risk and ambiguity preferences that stem from direct elicitation with incentivized field experiments (Ihli & Musshoff, 2013; Liu, 2012; Love et al., 2014). And third, we investigate spatial patterns, as previous studies show agricultural decisions depicts spatial patterns within a territory. These spatial patterns reveal whether a producer's decision to adopt and his/her characteristics influence neighboring producers' decisions to adopt (Bichler et al., 2005; Roe et al., 2002; Wollni & Andersson, 2014).

3.2.2 The role of a producer's risk and ambiguity preferences on technology adoption

In this research we analyze a producer's uncertainty aversion as composed of a producer's risk and ambiguity aversion (Klibanoff et al., 2005). Risk aversion arises when in uncertain scenarios a producer knows information about the outcomes and the probability distribution associated with these outcomes (Liu, 2012; Tanaka et al., 2010). As a counterpart, ambiguity aversion occurs when in uncertain scenarios a producer does not have enough information regarding the outcomes and the probability distribution associated with these outcomes (Ward & Singh, 2015; Warnick et al., 2011). In both cases, literature suggests that a producer who is risk and ambiguity averse would not be willing to move from his/her status quo, because his/her aversion forces him/her to avoid all additional uncertainty in the production system (Barham et al., 2014; Klibanoff et al., 2005).

Many researchers report mixed evidence about the role of a producer's risk preferences on technology adoption decisions. For instance, Ward & Singh (2015) show that risk and loss aversion increases a producer's adoption likelihood of improved varieties on rice producers in rural India. Ray et al. (2016) report that loss averse producers and producers who tend to over-weigh unlikely events are more likely to adopt climate smart technologies. Also, Bezabih & Sarr (2012) show that risk aversion increases producers' probability of crop diversification in Ethiopia. However, Liu (2012) shows that Chinese cotton producers who are strongly risk and loss averse are less likely to adopt these improved cotton varieties, but individuals that over-weigh unlikely events are more likely to adopt improved varieties. Finally, Takahashi (2013) finds that risk aversion reduces producers' adoption probability of rice intensification systems in Indonesia.

In addition, there is also mixed evidence regarding a producer's ambiguity preference's role on technology adoption. For instance, Alpizar et al. (2011) report that a producer's ambiguity aversion increases the likelihood of coffee a producer to adopt strategies to adapt to climate change in Costa Rica. Moreover, Ross et al. (2010) and Warnick et al. (2011) report that ambiguity aversion is negatively associated with the probability of adoption of new technologies and portfolio diversification in Lao PDR and Peru, correspondingly. However, Ward & Singh (2015) and Takahashi (2013) find no evidence that ambiguity preference influences the adoption of improved rice seeds and rice intensification system in India and Indonesia, respectively. Given these mixed findings, we contribute with empirical evidence on the role of a producer's risk and ambiguity preferences play on a producer's agricultural technology adoption decisions in a developing country context.

3.2.3 The role of spatial patterns on a producer's technology adoption

There is an increasing number of studies that consider the influence of spatial patterns on agricultural decision-making processes. Most of these studies, focus on technology adoption decisions, and reveal that a producer's attitude towards a technology could influence neighboring producers' farm-related decisions (Bichler et al., 2005; Holloway et al., 2002; Läpple & Kelley, 2014; Lewis et al., 2011; Roe et al., 2002; Schmidtner et al., 2011; Wollni & Andersson, 2014). In this research we follow Läpple & Kelley (2014) and Wollni & Andersson (2014) and consider that spatial patterns are made up of two components: spatial dependence among producers and spatial spill-over effects.

Regarding spatial dependence among producers refers to whether a producer's decision to adopt a technology influences his/her neighboring producers' decisions to adopt the same technology (Läpple & Kelley, 2014). In the current literature, we find some possible explanations for this spatial dependence effect to be present within a specific territory. For instance, social norms and cultural factors, local natural, ecological and agricultural conditions, social learning and informal sharing between producers, and regional and local agglomeration effects. First, as according to di Falco & Bulte (2011) the attitude of a producer towards a technology is a potential driver to incentivize neighboring producers' adoption. Furthermore, in rural areas of developing countries a strong social influence exists for producers to behave in a similar way as their peers. Consequently, this social influence could assist or constraint a producer's technology adoption in some communities or villages (Maertens & Barrett, 2012).

Second, local natural, ecological and agricultural conditions can create positive economic environments, which could influence technology adoption. For instance, soil quality, rainfall, temperature and microclimate are factors that could affect technological performance in certain areas. Hence, these conditions could influence a producer's decision to adopt technologies in specific areas (Bichler et al., 2005; Läpple & Kelley, 2014).

Third, it is common that high quality technical information is only accessible in specific areas, which usually coincide with villages and/or communes where agricultural agents assist producers (Wollni & Andersson, 2014). This is noticeably relevant in developing countries, where producers usually do not have sufficient access to technical information (Läpple & Kelley, 2014). Consequently, interaction between producers in and outside of these areas could increase social learning and reduce the cost of access to technical information, influencing a producer's technology adoption (Bhargava et al., 2015). Finally, some villages or communes have agglomeration effects that could assist or constraint a producer's decision-making process in specific locations. These regional and local agglomeration effects could include: production input costs, harvest transportation costs, presence of local markets, access to qualified labor, and technological spatial spill-overs (Bhargava et al., 2015; Eades & Brown, 2006; Lakner et al., 2011; Schmidtner et al., 2011; Wollni & Andersson, 2014).

Regarding spatial spill-over effects, these effects capture whether a change in a producer's characteristics influence neighboring producers' decisions to adopt. Also, similar to Läpple & Kelley (2014) and Wollni & Andersson (2014), we account these effects by combining a producer's characteristics and a spatial weight matrix into our model.

The majority of the studies in the current literature that analyze the role of spatial patterns on a producer's decision to adopt report significant effects for spatial dependence among producers. However, most of these studies are conducted in developed countries. Even though we do not expect this spatial dependence to be different in developing countries, we do expect that the spatial spill-over effects to differ in these countries. Since small-scale producers have different characteristics and face harder constraints to adapt to production uncertainty, compared to producers in developed countries, it is also likely that the spatial spill-over effects are different (Feder, et al., 1985; Handschuch et al., 2013).

As a result, we contribute with empirical evidence regarding the role spatial patterns play on a producer's technology adoption decisions in developing countries. Furthermore, we are not aware of previous studies that combine elicited producers' risk and ambiguity preferences, which are elicited through field experiments, and spatial dependence in order to analyze a producer's decision to adopt technology.

3.3 Data source and description of variables

In this study we use the same data as Cárcamo & von Cramon-Taubadel (2016). In their study, they conducted field experiments to elicit producers' risk and ambiguity preferences, and a survey to collect producer's socioeconomic and farm characteristics. This elicitation and collection process was conducted with 102 small-scale raspberry producers in rural communes of Maule region, Chile (Figure 2-1). Nevertheless, nine producers made errors during field experiments, and it was not possible to estimate their risk and ambiguity preferences; therefore, we exclude these producers from the analysis.

Regarding producers' decision to adopt, we notice that one third of the sampled producers have adopted drip irrigation or improved raspberry varieties within the past five years (Table 3-1). Also, during their field work, Cárcamo & von Cramon-Taubadel (2016) asked producers whether they had adopted improved varieties, what variety they adopted, and the reason for adopting them. In this regard, more than seventy percent of adopter producers confirmed that they adopted Heritage as an improved variety, while the rest of adopter producers adopted

Chilliwack, Meeker, Regina and Amity. Regardless, more than ninety percent of the adopter producers claimed to have adopted improved varieties to increase their current production.

Table 3-1. Descriptive statistics for the sample

Variable	Mean	Standard error
Adoption variables		
Producers who adopted improved raspberry varieties	0.34	0.05
Producers who adopted drip irrigation	0.31	0.05
Producer's characteristics		
Household and farm characteristics		
Age	51.26	51.26
Household size	3.46	0.12
Education	8.14	0.34
Off-farm income	0.33	0.05
Access to saving accounts	0.48	0.05
Access to agricultural loans	0.54	0.05
Household expenditure	234·129	11·276
Raspberry area	0.52	0.06
Farm size	4.04	0.70
Raspberry experience	10.48	0.67
Members of farmers' association	0.19	0.04
Risk and ambiguity preferences		
Producers' curvature of the prospect value function	0.66	0.04
Producers' loss aversion	3.54	0.28
Producers' probability weighing	0.85	0.03
Producers' ambiguity preference	1.50	0.24
Total observations	**93**	

Authors' own estimations based on Cárcamo & von Cramon-Taubadel (2016)

Regarding producers' household and farm characteristics, producers are on average older than 51 years old, their household is composed of three to four members, and have more than eight years of education. In addition, one third of sampled producers have an off-farm income, roughly half of them have access to saving accounts and to agricultural loans, and their monthly household expenditure is around 234·000 Chilean pesos[8]. In addition, on average these producers yield raspberries on roughly half of a hectare, and their total farm size is approximately four hectares. Also, these producers have more than ten years' experience working with the raspberry crop.

