J. Agr. Sci. Tech. (2020) Vol. 22(3): 597-610

Impact of Technological Innovation on Performance in Dairy Sheep Farms in Spain

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ABSTRACT

The objective of this study was to evaluate the causal relationship between technological innovation and sheep farm's results, based on a Structural Equation Modeling Approach (SEM) in dairy sheep systems in the center of Spain. Different from traditional multiple-trait models, SEM analysis allows assessment of potential causal interrelationships among outcomes and can effectively discriminate effects. Information from 157 dairy sheep farms in Castilla La Mancha was used. The questionnaires included 38 technological innovations and 188 questions on productive, economic and social data. Four hypotheses were formulated oriented to understand how the farm's technological innovation will affect the productive structure and farm's performance. The results derived from the SEM analysis showed a positive relationship between the technological indicator and the farm's structure, productivity, and economic results. The variable technological adoption could be regarded as a predictable measure of structure, productivity, and economic performance. Technology is associated with the productive structure. Independent of sheep farms' size, dairy sheep farms can be positioned in the growing returns area as a consequence of a proper use of it. SEM approach to observational data in the context of dairy sheep system suggests that there is not a single optimal structure. The model built constitutes a tool of great utility to make decisions, as it allows predicting the impact of technologies on final results *ex-ante*.

Keywords: Adoption of technology, Causal relationship, Dairy sheep system, Structural equation modeling.

INTRODUCTION

Mixed livestock is the most widespread system in the developing world and small-scale farms represent 19 and 12% of the world's production of meat and milk, respectively (FAO, 2014). The small-scale farms are key tools in terms of security, supply, access, and stability of food. However, small-scale and family farms are characterized by low levels of technology adoption and low competitiveness. Moreover, an extreme vulnerability of smallholder farmers to environmental risks and market change has been observed (Van't Hooft *et al.*, 2012).

The lack of technological innovation, in small farms, is due to multiple factors, such as low dimension, poor financial capability, lack of support to technological adoption, poor structures, risk aversion, misalignment between technological improvements and farm's objectives, amongst others (Dubeuf, 2014; Ryschawy *et al.*, 2012; Noltze *et al.*, 2012). Technological innovation is a key element in farm's competitiveness. Innovation is a strategic variable and previous

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[DOR: 20.1001.1.16807073.2020.22.3.11.1]

research has shown the relationship amongst technological innovation with competitiveness, productivity, quality, and sustainability (De-Pablos-Heredero *et al.*, 2018; Rangel *et al.*, 2017).

Le Gal *et al*. (2012) and García *et al*. (2016) defined innovation from an integrated view oriented to improve productivity and agroecosystems' resilience within a synergistic relationship among activities. Innovation is a process by which new ideas are transformed into practices. Mukute *et al*. (2015) indicate that agricultural innovation presents a dynamic view and is seen as a complex and collaborative adoption system. Tohidyan *et al*. (2017) established the relationship between technological innovation and smart farms. Yi *et al*. (2006) described a relationship between personal innovativeness and perceived ease of use, result demonstrability, perceived behavioral control, and subjective norm. Cortéz-Arriola *et al*. (2015) and Cuevas-Reyes *et al*. (2013), mention that the dimension or size is the main factor to determine the technology adoption level.

Technology exerts a strong impact on results. To count on tools that evaluate *a priori* the impact of technology on the results would be very useful to promote the technological adoption of smallholders. There are questions that need to be answered: Which would be the role of technology in small-scale farms? How can these farms achieve successful technology adoption? Furthermore, how technology is related to structure-size, productivity, and economic results is a perennial issue for researchers and presents important implications for public policy.

Understanding previous aspects is required to enable the access to technology to small-scale producers and favor the improvement of their competitiveness. Equally, an inverse relationship between farm's size and land productivity (Rada *et al.*, 2018; Foster and Rosenzweig, 2017) are also relevant.

Complex simulation models have been used for the past 45 years to describe dynamic agricultural systems that include applications of various types of linear or non-linear programming models. Le Dang *et al*. (2014) and Tohidyan Far and Rezaei-Moghaddam (2015) link economic simulation models to bio-physical models to evaluate impacts of technology, policy, and environmental changes on sustainability.

Structural econometric models are often applied to the analysis of economic issues that impact agriculture because of their rigour in modelling the behavioural nature of the relationships amongst the major variables (De-Pablos-Heredero *et al.*, 2018). The Structural Equation Model (SEM) combines simultaneously the factorial analysis and linear regression for the verification of the hypotheses. With this approach, the latent variables (constructs) represent the concepts and the indicators are the input data. SEM searches for causal relationships between latent variables and assumes complex relationships (with direct and indirect effects). In fact, the use of the econometric model provides an evaluation dimension beyond the production system. According to Vere and Griffith (2004), technology evaluation is an important requirement of economic analysis and SEM is considered to be capable of making a valuable contribution to this process. SEM models have just been sparsely implemented in the context of food consumption, diversification of production, climate change, veterinary epidemiology, animal genetics and genomic genetics (Senger *et al.*, 2017; Cha *et al.*, 2017; Tohidyan *et al*., 2017; Le Dang *et al.*, 2014; Vere and Griffith, 2004). From the literature review, there is a lack of quantitative models centered on forecasting the impact of technological adoption in small scale systems.

