I Learn, You Learn, We Gain. Experience in Crop Insurance Markets

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April 2016

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April 26, 2018

Abstract

The relevance and the impact of experience in insurance markets are under-investigated. From Italian farm-level data we estimate a dynamic discrete choice model of participation to investigate the role of experience. The methodology, coupled with exploratory analysis, allows one to compare how different sources of experience influence the crop insurance decision making process. We found that direct experience is a catalyst for insurance participation of medium and large farms. The experience indirectly acquired is also relevant, especially for small farms. Policy implications are discussed: in particular, we discuss on the importance of information campaigns and of bolstering uptake to exploit the advantages of the inertia and spillover effects that emerge from experience.

Keywords: Direct Experience, Dynamic Probit, Imperfect Knowledge, Indirect Experience, State Dependence.

JEL: G22,Q12, Q18

[*]The author thanks B. K. Goodwin, R. Rejesus, D. Thomas, W. Thurman, X. Y. Wang, X. Zheng, P. Arcidiacono, N. Piggott, and the participants in seminars at Duke University, University of Bari, and North Carolina State University.

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[§]A revised version has been accepted in *Applied Economic Perspectives and Policy*.

I Learn, You Learn, We Gain
Experience in Crop Insurance Markets

L'expérience de chacun est le trésor de tous

(Gerard de Nerval)

During recent decades, crop insurance programs have increased in prominence in developed and developing countries, and participation has been increased through subsidies (Mahul and Stutley, 2010). The world's largest risk management program - the United States of America's one - supports farmers through hedge funds, revenue insurance programs, mutual funds, and weather indexes. In the European Union, Member States have adopted autonomous national policies for assisting farmers through subsidized crop insurance or mutual funds (Santeramo and Ramsey, 2017).

Italy has a long tradition of farm subsidies for risk management strategies, but it has been difficult to achieve high level of crop insurance participation. The public intervention started in 1970, with the so called Fondo di Solidarietá Nazionale (FSN), intended to compensate farmers who had been affected by natural disasters. Starting in 2004 (through the Legislative Decree No. 102/2004) the system switched from *ex post* compensations to *ex ante* subsidies. The FSN, and the subsequent crop insurance programs, have been criticized by farmers' unions due to repeated delays in payments, heavy bureaucracy and complex procedures. Moreover, due to high costs of bureaucracy, ineffectiveness of Defense Consortia, and lack of experience with crop insurance contracts, farmers have been reluctant to participate in crop insurance programs. It is not surprising that participation has remained as low as 15% (Santeramo et al., 2016).

A vast number of studies have analyzed the determinants of participation in crop insurance programs (Skees and Reed, 1986; Goodwin, 1993; Smith and Goodwin, 1996; Sherrick et al. 2004; Walters et al., 2014; Tolhurst and Ker, 2015; Menapace et al., 2015), the dynamics of subsidized crop insurance programs (Coble and Barnett, 2013), and the potential effects of innovative contracts (Maestro et al., 2016). Santeramo et al. (2016) analyzed the drivers of enter and exit from the crop insurance market. However, the existing research, with few exceptions (e.g. Cole et al., 2014; Santeramo, 2018), has stopped short of providing a deeper investigation into the role of experience on participation in crop insurance programs. Rothschild and

Stiglitz (1976), and Chassagnon and Chiappori (1997) argue that imperfect knowledge and asymmetric information are likely to play a substantial role in the insurance decision-making process. Analyzing the automobile insurance market, Chassagnon and Chiappori (1997, p.75) concluded on the role of imperfect knowledge and experience: "learning can be expected to modify this situation and [...] driver's experience allows her to learn about her true ability faster than the insurance company."

Because a deeper comprehension of the frictions to participation in (subsidized) crop insurance programs is a pressing issue for European Union (EU) policymakers, exploring the role of experience (and information) is a promising area of research. Given for granted that imperfect information influence participation (e.g. Goodwin, 2001; Walters et al., 2014), it is worth asking further questions: Does What is the role of experience on participation? Are there knowledge spillover effects among farmers?

We investigate how experience influence crop insurance decisions through a dynamic model of participation. In particular, we focus on the role of direct and indirect experience using a detailed 7-years firm-level panel of Italian farms. We found that experience in crop insurance contracts tend to increase participation: the experience acquired in past harvest seasons is likely to reduce the imperfect knowledge both on farmers' and insurees' sides, and thus to increase uptake. We conclude with a discussion directed to a better implementation of policy interventions in the reformed EU Common Agricultural Policy.

The Italian crop insurance system

The Italian system for risk management started in 1970 with the FSN, and has evolved over time (Figure 1). Since early 2000s, risk management has been based on *ex-post* compensations. In 2000, the Defense Consortia were introduced in order to facilitate the match of supply (insurers) and demand (farmers) in the subsidized crop insurance market. Since 2004, the Legislative Decree 102/2004 introduced the multi-risks (i.e. multiple perils) contracts, that covers all adversities, and ended the subsidies to mono-risk (i.e. single peril) contracts, which have rapidly decreased in prominence (Table 1). The share of contracts providing coverage only against one adversity has decreased from 92.0% in 2004 to 50.2% in 2010. The Italian crop insurance policies are subsidized through EU funds: subsidies were as high as 80% of the insurance premium for contracts covering losses due to adverse weather conditions and other natural disasters (indemnities are triggered by damages exceeding at least 30% of assured production), and up to 50% for contracts against losses due to frequent adverse weather conditions as well as to animal or plant diseases. In 2010, due to the EU Reg. 73/2009, the subsidies have been lowered to 65%. Moreover, since 2014 the subsidized crop insurance policies must cover at least three climatic adversities eligible for pluririsks policies, which do not need to be mutually exclusive. The indemnities paid for mono- and pluri-risks policies are computed through qualitative and quantitative assessments of the percentage of losses due to the insured adversities; the multi-risk policy, also known as yield insurance, compensates farmers for losses due to a realized yield below the average (three or five years) historical yield. In 2015 a new set of contracts has replaced the previous system: types A, B and C offer coverage against different combinations of infrequent perils, frequent perils, and additional adversities.

See table 1

Currently, the vast majority of contracts are purchased by farms located in Northern Italy: in terms of insured value, in 2016 the North accounted for almost 85.5%, the Centre for 8.6%, and the South for 5.9%. The number of insured crops has increased from 58 (in 2002) to 164 (in 2010), although (in 2016) four crops accounted for more than half of the total insured value: wine grapes, apple, rice, and corn.

The market structure consists of one public-private coinsurance pool, twenty-five private insurance companies, and several mutual/cooperative entities participating in the agricultural insurance system. Major insurance companies are FATA Assicurazioni (13% of market share in 2005), Toro and ARA Assicurazioni (7% of market share) (Mahul and Stutley, 2010), and Cattolica Assicurazioni. While (private) insurance companies may set their own premium rates, the companies coordinate pricing policies and set the maximum levels of insurance premium eligible for public subsidies: as a result, "*competition is predominantly based on quality of insurance services*" (Mahul and Stutley, 2010, Annex E p.118).

The individual demand for crop insurance contracts is aggregated through Defense Consortia, local institutions aimed at enhancing insurance uptake by matching insurers' supply and farmers' demand. Farmers are offered contracts from different insurance companies, and select the contract with the highest perceived quality. The existence of Defense Consortia is symptomatic of asymmetric information among insurers and farmers.

On participation level and imperfect knowledge

Participation in crop insurance programs is usually promoted through subsidies, and by offering a wide set of contracts. However leveraging crop insurance demand with subsidies comes with large marginal costs. According to Glauber (2013), in the US an increase in subsidies from 2.73 (in 1981-1994) to 7.76 dollars per acre (in 1999-2003) boosted marginal costs from 3.31 to 25.99 dollars per acre: the policy became costly and, in the long-run, unsustainable. The implications of crop insurance subsidies go far beyond an increase in participation. As extensively described in Coble and Barnett (2013) and in Lusk (2017), subsidies increase regional differences in terms of subsidies received, may hide *ex-ante* and *ex-post* opportunistic behavior (i.e. adverse selection and moral hazard), and may favor rent seeking strategies. How to design alternative (and not distortionary) policies is a legitimate and important question. We focus on the impacts generated by imperfect knowledge.