Regarding a producer's risk and ambiguity preferences, Cárcamo & von Cramon-Taubadel (2016) estimate four parameters to identify these preferences: producer's curvature of the prospect value function, loss aversion, probability weighing, and ambiguity preference. The interplay of these four parameters reveal a producer's risk and ambiguity preferences, in Figure A-1 we depict the distribution of these parameters. The first two parameters capture producers' risk aversion in gains and losses domains, correspondingly (Liu, 2012; Ward & Singh, 2015). Producers' probability weighing measures whether producers distort probabilities associated to events. And ambiguity preference measures whether producers'

[8] When the field work was conducted the exchange rate was 698 Chilean pesos per Euro

decisions vary when there is incomplete information in their decision-making scenarios (Ward & Singh, 2015).

Table 3-2. Description of variables

Variable	Description	Hypothesized sign
Dependent variables		
Producers who adopted improved raspberry varieties	Producers adopted improved raspberry varieties = 1, 0 otherwise	
Producers who adopted drip irrigation	Producers adopted drip irrigation = 1, 0 otherwise	
Independent variables		
Household and farm characteristics		
Education	Producer's schooling level, measured in years	+
Farm size	Total utilizable area in the farm, measured in hectares	±
Raspberry experience	Producers experience working with raspberry measured in years	+
Members of farmers' association	Producer is member of a farmers' association = 1. 0 otherwise	+
Risk and ambiguity preferences		
Producers' risk aversion in gains domains	Ranges from 0 to 1. Higher value = less risk aversion	-
Producers' risk aversion in losses domains	Higher value = more loss aversion	-
Producers' probability weighing	Ranges from 0 to 1.5. Higher value = producers assign less probability to unlikely events	+
Producers' ambiguity preference	Higher value = more ambiguity aversion	-

Authors' own estimations based on Cárcamo & von Cramon-Taubadel (2016)

In Table 3-2, we describe the variables we use in our models and our expectations from these variables based on the current literature. Regarding our dependent variables, in the field Cárcamo & von Cramon-Taubadel (2016) observed whether producers adopted drip irrigation and/or improved raspberry varieties, and capture this information with two dummy variables. These variables take the value of 1 if a producer adopted drip irrigation or improved raspberry varieties, and 0 otherwise.

According to the independent variables we use in our model, we expect that a producer's years of education will have a positive effect on their decision to adopt technology (Cavatassi et al., 2011; Maertens & Barrett, 2012). As Wollni & Andersson (2014) state, there is mixed evidence about the role of farm size on technology adoption; therefore, we expect this variable to be positive or negative depending on the technology adopted. Also we expect that a producer's experience will play a positive role on their decision to adopt technology (Alpizar et al., 2011; Edirisinghe et al., 2013). And finally, we expect that producers who are members of a farmers' association are also more likely to adopt (Nkegbe & Shankar, 2014; Uaiene et al., 2009).

Regarding a producer's risk and ambiguity preferences, we expect that producers who are averse to risk in gains and loss domains, and to ambiguity scenarios would be reluctant to adopt technologies (Ihli & Musshoff, 2013; Warnick et al., 2011). However, as Liu (2012) shows, the producers who over-weigh unlikely events are more likely to adopt; thus we also expect that producers who show the same behavior would be more willing to adopt technology.

3.4 Empirical framework

As outlined above, we hypothesize that producers' technology adoption is influenced by three components: a producer's socioeconomic and farm characteristics, his/her risk and ambiguity preferences, and spatial patterns. As a result, we need a limited dependent variable model that allows us to include these components into a model. Consequently, we analyze a producer's decision to adopt by using a Spatial Durbin probit model (SPDM) which takes the following general form:

$$y = \rho W y + X_1 \beta + X_2 \beta + \varepsilon \qquad (3.1)$$

where y reflects our dependent variable, in our case a producer's decision to adopt drip irrigation or improved varieties. W represents the spatial weight matrix, which reflects the relation of producers' locations and the Euclidean distance between them; hence, Wy represents our dependent spatial lag variable. X_1 represents the matrix containing the producers' socioeconomic and farm characteristics, and X_2 represent producer's risk and ambiguity preferences. In addition, ρ and β are unknown coefficients to be estimated, and ε is the normally distributed error term with a mean of zero and a variance of σ^2 (Lacombe & LeSage, 2015; LeSage & Pace, 2010; LeSage, 2014; Roe et al., 2002).

To create our W we consider the influence of two factors: the distance between producers and the number of producers in given neighborhoods (Läpple & Kelley, 2014; LeSage, 2014). To capture these factors in our W, we first apply an inverse transformation to the distance between producers; thus, a producer's decision exerts more influence on closer producers (Läpple & Kelley, 2014). Second, we create W to be row-standardized, therefore regardless of the number of producers in a neighborhood, every row in W sums up to one. Hence, a producer's spatial effects' influence on an individual neighboring producer's decision to adopt decrease as the number of producers in the given neighborhood increases (Holloway et al., 2002).

In addition, to create our W we also follow Roe et al. (2002), Lapple & Kelley (2014) and Wollni & Andersson (2014) and specify maximum distance thresholds (D). We assume that beyond these thresholds there is no spatial dependence among producers. In other words, if the distance (d) between producer i and their neighboring producers j (d_{ij}) is larger than D, then the spatial weights (w_{ij}) are zero. Contrary, if d_{ij} is smaller than D, then w_{ij} take values of the inverse distance between producers and their neighboring producers (${d_{ij}}^{-1}$).

To define D, we select a distance of 10.9 km which is the minimum distance for every producer to have at least one neighbor[9]. Also, by selecting this threshold we achieve the largest t-value test for our spatial dependence term. Nonetheless, as a robustness check, we also test our model with three additional threshold distances[10]: 15, 20 and 30 km. These distance thresholds are similar to others in current literature, for instance: Roe et al. (2002) also compared their model at different thresholds that range from 50 to 300 miles, and Lapple & Kelley (2014) consider thresholds from 20 to 50 kilometers.

One of the advantages of using SPDM is that it allows us to estimate three types of marginal effects: direct, total and indirect effects. The direct effects capture how a change in a producer's explanatory variables x_i affect his/her adoption decision y_i. Total effects capture how a change in x_i influences the adoption likelihood of all producers (producers and neighboring producers). Indirect effects (or spatial spill–over effects) measure how a change in a producer's explanatory variables x_i influence neighboring producers' adoption decisions, and it is calculated by subtracting direct effects from total effects (LeSage, 2014; LeSage & Pace, 2010). These spatial spill-over effects are cumulative; consequently, these effects measure a producer's influence on all neighboring producers. Also, these spatial spill-over effects are stronger for closer producers and for producers with few neighboring producers (Lacombe & LeSage, 2015; Läpple & Kelley, 2014; Wollni & Andersson, 2014).

However, there is an ongoing discussion in the literature that states that the frequentist approach of the SPDM has some issues dealing with latent dependent variables; consequently, some researchers such as Edirisinghe et al. (2013) and Lacombe & LeSage (2015) favor a Bayesian SPDM. The latter is preferred mostly because it assumes that model coefficients have distributions instead of point estimates. Even though we are not using a latent dependent variable in our model, to be consistent with current literature we use the Bayesian approach for the SPDM (Läpple & Kelley, 2014; Wollni & Andersson, 2014). Also, this model has the advantage of converging towards a non-spatial probit model if $\rho = 0$ (LeSage & Pace, 2010; Loomis & Mueller, 2013).

3.5 Results

To justify the usage of a spatial method in our study, we compare the results of a non-spatial probit model with those of a SPDM. As we notice from Table 3-3, both models deliver the

[9] On average using a 10.9 km radius every producer has 18 neighbors

[10] The results from these models are similar (available from the authors)

same significant variables, with exception of a producer's experience which is barely insignificant with the SPDM.