Castilla La Mancha is a region in the Centre of Spain with a tradition of a typical mixed crop-dairy sheep system under continental Mediterranean conditions, with a census that reaches 839,000 adult females spread over 2.798 farms. Most of them are Manchega breed (600,000 ewes). This autochthonous breed has been selected for its rusticity, adaptability to the environment, and higher

[DOR: 20.1001.1.16807073.2020.22.3.11.1]

milk yield compared to other autochthonous breeds. Their milk production is entirely allocated to cheese making into the Protected Designation of Origin (PDO) "Queso Manchego". Manchego Cheese PDO links a product of quality to a territory and a traditional and sustainable production system. It is also a guarantee of food safety and food processing. However, more than 30% of producers have run out of business because of lack of viability of the farms (De-Pablos-Heredero *et al*., 2018). In Spain, dairy sheep farms have experienced a structural crisis and a deep transformation based on the reduction in the number of farms and the increase of the flock size with progressive productive intensification (Dubeuf, 2014; Ripoll-Bosh *et al.*, 2013; Milán *et al.*, 2011). If this direct causal relationship amongst technological innovations and farm's performance can be confirmed in the case of dairy sheep, actions should be taken to decrease the deficiencies in the technological aspects that would lead to a substantial improvement in the results (Morantes *et al.*, 2017).

Understanding the relationship amongst technologies with structure and productive and economic results would mean an important advance to understanding the main reasons for the lack of technological adoption in small farms. The building of explanatory and predictive models would become important tools to predict "*ex-ante*" and show in a reliable way, the impact of technology on final results, enabling the adoption of more successful technologies.

Therefore, the objective of this research consisted of evaluating the causal relationship between technological innovation with sheep farm's structure and results.

MATERIALS AND METHODS

A random sample of 157 Manchega sheep dairy farms was selected, 17.2% of the whole population of 907 from "La Mancha" region into the Protected Designation of Origin (PDO) "Queso Manchego". The information was collected by using *in situ* visits to the farms from 2012 to 2014. The questionnaires included 38 selected technological innovations (Table 1) and 188 questions related to productive structure, land use, productivity and economic and social data according to Rivas *et al*. (2015).

Values obtained for each indicator are shown in Table 2. The mean flock size was 867.75 sheep in 1117.69 ha of total farm surface; 83% for grazing and the rest corresponded to cultivated surface. 58% of farms applied unified and the consumption of concentrate that was around 0.8 kg/ewe/d (61.23% external feeds). In 82% of farms, three seasons mating takes place and the rest maintained the ram with the ewes permanently throughout the year (341.4 days of lambing interval). The mean production was 133.92 kg ewe^{-1} per lactation, 1.4 lambs per parity, 3.4 annual work units (57.09% familiar). The total incomes per sheep was 266.16 € ewe^{-1}, while the mean unit cost was 2.18 € kg^{-1} of milk and the break event point was calculated in 96.592 kg of milk. Toro-Mújica *et al*. (2012) and Rivas *et al*. (2015) widely describe Manchego dairy mixed system in Castilla La Mancha.

Statistical Analyses

-Constructs: Technology, Structure, Productivity and Economic Performance

There are several ways to study the process of technological adoption; according to Senger *et al*. (2017) and Le Dang *et al* (2014) with the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), in dairy farms. Apart from this, De-Pablos-Heredero *et al*. (2018) propose identifying technologies that have been implemented in small-scale farms and evaluate their impact on performance. In Table 1, the identification of technologies and the grouping of technologies in areas according to García *et al*. (2016) are presented. Initially, the percentages of the farmers that accomplished the indicator were calculated regarding each latent variable. All

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Table 1. Livestock innovations and technological innovation areas (Rivas *et al.*, 2015)

Livestock innovations	Technological innovation areas
1) Animal identification 2) Records 3) Milk recording 4) Planning and organization functions 5) Usage of records in decision making 6) Reproductive planning 7) Breeding program	T_1: Management
8) Feeding lots 9) Unifeed 10) Supplements (Multi nutritional blocks) 11) Concentrated feeding 12) Agro-industrial by-products	T_2: Feeding (External inputs)
13) Vaccine contagious agalactia 14) Vaccine staphylococci 15) Vaccine enterotoxaemia sheep 16) Antibiotic dry therapy 17) Brucellosis control 18) Parasite control 19) Post dipping 20) Hygiene practices good	T_3: Animal health and Biosecurity
21) Paddock-fencing off grazing 22) Green fodder 23) Hay–silage making 24) Grazing management 25) Grazing planting/Crop residues	T_4: Land use
26) Milking machine and dairy 27) Milk cooling tank 28) Automatic teat cup (cluster) remover 29) Automatic washing machine 30) Feeding belt 31) Artificially reared lambs pens	T_5: Milking equipment and dairy
32) Male effects 33) Flushing 34) Estrus synchronization (PMSG) 35) Pregnancy diagnosis 36) Artificial insemination 37) Merit genetic for selection 38) Merit genetic for discarding	T_6: Reproduction-genetic

the attributes used for the indexes implementation are shown in Figure 1.

Four latent variables or constructs were defined: Technology, structure, productivity, and economic returns. Rivas *et al*. (2019) show the discriminant power of the set of variables used (technology, structure, productivity and economic returns).

Technology was represented by the variables including: Management (T_1), animal feeding (T_2), animal health and biosecurity (T_3), land use (T_4), milking equipment and dairy (T_5), reproduction and genetic (T_6). Each technology indicator comprises a group of innovations, technologies and organizational practices, as shown in Table 2. It was based on the proportion of innovations implemented in each farm over all innovations identified, with values from 0 to 100%. Moreover, the indicators built by Espinosa-García *et al*. (2015), Rangel *et al.* (2017), and Mekonnen *et al*. (2010) were taken into account.

[DOR: 20.1001.1.16807073.2020.22.3.11.1]

Table 2. Descriptive statistics of technological, structural, productive, and economic variables.

