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Interaction between crop insurance and technology adoption decisions: The case of wheat farmers in Chile*

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This paper examines relationships between crop insurance and input technology decisions among Chilean wheat farmers. Using nationwide farm-level data, a bivariate probit model is estimated. We investigate the extent to which the adoption of production input technologies is associated with farmers' participation in the insurance program. We find that relationships between insurance and technology decisions are significant only for family farmers. In particular, there is a negative relationship between participation in the insurance program and the adoption of modern irrigation. Interpretations based on the role of input technologies on insurance adoption and adverse selection behaviours are discussed.

Key words: adverse selection, bivariate probit model, farming technologies, insurance adoption.

1. Introduction

Agricultural production is frequently exposed to a variety of risks, including climatic sanitary, geological, market, and man-made risks (Zorrilla 2002). In theory, there is a wide array of risk management strategies that farmers can use in order to mitigate agricultural risks. These strategies include crop diversification, savings accumulation, off-farm activities, and adoption of risk-reducing production technology. Among more formal strategies are forward contracts, futures and options commodity markets, revenue insurance and crop insurance (Dercon 2002). In developing countries, credit and insurance markets are incomplete or do not function well. Consequently, ex-

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post-coping mechanisms cannot be totally relied upon to protect against risk (Paxson 1992; Townsed 1994), resulting in a low adoption.

In Latin America, despite the promotion of multi-peril crop insurance and state-funded disaster relief programs as public policy for risk management in agriculture (Vila *et al*. 2011),[1] a low level of participation, especially among small farmers, has been reported (Wenner 2005). In the case of Chile, in particular, the crop insurance participation rate has been rather low, reaching approximately 10 per cent of the total arable farming area in the coverage area in 2012 (COMSA 2012).

This paper addresses the problem of low participation in crop insurance by exploring the determinants in a more general way and how farmers' insurance decisions are connected with production technology choices, in particular. The discussion is contextualised in the Chilean case, a small emerging market economy with a relatively recent implementation of a farm multi-peril weather insurance program, strongly dependent on government support and direction, that exhibits a low participation rate.[2] Focus is also displayed on small wheat farming. This segment reports a lower participation in the insurance program, which has needed larger subsidies to cover the premium cost. Many studies have attempted to explain the low crop insurance adoption by focusing on the incompleteness of risk markets, or malfunctioning capital markets. Incompleteness or malfunctioning in crop insurance markets has mainly two sources: systemic risk that makes insurability expensive, especially when there is no reinsurance available. In this case, insurance is partial and at very high costs. The other source is information asymmetries, adverse selection, and moral hazard. Adverse selection occurs when insured agents know their risk exposure better than the insurer. As a consequence, insurers set premium prices that are too high for people with low exposure and too low for people with risky prospects. Moral hazard is present when insured agents are able to shift towards riskier behaviour or neglect precautionary measures and these changes cannot be observed or verified by the insurer. The result is the same. Insurance is taken only by risky agents at eventually high premiums (on asymmetric information in crop insurance markets, see e.g. Gardner and Kramer 1986; Quiggin *et al*. 1993; Coble *et al*. 1996; Makki and Somwaru 2001; Skees and Barnett 2006; Barnett and Mahul 2007; Mahul and Stutley 2010). In developing countries, information asymmetries are exacerbated by budgetary restrictions and high administrative costs, as well as inadequate procedures for assessing

[1] These risk management policies are implemented in different modalities across the region. In Brazil, Colombia, Chile, Ecuador, Mexico, Peru, and Uruguay, the public sector supports the private insurance industry with subsidies for crop insurance, while Bolivia runs a universal coverage agricultural insurance program (Vila *et al*. 2011). In contrast, Argentina has chosen to develop a private crop insurance industry and ease access to derivative markets for the most important agricultural products.

[2] The insurance program was created in 2000 by the Chilean Ministry of Agriculture (COMSA 2012).

indemnities (Hazell 1992). A somewhat different approach to this problem focuses on the variety of risks and different risk management tools that farmers have at their disposal. A multi-layered strategy to cope with risk may reduce the value of one single instrument like crop insurance, and therefore, farmers will not be encouraging to take it up unless there is a significant discount on premiums. A series of studies look how these strategies might be affecting agriculture insurance demand (Ke and Wang 2002; Giné and Yang 2009; Velandia *et al.* 2009; Chakir and Hardelin 2012; Chang and Mishra 2012). This paper is consistent with this literature addressing the problem of low participation in crop insurance by exploring how farmers' insurance decisions are connected with production technology choices.

We know that irrigation effectively reduces yield variability and is in this way influence the risk that farmers have to face (Foudi and Erdlenbruch 2012; Salazar and Rand 2016). That fact makes the decision to irrigate a risk management tool. We expand this view to a broader set of input technologies, such as crop seed selection and biological control. Each technology is expected to interact with agricultural insurance in a different way, depending on its characteristics, as well as on the scale of the farming operation. While modern irrigation is expected to reduce vulnerability to water shortages in a similar manner to insurance, improved seeds, as being more resistant to droughts, may somewhat relate to climate risk and thus to insurance decisions. In contrast, the adoption of biological control is less likely to be affected by climate considerations and should be regarded as a placebo. These technologies are relevant for wheat production. Improved seeds and modern irrigation benefit wheat production in the short-run and long-run, respectively.

Only a small proportion of producers can afford irrigation. This makes the understanding of the interplay of technology and insurance decisions even more relevant. If we effectively find that decisions are connected, and farmers adopt insurance as substitute/complement of a risk-coping technology that would be an indication of incompleteness or malfunction in the market.

Available data come from the 2007 National Agriculture and Forestry Census is used. In particular, we want to discover if there is any relationship between the farmer's decision whether or not to buy insurance and the decision whether or not to adopt a specific technology. A problem of endogeneity may arise because these decisions might be affected jointly by an unknown underlying process (simultaneity) or they could affect each other in both directions (reverse causality). We deal with this econometric problem by setting up and estimating a bivariate probit model as a joint model for these two binary outcomes.

The rest of the article is organised as follows. Section 2 describes the characteristics of the agricultural sector and crop insurance program in Chile. Section 3 discusses the related literature. Section 4 reviews a conceptual framework that links insurance and technology adoption decisions. Section 5 presents the data and Section 6 the econometric model. Section 7 discusses the main results. Section 8 considers a number of robustness tests and Section 9 concludes the paper.

2. The agricultural sector and crop insurance in Chile

The agricultural sector in Chile accounts for around 15 per cent of the country's Gross Domestic Product (GDP) and employs 12 per cent of the labour force. More than 50 per cent of its production is sold in international markets. Some major agricultural products include fruits (grapes, apples, pears, peaches, and berries), horticulture (garlic, onions, and asparagus) and cereal and tuber (wheat, maize, and potatoes). Wheat is the most relevant annual crop in the world, in general, and in Chile it accounts for approximately 50 per cent of the surface devoted to annual crops. Small-scale agricultural represents one-third of agricultural GDP and contributes 1.2 per cent of the GDP in Chile. Family farms account for 85 per cent of total farms in the country, comprising 1.2 million people. These farms employ approximately 60,000 people directly or indirectly (INDAP 2011). These producers are mainly involved in traditional farming activities, hire family members, and operate at low levels of working capital. For policy interventions, the Ministry of Agriculture defines small farmers within the framework of family farmers as those holding 12 hectares or less of basic irrigation (HBI) (FAO 2009). We follow this definition in this paper.

The Farm Insurance Program (FIA) was created in 2000 by the Chilean Ministry of Agriculture. Its main goal is to protect farmers against economic loss resulting from the most frequent climate events, such as droughts, heavy or untimely rains, freezes, blizzards, and hail. The program subsidises farmers who buy crop insurance. The insurance covers not only annual crops, but also fruit plantations. The insurance policy assures the farmer of up to two-thirds of the potential value of the crop.