Table 3-3. Regression estimates of producers' drip irrigation adoption on a set of producers' characteristics, using different probit regression methods

Variable	SPDM				Non-spatial probit			
	Estimate	t value	Pr(>|z|)		Estimate	z value	Pr(>|z|)	
Intercept	0.260	0.534	0.593		0.114	0.147	0.883	
Producer's socioeconomic and farm characteristics								
Years of education	0.014	1.096	0.273		0.067	1.401	0.161	
Total farm size	-0.020	-2.668	0.008	***	-0.079	-2.284	0.022	**
Producer's experience	0.011	1.586	0.113		0.048	1.923	0.055	*
Member of farmers' association	0.343	2.712	0.007	***	1.171	2.849	0.004	***
Producer's risk and ambiguity preferences								
Risk preference (gains domain)	0.004	0.033	0.974		0.027	0.060	0.952	
Risk preference (losses domain)	-0.030	-1.814	0.070	*	-0.122	-1.868	0.062	*
Probability weighing	-0.358	-2.499	0.012	**	-1.425	-2.405	0.016	**
Ambiguity preference	-0.023	-1.267	0.205		-0.067	-0.979	0.323	

Significance codes: *** p<0.01, ** p<0.05, * p<0.1

Even though both models deliver similar results, we prefer the SPDM, because of its property to let us identify whether spatial patterns influence neighboring producers' technology adoption decisions.

3.5.1 The role of spatial dependence on producers' drip irrigation adoption

We find our spatial dependence coefficient to be -0.366 for our selected model (10.9 km) (Table 3-4). Regarding the magnitude of this coefficient, it is similar to other studies in developing countries: Wollni & Andersson (2014) ($\rho = 0.321$), Edirisinghe, et al. (2013) ($\rho = 0.447$) and Holloway et al. (2002) ($\rho = 0.540$). However, our findings report a negative sign for this coefficient, which contradicts previous literature. This negative sign implies that, on average a producer's decision to adopt drip irrigation, negatively influences neighboring producers' decision to adopt the same technology.

Table 3-4. Spatial dependence estimates for producers' adoption of drip irrigation model at different distance thresholds

Distance threshold (km)	t-value test	Spatial dependence coefficient	95 percent credible interval
10.9	4.45 ($p = 0.003$)	-0.366	-0.654 – -0.079
15.0	4.29 ($p = 0.004$)	-0.398	-0.713 – -0.082
20.0	4.56 ($p = 0.003$)	-0.444	-0.771 – -0.117
30.0	4.12 ($p = 0.004$)	-0.456	-0.812 – -0.100

We could not find previous studies that report a negative coefficient for this spatial dependence coefficient; however, we have two possible explanations for this negative effect. First as Bhargava et al. (2015) argue, there is a learning process between a producer and his/her neighboring producers, which plays a significant role on influencing neighboring producers' technology adoption decisions. Usually, this learning process is beneficial for neighboring producers' technology adoption, since they learn from the adopter producer's experience, avoid mistakes and take shortcuts, making adoption easier. However, we believe that this learning process could be a double-edged sword, since neighboring producers could also learn from an adopter producer's negative attitudes and experiences, constraining neighboring producers' adoption. These negative attitudes and experiences can arise from many sources, such as: lack of technical assistance and follow-up after adoption, incremental operational costs, and high initial investment, among others. In addition, this learning process in combination with the technical complexity of drip irrigation, and a producer's risk and ambiguity preferences, could decrease a producer's expected benefits from adopting drip irrigation, resulting in a combination of factors that could constraint neighboring producers' technology adoption (Friedlander et al., 2013).

Second according to Green et al. (1996) and Pokhrel et al. (2016), for producers with farms on good soil conditions, adopting water saving irrigation technologies, such as drip irrigation, are not always profitable. In Maule, raspberry producers are located on central valley alluvial soils, that are characterized for being deep, well-structured and with high contents of organic matter (Sistema Integrado de Información Territorial (SIIT), 2014; Universidad de Chile, 2013). In addition, Figure A-2 shows that raspberry producers are located on soils with less than three percent of slope. Furthermore, we find that all producers in our sample have manual or flood irrigation systems on their farms. Hence, since raspberry production is located on good and flat soils, and producers have at least one irrigation system, then it is likely that drip irrigation results in any increment in a producer's profit. However, even if at the moment this technology does not improve adopter producers' profit, considering the future rain scenarios described by Minetti et al. (2003), Universidad de Chile (2006) and Gobierno de Chile (2013), in the future producers' motivation to adopt drip irrigation should not increase their profits, but enable them to produce on their current farm location.

Even though we do not have data to prove any of these possible explanations, we conducted some efforts to identify if our estimate for spatial dependence coefficient reflects the current situation of the Chilean raspberry sector. Consequently, we discussed this finding with some Chilean berries experts, who stated that it is common to see producers who abandon drip irrigation to go back to flood irrigation. Therefore, even if we do not find previous reports for a negative spatial dependence coefficient in the current literature, our finding captures a disadoption effect for the drip irrigation in the Chilean raspberry sector.

3.5.2 The role of a producer's risk and ambiguity preferences, and socioeconomic and farm characteristics on drip irrigation adoption

In addition to spatial dependence influences on a producer's decision to adopt, we note four variables that significantly explain producers' drip irrigation adoption (Table 3-5). In addition, we find one variable that has a significant spatial spill-over effect. This spatial spill-over effect is larger in magnitude than its direct effect, however this spatial spill-over is cumulative over all neighboring producers (Läpple & Kelley, 2014; Wollni & Andersson, 2014).

Table 3-5. Marginal effects for SPDM regression of producers' adoption of drip irrigation on their socioeconomic, farm and preferences characteristics

Variable	**Direct effects**			**Indirect effects**			**Total effects**		
	Estimate	**95 percent credible interval**		Estimate	**95 percent credible interval**		Estimate	**95 percent credible interval**	
		Lower	Upper		Lower	Upper		Lower	Upper
Producers' household and farm characteristics									
Years of education	0.015	-0.005	0.038	-0.016	-0.053	0.021	-0.001	-0.045	0.041
Total farm size	-0.020***	-0.035	-0.008	0.000	-0.020	0.018	-0.020*	-0.040	0.001
Producers' experience	0.009	-0.003	0.022	0.023**	0.008	0.042	0.033**	0.014	0.051
Member of farmers' association	0.353***	0.130	0.578	-0.118	-0.426	0.171	0.236	-0.071	0.483
Producers' risk and ambiguity preferences									
Curvature prospect value function	-0.028	-0.224	0.197	0.348	-0.041	0.722	0.320	-0.097	0.760
Loss aversion	-0.031*	-0.062	-0.005	0.013	-0.046	0.074	-0.019	-0.080	0.057
Probability weighing	-0.358**	-0.602	-0.111	0.005	-0.453	0.450	-0.353	-0.829	0.162
Ambiguity preference	-0.024	-0.055	0.006	0.009	-0.049	0.073	-0.015	-0.084	0.059

Significance codes: *** p<0.01, ** p<0.05, * p<0.1

In terms of a producer's household and farm characteristics, we find that farm size has a negative effect on adopting drip irrigation technology. Our results show that for every additional hectare available for producers to cultivate, the likelihood of adoption decreases by two percent. Similar results for farm size in developing countries are reported by Wossen et al. (2015), Uaiene et al. (2009) and Holloway et al. (2002).

We find that the direct effect for a producer's experience is not significant at the ten percent level, however we find significant indirect and total effects for this variable. Our results suggest that one additional year of experience of a producer, increases neighboring producers' adoption likelihood by a cumulative 2.3 percent. In total this variable increases adoption likelihood of all producers by 3.3 percent. Positive effects for a producer's experience on technology adoption are widely documented in the literature; Roco et al. (2014), Gbetibouo (2009) and Adesina & Chianu (2002) report similar findings.

Also, our results show that producers who are members of a farmers' association are more likely to adopt drip irrigation by 35 percent. Previous studies such as Nkegbe & Shankar (2014) and Wollni & Andersson (2014) highlight positive effects for the role of a farmers' association on a producer's technology adoption.

According to related studies, producers who are averse to risk and ambiguity scenarios would be reluctant to adopt agricultural technologies (Ihli & Musshoff, 2013; Tanaka et al., 2010; Warnick et al., 2011). Our results support this statement; we find that producers who are loss averse are less likely to adopt drip irrigation. Previous studies, such as Liu (2012) and Love et al. (2014) report similar effects for technology adoption in China and Kenya, correspondingly.

We also find that producers who tend to over-weigh unlikely events are more likely to adopt drip irrigation. Our results are similar to those of Liu (2012), Love et al. (2014) and Ray et al. (2016), who report similar effects for this variable on producers' technology adoption in China, Kenia and India, respectively.

3.5.3 The role of spatial dependence on a producer's adoption of improved varieties

Similar to our results for a producers' drip irrigation adoption, we find that the spatial dependence coefficient for improved varieties is also significant in all our scenarios at the 95 percent level (Table 3-6). Contrary to our finding for drip irrigation adoption mentioned above, we find that for our selected threshold distance our spatial dependence coefficient is equal to 0.378. This finding suggests that a producer's decision to adopt improved raspberry varieties positively influences the adoption on neighboring producers for the same technology. This result is similar in both magnitude and effect to previous reports in developing countries, such as Wollni & Andersson (2014), Edirisinghe, et al. (2013) and Holloway et al. (2002).