Imperfect and asymmetric information (i.e. lack of information on farmer and/or insuree sides), through adverse selection (i.e. self-selection of riskier farmers in the insurance market) and moral hazard (i.e. riskier behavior adopted by insured farmers), are key factors to explain low participation in insurance markets (Chiappori and Salanie, 2013). On one side, riskier insurees have private knowledge on the risks they face: they find profitable to insure at the rate that insurers set for average-risky customers. Such adverse selection mechanism pushes insurers to compensate their financial exposure by setting higher rates (Goodwin and Smith, 2013; Glauber, 2013). On the other side, insurers have private knowledge on the type of contract they offer[1], at the detriment of clarity and transparency of contracts to farmers (Chiappori and Salanie 2000, 2013). A third channel through which imperfect knowledge disfavors participation consists of transaction costs implied by bureaucracy - the (cumbersome) process to obtain subsidies for the premium and to claim reimbursements for claimed losses. This channel disfavors participation of farmers who are vulnerable to liquidity constraints (EC, 2001). In all these cases the imperfect knowledge is likely to be resolved (at least partially), under the insurance contract, at the end of the harvest season. In other terms, a farmer who has stipulated an insurance contract will reveal (at the end of the season, through the realization of her business) some of

[1] An alternative way to look at this problem is that insurance contract tend to be overcomplicated by commas, clauses and footnotes that are not transparent when the contract is accepted, or are not fully taken into consideration by the insuree.

the private knowledge in terms of riskiness. On the other end, the insurer will reveal to the insured farmer (at the end of the season, by honoring the contract in case losses have been claimed) some of his own private knowledge on the goodness of the contract. Finally, both the insurer and the farmer will gain experience on the bureaucracy of insurance at the end of each season. All in all, it is likely that the more contracts are stipulated, the higher the experience on both sides, the lower the frictions due to imperfect knowledge. A similar mechanism has been hypothesized and tested in automobile (Cohen, 2005) and health care markets (Finkelstein and McGarry, 2006), which share with the crop insurance markets the characteristics of dealing with slowly depletable goods. The quality-based competition of Italian crop insurance companies is likely to produce a similar type of asymmetric information. Crop insurers put large effort on advertising their insurance policies and provide large set of contracts. Despite this, farmers encounter difficulties when stipulating insurance contracts and look for assistance from Defense Consortia, both catalyst of the demand for insurance and impartial guarantors of the goodness of the contract. We model imperfect knowledge and evaluate how it impacts on participation in crop insurance programs.

The model

Foster and Rosenzweig (1995) argue that the existence of learning by doing (private knowledge) and learning from neighbors' experience (shared knowledge) enhance technology adoption. Thompson (2010) synthesizes how (passive) learning influence strategic behavior. Chassagnon and Chiappori (1997), Cohen (2005) and Finkelstein and McGarry (2006) deepen on the role of private and shared information (through experience) on the likelihood of buying insurance contracts. Our model focuses on the role of experience in crop insurance decisions.

In standard expected-utility models of crop insurance participation (e.g. Goodwin, 1993; Coble et al., 1996; Vedenov and Barnett, 2004), farmers maximize the expected profit choosing inputs and farming strategies (Z), and whether or not to purchase crop insurance ($Insurance = \{1, 0\}$). They will choose insurance if the expected utility from profit with insurance is greater than the expected utility from profit without insurance. What is left out so far is the role of private information.

Learning-by doing and learning from others (Foster and Rosenzweig, 1995), information and social learning (Conley and Udry, 2010) are likely to influence strategic behavior (Conley and Udry, 2001; Thompson, 2010): private information includes risk aversion (μ), and the familiarity (Ω) with the insurance schemes that is gained experiencing - either directly or indirectly - realizations of yields, claims, and indemnities. The probability of participating in the insurance scheme depends on risk aversion (μ) and familiarity (Ω). Again, farmers buy insurance if the expected utility with insurance is greater than the expected utility without insurance:

$$(1)\ E[U(\pi(Z,1),\mu,\Omega)] > E[U(\pi(Z,0),\mu,\Omega)]$$

Risk averse farmers are more likely to adopt crop insurance, while the role of familiarity with an insurance scheme is unclear. A farmer who is better informed on the functioning of insurance contracts may be more or less willing to adopt crop insurance, depending on how well the insurance program works, and on how much are the net benefits (or losses) for participating farmers. Hence, *a priori* we cannot conclude on the role of familiarity with the program. Familiarity ($\Omega_{i,t} = \{Exp_{i,t}, Exp_{-i,t}\}$) is gained through direct ($Exp_{i,t}$) and indirect ($Exp_{-i,t}$) experience: a farmer (i) may gain direct experience by participating in the program, and indirect experience from other farmers ($-i$) who have participated in the program. In particular, by stipulating insurance contracts (at time $t-1$) the farmer become experienced (at time t); in addition, indirect experience is transferred from insured farmers to uninsured farmers (at time $t-1$) that become more experienced (at time t) on the insurance program. The econometric specification of the model is described in the subsequent section.

Empirical analysis

The section presents how we define experience, the data employed, the empirical strategy and the results of the analysis.

Defining Experience

Farmers take advantage of gained experience to make their decision on insurance. Experience is gained by insuring or by collecting information from others. Direct experience is expected to convey more information than indirect experience and therefore to be a stronger driver for participation than indirect experience. Empirically, we expect the coefficients for direct experience to be statistically significant and of larger magnitude with respect to those of indirect experience. We consider two polar cases: experience is purely transitory (if the knowledge accumulation process has very short memory), or it is permanent (if the knowledge accumulation process has infinite memory). By modeling the variable with polar cases we are able isolate its extreme effects: they represent lower and upper bounds for different specifications of experience (i.e. a continuous variable to assess the role of cumulated experience induced).

If direct experience is purely transitory, an experienced farmer will exploit only the information gained in the previous year. Direct transitory experience (DTE) is as follows:

$$(2)\ DTE \equiv Exp_{i,t} = Insurance_{i,t-1}$$

If direct experience is permanent, the information gained through insurance lasts forever (i.e. once farmers have purchased insurance, the timing of insurance is irrelevant). Direct permanent experience (DPE) is an indicator function equals to one if the lagged dependent variable has been one at least once in previous periods:

$$(3) DPE \equiv Exp_{i,t} = \begin{cases} 1 & \text{if } \sum_{l=1}^{t-1} Insurance_{i,t-l} > 0 \\ 0 & \text{otherwise.} \end{cases}$$

with $Insurance_{i,t-l}$ being equal to one if the farmer i had insurance in year $t-l$ and 0 otherwise (for instance, in the third period, with $t = 3$, we have $Exp_{i,t} = 1$ if $Insurance_{i,t-1} + Insurance_{i,t-2} > 0)$[2]. In analogy with the specification of direct experience, within each Region x (at time t), indirect transitory experience (ITE) corresponds to the number of farmers who have stipulated a crop insurance contract at time $t-1$, and indirect permanent experience (IPE) corresponds to the number of farmers who have stipulated a crop insurance contract at least once in the previous years (at time $t-l$, with $l \geq 1$). The indirect experience variable proxies how popular is crop insurance in a specific Region. The indirect transitory experience sums the lagged dependent variables for all farmers (n_x) located in a Region (x):

$$(4)\ ITE \equiv Exp_{-i,t} = \sum_{j=1}^{n_x} Insurance_{j,t-1}$$

$$\text{with } j \neq i \text{ , and } j = 1, ..., n_x$$

The indirect permanent experience sums, within a Region, all indicator functions (I_j), defined to be equal to one if the lagged dependent variable has been one at least once in previous periods:

$$(5)\ IPE \equiv Exp_{-i,t} = \sum_{j}^{n_x} I_{j,t}$$

$$\text{with } j \neq i \text{ , and } j = 1, ..., n_x$$

with

[2] We gratefully acknowledge the referee for his/her help on the correct definition of the notation.

$$I_{j,t} = \begin{cases} 1 & \text{if } \sum_{l=1}^{t-1} Insurance_{j,t-l} > 0 \\ 0 & \text{otherwise.} \end{cases}$$

We assumed that information is spread at Regional level for at least three motivations: first, the historical data on production that are used to compute multi-risk policies are computed and administered at regional level; second, the insurance contracts are offered by Defense Consortia that are coordinated at regional level; third, the requests for subsidies (and indemnities) need to be directed to Regional offices, which are also in charge of processing reimbursements for claimed losses.

Data

We use data from the Farm Accountancy Data Network (FADN), a databank representative of European commercial agriculture. The dataset consists of a balanced panel data of 18,382 observations (2,626 Italian farms), continuously observed from 2004 to 2010, located in nineteen different Italian Regions.

The uptake for crop insurance is spatially heterogeneous and (at aggregate level) is low. Our dataset shows that a vast majority of farmers did not stipulate insurance contracts, and only small fractions (less than 10%) of insured farmers stipulated contracts for two or more consecutive years (table 2). A smaller fraction of farmers (around 5%) has been insured for at least 4 consecutive years (from 2004 to 2007), dropping coverage in 2008, when new insurance contracts (e.g. insurance contracts with no threshold or against plant diseases) started to be offered. In our dataset demand for insurance dropped by 50% in 2009 (with respect to the sample average, μ), with a recovery to up 40% in 2010. A similar dynamic is observed for the entire Italian crop insurance market: participation collapsed in 2009 and started to increase again from 2010.

