Determinants of ICT Innovation and Imitation in the Agrifood Sector

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Abstract. Diffusion of innovations has gained a lot of attention and concerns different scientific fields. Many studies, which examine the determining factors of technological innovations in the agricultural and agrifood sector, have been conducted assuming the widely-used Technology Accepted Model (TAM), for a random sample of farmers or firms in agricultural sector. In the present study, a holistic examination of the determining factors that affect the propensity of firms to innovate or imitate, is conducted. The diffusion of ICT tools of firms which are engaged in the NACE 02/03 as well as in the NACE 10/11 classifications for 49 heterogeneous national markets is examined, using the Bass model. The innovation parameter is positively associated with rural income, female employment, export activity and education of farmers, while the imitation parameter is increased in societies with large uncertainty avoidance.

Keywords: Diffusion of ICT, Agrifood sector, Bass model, Innovation/Imitation, Beta - Regression.

1   Introduction

The adoption of technological innovation by firms in the agricultural and food sector is not something new and inevitably has gained a lot of importance, due to the fact that technological updates contribute in the increase of production, employment and eventually income (Feder et al., 1985).

Other scholars argue that an increase in growth productivity of the agricultural sector may cause a de – agriculturalization and therefore a decline of the employment in agriculture (Üngör, 2013). Many related studies have investigated the adoption of ICT tools in the agrifood sector in specific countries using questionnaires (e.g Domenech et al., 2014; Batterink et al., 2006; Mondal and Basu, 2009). The majority of the papers published examine the effect of Rogers' (1995) dimensions, regarding *compatibility*, *relative advantage*, *perceived usefulness*, *perceived risk* and others dimensions on the adoption of innovation in the agricultural sector.

The present study contributes to the relevant literature by identifying factors, which affect the propensity of innovation and imitation at an aggregate level using a sample of heterogeneous countries. These factors can be further divided into three main categories: *socioeconomic*, *environmental* and *cultural*. In the *socioeconomic variables* the income of farmers (Rogers, 1995; Domenech et al., 2014), exporting activity (Domenech et al., 2014), female employment (Chandrasekaran and Tellis, 2008; Stremersch and Tellis, 2004) and the participation of countries in international organization (Tellis et al., 2003) tend to have a positive effect on the probability of innovation adoption. On the contrary, regarding the *environmental variables*, probability of adoption is higher in countries where there are low temperatures compared to countries with high temperatures, while in countries where subjects are risk avenging, innovations are less likely to be adopted (Chandrasekaran and Tellis, 2008; Tellis et al., 2003).

The rest of the paper is organized as follows: Section 2 presents the methodology which includes the description of data and description of the basic diffusion model as well as the model employed to assess the effect of factors on the propensity to innovate and imitate. Section 3 presents the results of the estimated model and conclusions are drawn in Section 4.

2 Methodology

2.1 Data

The data were collected from various online databases: data about the time at which firms engaged in agrifood sector have adopted a website (their main activities lies in classification NACE 2, 3, 10 and 11) were collected from the *Orbis* database (Bureau van Dijk), while data series for the explanatory variables were collected from the Euromonitor and World Bank online database. For the correct identification of the time at which firms in agrifood sector adopted and launched their website, more than 30,000 companies' websites were collected and analyzed using the Web Archive (https://web.archive.org). The time at which websites were launched, spans from 1996 to 2016 and concern 49 countries (Figure 1).

Overall, 1,407 observations were used to examine the speed of website adoption, as well as its determinants. Analytically, the *rural wealth* (WEALTH) is measured in million US$, at constant 2016 prices and fixed 2016 exchange rates and refers to disposable income of household in rural areas per rural population, which is which is the gross income less social security contributions.

Rural education (EDUC) is measured as the number of graduates in Agriculture ISCED 97 classification 6. This classification includes agriculture, crop and livestock production, agronomy, animal husbandry, horticulture and gardening, forestry and forest product techniques, natural parks, wildlife, fisheries, fishery science and technology, veterinary medicine and veterinary assisting.