Table 3-6. Spatial dependence estimates for producers' adoption of improved varieties model at different distance thresholds

Distance threshold (km)	t-value test	Spatial dependence coefficient	95 percent credible interval
10.9	2.29 ($p = 0.024$)	0.378	0.056 – 0.684
15.0	2.16 ($p = 0.034$)	0.383	0.034 – 0.722
20.0	2.18 ($p = 0.032$)	0.410	0.051 – 0.760
30.0	2.09 ($p = 0.039$)	0.421	0.046 – 0.828

3.5.4 The role of a producer's risk and ambiguity preferences, and socioeconomic and farm characteristics on adoption of improved raspberry varieties

In addition to the influence of the spatial dependence on producers' adoption of improved varieties, we find four variables that explain producers' adoption of improved varieties. Also, two of these variables show spatial spill-over effects on neighboring producers (Table 3-7).

In terms of socioeconomic and farm characteristics, we notice that a producer's education plays a positive role in producers' decisions to adopt. Therefore, one additional year of education by a producer increases his/her direct probability of adoption by 2.7 percent, and also increases adoption likelihood of neighboring producers by a cumulative 1.8 percent. In total, one additional year of education increase adoption likelihood of improved varieties by 4.5 percent over all producers. This result is in accordance to previous related studies, such as Paxton et al. (2010), Wossen et al. (2015) and Takahashi (2013) who report similar effects for a producer's education influence on technology adoption in developing countries.

Table 3-7. Marginal effects for SPDM regression of producers' adoption of improved varieties model on their socioeconomic, farm and preferences characteristics

Variable	**Direct effects**			**Indirect effects**			**Total effects**		
	Estimate	**90 percent credible interval**		**Estimate**	**90 percent credible interval**		**Estimate**	**90 percent credible interval**	
		Lower	Upper		Lower	Upper		Lower	Upper
Producers' socioeconomic and farm characteristics									
Years of education	0.027*	0.005	0.050	0.018*	0.000	0.044	0.045*	0.008	0.089
Farm size	0.012*	0.002	0.021	0.007	0.000	0.018	0.019*	0.003	0.036
Producers' risk and ambiguity preferences									
Risk preference (gains domain)	0.237*	0.031	0.444	0.148*	0.003	0.399	0.384*	0.054	0.763
Risk preference (Losses domain)	0.006	-0.022	0.036	0.005	-0.014	0.029	0.011	-0.034	0.064
Probability weighing	-0.110	-0.356	0.136	-0.066	-0.275	0.094	-0.176	-0.610	0.222
Ambiguity preference	-0.153*	-0.296	-0.003	-0.099	-0.264	0.001	-0.252*	-0.531	-0.005

Significance codes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In addition, we identify that one additional hectare of farm increases a producer's adoption likelihood by 1.2 percent. Also, this variable has a total effect, which increases a producer's adoption likelihood 1.9 percent over all producers. In previous literature, many studies report a significant role of farm size on technology adoption, such as: Kassie et al. (2009), Wossen et al. (2015) and Kallas et al. (2010).

In addition, our results for producers' risk preferences confirm that producers who are risk averse are reluctant to deviate from status quo and adopt improved varieties (Liu, 2012; Love et al., 2014; Yesuf & Köhlin, 2009). In addition, this variable has a spatial spill-over effect, which reflects that producers who are risk averse decrease adoption likelihood of neighboring producers.

In addition, we find that ambiguity aversion has a negative direct effect on adoption probability. Producers who are ambiguity averse are less likely to adopt improved raspberry varieties. Furthermore, we also find that a producer's ambiguity aversion correlates negatively with adoption likelihood over all producers. This result is in accordance with previous studies that report that a producers' ambiguity aversion constraints neighboring producers' adoption of improved technologies (Ross et al., 2010; Ward & Singh, 2015; Warnick et al., 2011). However, despite ambiguity preference's spatial spill-over effect it is not significant; it just barely over the significance level and its total effects are significant. Therefore, our results could be pointing to a weak influence of a producer's ambiguity aversion's spatial spill-over effect on neighboring producers' decisions to adopt.

3.6 Conclusions

As we outlined above, we hypothesize that a producer's decision to adopt is influenced by three aspects: his/her socioeconomic characteristics, risk and ambiguity preferences and spatial patterns among producers. Hence, we use a SPDM to consider the roles of these aspects on a producer's decision to adopt drip irrigation and improved raspberry varieties. As expected, a producer's socioeconomic and farm characteristics are in accordance with related literature. A producer's characteristics, such as: years of education, experience working with raspberry, farm size, and being a member of a farmers' association influence a producer's decisions to adopt drip irrigation and/or improved raspberry varieties.

In addition, our findings support previous literature that state that a producer's risk and ambiguity preferences constrain a producer's decision to adopt technology. Our results confirm that with exception of a producer's weighing probability, the remaining risk and ambiguity preference's parameters constrain a producer's decision to adopt drip irrigation and improved raspberry varieties.

Regarding the role of spatial patterns on producers' adoption of drip irrigation and improved raspberry varieties, we expect that a producer's socioeconomic and farm characteristics have spatial spill-over effects. In this context, we find that a producer's characteristics such as: a producer's experience working with raspberry, and years of education generate positive spatial spill-over effects that influence neighboring producers' decisions to adopt. In addition, we find that a producer's risk preference in gains domains have spatial spill-over effects that influence neighboring producers' decisions to adopt. Similar to the direct effect of a producer's risk preference in gains domains, this spatial spill-over effect reflects that producers who are risk averse constrain the technology adoption likelihood of neighboring producers.

Furthermore, we identify an influence of spatial dependence among producers on neighboring producers' decisions to adopt. This finding reveals that a producer's decision to adopt drip irrigation or improved varieties influences neighboring producers' decisions to adopt. Regarding a producer's decision to adopt improved varieties, as we expected, the coefficient for this spatial dependence reveals that a producer's adoption of improved raspberry varieties increases the adoption likelihood of neighboring producers. However, regarding drip irrigation adoption, contrary to our expectations, we find a negative coefficient for spatial dependence among producers. This negative coefficient represents that a producer's decision to adopt drip irrigation negatively influences neighboring producers' decisions to adopt. Even though we do not find previous evidence in current literature that supports this finding, we discussed this finding with some Chilean soft-fruits experts, who stated that despite not having the data to prove any possible explanations for this coefficient, it captures what is happening with drip irrigation among raspberry small-scale producers in rural Maule.

We have three possible limitations for our study, these limitations at the same time should motivate further studies in this field. First, regarding the construction of the spatial weight matrix; to create this matrix we consider two characteristics: distance between producers and the number of producers in the neighborhood. However, there are other characteristics that could influence this spatial matrix that we do not consider in our analysis. For instance: a producer's leadership within the villages, a producer's experience, early adopters and if family members who also produce raspberry have adopted drip irrigation or improved raspberry varieties.

Second, in the current literature there are many possible explanations about the presence of spatial patterns in a specific area: climate and soil characteristics, local markets, and competitive advantages, among others. However, even though we identify the influence of spatial patterns on small-scale producers' decisions to adopt, we are not able to identify what local characteristics generate these spatial patterns in the Maule region.

And third, due to our data constraints, we could not explore in detail our negative coefficient for spatial dependence among producers. Therefore, future studies that capture a producer's attitude towards drip irrigation, government subsidies, and a producer's financial constraints, among others could help to provide further details and policy implications for a producer's technology adoption in rural Maule.