See table 2

Our dataset provides yearly information on land size, altitude, farmers' age, diversification of farming activities, adoption of irrigation, farms' revenue. We compute revenue variability as standard deviation of farms' revenue (over the entire period, 2004-2010), and expected premium per hectare, by averaging across Regions and farming systems the (crop-specific) total premia, as proposed in Santeramo et al. (2016) and Goodwin (1993)[3]. The variable proxies farming system-specific and region-specific levels of riskiness. The variables "Altitude", "Revenue Variability" and "Expected premia" are

[3]Farm-level premium rates are not available in our dataset.

fixed across time[4]. Descriptive statistics on experience variables are shown in table 3 and figures 2 and 3, while statistics on control factors are reported in table 4.

See table 3

See table 4

See figure 2

See figure 3

On average, farm size is small: in Emilia-Romagna, Toscana, Lombardia and Piemonte , it is eighteen hectares, compared to an average size of US farms that is twenty-five times larger (500 hectares). A vast majority of farms are not insured, and not irrigated: at regional level the participation in crop insurance programs, and the adoption of irrigation do not exceed, respectively, 23 and 43 percent (exception made for Liguria).

[4]Under the normative in place from 2004 to 2010 (cfr. figure 1) the subsidies have been steadily at 80%, thus the (potential) effects of subsidies are captured by the constant term. We gratefully acknowledge the comment of a reviewer on this issue.

Econometric framework

Our data comprise seven years, up to 2010, of thousands of farms representative of the entire national population of Italian farms[5]. The (balanced) panel data allows one to estimate the dynamics of the decision-making process in the insurance program. We use a linear approximation of the equation (1) for participation in crop insurance contracts:

$$(6)\ Prob(Insurance_{it} = 1|\Omega_{i,t}, Z_{i,t}, \mu_i) = \Phi(\gamma Exp_{i,t} + \delta Exp_{-i,t} + Z'_{i,t}\beta + \mu_i)$$

Given that $Prob(Insurance_{it} = 1|\Omega_{i,t}, Z_{i,t}, \mu_i)$ is not observed, experience is gained through participation (e.g. $Exp_{i,t} = Insurance_{i,t-1}$), and farmers' specific factors need to be taken into account, the model is estimated as a dynamic random effects probit model (DREPM), following the Heckman procedure.

The model requires an assumption on the relationships between the initial observation ($Insurance_{i,1}$) and the unobserved heterogeneity (μ_i). If the initial observation is exogenous, the model can be estimated as a standard Random Effects (RE) Probit Model. Instead, if the initial observation is

[5] More specifically, the farms included in the dataset (a subsample of the FADN dataset) are selected on the basis of a survey plan, conducted by each EU Member State of the EU in order to guarantee the representativeness. In particular, the dataset is constructed after stratification of the universe of farms, according to the type of farms (e.g. type of crops, livestocks, etc.), and the geographical distribution.

correlated with the unobserved heterogeneity, the RE probit estimator is inconsistent and overestimates γ (i.e. the state dependence is overestimated). Following Heckman (1981), we use a reduced form equation for the initial observation ($I_{i,1}$) with instruments ($X_{i,1} = \{\Omega_{i,1}, Z_{i,1}, w_{i,1}\}$) which includes the sets of explanatory variables and of exogenous instruments ($w_{i,1}$). The instruments are assumed to be correlated with the farmers' specific (random) effects and uncorrelated with the error term.

Results

As preliminary analysis, we investigate whether data support the presence of asymmetric information (Chiappori and Salanie, 2000): we found that the (average) variability of production for insured farmers exceeds the (average) variability of production for uninsured farmers. The analysis does not allow us to disentangle adverse selection from moral hazard, but is valid to conclude that insured farmers have larger variability in production and therefore asymmetric information is likely to exist (Einav, Finkelstein and Levin, 2010).

The estimates using a pooled probit model (PP), a standard random effects probit model (RE), linear probability models (LPM), and a dynamic random effects probit model (DREPM) show that the effects of experience tend to be larger in PP and RE models (table 5), while the opposite is true for linear probability models (LPM)[6]. The signs of control factors are consistent across estimators, but the coefficients for direct and indirect experience tend to be larger for PP and RE models. The pooled probit estimates fail to control for cross-correlation across the individual composite errors in different periods. The LPMs investigate potential bias due to correlation across space and time[7]: results are stable across specifications. By controlling for the endogeneity of initial conditions (Heckman, 1981; Stewart, 2005), the effect of the variable of interest is largely reduced. We estimate all remaining models with the dynamic random effects probit model[8].

[6]For the LPM the usual caveats apply: 1) the LPM can predict probabilities either less than zero or greater than one; 2) conceptually, it seems not appropriate to model a probability linearly to a continuous independent variable for all possible values in that it would (implicitly) allow for values of the dependent variable above one or below zero. The LPM model with fixed effects predicts 3328 observations outside of the [0,1] interval, which account for 24.7% of the total sample. These caveats (nothing bindings value of the dependent variable between 0 and 1, and linearity issues) can be addressed by using a nonlinear binary response model such as a probit model. We are grateful to a review for having pointed this out.

[7]We gratefully acknowledge the suggestions of a reviewer to investigate, through LPMs, the correlation across space and time and the robustness of the results to the inclusion of farm fixed effects and aggregate level premium rate at provincial level. We have also computed standard errors robust to spatial correlation across Regions.

[8]We adopted, as instruments, two variables that capture the geographical location of farmers (i.e. a dummy for South and a dummy for Centre) and a dummy that indicates if the farm is organic. In the online appendix we show that the instruments satisfy the conditions to have valid instruments, stated by Heckman (1981)

See table 5

For sake of interpretability, we compute average partial effects (APE) for direct and indirect experience: a consistent estimator is the change in the probability distribution function (PDF) evaluated at the sample mean, after normalization of the maximum likelihood (MLE) coefficients (Wooldridge, 2005).

The measures for direct and indirect experience are positive and statistically significant. As already argued, direct experience tend to be more influential than indirect experience[9]. Farmers who bought crop insurance contracts in the past are more likely to buy (again) crop insurance: the opposite is true for farmers who never bought crop insurance contracts. Farmers with direct experience in crop insurance are 10% more likely to buy (again) insurance with respect to uninsured farmer; the coefficient for indirect experience, which refers to a change from no insured neighbor to the average regional value of insured farmers, is statistically not different from zero (table 5). Moreover, transitory direct experience is stronger than permanent direct experience (table 6): the likelihood of purchasing insurance is as high as 10%

[9]As suggested by one of the reviewers, the effects of permanent and transitory direct experience coincide (and are largest) when the farmer buy crop insurance for the first time. Subsequently, the effects of direct permanent experience tend to decrease over time.

if a farmer has experienced insurance during the previous season, and only 3.5% if she had experience in earlier seasons (i.e. permanent experience). The same conclusion cannot be drawn for indirect experience: transitory experience is not relevant, whereas permanent experience increases the likelihood of insurance by 0.003%. This result reflects the intuition that indirect experience is slowly transmitted, or, put differently, that the spillover effects due to the familiarity with a crop insurance program are exploited after several years. Albeit statistically significant, the impact of indirect experience is rather small: this is in line with the common wisdom that indirect information influence risk perception only if agents lack direct experience (Siegrist and Gutscher, 2006; Wachinger et al., 2013).

See table 6

Other factors influence participation in crop insurance markets. Large and irrigated farms are more likely to be insured, while farms located at high altitude are less likely to be insured. The results are consistent with the existing literature on crop insurance (Goodwin, 1993; Smith and Goodwin, 1996; Enjolras and Sentis, 2011; Foudi and Erdlenbruch, 2012; Singerman, Hart and Lence, 2012)[10]. We observe a positive correlation between partic-

[10]Although not statistically significant, we found a negative relationships between farm-

ipation in insurance schemes with the variables "Revenue variability" and "Expected premia": the higher the revenue variability, the higher the likelihood of buying insurance contracts; the higher is the expected premium, which reflects a higher level of underlying risk, the higher is the participation in crop insurance programs. This seemingly counterintuitive result is explained by the crop data scarcity which is likely to impose higher premia in some areas of Italy (Shen et al., 2016). In order to disentangle the effects of premia we would need to rely on expert knowledge of the degree of riskiness: unfortunately, those data are not available.

