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Assessing the effect of the CAP on farm innovation adoption. An analysis in two French regions

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Assessing the effect of the CAP on farm innovation adoption. An analysis in two French regions.

Bartolini F., Latruffe L. and Viaggi D.

Abstract

Literature on innovation adoption mechanism has emphasised the positive effect of Single Farm Payments (SFP) and Rural Development Payments on adoption of new technologies. In this context, the expected process of CAP reforming after 2013 is likely to strengthen the role of innovation in the European Union (EU). The objective of this paper is to identify the determinants of the adoption of future innovation, in particular in connection to past innovation, and to assess the role of agricultural policy in the promotion of innovation adoption. The analysis is applied to two regions (Centre and Midi-Pyrénées) in France. Two separate Count models are developed in order to explain famers' stated intention concerning different intensities of innovation adoption under two different policy scenarios. Preliminary results highlight that the CAP strongly affects the decision to innovate and the innovation intensity, even if there is no statistical significance for the variable connected to the amount of payments or the level of payment per hectare.

Keywords: innovation, sequences of innovation, CAP, zero inflated Poisson model

JEL classification: Q12 - Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets Q18 - Agricultural Policy; Food Policy

1. INTRODUCTION

New technology adoption and innovation diffusion represent two central elements for the enterprise and industry development process in all sectors of the economy. Innovation is one of the main drivers of economic growth and an important instrument for achieving sustainability and cohesion. This is also a central element of the future European Union (EU) strategy, as stated in the Innovation document by the EU (European Union, 2010). Innovation adoption and the re-organization of agri-food chains are two of the Common Agricultural Policy (CAP) priorities.

Literature on innovation adoption mechanism has emphasised the positive effect of the Single Farm Payments (SFP) and Rural Development Payments on the adoption of new technologies (Janssen and van Ittersum, 2007). In this context, the expected process of CAP reforming after 2013 is likely to affect the adoption of new technology and the process of modernisation of farms in the EU.

The objective of this paper is to identify the determinants, and in particular previous adoption of innovations, of the adoption of future innovation by farmers, and to assess the role of agricultural policy in the promotion of innovation adoption at the farm level. The analysis is applied to two NUTS2 regions (Centre and Midi-Pyrénées) in France. Two separate Count models are developed in order to explain famers' stated intention concerning different intensities of innovation adoption under two different policy scenarios. The latter are defined as:

i) a baseline scenario of the CAP framework in year 2009, that includes the current (2009) level of payments plus the already planned measures such as milk quota abolition at year 2015, and ii) a scenario assuming a complete abolition of all CAP instruments. The innovation considered is the sum of adoption of alternative innovation typologies as a proxy of innovation intensity.

2. METHODOLOGY

2.1. Overview

Several models have been implemented in order to explain the determinants of innovation adoptions by farmers (Feder and Umali, 1993; Ruttan, 1996; Encaoua et al., 2000). Some models of innovation adoption have been simulated as binary choices, where the choices are adoption or non-adoption, or as multiple choices, in which innovation options include several alternatives (Batz et al., 1999). Models implemented under the second approach have estimated the determinants of innovation adoption as a process composed of two or more stages (Dimara and Skuras, 2003). These models are more coherent with the literature that identifies some factors connected to the farm fixed structure (e.g. social capital, age and access to credit) as determinants of the decision to implement an innovation (Diederen et al., 2003) different to other variables that are determinants of the amount of innovation adopted (Encaoua et al., 2000).

However, the determinants of adoption of a specific innovation, or the intensity of different innovations, could be connected with the farming systems, the public payments received, the farm strategy and the already implemented innovations on the farm (Ruttan, 1996; Encaoua et al., 2000). Literature regarding innovation adoption as a sequential process where the farmer chooses continuously to adopt new technology over time is quite poor. The role of past innovation adoption behaviour in determining future adoption decisions has rarely been investigated in the existing literature. This paper proposes to contribute to this issue. For this purpose the methodology is divided into two main parts:

- identification of homogenous groups based on different innovation behaviour using data obtained from past adoptions (past 10 years);
- analysis of the determinants of future innovation adoption under two different policy scenarios (next 10 years).