Indicators	Mean	SD
Technology		
T_1: Management (%)	46.75	21.22
T_2: Feeding (%)	56.87	19.71
T_3: Health and biosecurity (%)	71.55	11.21
T_4: Land use, %	34.14	23.67
T_5; Milking equipment (%)	51.71	17.92
T_6: Reproduction and genetic (%)	38.57	29.55
Structure productive		
S_1: Surface (ha)	1,117.69	1,359.88
S_2: Ewes (no)	867.75	798.79
S_3: Own surface (%)	15.06	31.95
S_4: Family labour (%)	57.09	40.96
S_5: External feeds (%)	61.23	31.55
S_6: Stocking rate (Ewes ha^{-1})	1.04	0.97
Productivity		
P_1; Lamb yield (Lambs AWU^{-1a})	345.82	170.37
P_2: Sanitary cost (€ ewe^{-1})	15.48	3.16
P_3: Milk yield (kg ewe^{-1})	133.92	66.27
P_4: Lambing interval (d)	341.4	70.6
P_5: Lambs sold (%)	77.50	9.59
P_6: Feed cost (€ ewe^{-1})	78.60	40.17
Economic performance		
E_1: Profitability (%)	14.39	13.62
E_2: Cash-flow (€)	121,173	217,454
E_3: Net margin per work (€ AWU^{-1})	15,450	22,448
E_4: Total incomes per ewe (€ewe^{-1})	266.16	82.29
E_5: Subsidies per ewe (€ ewe^{-1})	34.16	8.29
E_6; Unit cost[b] (€ kg^{-1})	2.183	0.954
E_7: Breakeven point (kg)	96,592	129,291

[a] AWU: Annual Work Units, [b] Unit cost: Total costs of milk and meat production included.

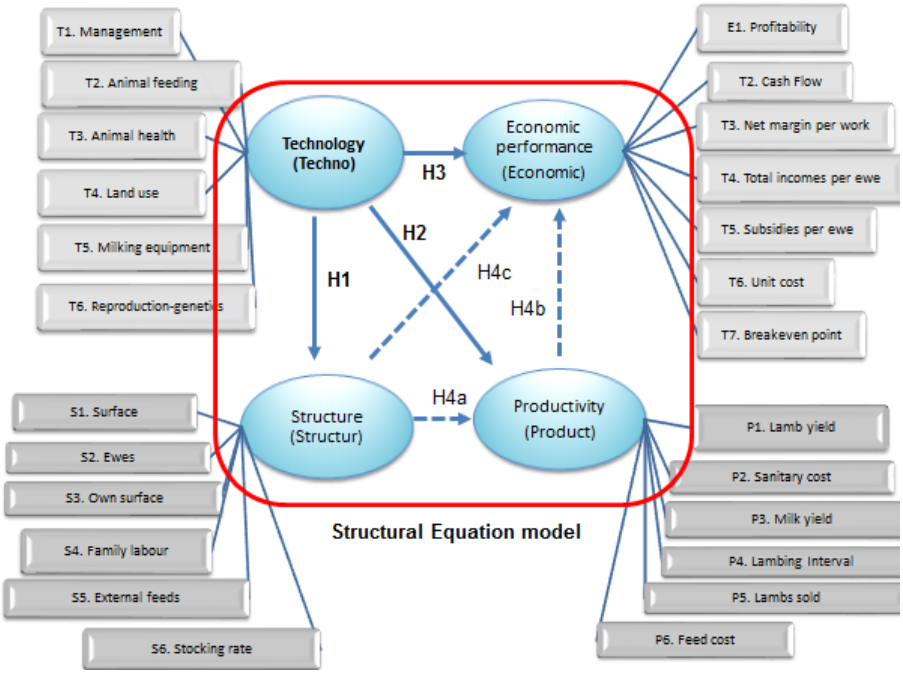

Figure 1. Theoretical framework and hypothesis from H1 to H4.

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Previous research by Caballero (2009), Toro Mújica *et al*. (2012) and Rivas *et al*. (2015) analyzed widely the diversity and viability of Manchego dairy sheep system through multivariate analysis that enabled the selection of the rest of indicators. Structure was composed by the following indicator variables: Surface (S_1), ewes (S_2), own surface (S_3), family labour (S_4), external feeds (S_5) and stocking rate (S_6). The indicator variables used for building the productivity included: Lamb yield (P_1), sanitary cost (P_2), milk yield (P_3), lambing interval (P_4), lambs sold (P_5) and feed cost (P_6). Economic returns includes the indicator variables: Profitability (E_1), cash-flow (E_2), net margin per work (E_3), total incomes per ewe (E_4), subsidies per ewe (E_5), unit cost (E_6), breakeven point (E_7). Moreover, the indicators used by Milán *et al*. (2011), Morantes *et al*. (2017), Rangel *et al*. (2017), Angón *et al*. (2015), Ripoll-Bosh *et al*. (2013) were also considered.

Several types of models have been used in the past to describe different components of mixed livestock systems. Structural Equation Modelling (SEM) was used to evaluate the impact of technologies on the farm's performance; an empirical analysis with four hypotheses has been formulated as displayed in Figure 1.

Hypothesis 1 (H1): The farm's technological innovation (Techno) will positively affect the productive structure and the farm size (Structure).

Hypothesis 2 (H2): The farm's technological innovation (Techno) will positively affect the productiveness (Product) as performance indicator.

Hypothesis 3 (H3): The farm's technological innovation (Techno) will positively affect the economic results (Economic) as performance indicator.

Hypothesis 4: Size or productive structure provides a positive effect on productivity (H4a). Besides, productivity presents a positive effect on economic results (H4b) and the productive structure presents a positive effect on economic results (H4c).