The FIA is supervised by the Agricultural Insurance Committee (hereinafter COMSA), a government agency in which the Agriculture, Finance, and Economy ministries are represented. This agency is operated by private insurance companies, supported by an extensive network of government institutions, private agents and brokers. Subsidy payments are channelled through CORFO, a governmental business promotion agency, directly to the insurance companies according to the number of policies issued. According to COMSA (2012), the premium cost subsidy consists of a fixed contribution of 1.5 Foment Units (UF by its Spanish acronym) (USD 50) for each policy, plus 50 per cent of the net premium cost with an 80 UF (USD 3,000) cap payment per farmer (all values for one season). For family farmers, the subsidy may account for up to 80 per cent of the premium cost. The coverage areas account for approximately 70 per cent of the Chilean territory.

The crop insurance policy covers two-thirds (i.e. 66.7 per cent) of the expected crop yield. Under some conditions for specific crops, coverage might reach three-fourths (i.e. 75 per cent). For example, with a two-third coverage, if the expected yield is 30 units per hectare, and the farmer obtains 15 units per hectare due to some of the climate events specified in the policy, the insurance company will compensate the farmer for 5 units per hectare, at the market price per unit. This price must be below a maximum price that is determined beforehand. Coverage percentage, standard yield range, maximum compensation prices, maximum and minimum premium rates, and other technical parameters of the insurance contract are specified for every crop, crop type, geographic area, and sowing-harvest calendar in a document known as ‘Subscription Norms’, which is issued annually by COMSA before each farming season. Insurance coverage begins at the start of sowing period and ceases at the end of harvest of the entire crop. If an adverse climate event occurs that is included in the insurance policy, the farmer must immediately notify the insurance company. The insurance company will designate a claim adjuster who, in his turn, will name an inspector with the necessary expertise to verify and evaluate the damage in the crop. The farmer must inform in advance the start of harvest, in order to verify the real yield obtained from the crop. The insurance company, based on the incident reports and the real crop yield, will issue an insurance adjustment report establishing the amounts and date of any compensation payment.

According to figures provided by the Information System of Agro-Insurance (SISA, in Spanish), insurance participation is quite low in Chile. In 2014, only 6.4 per cent of total farm area was insured. For cereal crops, this situation is slightly better, with 9.4 per cent of total cereal area covered by a crop insurance, which represents approximately 7,200 policies.

3. Literature review

One of the first empirical studies on crop insurance participation decisions was conducted by Gardner and Kramer (1986). Using county-level data, the authors found a positive and statistically significant effect of the expected return on crop insurance participation. This result was also supported by subsequent similar studies (Hojjati and Bockstael 1988; Barnett *et al*. 1990), suggesting adverse selection as one of the reasons for the low participation rate observed in crop insurance markets. Quiggin *et al*. (1993) stressed the problem of distinguishing between adverse selection and moral hazard when explaining insuring behaviour. They used cross-sectional data to estimate a corn farm production function. They found a negative association between insurance adoption and expected output and questioned the viability of a multi-peril crop insurance program in light of the contradicting incentives for farmers. Similarly, Coble *et al*. (1996), using cross-sectional data at the farm level, developed a formal crop insurance participation model, finding statistically significant effects on participation of both market return and return to insurance, as well as both market return and return to insurance variance. Just *et al*. (1999) examined adverse selection in U.S. crop insurance using nationwide data. They suggest that farmers who participate in the crop insurance program have positive expected benefits from insurance, and uninsured farmers have negative expected benefits from insurance, reflecting deficiencies in pricing insurance for lower-risk farmers. In the same direction, Makki and Somwaru (2001) concluded that high-risk farmers are more likely to purchase revenue insurance and are undercharged with respect to lower-risk farmers for a comparable insurance contract. Sherrick *et al.* (2004) also concluded that farmers who engage more extensively in crop insurance have higher yield risks. Later studies have stressed the role of risk aversion in insurance adoption using randomised field experiments. In this regard, Cole *et al.* (2013) and Karlan *et al.* (2014) identified trust in insurance, suggesting institutions as a determinant of demand for insurance within farmers who are highly risk averse. In these groups, risk aversion discourages insurance adoption because farmers are not sure the insurance companies will pay the expected compensations. Similarly, Elabed and Carter (2015) studied the case of index insurance under the presence of basis risk. They found that individuals presenting ambiguity aversion prefer not to be insured so they do not have to bear the uncertainty of not receiving compensation in case of damage. This implies that highly risk-averse people avoid compound lotteries that is (a lottery of adverse events and a lottery of compliance by insurer).

An interesting aspect in the crop insurance literature is the interplay between insurance and technology adoption decisions. In particular, the farmer's choice of the specific amount of some production inputs may modify the risk-return profile of the farm operation, making room for the appearance of moral hazard issues in the market of the agricultural insurance. Horowitz and Lichtenberg (1993) found that insured farmers use more fertilisers, herbicides, and pesticides, suggesting the presence of moral hazard if these inputs are considered risk-increasing production technologies. In contrast, Babcock and Hennessy (1996) found no support for the hypothesis, concluding that nitrogen fertiliser and insurance are substitutes. Similarly, Smith and Goodwin (1996), Goodwin *et al.* (2004), and Mishra *et al.* (2005) noticed that crop insurance participation has a significant negative effect on total chemical input expenditures. This result suggests a moral hazard issue in the sense that insurance might not encourage farmers to expend sufficiently on inputs that would reduce the chance of having a poor harvest.

A different way to tackle this issue is to look at the relationship of crop insurance participation and a wider variety of risk management tools. Such approach demands the recognition of a decision process that considers a number of factors simultaneously. Ke and Wang (2002) searched for a combination of crop rotation, future contracts, and income farm insurance that would be optimal within an expected utility theoretical model. Giné and Yang (2009) conducted a field experiment in Malawi looking at the interaction of insurance purchase, lending, and technology investment decisions. Velandia *et al.* (2009) used a multivariate and multinomial probit approach and found a correlation between farmers' decisions regarding adopting crop insurance, forward contracting, and spreading sales as risk management tools. Chang and Mishra (2012) shed light on the ambiguity in the association between agriculture insurance and input usage, by relating these decisions with another risk management tool, off-farm income. They found that both insurance and off-farm work have significant effects on chemical inputs usage. Moreover, they found insurance and off-farm income to be correlated. Foudi and Erdlenbruch (2012) focused on the role of irrigation as a production technology to manage agriculture risk by setting up a joint decision probit model for irrigation and yield insurance. They found that being insured decreases the probability of adopting irrigation, suggesting a substitute relationship as risk management tools. Chakir and Hardelin (2012) found an endogenous interrelation between chemical use and hail insurance demand among farmers in France, confirming a positive effect of insurance on chemical input usage (pesticide) and the role of diversification as a complementary tool for risk management. Deryugina and Konar (2017) focused on the impact of insured farming on water consumption. They used an instrumental variable approach to establish causality between the adoption of agriculture insurance and the use of water withdrawals for irrigation in the United States. These results demonstrated that crop insurance causally leads to more irrigation use, due to the increasing acreage destined to farming and the risk-taking incentive that farmers get for insurance (a moral hazard consequence like the one identified by Horowitz and Lichtenberg 1993).

In line with the above insights, this paper extends the discussion to developing countries with an increasing commercial openness. In these emerging economies, the participation rate in weather insurance programs is low, especially among family farmers. We use the case of wheat farmers in Chile, a small open economy, to test three hypotheses. First, the farmers' insurance decision is not independent from the adoption of technical change. Secondly, risk-decreasing technologies are expected to be substitutes to a subsidised crop insurance. Thirdly, the adoption of risk-decreasing technologies exacerbates the adverse selection problem when technological risk is unobserved by the insurance companies. In order to assess the above conjectures, we use the expected utility approach to formalise the relationship between the insurance and technological adoption decisions.

