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DETERMINANTS OF AGRICULTURAL INNOVATION AMONG SMALL FARMERS IN MEXICO. AN ECONOMETRIC APPLICATION OF THE TOBIT MODEL

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ABSTRACT

Understanding agricultural innovation is crucial as it involves establishing conditions for productivity growth in the agrifood sector through strategies and public policies that improve farmers' production, profitability, and management practices. The objective of this article was to measure agricultural innovation among small farmers and to identify the factors that determine it. A Tobit-type econometric model was used to identify the characteristics of the producers, the economic and productive profile of the farms, and the size of the extension groups, all of which influence innovation. Information on rural extension policy beneficiaries in Mexico for the period 2014-2017 was integrated. The statistical population was 2976 farmers. The findings reveal that higher education levels and a younger age of producers had a positive effect; producers with small farms were more likely to adopt technological practices. On the other hand, factors negatively affecting innovation were higher on-farm and off-farm incomes. The article concludes with public policy recommendations to promote agricultural innovation in Mexico.

Keywords: Rural extensionism, technology adoption, linear regression.

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INTRODUCTION

The study of agricultural innovation is a fundamental topic at the international level due to its importance as one of the main factors for improving productivity, profitability, and sustainability in agrifood systems. Furthermore, it is considered a key player in generating better conditions for small agricultural production units to strengthen their livelihoods in an environment that aims to foster competitive and sustainable economic development (Läpple *et al*., 2015; Sewell *et al*., 2017).

The most widespread meaning of innovation implies the application and use of new ideas, concepts, products, services, and practices with the purpose of increasing productivity (Amaro and Morales, 2016). In rural areas, innovation is seen as a trigger for processes through which small farmers can improve production and management practices in their production units in order to increase their profitability. In this context, the Food and Agriculture Organization of the United Nations (FAO) defines agricultural innovation as a process through which individuals and organizations use new or existing products, processes, or organizational forms for the first time in a specific context with the aim of increasing efficiency, competitiveness, and resilience to shocks or environmental sustainability and thereby contributing to food security and economic and sustainable development (FAO, 2018).

In Mexico, 71.3 % of agricultural properties are small production units with an average area of up to 10 ha, accounting for 22.6 % of the national agricultural area (INEGI, 2019). They produce food both for self-consumption and market consumption, and therefore are essential to guarantee food security, alleviate rural poverty, and contribute to the country's overall economic development. These objectives can only be met if these types of farms become more productive, competitive, and therefore more innovative.

Until the 1980s, agricultural innovation was conceived under a vertical approach that began with public-sector research and continued with the transfer of technologies and technology packages through rural extension organizations. This assumed that innovation was the primary outcome of research and that the users or beneficiaries (agricultural producers) were the targets of public policies, to whom technologies and new techniques had to be transferred without considering their own knowledge. In contrast, Klerkx *et al.* (2017) have pointed out that innovation among small farmers, occurs when they interact with each other, as well as with input suppliers and advisory service providers, resulting in knowledge generation that allows articulating the needs of the former towards the resolution of their problems, decision making, and more effective agricultural management through different services where the main input is knowledge.

Agricultural innovation is the result of interactions among actors, production systems, value chains and economic systems, public policies, and research and extension systems, which are reflected in three areas: the improvement of capacities and development of individual knowledge; the improvement of processes within organizations and farms; and the creation of a policy environment that generates the establishment of links, communication channels, and networks that allow organizations and individuals to exchange knowledge (Klerkx *et al*., 2017; FAO, 2018), thereby configuring territorial systems of innovation. Lundvall (2007) emphasizes that innovation is a process of change that occurs as a result of interactions among multiple actors, thus recognizing that it goes beyond the adoption of technologies since it encompasses alternative ways of organizing social and economic systems to foster an environment that, on a *continuum*, articulates the resolution of problems for different actors based on the generation of knowledge. This should lead to the adoption and adaptation of technologies in specific socioeconomic contexts, leading to co-innovation in which farmers interact with their peers, connect with the value chains links, and exchange knowledge with researchers and extensionists to address problems in order to generate social learning and value.