The results for North, Centre and South provide further insights: the role of experience is less relevant where participation is higher (e.g. North). Two (opposite) explanations help understanding these findings. On one hand, since participation is likely to be driven by a diffused knowledge of insurance contracts, the higher the participation, the lower the relevance of direct experience should be (Foster and Rosenzweig, 1995; Conley and Udry, 2010). On the other hand, if insured farmers are self-selected, the insured farmers of low-participation areas are expected to have stronger experience on insurance

ers' age and crop diversification with participation in crop insurance programs. The results are consistent with Smith and Goodwin (1996), Foudi and Erdlenbruch (2012), among others.

(and possibly higher benefits from insurance), and therefore are more likely to buy insurance for consecutive years (Roy, 1951; Heckman and Sedlacek, 1985). The lower relevance of indirect experience in the North, where uptake is higher, indicates decreasing returns to indirect experience and suggests that information campaigns should be replicated on a regular basis[11].

See tables 7 and 8

Direct and indirect experience have different impacts for farms differing in (economic or land) size. The vast majority of farmers (medium farms) takes advantage of direct and indirect experience: the higher the experience, the higher the likelihood to participate in the program. For small farmers direct experience is (relatively) less important than indirect experience (cfr. columns 2 and 3). In order to understand this result, you need to consider that small farms are usually owned by professionals with more remunerative off-farm opportunities: their efforts (and the time invested) on farming activities are relatively low, so that farming strategies are (partially) guided by neighbors' suggestions or by common wisdom. As one should expect, insurance decisions for large farms are not influenced at all by indirect ex-

[11]Similarly, the direct experience shows decreasing returns. The results in appendix (not attached) show that, *ceteris paribus*, the cumulated direct experience has a negative and statistically significant coefficient.

perience, but it is also true that direct experience is very important. Lastly, transitory experience is more important than permanent experience: a result that is consistently explained by the dynamic alternation of managing directors in large-size farms (rather than in small-size farms). The impact of indirect experience is statistically significant in several cases, but it is economically small: again, in line with the literature (Siegrist and Gutscher, 2006; Wachinger et al., 2013), we found that agents benefit from indirect experience (*second best*) only when direct experience (*first best*) is lacking.

What have we learned from farmers' experience?

Participation in crop insurance programs has been low for decades in the EU, despite large subsidies granted by the governments. Further increases in subsidies, implemented during recent years in the US, are likely to create distortive effects: subsidizing risk leads agents to assume more risks and costs to raise rapidly (Smith and Goodwin, 1996; Goodwin and Smith, 2013). A different, complementary, strategy to approach the problem is highly desirable for policymakers and taxpayers.

The factors affecting the demand for agricultural insurance have been extensively studied, and the literature allows to draw conclusions on the role of assets (e.g. Goodwin, 1993; Smith and Goodwin, 1996; Enjolras and Sentis, 2011; Singerman, Hart and Lence, 2012;), human capital (Smith and Bacquet, 1996), farmers' strategies (Foudi and Erdlenbruch, 2012) and asymmetric information (Coble et al., 1997; Walters et al., 2014) on insurance decisions. However, little evidence has been provided to establish the role of experience in the crop insurance decision making process (exception made for Cole et al., 2014 and Santeramo, 2018). We use a detailed farm-level dataset to assess how experience influences the crop insurance decision making process. We disentangle the role of direct and indirect experience.

We conclude that experience in crop insurance increases participation. Intuitively, the direct experience acquired during the previous harvest season (or acquired over time) is likely to reduce the imperfect knowledge and act as catalyst for participation. The indirect experience is also valuable: the experience that farmers gain when they buy crop insurance contracts influence neighbors' decisions. However, relevant geographic differences exist, and policymakers should take them into account to promote participation. The role of information, in terms of experience, is also differing by farm size. Policymakers should take this dimension into consideration to improve the efficacy of planned interventions. They should pursue strategies to increase participation (potentially even at a significant short-run cost) to take advantage of the inertia and the spillover effects that emerge from experience. Once experience is gained, there may be less frictions to participate in insurance programs, hence the leverage of subsidies may be diverted from old clients (farmers who have already experienced crop insurance) to new clients (farmers who have never experienced crop insurance).

Ad hoc measures may be implemented to increase participation of small farms, which (traditionally) are more reluctant to adopt insurance. For instance, participation of small farms may be promoted through one-time (heavily) subsidized premia, through targeted informative campaigns, or by discounting premium rates. Lastly, multi-year insurance contracts (e.g. at lower premia) may be appealing for uninsured farms. The proposed measures are not new: proposing competitive tariffs for new clients is the normality for companies in the markets of telephony, or car insurance. We are proposing to import new scheme of business in a market that presents several frictions to entry, especially for small farmers.

The importance of imperfect information has been highlighted, but few possible limitations need to be underlined. The external validity of our results is limited by the lack of information about the type of contracts stipulated. However, even if such data were available, the main results should not change: the asymmetric information between farmers and insurers is partially resolved through experience, which stimulates insurance coverage renewals. In addition, potential omitted variables bias may be a drawback: however, the sensitivity analyses conducted by using fixed effects across space and time exclude major temporal/spatial systematic errors.

To the extent that increasing uptake in crop insurance markets is a main goal for policymakers in most developed countries, understanding how imperfect knowledge is resolved represents a promising area for future research. With data availability increasing more and more, understanding how farmers decide to switch among contracts is also an important research question to help planning policy interventions. Extension for this analysis should move in this direction.

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Online Appendix A: The model

Foster and Rosenzweig (1995) argue that the existence of learning by doing and learning from neighbors' experience enhance technology adoption. Thompson (2010) synthesizes how passive learning influence strategic behavior. Similarly, it is likely that private and shared information influence the likelihood of insurance. Our model allows to conclude on the role of experience in crop insurance decisions.

Assume the profit of a farmer to be additively separable over two variables: the insurance decision ($I = \{0, 1\}$) and a set of variables (Z) describing the economic environment of the farm (such as land size, irrigation, number of crops, etc.). Farmers maximize the expected profit choosing input, farming strategies, and whether or not to purchase crop insurance. If insurance is actuarially fair, farmers' expected profit ($E[\pi(Z, I)]$) under insurance ($I = 1$) and under not insurance ($I = 0$) (conditional on other factors, Z) should be equal:

$$(1)\ E[\pi(Z, 1)] = E[\pi(Z, 0)]$$

However, insurance decision is a personal one, and it is influenced by several factors that are private for the farmer. The farmers' problem is to insure or not in order to maximize (subjective) expected profits. Assuming risk aversion, they will choose insurance if the expected utility from profit with insurance is greater than the expected utility from profit without insurance[12]:

$$(2)\ E[U(\pi(Z,1))] > E[U(\pi(Z,0))]$$

What is left out so far is the role of private information[13]. Information, learning-by doing and learning from others (Foster and Rosenzweig, 1995), social learning (Conley and Udry, 2010) are likely to influence strategic behavior (Conley and Udry, 2001; Thompson, 2010): private information includes risk aversion (μ) and familiarity (Ω) with the insurance scheme which is gained through experience - either directly or indirectly - and the observation of past realizations. We assume the probability of participating in the insurance scheme to be a function of risk aversion (μ) and familiarity (Ω) , and therefore farmers will choose insurance if the expected utility with insurance is greater than the expected utility without insurance:

$$(3)\ E[U(\pi(Z,1),\mu,\Omega)] > E[U(\pi(Z,0),\mu,\Omega)]$$

Risk averse farmers are more likely to adopt crop insurance, while the role of familiarity with an insurance scheme is unclear. A farmer who is better informed on the functioning of insurance contracts may be more or less willing to

[12] Our data support the hypothesis that expected profit under insurance is greater than expected profit under no insurance.

[13] Other non-private information factors such as liquidity, product quality, trust, risk aversion, wealth, or culture, are likely to be (at least partially) captured by the farmers fixed effects.

adopt crop insurance, depending on how well the insurance program works, and on how much are the net benefit (or loss) for participating farmers. Hence, *a priori* we cannot conclude on the role of familiarity with the program. Familiarity ($\Omega_{i,t} = \{Exp_{i,t}, Exp_{-i,t}\}$) is gained through direct ($Exp_{i,t}$) and indirect ($Exp_{-i,t}$) experience: a farmer (i) gains direct experience by participating in the program; he may also gain indirect experience from others ($-i$), by interacting with farmers who have experienced the insurance scheme[14].

[14]To make it clearer, farmers are expected to know Ω_t at time t. Direct experience is gained only by stipulating an insurance contracts, while indirect experience is transferred from insured farmers (at time $t-1$) to uninsured farmers (at time $t-1$) and is exploited at time t.