The set of technologies has been related to productive and farm's structure size (Structure), productivity (Productivity) and economic results (Economic). Besides, in hypothesis 4, the productive structure or size (Structure), is related to productivity (Product) and economic results (Economic). The relationship of technology with performance can be explained through growth theory, the law of Decreasing Returns (DR), the law of variable proportions and the effect of economies of scale (Sheng *et al*., 2018; Gautam *et al*., 2018; Nuthall, 2011).

The estimation of the structural model evaluated the relationships amongst the different constructs, through path coefficients, significance level, and cross-validated redundancy (Cha *et al*., 2017). The focus has been on graphs without feedback loops between nodes, such as the one presented in Figure 1. To test the posited hypotheses, we propose a non-linear model (Figure 2) with statistical estimates derived from PLS regression analysis using Warp PLS 6.0 (Kock, 2018). PLS regression aims to produce a model that transforms a set of correlated explanatory variables into a new set of uncorrelated variables. This procedure uses two-stage estimation algorithms to obtain weights, loadings, and path estimates. The constructs of the model are unobservable (latent) variables indirectly described by a set of observable variables. The use of multiple questions for each construct increases the precision of the estimate.

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The algorithm tries to identify nonlinear functions between pairs of latent variables in structural equations models and calculate their association coefficients, accordingly, finding a set of functions:

F1(LVp1), F2(LVp2) relating blocks of Latent Variable predictors (LVp1, LVp2 ...) to a criterion Latent Variable (LVc), as in LVc= p1×F1(LVp+p2×F2(LVp2)+ … +e

Where, *p1, p*2 ... are path coefficients and *e* is the equation error term.

Path (beta) coefficients were normalized, taking values between -1 and 1, measuring the strength and direction of the relationship. Table 3 summarizes model fit, quality ratios, and their interpretation. All quality ratios met the recommended thresholds. The more curvilinear the functions F1(LVp1), F2(LVp2) the higher will be the difference between the path coefficients p1, p2 ... and those that would have been obtained via a linear analysis. The procedure was done for a wide range of functions, with modification constants included, and 5,000 resamples were performed (Hair *et al.*, 2011). The model was estimated by means of Warp PLS 6.0 software.

RESULTS

The causal effects among research variables were measured by Structural Equation Modeling (SEM) and they are presented in Figure 2. A summary of the main model parameters values is presented in Table 4, and their corresponding P-values. This table shows the influence of the four indicator sets.

Estimation results showed that H1, H2 and H3 were accepted (Tables 3 and 4; Figure 2). H1 showed a strong influence of technology on farms structure, with a direct effect of 0.673 (P< 0.01), and R^2= 0.45. Moreover, the farm's technological factor (Technol) will positively influence the productive performance (Product) (P< 0.01), and economic performance (Economic) (P< 0.01). H4 was partially accepted. Surprisingly, results relative to H4a were

Table 3. Model fit and quality indices overview.

Index	Value	Value Interpretation
Average Path Coefficient (APC)	APC= 0.273, P<0.001	Significant if P< 0.05
Average R-Squared (ARS)	ARS= 0.268, P<0.001	Significant if P< 0.05
Average Adjusted R-Squared (AARS)	AARS= 0.258, P<0.001	Significant if P<0.05
Average block VIF (AVIF)	AVIF= 1.565	Acceptable if <= 5, Ideally <= 3.3
Average Full collinearity VIF (AFVIF)	AFVIF= 1.517	Acceptable if <= 5, Ideally <= 3.3
Tenenhaus GoF (GoF)	GoF= 0.323	Small >= 0.1, Medium >= 0.25, Large >= 0.36
Sympson's Paradox Ratio (SPR)	SPR= 0.833	Acceptable if >= 0.7, Ideally = 1
R-Squared Contribution Ratio (RSCR)	RSCR= 0.985	Acceptable if >= 0.9, Ideally = 1
Statistical Suppression Ratio (SSR)	SSR= 1.000	Acceptable if >= 0.7
NonLinear Bivariate Causality Direction Ratio (NLBCDR)	NLBCDR= 0.917	Acceptable if >= 0.7

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Table 4. Direct effects and p values in brackets.

	Technology	Structure	Productivity
Structure	0.673 (< 0.001)		
Productivity	0.225 (< 0.002)	-0.063 (0.212)	
Economic	0.222 (< 0.002)	0.357 (< 0.001)	0.100 (0.102)

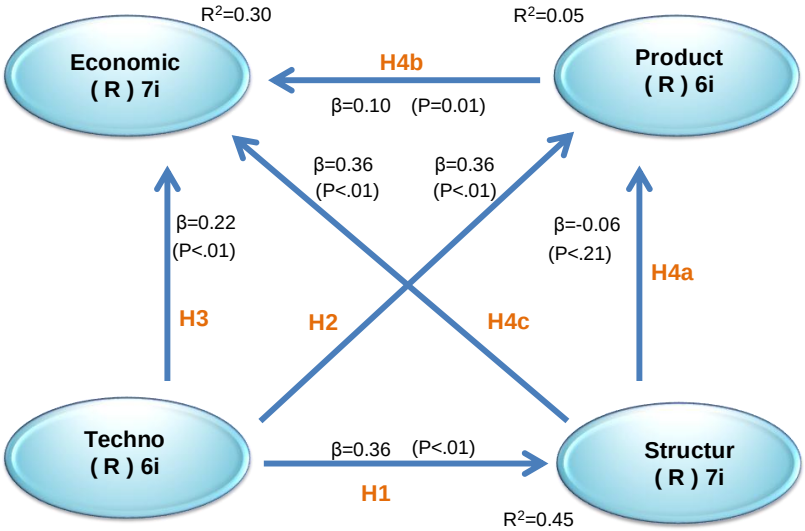

Figure 2. Research model scheme and main results. R^2= 0.30: Including the effect on the variability of economics returns from technology, structure, and productivity; R^2= 0.05: Including the effect on the variability of productivity from technology and structure; R^2= 0.45: Including the effect of structure from technology. H1 to H4: Hypothesis.

rejected, no significant relationship was found between the productive structure and productivity (P= 0.212), and on top of that, the parameter sign was opposite to the expected (−0.063). In H4b, there was a weak relationship between productivity and economic results (path of 0,100 and P= 0.102). H4c showed that the farm's structure exerted strong positive influence on the economic results, with a path of 0.357 (P<0.01).