Strengthening agricultural innovation fosters solutions to practical problems while providing opportunities to improve the competitiveness and sustainability of the different actors in the agricultural field (Cristiano and Proietti, 2019). An innovation is a collective action that should result in observable changes in the economic, social, productive, and environmental fields in the farm and territory level. Therefore, knowledge generation remains a prerequisite for innovation and is a critical component of agrifood sector policies, since it is intended to encourage the best technological, commercial, and organizational practices for the primary sector.

The study of agricultural innovation considers several dimensions that explain it. For example, Jensen *et al.* (2014) found that the determinants of innovation are related to the characteristics of the production unit, the socioeconomic profile of the producer, the land area, access to credit, labor, infrastructure, access to markets, agroecological conditions, and risk and uncertainty. For his part, Andersen (2015) states that most research on agricultural innovations is focused on estimating adoption rates and understanding the relationship between adoption, its intensity, and the variables that explain it. This research has largely focused on the impact of innovation in developing countries and in territories where it is estimated that most of the population has agricultural forms of production associated with their livelihoods. As a result, agricultural innovation analysis in these countries provides opportunities to improve food production and alleviate poverty through increased productivity and economic growth (Baloch and Thapa, 2016; Simtowe *et al*., 2016).

Innovation refers to the introduction of a new or significantly improved product (good or service), process, organization, and marketing method into a company's internal practices (OECD and Eurostat, 2005). Innovation constitutes a system that includes networks of organizations, companies, and individuals interested in generating new products and forms of organization within a given socioeconomic context (World Bank, 2006). The most common way to measure agricultural innovation has been through the use of indicators by production system, with the latter using this measure as a *proxy* for innovation. For example, in Mexico, Martínez-González *et al.* (2018) evaluated innovation in the case of beekeeping, while Luna *et al.* (2016) analyzed the adoption of improved seeds in maize. Internationally, beef (Dhein *et al*., 2015) and pea bean production (Simtowe *et al*., 2016) has been analyzed in Brazil and Malawi. However, there is a debate that alludes to the observation that any innovation *per se* is not sufficient to evaluate its effects at the farm level, nor to identify whether such an innovation solves problems or improves the conditions of agricultural producers (Cristiano and Proietti, 2019).

Therefore, it is still important to contribute to the understanding and measurement of agricultural innovation using data at the production unit level. Based on the research question "Which factors determine the adoption of agricultural innovations in Mexico?", the objective of this research was to measure the levels of agricultural innovation among small producers and identify the factors that determine it. The hypothesis of the research was that farm characteristics, such as the size of the production unit and the level of assets, do not have a determining influence on agricultural innovation. The population studied was derived from the systematization of information related to the beneficiaries of the national rural extensionist policy in the period 2014–2017, which came from statistical sampling of the target population of the aforementioned programs.

MATERIALS AND METHODS

Analytical framework for measuring agricultural innovation

This research assumes that innovation, in its broadest sense, refers to a set of variables that account for four innovation factors: product, process, marketing method, and organizational method. Six dimensions that are considered to account for agricultural innovation among small producers were analyzed, resulting in six indexes per category and a general index of innovation adoption were constructed. Each dimension, as well as the method of measurement, is presented below.

At the farm level, where the effects of innovations can be observed in improvements or changes in production techniques, the knowledge generation dimension was analyzed. It measures the strengthening of the individual capital of producers, which conceptually stimulates innovative capabilities in agriculture. The dimension assumes that producers need innovations to increase their efficiency and competitiveness; therefore, it explores whether there has been a reconversion in technological and/or organizational practices on each producer's farm. The second dimension was the level of organization, which evaluates the degree of interaction between producers and assumes that such interaction allows for the co-production of practical solutions to common problems. The dimension of production and accounting records assesses whether producers keep any type of these records and whether they are used during the production cycle (Figure 1).

Dimensions four and five were related to backward and forward linkages; both analyze the strengthening of individual and social capital to determine whether innovation

