Imperfect Information and Participation in Insurance Markets: Evidence from Italy

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Abstract

Participation in crop insurance programs is lowered by imperfect knowledge resulting in adverse selection and moral hazard problems. We aim at investigating how experience in insurance contracts may influence participation in the Italian crop insurance market. 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 of the data, allows one to compare the relevance of different sources of experience in the crop insurance decision making process. We found that experience tend to be a catalyst for insurance participation. Policy implications are discussed: in particular we discuss on the importance of bolstering uptake to exploit the advantages of the inertia and spillover effects that emerge from experience. To the best of our knowledge, the role of experience has been underinvestigated. Our analysis has the specific contribution of modeling the potential role of experience (exploited after buying an insurance contract) on uptake in crop insurance programs.

Keywords: Asymmetric information, Dynamic model, Familiarity, Imperfect Knowledge, Uptake.

JEL: G22, Q12, Q18

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Risk management in agriculture is receiving growing attention in developing and develoed countries, as attested by the increase in prominence of crop insurance programs, where participation has been enhanced through subsidies (Mahul and Stutley, 2010). While 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, the tools are still not much diffused. The EU regulation 1305/2013 promotes the use of subsidized crop insurance contracts (art. 37), of mutual funds (art. 38) and of the Income Stabilization Tool (art. 39), and leaves to Member States the flexibility to adopt autonomous national policies that fall into one of the mentioned set of tools (Meuwissen et al., 2013; Cordier, 2014; Liesivaara and Myyra, 2014; Santeramo and Ramsey, 2017).

Italy has a long tradition of farm subsidies, but has had difficulty in achieving crop insurance participation. Participation in Italian crop insurance programs is generally low: around 15% of farmers participate in crop insurance programs. High costs of bureaucracy, ineffectiveness of Defense Consortia, and lack of experience with crop insurance contracts are some of the factors that have contributed to keep uptake low and farmers reluctant to participate in crop insurance programs.

Chassagnon and Chiappori (1997) argue that imperfect knowledge and asymmetric information are likely to play a substantial role in the insurance decision-making process, and are potential drivers of low participation

(Chiappori and Salanie, 2013). 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."

Several papers have analyzed the determinants of participation in crop insurance programs (e.g. Santeramo et al. 2016, Seo et al., 2017), and 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; Enjolras and Sentis, 2011; Singerman, Hart and Lence, 2012;), human capital (Smith and Bacquet, 1996), and farmers' strategies (Foudi and Erdlenbruch, 2012) on insurance decisions. However, little evidence has been provided to establish the role of experience in the crop insurance decision making process. Indeed, learning by doing and learning from others may stimulate technology adoption (Conley and Udry, 2010), and reduce the asymmetric information (Chiappori and Salanie, 2013). Santeramo et al. (2016) analyzed what drives a farmer to enter and exit the Italian crop insurance market.

However, the existing research, with very few exceptions (Cole et al., 2014; Ye et al., 2017), has dedicated relatively lower attention to the role of experience on participation in crop insurance programs, especially in the EU. Put differently, the role of experience on uptake in crop insurance programs is not much discussed, and has not been quantified. Indeed, as follows from Chassagnon and Chiappori (1997) and Chiappori and Salanie (2013), experience is likely to be important. Little evidence has been provided on the role of experience in the crop insurance decision making process. Indeed, learning by doing and learning by watching others are mechanisms that may stimulate technology adoption in agriculture (Conley and Udry, 2010), and they are likely to help reducing the imperfect and asymmetric information that characterize insurance markets (Chiappori and Salanie, 2013).

Understanding the determinants of uptake is an important goal for European Union (EU) policymakers, and exploring the role of experience (and information) is a promising area of research. Several empirical inquiries deserve investigation: Does imperfect information discourage participation in crop insurance markets? What is the influence of experience on participation? We investigate if and how experience (i.e. buying crop insurance contracts) may help enhancing uptake.

