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Innovation and productivity in agricultural firms: evidence from a country-wide farm-level innovation survey

Diego Aboal [a,b,c], Mario Mondelli[a] and Maren Vairo[a]

[a]CINVE – Centro de Investigaciones Económicas, Montevideo, Uruguay; [b]Facultad de Administracion y Ciencias Sociales, Universidad ORT Uruguay, Montevideo, Uruguay; [c]Facultad de Ciencias Económicas y Administración, Universidad de la República, Montevideo, Uruguay

ABSTRACT

The literature on the links between innovation and productivity at the firm level in agriculture is almost nonexistent. In this paper, we analyze the factors behind the innovation effort of farms and the impact that innovation effort has on farm's productivity, exploiting a unique farm-level agricultural innovation survey carried out in Uruguay. The results indicate that farm size, cooperation with other agents to perform R&D, the education of the owner of the farm, the participation of foreign capital and the existence of links with other organizations, in particular scientific, horizontal and vertical ones, are positively correlated with innovation effort. Public and private financial support are not clearly linked with innovation effort. The innovation effort has a positive effect on farm's productivity. Some heterogeneities across industries in agriculture are found.

KEYWORDS

innovation; productivity; agriculture; innovation surveys

JEL Classification

O12; O13; O31; O33; O40

Introduction

Technological change and innovation have been major factors shaping agriculture in the last hundred years (Sunding and Zilberman 2001) and have motivated a large volume of studies. Most studies on innovation in agriculture focus the analysis at the sector or industry level (rather than the firm level) in issues such as the rate of return to R&D investments and technological adoption and diffusion of technologies. This also applies to Uruguay where studies show that technological change in the last three decades accounts for 46% of the agricultural output in 2010, calculated as the difference between the agricultural output in 2010 and the output that would be generated using the same inputs with the 1980 technology (Bervejillo, Alston, and Tumber 2012).

The empirical literature is very limited when it comes to studies assessing the relationship between innovation and productivity at the farm level. We are aware of only two studies that assess the effect of innovation adoption on productivity (Nossal and Lim 2011 and Sauer 2017). This gap is surprising given that there is extensive evidence showing that innovation improves productivity at the firm level in manufacturing (Hall 2011; Mohnen and Hall 2013), pointing to the fact that productivity is the result not only of the adoption of technology but also of the ability to generate and integrate innovations in the farming system (EU SCAR 2012). Probably what explains this gap is the worldwide unavailability of firm or farm level agricultural innovation surveys.

Nossal and Lim (2011) study the factors that make a farmer innovative and how innovation adoption by farmers influences productivity in grain production in Australia. They use a two-stage

CONTACT Diego Aboal aboal@cinve.org.uy

regression analysis with farm-level data for 2006–2008 from the Australian Department of Agriculture. They find that higher innovative effort leads to higher productivity.

A recent paper by Sauer (2017) investigates the determinants of the innovation decision, the innovation intensity, the innovation output and the effects of innovation on productivity using data from dairy and crop farms in the Netherlands. The author estimates a multi-stage model. The main findings indicate that regulation and standards are a demand-pull for innovations, that the cooperation with knowledge institutions increases the probability of introducing innovations. In addition, farm-size, age of farm operator, confidence in the growth of business and sector, and process and product development activities are positively correlated with the size and success of innovations. Innovation investment is positively correlated with the introduction of innovations. Finally, process, organization and marketing innovations are positively correlated with productivity.

Sauer (2017) and Sauer (2014) review some other related studies and we refer to these studies for additional references.

In this context, it is important to generate evidence about how farms innovate and the way in which innovations affect productivity at the farm level. These are precisely the research questions of this article. For this purpose, we are using, as far as we know, the first agricultural innovation survey in the world that is based on the well-known Oslo Manual and covering farm activities that account for more than 90% of the agricultural GDP of a country.[1]

This article contributes on several ways to the literature. First, it brings new evidence to understand the drivers of productivity in agriculture and, specifically, the effect of innovation on productivity at the farm level. Second, it generates evidence to understand the main factors behind innovation in agriculture at the farm level. This analysis is novel because it allows comparing the potential determinants of innovative efforts and the effects of innovative efforts on productivity in different industries in the agricultural sector – oilseed and grain (non-irrigated), dairy, beef cattle and sheep, and irrigated rice farming. That is, it addresses the idiosyncratic attributes of industry specificities. An additional contribution of this paper is the comparison of the effects of innovation in productivity between agriculture, service, and manufacturing sectors. Although there is extensive evidence in manufacturing, the empirical literature is limited in the service sector (Mohnen and Hall 2013) and, as mentioned, almost inexistent in agriculture. This is possible because the agricultural innovation survey used in this study shares the same approach and questionnaire design with the manufacturing and services innovation surveys.

In what follows, in Section 2 we discuss the empirical strategy. Section 3 describes the data used in the empirical exercise. The results of the econometric analysis are presented in Section 4. Finally, in Section 5 we conclude.

Empirical strategy

Crepon, Duguet, and Mairesse (1998) developed a recursive model (CDM model) suggesting an econometric method to assess the causal link between innovation and productivity at the firm level. The original CDM model is composed by three stages: one that formalizes the determinants of investment on innovation (both at the extensive and the intensive margins); a second stage where the innovation effort materializes through innovation results; and a final stage which uses a Cobb–Douglas production function to model the casual effect from innovation to productivity. Thus, the CDM model encompasses the entire process that starts at the firm´s decision to invest in innovation (the acquisition of *innovation inputs*); the transformation of such inputs into innovation outputs; and the role of those outputs on firm´s productivity. In the original version of the model, innovation effort was captured through R&D expenditure and innovation outputs through patents.

Given the recent development of innovation surveys in Latin America, Crespi and Zúñiga (2012) suggest an alternative version of the CDM model making it more adaptable to the availability of data in the region. The main changes to CDM introduced by Crespi and Zúñiga (2012) are twofold: the inclusion of expenditure in *any* innovation activities (not just R&D) as a proxy of innovation effort. Another novelty introduced by Crespi and Zúñiga (2012) is the use of information on innovation outputs provided by surveyed firms instead of patents.

The empirical exercise presented in the following sections follows Crespi and Zúñigás version of the CDM model, with some modifications which were introduced due to the particular characteristics of the innovation survey used in this study. In addition, given that the model was originally conceived to assess the innovation behavior of manufacturing firms, we changed the specification of the model to account for some special characteristics of the agricultural sector. As a result, we propose a model composed by two equations: the first one models innovative effort, which is defined as the number of innovation activities carried out by the firm; while the second one uses the results of the first stage to establish the effect of innovative behavior on farmś productivity. Both equations are estimated using Ordinary Least Squares (OLS) and estimates are reported for both the entire sample and for each farming activity separately (i.e. rice, dairy, beef cattle and sheep, and oilseed and grain).

Along the paper, we will make some comparisons with results found in other papers for manufacturing or services firms. We would like to be explicit in that this comparison must be taken with a grain of salt, since variables' definitions, model specifications, estimation approaches and contexts could be very different.