Figure 3 shows the relationships between technology and the remaining indicators. The technology in Figures 3-a, -b, and -c behaves as a production curve. Farms with very low technological level (from -2 to -0.5), have tended to show a constant or increasing returns on the variables structure (H1), productivity (H2) and the economic results (H3), with a very strong positive association between the technologies and the remaining indicators (H4a, H4b and H4c). Farms with low technological level (from -0.5 to 0.5, approximately) showed fits through the Cobb-Douglas function with decreasing returns with respect to the technology factor. Finally, in the right part of the curve, the area of *medium technological level* (from 0.5 to 2.08) farms were distributed with increasing returns with respect to structure, productivity, and economic results.

Figures 3-d, -e, and -f show the relationships between technical and economic indicators collected in hypotheses 4a, 4b, and 4c, respectively. A strong relationship between structure and economic performance was found with a sigmoid shape curve similar to that described by technology.

DISCUSSION

The answer provided by technology corresponds to a production function and it is derived from the assumptions of

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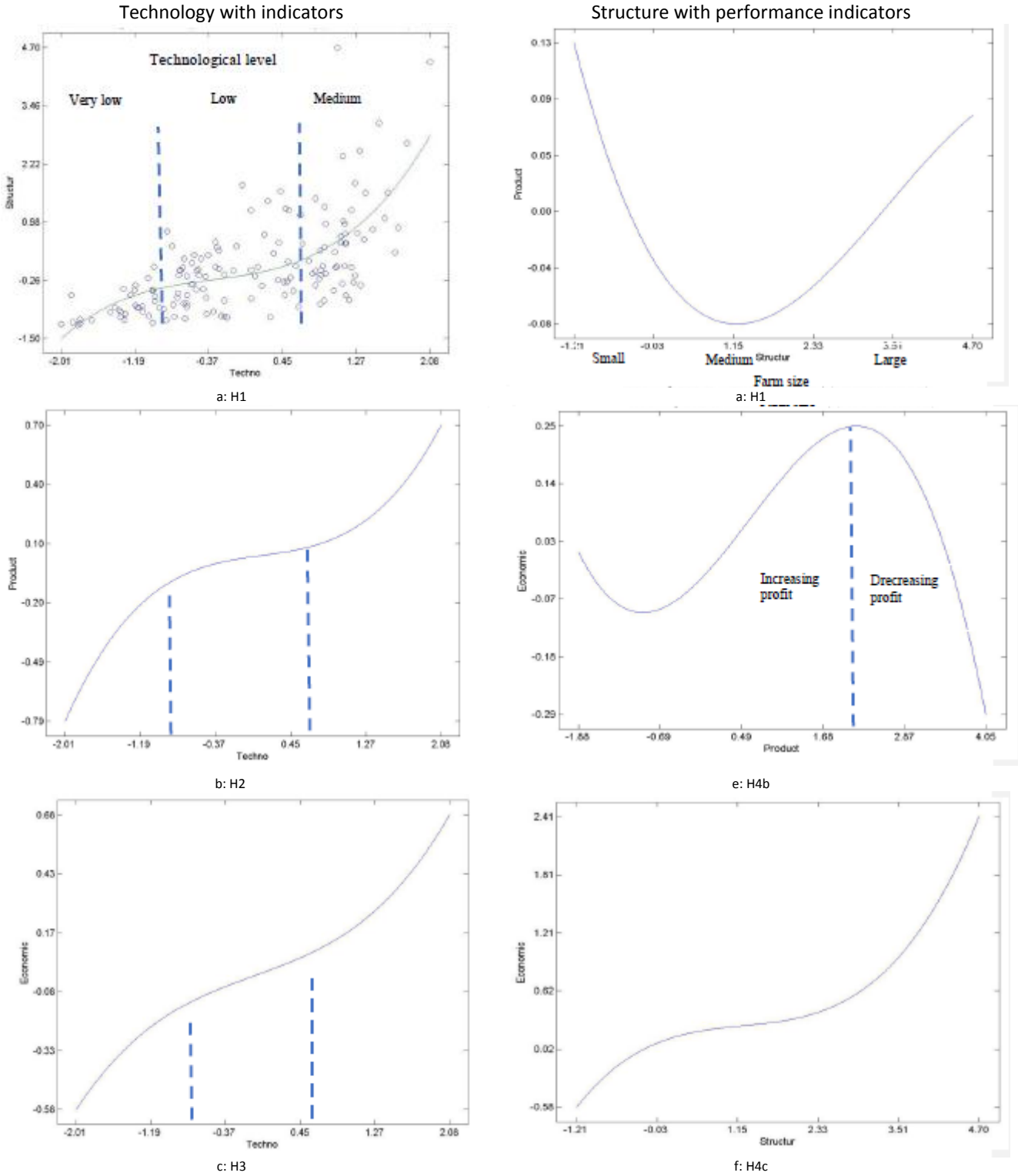

Figure 3. Best fitting curves (meaning utility) relationship between: Figure 3-a, (H1) Technology with Structure; Figure 3-b, (H2) Technology with Productivity; Figure 3-c, (H3) Technology with Economic returns; Figure 3-d, (H4) Structure with Productivity; Figures 3-e, (H4b) Productivity with Economic returns; Figure 3-f, (H4c) Structure with economic returns.