The analysis is devoted to assess the role of experience through a dynamic model of participation and a detailed 7-years firm-level panel of Italian farms. We show that experience in crop insurance is positively related with uptake. The rationale is that the experience acquired in past harvest seasons is likely to reduce the imperfect knowledge on both sides, and thus enhance uptake. Our conclusions pose emphasis on suggestions for a better implementation of policy interventions at EU and national levels.

The Italian crop insurance system

Public intervention started in 1970, with the so called Fondo di Solidarieta Nazionale (FSN), intended to compensate farmers who had been affected by natural disasters. The FSN has evolved over time, but, until early 2000s, the interventions have been mainly in form of ex-post compensations.

Starting in 2000, the Consorzi di Difesa were introduced in order to facilitate the match of supply and demand in the subsidized crop insurance market, and to facilitate the transition from mono-risk to pluri-risks contracts. In 2004, the Legislative Decree No. 102/2004 modified the intervention from *ex post* compensations to *ex ante* subsidies, introduced pluri-risks and multi-risks contracts (that three or all adversities) and ended the subsidies to mono-risk (i.e. single-peril) contracts. Starting from 2014 the insurance policy must cover at least three climatic adversities eligible for pluririsks policies. The pluririsks policies ensure farmers against losses due to three or more climatic adversities, which need not be mutually exclusive. The multi-risks policies ensure against losses due to any type of climatic adversity included in the Annual Insurance Plan (Piano Assicurativo Annuale). Currently, the Italian crop insurance policies are subsidized through EU funds: subsidies were as high as 80% of the insurance premium for policies against damages (reaching at least 30% of assured production) caused by adverse weather conditions and other natural disasters, and it is up to 50% of the cost of the premium if the insurance contract also covers other losses caused by adverse weather conditions that are not considered to be widespread natural disasters, or losses caused by animal or plant diseases. Since 2010, due to the EU Reg. 73/2009, the subsidies have been decreased to 65%. In 2015 a new set of contracts has been offered an replace the previous system: types A, B and C offer coverage against different combinations of infrequent perils, frequent perils, and additional adversities. 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 when the realized yield is below the average historical yield by a certain threshold[1].

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 (Mahul and Stutley, 2010). While (private) insurance companies may set their own premium rates, the companies coordinate pricing policies and the maximum levels of insurance premiums eligible for a subsidy, with the Ministry of Agriculture, *"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, a local institution 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 a clear asymmetric information that separate insurers and farmers.

During the decade 2000-2010 the total coverage (crops, livestock and farm's capital) has increased slowly but steadily from 1 million to 1.1 million hectares, out of 13 millions of total insurable land, the number of insured farmers has remained low, but the number of contracts and the insured value grew by more than 40 % from 2004 to 2010: such a increase is mainly due to the spread of multi-risks contracts to cover almost every single crop of the insured farms.

Contracts that cover losses from multiple risks have increased in promi-

[1]Usually the threshold is 30%, but there are contracts with lower thresholds, such as 10%, 15% or 20%.

nence. Between 2003 and 2009, the share of single-peril insurance contracts against hail has halved while the share of multiple risk contracts has increased.

See table 1

Currently, the vast majority of contracts are purchased by farms located in Northern Italy: in 2010 the North accounted for 78% of the insured value, the Centre for 8% and the South for the remaining 14%. The number of insured crops has increased from 58 (in 2002) to 164 (in 2010), although four crops account for half of the total insured value: wine grapes, apple, rice, and corn.

Participation level and imperfect knowledge

In order to increase uptake, crop insurance programs are usually incentivized: premia are subsidized and the set of subsidized policies is generally widened. A drawback of leveraging crop insurance demand with subsidies is due to the increasing marginal costs that derive from the inclusion of farmers that have low propensity of being insured. According to Glauber (2013), in US an increase in subsidies from 2.73 (in 1981-1994) to 7.76 (in 1999-2003) boosted marginal costs from 3.31 to 25.99, making the policy costly and, in the long-run, unfeasible. The implications of crop insurance subsidies go far beyond an increase in participation. The subsidies tend to 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. Furthermore, subsidies may promote a crowding out effect of alternative risk management strategies (Goodwin, 2001; Du et al., 2015), distorting the demand for risk management strategies. Thus, how to design crop insurance policies with (relatively low) unintended consequences is a legitimate and important question. The present analysis focuses on the impacts generated by imperfect knowledge.