2.2. Identification of homogenous groups of farmers with respect to their innovation behaviour

The analysis of innovation behaviour is not a novelty in the agricultural economics literature. Earlier works on this issue have described innovation diffusion as an S-shape function (Rogers, 1962), where the new technology is firstly introduced by a group of innovators, then followed by other groups that Rogers (1983) has identified as Earlier Adopters, then by Early and Late Majority, and finally by Laggards. The belonging to one of the above mentioned categories is dependent on several variables that could be grouped into farmers' behaviour toward risk; human capital such as age, experience, and educational level; or other constraints such as purchasing power, access to credit, access to, use and quality of information (Sunding and Zilberman 2001; Bartolini and Viaggi 2009).

The aim of this part of the methodology is to identify groups of homogenous farmers as regards their innovation behaviour. Such behaviour is obtained through a cluster analysis[1] considering three variables: a) the number of innovations adopted in the last 10 years; b) the timing of adoption and c) the age of the farm owner. Following Rogers (1983) such three variables could be considered, among others, as determinants of the innovation behaviour. The information about innovation adopted in the last 10 years and its timing was obtained through a questionnaire, in which the farmers were asked about the innovations that they adopted and the timing of the adoption of innovations based on categories suggested by Sounding and Zilberman (2001). Such categories are: Farming systems innovations; Mechanical innovations; Biological innovations; Agronomic innovations; Chemical innovations; Biotechnology innovations, Marketing innovations, Processing innovations (more information about the categories and the list of innovations adopted is presented in Bartolini et al., 2009 and Bartolini et al., 2010).

2.3. Identification of the determinants of innovation adoption

The second part of the methodology concerns the identification of the determinants of the future intensity of innovation adoption. Future innovation adoptions were asked on a time horizon until 2020, to the same farm sample as for the previous stage related to past innovations. The future innovation typologies considered are the following:

- Robotisation/precision farming, in order to consider innovation strongly connected with high investment costs and mainly connected to the reduction of the labour needed for farming activities.
- New irrigation systems.
- E-commerce/direct selling or other innovation in commercialisation of the farmer's production.
- Energy crops or production of energy by the farm through solar panel, wind or biogas etc.
- Other innovation, a category let "blank" for adding other innovations that surveyed farmers could intend to adopt in the next years.

To highlight the role of the CAP on the diffusion of the innovation, two policy scenarios have been identified: one with the current CAP situation (baseline scenario) and the other with the complete abolishment of all components of the CAP (NO CAP scenario).

For this reason, in this part of the analysis two separate Count models are developed in order to explain the stated intention concerning different intensities of innovation adoption under the two different policy scenarios. The two models considered are realised in the case of the baseline scenario (first model) and under the NO CAP scenario (second model) respectively.

[1] Cluster analysis has been realised through k-means cluster analysis.

Such two policy scenarios are referred to the current (year 2009) CAP framework, that includes the actual level of payments plus the already planned measures such as milk quota abolition at year 2015, and the scenario assuming a complete abolition of all CAP instruments.

In either model the intensity of innovation is obtained summing for each farm the number of stated intentions about the adoptions of all five types of innovation considered. The model considered allows to combine the categorical data (adoption or not of any innovation) with the count data (number of innovations adopted). This enables to consider the adoption of several innovations as two steps models. In fact to account for the excessive amount of zero values in a discrete count variable, the literature (Lambert, 1992; Green, 1994) suggests applying a zero inflated model, such as Zero-Inflated Poisson regression (ZIP). Application of ZIP model to the count of innovation adopted is quite common in the literature (see for example Karantininis et al (2010))