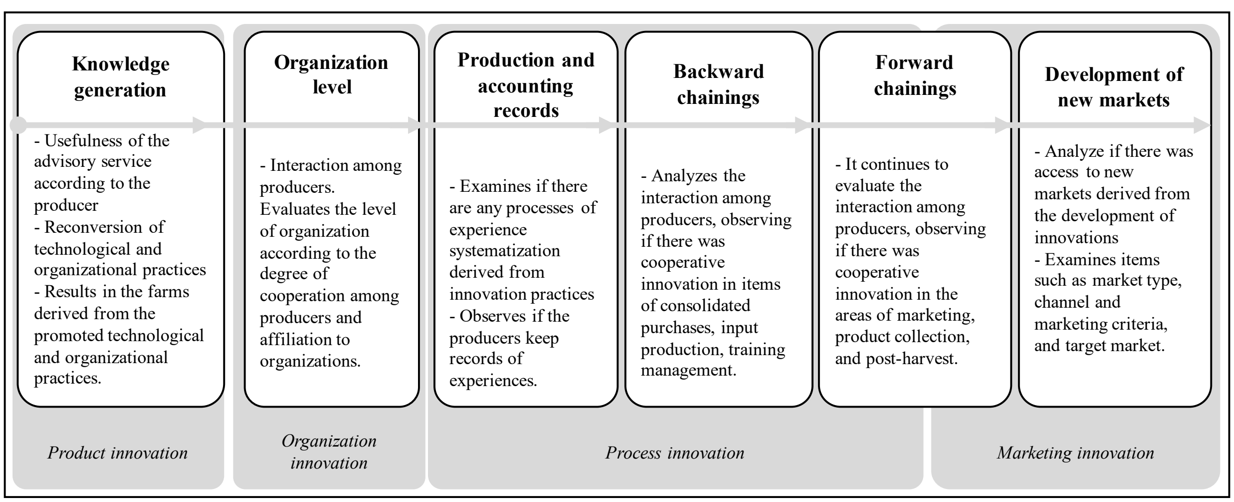

Figure 1. Dimensions included in the agricultural innovation index.

capabilities have been promoted in agriculture and, consequently, producers have been brought closer to the various links in the chains. The new market development dimension explores if new market niches were developed. It is an aggregate analysis metric that evaluates the effectiveness of innovation in terms of the market opportunities created.

The proposed index aggregates the sub-indices of the six dimensions into a single mean, whose values are continuous in the interval from 0 to 1, where 0 is the lowest value, and considers that technologies or knowledge were adopted. A value of 1 is related to producers who promoted changes in the farms derived from the generation of knowledge and that these contributed with new products or production processes, as well as the inclusion of new linkages and markets, respectively.

Data integration

From 2014 to 2017, FAO evaluated the programs and components of the extensionist policy at the national level implemented by the then Ministry of Agriculture, Livestock, Rural Development, Fisheries, and Food. Using this information, a database (DB) was generated considering the beneficiaries interviewed in the monitoring and the evaluation of the rural extension policy during the same time period. The annual databases were integrated to estimate the innovation index, resulting in a DB of 2976 beneficiaries distributed among 13 states (Table 1). A stratified sampling with state representativeness was used in each state, with a confidence level of 95 % and an error of 10 %.

Table 1. Database characteristics used in the analysis.

State	n	Sex (%) Men	Age	Education (years)	Size of the farm (ha)	Productive assets (MXN $)	Property income (MXN $)	Group size extension
Chiapas	341	83.6	50.8	5.8	14.76	40 210.6	69 425.3	25.6
Durango	136	83.8	55.5	7.4	39.71	167 467.4	138 473.4	28.2
State of Mexico	276	69.2	50.4	9.1	4.42	250 126.9	95 656.0	20.0
Guanajuato	354	80.2	53.7	6.4	14.41	148 463.6	346 181.4	20.3
Michoacán	346	80.1	51.8	6.7	11.64	191 994.3	163 849.4	28.7
Nuevo León	84	91.7	56.6	6.3	15.24	134 330.1	72 994.0	16.5
Oaxaca	383	70.2	50.8	6.7	9.29	89 274.5	112 232.2	24.4
Puebla	337	65	50.9	7.3	5.19	46 749.5	66 967.3	23.8
San Luis Potosí	185	75.1	49.7	6.7	16.32	121 733.8	79 667.6	28.7
Sinaloa	237	82.3	51.8	8.5	15.54	169 919.5	323 053.0	26.1
Sonora	52	86.5	54.4	10.0	15.01	241 842.8	264 504.4	29.7
Tabasco	69	88.4	56.0	7.6	19.77	131 346.9	109 526.1	19.2
Zacatecas	176	85.2	52.9	7.9	31.09	496 966.3	170 583.1	15.7
Totals/Average	2976	77.5	51.9	7.2	13.61	153 851.2	155 477.4	23.9
Variation coefficient	-	-	27.31	61.59	191.83	253.79	383.51	42.59

MXN 2018 = 100.