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Appendix

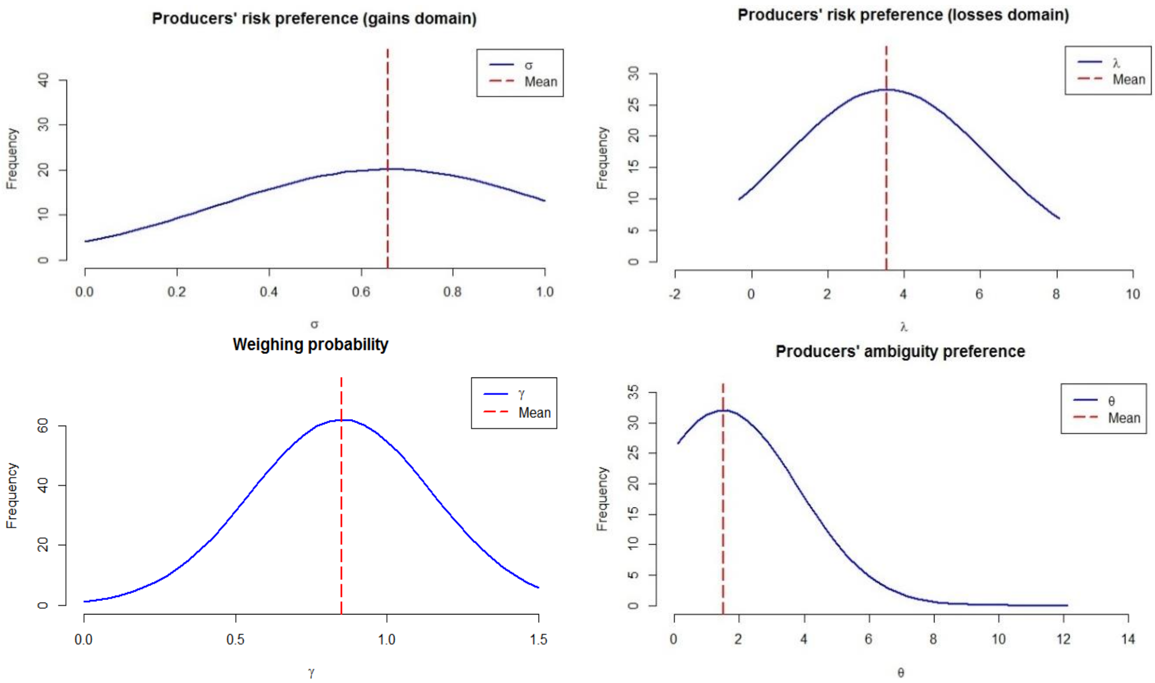
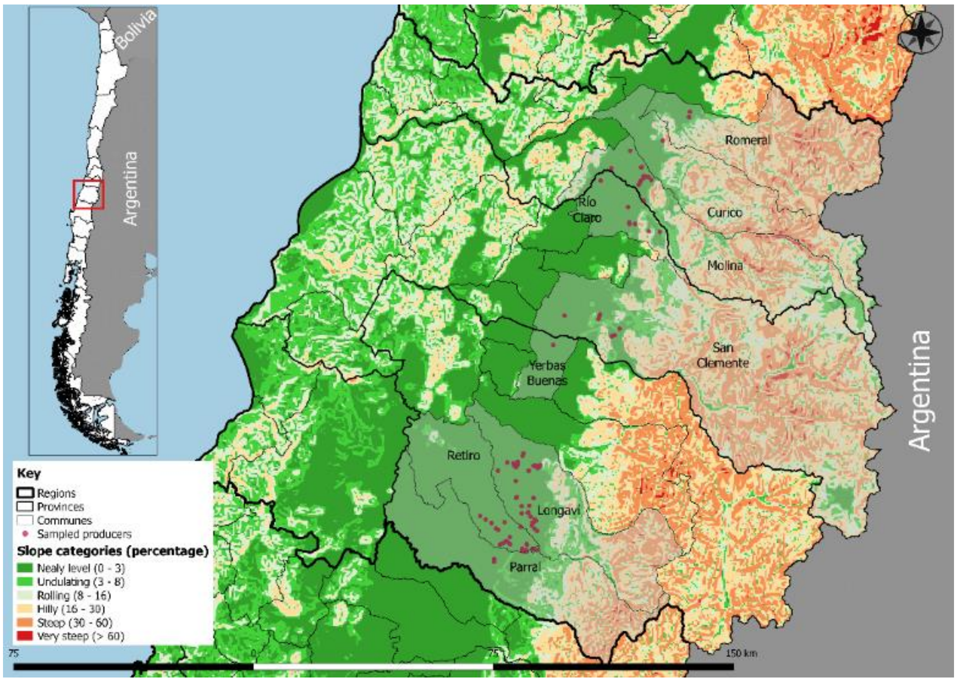


Figure A-1. Distribution of producers' risk and ambiguity preferences

Authors' own calculations based on Cárcamo & von Cramon-Taubadel (2016)



Source: Authors' own calculations based on Sistema Integrado de Información Territorial (SIIT) (2014)

Figure A-2. Producers' location and slope categories

4 Concluding remarks

In this dissertation we study two aspects that help Chilean small-scale raspberry producers cope with production uncertainty: characterize producers' behavior in decision-making process under uncertainty, and analyze producer's decision to adopt technologies (Liu, 2012; Ward & Singh, 2015). To characterize producers' behavior under uncertainty we first use incentivized field experiments to elicit the risk and ambiguity preferences of small-scale producers. We complement these experiments with a questionnaire which provides information on producer's socioeconomic and farm characteristics that could influence these preferences. In the second paper, we study how producer characteristics, preferences, and spatial patterns influence decisions to adopt technology.

In the following two sections, we summarize both studies that compose the main chapters of this dissertation and describe our research questions, methods, key findings, limitations and suggestions of research prospects for future studies. Furthermore, since both chapters aim to help producers cope with production uncertainty, then we find a link between both chapters. Therefore, our third section summarizes key findings and limitations from both chapters jointly.

4.1 Assessing small-scale raspberry producers' risk and ambiguity preferences: evidence from field-experiment data in rural Chile

In this study, we have three research questions, which lead us to identify producers' risk and ambiguity preferences. First, do producers' risk preferences differ regarding the method we use to estimate these preferences from Tanaka's et al. (2010) field experiment design? Second, what is producers' preference towards risk and ambiguity scenarios? And third, what socioeconomic and farm characteristics influence a producer's risk and ambiguity preferences?

To answer our research questions, we use incentivized field experiments on a sample of 102 Chilean small-scale raspberry producers in rural Maule. During these experiments, producers face a series of binary choices, composed of a certain lottery with a certain outcome, and a risk/ambiguous lottery which have two possible outcomes, winning and losing. These winning and losing outcomes involve a larger and a smaller payment compared to the certain lottery, correspondingly. In addition, to capture true producers' risk and ambiguity preferences in these experiments we use a monetary incentive. To pay this incentive we select randomly one round from the experiments and play it for real, the amount of money that producers receive would depend at the decision they take during the experiments. Hence, at the beginning of the experimental session we explain to producers how this incentive works, and encourage them to take every decision as serious as possible. Finally, we complement our experiments with a questionnaire that allow us to collect producer's socioeconomic, demographic and farm characteristics. The results from this questionnaire allow us to explore and identify producer's characteristics that influence their risk and ambiguity preferences.

With regards to our first research question, we use two methods that are standard to estimate producers' risk preferences from field experiments: the midpoint method and the structural method. We find that our results of producers' risk preferences from both methods are similar, but with three important differences. First, our results with the structural method suggest that producers correlate with a strong risk aversion, however our results with the midpoint method points that producer correlate with a moderate risk aversion. Second, the asymmetry between producers' risk preferences in the gain and losses domains increases with the midpoint method. And third, we find that with the structural method producers' probability weighing parameter hints that producers do not distort probabilities of events. However, with the midpoint method, we find that producers distort these probabilities by over-weighing unlikely events. As a consequence, the method we use to estimate producers' risk preferences could lead to analyze different estimates.

About producers' preference in ambiguity scenarios, we find that producers preferred to choose the certain lottery and earn a smaller outcome, than selecting the ambiguity lottery and the opportunity to earn a larger outcome. This result reflects that there is ambiguity aversion among producers, and implies that it is likely for producers to avoid decision-making scenarios where ambiguity is present.

In relation to our third research question, we find that producer's age, farm size, household expenditure, farmers' association membership and whether producers have agricultural loans associate with producers' risk preferences. Furthermore, we find that producer's gender, household size, household expenditure and experience working with raspberry correlate with producers' ambiguity aversion.

Through the elicitation of producers' risk and ambiguity preferences, and the analysis of producer's characteristics as determinants of these preferences, we provide useful inputs to strengthen plans of action of current agricultural policies. However, our study has at least two potential limitations. The first limitation is related to producers' behavior during experiments. Decision-making process is complex, and producers could have many objectives to accomplish; also, in real life producers could foresee and plan to face risk and ambiguity scenarios. Our experiments are a simplification of decision-making scenarios, and producers do not have time to plan and decide. As a result, it is possible that producers could behave in different manner during experiments, and as consequence do not capture producer's true risk and ambiguity preferences (Ihli & Musshoff, 2013).

Second, in the current literature there is a debate about the external validity of experimental approaches. According to some authors the use of experiments to reveal insights about producers' behavior is limited, because such experiments lack of external validity, and therefore it is difficult to generalize results to other producers, and/or crops. Nevertheless, most researchers agree that the benefits from experiments' internal validity are more relevant than the lack of external validity (Guala & Mittone, 2005; Schram, 2005). Thus, producers could be more risk averse in real life situations, which imply that our estimations underestimate producers' real risk and ambiguity preferences. As a result, from these two limitations, our estimations could underestimate real producers' risk and ambiguity preferences.