In this analysis a ZIP regression model has been considered instead of a Poisson Regression Model (PRM), due to excess of zeros (Lambert, 1992). The mechanism underlying the ZIP model is regarding how zero is generated, in fact such value could be generated from two regimes: one regime where the outcome is always zero and the other one with the usual Poisson regime that the outcome could produce any non negative integer values (Green 2003) in fact ZIP model generate a two separate models and then are combined. First model is a logit model that analyses the discrete choice about whether innovate or not (first regime). The second model is a Poisson model that generated a prediction of the count of the innovation (second regime). Following Mullahy (1986) and Lambert (1992) it is possible to describe the choice as:

$Y_i = 0$ with probaility ω_{it}

$Y_i \sim Poisson(\alpha_{it})$ with probaility $1\text{-}\,\omega_{it}$

Then the probability of the zero positive outcome can be expressed as:

$$\Pr[Y_i = 0] = \{\omega_i + (1-\omega_i)g(0)$$

$$\Pr[Y_t = k] = (1-\omega_{it}) + (1-\omega_{it})g(k) \quad \mathrm{k} = 1,2,3...$$

Where $g(.)$ is the Poisson probability function that corresponds to: $\log(\alpha_{it}) = \alpha_i + x_{it}\beta$.

3. DATA

Data were obtained within the EU FP7 CAP-IRE project from a farm-household survey of 295 respondents in two regions in France (NUTS2 regions Midi-Pyrénées and Centre). The composition of the sample is balanced between the two regions: 140 respondents in Centre and 155 respondents in Midi-Pyrénées. The questionnaire is available from Viaggi et al. (2009); the sampling procedure is available in Raggi et al. (2009).

In either model the intensity of innovation is obtained summing for each farm the number of stated intentions about the adoptions of all innovation typologies. The dependent variable (innovation intensity) is expressed as count data with a value between 0 (no intention to adopt any of the suggested innovations) to 5 (stated intention concerning the adoption of all suggested innovations). In Table 1 the value for all modalities of the innovation intensity is presented for respectively the baseline scenario and the NO-CAP scenario. These variables have been used as dependent variables for the two count data models.

Table 1 – Innovation intensity: number and % of adoption (between brackets) among the farmers.

Number of innovation adopted	BASELINE	NO –CAP scenario
0	78	75
	(31.2)	(38.86)
1	89	63
	(35.6)	(32.64)
2	45	35
	(18)	(18.13)
3	29	14
	(11.6)	(7.25)
4	7	4
	(2.8)	(2.07)
5	2	2
	(0.8)	(1.04)
Total	250	193
	(100)	(100)

In both scenarios, the farmers interviewed who stated their intention to exit from agriculture are excluded from the analysis. In fact, over a sample of 295 farmers, 250 farmers were considered under the baseline scenario and only 193 in the NO-CAP scenario. The difference of 57 farmers is given by those farmers who intend to remain in the baseline scenario and exit with the complete CAP abolishment (under the NO-CAP scenario).

An important part of the farmers under the baseline scenario state the intention to adopt at least one innovation among those suggested (36% of the farmers). The percentage of adopters decreases as the number of innovation adoptions increases, with the percentage of adopters equal to 18% for 2 innovations adopted, 12% for 3 innovations adopted; 3% for 4 innovations adopted, and finally 1% for 5 innovations adopted. With the abolishment of the CAP (NO-CAP scenario) the modality with higher frequency is the no adoption intention (38%), while the percentage of those intending to adopt 1 innovation drops to 32%. Increasing the number of adoptions, the percentage of farmers in each group remains basically the same as in the baseline scenario.

RESULTS

3.1. Results of the cluster analysis

Following part one of the methodology, the farmers have been grouped based on past innovation behaviour (number of innovations adopted and timing of adoption) and the age of the farm owner (young or old) with the help of a cluster analysis. The qualification, the frequencies and the main descriptives of the clusters generated are presented in Table 2.

Table 2 – Descriptive of the clusters identified.