Exporting activity (EXPORT) is measured as the ratio of exports (fob) to the imports (cif) of animal & animal products. These include exports and imports of live animals meat and edible meat offal, fish, crustaceans, mollusks and aquatic invertebrates, dairy products, eggs, honey, and other edible animal products and other products of animal origin and correspond to HS classification 01-05. Exports and imports are measured in million US$ current prices.

Female employment (FEM_EMPL) in agricultural sector includes the percent of female population employed in the agricultural sector and consists of activities in agriculture, hunting, forestry and fishing.

Participation in *International Organizations* (EU) is a dummy variable receiving value of 1 if a country is EU member and 0 otherwise.

In addition, the *climate* (CLIMA) in each country is measured using average daily air temperature in Celsius. Moreover, *risk* is measured by Hofstede's (2001) dimension uncertainty avoidance.

Uncertainty Avoidance (UAI) is defined as the degree to which members of a society fear anything new and innovative.

Finally, *long Term Orientation* (LTO) from Hofstede's (2001) dimensions is used so as to examine how culture of countries affect speed of ICT diffusion in agrifood sector. *Long Term Orientation* is defined as the degree to which members of a society are focused on the future. They are willing to delay short-term material or social success or even short-term emotional gratification in order to prepare for the future.

In Table 1, the correlation coefficients between explanatory variables are presented as well as their descriptive statistics. All correlation coefficients are low and the variance inflation index (VIF) does not exceed 2.5, which is a threshold signaling multicollinearity (Greene, 2008).

2.2 Statistical Methodology

In order to examine the diffusion of ICT in agrifood sector, the Bass (1969) model is used. Let $x_i(t)$ be the cumulative number of firms in country *i,* which has adopted a website at time *t* then the Bass model, in discrete time notation, can be formulated as follows:

$$\frac{dx_i(t)}{dt} = [p + q \cdot x(t-1)] \cdot [m - x(t-1)] . \tag{1}$$

In Equation 1, *p* denotes the propensity to innovate, *q* the propensity to imitate and *m* the maximum potential of a market (Bass, 1969). *Bass model* is widely used due to the fact that it can adjust to monotonically increasing data without incorporating any explanatory variable (Bass et al., 1994) and it can be estimated using maximum likelihood method (Schmittlein and Mahajan, 1982), non − linear

least squares (Srinivasan and Mason, 1984) and ordinary least squares (Bass, 1969). In the present study, the method of estimation which is chosen is the non – linear least squares, due to the fact that the parameters p, q and m and their standard errors can be estimated directly, while estimating Bass model using maximum likelihood method underestimates the standard errors of p, q and m (Schmittlein and Mahajan, 1982). Bass coefficients, namely p and q for each country and NACE classification category, receive values in the range (0, 1). Therefore, the appropriate model to assess the effect of independent variables on the estimated coefficient of innovation ($\hat{p}_i$) and on the estimated coefficient of imitation for each country ($\hat{q}_i$) is the *beta* regression (Ferrari and Cribari-Neto, 2004). This model is based on a different parameter specification of the *beta* density in terms of the variate mean and precision parameter (Cribari-Neto and Zeileis, 2009). Let $\hat{p}_i : \hat{p}_1,...,\hat{p}_n$ and $\hat{q}_i : \hat{q}_1,...,\hat{q}_n$ be random variables such that $\hat{p}_i, \hat{q}_i \sim B(\mu_i, \varphi)$, where φ is the precision parameter, then the *beta* regression model is defined as:

$$g(\mu_i) = \mathbf{x}_i^T \beta .\tag{2}$$

Where β is the vector of coefficients to be estimated $\mathbf{x}_i$ the matrix of independent variables' values and $g(\cdot)$ is the link function. Several link functions are tested, in order to choose the best fit. These link functions are the following: *Logit* $g(\mu) = \log\left[\mu/(1-\mu)\right]$, *Probit* $g(\mu) = \Phi^{-1}(\mu)$ where $\Phi(\cdot)$ is the standard normal distribution function and *Log – Log* $g(\mu) = -\log\left[-\log(\mu)\right]$. Coefficients of model in Equation 2 (β), for each specification chosen, are estimated using maximum – likelihood method. The log – likelihood function of *beta* regression is defined as follows:

$$L(\mu_i, \varphi) = \log\left[\frac{\Gamma(\varphi}{\Gamma(\mu_i\varphi) \cdot \Gamma((1-\mu_i)\varphi)}\right] + (\mu_i\varphi - 1)\log y_i + \left[(1-\mu_i)\varphi - 1\right]\log(1-y_i) .\tag{3}$$
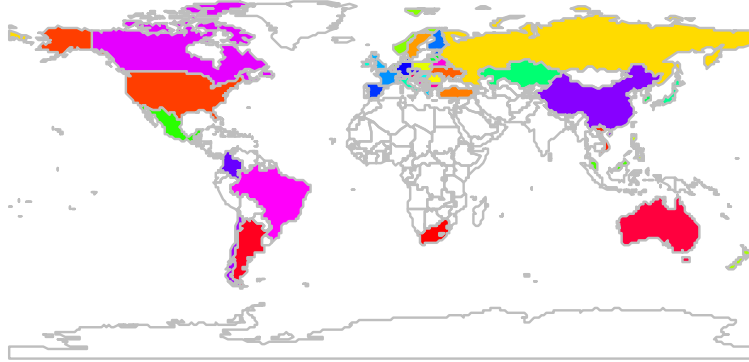
Fig. 1. The countries of the sample

Table 1. Correlations and descriptive statistics for all explanatory variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
EXPORT [1]	1						
EDUC [2]	-0.13	1					
CLIMA [3]	0.09	0	1				
WEALTH [4]	0.1	-0.21	-0.26	1			
FEM_EMPL [5]	-0.06	0.08	0.22	-0.54	1		
LTO [6]	-0.34	0.22	-0.28	-0.11	-0.03	1	
UAI [7]	-0.18	0.05	0.08	-0.48	0.3	0.31	1
EU [8]	-0.25	-0.26	-0.26	0.02	-0.22	0.21	0.12
VIF	1.33	1.55	1.37	1.74	1.47	1.37	1.58
Min	0.02	4	-0.01	0.21	0.002	0.13	0.23
Q1	0.54	1017	0.07	2.74	0.017	0.36	0.49
Q2	1.09	3628	0.1	10.86	0.035	0.52	0.68
Q3	2.39	8944	0.14	17.31	0.083	0.68	0.86
Max	51.6	205900	0.27	36.44	0.72	1	1
Mean	2.93	11030	0.11	10.91	0.084	0.53	0.67
Std Dev	6.13	25334	0.06	8.31	0.13	0.21	0.23

3 Results

The diffusion of ICT in firms, whose main activities are included in NACE classification 02 and 03, subjects to considerable variations across countries. In specific, in the USA the diffusion of ICT tools for firms in NACE 02 and 03 classifications is faster and more intense compared to other countries, while in Norway and UK the diffusion pattern is identical (Figure 2). In Figure 3, the diffusion curves of ICT adoption for firms engaged in NACE 10 and 11 classification activities are presented. The diffusion process in Germany and Italy co – moves and is considerably faster compared to other countries of the sample. On the contrary, Netherlands seems to lead among Greece, Brazil and Argentina, however diffusion of ICT tools in businesses engaged in NACE 10 and 11 sectors lacks speed and is characterized by low market penetration.

Several link function specifications have been tested in order to identify the link function of the *beta* regression model which adjusts data properly. In Table 2, the AIC values for each link function are reported.

Log – Log link is the most appropriate link function for *beta* regression models assuming as dependent variable the estimated coefficients of innovation (p), for the data concerning the NACE 02 – 03 classification firms. For the *beta* regression model where the dependent variable is the estimated coefficient of imitation (q), *Logit* specification fits better to data. Nevertheless, for the dataset of firms which are engaged in the NACE 10 and 11 classifications, *Logit* link function adjusts better to the explanatory variables than the other specification, namely *Log – Log* and *Probit*.