There are many opportunities for future research, for instance to consider other behavior preferences could contribute to a better characterization of producers' behavior, such as: time preferences and producer's learning process (Barham et al., 2015; Tanaka et al., 2010). In addition, we do not identify whether there is influence of spatial patterns on these preferences (Bhargava et al., 2015). Also it is possible that producers' behavior could be correlated with psychological factors such as: intelligence quotient, emotional intelligence and psychological inertia (Ihli & Musshoff, 2013; Samuelson & Zeckhauser, 1988). Analyzing these topics could reveal additional contributions for a better characterization of producers' decision-making process under uncertainty.

4.2 The role of spatial patterns, and producers' risk and ambiguity preferences on small-scale agricultural technology adoption

In our third chapter, we follow four research questions to analyze producer's decision to adopt technology. First, what producer's socioeconomic and farm characteristics influence producer's decision to adopt technology? Second, how producers' risk and ambiguity preferences influence producer's decision to adopt technology? Third, does producer's decision to adopt a technology influence neighboring producers to adopt the same technology? And fourth, do producer's socioeconomic and farm characteristics, and their risk and ambiguity preferences generate spatial spill-over effects that influence neighboring producers' decisions to adopt technology?

To answer these research questions, we combine our dataset and results from producers' preferences study, with a SPDM that allow us to analyze producer's characteristics, and spatial patterns influence on producer's decision to adopt technology. Furthermore, since in

Chile adoption of water-saving irrigation techniques, improved varieties, and other water-saving techniques are national strategic priority, we focus our research on producer's adoption of improved raspberry varieties and drip irrigation (Gobierno de Chile, 2013; Universidad de Chile, 2006). These technologies could help producers to cope with production uncertainty, especially the one that arises from climate variability and climate change in Chilean central regions.

Regarding our first research question, we find three socioeconomic and farm characteristics that influence a producer's decision to adopt. According to our expectations, producers who are members of a farmers' association and producer's years of education increase producer's likelihood to adopt drip irrigation and improved raspberry varieties, respectively. Also, we find that producer's farm size decreases adoption likelihood of drip irrigation, but increases adoption likelihood of improved raspberry varieties.

As expected, we find that risk aversion in the gains domain, and ambiguity aversion both decrease a producer's likelihood of adoption improved raspberry varieties. In addition, risk aversion in the losses domain reduces the likelihood that a producer will adopt drip irrigation. However, a producer's probability weighing preference increases the likelihood that he/she will adopt drip irrigation. In other words, those producers who over-weigh probabilities of unlikely events are more likely to adopt drip irrigation.

Previous studies suggest that spatial dependence positively influences producers' decisions to adopt technology. This statement makes sense, because producers could learn from adopter producer's experience, avoid mistakes and take shortcuts, which results in an easier adoption process for neighboring producers. Our results show that a producer's decision to adopt improved raspberry varieties has a positive effect on neighboring producers. This implies that if a producer decides to adopt improved varieties, then neighboring producers are more likely to also be willing to adopt. However, contrary to our expectations and to what previous studies suggest, our estimate for producer's spatial dependence for drip irrigation reflects a negative effect on neighboring producers' decisions to adopt the same technology. We discussed this finding with some berry production and irrigation specialists in Maule region, and they claim that our finding captures the dis-adoption of drip irrigation that is currently taking place in the industry.

Regarding our fourth research question, we find three variables that generate spatial spill-over effects. In terms of producer's socioeconomic and farm characteristics: producer's experience working with raspberry, and years of education generate positive spatial spill-over effects that increase neighboring producers' adoption likelihood of drip irrigation and improved varieties, respectively. In terms of producers' risk and ambiguity preferences, we find that risk preference in the gains domain has a spatial spill-over effect that decreases neighboring producers' adoption likelihood of improved raspberry varieties. We are not aware of previous studies that combine producers' preferences that stems from direct elicitation with spatial methods, therefore there are no previous evidence of producers' risk and ambiguity preferences to have spatial spill-over effects.

Our results provide empirical evidence about small-scale raspberry producer's adoption of drip irrigation and improved varieties in rural Maule. Since both technologies are national strategic priority in the agricultural sector, then our results could help Chilean policy-makers to redefine and/or strengthen plans of action of current agricultural policies. However, our study has three potential limitations that restrict our findings.

The first limitation is a lack of information about the local characteristics that trigger spatial dependence among producers. As outlined above, we find a spatial dependence effect on producer's decision to adopt. If the characteristics that trigger spatial dependence change over time, then this change could affect producers' decisions to adopt (Läpple & Kelley, 2014). Characteristics such as the presence of local markets, better access to markets, and other competitive advantages could change over time and influence producer's decision to adopt. Therefore, investigating local characteristics that triggers spatial dependence, the way these characteristics change over time, and whether these changes influence spatial dependence, could provide policy-makers with meaningful inputs for agricultural policies (Lakner et al., 2011; Läpple & Kelley, 2014; LeSage et al. 2011).

The second limitation concerns the estimation of the influence of a producer's decision and characteristics on his/her neighboring producers. We consider the distance between producers, and the number of producers in a neighborhood to determine whether and how a producer influences nearby producers. However, in reality there are many characteristics that could affect this influence: a producer's leadership, attitude from early adopters, and family members who adopted technology could also influence producers decisions to adopt (Läpple & Kelley, 2014; Roe et al., 2002). The consideration of any additional characteristics to analyze the influence of a producer's decision and characteristics on his/her neighboring producers, could change the interpretation and coefficients for indirect and total marginal effects in our study.

Third, raspberry production in Chile is concentrated in central regions, and it is likely that there are cultural, social and economic similarities among producers in these regions. However, there are also differences in characteristics that influence technology performance within an area, such as climate, and soil quality. These differences make it difficult to generalize our results to other regions.

The opportunities for future studies in this topic are many. Although the use of spatial methods to analyze producers' technology adoption is growing, comparatively little work has been done in developing countries. Even though we do not expect that spatial dependence to differ in developing countries, we do expect some differences on producer's spatial spill-over effects. As a result, analyzing producers' decisions to adopt technology with spatial methods in these countries, could contribute with key elements for policy-making design. Furthermore, the use of spatial panel data methods could contribute to a better understanding about spatial dependence and spatial spill-over effects, and if these characteristics change over time. Finally, including group field experiments with producers in the analysis could reveal key aspects for technology adoption. Some examples of these experiments are: producer's leadership, trust games, and coordination among producers (Alpizar et al., 2011; Colomer, 1995; Rigdon et al., 2007).

4.3 General concluding remarks

We explore methods to help Chilean small-scale raspberry producers cope with production uncertainty. We focus on characterizing producers' risk and ambiguity preferences, and on analyzing producer's decision to adopt drip irrigation and improved raspberry varieties. Both studies in this dissertation are based on the same dataset. Furthermore, the link between producers' risk and ambiguity preferences, and producer's decision to adopt technology has been widely explored in the current literature (Liu, 2012; Ward & Singh, 2015; Barham, et al. 2015). Therefore, in this section we discuss findings and limitations to both studies jointly.

We notice that producers' risk and ambiguity preferences correlate negatively with producer's decision to adopt technology. Therefore, agricultural policies that focus on helping producers to cope with risk and ambiguity would lead to an increase in technology adoption. Furthermore, there is a spatial spill-over effect that derives from producers' risk preference in gains domain. This spatial spill-over effect suggests that helping some producers to cope with risk would also have effects on neighboring producers.

However, we find one limitation that affects both of our chapters simultaneously. Even though we can explore small-scale raspberry producers' risk and ambiguity preferences and technology adoption behavior, our sample is not representative for the Chilean raspberry sector. Chilean policy-makers should take this fact in consideration if they consider generalizing our results to producers in other regions.

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Appendix

Field work instructions

Introducción

Gracias por brindarme un poco de su tiempo el día de hoy, el ejercicio que realizaremos tomará un aproximado de una hora y media. Si usted no cuenta con el tiempo suficiente le ruego me lo haga saber, así podremos hacer este trabajo cuando usted tenga más disponibilidad.

En esta ocasión desarrollaremos dos juegos, es importante que escuche atentamente las instrucciones que le daré. Si tiene alguna pregunta, por favor hágamela saber y con gusto le aclararé su duda. *Si esta sesión se está desarrollando para dos o más productores simultáneamente:* le suplico que cualquier duda que tengan no la hagan a su compañero, comuníqueme su inquietud y le daré más detalles con respecto a su consulta.

En este juego usted ganará dinero por participar, sin embargo la cantidad de dinero que usted recibirá **dependerá de las decisiones que usted tome y, en parte, de su suerte.**

En qué consiste el juego y cómo se hará el pago

Le mostraré un total de cinco secciones del juego, que hacen un total de 57 preguntas, cada pregunta está debidamente numerada a lo largo del juego. Después de terminado el juego, le acercaré una bolsa que contiene 57 fichas numeradas desde el 1 al 57. Usted tomará un número de esta bolsa y el número seleccionado será comparado con la decisión que usted tomó en la pregunta con el mismo número y se le pagará este monto en efectivo. Ese dinero es suyo y puede quedarse con él.