The innovation equation

We use the number of innovation activities carried out by the farmer as an indicator of innovation intensity. Given that every farm in the sample declares to have performed at least one innovation activity (see Table 3), there are no issues with selection bias. In the traditional version of the CDM model, firms' innovation effort is proxied by their expenditure in innovation activities. However, the information on innovation expenditure provided by the Agricultural Innovation Survey used in this study is very limited due to the questionnairés design and low rate of response in the expenditure section of the survey.[2]

The innovation equation can be expressed as follows:

$$IE_i = z_i\beta + \varepsilon_i, \tag{1}$$

where IE is the ratio of innovation activities carried out by farms to the total number of activities in the survey. Since the number of innovation activities is different across farm activities, this statistic is normalized to 1. z is a vector of explanatory variables (size, foreign ownership, public financial support, farmeŕs educational level, cooperation dummies, and main farming activity dummies); β is a vector of parameters and ε is the error term.

We are estimating a linear LS model, with the known consequence that the range of the predicted values of IE will be outside the interval [0, 1]. This is not a problem since we are using this predicted value only as a ranking of firms according to their innovative effort.[3]

The version of the CDM model used here skips the second stage were innovative effort explains the production of innovation outputs. We chose to synthesize the first two stages in one equation, under the assumption that the intensity in the development of innovation activities is a good proxy for innovation outputs. There is also a more practical justification for this decision: the question about innovation outputs was asked only to those firms that introduced at least one innovation activity *for the first time* in the period 2007–2009. Therefore, those firms that introduced all the innovation activities they were performing during 2007–2009 before 2007, do not answer this question. In any case, and just as a robustness check, in section 4.4 we will run a regression for process and product innovation.

The productivity equation

The productivity equation is modelled through the log-transformation of a Cobb–Douglas production function, where the set of inputs is composed by physical capital and labor (skilled and unskilled). The production function also includes a total factor productivity (TFP) component that is explained by innovation.

$$y_i = TFP_i + \pi_1 k_i + \pi_2 l_i + \pi_3 sl_i + x_i \alpha + u_i, \tag{2}$$

$$TFP_i = \pi_4 \widehat{IE}_i + v_i. \tag{3}$$

This results in the following reduced form equation:

$$y_i = \pi_1 k_i + \pi_2 l_i + \pi_3 sl_i + \pi_4 \widehat{IE}_i + x_i \alpha + z_i \tag{4}$$

Where *y* is the log of sales per hectare of productive land (land productivity); *TFP* is the total factor productivity; *k* is the log of total hectares (size); *l* and *sl* are the log of the number of unskilled and skilled workers per hectare, respectively; $\widehat{IE}$ is the predicted ratio of innovative activities in the previous equation; π_1, π_2, π_3 and π_4 are parameters; *x* is a vector of additional control variables (industry dummies, soil quality and region dummies), α is a vector of parameters, and *u, v, z* are disturbance terms.

The reduced form Equation (4) is the equation that will be estimated in the next sections.

Data and descriptive statistics

We use the Agricultural Innovation Survey (AIS) performed in Uruguay in 2010 by the Uruguayan Research and Innovation Agency (ANII). This survey provides information regarding farmś innovative behavior in eleven farming activities during the period 2007-2009.[4] As shown in Table 2, the farming activities covered by the AIS account for 94% of the agricultural GDP in 2009. The AIS is carried out at the *farm* level. This is a limitation when capturing the behavior of large firms, given that technological strategies are usually conceived considering the productive organization as a whole (Table 1).

Given the heterogeneity in the innovative behavior of farms among agricultural activities, we focus on four of the most relevant activities (in terms of production). As a result, our final sample is composed by farms that carry out one of the following activities: rice, oilseed and grain, beef cattle and sheep or dairy farming. These farm activities account for 77% of the agricultural GDP in 2009.

In sum, the AIS contains a comprehensive set of information about the innovative behavior of the agricultural sector with regards to relevant issues such as innovative effort, the role of cooperation with other agents from the innovation system, among others.

Table 1. Contribution of farming activities to total agricultural production in 2009.

Farming activity /a	% of total production
Rice[a]	7
Non-irrigated agriculture[a]	35
Wheat farming[a]	12
Barley farming[a]	2
Corn and sorghum farming[a]	4
Soybean and sunflower farming[a]	11
Grassland farming[a]	6
Legumes and vegetables production	4
Fruit farming	7
Dairy production[a]	8
Beef cattle and sheep farming[a]	26
Wool and leather production[a]	1
Cattle and other livestock breeding[a]	25
Forestry and logging	7
Other activities not included in the AIS	6
Total	100

Source: Central Bank of Uruguay.
[a]Included in empirical analysis of this paper. /a. ISIC classification.

Table 2 provides a description of the sample. The final number of farms included in the empirical exercise is 1258: 87 from rice farming, 654 from beef cattle and sheep farming, 170 from dairy farming, and 347 from oilseed and grain farming. Given the heterogeneity among farming activities, we also carry out the empirical exercises separately for each subsector whenever sample size allows this fractioning.

As for innovative effort of farms, Table 2 provides insights on the decision of carrying out innovation activities. Every farm in the sample carried out at least one innovation activity in 2007-2009. Nonetheless, results vary largely among areas of innovation activities: while technologies related to productive management, inputs, capital goods, and management seem to be the most widely used, experimental R&D appears to be notably less incorporated in farms' innovation strategies.

When analyzing separately the strategies by farming activity, the results show that rice farmers focus mostly on productive management and information & communication technologies (ICTs) issues; beef cattle and sheep farming on productive management and capital goods; while dairy, and oilseed and grain producers focus mainly on productive management and inputs related innovative activities. Finally, rice farmers stand out for being the most active when it comes to R&D activities, being that almost half of them carried out some type of experimentation.

Table 2. Descriptive statistics.[8]

Descriptive statistics/Industry N	Rice 87	Beef cattle and sheep 654	Dairy 170	Oilseed and grain 347	Total 1258
Innovative effort /a					
Productive management	0.99	0.98	0.99	0.97	0.98
Inputs	0.53	0.98	1.00	0.95	0.94
Technical assistance	0.93	0.83	0.96	0.93	0.88
Capital goods	0.94	0.97	0.88	0.92	0.94
Management	0.68	0.94	0.98	0.91	0.92
ICTs	0.99	0.82	0.86	0.86	0.85
Training	0.89	0.65	0.77	0.74	0.71
Experimental R&D	0.47	0.26	0.25	0.34	0.29
Any innovation activity	1.00	1.00	1.00	1.00	1.00
Policy related variables /b					
Public financial support /c	0.01	0.04	0.05	0.01	0.03
R&D cooperation /d	0.49	0.20	0.39	0.27	0.27
Scientific cooperation /e	0.80	0.56	0.67	0.64	0.61
Vertical cooperation /f	0.78	0.60	0.59	0.67	0.63
Horizontal cooperation /g	0.90	0.74	0.88	0.77	0.77
Financial cooperation /h	0.57	0.23	0.34	0.39	0.32
Public cooperation /i	0.37	0.37	0.31	0.27	0.33
General characteristics					
Productivity /j	1941.33	230.88	1429.42	871.24	655.59
Size /k	497.91	2562.63	704.73	1273.00	1812.85
Foreign property /l	0.03	0.04	0.04	0.07	0.05
Main activity /m	0.94	0.88	0.86	0.74	0.84
Professional or technical producer /n	0.82	0.79	0.72	0.72	0.76
Unskilled labor intensity /o	0.02	0.01	0.02	0.02	0.01
Skilled labor intensity */p*	0.007	0.001	0.003	0.002	0.002
Non suitable land /q	0.58	0.62	0.46	0.48	0.55
Moderately suitable land /q	0.08	0.13	0.18	0.20	0.16
Highly suitable land/q	0.34	0.25	0.35	0.32	0.29