Imperfect and asymmetric information (i.e. lack of information on farmer and/or insuree side), through adverse selection (i.e. self-selection of riskier farmers to enter the insurance market) and moral hazard (i.e. riskier behavior adopted by insured farmers), are the main factors that help explain low participation in insurance markets (Chiappori and Salanie, 2013). On one side riskier insurees have private knowledge on the risks they face and 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)[2]. On the other side, insurers have private knowledge on the type of contract they offer[3], at the detriment of clarity and transparency of contracts to farmers (Chiappori and Salanie 2000, 2013). A third channel

[2]We acknowledge comments from a reviewer. We specify why adverse selection (and imperfect information on both sides) tend to lower participation. We distinguish two chains of behaviors when imperfect information is on both sides. First case: premia are set by insurers on lower risk profiles (i.e. insurers tend to underestimate risks and therefore the premium rates); premia are lower; only the (above the threshold) farmers tend to insure. In this case, the imperfect information on farmers side discourages participation. Second case: premia are set by insurers on higher risk profiles (i.e. insurers tend to overestimate risks and therefore the premium rates), participation is discouraged normal-risk farmers, and for high-risk farmers (regardless of strategic behaviors of farmers). In this case, the imperfect information on insurers side and the imperfect information on farmers side discourage participation.

[3]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.

through which imperfect knowledge disfavors participation consists of high transaction costs implied by heavy bureaucracy - the cumbersome process to obtain subsidies for the premium, to claim reimbursements for yield losses, and the delays in payments for subsidies and claimed losses. This channel disfavors participation of farmers who are vulnerable to liquidity constraints. 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 his decisions and production strategies) some of their private knowledge in terms of riskiness. On the other hand, the insurer will also reveal to the insured farmer (at the end of the season, by honoring the contract) some of their 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 complex contracts. Despite this, farmers encounter difficulties when stipulating insurance contracts and look for the assistance of defense consortia, both catalyst of the demand for insurance and impartial guarantors of the goodness of the contract.

Empirical setting

We use a reduced form expression of the probability for farmer to stipulate an insurance contract (regardless of the type of insurance contract, that is regardless of buying a single-peril or a multi-peril contract) as function of risk attitudes, familiarity and other determinants that we collect under the category of control factors. The theoretical basis is in line with numerous studies on demand for crop insurance (Goodwin, 1993; Enjolras and Sentis, 2011; Santeramo et al., 2016). The probability depends on risk attitudes (μ_i), familiarity ($\Omega_{i,t}$), and other (control) factors (Z_t):

$$(1)\ Prob(Insurance_{it} = 1|\mu_i, \Omega_{i,t}, Z_{i,t}) = f(\mu_i, Exp_{i,t}, Z_t)$$

We assume that the familiarity with an insurance scheme may play a role in the decision-making process. Experience is gained after buying an insurance contract, regardless of the payment of an indemnity. 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 benefit (or loss) for participating farmers (Gin et al., 2008; Akter et al., 2009; Sibiko and Qaim, 2017). Hence, *a priori* we cannot conclude on the role of familiarity with the program.[4] Familiarity ($\Omega_{i,t} = \{Experience_{i,t}\}$) is gained through experience:

[4]We gratefully acknowledge the comments of the reviews on two aspects of our model. First, the model is free of assumptions on aversion or propensity toward risks. Second, our model is not able to disentangle the effects of the experience of the insurer and of the experience of the insuree in that they both work in the same direction (i.e. solving the imperfect information).

a farmer (i) gains experience by participating in the program.

A number of control factors have been adopted for two specific reasons: first, the dataset we used contains a limited number of variables; second, we adopted variables that have been adopted and have been found relevant in previous studies on crop insurance participation in Europe (cfr. Enjoras and Sentis, 2011; Di Falco et al., 2015; Santeramo et al., 2016).

Experience

Farmers take advantage of gained experience to make their decision on insurance. Experience is gained by insuring and thus collecting information on how the program works. We assume experience can be purely transitory (if the knowledge accumulation process has very short memory), or permanent (if the knowledge accumulation process has infinite memory)[5].