4. Theoretical framework

Our theoretical approach adapts the insights and theory proposed by Giné and Yang (2009) and Mobarak and Rosenzweig (2012). Assume that a family (or non-family) farmer is endowed with L acres (or hectares) of land that is suitable for growing crops. Soil characteristics and weather conditions are exogenous, and the harvest after the season is known a priori and equal to Y_T. In order to increase profits from farming, suppose that this farmer has to make a decision about the implementation of a technical change, TA, which has three potential forms: hybrid seeds (S); enhanced irrigation (I); and biological control (B). All of them involve a higher but riskier average yield. That is, if the farmer does not implement one of the above improvement alternatives, then the yield will be equal to Y_T. If the farmer introduces the improvement TA, then he could produce a higher yield Y_H with probability p or a lower yield Y_L with probability $(1 - p)$. As pointed out by Mobarak and Rosenzweig (2012), let us assume that probability p further captures whether the technical change is a risk-decreasing or risk-increasing technology. That is to say, if $p'(\mathrm{TA}) > 0$ and $p''(\mathrm{TA}) < 0$, then the farmer has chosen a risk-decreasing technology. Conversely, it holds that p' (TA) < 0 and p'' (TA) > 0 for a risk-increasing technology.

Moreover, the adoption of the technical change guarantees that:

$$Y_T < p(\mathrm{TA})\,Y_H + (1 - p(\mathrm{TA}))\,Y_L, \tag{1}$$

where the variable TA denotes the technical change adopted by the farmer. Therefore, p(TA) is the probability for a higher yield Y_H after adopting the technical change TA. The inequality stated in Equation (1) holds for all the improvement alternatives, and implicitly suggests that the farmer discriminates among them. Given that the competitive price of the crop is normalised to one and that technical change is costly, C, it is assumed that $C < Y_L$. Therefore, if a farmer draws a distinction among two technologies i and j, then the farmer strictly prefers technical change i over the alternative j if the following condition is true:

$$p(i)\,Y_H + (1 - p(i))\,Y_L - C^i > p(j)\,Y_H + (1 - p(j))\,Y_L - C^j; \quad \text{for } i \neq j, \tag{2}$$

where $p(i)$ and $p(j)$ are the probabilities for a higher yield Y_H related to technical improvement i and j, respectively, while C^i and C^j represent the cost of implementing the above technologies, $C^i \neq C^j$. Thus, the farmer will select a technical change that rewards a larger expected utility, which comes from profit after deducting the cost of its implementation, a decision that implicitly considers farmer's preferences towards risk.

In order to address the decision of insurance adoption, assume that farmers hold a set of illiquid assets, W, where $C < W$. Hence, under the uninsured scenario, the expected utility of a farmer who chooses the productive enhancement i, U_u^i, will be equal to:

$$U_u^i = p(i)\,U(Y_H - C^i + W) + (1 - p(i))\,U(Y_L - C^i + W), \tag{3}$$

where $U(\cdot)$ is a continuous and increasing utility function.

On the other hand, the financial system offers rainfall insurance that allows distributing risk costs over time and among producers. The insurance contract includes an indemnity equal to R, which covers the technology investment, C, and the potential loss from the casualty, M. The contract further assumes that q is the probability of high rainfall (h) and $(1 - q)$ the probability of poor rainfall (l).

Additionally, suppose that the insurer faces problems of adverse selection, which could be avoided by setting a premium that considers the characteristics and risk profile of the farmer. Although farmer's profile could be unobservable or unknown by the insurance company, assume that, the insurance premium, D, depends on technological risk, γ, crop risk, ϕ, farmer's wealth, W, and farmers risk attitudes. As remarked by Giné and Yang (2009), if the insurance premium D is fairly priced, then it will be equal to $(1 - q)R$. Thus, the expected utility of a farmer who decides to adopt a productive enhancement i and take the rainfall insurance, $U_{\mathrm{I}}^{\mathrm{i}}$, will be equal to:

$$U_{\mathrm{I}}^{\mathrm{i}} = \begin{array}{c} f(Y_{\mathrm{H}}, \mathrm{TA}, h)U[Y_{\mathrm{H}} - C^{\mathrm{i}} - D(\gamma, \phi, W) + W] \\ +f(Y_{\mathrm{H}}, \mathrm{TA}, l)U[Y_{\mathrm{H}} - D(\gamma, \phi, W) + R + W] \\ +f(Y_{\mathrm{L}}, \mathrm{TA}, h)U[Y_{\mathrm{L}} - C^{\mathrm{i}} - D(\gamma, \phi, W) + W] \\ +f(Y_{\mathrm{L}}, \mathrm{TA}, l)U[Y_{\mathrm{L}} - D(\gamma, \phi, W) + R + W], \end{array} \tag{4}$$

where $f(\cdot)$ is the joint probability density function for yield, technology, and rainfall. Therefore, when a farmer decides to buy the weather insurance, then technologies i and j are substitutes if the following condition holds:

$$\begin{aligned} & f(Y_{\mathrm{H}}, i, h)U(Y_{\mathrm{H}}, C^{\mathrm{i}}, D^{\mathrm{i}}, W) + f(Y_{\mathrm{H}}, i, l)U(Y_{\mathrm{H}}, D^{\mathrm{i}}, R, W) \\ & + f(Y_{\mathrm{L}}, i, h)U(Y_{\mathrm{L}}, C^{\mathrm{i}}, D^{\mathrm{i}}, W) + f(Y_{\mathrm{L}}, i, l)U(Y_{\mathrm{L}}, D^{\mathrm{i}}, R, W) \\ & = f(Y_{\mathrm{H}}, j, h)U(Y_{\mathrm{H}}, C^{\mathrm{j}}, D^{\mathrm{j}}, W) + f(Y_{\mathrm{H}}, j, l)U(Y_{\mathrm{H}}, D^{\mathrm{j}}, R, W) \\ & + f(Y_{\mathrm{L}}, j, h)U(Y_{\mathrm{L}}, C^{\mathrm{j}}, D^{\mathrm{j}}, W) + f(Y_{\mathrm{L}}, j, l)U(Y_{\mathrm{L}}, D^{\mathrm{j}}, R, W). \end{aligned} \tag{5}$$

In addition, a risk-decreasing technology i can be thought of as a substitute for weather insurance, or vice versa. For instance, drought insurance and irrigation technology are expected to be substitutes, which can be formalised as follows:

$$\begin{aligned} & f(Y_{\mathrm{H}}, i, h)U(Y_{\mathrm{H}} - C^{\mathrm{i}} + W) + f(Y_{\mathrm{H}}, i, l)U(Y_{\mathrm{H}} - C^{\mathrm{i}} + W - M) \\ & + f(Y_{\mathrm{L}}, i, h)U(Y_{\mathrm{L}} - C^{\mathrm{i}} + W) + f(Y_{\mathrm{L}}, i, l)U(Y_{\mathrm{L}} - C^{\mathrm{i}} + W - M) \\ & = qU(Y_{\mathrm{T}} - D(\gamma, \phi, W) + W) + (1 - q)U(Y_{\mathrm{T}} - D(\gamma, \phi, W) + R + W), \end{aligned} \tag{6}$$

where the left-hand side of Equation (6) redefines the expected utility for an uninsured farmer who adopted the technical change i, $U_{\mathrm{u}}^{\mathrm{i}}$, while the right-hand side is the expected utility when he decided not to adopt the technical change, but did buy rainfall insurance, $U_{\mathrm{I}}^{\mathrm{T}}$. Thus, the insurance adoption decision for farmer k can be simplified through the following indicator function, d_k:

$$d_k(Y, C, D(\gamma, \phi, W), M, R, W) = \begin{cases} 1 & \text{If } U^{\mathrm{i}}_{\mathrm{I},k} > U^{\mathrm{i}}_{\mathrm{u},k} \text{ or } U^{\mathrm{T}}_{\mathrm{I},k} > U^{\mathrm{i}}_{\mathrm{u},k} \\ 0 & \text{If } U^{\mathrm{i}}_{\mathrm{u},k} \geq U^{\mathrm{i}}_{\mathrm{I},k} \text{ or } U^{\mathrm{i}}_{\mathrm{u},k} \geq U^{\mathrm{T}}_{\mathrm{I},k} \end{cases}; \quad k = 1, 2, \ldots, m; \mathrm{i} = \mathrm{S, I, B}. \tag{7}$$

In addition, it is straightforward to show that the insurance adoption rate can be computed from the aggregation of individual decisions depicted by Equation (7). Now suppose that the government subsidises crop insurance in order to promote hedging behaviour among farmers. The subsidy reduces the amount of the insurance premium by α per cent. Therefore, the insurance would be strictly preferred by the farmer if the following inequality holds:

$$\begin{aligned} U^{\mathrm{i}}_{\mathrm{u}} < & f(Y_{\mathrm{H}}, i, h)U[Y_{\mathrm{H}} - C^{\mathrm{i}} - (1-\alpha)D(\gamma, \phi, W) + W] \\ & + f(Y_{\mathrm{H}}, i, l)U[Y_{\mathrm{H}} - (1-\alpha)D(\gamma, \phi, W) + R + W] \\ & + f(Y_{\mathrm{L}}, i, h)U[Y_{\mathrm{L}} - C^{\mathrm{i}} - (1-\alpha)D(\gamma, \phi, W) + W] \\ & + f(Y_{\mathrm{L}}, i, l)U[Y_{\mathrm{L}} - (1-\alpha)D(\gamma, \phi, W) + R + W]. \end{aligned} \tag{8}$$

Under this scenario, the subsidy will encourage participation in the insurance program, particularly among farmers who were indifferent before this public policy was in force, that is, $d_k = 0$ for some farmer k.