Notes: /a Share of farms that carried out at least one of the innovation activities from that area, in 2007–2009. /b Share of farms that qualify into the corresponding category. /c. Established links with public organizations with the purpose of receiving financing. /d. Established links with other agents with the purpose of performing experiments. /e. Established links with scientific organizations (INIA, Universities and/or laboratories). /f. Established vertical links (with buyers or suppliers). /g. Established horizontal links (with individual or grouped producers). /h. Established links with financial organizations. /i. Established links with public organizations. /j Mean of sales (dollars) per hectare. /k Mean of farm's area in hectares. /l Share of farms with over 10% of foreign capital. /m Share of farms where the corresponding activity is the main source of income. /n Share of farms where the producer achieved technical or professional educational level. /o Mean of unskilled workers (less than technical educational level) per hectare. */p* Mean of skilled workers (with technical or professional level) per hectare. /q Share of non-suitable, moderately suitable or highly suitable for agricultural land (respectively) in total hectares.

Only a marginal share of farms received public financial support. However, other forms of cooperation appear to be widely carried out by the agricultural sector. In particular, horizontal linkages (with other producers) and vertical linkages (with suppliers or buyers) stand out for being the most frequent way of cooperating with other agents. Thus, the productive sector appears to be a fundamental source of support for farmerś innovation strategies. Scientific cooperation (with universities or laboratories) is widespread too. At the farming activity level, once again rice producers show the most active behavior regarding R&D efforts, being that 49% of rice farmers cooperated with other agents with the purpose of carrying out R&D and 80% of them collaborated with scientific organizations.

As for size and productivity, Table 2 shows that, while beef cattle and sheep, and oilseed and grain farming are carried out by larger farms (in hectares), rice and dairy producers attain larger sales per hectare. The higher productivity of dairy and rice farms can be related to the quality of the land, given that these farm activities have, on average, a higher share of highly suitable land for agriculture. Moreover, dairy and rice farms present the higher share of skilled workers per hectare too. Foreign property is very low in all four farm activities, and most farms have a technical or a professional producer and declare that the corresponding farming activity is their main source of income.

Econometric analysis

Innovation equation

As discussed in the methodological section, we use the *ratio of innovation activities performed* by the firm to the total number of innovation activities listed in the innovation surveys as a proxy for firm *innovation performance*. This is our dependent variable in Table 3. We are reporting the regression results for the whole sample (all 4 industries or farm activities) in column (3), for the sample of oilseed and grain farms (column 1), and for beef cattle and sheep farms (columns 2). We do not report the results in rice and dairy because of small sample size which might make the estimators for those farm activities unreliable.[5]

The first thing to notice is that *size* is highly significant in all regressions. This is according to the hypothesis that important fixed costs exist in the innovation process and consistent with most of the available evidence for other sectors such as manufacturing. As Cohen (2010) points out, this is one of the most robust findings of the empirical literature. This finding is usually interpreted as signaling the advantage that large firms have of spreading the fixed cost of innovation on a larger number of units of output.

The variable *foreign ownership* shows a positive coefficient in regressions (1) and (3) – oilseed and grain, and the whole sample. That is, firms where foreign owners participate in more than 10% of the firm´s capital tend to innovate more. To that extent, inward foreign direct investment (FDI) has long been understood as a channel for technological spillovers. Keller (2010), summarizing the findings of this literature, concludes that there is important evidence of technology spillovers of inward FDI. The existence of a positive coefficient could be either because foreign investors buy more innovative firms or because they introduce more innovations in firms (perhaps adopting foreign technologies) or even both. A recent study for manufacturing firms in Spain (Guadalupe, Kuzmina, and Thomas 2012) finds that multinational firms acquire the most productive domestic firms, which, on the acquisition, conduct more innovation and adopt foreign technologies. This evidence seems to suggest that it is more appropriate to interpret the coefficient of our foreign ownership variable as a correlation, rather than implying causality. In the case of beef cattle and sheep, foreign ownership is marginally observed (4% of the sample) and this variable is not statistically associated with more innovation.

In the case of Uruguay, qualitative evidence suggests that in the last decade foreign investors in the oilseed and grain farming had brought not only funds but also new technologies that are closer to the technological frontier than the available ones, and that they also introduced important non-technological innovations, e.g. new organizational and business models (Errea et al. 2011). The

Table 3. Innovation activities equation.

Variables	Label	(1) Oilseed & grain	(2) Beef cattle & sheep	(3) Total
Size	log_size	0.0444***	0.0475***	0.0492***
		(0.00571)	(0.00420)	(0.00312)
Foreign ownership	foreign_own	0.0562**	0.0252	0.0610***
		(0.0219)	(0.0450)	(0.0226)
Funding from public organization	pub_fin	−0.0132	0.0456*	0.0266
		(0.0472)	(0.0274)	(0.0220)
Cooperation in R&D	rd_coop	0.0355**	0.0426***	0.0346***
		(0.0179)	(0.0132)	(0.00919)
Link with a scientific org.	scien_link	0.0711***	0.0830***	0.0728***
		(0.0170)	(0.0138)	(0.00994)
Vertical link	vert_link	0.0392**	0.0381***	0.0427***
		(0.0170)	(0.0131)	(0.00918)
Horizontal link	hor_link	0.0409**	0.0777***	0.0686***
		(0.0180)	(0.0147)	(0.0108)
Link with financial organization	fin_link	0.0134	0.000986	0.00262
		(0.0149)	(0.0136)	(0.00891)
Link w/ public non-scientific org.	pub_link	0.0383**	0.0234*	0.0237***
		(0.0163)	(0.0125)	(0.00882)
Farmer w/ higher education	proftecprod	0.0636***	0.00889	0.0386***
		(0.0183)	(0.0149)	(0.0101)
Primary farm activity	main_act	0.0544***	−0.0431**	0.0116
		(0.0160)	(0.0194)	(0.0116)
Rice				0.0143
				(0.0161)
Beef cattle and sheep				−0.205***
				(0.0574)
Dairy				0.0196
				(0.0130)
Cow-calf			0.100**	0.0966*
			(0.0478)	(0.0543)
Finishing			0.220***	0.215***
			(0.0478)	(0.0545)
Sheep			−0.0482	−0.0626
			(0.0430)	(0.0449)
Cow-calf and sheep			0.0661*	0.0727*
			(0.0368)	(0.0383)
Cow-calf and finishing			−0.119***	−0.118**
			(0.0448)	(0.0506)
Finishing and sheep			−0.0256	−0.0230
			(0.0288)	(0.0294)
Constant		0.00642	−0.133**	0.00924
		(0.0336)	(0.0574)	(0.0221)
Observations		342	637	1234
R-squared		0.511	0.513	0.482

Note: Robust standard errors in parentheses. ***$p < .01$, **$p < .05$, *$p < .1$.

available evidence for the manufacturing and service sectors in Uruguay shows no systematic correlation between the variable foreign ownership and the innovative effort of firms (Aboal and Garda 2016), therefore this seems to be a particular channel that is present only in the case of some agricultural industries in Uruguay.