The results of *beta* regression model for the effect of independent variables on the estimated Bass coefficients p and q for the firms which are engaged in the NACE 02 – 03 and NACE 10 – 11 classifications, are presented in Table 3.

Table 2: AIC values for *beta* regression models

| Link function | NACE 02 – 03 | | NACE 10 – 11 | |
	$\hat{p}$	$\hat{q}$	$\hat{p}$	$\hat{q}$
Logit	-1111.07	-471.64	-2561.64	-1303.09
Probit	-1112.62	-471.21	-2561.25	-1302.89
Log – Log	-1113.89	-470.81	-2560.87	-1302.50

Exporting activity is related with coefficient of innovation positively ($b = 0.0036$, $p < 0.01$) and negatively with coefficient of imitation ($b = -0.013$, $p < 0.01$), for the firms which are engaged in the NACE 02 – 03 classification. The number of educated farmers is positively associated with innovative trends in the firms whose main activities lie in the NACE 02 – 03 classifications ($b = 0.074$, $p < 0.01$) and negatively associated with imitation ($b = -0.182$, $p < 0.01$). Innovations tend to prosper in countries where temperature is high ($b = 0.234$, $p < 0.1$), while firms in countries where climate is colder tend to imitate ($b = -1.91$, $p < 0.01$).

Rural income and female employment in agriculture do not seem to have a statistically significant impact on the coefficient of innovation and imitation for the firms in the NACE 02 – 03 classifications. ICT innovations are hindered in countries

high in uncertainty avoidance (b = -0.138, p < 0.01) while it seems that it encourages imitating of innovations (b = 0.148, p < 0.01).

Firms which are located in EU countries are more probable to innovate (b = 0.169, p < 0.01) than imitate (b = -0.422, p < 0.01). Both the *beta* regression models, which for coefficient of innovation (p) and imitation (q) for firms which are engaged in the NACE 02 – 03 classifications perform very good fit to the data, as the Pseudo R^2 index exceed the threshold of 20% as suggested by (McFadden, 1976) (52.1% and 29.15% respectively). In addition, both models are statistically significant (LR = 157.82, p < 0.01 and LR = 69.88, p < 0.01).

Adoption of ICT tools, in the case of firms in NACE 10 – 11 classifications, is facilitated with exporting activity (b = 0.062, p < 0.1). Education is positively associated with innovating (b = 0.104, p < 0.01) and negatively associated with imitating (b = -0.074, p < 0.01). Innovation of ICT tools in agrifood sector is increasing in wealth countries (b = 0.073, p < 0.05) as well as in countries where women have an active role in agricultural employment (b = 1.462, p < 0.01).

The fact that EU countries tend to innovate more than imitate is verified for ICT tools which are adopted by firms which are engaged in the NACE 10 – 11 classifications. Cultural dimensions do not affect statistically significant both innovation and imitation parameters.

Beta regression models, which evaluate the effect of factors on the coefficient of innovation and imitation, do not exhibit good fit to the dataset, as the corresponding Pseudo R^2 indices do not exceed the threshold of 20%.
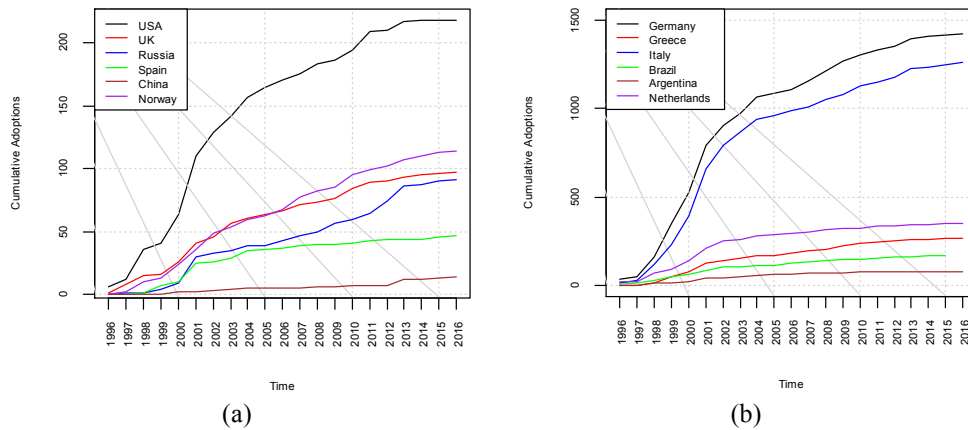