The relationship between insurance and technological decisions is determined by the technological risk γ and the farmer's knowledge of this risk. If the insurer knows the technological risk, then lower risk will reduce the amount of the premium. Hence, the probability of insurance adoption will be larger among farmers who implement a risk-decreasing technology (e.g. enhanced irrigation). This is valid provided there are no information asymmetries. Conversely, if γ is not observable, then the insurer is unable to properly assess the differences in the risk profile of individual farmers and therefore charges a relatively high 'average risk' insurance premium to all farmers. This flat-rate policy introduced by insurance companies will exacerbate the adverse selection issue.

5. Data

This study uses data from the 7$^{\text{th}}$ National Agriculture and Forestry Census (INE 2007). This survey constitutes the main data source on the current state of agricultural and forestry resources and rural population in Chile. Data was collected from rural areas within 15 regions of the country, covering 256,711 agricultural producers spread across the whole country. The Ministry of Agriculture distinguishes family farmers from non-family farmers by employing a criterion based on size, which defines family farmers as those who hold 12 or fewer hectares of basic irrigation (HBI).[3] The Census data allow us to explore differences between these types of farmers. This distinction is important for public policy, given different conditions and levels of development of family compared to non-family farmers. Thus, we expect to have dissimilar results in terms of interaction between technology and insurance adoption between these two segments.

We focus on wheat producers because of three reasons. First, due to the heterogeneity in geographic and climatic conditions in Chile, this is the only crop that can be grown along the country. Second, wheat production is benefited from the set of production technologies under analysis. Third, this crop is covered by the FIA.

To measure crop insurance and technological decisions, we use farmers' responses reported in the Census. We focused on three key technologies: improved seed (S); modern irrigation (I); and biological control (B), as previously mentioned. The purchase of improved seeds provides a determined crop variety with uniform germination and resistance to disease, which may lower the risk of output losses at the face of droughts. Biological control promotes the use and combination of natural factors and agricultural practices to prevent damage caused by pests while minimising human health risk and collateral effects on non-targeted organisms and the environment. Finally, the adoption of modern irrigation is an alternative to increase effectiveness in water application and improve crop productivity.[4] We expect strong interaction between modern irrigation and insurance decisions because both are climate risk-decreasing strategies. In contrast, the adoption of improved seed may somewhat relate to climate risk and thus to insurance decisions, the adoption of biological control is less likely to be affected by climate considerations and therefore will be regarded as a placebo.[5]

[3] Computing HBI requires transforming information about irrigated and dry land into HBI by using coefficients of conversion that captures differences in soil quality across zones. For these purposes, and following FAO (2009), we utilise the coefficients defined in Law 16.640 enacted in 1967 under the agrarian reform.

[4] Despite furrow irrigation is a commonly used technology for wheat production in Chile compared with modern irrigation, the latter is also adopted among family and non-family farmers (INE 2007). Because farmers' decisions regarding the uptake of modern irrigation are more relevant to understand farmers' behaviour regarding the adoption of the agricultural insurance, we believe focusing on this technology will provide important insights into the analysis, not only for the sub-sample of modern irrigators, but also for the design of support instruments aimed at promoting the adoption of this input production technology.

[5] Although we are aware that there may be other input production technologies that are relevant for wheat production such as fertilisers and pesticides, limited information prevented us from including it into the analysis. However, because the use of these technologies is not related with the crop insurance, their exclusion does not affect the scope of the analysis. Moreover, because they operate in a similar manner than biologic control, results from our placebo test can be extrapolated to the broader set of input technologies.

Table 1 List of variables included in the regressions

Variable	Description
Crop insurance	
Crop insurance	Self-reported adoption status (= *1 if adopted; = 0 otherwise*)
Socioeconomic characteristics	
Age	Farmer's age (*number of years*)
Male	Farmer's sex (= *1 if male; = 0 otherwise*)
Reside in plot	Place of residence (= *1 if agricultural plot; = 0 otherwise*)
Education	Farmer's level of education (*number of years*)
Dependence	% total income obtained from agriculture (*1 = less than 25%, …, 4 = 75% or more*)
Institutional characteristics	
Credit	Access to credit instruments by either public or private institutions during the last 2 years (= *1 if yes; = 0 otherwise*)
Secure tenure	% family-owned and rental land hectares over total hectares of the farm (*% hectares*)
Extension services	Benefited from extension services during the last 2 years (= *1 if yes; = 0 otherwise*)
Participation in organisations	Membership in agricultural organisations (= *1 if yes; = 0 otherwise*)
Number insurance adopter	Insurance adopters per locality, regardless of crops (*number of adopters*)
Farm size	
Yield	Agricultural yield (*kg/hectare*)
Total surface	Size of the agricultural land/farm (*number of hectares*)
Capital	Agricultural machinery and tools available in the farm (*index*)†
Technology adoption	
Improved seed	Self-reported adoption status (= *1 if adopted; = 0 otherwise*)
Modern irrigation	Self-reported adoption status (= *1 if adopted; = 0 otherwise*)
Biological control	Self-reported adoption status (= *1 if adopted; = 0 otherwise*)
Environmental and location variables	
Rainfall	Cumulative precipitation (*millimetres*)‡
Soil quality	% of agricultural land with non-eroded and slightly eroded soil (*% hectares*)§
Location variables	
North zone	Agricultural land/farm located in the North zone (= *1 if yes; = 0 otherwise*)
Central zone	Agricultural land/farm located in the Central zone (= *1 if yes; = 0 otherwise*)
South zone	Agricultural land/farm located in the South zone (= *1 if yes; = 0 otherwise*)

Note: †The measure of capital was built using information with respect to ownership of draft mechanical capital (i.e. ploughs, trucks, vans, carts, choppers, harvesters, cultivators, zero tillage, spray machines, harrows, rakes, reapers, seeders, hoppers, and tractors). These assets were weighted by applying the principal component method. ‡Cumulative precipitations were obtained from the agro-climatic system FDF-INIA-DMC. Climate measures per locality were obtained by matching localities with the nearest meteorological station. §Soil quality was proxied using information on soil erosion (CIREN 2010). The measure of erosion integrates a set of soil, topographic, climatic, and biological characteristics. Thus, erosion will be more severe to the extent that soils are more porous and sandier and that fields are more sloped and hold less vegetation, as well as in locations where a large amount of rain falls in a short time.
Source: Authors' analysis.