Cluster	Cluster description	Farmers (#)	Age (average)	Innovations adopted last 10 years (#)	Innovations adopted last 5 years (#)	Innovation adopted last 3 years (#)
CL1	Late majority and young	77	26.55	0.86	0.84	0.81
CL2	Innovators and old young	31	27.55	2.16	1.96	0.71
CL3	Innovators and old	39	49.12	2.33	0.71	0.38
CL4	Laggards and old	64	55.54	0.67	0.54	0.34
CL5	Late majority	82	41.39	1.06	0.78	0.59

Five clusters have been identified. Such clusters represent different behaviours with respect to the innovation timing. The first cluster "CL1" is composed by homogenous farmers whose behaviour to adopt the innovations presents some time lag with the early adopters, or even do not adopt. In fact the number of innovations adopted in the past is low for this cluster: 0.86 per farm. In addition, such cluster is characterised by young farmers (average of 26.55 years). Cluster 2 "CL2" has a low frequency of farmers compared to the previous cluster and is composed by young farmers (average of 27.55) but, differently than the previous one, by innovators. In fact the number of innovations adopted is higher than the previous cluster: 2.16 innovations per farm.

Cluster 3 and cluster 4 are composed by mostly more aged farmers: in fact the age average is respectively 49.12 for cluster 3 and 55.54 for cluster 4. The main difference between the two clusters is the number of the past innovations adopted: while cluster 3 is mostly composed by innovators (average innovation number per farm equal to 2.33), cluster 4 is composed by laggards or no innovators (0.67 innovations adopted in the past 10 years).

Finally cluster 5 contains a group of farmers with an age between young and old (average age of 41.39) and a late majority behaviour with respect to the adoption of innovations.

In table 3 the stated adoptions of new technologies under the baseline scenario are shown.

Table 3 – Stated intentions concerning the future innovation adoption under the baseline scenario: number and % of adoption (between brackets) among the farmers.

Cluster	No adoption	Robotisation/ precision farming	New irrigation systems	e-commerce	Energy crops/energy production.	Other innovation
CL1	21	34	9	20	27	8
	(30.00)	(48.57)	(12.86)	(28.57)	(38.57)	(11.43)
CL2	6	17	0	6	14	4
	(20.00)	(56.67)	(0)	(20.00)	(46.67)	(13.33)
CL3	12	10	4	6	11	4
	(36.36)	(30.30)	(12.12)	(18.18)	(33.33)	(12.12)
CL4	20	10	4	5	14	3
	(45.45)	(22.45)	(9.09)	(11.36)	(31.82)	(6.82)
CL5	19	22	9	14	29	15
	(26.76)	(30.99)	(12.68)	(19.72)	(40.85)	(21.13)

Future new technology adoptions are connected with the innovation behaviour observed with the past innovation adoptions. This can be seen comparing the percentage of no adoption across the different clusters. In fact, innovative groups have a lower percentage of no adoption: respectively about 10% less for young farmers (difference between CL2 and CL3) and 8% less for old farmers (differences between CL3 and CL4).

The future adoption of the different innovation typologies is quite heterogeneous across the five clusters. Among the technologies proposed, the robotisation/precision farming technology and the e-commerce and direct selling have percentages of stated intentions about the adoption that are differentiated between innovators and laggards (about 8-9% in favour to innovator farms for both innovations). These innovations, in fact, require a past sequence of innovation and high know-how. Other innovations, which do not require a specific know-how, or a sequence of innovation, do not show significant difference in percentage between innovators and laggards.

In Table 4 the stated adoptions of new technology with CAP abolishment are shown.

Table 4 – Stated intentions concerning the future innovation adoption under the NO-CAP scenario: number and % of adoption (between brackets) among the farmers.