The coefficient of public financing (pub_fin) is marginally significant (at 10%) only for beef cattle and sheep. This dummy variable indicates if the firm had a link with a public organization with the purpose of obtaining funding for innovation activities. Therefore, this result suggests that public funding has played only a limited role on innovation in agricultural firms. However, this conclusion must be taken with caution, since we cannot be certain if firms received public funding, we only know if they have been in contact with public organizations for this purpose. In addition, the no-effect result could come, for example, from the small amount of public support that firms could have received in other sectors rather than implying the irrelevance of public financial support *per se*.

The variable cooperation in R&D has a positive significant coefficient in all the three regressions. This variable indicates whether a firm established a link with another organization in order to carry out experimental work. Collaboration is important if there are economies of scale or scope in the production of innovations, but also to cope with the risks and complexity that the innovation process entails. The evidence shows that firms that have established this link perform more innovation activities than those firms that do not. This result is in line with results found in previous works in other sectors. For example, Becker and Dietz (2004), for the German manufacturing industry, find that joint R&D enhances product innovation. Aboal and Garda (2016) show that cooperation in R&D is positively correlated with the decision to invest in innovation activities and also with the amount invested in innovation activities of manufacturing and services firms in Uruguay.

The innovation survey asks firms if they have established a link with any of a list of agents and organizations. In order to explore the importance of the different types of linkages and collaborations for innovation, we introduced a set of dummies indicating if the firm has established a link with the following organizations: a scientific organization (scien_link), a vertical link (with consumers or suppliers, vert_link), a horizontal link (with other producers or groups or associations of producers; hor_link), a link with a financial organization (fin_link), or a link with a public non-scientific organization (pub_link).

Table 3 reports a positive and significant link between all these variables and our innovation proxy variable, with the exception of the variable that shows the link with financial organizations, which is not significant in all the regressions. The magnitude of the coefficients shows that the most important link associated with the introduction of innovation activities is with scientific organizations, followed, respectively, by the horizontal links, vertical links and finally the links with non-scientific public organizations.

It is worth noting that the importance of these links varies among farm activities (for instance for oilseed and grain, and beef cattle and sheep). The horizontal links are more important for beef cattle and sheep than for oilseed and grain. The links with public organizations are more important for oilseed and grain than for beef cattle and sheep.

In order to explore the role of the education of the farmer[6] in the introduction of innovation activities, we included a dummy that indicates if the farmer is a technician or a professional. This variable is highly significant for oilseed and grain and the whole sample regressions and has a positive sign as expected, but it is not significantly different from zero in the case of beef cattle and sheep production. This different result probably has to do with the requirement of knowledge to introduce innovation activities in one sector versus the other, in other words, with the different level of complexities of technologies in both sectors.

In order to capture the role of the specialization of the firm, we include in the regressions a dummy variable that takes value one if the firm is generating the biggest share of its income with the activity for which it was surveyed. This variable seems to be positively associated to the level of innovation activities in the case of oilseed and grain, suggesting that specialization is important for innovation performance in the sector. In the case of beef cattle and sheep, the sign is negative, but note that the specialization of the firm for this industry is also captured by the dummy variables that are commented in the next paragraph. Therefore, the net effect could still be positive for some subsectors in the beef cattle and sheep industry.

Finally, we included sectorial fixed effects to account for heterogeneities across industries when running the whole sample regression. Note that in addition to the beef cattle and sheep, rice and dairy dummies (oilseed and grain is the excluded dummy, to avoid collinearity) we included six dummy variables distinguishing the beef cattle and sheep industry according to specialization: cow-calf, finishing, sheep operations, and their interactions. These last six dummies where also included in the beef cattle and sheep regression.

Productivity equation

Table 4 presents the results of the estimations of the productivity equation. Note that this equation is basically a modified production function. The productivity is measured as firm sales per hectare.

Our main variable of interest is 'innact_ratio_pred', that is the predicted innovation activities ratio from the previous stage. The coefficient of this variable is positive and significant in all four regressions. The magnitude of the coefficient is similar in the first three regressions (oilseed and grains, beef cattle and sheep, and whole sample). In regression (4) we interact the dummies rice, beef cattle and sheep, and dairy (oilseed and grain is the excluded variable) with the variable 'innact_ratio_pred', in this way we are allowing for different impacts of innovation on productivity for each sector. Since the coefficient of the variable 'beef cattle and sheep x innact_ratio_pred' is not significantly different from zero, this means that the impact of innovation on

Table 4. Productivity equation.

Variables	(1) Oilseed & grain	(2) Beef cattle & sheep	(3) Total	(4) Total
log_size	−0.045	−0.028	−0.058	−0.059
	(0.059)	(0.063)	(0.045)	(0.045)
log_nhk	1.440	3.804	3.826**	4.196**
	(1.363)	(8.135)	(1.901)	(1.925)
log_hk	−16.90*	18.86	−5.233	−4.571
	(9.660)	(20.158)	(9.078)	(9.035)
innact_ratio_pred	1.268**	1.124***	1.247***	2.067***
	(0.646)	(0.434)	(0.377)	(0.641)
rice x innact_ratio_pred				−0.0396
				(1.421)
beef cattle and sheep x innact_ratio_pred				−0.873
				(0.744)
dairy x innact_ratio_pred				−2.620*
				(1.444)
mod_suit_land	0.705*	0.658**	0.799***	0.868***
	(0.397)	(0.306)	(0.227)	(0.212)
high_suit_land	0.362	0.309	0.274	0.305*
	(0.238)	(0.262)	(0.182)	(0.184)
centre	−0.0321	0.0995	0.116	0.136
	(0.245)	(0.256)	(0.134)	(0.131)
coastline	0.0944	0.206	0.155	0.157
	(0.148)	(0.258)	(0.130)	(0.133)
southeast	−0.0499	0.128	−0.0216	−8.13e-05
	(0.351)	(0.265)	(0.139)	(0.140)
northwest	−0.232	0.00673	−0.136	−0.116
	(0.236)	(0.261)	(0.134)	(0.141)
northeast	0.402	0.0735	−0.0744	−0.0576
	(0.268)	(0.253)	(0.166)	(0.169)
beef cattle and sheep			−1.065***	−0.643
			(0.116)	(0.414)
dairy			0.114	1.454*
			(0.155)	(0.820)
rice			1.370***	1.341*
			(0.156)	(0.766)
cow-calf		−1.230*		
		(0.687)		
finishing		−0.762		
		(0.711)		
sheep		−0.820**		
		(0.397)		
cow-calf and sheep		0.377		
		(0.295)		
cow-calf and finishing		0.729		
		(0.675)		
finishing and sheep		0.324		
		(0.234)		
Constant	5.483***	5.416***	5.432***	5.004***
	(0.301)	(0.968)	(0.234)	(0.320)
Observations	261	441	845	845
R-squared	0.077	0.194	0.464	0.469