Table 2 Descriptive statistics of major explanatory variables (type of farmer)

Category	Total		Family		Non-family	
	Mean	SD	Mean	SD	Mean	SD
Crop insurance	0.022	0.148	0.015	0.122	0.120	0.325
Socioeconomic variables						
Age	57.890	14.462	57.816	14.458	59.017	14.491
Male	0.753	0.431	0.751	0.433	0.796	0.403
Reside in plot	0.748	0.434	0.772	0.420	0.441	0.497
Education	1.909	1.761	1.784	1.609	3.806	2.655
Dependence	1.411	1.219	1.371	1.214	1.940	1.176
Institutional variables						
Credit	0.084	0.277	0.060	0.237	0.394	0.489
Secure tenure (% hectares)	0.851	0.329	0.843	0.337	0.948	0.196
Extension services	0.220	0.414	0.226	0.419	0.141	0.348
Participation in organisations	0.204	0.403	0.184	0.388	0.457	0.498
Number insurance adopter	25.374	35.352	24.641	34.875	34.781	39.801
Farm size						
Yield (kilos per hectare)	2,814.4	3,315.3	2,682.4	3,349.4	4,505.5	2,234.5
Total surface (hectares)	38.063	194.710	17.199	22.458	305.503	663.655
Capital	0.083	1.208	−0.092	0.585	2.317	3.226
Technology adoption						
Certified seed	0.213	0.409	0.180	0.384	0.628	0.483
Biological control	0.038	0.191	0.030	0.170	0.142	0.350
Modern irrigation	0.050	0.218	0.041	0.198	0.171	0.377
Environmental and location variables						
Rainfall (millimetres)	911.195	327.369	917.788	323.163	826.687	366.860
Soil quality (ratio)	0.283	0.189	0.283	0.186	0.289	0.223
Location variables						
North zone	0.007	0.081	0.005	0.073	0.024	0.153
Central zone	0.159	0.366	0.145	0.352	0.352	0.478
South zone	0.833	0.373	0.850	0.357	0.624	0.485
Observations	42,531		39,874		2,642	

Source: Authors' estimates based on 2007 Census data.

To explain crop insurance decisions, we use a series of controls. While farmers' controls come from the Census data, climate and locations variables are obtained from alternative sources.[6] The definitions and descriptive statistics of these variables are summarised in Tables 1 and 2.

Regarding farmers' characteristics and the institutional setting in which they operate, it was observed that schooling rates are rather low; in fact, family farmers do not manage to surpass the primary educational level. In addition, only 8 per cent of farmers report to have used credit instruments.

[6] Cumulative precipitations were obtained from the agro-climatic system FDF-INIA-DMC. Soil quality was proxied using information on soil erosion (CIREN 2010).

In relation to extension services, 22.6 per cent of family farmers have received this kind of government support in 2006, which compares to the 14 per cent observed among larger wheat producers. Approximately 20 per cent of wheat farmers participate in organisations. This figure is larger among non-family wheat farmers, amounting to 45 per cent. Regarding land property status, 85 per cent of total land corresponds to own land with a registered title or rented land. This percentage is also larger among large-scale farmers.

The figures suggest a low level of insurance and technology adoption, especially among family farmers. Only 2 per cent of wheat farmers report using crop insurance, a proportion that is slightly reduced to 1.5 per cent in the family farmer group. Insurance participation is greater among non-family farmers, amounting to 12 per cent of the total.

Figures also suggest that the use of new technology is also low and less widespread among family farmers relative to larger farmers. Modern irrigation and biological control adoption do not surpass 5 per cent of total wheat farmers. Improved seed is more broadly used among wheat producers. While 18 per cent of the family farmers report purchasing certified seeds, this figure surpasses 60 per cent among larger farmers. The use of certified seeds depends on a purchase decision whose benefits are more evident in the short term. In contrast, biological control and modern irrigation adoption involve investment decisions with unknown potential benefits in the long run. Differences in technology adoption between family and non-family farmers may also be the result of severe liquidity constraints family farmers face. Thus, small farmers are more probable to afford seeds, which they can buy by using a fraction of revenues from the current crop season, but cannot afford more expensive capital expenditures for irrigation and expensive high-tech biocontrol technologies. Arguments based on credit constrains have been largely discussed as one of the main drivers for technology adoption in agriculture (Zeller *et al.* 1998; Moser and Barrett 2006; Simtowe *et al.* 2009; Foster and Rosenzweig 2010)

6. Empirical strategy

We investigate the extent to which the adoption of the agricultural insurance is associated with the adoption of input production technologies that could be perceived by farmers as either risk-increasing or risk-decreasing; that is to say, decisions are allowed to be interrelated, which follows from Equation (7) outlined in our theoretical framework. This equation implies that a farmer chooses the technological improvement before deciding to buy a crop insurance policy. However, a farmer could be covered by insurance prior to implementing a technical change. In that regard, it is plausible to add an indicator function, td_k, for the technology adoption decision and redefine Equation (7). Thus, the decision tree for the farmer k could depict through the following equation system:

$$d_k(\alpha, D(\gamma, \phi, W), M, R, W, \mathrm{td}_k) = \begin{cases} 1 & \text{If } U^{\mathrm{i}}_{\mathrm{I},k} > U^{\mathrm{i}}_{\mathrm{u},k} \text{or } U^{\mathrm{T}}_{\mathrm{I},k} > U^{\mathrm{i}}_{\mathrm{u},k} \\ 0 & \text{If } U^{\mathrm{i}}_{\mathrm{u},k} \geq U^{\mathrm{i}}_{\mathrm{I},k} \text{ or } U^{\mathrm{i}}_{\mathrm{u},k} \geq U^{\mathrm{T}}_{\mathrm{I},k} \end{cases}; \quad (9)$$
$$k = 1, 2, \ldots, m; \mathrm{i} = \mathrm{S},\ \mathrm{I},\ \mathrm{B},$$

$$\mathrm{td}_k(Y, C, W, d_k) = \begin{cases} 1 & \text{If } U^{\mathrm{i}}_{\mathrm{s},k} > U^{\mathrm{j}}_{\mathrm{s},k} \text{ or } U^{\mathrm{i}}_{\mathrm{s},k} > U^{\mathrm{T}}_{\mathrm{s},k} \\ 0 & \text{If } U^{\mathrm{j}}_{\mathrm{s},k} \geq U^{\mathrm{i}}_{\mathrm{s},k} \text{ or } U^{\mathrm{T}}_{\mathrm{s},k} \geq U^{\mathrm{i}}_{\mathrm{s},k} \end{cases}; \quad (10)$$
$$k = 1, 2, \ldots, m; \mathrm{i},\ \mathrm{j} = \mathrm{S},\ \mathrm{I},\ \mathrm{B}; \mathrm{s} = \mathrm{u},\ \mathrm{I}.$$

Therefore, both farmer decisions seem to be related and the direction of causality could be misunderstood, an issue that should be addressed on empirical testing in order to properly estimate the interaction between crop insurance and technology adoption decisions. Based on these insights, we model the adoption of agricultural insurance, assuming that farmers' adoption decisions are related through some unobservable channel. Thus, farmers' decisions can be represented as follows:

$$\begin{aligned} y_1^* &= x_2^*\beta + z_1\gamma + \varepsilon_1 \\ x_2^* &= z_2\gamma + \varepsilon_2, \end{aligned} \quad (11)$$

where y_1^* and x_2^* are unobservable and related to the binary dependent variables y_i according to the rule:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}; y_i^* = y_1^*, x_2^*. \quad (12)$$

Specifically, y_i are binary variables denoting the adoption of agricultural insurance and agricultural technologies, respectively. Similarly, z_1 and z_2 denote the vectors of explanatory variables explaining farmers' decisions regarding the adoption of agricultural insurance and agricultural technologies, respectively. These vectors include variables at the farmer level (e.g. socioeconomic characteristics), farm-level characteristics (including institutional aspects), and environmental and location factors (e.g. rainfall and soil characteristics). In addition, there are no constraints regarding the covariates embedded in z_1 and z_2. The most important feature of this model, however, is the relationship between the error terms. In particular, if the error terms in the equations above are independent of one another, $\mathrm{Cov}[\varepsilon_1, \varepsilon_2] = 0$, then the model can be estimated by means of two separate probit regressions. This would give us an indication that farmers' decisions are independent. By contrast, if the error terms are interrelated, it will be the case that Cov[$\varepsilon_{1,}$ ε_2] $\neq 0$, and farmers' decisions will be driven by the same underlying process. To take account of the relationship between these processes, the error terms above can be represented as follows:

$$\begin{aligned} \varepsilon_{1i} &= \eta_i + u_{1i} \\ \varepsilon_{2i} &= \eta_i + u_{2i} \end{aligned}. \tag{13}$$

It can be seen from Equation (13) that, while there is a component of the error term that is unique to each equation, there is another component that is common to both. This term allows us to capture the relationship between the equations (Greene 1999). If it is assumed that the error terms are normally distributed, then ε_1 and ε_2 will not only be normal but also dependent. Let us further assume that ρ denotes the extent to which these errors are correlated. Because of our interest in the joint probability of y_i (i.e. y_1 and x_2), and because of the assumption that the error terms are normally distributed, the equations above can be consistently estimated by means of bivariate probit models.[7] The significance of the coefficient rho ρ will provide information on whether or not insurance and technology decisions are interrelated. If ρ is not statistically significantly different from zero, the underlying process of the insurance decision is more likely to be characterised by a probit model. The estimation of a bivariate probit model provides an estimate of the inverse hyperbolic tangent of rho denoted as athrho, which measures the correlation between the disturbances in the insurance and technology adoption decisions.