If experience is purely transitory, farmers only benefit from the information gained in the previous year, and the variable transitory experience reduces to the lagged dependent variable:

$$Experience_{i,t} = Insurance_{i,t-1}$$

On the contrary, if experience is permanent, the information gained through insurance lasts forever, therefore the timing of insurance is not relevant once farmers have purchased insurance. The variable permanent experience reduces to an indicator function equal to one if the lagged dependent variable has been one at least once in previous periods:

[5]By modeling the variable with polar cases we are able to conclude on the role of experience. We also use a continuous variable to assess the role of cumulated experience and found no differences.

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

with T standing for the total number of years.

Econometric specification

Our data comprise six years, up to 2010, of thousands of farms representative of the entire national population of Italian farms. 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. The (strongly balanced) panel data allows one to estimate the dynamics of the decision-making process in the insurance program.

A linear approximation of equation for participation in crop insurance contracts can be easily estimated:

$$(2)\ Prob(Insurance_{it} = 1 | \mu_i, \Omega_{i,t}, Z_{i,t}) = \Phi(\gamma Experience_{i,t} + Z'_{i,t}\beta + \mu_i)$$

Given that the probability of being insured ($Prob(Insurance_{it} = 1 | \Psi_i, \Omega_{i,t}, Z_{i,t})$) is not observed, and experience is gained through participation (e.g. $Experience_{i,t} = Insurance_{i,t-1}$), the model is estimated as a dynamic probit model.

It is worth noting 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)[6]. 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 model requires an assumption on the relationships between the initial observation ($Insurance_{i,1}$) 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[7]. 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 ($Insurance_{i,1}$) with instruments ($X_{i,1}$) which includes the set of explanatory variables ($Experience_{-i,1}, Z_{i,1}$) 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.

We evaluate the estimates by computing the average partial effects (APE) of state dependence ($Insurance_{i,t-1}$). We multiply the coefficient $\hat{\gamma}_\mu$ by a weighted sample average of the distribution:

[6]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.

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

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

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

Empirical results

Data

Our analysis is based on a dataset drawn from the Farm Accountancy Data Network, a database representative of European commercial agriculture. The dataset employed in the present analysis consists of a strongly balanced panel data of 18,382 observations: 2,626 Italian firms, continuously observed from 2004 to 2010, whose main activity is farming, located in nineteen different Italian Regions. We collected information on the entire sample available from the FADN, that is constructed to be representative of the entire population of Italian farms.

The uptake for crop insurance is heterogeneous across space, in general, is rather low. The dataset shows that a large number of farmers do not buy insurance contracts, and only a small fraction of insured farmers buy insurance contracts for consecutive years (table 2). Notably, a small share of farmers (almost five percent) has been insured for four (or more) consecutive years during the period 2004-2007. It is also remarkable the drop in coverage occurred in 2008, when new insurance contracts, such as insurance contracts with no threshold or against plant diseases, started to be offered. The data reveal that the demand for insurance felt by 5% in 2009 (with respect to the period average), and increased up to 9% in 2010. Te same trend can be observed in the Italian crop insurance market: in 2009 the number of Insurance contracts dropped by 2.5% with respect to 2007, with a recovery of the market from 2010 (in fact we observe a positive trend of total insured value).

See table 2

Our dataset provides yearly information on land size (i.e. the number of cultivated hectares), altitude (a dummy equal to one if the farm is located 600 meters above sea level), farmers' age (expressed in years), diversification of farming activities (a dummy equal to one if the number of cultivated crops in one year is larger than one), adoption of irrigation (a dummy equal to one if the farm is partially or entirely irrigated). The variable "Revenue Variability" is obtained as standard deviation of farms' revenue (over the entire period, 2004-2010), and expected premium per hectare[8]. We do not observe farm-level premium rates. We compute the variable "Expected Premia" by averaging, across Regions and farming systems, the crop-specific total premia. The aggregate premium is a proxy of the premium farmers are expected to pay, and a proxy for the level of riskiness for all farms of a given type and located in a specific region. The approach is similar to that adopted by Goodwin (1993) and Santeramo et al. (2016). Descriptive statistics of control factors are shown in tables 3.