Note: Bootstrap standard errors in parentheses. ***$p < .01$, **$p < .05$, *$p < .1$.

productivity in beef cattle and sheep is similar to that of the oilseed and grain farming, and this is consistent with the results shown in regressions (1) and (2). What is interesting to see is that regression (4) adds information about the rice and dairy sectors. The interaction term for the rice sector is not significantly different from zero, therefore the innovation in this sector has on average the same impact on productivity than in oilseed and grain farming. The case is different for the dairy industry, where the coefficient of the interaction term is significant (at 10%) and negative, which means that the impact of innovations in the dairy industry's productivity is significantly below the impact that it has on the oilseed and grain industry. In fact, we are not able to reject the null hypothesis that 'innact_ratio_pred' + 'dairy x innact_ratio_pred' is equal to zero, meaning that the impact of innovation on productivity in the dairy industry is zero.

The coefficient of the variable size shows the returns to scale in the production function. This coefficient is not significantly different from zero in all regressions, implying constant returns to scale.

The variables log_nhk and log_hk measure the unskilled and skilled labor intensity (per hectare), respectively. Increasing the number of skilled labor per hectare has no effect on productivity (the coefficient of the variable log_hk is zero in all regressions), meanwhile increasing the number of unskilled labor seems to increase productivity for the whole sample, but not in the beef cattle and sheep, and oilseed and grain industries. This result is probably showing the positive effect that this variable has on the dairy industry (result not reported here).

The variables mod_suit_land and high_suit_land controls for the quality of the land. The first one is the proportion of land of medium quality of the farm and the second one the proportion of land of the high quality of the farm. As expected, they matter in terms of our measure of productivity.

All regressions control for industry and region. We also ran alternative versions of regressions (3) and (4) including dummy variables distinguishing the beef cattle and sheep farming according to specialization: cow-calf, finishing, sheep operations, and their interactions. The results are qualitatively similar. We have also run equation (3) including an interaction term of log_hk and innact_ratio_pred, the results are similar and the interaction term is not significant.

Innovation and productivity in small farms

Table 5 reports results on the innovation equation when restraining the sample to small farms. Small farms are defined as farms with less than 200 hectares for rice and oilseed and grain, 70 for dairy farming and 500 for beef cattle and sheep.

Similarly to what happens with the entire sample of farms, we find that size is positively linked with innovation performance; so that even when restraining the analysis to small farms, size is a relevant dimension for innovation decisions.

On the contrary, foreign ownership is a significant variable in the innovation activities equation only when it comes to beef cattle and sheep small farms. This result is different from those found in section 5.1 where foreign ownership was significant for the entire sample and not for beef cattle and sheep farming alone. As a result, in the beef cattle and sheep industry, foreign capital appears to be more relevant for small farms innovation decisions than it is for larger ones. As for public financial support, this variable does not influence small farms' innovative decisions. This result is similar to that from section 5.1.

However, differences arise when analyzing the impact of linkages with other agents. While the variables accounting for farms' innovation linkages (i.e. rd_coop, scien_link, vert_link, hor_link, fin_link and pub_link) were mostly significant for the entire sample, the results for small farms show that scientific and horizontal linkages are positively related to their innovation performance, while vertical linkages (with suppliers and/or buyers) and public organizations have no effect.

These results are in a way in line with those from the previous section, since the analysis for the entire sample showed that scientific and horizontal linkages were the most relevant for explaining innovation decisions. Finally, similarly to results shown earlier, the educational level of the farmer

Table 5. Innovation activities equation for small farms.

Variables	Label	(1) Beef cattle and sheep	(2) Total
Size	log_size	0.0456***	0.0582***
		(0.0129)	(0.00848)
Foreign ownership	foreign_own	0.0836*	0.0598
		(0.0459)	(0.0612)
Funding from public organization	pub_fin	0.0690	0.0470
		(0.0470)	(0.0447)
Cooperation in R&D	rd_coop	0.0653*	0.00979
		(0.0356)	(0.0247)
Link with a scientific org.	scien_link	0.101***	0.0889***
		(0.0262)	(0.0194)
Vertical link	vert_link	0.0274	0.0246
		(0.0275)	(0.0193)
Horizontal link	hor_link	0.0919***	0.0868***
		(0.0267)	(0.0195)
Link with financial organization	fin_link	−0.0194	−0.00727
		(0.0330)	(0.0215)
Link w/ public non-scientific org.	pub_link	−0.0216	0.00639
		(0.0282)	(0.0198)
Primary farm activity	main_act	−0.0578	0.0116
		(0.0400)	(0.0228)
Farmer w/ higher education	proftecprod	0.00265	0.0398**
		(0.0261)	(0.0168)
Cow-calf		0.0372	−0.0363
		(0.0654)	(0.0780)
Finishing		0.183***	0.0959
		(0.0617)	(0.0770)
Sheep		−0.0903	−0.168**
		(0.0648)	(0.0789)
Cow-calf and sheep		0.0881	0.155*
		(0.0687)	(0.0801)
Cow-calf and finishing		−0.128**	−0.0462
		(0.0621)	(0.0774)
Finishing and sheep		0.0155	0.00731
		(0.0473)	(0.0468)
Beef cattle and sheep			−0.0690
			(0.0767)
Dairy			−0.00460
			(0.0308)
Rice			−0.00339
			(0.0356)
Constant		−0.0288	−0.0175
		(0.0667)	(0.0403)
Observations		145	293
R-squared		0.556	0.477

Note: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

is irrelevant for beef cattle and sheep innovation decisions, while its effect is positive when considering the four farming activities together.

When looking at the results for the productivity equation in Table 6, conclusions about the impact of innovation performance on productivity are similar to those obtained in the previous section, being that the ratio of innovation activities performed by the farm is significant and positively linked to productivity in any of the three specifications proposed. Additionally, the magnitude of the coefficients associated to innact_ratio_pred turns out to be larger in comparison with the results for the entire sample regression. Therefore, the impact of innovation activities on productivity seems to be larger for small firms. In addition, the interaction term dairy x innact_ratio_pred in column (3) is significant and negative. This result, which implies that innovation has a smaller impact on productivity in dairy farms than for the entire sector, is similar to that found for the entire sample.

Table 6. Productivity equation for small farms.