Online Appendix B: Econometric details

The linear approximation of equation for participation in crop insurance contracts can be easily estimated using the following specification:

$$Prob(I_{it} = 1|\mu_i, \Omega_{i,t}, Z_{i,t}) = \Phi(\gamma Exp_{i,t} + \delta Exp_{-i,t} + Z'_{i,t}\beta + \mu_i)$$

Given that $Prob(I_{it} = 1|\mu_i, \Omega_{i,t}, Z_{i,t})$ is not observed, and experience is gained through participation (e.g. $Exp_{i,t} = I_{i,t-1}$), the model is estimated as a dynamic probit model.

It must be noted that even if the error terms of the probit model are assumed serially independent, there exists serial correlation induced by the time-invariant term (μ_i)[15]. Since the dependent variable (I_{it}) is a binary variable (the decision to insure or not), we normalize it by imposing a unitary value for the variance of the error term $(\sigma_u^2 = 1)$. The (conditional) transition probability for i at time t is as shown in Heckman (1981)[16]:

$$Prob(I_{i,t} = 1|\mu_i, I_{i,t-1}, Exp_{-i,t}, Z_{i,t}) = \Phi[(\gamma I_{i,t-1} + \delta Exp_{-i,t} + Z'_{i,t}\beta + \mu_i)(2I_{i,t} - 1)]$$

[15]This specification implies equi-correlation between $v_{i,t} = \mu_i + u_{i,t}$ in any two different periods: $\lambda = Corr(v_{i,t}, v_{i,s}) = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_u^2}$. We may also estimate a more general model by relaxing the assumption of no autocorrelation of the error term. The model requires T-dimensional integrals of normal densities but, although feasible, it requires a great computation effort (Stewart, 2005). The estimates of the state dependence coefficient are generally slightly lower, therefore the model we estimate represents an upper bound, a conservative measure to not overestimate the effects of experience.

[16]The result follows from the the normality assumption of the probit model error term $(u_{i,t})$

where Φ is the cumulative distribution function of the standard normal distribution. The model requires an assumption on the relationships between the initial observation ($I_{i,1}$) and the unobserved heterogeneity (μ_i). The simplest solution is to assume the initial observation exogenous, but this is a strong assumption for the vast majority of datasets, whose start period does not coincide with the start of the process[17]. If the initial observation is correlated with the unobserved heterogeneity, the standard Random Effects (RE) probit estimator is inconsistent and overestimates γ (i.e. the state dependence is overestimated). Following Heckman (1981), we use a reduced form equation for the initial observation ($I_{i,1}$) with instruments ($X_{i,1}$) which includes the set of explanatory variables ($Exp_{-i,1}, Z_{i,1}$) for the main model and exogenous instruments ($x_{i,1}$). The instruments are assumed to be correlated with the random effects and uncorrelated with the error term[18]

The joint probability for the sequence of $I_{i,t}$ is as follows (Heckman, 1981):

$$\Phi[(X'_{i,1}\zeta + \theta\mu_i)(2I_{i,t} - 1)]\Pi_{t=2}^{T}\Phi[(\gamma I_{i,t-1} + \delta Exp_{-i,t} + Z'_{i,t}\beta + \mu_i)(2I_{i,t} - 1)]$$

and the model is estimated by maximizing, over $\mu^* = \frac{\mu}{\sigma_\mu}$ and $\sigma_\mu = \sqrt{\frac{\lambda}{1-\lambda}}$, the likelihood overall all farmers:

$$\Pi_i \int_{\mu^*} \Bigg\{ \Phi[(X'_{i,1}\zeta + \theta\mu^*\sigma_\mu)(2I_{i,t} - 1)]$$

[17] If the assumption is correct, the model can be estimated as a standard Random Effects (RE) Probit Model.

[18] For details on the treatment of unobserved heterogeneity, the interested reader may refer to Wooldridge (2005, p.41).

$$\Pi_{t=2}^{T}\Phi[(\gamma I_{i,t-1}+\delta Exp_{-i,t}+Z'_{i,t}\beta+\mu^*\sigma_\mu)(2I_{i,t}-1)]\Big\}dF(\mu^*)$$

The integral has been evaluated using the Gaussian-Hermite quadrature (Butler and Moffitt, 1982 ; Stewart, 2005). Following Wooldridge (2005), we evaluate the estimates by computing the average partial effects (APE) of state dependence ($I_{i,t-1}$). We multiply the coefficient $\hat{\gamma_\mu}$ by a weighted sample average of the distribution:

$$N^{-1}\sum_{i=1}^{N}\Phi(\hat{\gamma_\mu}I_{i,t-1}+\hat{\delta_\mu}Exp_{-i,t}+Z'_{i,t}\hat{\beta_\mu})\hat{\gamma_\mu}$$

where the subscript μ indicates that the parameter need to multiplied by $(1+\sigma_\mu^2)^{-1/2}$, and in particular $\hat{\gamma_\mu}=\gamma(1+\sigma_\mu^2)^{-1/2}$, $\hat{\delta_\mu}=\delta(1+\sigma_\mu^2)^{-1/2}$, $\hat{\beta_\mu}=\beta(1+\sigma_\mu^2)^{-1/2}$, and the coefficients γ, δ and β are the MLE estimates.

In order to compute average partial effects (APE) for direct and indirect experience we compute the change in the probability distribution (PDF) function evaluated at the sample mean, after normalization of the maximum likelihood (MLE) coefficients. Empirically, we multiply the MLE parameters by $(1+\hat{\sigma_\mu^2})^{-1/2}$, and evaluate the PDF under different values for "Experience" at the sample mean[19].

[19]Knowing that $\lambda=\frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_u^2}$ and $\sigma_u^2=1$, we compute $\hat{\sigma_\mu^2}=\frac{\lambda}{1-\lambda}$.

Online Appendix C: On the appropriateness of instrumental variables

In order to show the validity of the instruments, we describe the approach we follow (proposed by Heckman, 1981). The variables adopted as instruments respect the conditions stated by Heckman (1981). For clarity we will restate the notation of our manuscript and emphasize the differences with the notation adopted in Stewart (2006).

The latent equation for the dynamic random effects probit model (the equation 6 in our paper: $Prob(Insurance_{it} = 1|\Omega_{i,t}, Z_{i,t}, \mu_i) = \Phi(\gamma Exp_{i,t} + \delta Exp_{-i,t} + Z'_{i,t}\beta + \mu_i))$ is equivalent to the specification in Stewart (2006). It allows us to recover the fixed terms (μ_i in equation 6, and named α_i in Stewart, 2006) and the error terms ($u_{i,t}$ in Stewart, 2006). We estimate the econometric specification (equation 1 in Stewart, 2006) that allows us to recover α_i and $u_{i,t}$:

$$y^*_{i,t} = \gamma y^*_{i,t-1} + x'_{i,t}\beta + \alpha_i + u_{i,t}$$

where $y^*_{i,t}$ represents $Insurance_{i,t}$, $x'_{i,t}$ is the vector of explanatory variables (in our manuscript $Z'_{i,t}$), and α_i are individual-specific effects (in our manuscript μ_i).

Again, we are interested in α_i and $u_{i,t}$, so we store these elements for the diagnostics. As further step, and in order to recover (and store) the elements $u_{i,1}$, we estimate a regression for the initial value of the latent variable (i.e. being insured in 2004):

$$y^*_{1,t} = z'_{i,1}\pi + \theta\alpha_i + u_{i,1}$$

It should be noted that $\eta_i = \theta\alpha_i + u_{i,1}$, therefore the above equation may be rewritten as $y^*_{1,t} = z'_{i,1}\pi + \eta_i$ (cfr. Stewart, 2006). We recover (and store) the elements η_i for the diagnostics.

The approach to the initial conditions problem proposed by Heckman (1981) requires to estimate an equation for the initial value of the latent variable with appropriate instruments. The appropriateness of the instruments is validate by the satisfaction of several conditions on the correlations across individual effects and error terms. Here are the conditions:

1) $Corr(\alpha_i, \eta_i)$ has to be high

2) $Corr(u_{i,t}, \eta_i)_{|t\geq 2}$ has to be lower than $Corr(u_{i,t}, \eta_i)_{|t=1}$

3) $Corr(\alpha_i, u_{i,1})$ has to be low

Our results are in line with the conditions stated above. In particular, we found $Corr(\alpha_i, \eta_i) = 0.672$, that is the individual effects are correlated with residuals of the equation for the initial value of the latent variable. Moreover, we found that $Corr(u_{i,t}, \eta_i)_{|t \geq 2} < Corr(u_{i,t}, \eta_i)_{|t=1}$, where $t = 1$ refers to 2004. In particular, we found the correlations to be respectively equal to 0.61 and to 0.73 for $Corr(u_{i,t}, \eta_i)_{|t \geq 2}$ and $Corr(u_{i,t}, \eta_i)_{|t=1}$. Finally, we found that $Corr(\alpha_i, u_{i,1}) = 0.15$. Based on these results, which show that the conditions stated by Heckman (1981) are satisfied, we are able to state that the chosen instruments are valid for credible identification of the latent variable in the first period.