The DB analysis shows that the population is primarily male (77.5 %) with an average age of 52 years and elementary school completed (7.2 years in the school system). Its production units have an average area of 13.6 ha and an asset level (infrastructure, equipment and machinery, as well as means of transportation) of \$153 851 MXN (2018 = 100). The average annual income inside and outside the production unit was \$155 477 and \$19 972 MXN (2018 = 100), respectively, with the latter composed mainly of government transfers.

Tobit model

The Tobit regression model (Tobin, 1958) is an application of the multiple regression model to a limited dependent variable, which are those with a substantially restricted range of values (Wooldridge, 2015). The general framework for modeling agricultural innovation phenomena relies on regression models where the response variable is a limited dependent variable. For example, in Logit and Probit models, which are binary response models where the interest lies mainly in the response probability, the dependent variable function is a nonlinear function between 0 and 1. These are appropriate if innovation is reduced to a dichotomous effect, with values of 1 when there is innovation and 0 when there is not.

The Tobit regression model allows innovation assessment in its most complex sense. In this case, the response variable takes continuous values between 0 and 1. Furthermore, given the nature of the innovation index values, where the response variable is limited but one has a corner solution response, i.e., a variable that is zero for a non-trivial fraction of the population and has an approximately continuous distribution across positive values, the Tobit model may be very useful for these purposes. In this model, the y variable is continuous through strictly positive values but assumes zero with positive probability (Wooldridge, 2015). The Tobit model transforms the observed y values into an underlying latent variable, which is given by:

$$y^* = \beta_0 + x\beta + \varepsilon, \ \varepsilon \mid x \sim N\,(0, \sigma^2) \tag{1}$$

$$y_i = \begin{cases} y_i^* \ si \ y_i^* > 0 \\ 0 \ si \ y_i^* \leq 0 \end{cases} \tag{2}$$

The latent variable y^* satisfies the theoretical assumptions of the classical linear model, has a normal, homoscedastic distribution, and a linear conditional mean. Given equation (1), it can be seen that the parameters $\hat{\beta}_j$ measure the partial effects of the x_j over, $E\,(y^* \mid x)$ where y^* is the latent variable. Based on equations (1) and (2), it is important to analyze the effect of each independent variable on the dependent variable, in this case, the innovation index. According to Wooldridge (2015) knowing the sign of $\hat{\beta}_j$ is sufficient to determine whether the independent variables had positive or negative effect on the response variable, since the partial effects of x_j over $E\,(y \mid y > 0, x)$ and $E\,(y \mid x)$ have the same sign as the coefficient β_j.

The Akaike information criterion (AIC) was applied as an indicator of the model's goodness of fit. This criterion is commonly used in practice and is based on the Kullback-Leibler distance, which measures the approximation of the calculated model with the real data and is used to evaluate models by ranking them according to the AIC value; the one with the lowest AIC value is considered the best model (Faraway, 2015). Data analysis was performed in the statistical program RStudio version 4.1.2. The empirical model with the variables used was expressed as follows:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \varepsilon_i$$

Where y_i : agricultural innovation index; x_1: producers' sex; x_2: producers' age; x_3: producers' education; x_4: producers' farm size; x_5: farm assets; x_6: farm income; x_7: off-farm income; x_8: extension group size; and ε_i: random error.

The predictive and dependent variables included in the Tobit model are described (Table 2). Since the purpose of the research was to account for the behavior of one set of variables and their impact on the others, the agricultural innovation index was used as a response variable. The predictor variables included a *dummy* (sex of beneficiaries), and the rest were continuous. These were the age and education level of the producers, farm size and asset level, income inside and outside the production unit, as well as the size of the rural extension groups in which the producers participated.

Table 2. Definition of variables included in the Tobit model.