Variables	(1) Beef cattle & sheep	(2) Total	(3) Total
log_size	−0.590**	−0.376***	−0.355***
	(0.238)	(0.130)	(0.134)
log_nhk	−0.00726	1.557	1.864
	(5.829)	(2.054)	(2.128)
log_hk	12.17	−4.452	−2.884
	(27.647)	(9.117)	(9.583)
innact_ratio_pred	2.865**	2.049***	3.339***
	(1.286)	(0.677)	(1.042)
centre	0.390	0.274	0.209
	(0.398)	(0.354)	(0.357)
coastline	0.355	0.431**	0.355*
	(0.370)	(0.210)	(0.203)
southeast	0.491*	−0.0493	−0.0602
	(0.272)	(0.253)	(0.268)
northwest	0.427	−0.211	−0.213
	(0.356)	(0.266)	(0.278)
northeast	0.588	−0.0279	−0.0128
	(0.358)	(0.318)	(0.322)
mod_suit_land	0.630	0.555	0.650
	(0.704)	(0.539)	(0.495)
high_suit_land	0.711	0.444	0.482
	(0.554)	(0.344)	(0.388)
cow-calf	−1.346***		
	(0.515)		
finishing	−0.854		
	(0.574)		
sheep	−1.457**		
	(0.579)		
cow-calf and sheep	1.065		
	(0.723)		
cow-calf and finishing	1.021		
	(0.663)		
finishing and sheep	0.284		
	(0.457)		
beef cattle and sheep		−0.519***	−0.0262
		(0.191)	(0.479)
dairy		1.081***	3.392***
		(0.379)	(1.063)
rice		1.290***	1.148
		(0.342)	(1.533)
rice x innact_ratio_pred			0.00870
			(3.463)
beef cattle and sheep x innact_ratio_pred			−1.409
			(1.389)
dairy x innact_ratio_pred			−5.857**
			(2.311)
Constant	7.362***	6.305***	5.731***
	(1.287)	(0.557)	(0.580)
Observations	107	222	222
R-squared	0.401	0.450	0.467

Note: Bootstrap standard errors in parentheses. ***$p < .01$, **$p < .05$, *$p < .1$.

When considering the effect of size, results are different from those obtained for the entire sample. In fact, once we restrain the sample to small farms, size has a negative effect on productivity, so that evidence pointing out to the existence of negative returns to scale among small farms is found. When it comes to labor intensity, as was found before, skilled labor per hectare appears to have no effect on productivity; while unskilled labor, that had a positive effect on productivity when considering the entire sample of farms, turns out to be not significant for explaining small farms' productivity. Also differently from what was found in the previous section, the evidence for small farms shows that land quality has no effect on productivity.

Additional robustness analysis

In this section, we will run two additional robustness checks. In the first place, we will proxy innovation efforts by the variable experimental R&D (it takes value 1 if performed, 0 otherwise). We estimate a Probit model for this dichotomous variable and then use the predicted probability of performing experimental R&D as an explanatory variable in the productivity equation. In second place, we will estimate a Biprobit model for product and process innovation (both are dummy variables) and then use the predicted probability of declaring one or the other innovation or both at the same time as explanatory variables in the productivity equation. The other explanatory variables for the Probit and Biprobit are the same as in column (3) of Table 3. Both exercises are run for the total sample of farms.

Note that the results for experimental R&D in Table 7 (column (1)) are qualitatively similar to those presented in column (3) of Table 3. In other words, the variables that are correlated with the decision of performing experimental R&D are similar to those that are correlated with the number of innovation activities performed by farms. In particular, size, cooperation in R&D, link with a scientific organization, vertical links and horizontal links continue to be significant in Table 7. The difference is that education of the farmer, link w/ public non-scientific organization and foreign ownership are not significant in the experimental R&D regression.

Columns (2)-(4) are not directly comparable with column (3) of Table 3 since what they show are the variables that are correlated with the successful introduction in the market of product, process or product and process innovations and not the correlation with the efforts in order to generate innovations as in Table 3. Moreover, we have the filter problem pointed out at the end of section 2.1. However, and in particular for columns (2) and (3), some of the variables that are significant in column (3) of Table 3 repeat significance and sign.

Table 7. Innovation equation.

	(1)	(2)	(3)	(4)
	Probit		Biprobit	
Variables	Experimental R&D	Product and process innovation	Process innovation only	Product innovation only
Size	0.027**	0.010***	0.013	−0.0029
	(0.011)	(0.004)	(0.011)	(0.004)
Foreign ownership	0.027	−0.059	0.089	−0.031*
	(0.064)	(0.041)	(0.059)	(0.017)
Funding from public organization	0.084	0.046	0.061**	−0.0144*
	(0.084)	(0.044)	(0.028)	(0.009)
Cooperation in R&D	0.181***	0.067	0.001	0.009
	(0.0329)	(0.051)	(0.016)	(0.009)
Link with a scientific org.	0.106***	0.037**	0.043**	0.009
	(0.031)	(0.016)	(0.021)	(0.006)
Vertical link	0.103***	0.066*	−0.003	0.022***
	(0.028)	(0.039)	(0.027)	(0.004)
Horizontal link	0.079**	0.042*	0.051**	−0.011**
	(0.032)	(0.024)	(0.023)	(0.005)
Link with financial organization	−0.0427	−0.045**	−0.009	−0.005
	(0.026)	(0.023)	(0.019)	(0.005)
Link w/ public non-scientific org.	0.034	0.028*	0.012	−0.0001
	(0.029)	(0.016)	(0.039)	(0.015)
Farmer w/ higher education	0.006	−0.001	0.007	−0.003
	(0.033)	(0.012)	(0.022)	(0.008)
Primary farm activity	−0.008	0.011	0.031	0.010
	(0.036)	(0.015)	(0.027)	(0.011)
Observations	1,234	1,234		
R-squared				

Notes: Marginal effects. Robust standard errors in parentheses. We are also controlling for Rice, Dairy, Beef cattle and sheep, Cow-calf, Finishing, Sheep, Cow-calf and sheep, Cow-calf and finishing and Finishing and sheep. ***$p < .01$, **$p < .05$, *$p < .1$.

Table 8. Productivity equation.

Variables	(1) Total	(2) Total
log_size	0.003*	0.039
	(0.037)	(0.038)
log_nhk	3.863**	4.063**
	(1.902)	(1.930)
log_hk	−4.096	−3.260
	(8.985)	(9.147)
Probability of R&D_pred	0.567***	
	(0.199)	
Probability of Product and process Innovation_pred		0.045
		(0.446)
Probability of Product innovation_pred		6.662**
		(3.180)
Probability of Process innovation_pred		1.102
		(1.248)
Observations	845	845
R-squared	0.46	0.46

Bootstrap standard errors in parentheses. We are also controlling for mod_suit_land, high_suit_land, beef cattle and sheep, dairy, rice, region and a constant. ***$p < .01$, **$p < .05$, *$p < .1$.

With respect to the productivity equation, the results reported in column (1) of Table 8 are qualitatively similar to those presented in column (3) of Table 3. In particular, the innovation efforts, proxied by the probability of performing experimental R&D, are positively correlated with the productivity.