Luego del juego, le haré una encuesta corta relacionado a algunos aspectos sociales, económicos y productivos relacionados a usted y su familia, esta información nos será de utilidad para enriquecer los resultados del juego.

Ronda 1

Como lo expliqué anteriormente, en esta ronda sus ganancias dependerán de sus decisiones y de su suerte. Esta primera etapa consta de tres secciones, las primeras dos tienen 11 preguntas cada una. Haciendo, de esta forma, un total de 22 preguntas.

Para cada pregunta en esta sección usted tiene dos posibles alternativas: la opción A que es la ***"elección segura"*** solo por elegir esta opción usted asegura cierta cantidad de dinero. Por otra parte, la opción B que es ***"la apuesta"*** en esta alternativa usted podrá ganar más dinero que con la "elección segura", pero si pierde la apuesta, entonces recibirá menos dinero que la opción A.

Yo le mostraré **todas** las preguntas de la primera sección, **su punto de partida es la opción B** y usted debe decirme en **<u>cuántas preguntas desea seleccionar la opción B y en cuántas la opción A</u>**. A continuación, le mostraré unos ejemplos:

Ejemplo 1: Usted en algún momento cambia entre las opciones

Round	Opción A	Opción B	
		Bola azul (gana)	Bola verde (pierde)
1	3,400	6,800	3,400
2	3,400	6,800	2,800
3	3,400	6,800	2,000
4	3,400	6,800	1,500
5	3,400	6,800	1,150
6	3,400	6,800	950
7	3,400	6,800	750
8	3,400	6,800	550
9	3,400	6,800	400
10	3,400	6,800	200
11	3,400	6,800	0

Respuesta:

Elijo la opción B desde la pregunta 1 - ____________3__________

Elijo la opción A desde la pregunta _______________4_____- 11

Ejemplo 2: Nunca cambiar hacia la opción A

Round	Opción A	Opción B	
		Bola azul (gana)	Bola verde (pierde)
1	3,400	6,800	3,400
2	3,400	6,800	2,800
3	3,400	6,800	2,000
4	3,400	6,800	1,500
5	3,400	6,800	1,150
6	3,400	6,800	950
7	3,400	6,800	750
8	3,400	6,800	550
9	3,400	6,800	400
10	3,400	6,800	200
11	3,400	6,800	0

Su respuesta:

Elijo la opción B desde la pregunta 1 - ____________11_________

~~Elijo la opción A desde la pregunta _______________ _____- 11~~

Ejemplo 3: Cambiar y elegir la opción A desde el inicio del juego

Round	Opción A	Opción B	
		Bola azul (gana)	Bola verde (pierde)
1	3,400	6,800	3,400
2	3,400	6,800	2,800
3	3,400	6,800	2,000
4	3,400	6,800	1,500
5	3,400	6,800	1,150
6	3,400	6,800	950
7	3,400	6,800	750
8	3,400	6,800	550
9	3,400	6,800	400
10	3,400	6,800	200
11	3,400	6,800	0

Su respuesta:

~~Elijo la opción B desde la pregunta 1 ___________________~~

Elijo la opción A desde la pregunta _________1_____ ______- 11

Sección 1

Pregunta	Opción A	Opción B	
		Bola azul (gana)	Bola verde (pierde)
1	2,000	4,000	2,000
2	2,000	4,000	1,600
3	2,000	4,000	1,050
4	2,000	4,000	520
5	2,000	4,000	210
6	2,000	4,000	70
7	2,000	4,000	20
8	2,000	4,000	10
9	2,000	4,000	5
10	2,000	4,000	1
11	2,000	4,000	0

Respuesta:
Elijo la opción B desde la pregunta 1 - ____________________
Elijo la opción A desde la pregunta ____________________- 11

En el juego que acaba de responder ¿Cuántas bolas azules y verdes cree que hay en la bolsa?

Bolas azules (ganar): ______________ Bolas verdes (perder): ______________

Instrucciones Sección 2

Las reglas para esta sección, son las mismas que en el juego anterior y la cantidad de dinero que usted puede ganar también es igual. Sin embargo ahora le hago saber que en la bolsa hay **cinco (5) bolas azules y cinco (5) bolas verdes**, si usted selecciona una bola azul gana, si elige una bola verde pierde. Ahora usted conoce las probabilidades de ganar y de perder en la opción B.

Por favor considere esta nueva información antes de hacer una elección

Pregunta	Opción A	Opción B	
		Bola azul (gana) **5 de 10**	**Bola verde (pierde)** **5 de 10**
12	2,000	4,000	2,000
13	2,000	4,000	1,600
14	2,000	4,000	1,050
15	2,000	4,000	520
16	2,000	4,000	210
17	2,000	4,000	70
18	2,000	4,000	20
19	2,000	4,000	10
20	2,000	4,000	5
21	2,000	4,000	1
22	2,000	4,000	0

Su respuesta:
Elijo la opción B desde la pregunta 12 - ____________________
Elijo la opción A desde la pregunta ______________________- 22

Instrucciones ronda 2

En este juego, sus ganancias también dependerán de sus decisiones y de su suerte. Hay tres secciones en esta segunda ronda. La primera y segunda sección consta de 14 preguntas cada una, mientras que la tercera parte tiene siete preguntas. Para un total de 35 interrogantes.

Igual que en el juego anterior, por cada sección le mostraré el total de las preguntas y usted me debe decir en cuáles desea seleccionar la opción A y en cuáles en la opción B. No obstante su **punto de partida es la opción A**.

Esta primera sección, al igual que en la ronda anterior, la opción A es la **"elección segura"**, mientras que la opción B es la **"elección apuesta"**, en este caso puntual le acercaré una bolsa que contiene **una (1) bola azul** y **nueve (9) bolas verdes**. Si usted extrae la bola azul gana la apuesta, si selecciona una bola verde, entonces pierde.

Le recuerdo una vez más, que sus decisiones se pueden convertir en dinero real, así que por favor considere cuidadosamente su respuesta.

Al igual que en la ronda anterior, le voy a mostrar algunos ejemplos:

Ejemplo 1: Cambia a la opción B en algún momento del ejercicio

Pregunta	Opción A	Opción B	
		Bola azul (Gana) 1 de 10	Bola verde (Pierde) 9 de 10
23	2,400	4,100	800
24	2,400	4,400	800
25	2,400	5,000	800
26	2,400	5,600	800
27	2,400	6,200	800
28	2,400	6,800	800
29	2,400	7,700	800
30	2,400	8,200	800
31	2,400	10,650	800
32	2,400	15,200	800
33	2,400	18,500	800
34	2,400	25,000	800
35	2,400	35,000	800
36	2,400	40,000	800

Su respuesta:
Elijo la opción A desde la pregunta 23 - ____________32__________
Elijo la opción B desde la pregunta _______________33_____- 36

Ejemplo 2: Nunca cambiar a la opción B

Pregunta	**Opción A**	**Opción B**	
		Bola azul (Gana) **1 de 10**	**Bola verde (Pierde)** **9 de 10**
23	2,400	4,100	800
24	2,400	4,400	800
25	2,400	5,000	800
26	2,400	5,600	800
27	2,400	6,200	800
28	2,400	6,800	800
29	2,400	7,700	800
30	2,400	8,200	800
31	2,400	10,650	800
32	2,400	15,200	800
33	2,400	18,500	800
34	2,400	25,000	800
35	2,400	35,000	800
36	2,400	40,000	800

Su respuesta:
Elijo la opción A desde la pregunta 23 - ____________36_________
~~Elijo la opción B desde la pregunta ____________________~~- 36

Ejemplo 3: Cambiar desde el inicio a la opción B

Round	**Opción (A)**	**Opción (B)**	
		Bola azul (Gana) **1 de 10**	**Bola verde (Pierde)** **9 de 10**
23	2,400	4,100	800
24	2,400	4,400	800
25	2,400	5,000	800
26	2,400	5,600	800
27	2,400	6,200	800
28	2,400	6,800	800
29	2,400	7,700	800
30	2,400	8,200	800
31	2,400	10,650	800
32	2,400	15,200	800
33	2,400	18,500	800
34	2,400	25,000	800
35	2,400	35,000	800
36	2,400	40,000	800

Su respuesta:
~~Elijo la opción A desde la pregunta 23 - ____________________~~
Elijo la opción B desde la pregunta ____________23____ _______- 36

Sección 1

Pregunta	Opción A	Opción B	
		Bola azul (Gana) 1 de 10	Bola verde (Pierde) 9 de 10
23	1,200	2,300	500
24	1,200	2,500	500
25	1,200	2,850	500
26	1,200	3,200	500
27	1,200	3,650	500
28	1,200	4,150	500
29	1,200	5,000	500
30	1,200	5,600	500
31	1,200	6,400	500
32	1,200	7,550	500
33	1,200	9,200	500
34	1,200	11,750	500
35	1,200	16,000	500
36	1,200	24,800	500

Su respuesta:
Elijo la opción A desde la pregunta 23 - ____________________
Elijo la opción B desde la pregunta _____________________- 36

Instrucciones Sección 2

Las reglas para esta sección, son las mismas que en la parte anterior, no obstante las probabilidades de ganar y perder en la opción B han cambiado, de igual manera la **cantidad de dinero en ambas alternativas también es diferente**. La bolsa en la "elección apuesta" contiene **siete (7) bolas azules** y **tres (3) bolas verdes**. Si usted selecciona una bola azul gana, si elige una bola verde pierde.