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separability, perfect knowledge, and homogeneity in factors and products (Nuthall, 2011). Morris *et al*. (2017) and Baráth *et al*. (2015) suggested that technological heterogeneity plays an important role in efficiency in Wales and Hungarian diversified farms. Besides, each technological level groups a combination of technological variables with interaction amongst them (synergies and trade-offs), generating different utility curves according to the variable proportions law. For each technology adoption level (very low, low, and medium) there is an optimal technical and an optimal economic position that moves according to the shape of function and the relation of prices (Morantes *et al.*, 2017; Rivas *et al.*, 2015.

In this research, very low level of technology adoption at farms showed constant or increasing returns concerning the three response indicators and decreasing mean variable costs (Figures 3-a, -b, -c). These farms showed an inverse relationship between technology and productivity according to Foster *et al*. (2017) and Rada *et al*. (2018) for size-productivity variables. According to Caballero (2009), this relationship is explained by the need of subsistence for smallholders and it allows them to obtain increasing returns and operate in the market in a competitive way. They develop a low-cost strategy characterized by the low or null opportunity cost of family labor, poor dimension, existence of local barriers with access to some local endogenous resources, high levels of producers' know-how to combine resources and an efficient use of marginal raw materials. High diversification of activities in less-favored areas and the diversity of activities and resources in a very unpleasant environment makes them evolve towards a multifunctional family model of subsistence described in the EU (Morris *et al.*, 2017; Senger *et al.*, 2017). Certain small farms face relative productivity advantages, but with economic and market growth, that smallholder's advantage will likely attenuate (Rada *et al.*, 2018; Sheng *et al.*, 2018).

Farms presenting upper levels of technology adoption (medium) generally showed the upper size to technology in decreasing returns. They are named as technified specialized farms; similar groups to the ones described in the typology built by Rivas *et al*. (2015) in dairy sheep. Technology allows increasing productivity (decreasing mean variable costs). Apart from this, the high volume of production favors the use of scale effects to reduce operational costs (decreasing mean fixed costs). These firms displace the cost curve close to minimum costs and become more efficient (Rada *et al.*, 2018; Sheng *et al.*, 2018; Gautam *et al.*, 2018).

The intermediate group that responds to decreasing returns is named as farms in technological transition. There are firms that have achieved an important advancement in technification although they maintain attributes as family labor force and traditional management system that avoids making the best of advantages and limits the opportunity to make the best of advantages. They are located in the area of decreasing returns (Morantes *et al.*, 2017).

The model between structure and productivity (Figure 3-d; H4a) generated a U-shaped structure-productivity pattern, with the highest level being achieved by the smallest and large sheep farms. Farms in the middle of the curve showed the lowest productivity level (Rada *et al.*, 2017). According to Foster and Rosenzweig (2017) "farms in the middle are too large to rely solely on family labor, but are large enough to efficiently adopt labor-saving machinery".

Surprisingly, the relationship between productivity and economic results showed the shape of an inversed parable (Figure 3-e; H4b). In farms with mean productivity, economic performance is increasing (productivity from 0 to 2 approximately) and when levels of productivity increase, decreasing economic returns are generated. Angón *et al*. (2015) established for the Argentinian dairy cattle efficient production levels characterized by a sustainable increase of productivity; these farms used

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roughage and concentrated feeding. According to Nuthall (2011), Toro-Mújica *et al*. (2012), and Rangel *et al*. (2017), production is driven to the "extensive margin", mean decreasing variable costs (Marginal cost< Mean variable cost). In case productivity keeps on increasing over the system, right part of Figure 3e, the production is located at a non-sustainable productive intensification area of "intensive margin" oriented to mean increasing variable cost (Marginal cost> Mean variable cost). Regardless of productivity in a scenario with low international prices and high production costs, technology adoption is delayed. Also, the marginal cost can surpass the marginal returns and move us far away from the economic optimal (Sheng *et al.*, 2018). Rangel *et al*. (2017) explain that locating production in an area of increasing returns does not imply generating scale economies in double-purpose cattle. Moreover, Toro-Mújica *et al*. (2012) indicated how technical efficiency does not imply economic efficiency for the ecological dairy sheep.

Therefore, the structure positively affects economic results, but size is not enough to explain the efficient use of resources and locate it in optimal situations (Rada *et al.*, 2018; Sheng *et al.*, 2018; Nuthall, 2011). From this perspective, Baráth *et al*. (2015) suggested that there is no room to improve productivity by increasing farm size unless farms switch technologies. Farms on technological transition are the ones that require more technical support and a plan of actions to move to an area of growing returns with higher levels of specialization and promoting competitiveness (Toro-Mújica *et al.*, 2012; Morantes *et al.*, 2017).

CONCLUSIONS

A Structural Equation Model (SEM) has been built to evaluate the impact of technology on farm's structure and performance for the case of Manchego dairy sheep farms in Castilla La Mancha, Spain. Furthermore, a deep understanding of the relationship between technology and performance has been obtained. The model is replicable to other systems with smallholders; e.g. small ruminant systems in Mediterranean areas and dual-purpose cattle in tropical areas from Latin America, Africa, and Asia.