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Tables and figures

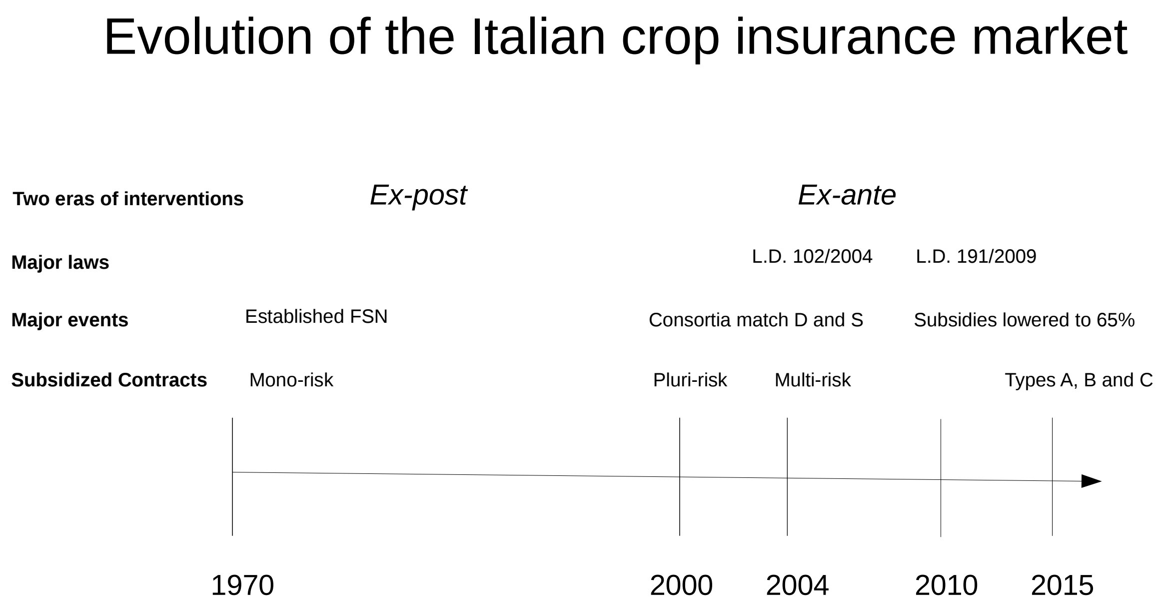

Figure 1: Timeline for the evolution of the insurance system

Table 1: Characteristics of the Italian insurance market

		2004	2006	2008	2010	2012	2014
The size of the insurance market							
Number of policies	(.000)	212	211	265	208	214	206
Insured Land	(.000 ha)	982	1125	1450	1153	na	na
Insured Value	(mln €)	3710	3789	5436	5313	6826	7951
Premia	(mln €)	177	265	338	285	321	485
Indemnities	(mln €)	152	149	272	169	231	316
Market shares by types of contract							
Monorisk	(%)	92.0	77.4	53.7	50.2	40.2	0.0
Pluririsk	(%)	7.7	19.6	40.0	46.6	52.8	73.2
Multirisk	(%)	0.3	2.9	6.3	3.3	6.9	26.8

Source: SicurAgro - ISMEA. Available at www.ismea.it

Table 2: Crop insurance participation by year

	2004	2005	2006	2007	2008	2009	2010	Total
Consecutive contracts								
0	2,427	2,424	2,410	2,402	2,552	2,539	2,375	17,129
1	199	52	48	45	15	22	196	577
2		150	33	27	10	9	15	244
3			135	25	9	9	6	184
4				127	8	9	7	151
5					32	6	3	41
6						32	3	35
7							21	21
Further statistics								
Percentage changes from μ	11	13	20	25	-58	-50	40	
Non-zero contracts (NZC)	199	202	216	224	74	87	251	$\mu = 179$
Percentages of NZC	7.6	7.7	8.2	8.5	2.8	3.3	9.5	

Number of farms insured for zero, one or consecutive years. μ is the average number of insured farms.

Table 3: Descriptive statistics of experience variables (averages)

	DTE	DPE	ITE	IPE
Valle DAosta	0.00	0.00	0.00	0.00
Piemonte	0.06	0.06	9.12	12.00
Lombardia	0.10	0.18	15.00	31.41
Trentino	0.44	0.51	19.52	42.01
AltoAdige	0.29	0.38	10.06	25.42
Veneto	0.09	0.12	12.58	31.11
Friuli-Venezia-Giulia	0.14	0.22	6.57	18.53
Liguria	0.01	0.01	0.47	3.14
Emilia Romagna	0.02	0.09	1.84	2.85
Toscana	0.08	0.09	5.05	11.51
Marche	0.01	0.01	0.57	0.71
Umbria	0.16	0.25	5.05	6.71
Lazio	0.01	0.03	0.68	1.57
Abruzzo	0.05	0.09	4.48	13.01
Molise	0.02	0.05	1.92	7.42
Calabria	0.00	0.00	0.00	0.00
Puglia	0.09	0.15	9.18	21.02
Basilicata	0.02	0.03	1.61	2.14
Sicilia	0.05	0.06	6.50	14.02

The averages are for the entire sample period: 2004-2010. DTE stands for Direct Transitory Experience; DPE stands for Direct Permanent Experience; ITE stands for Indirect Transitory Experience; IPE stands for Indirect Permanent Experience.