Por favor considere esta nueva información antes de hacer una elección

Sección 2

Pregunta	Opción A	Opción B	
		Bola azul (gana) 7 de 10	Bola verde (Pierde) 3 de 10
37	4,000	4,300	500
38	4,000	4,350	500
39	4,000	4,600	500
40	4,000	4,750	500
41	4,000	5,000	500
42	4,000	5,300	500
43	4,000	5,650	500
44	4,000	6,000	500
45	4,000	6,350	500
46	4,000	6,700	500
47	4,000	7,300	500
48	4,000	8,100	500
49	4,000	9,200	500
50	4,000	10,600	500

Su respuesta:
Elijo la opción A desde la pregunta 37 - ____________________
Elijo la opción B desde la pregunta ____________________- 50

Instrucciones Sección 3

Las reglas para esta sección son similares a las anteriores, no obstante en esta ocasión no existe “opción segura”, ambas alternativas incluyen la probabilidad de ganar y perder. De igual manera, la cantidad de dinero que se puede ganar o perder es diferentes para ambas opciones.

Por favor considere que en esta sección podría perder parte del dinero del incentivo que se le dará en esta sesión.

Pregunta	**Opción A**		**Opción B**	
	Bola azul (gana) 5 de 10	**Bola verde (pierde) 5 de 10**	**Bola azul (gana) 5 de 10**	**Bola verde (pierde) 5 de 10**
51	10,000	Pierde 4,000	15,000	Pierde 12,000
52	4,000	Pierde 4,000	15,000	Pierde 12,000
53	1,000	Pierde 4,000	15,000	Pierde 12,000
54	1,000	Pierde 8,000	15,000	Pierde 12,000
55	1,000	Pierde 8,000	15,000	Pierde 12,000
56	1,000	Pierde 8,000	15,000	Pierde 12,000
57	1,000	Pierde 8,000	15,000	Pierde 12,000

Su respuesta:
Elijo la opción A desde la pregunta 51 - ______________________
Elijo la opción B desde la pregunta ______________________- 57

Nombre: ____

Lugar: ___________________________ Fecha: ______________________________

Género: ☐ Hombre ☐ Mujer Edad productor: ________________ años

Sección Socio-Económica

1. ¿Cuál es el ingreso total mensual de su hogar (sumando el de todos los miembros de su hogar)?

   ☐ Menos de 135.000 pesos
   ☐ 135.001 – 247.000 pesos
   ☐ 247.001 – 450.000 pesos
   ☐ 450.001 – 840.000 pesos
   ☐ Más de 840.001 pesos

2. ¿Cuál es su ingreso total mensual proveniente del cultivo de frambuesa? ______ Pesos/mes
3. Insumos utilizados en el cultivo de la frambuesa

Ítem	**Unidad**	**Cantidad**	**Costo unitario**	**No usó o no compró ésta temporada**
Plantas				
Herbicidas				
Pesticidas				
Fertilizantes convencionales				
Fertilizantes Orgánicos				
Abono Foliar				

4. Mano de obra contratada temporada 2014 – 2015

Labor	**Jornada/hombre**	**Costo unitario por jornada**
Cosecha		
Poda		
Aplicaciones		
Otros, ¿cuáles?____________		

5. ¿Tiene acceso a una cuenta bancaria? ☐ Si ☐ No
6. ¿Tiene acceso a préstamos agrícolas? ☐ Si *continúe* ☐ No *salte pregunta 8*
7. ¿Cuál es la Fuente de este préstamo?

   ☐ INDAP
   ☐ Servicios bancarios
   ☐ Empresa de insumos
   ☐ Asociación de productores
   ☐ Agroindustria
   Otro: ___________________________

Sección de producción y comercialización

8. ¿Cuántos años tiene trabajando con el cultivo de frambuesa? ____________________ Años
9. ¿Cuál su área total de producción agrícola? ______________________________ Hectáreas
10. ¿Cuál es su área de producción de frambuesa? ___________________________ Hectáreas

11. De ese total ¿Cuánto es suyo y cuánto renta? Propio: ___________ Renta: __________ Has

12. ¿Es usted miembro de alguna asociación de productores? Si: __________ No: ___________

13. ¿Cuánto tiempo invierte trabajando en su finca? ______________________ horas/semana

14. ¿Cuánto tiempo invierte trabajando fuera de su finca? __________________ horas/semana

15. ¿Ha adoptado nuevas variedades de frambuesa en los últimos cinco años?

☐ Si *continúe* ☐ No *pase a pregunta 18*

16. ¿Qué variedades ha adoptado?

____

____

17. ¿Por qué razones decidió adoptar nuevas variedades de frambuesa?

____

____

____*Pase a pregunta 20*

18. ¿Por qué motivos ha decidido conservar su actual variedad de frambuesa?

____

____

19. ¿Cuándo fue la última vez que cambió la variedad de frambuesa en el pasado?

____

20. ¿Cuál es la procedencia de la variedad de frambuesa que cultiva actualmente?

☐ De institución técnica (ejemplo INDAP)

☐ De un vecino

☐ Propagación propia

☐ Vivero formal (certificado)

☐ Otra: _________________________

21. ¿Tiene sistema de irrigación en su finca? ☐ Si *continúe* ☐ No *pase a pregunta 23*

22. ¿Qué tipo de Sistema de riego posee?

☐ Surco ☐ Tendido ☐ Goteo ☐ Otro: ________________________

23. ¿Ha adoptado en su producción alguna de las siguientes prácticas? *Marcar todas las que aplican*

Infraestructura para cultivos

☐ Bodega para insumos

☐ Bodega materiales cosecha

☐ Sala de cosecha o packing

☐ Zona de acopio

☐ Baño

☐ Cercos (cierre perimetral)

☐ Señaletica

☐ Equipo de protección personal

☐ Botiquín para emergencias
☐ Comedor

Buenas prácticas agrícolas y gestión

☐ Registro SAG
☐ Registros productivos
☐ Registros de cosecha
☐ Registro de aplicaciones hechas
☐ Registro de costos
☐ Fue auditado por BPA de INDAP
☐ Inicio de actividades

Prácticas culturales

☐ Monitoreo de plagas
☐ Cobertura entre hileras
☐ Cercos vivos
☐ Cultivos camellón
☐ Uso de compost/guano/estiércol
☐ Cultivos entre hileras asociados
☐ Control de malezas mecánico (sin herbicida)
☐ Compra de pesticidas orgánicos
☐ Uso de mulch sobre hileras

24. ¿Cuánta frambuesa produjo en la última cosecha? ________________________ kg/hectárea
25. De la producción total obtenida en la cosecha anterior, ¿Cuánto comercializó? ________ %
26. ¿Cómo comercializa su producción?

☐ Producto fresco
☐ Unidades congeladas (IQF)
☐ Block (Producto residual)
Otro: ___________________________

27. ¿A quién le vende su producción?

☐ Conchencho (intermediario)
☐ Supermercados
☐ Exportadora
☐ Agroindustria
☐ Centro de acopio
☐ Otro: ________________________

Sección Socio - demográfica

En esta sección la mayoría de las preguntas que le haré son descriptivas, algunas veces pudiera parecer que son personales, sin embargo, su respuesta nos ayudará a analizar los resultados de los juegos que recién terminamos. Todas sus respuestas son completamente confidenciales. Por favor piense cuidadosamente antes de responder.

28. Estado civil: ☐ Soltero ☐ Divorciado ☐ Viudo ☐ Casado
29. ¿Cuál es su orientación política?

☐ Izquierda ☐Centro izquierda ☐Centro ☐Centro derecha ☐Derecha ☐No tengo

30. ¿Cuántas personas viven con usted en su grupo familiar? __________________ personas
31. ¿Cuántos años estudió? ____ Años
32. ¿Es usted una persona religiosa? ☐ Si ☐ No