When the predicted probability of introducing product, process or simultaneously process and product innovations are introduced in the productivity equation (column (2) of Table 8) we can see that only product innovation is positively correlated with productivity. The other variable that is significant in this regression, log_nhk, have the same sign and similar coefficient size as in column (3) of Table 3.

Therefore, the results presented in this section show additional evidence that the results discussed in previous sections are relatively robust to important model changes.

Conclusions

The literature on the links between innovation and productivity at the firm level in agriculture is almost inexistent, probably because of the unavailability of farm-level innovation surveys. In this paper, we analyzed the factors that are correlated with the innovation effort of farms and the impact that this innovation effort has on productivity, exploiting a unique farm-level agricultural innovation survey carried out in Uruguay.

We found that the variables that are consistently correlated with innovation effort are farm size, cooperation with other agents to perform R&D, links with scientific organizations and the existence of horizontal and vertical links. The existence of links with public non-scientific organizations is also correlated with innovation effort, but only at 10% confidence in the case of beef cattle and sheep. The importance of size for innovation effort is a very well-known empirical fact in the case of manufacturing firms that seems to apply to agricultural firms as well according to the evidence presented here. This implies that public policy must pay special attention to small firms, since probably these firms face restrictions associated with scale to innovate. The links with other organizations, and almost with any (except financial ones) and in any form, is relevant. Since coordination among agents is relevant, and probably there are coordination failures, there is a role for public policy. The education level of the owner of the farm is also positively correlated (except in the case of beef cattle and sheep, where it is not significant) with innovation effort. This evidence could have implications that go beyond innovation policy, and in particular, for training and educational policy. On the other hand, public and private financial support are not clearly linked with greater innovation effort. Taken at a face value, this could imply that financial constraints for innovation were not operating in the sector in the period 2007–2009. The foreign ownership of the farm is a factor that also seems to be positively correlated with the level of innovation effort for most subsectors. This evidence is probably pointing to the fact that foreign ownership in some subsectors is generating technological (and non-technological) transfers that are reflected in greater innovation effort.

When it comes to productivity, innovation effort seems to be clearly generating gains in almost all subsectors, with the exception of the dairy industry where the impact is null in our estimations.

Notes

1. The survey follows the Bogota Manual that follows the Oslo Manual. The Bogota Manual is the base of the manufacturing and services innovation surveys in Latin America.
2. The questions for expenditure on innovation activities are nested: the question only applies to those farms that declare to have *introduced* the respective innovation activity in 2007–2009. Thus, we do not have information on expenditure for farms that were carrying out the activity before 2007.
3. An alternative could have been to estimate a fractional logit model that will generate predictions in the range [0,1].
4. Detailed methodological aspects and analysis of the results of this survey are published in Spanish in Mondelli et al. (2013).
5. For the innovation stage, we have 87 observations for rice and 168 for dairy. For the productivity equation, we have only 45 observations for rice and 98 for dairy.
6. Or manager of the firm in case of partnerships or corporations where is not possible to identify the farmer.
7. The composition of hectares according to agricultural aptitude is deduced from the land composition of the area surrounding the nearest police station. The three categories of land quality defined are marginally or not suitable; moderately suitable; and highly suitable. The share of marginally or non-suitable hectares is omitted due to collinearity issues.
8. See Appendix Table A1 for variables definitions.

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ORCID

Diego Aboal http://orcid.org/0000-0002-6217-962X

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Appendix

Table A1. Definition of variables.

Variable	Definition
innact_ratio	Share of innovation activities performed in 2007–2009 from the total of activities gathered in the survey
log_prod	Logarithm of productivity, where productivity is measured as sales (US$) over surface (hectares) in 2009
log_size	Logarithm of size, where size is measured as surface (hectares)
fore_prop	Foreign property: dummy variable that equals 1 if the share of foreign capital in the total capital of the company is more than 10% in 2009.
pub_fin	Public financing: dummy that equals 1 if the company established links in 2007–2009 with public organizations with the purpose of receiving financing.
rd_coop	Cooperation in R&D: dummy that equals 1 if the company established links in 2007–2009 with other agents with the purpose of performing experiments.
scien_link	Scientific linkages: dummy that equals 1 if the company established links in 2007–2009 with scientific organizations (INIA, Universities and/or laboratories)
vert_link	Vertical linkages: dummy that equals 1 if the company established vertical links (with buyers or suppliers) in 2007–2009
hor_link	Horizontal linkages: dummy that equals 1 if the company established horizontal links (with individual or grouped producers) in 2007–2009
fin_link	Financial linkages: dummy that equals 1 if the company established links in 2007–2009 with financial organizations
pub_link	Public linkages: dummy that equals 1 if the company established links in 2007–2009 with public organizations
main_act	Main activity: dummy that equals 1 if the corresponding activity was its main source of income in 2009
proftecprod	Professional or technician producer: dummy that equals 1 if the producer achieved tertiary educational level
log_hk	Logarithm of the number of professional or technician employees per hectare in 2009
log_nhk	Logarithm of number of non professional or technician employees per hectare in 2009
rice, beef cattle and sheep, dairy, oilseed and grain	Dummies that identify the firm´s farming activity
cow-calf, finishing, sheep	Dummies that identify the main activity (calf breeding, calf fattening or sheep breeding or fattening) for farms in beef cattle and sheep industry
innact_ratio_pred	Predicted ratio of innovation activities (in stage 1)
non_suit_land	Share of marginally or non-suitable for agriculture hectares on the total surface[7]
mod_suit_land	Share of moderately suitable for agriculture hectares on the total surface
high_suit_land	Share of highly suitable for agriculture hectares on the total surface
south centre coastline southeast northeast northwest	Regional dummies: dummies identifying the region where the company is located

Table A2. Descriptive statistics for variables used in the estimation: total sample.

Variable	Obs	Mean	Std. dev.	Min	Max
innact_ratio	1258	0.503	0.190	0.000	1.000
log_prod	1103	5.485	1.262	1.522	11.312
log_size	1253	6.549	1.481	0.693	11.364
fore_prop	1246	0.045	0.207	0.000	1.000
pub_fin	1251	0.031	0.174	0.000	1.000
rd_coop	1258	0.267	0.443	0.000	1.000
scien_link	1258	0.613	0.487	0.000	1.000
vert_link	1258	0.632	0.482	0.000	1.000
hor_link	1258	0.774	0.418	0.000	1.000
fin_link	1258	0.316	0.465	0.000	1.000
pub_link	1258	0.332	0.471	0.000	1.000
main_act	1258	0.840	0.367	0.000	1.000
proftecprod	1258	0.763	0.425	0.000	1.000
rice	1258	0.069	0.254	0.000	1.000
beefcattle and sheep	1258	0.520	0.500	0.000	1.000
dairy	1258	0.135	0.342	0.000	1.000
oilseed and grain	1258	0.276	0.447	0.000	1.000
cow-calf	1258	0.444	0.497	0.000	1.000
finishing	1258	0.423	0.494	0.000	1.000
sheep	1258	0.328	0.470	0.000	1.000
log_nhk	1219	0.013	0.031	−0.004	0.519
log_hk	1253	0.002	0.006	0.000	0.065

(*Continued*)

Table A2. Continued.