A strong positive influence amongst technologies and indicators of structure, productivity, and economic results was found. Therefore, technological adoption could be regarded as a predictable measure of structure, productivity, and economic performance. The causal relationship amongst technology and the rest of constructs were non-linear. Technology is associated with productive structure, but independently of sheep farms' dimension, it can situate them in a growing area of returns. Evidence from this research suggests that there is no single optimal structure from the economic perspective. Consequently, agricultural policies for increasing productivity should be focused on technological progress

ACKNOWLEDGEMENTS

The authors thank Essential Research Project on agricultural resources and technology run by the Spanish National Institute of Agricultural and Food Research and Technology in conjunction with regional authorities (RTA2011-00057-C02), for providing financial support for the survey.

REFERENCES

1. Angón, E., Perea, J., Toro-Mújica, P., Rivas, J., De-Pablos-Heredero, C. and García, A. 2015. Pathways to Improve the Feasibility of Dairy Pastoral System in La Pampa (Argentine). *Ital. J. Anim. Sc.*, **14:** 643-649.
2. Caballero, R. 2009. Stakeholder Interactions in Castilla-La Mancha Spain's Cereal-Sheep System. *Agric. Hum. Values*, **26:** 219–231.
3. Cha, E., Sanderson, M., Renter, D., Jager, A., Cernicchiaro, N. and Bello, N. 2017.

[DOR: 20.1001.1.16807073.2020.22.3.11.1]

Implementing Structural Equation Models to Observational Data from Feedlot Production Systems. *Prev. Vet. Med.*, **147**:163–171.
4. Cortéz-Arriola, J., Rossing, W. A. H., Améndola-Massiotti, R. D., Scholberg, J. M. S., Groot, J. C. J. and Tittonell, P. 2015. Leverages for On-Farm Innovation from Farm Typologies? An Illustration for Family-Based Dairy Farms in North-West Michoacán, Mexico. *Agri. Syst.*, **135:** 66–76.
5. Cuevas Reyes, V., Baca del Moral, J. F., Cervantes, J.A., Espinosa-García, J. and Aguilar-Loaiza, A. 2013. Factores Que Determinan el Uso de Innovaciones Tecnológicas en la Ganadería de Doble Propósito en Sinaloa, México. *Rev. Mex. Cienc. Pec.*, **4:** 31–46.
6. De-Pablos-Heredero, C., Montes-Botella, J. L. and García, A. 2018. Sustainability in Smart Farms: It's Impact on Performance. *Sustainability*, **10:** 1713-1729.
7. Dubeuf, J.P. 2014. The Social and Environmental Challenges Faced by Goat and Small Livestock Local Activities: Present Contribution of Research-Development and Stakes for the Future. *Small Rumin. Res.*, **98:** 3–11.
8. Espinosa-García, J. A., Quiroz, J., Moctezuma, G., Oliva, J., Granados L. and Berumen, A. C. 2015. Technological Prospection and Strategies for Innovation in Production of Sheep in Tabasco. México. *Rev. Científ. FCV-LUZ.*, **25:** 107-115.
9. FAO. 2014. World Mapping of Animal Feeding Systems in the Dairy Sector. Food and Agriculture Organization, Rome.
10. Foster, A. D. and Rosenzweig, M. R. 2017. *Are There Too Many Farms in the World? Labormarket Transaction Costs, Machine Capacities and Optimal Farm Size*. NBER Working Paper No. 23909. National Bureau of Economic Research, Cambridge, MA, USA.
11. García, A., J. Rivas, J. Rangel, J.A. Espinosa-García, C. Barba and De-Pablos-Heredero, C. 2016. A Methodological Approach to Evaluate Livestock Innovations on Small-Scale Farms in Developing Countries. *Future Internet*, **8:** 25. DOI: 10.3390/fi8020025.
12. Gautam, M. and Ahmed, M. 2018. Too Small to Be Beautiful? The Farm Size and Productivity Relationship in Bangladesh. *Food Policy*, DOI: 10.1016/j.foodpol.2018.03.013.
13. Hair, J. F., Ringle, C. M. and Sarstedt, M. 2011. PLS-SEM: Indeed a Silver Bullet. *J Market. Theor. Pract.*, **19:** 139–151.
14. Kock, N. 2018. *Warp PLS 6.0*. ScriptWarp Systems. Laredo, TX., USA.
15. Le Dang, H., Li, E., Nuberg, I. and Bruwer, J. 2014. Understanding Farmers' Adaptation Intention to Climate Change: A Structural Equation Modelling Study in the Mekong Delta, Vietnam. *Environ. Sci. Policy*, **41:** 11-22.
16. Le Gal, P. Y., Dugué, P., Faure, G. and Novak, S. 2012. How Does Research Address the Design of Innovative Agricultural Production Systems at the Farm Level? A Review. *Agri. Syst.*, **104:** 714-728.
17. Mekonnen, H., Dehninet, G. and Kelay, N. 2010. Dairy Technology Adoption in Smallholder Farms in Dejen District, Ethiopia. *Trop. Anim. Health Pro.*, **42:** 209-216.
18. Milán, M. J., Caja, G., González-González, R., Fernández-Pérez, A. M. and Such. X. 2011. Structure and Performance of Awassi and Assaf Dairy Sheep Farms in Northwestern Spain. *J. Dairy Sci.*, **94:** 771-784.
19. Morantes, M., Dios-Palomares, R., Peña, M. E., Rivas, J., Perea, J. and García, A. 2017. Management and Productivity of Dairy Sheep Production Systems in Castilla-La Mancha, Spain. *Small Rumin. Res.*, **149:** 62-72.
20. Mukute, M. 2015. Developmental Work Research. A Tool for Enabling Collective Agricultural Innovation. First Edition, Wageningen Academic Publisher, Netherlands.
21. Noltze, M., Schwarze, A. and Qaim, M. 2012. Understanding the Adoption of System Technologies in Smallholder Agriculture: The System of Rice Intensification (SRI) in Timor Leste. *Agri. Syst.*, **108:** 64-73.
22. Nuthall, P. 2011. Farm Business Management. Analysis of Farming Systems. CAB, UK.
23. Rada, N. and Fuglie. K. O. 2018. New Perspectives on Farm Size and Productivity. *Food Policy*, DOI: 10.1016/j.foodpol.2018.03.015
24. Rangel, J., Espinosa-García, J. A., De-Pablos-Heredero, C., Rivas, J., Perea, J., Angón, E. and García, A. 2017. Is the Increase of Scale in the Tropics a Pathway