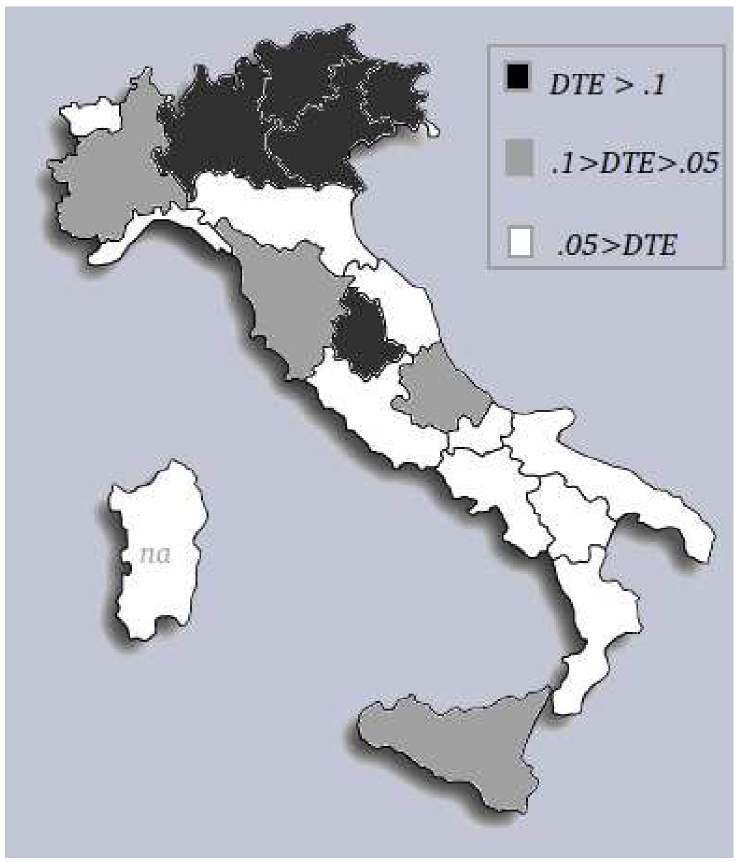

Figure 2: Direct Transitory Experience

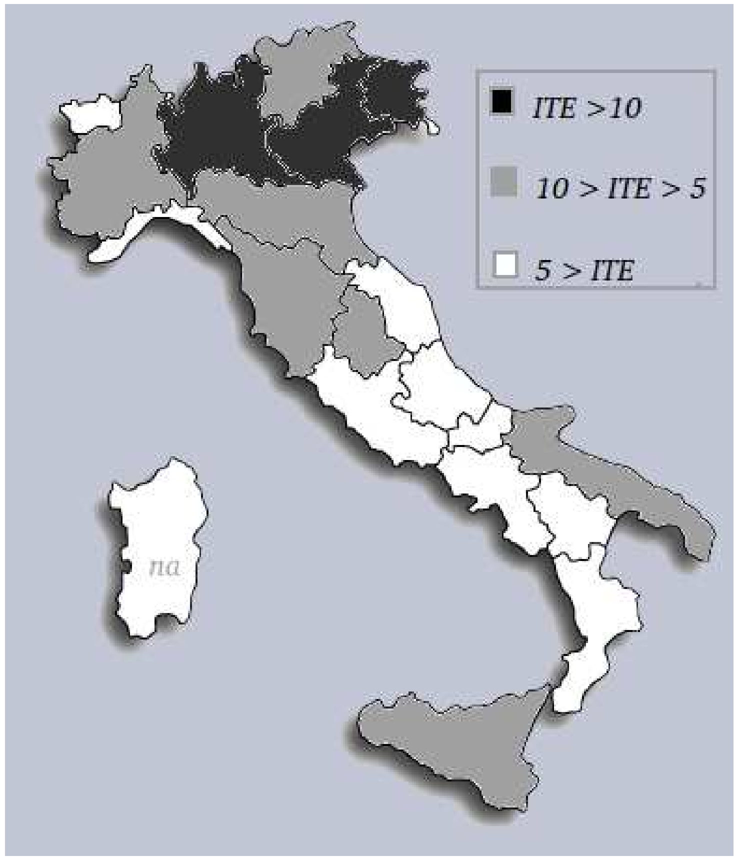

Figure 3: Indirect Transitory Experience

Table 4: Descriptive statistics of explanatory variables

		2004 Mean	2010 Mean	2004-10 Mean	2004-10 St. Dev.	Min	Max
Land Size	(ha)	33.3	28.3	29.7	61.5	0.11	1072
Altitude	(Dummy)	0.50	0.50	0.50	0.49	0	1
Age	(Years)	53.1	58.2	55.4	13.5	18	89
Revenue variability	(.000)	31.7	31.7	31.7	124.6	0.2	292
Diversification	(Dummy)	0.8	0.8	0.8	0.4	0	1
Irrigation	(Dummy)	0.3	0.3	0.3	0.44	0	1
E[Premium/Ha]	(.000)	0.1	0.3	0.1	0.1	0.01	0.3

The variables Altitude, Revenue Variability and Expected premium, are fixed across time.

Table 5: Comparison of Estimators

	PP	RE	LPM	LPM	LPM	LPM	LPM	DREPM
Direct Experience	2.25^{*}	2.14^{*}	0.58^{*}	0.63^{*}	0.59^{*}	0.15^{*}	0.13^{*}	1.08^{*}
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Indirect Experience	0.0057^{*}	0.0058^{*}	-0.0014^{*}	0.0012^{*}	-0.0004	0.0001	0.0007^{*}	0.0031
	[0.01]	[0.02]	[0.32]	[0.01]	[0.12]	[0.73]	[0.01]	[0.32]
Control factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	No	No	Yes	No	Yes	No	No	No
Annual FE	No	No	No	Yes	Yes	No	Yes	No
Farm FE	No	No	No	No	No	Yes	Yes	No
Logit λ								0.44^{*}
								[0.00]
Ln θ								0.73^{*}
								[0.00]
λ								0.61^{*}
								[0.00]
θ								2.07^{*}
								[0.00]
Observations	13926	13926	13926	13926	13926	12738	12738	18382

p-values in brackets. $^{+}$ $p < 0.10$, * $p < 0.05$

PP, RE and LPM stand, respectively, for pooled probit model, standard random effects model and linear probability model. Estimations refer to transitory direct experience and transitory indirect experience. Control factors include land size, altitude, age, revenue variability, diversification, irrigation, expected premia. In column seven, expected premia is replaced by the aggregate level premium rate, at provincial level). As for LPM, we have computed standard errors robust to spatial correlation. The observations are independent across groups but not necessarily within groups (identified by the Region).

For sake of comparability, the last column reports the APE computed as described in the manuscript. The estimate of λ implies that 61% of the composite error variance is due to individual-specific effects. The parameter is originally estimated as a logit transformation ($ln(\frac{\hat{\lambda}}{1-\hat{\lambda}})$) and therefore it is computed as transformed as follows: $\lambda = \frac{e^{\hat{\lambda}}}{1+e^{\hat{\lambda}}}$. The parameter θ is statistically greater than one indicating that the composite error (v_{it}) is correlated with the individual-specific effects.

Table 6: Alternative Experience Measures

	1	2
Transitory Direct Experience	1.07*	
	[0.00]	
Permanent Direct Experience		0.92*
		[0.00]
Transitory Indirect Experience	0.0031	
	[0.32]	
Permanent Indirect Experience		0.0076*
		[0.00]
Land Size	0.0020*	0.0019*
	[0.00]	[0.00]
Altitude	-0.15+	-0.093
	[0.10]	[0.30]
Age	-0.0027	-0.0067*
	[0.40]	[0.03]
Revenue variability	0.53+	0.38
	[0.08]	[0.19]
Diversification	-0.014	-0.0026
	[0.88]	[0.98]
Irrigation	0.88*	0.91*
	[0.00]	[0.00]
E[Premium/Ha]	0.91+	0.72
	[0.06]	[0.12]
Logit λ	0.44*	0.24
	[0.00]	[0.25]
Ln θ	0.73*	0.38*
	[0.00]	[0.00]
λ	0.61*	0.56
	[0.00]	[0.26]
θ	2.07*	1.46*
	[0.00]	[0.00]
Observations	18382	18382

p-values in brackets. $^{+}$ $p < 0.10$, * $p < 0.05$
Reported coefficients are APEs computed as described in the manuscript. Control factors include land size, altitude, age, revenue variability, diversification, irrigation, and expected premium per hectare. Land size is expressed in hectares, age in years, sigma revenues is expressed in mln of euro, and expected premium per hectare in .000 of euro. Altitude, diversification and irrigation are dummy variables.

Table 7: Geographical analysis

	North		South		Centre	
Transitory Direct Experience	1.01*		1.43*		1.63*	
	[0.00]		[0.00]		[0.00]	
Permanent Direct Experience		0.94*		1.10*		1.76*
		[0.00]		[0.00]		[0.00]
Transitory Indirect Experience	0.007*		-0.017+		0.0038	
	[0.04]		[0.06]		[0.85]	
Permanent Indirect Experience		0.0091*		-0.010		0.0050
		[0.00]		[0.17]		[0.73]
Control factors	Yes	Yes	Yes	Yes	Yes	Yes
Logit λ	0.46*	0.11	-0.12	-0.076	-0.77	-2.61
	[0.01]	[0.69]	[0.65]	[0.88]	[0.15]	[0.18]
Ln θ	0.60*	0.31*	3.14	0.76*	2.43*	2.48
	[0.00]	[0.02]	[0.35]	[0.01]	[0.04]	[0.70]
Observations	8785	8785	7077	7077	2520	2520

p-values in brackets. $^{+}$ $p < 0.10$, * $p < 0.05$

Reported coefficients are APEs computed as described in the manuscript. Control factors include land size, revenue variability, expected premia, and indirect experience.

Table 8: Farm size analysis

	Small		Medium		Large	
Transitory Direct Experience	1.08^{*}		1.16^{*}		1.16^{*}	
	[0.00]		[0.00]		[0.00]	
Permanent Direct Experience		0.99^{*}		1.13^{*}		1.03^{*}
		[0.04]		[0.00]		[0.00]
Transitory Indirect Experience	0.019^{*}		0.0039		0.0038	
	[0.02]		[0.28]		[0.53]	
Permanent Indirect Experience		0.020^{*}		0.0087^{*}		-0.0050
		[0.00]		[0.00]		[0.77]
Control factors	Yes	Yes	Yes	Yes	Yes	Yes
Logit λ	0.83^{+}	0.35	0.13	-0.42	0.028	-0.036
	[0.05]	[0.64]	[0.48]	[0.19]	[0.93]	[0.93]
Ln θ	1.21	0.68^{+}	0.98^{*}	0.50^{*}	0.97^{*}	0.36
	[0.12]	[0.07]	[0.00]	[0.00]	[0.02]	[0.10]
Observations	3626	3626	11102	11102	3654	3654

p-values in brackets. $^{+}$ $p < 0.10$, * $p < 0.05$

Reported coefficients are APEs computed as described in the manuscript. Control factors include expected premia. Small farms (20% of sample size) are less than 5 hectares and produce, on average, a revenue less than 20K euro per year; large farms (20% of sample size) are larger than 35 hectares or produce, on average, a revenue higher than 1000K euro per year.