Variable	Obs	Mean	Std. dev.	Min	Max
south	1249	0.108	0.311	0.000	1.000
centre	1249	0.144	0.351	0.000	1.000
coastline	1249	0.274	0.446	0.000	1.000
southeast	1249	0.118	0.322	0.000	1.000
northeast	1249	0.114	0.319	0.000	1.000
northwest	1249	0.242	0.428	0.000	1.000
non_suit_land	997	0.553	0.205	0.188	1.000
mod_suit_land	997	0.156	0.141	0.000	0.809
high_suit_land	997	0.291	0.187	0.000	0.770

Table A3. Descriptive statistics for variables used in the estimation: rice farms.

Variable	Obs	Mean	Std. Dev.	Min	Max
innact_ratio	87	0.535	0.158	0.125	0.833
log_prod	77	7.374	0.673	5.282	9.027
log_size	87	5.805	0.919	3.807	8.243
fore_prop	87	0.034	0.184	0.000	1.000
pub_fin	87	0.011	0.107	0.000	1.000
rd_coop	87	0.494	0.503	0.000	1.000
scien_link	87	0.805	0.399	0.000	1.000
vert_link	87	0.782	0.416	0.000	1.000
hor_link	87	0.897	0.306	0.000	1.000
fin_link	87	0.575	0.497	0.000	1.000
pub_link	87	0.368	0.485	0.000	1.000
main_act	87	0.943	0.234	0.000	1.000
proftecprod	87	0.816	0.390	0.000	1.000
log_nhk	87	0.021	0.020	0.000	0.164
log_hk	87	0.008	0.008	0.000	0.036
south	87	0.000	0.000	0.000	0.000
centre	87	0.000	0.000	0.000	0.000
coastline	87	0.000	0.000	0.000	0.000
southeast	87	0.310	0.465	0.000	1.000
northeast	87	0.425	0.497	0.000	1.000
northwest	87	0.264	0.444	0.000	1.000
non_suit_land	51	0.576	0.195	0.225	1.000
mod_suit_land	51	0.082	0.110	0.000	0.490
high_suit_land	51	0.342	0.227	0.000	0.775

Table A4. Descriptive statistics for variables used in the estimation: beef cattle and sheep farms.

Variable	Obs	Mean	Std. Dev.	Min	Max
innact_ratio	654	0.498	0.200	0.000	1.000
log_prod	596	4.757	0.884	1.561	10.457
log_size	651	7.052	1.394	1.792	11.364
fore_prop	646	0.036	0.185	0.000	1.000
pub_fin	648	0.037	0.189	0.000	1.000
rd_coop	654	0.202	0.402	0.000	1.000
scien_link	654	0.558	0.497	0.000	1.000
vert_link	654	0.601	0.490	0.000	1.000
hor_link	654	0.735	0.441	0.000	1.000
fin_link	654	0.232	0.423	0.000	1.000
pub_link	654	0.370	0.483	0.000	1.000
main_act	654	0.876	0.330	0.000	1.000
proftecprod	654	0.792	0.406	0.000	1.000
cow-calf	654	0.853	0.354	0.000	1.000
finishing	654	0.813	0.390	0.000	1.000
sheep	654	0.631	0.483	0.000	1.000
log_nhk	631	0.008	0.025	0.000	0.519
log_hk	651	0.001	0.004	0.000	0.053
south	652	0.034	0.181	0.000	1.000
centre	652	0.153	0.361	0.000	1.000
coastline	652	0.135	0.342	0.000	1.000
southeast	652	0.176	0.381	0.000	1.000
northeast	652	0.155	0.362	0.000	1.000
northwest	652	0.347	0.476	0.000	1.000

(*Continued*)

Table A4. Continued.

Variable	Obs	Mean	Std. Dev.	Min	Max
non_suit_land	495	0.622	0.204	0.188	1.000
mod_suit_land	495	0.129	0.128	0.000	0.809
high_suit_land	495	0.249	0.191	0.000	0.777

Table A5. Descriptive statistics for variables used in the estimation. Dairy farms.

Variable	Obs	Mean	Std. Dev.	Min	Max
innact_ratio	170	0.518	0.176	0.056	0.944
log_prod	110	6.265	1.368	1.522	10.309
log_size	169	5.882	1.244	1.386	8.987
fore_prop	169	0.036	0.186	0.000	1.000
pub_fin	170	0.053	0.225	0.000	1.000
rd_coop	170	0.394	0.490	0.000	1.000
scien_link	170	0.671	0.471	0.000	1.000
vert_link	170	0.588	0.494	0.000	1.000
hor_link	170	0.876	0.330	0.000	1.000
fin_link	170	0.341	0.476	0.000	1.000
pub_link	170	0.306	0.462	0.000	1.000
main_act	170	0.859	0.349	0.000	1.000
proftecprod	170	0.724	0.449	0.000	1.000
log_nhk	158	0.018	0.015	0.000	0.105
log_hk	169	0.003	0.007	0.000	0.061
south	164	0.366	0.483	0.000	1.000
centre	164	0.268	0.444	0.000	1.000
coastline	164	0.341	0.476	0.000	1.000
southeast	164	0.000	0.000	0.000	0.000
northeast	164	0.000	0.000	0.000	0.000
northwest	164	0.024	0.155	0.000	1.000
non_suit_land	161	0.462	0.164	0.201	0.949
mod_suit_land	161	0.183	0.135	0.000	0.486
high_suit_land	161	0.355	0.146	0.009	0.707

Table A6. Descriptive statistics for variables used in the estimation. Oilseed and grain farms.

Variable	Obs	Mean	Std. Dev.	Min	Max
innact_ratio	347	0.497	0.183	0.033	0.900
log_prod	320	6.118	0.917	2.628	11.312
log_size	346	6.115	1.520	0.693	10.240
fore_prop	344	0.070	0.255	0.000	1.000
pub_fin	346	0.014	0.120	0.000	1.000
rd_coop	347	0.271	0.445	0.000	1.000
scien_link	347	0.640	0.481	0.000	1.000
vert_link	347	0.674	0.469	0.000	1.000
hor_link	347	0.767	0.424	0.000	1.000
fin_link	347	0.395	0.490	0.000	1.000
pub_link	347	0.265	0.442	0.000	1.000
main_act	347	0.738	0.440	0.000	1.000
proftecprod	347	0.715	0.452	0.000	1.000
log_nhk	343	0.020	0.045	−0.004	0.452
log_hk	346	0.002	0.006	0.000	0.065
south	346	0.153	0.361	0.000	1.000
centre	346	0.104	0.306	0.000	1.000
coastline	346	0.572	0.495	0.000	1.000
southeast	346	0.014	0.120	0.000	1.000
northeast	346	0.014	0.120	0.000	1.000
northwest	346	0.142	0.349	0.000	1.000
non_suit_land	290	0.481	0.183	0.188	0.949
mod_suit_land	290	0.200	0.155	0.000	0.679
high_suit_land	290	0.320	0.175	0.000	0.690