[DOR: 20.1001.1.16807073.2020.22.3.11.1]

to Smallholders? Dimension and Ecological Zone Effect on the Mixed Crop-Livestock Farms. *Span. J. Agric. Res.*, **15:** e0109
25. Ripoll-Bosch, R., Joy, M. and Bernués, A. 2013. Role of Self-Sufficiency, Productivity and Diversification on the Economic Sustainability of Farming Systems with Autochthonous Sheep Breeds in Less Favoured Areas in Southern Europe. *Animal*, **8:** 1229-1237.
26. Rivas, J., Perea, J., Angón, E., Barba, C., Morantes, M., Dios-Palomares, R. and García, A. 2015. Diversity in the Dry Land Mixed System and Viability of Dairy Sheep Farming. *Ital. J. Anim. Sc.*, **14:**179-186.
27. Ryschawy, J., Choisis, N., Choisis, J. P., Joannon, A. and Gibon, A. 2012. Mixed Crop-Livestock Systems: An Economic and Environmental-Friendly Way of Farming? *Animal*, **6:** 1722–1730.
28. Senger, I., Rossi, J. A. and Dessimon, J. A. 2017. Using Structural Equation Modeling to Identify the Psychological Factors Influencing Dairy Farmers' Intention to Diversify Agricultural Production. *Livest. Sci.*, **203:** 97–105.
29. Sheng, Y. and Chancellor, W. 2018. Exploring the Relationship between Farm Size and Productivity: Evidence from the Australian Grains Industry. *Food Policy*, DOI: 10.1016/j.foodpol.2018.03.012.
30. Tohidyan Far, S. and Rezaei-Moghaddam, K. 2015. Determinants of Iranian Agricultural Consultants' Intentions toward Precision Agriculture: Integrating Innovativeness to the Technology Acceptance Model. *J. Saudi Soc. Agr. Sci.*, **16:** 280–286.
31. Toro-Mújica, P., García, A., Gómez-Castro, G., Perea, J., Rodríguez-Estévez, V. and Angón, E. 2012. Organic Dairy Sheep Farms in South-Central Spain: Typologies According to Livestock Management and Economic Variables. *Small Rumin. Res.*, **104:** 28-36.
32. Vere, D. T. and Griffith, G. R. 2004. Structural Econometric Modelling in Australia's Livestock Production and Marketing Systems: The Potential Benefits of Model Integration for Industry Analysis. *Agri. Syst.*, **81:** 115–131
33. Van't Hooft, K. and Wollen, T. 2012. Sustainable Livestock Management for Poverty Alleviation and Food Security. CAB International, London, UK.
34. Yi, M.Y., Jackson, J.D., Park, J.S. and Probst, J.C. 2006. Understanding information technology acceptance by individual professionals: toward an integrative view. *Information & Management*, **43**: 350–363.

اثر نوآوری فناوری در عملکرد گوسفندان شیری در اسپانیا

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چکیده

هدف این پژوهش ارزیابی رابطه بین نوآوری فناوری و نتایج دامداری گوسفند بر مبنای روش مدل سازی معادلات ساختاری(SEM) در سامانه گوسفند شیری در مرکز اسپانیاست. تحلیل SEM با داشتن تفاوت از مدل های چند-صفته رایج، برآورد روابط بالقوه علیّ در میان نتایج (outcomes) را مقدور می سازد و می تواند اثرها را به گونه ای موثر از هم تمیز دهد. در این پژوهش، از اطلاعات ۱۵۷ دامداری گوسفند شیرده درمنطقه Castilla La Mancha استفاده شد. پرسشنامه های مورد استفاده شامل ۳۸ فناوری نوآورانه و ۱۸۸ سوال در مورد داده های بهره دهی، اقتصادی و اجتماعی بود. برای

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درک این مطلب که نوآوری فناوری چگونه برساختار تولیدی و عملکرد دامداری اثر میگذارد چهار فرضیه فرموله شد. نتایج به دست آمده از تحلیل SEM، رابطه ای مثبت بین شاخص های فناوری و ساختار، بهره دهی و نتایج اقتصادی دامداری نشان داد. متغییر اتخاذ فناوری را می توان به عنوان سنجه ای قابل پیش بینی از ساختار، بهره دهی و عملکرد اقتصادی قلمداد کرد. فناوری با ساختار تولیدی همراه است. فارغ از اندازه مزرعه دامداری گوسفند، استفاده درست و مناسب از دامداری های گوسفند شیری، آنها را در مسیر بازده های اقتصادی رو به افزایش قرار میدهد. روش تحلیل SEM از داده های مشاهداتی در زمینه سامانه گوسفند شیری چنین اشارت دارد که ساختار بهینه تنها یک مورد نیست. مدل ایجاد شده در این پژوهش شامل ابزاری است با مصارف مفید برای تصمیم گیری زیرا پیش بینی اثر فناوری ها روی نتایج نهایی را پیش از اقدام مقدور می سازد.

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