See table 3

[8]Computed by averaging within regions and farming systems the (crop-specific) total premia

The average farm size in Italy is rather small. For instance, the average size of farms in Emilia-Romagna, Toscana, Lombardia and Piemonte, home well known agro-food products, is only 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 with percentage at regional level that do not exceed, respectively, 23 and 43 percent (excluded Liguria).

Experience

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, a standard random effects probit model and a random effects model a-la-Heckman confirm that the effects of experience are overestimated if simple estimators are adopted (table 4). While the signs of control factors are unaltered over the three estimators, the coefficients for experience are much larger if a pooled or a standard random effects probit model is adopted. The pooled probit estimates ignore the cross-correlation between the individual composite errors in different periods. When we control for the endogeneity of initial conditions (Heckman, 1981; Stewart, 2005), the effect is largely reduced. We estimate all remaining models with the Heckman model.

See table 4

We compute average partial effects (APE) for experience. A consistent estimator for the APE is 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[9].

The measures for experience are positive and statistically significant. As we should expect, farmers who have experienced crop insurance contracts are much more likely to purchase insurance with respect to farmers who have never experienced insurance contracts, even if located in Regions where crop insurance programs are popular. Farmers with experience in crop insurance are 10% more likely to buy insurance with respect to a previously uninsured farmer.

Transitory experience is stronger than permanent experience: the likelihood of purchasing insurance is as high as 10% if farmers have experienced insurance during the previous season, and only 3.5% if they had experience in earlier seasons

See table 5

Other factors influence participation in crop insurance markets. We found that large and irrigated farms are more likely to be insured, while farms

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

located at high altitude are less likely to be insured. The results are consistent with the existing literature on crop insurance (Goodwin, 1993; Enjolras and Sentis, 2011; Foudi and Erdlenbruch, 2012; Singerman, Hart and Lence, 2012)[10]. In addition we observe a positive correlation between participation in insurance schemes with the variables ”revenue variability” and ”expected premium”: the higher the revenue variability, the higher the likelihood of stipulating an insurance contract; the higher is the expected premium, which reflects a higher level of underlying risk, the higher is the participation in crop insurance program. This seemingly counterintuitive result is explained by the crop data scarcity which imposes higher premiums in Italy (Shen et al., 2016). In order to disentagle the effects of premiums we would need to rely on expert knowledge of the degree of riskiness: unfortunately, those data are not available.

Conclusions

Risk management tools have a long history in the EU. Despite this, and the strong emphasis that the current Common Agricultural Policy has posed on risk management tools (namely subsidized crop insurance, Mutual Funds and Income Stabilization Tool), the participation in crop insurance programs in the EU has been low for decades. Several frictions are likely to lower uptake. We use a detailed farm-level dataset to investigate a determinant that has received relatively little attention. In particular, we investigate how experience, through learning-by-doing and learning-from-others mechanisms,

[10]Although not statistically significant, we found a negative relationships between farmers' age and crop diversification with participation in crop insurance programs. The results are consistent with Foudi and Erdlenbruch (2012), among others.

influence the crop insurance decision making process.

We conclude that experience in crop insurance tends to increase participation: in other terms, we found that farmers who have experienced crop insurance tend to insure in the subsequent years. The mechanisms we postulate is that the experience acquired during the previous harvest season is likely to reduce the imperfect knowledge and acts as catalyst for participation.

To the extent that increasing participation is an important goal for policymakers and insurance companies, reducing the imperfect knowledge through ad hoc measures (e.g. information campaigns, thematic workshops, may prove an effective strategy that should be encouraged at the EU, national and local levels.

We conclude with few sentences on possible limitations of the present study. First, 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, and this in turn stimulates insurance coverage renewals. Second, the present study does not take into account potential spill-over effects that may be induced by the contamination of experiences among farmers. IN other terms, would it be beneficial to learn from someone else's experience (i.e. indirect experience)? We leave this to future research.

To the extent that increasing uptake in crop insurance markets is a main goal for policymakers, 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.