Cluster	No adoption	Robotisation/ precision farming	New irrigation systems	e-commerce	Energy crops/energy production	Other innovation
CL1	21	16	7	18	19	4
	(37.50)	(28.57)	(15.50)	(32.14)	(33.93)	(7.14)
CL2	9	8	0	6	8	2
	(39.13)	(34.78)	(0)	(26.09)	(34.78)	(8.70)
CL3	10	7	2	6	7	6
	(37.04)	(25.93)	(7.41)	(22.22)	(25.93)	(22.22)
CL4	18	5	0	6	9	3
	(52.94)	(14.17)	(0)	(17.65)	(26.47)	(8.82)
CL5	17	11	6	13	22	10
	(32.08)	(20.75)	(11.32)	(25.39)	(41.51)	(18.87)

CAP abolishment reduces the technology adoption intention in all clusters. Such reductions are however quite differentiated across the five clusters. In particular the CAP abolishment reduces the adoption for the laggards, who are characterised in addition by an old age. Innovators have a different behaviour and the latter is associated to different ages of the farmers. In fact, old farmers and laggards have higher percentage of no adoptions (+15% of no adoption for laggards).

3.2. Results of models

Both models are structured with a set of independent variables. In addition to farm/farmer and household characteristics, the membership to the cluster identified with the future innovation behaviour has been included, as well as the sources of information used by the farmers to collect the information about the innovations adopted in the past.

In table 5 the explanatory variables used in both models are presented.

The dependent variables differ among the models, though the set of independent variables is mostly the same. Independent[2] variables can be classified as belonging to the following categories: farm innovation behaviour, sources of information used by farmers to collect information about the past innovations adopted, household characteristics, farmer characteristics, policy, farm structure, legal status, regions and geographical area characteristics.

In addition to the innovation behaviour, explained above, also the source from which the farmer has collected information about past innovation has been considered as explanatory variable.

Household variables are mainly related to the long term unemployed household members (unemp_c) and the weight of farm income with respect to the total household income (f_inco_more50; f_inco_more70 and f_inco_momecont), the presence/absence of household members younger than 18 (house18_d) and finally if the farm household lives on the farm (live_on_d).

The farmer characteristics included in the models are: the age of the farm owner (lnage_y), the education level representing the educational level lower than secondary school (edu_level_lower) and finally if the farmer has received an agricultural education (agri_edu_d).

In both models the farm characteristic variables are related to farming specialisation (Farm type field crop and Farm type mixed crop livestock), to the current farm size (land_UAA_ha), regarding utilised agricultural area (UAA) over a certain threshold (land_UAA_more50), to the amount of labour used (all_fulltimeeq) concerning the household plus external labour used on farm and concerning the only external labour used on farm

[2] The independent variables used in both models were selected coherently with the literature on determinants of farm expansion and the final model was, for each scenario, the one with lower BIC value (Bayesian Information Criterion).

(fulltime_eq). Finally in this category a dummy variable with the identification of other on-farm activity different to crops growing and animal reared is considered (ah_activty_other).

Table 5 – Explanatory variables used in the models.