7. Results

Estimation of the insurance decision process using the bivariate probit model is depicted in Tables 3 and 4 for the sub-samples of family farmers and non-family farmers, respectively.[8] Columns (1)–(2) display farmers' decisions regarding the adoption of agricultural insurance and certified seed. Similarly, farmers' decisions regarding the adoption of agricultural insurance and biological control are depicted in Columns (3)–(4). Columns (5)–(6) present estimated parameters associated with the interplay between adoption of

[7] This model provides an estimate of the inverse hyperbolic tangent of rho, denoted as athrho, which measures the correlation between the disturbances in the insurance and technology adoption decisions.

[8] Since these two segments are substantially different by definition, and therefore, estimated coefficients must differ between groups, we decided to explore differences and similarities across groups by splitting the sample. The latter assume a change in the slope for every independent variable. In contrast, keeping the whole sample and using an interaction variable for size assume a change in the slope of that particular independent variable, leaving all other slopes constant, which is questionable. In addition, bivariate probit models report a correlation coefficient informing on the interrelation between the insurance and technology decisions. It is also interesting to explore whether this interrelation differs across segments. In addition, the interpretation, significance, and magnitude of the interaction effect in non-linear models are not a trivial issue (Ai and Norton 2003).

Table 3 Estimates of the bivariate probit model for insurance adoption (family farmers)

Variables	Insurance (1)	Certified seed (2)	Insurance (3)	Biological control (4)	Insurance (5)	Modern irrigation (6)
Technology						
Certified seed	0.0296 (0.178)		0.256*** (0.0727)		0.222*** (0.0323)	
Biological control	0.0899 (0.0782)		−1.477*** (0.0563)		0.0511 (0.0444)	
Modern irrigation	0.132* (0.0792)		0.0554 (0.0490)		−1.573*** (0.0526)	
Household and farm characteristics						
Gender (Male = 1)	0.0655 (0.0484)	0.0715*** (0.0184)	0.0406 (0.0330)	0.0129 (0.0307)	0.0571* (0.0315)	0.0246 (0.0278)
Age	−0.00593*** (0.00145)	−0.000191 (0.000565)	−0.00263** (0.00132)	0.000936 (0.000966)	−0.00487*** (0.000964)	−0.00257*** (0.000854)
Reside in farm	−0.237*** (0.0470)	−0.0514** (0.0201)	−0.206*** (0.0371)	−0.120*** (0.0329)	0.0779** (0.0389)	0.334*** (0.0370)
Education	0.0231* (0.0123)	0.0646*** (0.00467)	0.0309*** (0.00822)	0.0384*** (0.00739)	0.0440*** (0.00794)	0.0602*** (0.00714)
Dependence	0.122*** (0.0178)	0.0720*** (0.00671)	0.0101 (0.0245)	−0.0764*** (0.0129)	0.121*** (0.0115)	0.100*** (0.00991)
Capital	0.167*** (0.0238)	0.259*** (0.0178)	0.194*** (0.0172)	0.189*** (0.0183)	0.121*** (0.0166)	0.0638*** (0.0200)
Land	0.00226*** (0.000785)	0.00122*** (0.000383)	0.00199*** (0.000586)	0.00117** (0.000585)	0.00164*** (0.000546)	−2.70e-05 (0.000564)
Yield	0.000578*** (0.000190)		0.000482** (0.000209)		0.000519*** (0.000200)	
Institutional variables						
Secure tenure	0.117* (0.0680)	0.0909*** (0.0248)	0.0726 (0.0474)	0.0127 (0.0431)	0.0766* (0.0428)	0.0285 (0.0354)
Extension	0.435*** (0.0440)	0.282*** (0.0183)	0.322*** (0.0455)	0.162*** (0.0314)	0.508*** (0.0280)	0.486*** (0.0247)
Credit	0.918*** (0.0492)	0.498*** (0.0299)	0.757*** (0.0590)	0.461*** (0.0476)	0.632*** (0.0402)	0.305*** (0.0432)
Participation	0.212*** (0.0453)	0.306*** (0.0188)	0.346*** (0.0349)	0.413*** (0.0306)	0.102*** (0.0302)	0.0299 (0.0291)
No. adopters	0.00894*** (0.000444)	0.00303*** (0.000222)	0.00506*** (0.000973)	−0.000242 (0.000457)	0.00219*** (0.000476)	−0.00646*** (0.000542)
Environmental and location variables						
Rainfall	−0.000196** (7.98e-05)	7.54e-05** (2.97e-05)	−0.000190*** (5.52e-05)	−0.000184*** (5.20e-05)	−0.000163*** (4.80e-05)	−0.000127*** (3.94e-05)
Soil quality	0.455*** (0.141)	−0.845*** (0.0500)	0.322*** (0.112)	0.0874 (0.0811)	0.217** (0.0867)	−0.0240 (0.0693)
North zone	−4.810*** (0.159)	1.058*** (0.0991)	−5.500*** (0.157)	−0.0539 (0.163)	−3.820*** (0.0962)	0.609*** (0.115)
Central zone	−0.163** (0.0766)	0.491*** (0.0266)	0.0163 (0.0695)	0.199*** (0.0432)	0.0380 (0.0474)	0.217*** (0.0391)
Constant	−2.845*** (0.141)	−1.418*** (0.0529)	−2.197*** (0.165)	−1.969*** (0.0914)	−2.270*** (0.0909)	−2.170*** (0.0791)
Athrho	0.268** (0.110)		2.193*** (0.710)		2.405*** (0.220)	
Observations	39,874		39,874		39,874	

Note: $^{***}P < 0.01$; $^{**}P < 0.05$; $^{*}P < 0.1$. Robust standard errors in parentheses.

Table 4 Estimates of the bivariate probit model for insurance adoption (non-family farmers)