References

1. Akter, S., Brouwer, R., Choudhury, S., Aziz, S., 2009. "Is there a commercially viable market for crop insurance in rural Bangladesh?." *Mitigation and adaptation strategies for global change*, 14(3), pp.215-229.

2. Chassagnon, A. and P. A. Chiappori, 1997. "Insurance under moral hazard and adverse selection: the case of pure competition", *DELTA-CREST Document*.

3. Chiappori, P. A., and Salanie, B., 2000. "Testing for asymmetric information in insurance markets", *Journal of political Economy* 108(1), pp. 56-78.

4. Chiappori, P. A., and Salanie, B., 2013. "Asymmetric information in insurance markets: predictions and tests". In *Handbook of Insurance* (pp. 397-422). Springer New York.

5. Cohen, A., 2005. "Asymmetric information and learning: Evidence from the automobile insurance market", *Review of Economics and statistics* 87(2), pp. 197-207.

6. Conley, T., and Udry, C., 2010. "Learning about a new technology: Pineapple in Ghana", *American Economic Review*, pp. 35-69.

7. Cole, S., Stein, D., and Tobacman, J., 2014. "Dynamics of demand for index insurance: Evidence from a long-run field experiment", *American Economic Review*, 104(5), pp. 284-290.

8. Cordier, J. 2014. "Comparative Analysis of Risk Management Tools supported by the 2014 Farm Bill and the CAP 2014-2020" (Rapport N IP/B/AGRI/IC/2014-044). Bruxelles, BEL : Parlement Europen.

9. Du, X., Ifft, J., Liu, L., and Zilberman, D., 2015. "How Does Crop Insurance Purchase Affect Marketing Contracts Participation", American Journal of Agricultural Economics. 97(5), pp. 1360-1370.

10. Einav, L., A. Finkelstein, and Levin, J., 2010. "Beyond Testing: Empirical Models of Insurance Markets", *Annual review of economics* 2, pp. 311-336.

11. Enjolras, G. and Sentis, P., 2011. "Crop insurance policies and purchases in France", *Agricultural Economics* 42, pp. 475-486.

12. Finkelstein, A., and McGarry, K., 2006. "Multiple dimensions of private information: evidence from the long-term care insurance market", *American Economic Review* 96(4), pp. 938-958.

13. Foudi, S., and Erdlenbruch, K., 2012. "The role of irrigation in farmers risk management strategies in France", *European Review of Agricultural Economics* 39(3), pp. 439-457.

14. Giné, X., Townsend, R., Vickery, J., 2008. "Patterns of rainfall insurance participation in rural India." *The World Bank Economic Review*, 22(3), pp. 539-566.

15. Glauber, J. W., 2013. "The growth of the federal crop insurance program, 19902011", *American Journal of Agricultural Economics* 95(2), pp. 482-488.

16. Goodwin, B.K., 1993. "An empirical analysis of the demand for multiple peril crop insurance", *American Journal of Agricultural Economics* 75, pp. 425-434.

17. Goodwin, B. K., 2001. "Problems with market insurance in agriculture", *American Journal of Agricultural Economics* 83(3), pp. 643-649.

18. Goodwin, B. K., Smith, V.H., 2013. "What harm is done by subsidizing crop insurance?", *American Journal of Agricultural Economics* 95(2), pp. 489-497.

19. Heckman, J. J., 1981. "Statistical models for discrete panel data". In: Manski, C. F., McFadden, D. (Eds.). (1981). Structural analysis of discrete data with econometric applications. Cambridge, MA: Mit Press.

20. Liesivaara, Petri, and Sami Myyra, 2014. "Willingness to pay for agricultural crop insurance in the northern EU." *Agricultural Finance Review* 74(4), pp. 539-554.

21. Mahul, O., and Stutley, C. J., 2010. "Government support to agricultural insurance: challenges and options for developing countries", World Bank Publications.

22. Meuwissen, M.P., Assefa, T.T. and Asseldonk, M.A., 2013. Supporting insurance in European agriculture: Experience of mutuals in the Netherlands. *EuroChoices*, 12(3), pp.10-16.