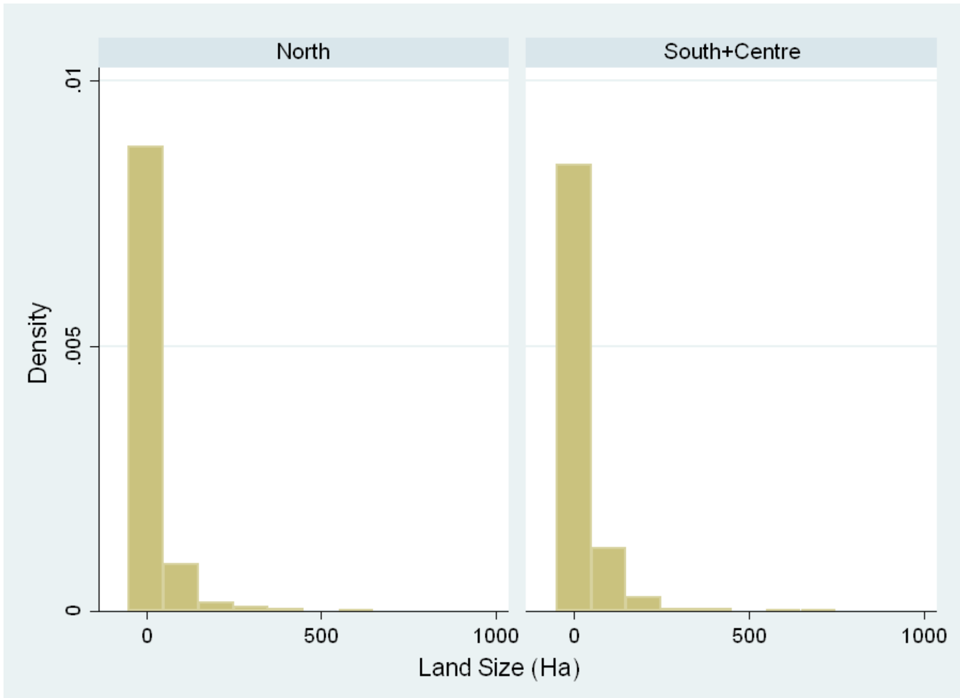

Figure 4: Land size by macroregions in 2010

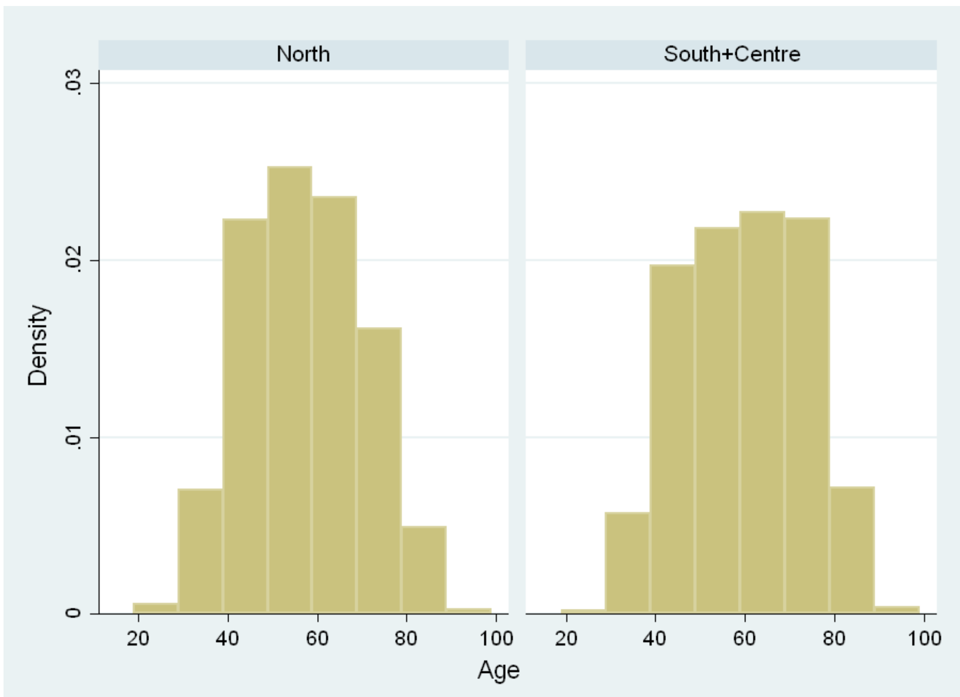

Figure 5: Farmers' age by macroregions in 2010

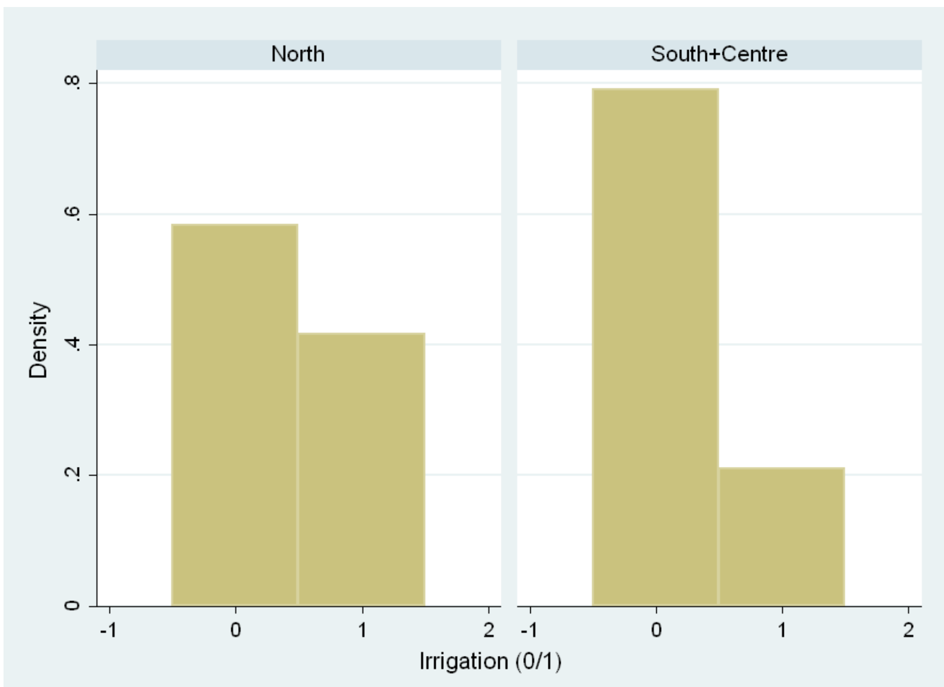

Figure 6: Irrgation by macroregions in 2010

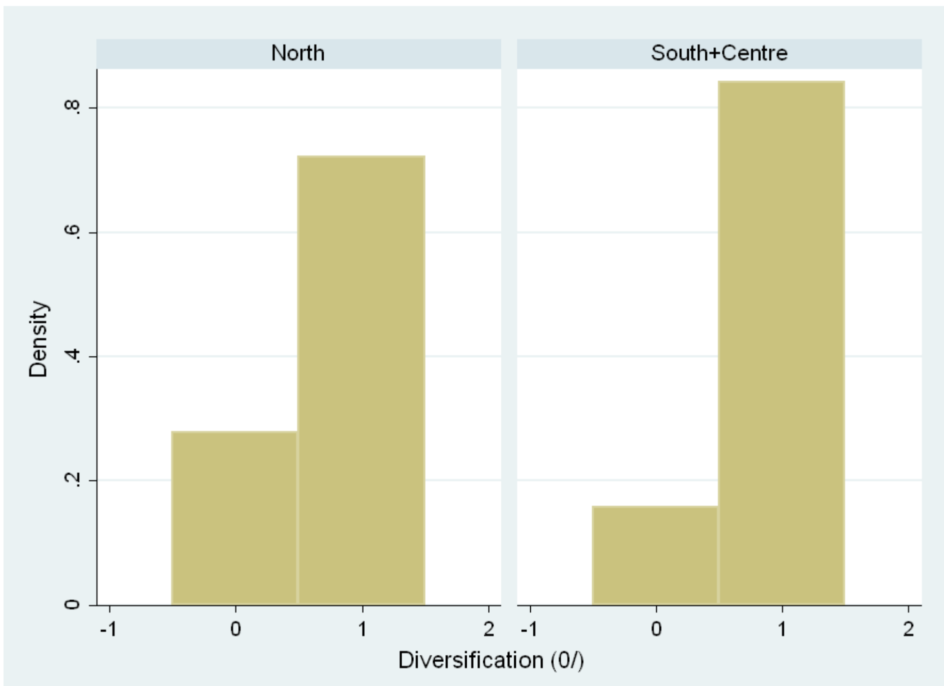

Figure 7: Diversification by macroregions in 2010