Variables	Insurance (1)	Certified seed (2)	Insurance (3)	Biological control (4)	Insurance (5)	Modern irrigation (6)
Technology						
Certified seed	−0.289 (0.326)		0.183* (0.0959)		0.163* (0.0910)	
Biological control	0.286*** (0.0943)		0.658 (0.841)		0.261*** (0.0977)	
Modern irrigation	0.184** (0.0923)		0.184* (0.0937)		−0.785 (0.579)	
Household and farm characteristics						
Gender (Male = 1)	−0.0452 (0.0849)	0.0103 (0.0683)	−0.0344 (0.0921)	−0.195** (0.0809)	−0.105 (0.0867)	−0.210*** (0.0754)
Age	−0.00330 (0.00271)	−0.00172 (0.00197)	−0.00309 (0.00272)	−0.000386 (0.00258)	−0.00322 (0.00259)	−0.00180 (0.00224)
Reside in farm	−0.0449 (0.0736)	−0.0538 (0.0581)	−0.0435 (0.0743)	0.0554 (0.0718)	−0.00980 (0.0729)	0.0918 (0.0680)
Education	0.0342** (0.0153)	0.0204* (0.0118)	0.0286* (0.0170)	0.0449*** (0.0140)	0.0517*** (0.0195)	0.0755*** (0.0133)
Dependence	0.0605* (0.0332)	0.0108 (0.0239)	0.0623* (0.0336)	−0.0359 (0.0310)	0.0708** (0.0318)	0.0593** (0.0287)
Capital	0.0564*** (0.0144)	0.116*** (0.0139)	0.0378* (0.0202)	0.0662*** (0.0120)	0.0650*** (0.0166)	0.0761*** (0.0114)
Land	0.000123* (6.93e-05)	2.50e-05 (8.16e-05)	0.000125* (7.26e-05)	−7.29e-05 (0.000100)	0.000128** (6.49e-05)	5.70e-05 (8.60e-05)
Yield	0.00789*** (0.00192)		0.00786*** (0.00195)		0.00718*** (0.00201)	
Institutional variables						
Secure tenure	0.366* (0.200)	0.250* (0.132)	0.350* (0.207)	−0.129 (0.171)	0.394** (0.198)	0.312 (0.196)
Extension	0.374*** (0.1000)	0.294*** (0.0775)	0.336*** (0.102)	0.0959 (0.0984)	0.367*** (0.0935)	0.179* (0.0936)
Credit	0.649*** (0.0812)	0.530*** (0.0606)	0.564*** (0.101)	0.336*** (0.0742)	0.602*** (0.0844)	0.235*** (0.0706)
Participation	0.282*** (0.0842)	0.553*** (0.0568)	0.183* (0.106)	0.428*** (0.0704)	0.248*** (0.0725)	0.162** (0.0659)
No. adopters	0.00519*** (0.000849)	0.00380*** (0.000749)	0.00490*** (0.000828)	−0.00192** (0.000918)	0.00462*** (0.000891)	0.000651 (0.000948)
Environmental and location variables						
Rainfall	−0.000380*** (0.000138)	−4.52e-05 (0.000102)	−0.000428*** (0.000161)	0.000522*** (0.000125)	−0.000482*** (0.000136)	−0.000431*** (0.000125)
Soil quality	−0.623** (0.250)	−0.884*** (0.150)	−0.526** (0.245)	0.186 (0.198)	−0.297 (0.326)	0.522*** (0.187)
North zone	−0.0381 (0.405)	0.676*** (0.218)	−0.134 (0.404)	−0.0498 (0.338)	−0.149 (0.369)	−0.138 (0.244)
Central zone	−0.0538 (0.121)	0.588*** (0.0829)	−0.146 (0.117)	0.247** (0.108)	−0.245* (0.135)	−0.442*** (0.107)
Constant	−2.287*** (0.376)	−0.647*** (0.230)	−2.460*** (0.356)	−2.087*** (0.299)	−2.319*** (0.401)	−1.647*** (0.294)
Athrho	0.272 (0.187)		−0.204 (0.469)		0.655 (0.532)	
Observations	2,642		2,642		2,642	

Note: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. Robust standard errors in parentheses.

agricultural insurance and modern irrigation. Estimated coefficients suggest a number of findings that are worth mentioning.[9]

Regardless of the sample chosen, dependence, yield, capital, extension, credit access, participation, number of adopters, and rainfall are statistically significant to explain adoption of crop insurance. Farmers who are more agricultural income-dependent are more likely to adopt insurance. Given that insurance covers losses from unpredictable weather events, farmers obtaining a larger proportion of their income from agriculture would be more inclined to buy crop insurance. A related explanation considers the extent of diversification into non-agricultural activities (Richards 2000; Mohammed and Ortmann 2005). Market return and return to insurance variables have also been found important in prior literature (Coble *et al*. 1996; Cabas *et al*. 2008; Garrido and Zilberman 2008).

Capital significantly and positively affects insurance adoption. Although somewhat unexpected in light of evidence that farmers' risk aversion decreases as their wealth increases (Serra *et al*. 2003), larger wealth size may promote the adoption of instruments to cover against higher potential losses (Santeramo *et al*. 2016). Furthermore, the cost structure of the insurance including a fixed cost makes it attractive for wealthier farmers who can exploit economies of scale. Finally, crop insurance demand can be constrained by liquidity constraints, as farmers must pay a premium which only wealthier farmers can afford. Previous evidence suggests that liquidity constraints reduce insurance demand (Giné *et al*. 2008; Cole *et al*. 2013). We also find that insurance is more broadly adopted in drier zones, as expected. This result is in line with the usual findings that higher-risk farms are more likely to be insured (Enjolras and Sentis 2011). For the family farmer segment, we find that age, residence on the farm, and farm size also matter. Age negatively influences the probability of adopting insurance. Sherrick *et al*. (2003) also find that those preferring revenue insurance are younger.

We find that the larger the farm, the more probable the adoption of insurance. Growers with operations spread over large areas may benefit from geographical diversification (Richards 2000; Sherrick *et al*. 2004; Santeramo *et al*. 2016). We also find that education is positively associated with insurance, and farmers who hold a larger ratio of both owned land and land under property rental contracts are more likely to take insurance. Fahad *et al*. (2018) also highlight the role of education in the process of crop insurance adoption.

There is evidence that family farmers' decisions are interrelated, regardless of the production technology under analysis. This finding is supported by the fact that the inverse hyperbolic tangent of rho (athrho) is positive and statistically significant at the 1 per cent level for all the technologies, indicating that both decisions are indeed linked. Consequently, farmers'

[9] Coefficient estimates for control variables are quite similar between the individually and simultaneously estimated insurance adoption models. Results are available upon request.

decisions should be analysed by means of a bivariate model. In contrast, the estimated coefficient of athrho was statistically insignificant among non-family farmers, indicating that the decisions are independent. This suggests that consumption of risk coverage through insurance demand is dependent on production technology decisions, and this is driven exclusively by the behaviour of family farmers. This is consistent with a well-known implication in the literature stating that when markets are incomplete, household consumption and production decisions are more likely to be interlinked (Benjamin 1992). Liquidity constraints are clearly more evident among family farmers.

We find that while adoption of certified seed by farmers in either sub-sample has no effect on the probability of being insured; both biological control and modern irrigation negatively affect the probability of being insured in the sub-sample of family farmers. The result for biological control was somewhat unexpected because agricultural insurance protects farmers against climatic risks exclusively and not from losses due to pest infection and other production shocks.[10] In contrast, the finding that a farmer adopting modern irrigation is less likely to adopt agricultural insurance is in line with Foudi and Erdlenbruch (2012). This implies that modern irrigation can be understood as a substitute for agricultural insurance (i.e. both insurance and modern irrigation protect farmers against climatic risks such as droughts), suggesting a high insurance participation rate among higher-risk profile farms. This finding suggests the existence of adverse selection problems in the Chilean crop insurance program.[11]

8. Robustness checks

8.1 Adoption decisions in homogeneous areas

It was pointed out in the sections above that agro-climatic conditions in Chile exhibit a great deal of heterogeneity. Because availability of water sources, soil nutrients and other geographical characteristics affecting agricultural activity significantly change when moving from north to south, it might be thought that farmers' choices regarding participation in the climate risk

[10] Although biological control is not directly related with insurance coverage – and it is therefore expected to be unrelated with insurance decisions – this finding could also suggest that pest control may be relevant for farmers when weather conditions are not optimal. In such cases, farmers' decisions are likely to be interdependent.

[11] It could be argued that, in absence of adverse selection problems, farmers adopting modern irrigation may receive a premium discount. However, information provided by COMSA (2012) indicates that the net premium is mainly calculated on the basis of the insured amount, which in turn depends on the expected yield, the total covered area, and crop prices. Moreover, there is no explicit mention of accounting for technological characteristics in the determination of insurance premiums. Thus, it is unclear that farmers adopting modern irrigation could benefit from premium discounts, compared with non-adopters. In the former case, disincentives may be even larger as they report larger yields.

insurance program are mainly driven by geography. In order to evaluate the sensitivity of the results to exposure to given agro-climatic characteristics, we estimate the bivariate probit model in Equations (11)–(13) on a sub-sample of farmers located in Central Chile. By construction, farmers in this sub-sample are located in more homogeneous zones. Estimated coefficients are displayed in Table A1 of Appendix S1. As can be seen, results are robust for modern irrigation technology and less clear for biological control, in that its interrelation with insurance becomes insignificant.