Variable	Definition	Value and unit of measure
Dependent Agricultural innovation index	Adoption of agricultural innovations at the property level	Continuous Values 0 ≤ y ≤ 1
Independent Sex	Farmers´ sex	*Dummy* 0= Male, 1= Female
Age	Farmers´ age	Continuous (years)
Education	Farmers' education	Continuous (years)
Size of the farm	Property surface	Continuous (hectares)
Property assets	Investment in infrastructure, machinery and equipment, means of transportation of the farm, etc.	Continuous (2018 pesos)
Property income	Property income inside	Continuous (2018 pesos)
Off-farm income	Off-farm income	Continuous (2018 pesos)
Group	Members of the extension groups	Continuous (number of producers)

RESULTS AND DISCUSSION

Estimation of the agricultural innovation index

The average value of the agricultural innovation index among small rural producers was 0.110 (coefficient of variation = 92.89). This reflects a low level of agricultural innovation, which is consistent with other similar studies. For example, in Ireland, Läpple *et al.* (2015) reported an average value of 0.4. Slightly low innovation rates have also been found in other European countries; 0.18 in Luxembourg, 0.27 in Greece, and 0.30 in Hungary, while higher values were found in the Netherlands (0.61), Belgium (0.51), and Norway (0.47) (Autant-Bernard *et al*., 2010).

When the analysis was disaggregated, it was possible to observe the behavior that determined the minimum value of the index. The lowest value was found in the area of new market development (0.0427), which shows that most producers sell their products mainly at the farm gate to intermediaries (Figure 2).

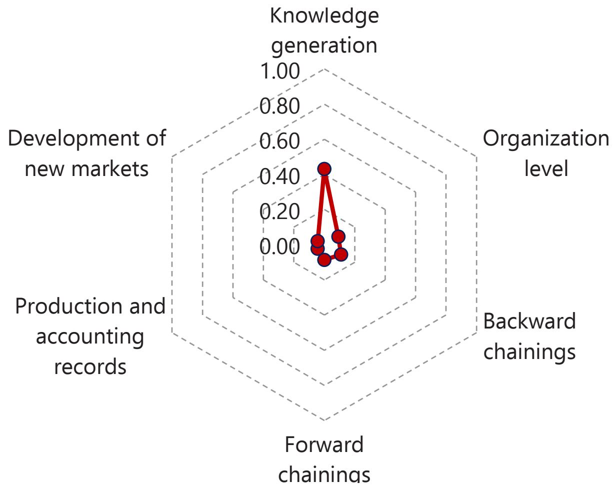

Figure 2. Estimation by dimensions of the agricultural innovation index.

The dimension of productive and accounting records (0.0434) shows that, although producers are participating in rural extension groups where one of the evaluation criteria is to keep productive and accounting records to systematize experiences, there are no mechanisms in place to encourage the internalization of these practices in farms in the medium term. Regarding the level of organization, a value of 0.092 was found, indicating that the producers are not working or interacting with their peers collectively; their sense of action is mainly individual (Figure 2).

Consistent with this type of individual action, the sub-indexes of forward linkages (0.086) and backward linkages (0.11) also reflect an important conflict: relationships that expand and diversify producers' production and marketing capacity have not been modified. Their behavior accentuates a preference for individual action, which sometimes leads to their exclusion from the links in agrifood chains.

The knowledge transfer sub-index showed the highest value (0.4262), indicating that, from the producers' perspective, there was an expansion of their capacities and possibilities for action derived from information flows. However, these capacities remained in individual actions at the farm level and did not exceed the possibilities of collective action as subjects, which demonstrates the low prevalence of collective actions of organization and support among producers.

The analysis of rural extension policy problems can help to establish hypotheses for the low level of agricultural innovation among small farmers in Mexico. One study found that the problems related to innovation phenomena included a lack of timeliness of technical assistance programs in relation to production schedules, a lack of continuity to extension groups, and low linkages between producers (Santos-Chávez *et al*., 2021).

Determinants of agricultural innovation with smallholder farmers in Mexico

The AIC value of the Tobit model was 47.58, which was substantially lower than other similar models. Läpple *et al.* (2015) exhibited an AIC value of 533.85 from their Tobit model. The calculated AIC allows us to establish that the analyzed data can be suitably expressed, in a compact manner, through the selected analytical model.

The model fit reveals that both higher education ($p = 8.75e - 10$) and farm assets ($p = < 2e - 16$) had a positive effect on the calculated innovation index. In contrast, the findings highlight that the larger size of the production unit ($p = 0.00735$) had a negative effect on the response variable (Table 3).

Table 3. Parameter estimation of the Tobit model.