23. Santeramo, F. G., Goodwin, B. K., Adinolfi, F., and Capitanio, F., 2016. "Farmer Participation, Entry and Exit decisions in the Italian Crop Insurance Program", *Journal of Agricultural Economics*. 67(3), pp. 639-657.

24. Santeramo, F. G., and Ramsey, A.F., 2017. "Crop Insurance in the EU: Lessons and Caution from the US", *EuroChoices*. 16 (3), pp. 34 39.

25. Seo, H., Kim, T., Kim, M. K., and McCarl, B. A., 2017. "Introduction of the trend-adjusted crop insurance program: Participation-and coverage-level responses", *Agricultural Finance Review*, 77(3), pp. 412-428.

26. Sibiko, K. W., Qaim, M., 2017. "Weather index insurance, agricultural input use, and crop productivity in Kenya". *GlobalFood Discussion Papers.*

27. Singerman, A., Hart, C. E., and Lence S. H., 2012. "Revenue Protection for Organic Producers: Too Much or Too Little?", *Journal of Agricultural and Resource Economics* 37(3), pp.415-434.

28. Shen, Z., Odening, M., and Okhrin, O., 2016. "Can expert knowledge compensate for data scarcity in crop insurance pricing?", *European Review of Agricultural Economics*, 43 (2), pp. 237-269.

29. Ye, T., Liu, Y., Wang, J., Wang, M., and Shi, P. 2017. "Farmers crop insurance perception and participation decisions: empirical evidence from Hunan, China". *Journal of Risk Research*, 20(5), pp. 664-677.

Tables

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

Table 3: Descriptive statistics of explanatory variables

		Mean	St. Dev.	Min	Max
Land Size	(Hectares)	28.81	60.62	0.11	1072.62
Altitude	(Dummy)	0.50	0.49	0	1
Farmer Age	(Years)	55.45	13.63	18	89
Revenue Variability	(.000 €)	31.73	124.64	0.21	292.46
Crop Diversification	(Dummy)	0.78	0.41	0	1
Irrigation	(Dummy)	0.27	0.44	0	1
Expected [Premium/Ha]	(.000 €)	0.14	0.09	0.01	0.32

Table 4: Role of (Transitory) Experience

	Probit	RE Probit	Heckman
Experience	2.251^{*}	2.143^{*}	1.081^{*}
	[0.00]	[0.00]	[0.00]
Control factors	Yes	Yes	Yes
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	18382
Log-Likelihood	-2176.2	-2174.2	-2594.6

p-values in brackets. $^{+}$ $p < 0.10$, * $p < 0.05$
We control for land size, altitude, farmer age, revenue variability, crop diversification, irrigation, and expected premia per hectare. The last column reports the APE. The estimate of λ implies that 61% of the composite error variance is due to individual-specific effects. The parameter, estimated as a logit transformation ($ln(\frac{\hat{\lambda}}{1-\hat{\lambda}})$), is computed as follows: $\lambda = \frac{e^{\hat{\lambda}}}{1+e^{\hat{\lambda}}}$. A value of θ statistically greater than one indicates that the composite error (v_{it}) is correlated with the individual-specific effects.

Table 5: Alternative Experience Measures

	1	2
Transitory Experience	1.072*	
	[0.00]	
Permanent Experience		0.921*
		[0.00]
Land Size	0.002*	0.002*
	[0.00]	[0.00]
Altitude	-0.152^{+}	-0.093
	[0.10]	[0.30]
Farmer Age	-0.003	-0.007*
	[0.40]	[0.03]
Revenue variability	0.531^{+}	0.382
	[0.08]	[0.19]
Crop Diversification	-0.014	-0.003
	[0.88]	[0.98]
Irrigation	0.881*	0.913*
	[0.00]	[0.00]
Expected [Premium/Ha]	0.912^{+}	0.721
	[0.06]	[0.12]
Observations	18382	18382
Log-Likelihood	-2594.6	-2655.8

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

Reported coefficients are APEs. We control for land size, altitude,farmer age, revenue variability, crop diversification, irrigation, and expected premia 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.