Category	Variable (Description)	Variable (Code)	Obs (#)	Mean	Std. Dev	Min	Max
Farm innovation behaviour (Cluster membership)	Late majority and young (dummy)	lagg_young	293	0.2627	0.4409	0	1
	Innovators and old (dummy)	inn_young	293	0.1058	0.3081	0	1
	Innovators and young (dummy)	inn_old	293	0.1331	0.340	0	1
	Laggards and old (dummy)	lag_old	293	0.218	0.4138	0	1
	Late majority	late_maj	293	0.2798	0.44	0	1
Source of information (specific for innovations)	Sources used to collected information about past innovations (#)	info_sources	295	1.3288	1.427	0	7
	Information collected directly by the farmer (dummy)	info_only_persona ly	295	0.1559	0.363	0	1
Household characteristics	Existence of household members younger than 18 years old (dummy)	house18_d	295	0.4440	0.497	0	1
	Unemployed (# in the household)	unemp_c	295	0.0169	0.129	0	1
	Share of farm income from agricultural activity in total household income (%)	farm_incomcon t	295	68.084 7	31.376	5	100
	Farm income from agricultural activity > 50% of total household income (dummy)	f_inco_more50	295	0.7016	0.4582	0	1
	Farm income from agricultural activity > 70% of total household income (dummy)	f_inco_more70	295	0.4779	0.5003	0	1
	Household lives on the farm (dummy)	live_on_d	295	0.7457	0.4361	0	1
Farmer characteristics	Age of respondent (Ln of age_y)	lnage_y	293	3.6402	0.3159	2.89	4.14
	Educational level lower than secondary school (dummy)	edu_level_low	295	0.1389	0.3465	0	1
	Agricultural education (dummy)	agr_edu_d	295	0.9355	0.2458	0	1
Farm Structure	Household labour + external labour used on farm (# of full time equivalents)	all_fulltimeeq	295	1.9186	1.798	0	17
	External labour used on farm (# of full time equivalents)	fulltime_eq	295	0.5440	1.6907	0	16
	Utilised Agricultural Area (UAA) (ha)	land_UAA_ha	295	105.10	96.126	0	738
	UAA greater than 50 ha (dummy)	land_UAA_mor e50	295	0.6983	0.4597	0	1
	Farm type field crop (dummy)	type_farm1	295	0.2915	0.4552	0	1
	Farm type mixed crop livestock (dummy)	type_farm7	295	0.0474	0.2129	0	1
	Other farm activity different from crop cultivation and animal rearing	ah_activity	295	0.2305	0.4218	0	1
Legal Status	Legal status: partnership (dummy)	legal_partnershi p	295	0.4677	0.499	0	1
	Legal status: limited liability company (dummy)	Legal_limited	295	0.0440	0.2055	0	1
Policy	Current SFP received (1000€)	pay_sfp1000€	295	20.779	24.467	0	143
Geographical	Plain (dummy)	plain_d	295	0.4677	0.499	0	1
	Hill (dummy)	hill_d	295	0.3762	0.4852	0	1
	Mountain (dummy)	mountain_d	295	0.1559	0.3634	0	1
Region	Centre (dummy)	region_8	295	0.4745	0.5002	0	1
	Midi-Pyrénées (dummy)	region_9	295	0.5254	0.5002	0	1

Two variables referred to the farm legal status are considered: partnership status (legal_partnership) or limited liability company status (legal_limited). The amount of SFP received is included into the policy category.

In both models the regions are presented as two dummies (Centre and Midi-Pyrénées). Geographical variables are represented by altitude, which is presented as three dummy variables (plain, hill and mountain).

Table 6 presents the ZIP model results.

Table 6 – Results of the ZIP models (variables not significant at 0.10 are omitted).

Variable (Description)	Variable (Code)	Parameter estimated under the baseline scenario (Model 1)	Parameter estimated under the NO-CAP scenario (Model 2)
Innovators and old (dummy)	inn_young	**+.4763**	
Laggards and old (dummy)	lag_old	**-.4601**	
Late majority	late_maj	**-.3642**	
Information collected directly by the farmer (dummy)	info_only_personaly		**-.3645**
Share of farm income from agricultural activity in total household income (%)	farm_incomcont	**-.0068**	
Household lives on the farm (dummy)	live_on_d	**+.3698**	**+.4243**
Educational level lower than secondary school (dummy)	edu_level_low	**-.7200**	
External labour used on farm (# of full time equivalents)	fulltime_eq	**+.831**	**+.1075**
UAA (ha)	land_UAA_ha		**+.0018**
Farm type mixed crop livestock (dummy)	type_farm7	**-1.3472**	
Legal status: partnership (dummy)	legal_partnership	**-.5063**	
Plain (dummy)	plain_d	**+.4780**	**+.7775**
Hill (dummy)	hill_d	**+.3551**	**+.5654**
ZERO INFLATED OUTCOME (Logit)			
Household labour + external labour used on farm (# of full time equivalents)	all_fulltimeeq	**-2.164**	
Age of respondent (Ln of age_y)	lnage_y	**+9.927**	
Midi-Pyrénées region (dummy)	csa_9	**-2.167**	
Share of farm income from agricultural activity in total household income (%)	farm_incomcont		**+.0349**
Sources used to collected information about past innovations (#)	info_sources		**-1.7898**
Late majority and young (dummy)	lagg_young		**+2.301**
Laggards and old (dummy)	lag_old		**+1.577**
Observations (#)		**248**	**193**
Zero observations (#)		**75**	**78**
Voung test		**2.47 (PRM rejected in favour to ZIP)**	**2.58 (PRM rejected in favour to ZIP**