8.2 Assessing technological change among irrigators

So far, the uptake of agricultural insurance by farmers adopting modern irrigation has been analysed by using the totality of farmers. Because a significant number of farmers do not irrigate, we might be comparing two groups of farmers that are systematically different (i.e. irrigators and non-irrigators). In order to account for the technological change due to the shifting from traditional to modern irrigation, the analysis was constrained to the sample of irrigators. Results are shown in Table A2 of Appendix S1. As can be seen, the sign and statistical significance of the estimated coefficient of modern irrigation technology on insurance participation remained robust to the exclusion of non-irrigators. Nonetheless, results did not hold for farmers adopting biological pest control.

8.3 Controlling for multiple relationships

In the results above, relationships between crop insurance and technology decisions were considered individually, assuming no correlation among different technologies. However, relationships among technologies may be important. To account for this, we estimate a multivariate probit model on the sub-sample of family farmers and irrigators for the central zone. Results are shown in Table A3 of Appendix S1, and confirm the significant relationship between insurance adoption and modern irrigation decisions. However, the relationship between insurance adoption and biological control becomes insignificant. Accordingly, we find that the probability of adopting insurance is lower among modern irrigators. We additionally find evidence of relationships between certified seeds and biological control technologies. Thus, results remained robust after controlling for multiple relationships.

8.4 Instrumental variable approach

The joint insurance adoption/agricultural technology adoption decision is estimated by means of bivariate probit models. The identification lies mainly in the structure of the model, which seems to overlook exclusion restriction considerations. Some authors argue that this is sufficient for identification (Wilde 2000). However, an IV approach might help in making the estimation results more robust to distributional misspecifications (Monfardini and Radice 2007). In this section, we apply an IV approach under the bivariate probit model. The systematic and strong significance of the athrho coefficient (ρ) in the insurance and modern irrigation model suggest that endogeneity may be problematic in this case. Consequently, we focus on the joint estimation of insurance and modern irrigation decisions. For identification, we exploit the characteristics of the water source used for irrigation. In particular, we assume that modern irrigation decisions respond to the availability of well water on the farm. Wasting water is more costly when pumped from groundwater sources. In that case, the availability of expensive water sources may promote adoption of water-saving technologies (Caswell and Zilberman 1986). Results are presented in Table A4 of Appendix S1. They show that our instrument is strongly correlated with modern irrigation but does not affect the insurance decision. Overall, our key results still stand. Modern irrigation reduces the likelihood of adopting crop insurance, suggesting that these two options are substitutes.

8.5 Matching and sample balancing

Another concern relates to the balance of the binary dependent variable. Since the percentage of insurance adoption is low, results might be highly influenced by the lack of variability of this variable. We use a matching procedure to improve the sample balancing as that described by Imbens and Wooldridge (2009). In the first stage, we estimate propensity scores for each farmer using a probit model for insurance adoption among family farmers as a function of control variables. After dropping the observations that fall outside the common support, farmers are matched on the basis of the propensity scores. Our model is then estimated on the matched sample by means of weighted regressions, in which observations are weighted based on the number of times they were included as matches. We use a nearest neighbour 1–4 with replacement and a calliper of 0.01 as the matching method (Abadie *et al.* 2004). We focus on modern irrigation technology. Results are presented in Table A5 of Appendix S1. They confirm previous findings, showing that insurance and irrigation are substitute.

9. Conclusions

Improvements in climate risk management by the adoption of modern technology and crop insurance are likely to become essential in order to reduce the vulnerability of agriculture in the future (MINAGRI 2006; FAO 2010). This paper examined the determinants of participation in the Chilean crop insurance program, with an emphasis on the interactions that emerge with technology adoption decisions. Results suggest that crop insurance is more likely to be adopted among more agricultural income-dependent farmers, farmers participating in extension programs, with a higher educational level, larger capital, and those with plots in drier zones. We found that relationships between insurance and technology decisions are strong and significant among family farmers, but not among large-scale farmers. In addition, the estimations of the bivariate probit model suggest that, whereas modern irrigation decisions are related to insurance participation, certified seed and biological control adoption are more likely to be independent of insurance decisions.

The empirical study provided evidence that modern irrigation reduces the likelihood of adopting crop insurance, suggesting that Chilean farmers perceive these two options as substitutes. The latter implies that farmers who cannot protect themselves against riskier situations, that is, those using traditional irrigation methods, preferentially participate in the insurance program, which can be taken as evidence of problems of adverse selection in the Chilean insurance market. These findings were found to be robust when reducing spatial variation and focusing on a more homogeneous agro-climatic zone. In addition, results were not driven by non-irrigators or by multiple technological decisions. Finally, the key results stand when implementing an instrumental variable approach and balancing adopter and non-adopter with matching techniques.

Nevertheless, a couple of caveats deserve attention. First, given the cross-sectional nature of the data, it was not possible to fully explore the dynamics of the relationship between insurance and technology decisions. These may be important, especially in examining the dynamic components embodied in exit and entry decisions in the insurance program (Cabas *et al*. 2008; Santeramo *et al*. 2016). Second, the database does not report information on some key control variables such as insurance premium, although it was proxied by including yield variables. Further, the low participation rate in the crop insurance program may be due to a lack of competition on the supply side. The existence of only two insurance operators suggests the emergence of market concentration issues, which may increase insurance premiums and then reduce the power of subsidies as economic incentives for participation. Third, our main results assumed that irrigation and insurance decisions are homogeneous, independent of the type of risk. For example, irrigation may smooth risks in drought-prone areas, but it may do the opposite in flood-prone areas. In the latter case, the model suggests insurance and irrigation will be complements. Although we have detailed information on main flood-prone areas in Chile, this phenomenon does not seem to be a main concern in Chile, at least for agriculture production. Thus, it is more probable that irrigation and insurance are substitutes.

Despite these caveats, these findings have important implications to address the low participation rate in the insurance program. First, adoption of crop insurance is quite low. This may be because of lack of diffusion and knowledge on the benefits of crop insurance instruments. In addition, insurance participation is also related to the level of education. Thus, our results suggest that policy interventions through extension and education programs providing insurance-related information are necessary to induce faster adoption and diffusion of the crop insurance among farmers. Diffusion channelised through famer organisations and credit programs present some advantages.

Second, to optimise a policy instrument aimed at increasing insurance participation, it is necessary to understand the risk character of the technology. Farmers adopting modern irrigation clearly face less risk than traditional irrigators, and therefore, they should pay a lower premium. However, because premiums paid by modern irrigators underwrite the program for traditional irrigators, the premium for modern irrigators may be so high that too few of them decide to buy insurance. It is probable that existing rigidity in the climate insurance program magnifies these market distortions. For example, the fixed cost part of the total insurance cost may be creating more incentive for adoption among larger and wealthier farmers. Another source of rigidity is the definition of a maximum subsidy per farmer. A subsidy per policy rather than per farmer would allow farmers to reduce insurance costs through the promotion of insurance of two or more plots with different characteristics in terms of size, crop variety, etc. Thus, insurance programs should be re-designed to allow greater flexibility in order to better match insurance premium with farmer profile, considering not only the climate risk associated with farm location but also the individual utilisation of risk management practices.

Third, our results highlight the importance of incorporating the family farmer segment in the design of an improved insurance scheme. We found that insurance demand and technology production decisions are more likely to be interlinked among family, and that liquidity constraints make insurance less affordable among family farmers. Although differences in access to insurance justify larger subsidies for the family famer group, greater financial support for traditional family irrigators may be aggravating the adverse selection problem as technology and insurance decisions are interdependent. This produces a trade-off between equity and market efficiency considerations that must be taken into account in the design of the insurance scheme. Thus, public policy in terms of insurance subsidies may be contributing to aggravate potential distortions in the Chilean crop insurance market. This interesting aspect is left for future research.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Table A1. Estimates of the bivariate probit model for insurance adoption (Family farmers and central zone).

Table A2. Estimates of the bivariate probit model for insurance adoption (Family farmers and irrigator sample).

Table A3. Estimates of the multivariate probit model for insurance adoption (Irrigator sample, family farmers and central zone).

Table A4. Estimates of the bivariate probit model for insurance and irrigation technology adoption with instrumental variables (Family farmers, central zone, and irrigator sample).

Table A5. Estimates of the bivariate probit model for insurance and irrigation technology adoption using a matching procedure (Family farmers).