Variable	Estimation	Standard error	z value	Pr(>|z|)
Intercept	1.882e-02	1.714e-02	1.098	0.27220
Sex: Woman	-2.729e-03	7.152e-03	-0.382	0.70283
Age	-4.294e-05	2.316e-04	-0.185	0.85289
Education	4.802e-03	7.833e-04	6.131	8.75e-10 ***
Size of the farm	-3.113e-04	1.161e-04	-2.681	0.00735 **
Property assets	1.375e-07	1.069e-08	12.866	< 2e-16 ***
Property income	-6.984e-10	7.570e-09	-0.092	0.92649
Off-farm income	-8.247e-08	7.073e-08	-1.166	0.24364
Group	3.948e-04	2.937e-04	1.344	0.17894
Log-likelihood value	-1.940e+00	1.939e-02	-100.028	< 2e-16 ***

Significance level: '***' 0.001, '**' 0.01, ' ' 1; *p-value*: < 2.22e-16; total observations: 2976; observations used in the model: 2650. A total of 326 observations were excluded due to incomplete information.

In relation to the profile of the producers, the results indicate that age ($p = 0.85289$) and sex ($p = 0.70283$) had no significant effect on explaining the innovation index. The age variable has a positive sign in the estimated parameter, which contrasts with another studies. For example, Läpple *et al.* (2015) showed that age has a negative effect on agricultural innovation in Ireland, emphasizing that as producers have a shorter time horizon, they do not invest economic resources and time in capacity-building actions. In contrast, older producers in Mexico have more time to attend the activities of rural extension groups; their investment is made in time rather than in economic resources. Furthermore, Simtowe *et al.* (2016) found that older producers have more experience in managing the production unit and, therefore, possess greater capacity to evaluate the feasibility of practices induced by extension services, compared to younger producers. Estimates for the sex showed a negative sign over the index value. No difference was found between men and women in the average value of the innovation index: men recorded a value of 0.1099, while women recorded a value of 0.1101 (Figure 3). The negative coefficient suggests that women who participate in innovation groups are less likely to adopt practices and technologies on their farms. This finding is consistent with the results of Simtowe *et al.* (2016), who discovered that being female reduces the likelihood of adopting innovations by 28 % in Malawi.

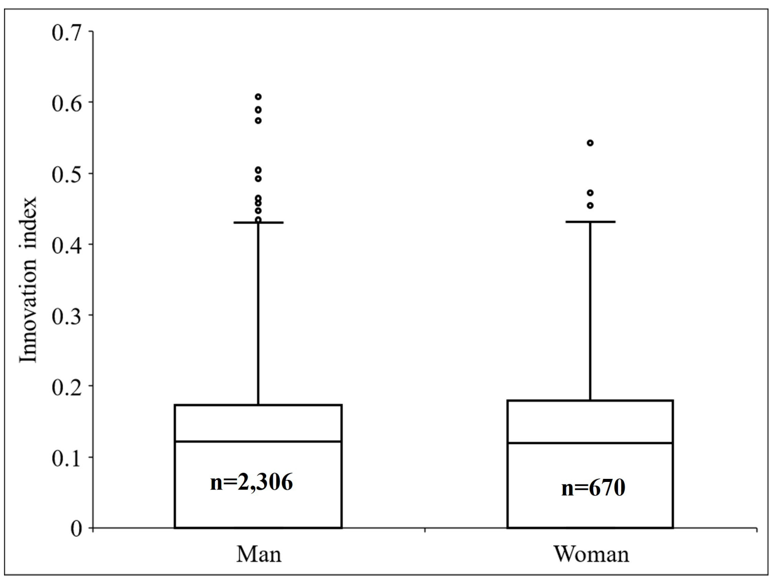

Figure 3. Box plot of the innovation index by sex.

It was observed that education is positively related to the increase in the rate of agricultural innovation. This aligns with several studies that have proven that often a higher education level has an impact on producers' perceptions of the need to adopt new technological practices through knowledge sharing activities (Jensen *et al*., 2014; Dhein *et al*., 2015).

When the analysis is expanded and the values of the education variable are recategorized by school grade, it was found that the producers with no education (7 % of the total population) presented the lowest average value in the innovation index (0.071). Producers are the most numerous at the elementary level (48 % of the total number of producers) and showed an average value of 0.099 in the response variable

(Figure 4). The highest value was found among producers with a bachelor's degree (0.144), although they represent 13 % of the total. Eight percent of the producers have a university degree, showing an average innovation index value of 0.141, while producers with a postgraduate degree (one out of every 100 producers) had an average innovation value of 0.124.