Fig. 2. Cumulative ICT adoptions for selected countries whose main activities lie in a) NACE 02 – 03 and b) in NACE 10 – 11

Table 3. Estimation results of beta regression

	NACE 10–11				NACE 02 - 03			
	Coefficient of Innovation (p)		Coefficient of Imitation (q)		Coefficient of Innovation (p)		Coefficient of Imitation (q)	
	B	Z	B	Z	B	Z	B	Z
Exporting Activity	0.0036***	3.59	-0.01***	-3.28	0.01*	1.77	-0.002n.s.	-0.93
Log(Rural Education)	0.07***	10.25	-0.18***	-6.11	0.10***	6.09	-0.07***	-4.87
Climate	0.23*	1.88	-1.91***	-3.76	0.25n.s.	0.63	1.27***	3.5
Log(Rural Wealth)	-0.02n.s.	-1.19	0.03n.s.	0.48	0.07**	2.75	-0.08***	-3.17
Female Employment	-0.22n.s.	-1.47	0.53n.s.	0.81	1.46***	6.97	-1.16***	-5.22
Long Term Orientation	-0.65***	-9.99	0.17n.s	0.63	0.21*	1.89	-0.15n.s.	-1.56
Uncertainty Avoidance	-0.14***	-3.9	0.15***	4.04	-0.10n.s.	-0.98	0.38***	4.01
EU	0.17***	9.23	-0.42***	-5.89	0.16***	3.33	-0.21***	-4.96
Log – Likelihood		566.9		245.8		1291		661.5
Pseudo R – squared		52.1%		29.15%		11.32%		16.3%
Likelihood Ratio(X2)		157.82***		69.88***		82.04***		96.87***