In the upper part of the table, the preliminary outcome of the count model is presented, while the preliminary outcome of the logit model is presented in the bottom part.

The coefficients of the count model (upper part of the table) represent the change in the expected count for the farmers who have intention to innovate. The coefficients of the logit model are interpreted relatively to observing a zero count, thus the positive coefficient of the significant variables means that farmers are more likely to expect value of zero count (that means no innovation adoption). Otherwise negative sign will reduce the expected value of count variable.

Under the baseline scenario, the past innovation behaviour is determinant of the future innovation adoptions. In fact laggards or late farmers have a negative coefficient, implying a lower amount of expected future innovation adoptions. On the contrary, the membership to the category of innovators (inn_old), has a positive coefficient and for such category is expected a higher adoption of innovations. Other variables that determine positive effects on the count of future innovation adoption under the baseline scenario are: the increasing of the external labour (express in full time equivalents), and then the plain or hill geographical location. The variables with negative effect on the count of future innovation are lower education, some farm specialisation and legal status. Finally the count model is reduced with the increasing weight of the farm income with respect the total household income. In the zero inflated outcome the variable increasing the probability to have no innovation is mainly the age of the owner, while those that effect negatively such probability is the total labour used and being located in Midi-Pyrénées region.

Concerning the second model (under the NO-CAP scenario) the variables which have a positive effect on the innovation intensity are those connected with the farm structure highlighted in the previous model (labour), plus the farm size and the geographical location. In addition, with respect to the previous model, the innovation specific sources of information become important in explaining the number of innovations adopted. In fact, the farmers who only collect information personally (without benefiting of information about innovation from a network of farmers or from up-stream or down-stream firms) show a significantly lower number of innovations. The source of information has become even more important in the access of the innovation (logit model). In fact increasing the number of sources of information implies that the probability to have no innovation is strongly reduced. With respect to the baseline model, with the CAP abolishment the past innovation behaviour is significant as a determinant of the no innovation behaviour, rather than determinants of the number of innovations adopted. In fact, belonging to late or laggards category will increase the probability to have zero innovation adopted in the future.

4. CONCLUSION

Preliminary results confirm in addition that under the current policy scenario the process of innovation adoption at farm level does not follow breakthrough, discontinuous, etc, process and in fact, the storyline about past innovation, and the number of past innovations adopted and the timing of adoption, are significant explanatory variables of the new technology adopting process.

Results highlight that the CAP strongly affects the decision to innovate and the innovation intensity, even if there is no statistical significance in the variable connected to the amount of payments or the level of payment per hectare, at least for three reasons. Firstly with the CAP abolishment there is an effect of exit also for those farmers who state intention to innovate in the future under the baseline scenario. Secondly the effect of CAP abolishment is observed on the future innovation adoption according to the innovation adoption behaviour. In particular the CAP abolishment will reduce the access to any innovation for those farmers who could be grouped in the category of laggards or late adopters. Thirdly the results highlight that in a scenario without CAP, the information and the source of information collected strongly affect the innovation adoption.

In addition to better targeting policy instruments aimed to encouraging innovation adoption or diffusion through financial incentive, there is a need of specific instrument aimed promoting innovation through a development of a system of consultancy specific for the innovations.

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