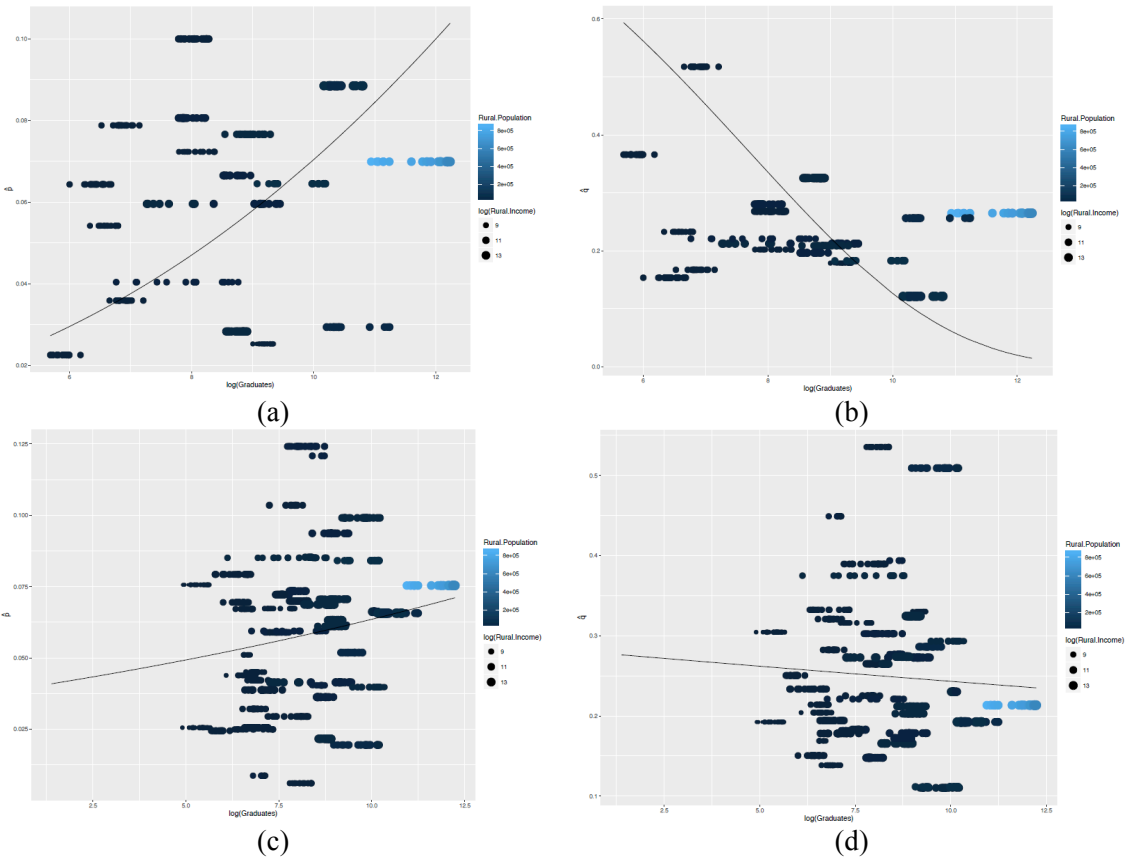Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$, n.s. not significant

Fig. 3. Coefficient of a) innovation against number of educated farmers with respect to rural population and rural income for NACE 02 – 03 classifications, b) imitation against number of educated farmers with respect to rural population and rural income for NACE 02 – 03 classifications, c) innovation against number of educated farmers with respect to rural population and rural income for NACE 10 – 11 classifications, d) imitation against number of educated farmers with respect to rural population and rural income for NACE 10 – 11 classifications.

4 Discussion

Diffusion of ICT in agrifood sector is proved to be in a multilevel way associated with economic and educational national characteristics (Smale et al., 1994). Rogers' (1995) characteristics of innovators and imitators seem to hold in the present study. In specific, firms in agrifood sector tend to innovate when they operate in wealthy countries and farmers are educated (Ervin and Ervin, 1982; Tey et al., 2017). The

propensity of innovation is enhanced in countries with increased female employment in the rural sector. Likewise marketing research theory, female tend to facilitate the adoption of new technologies in order to save time (Dekimpe et al., 2000; Ganesh and Kumar, 1996; Putsis et al., 1997).

The extraversion of economies tends to facilitate the propensity of firms in the agrifood sector to innovate. Firms which are engaged in the agricultural sector need to innovate so as to increase their productivity and supply markets with new products, incorporating low prices and high quality at the same time so as to meet consumers' challenges.

However, diffusion and consequently adoption of ICT tools does not depend only on economic conditions but also on cultural characteristics. Avenging risk and in general anything which is new and innovate is a typical characteristic of societies which tend to imitate rather than innovate (Rogers, 1995). Rural firms which operate in countries, whose societies are low in uncertainty avoidance, are more probable to take initiatives and innovate than imitate (Van den Bulte, 2000; Dwyer et al., 2005).

On the other hand, long-term orientation is a determining factor of innovation for firms, which are engaged in the NACE 02 – 03 sectors. This finding shows that farmers are willing to quit on their expectations in the present for the sake of better future earnings on their adoption in ICT tools.

Least but not last, firms in agrifood sector which belong to European countries tend to innovate more compared with other countries of the sample. The participation of countries in the European Union, facilitate the diffusion of innovations within their broad borders. Furthermore, various organizations aid firms in the agrifood and agricultural sector to incorporate new technologies or improve the underlying ones, with respect to the specific challenges and needs of consumers in one integrated market.

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