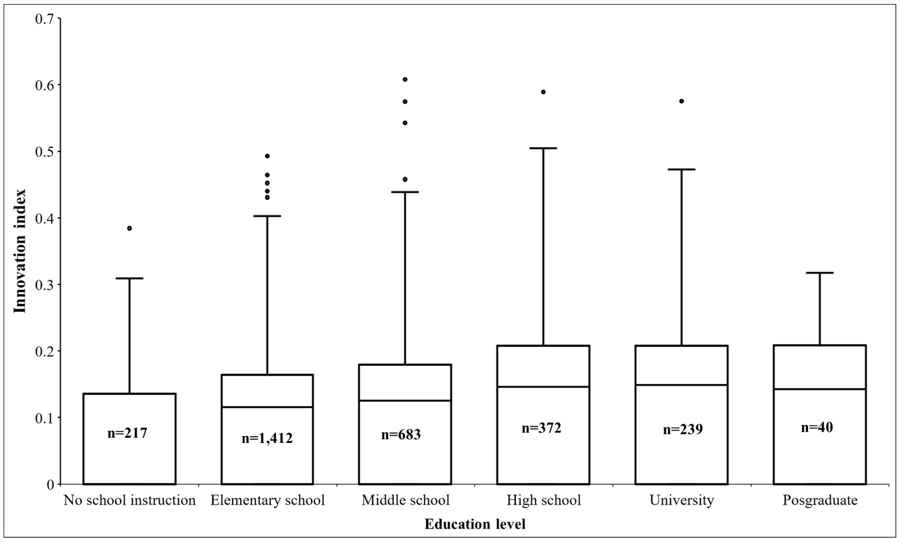

Figure 4. Box plot of the agricultural innovation index by education level.

Recent empirical evidence has confirmed that farm size and investment in productive assets are two key elements in explaining the determinants of agricultural innovation. In this regard, Läpple *et al.* (2015) found that farm size is generally associated with positive innovation rates; however, Tobit model results show that, although this variable has a significantly higher effect than the other variables, its value is negative. One explanation for this result is that farmers with a larger than average productive scale (13.6 ha) may perceive greater risk when applying new technological practices in their production units when compared to small producers. This phenomenon has been observed in other studies, and it was also found that the risk and uncertainty generated by the adoption of new technologies have a high incidence in farms with a larger productive scale (Jensen *et al*., 2014; Wossen *et al*., 2017).

According to the estimated values of the Tobit model, the level of productive assets is the most important variable among the factors that determine the agricultural innovation index. This variable has been used as a proxy measure to estimate a farm's ability to invest in new technologies or agricultural practices. The main argument is that most of the technologies promoted among small producers are mainly aimed at improving crop and livestock management, and in most cases require techniques based on some input, such as improved seeds, crop nutrition, or in the case of the livestock subsector, for herd health management, as well as specialized diets, which entail significant costs for producers. This explains why the level of assets is often used as a variable to evaluate the cash flow of a farm and is ultimately so relevant in explaining agricultural innovation.

On the other hand, income inside (p = 0.6365) and outside the production unit (p = 0.144) had a negative influence on the Tobit model response variable. In general, studies on the relationship between farm income and agricultural innovation are inconclusive. Atube *et al.* (2021) found that producers with higher incomes within the production unit are more likely to use new agronomic practices. However, among small and medium-sized producers in Mexico, income within the production unit has a negative influence on farmers' decision to adopt new agricultural practices. An additional explanation for this finding derives from the type of extension programs in which the rural producers included in the study participated: during the period 2014–2017, they were oriented towards small producers. Therefore, their evaluation shows that when high-income producers join, they are less likely to take advantage of technical assistance services because they are not designed to meet their needs, such as adding value to products, post-harvest management practices, or induction to new marketing channels; instead, the services are mainly oriented towards optimizing agronomic practices on the farms, such as crop nutritional improvement, pest and disease control, and in the case of animal husbandry, sanitary management and herd disease control.

In the case of off-farm income, the results show that producers who engage in off-farm activities miss out on the opportunity to implement and adopt agricultural innovations. This is consistent with the findings of Läpple *et al.* (2015), who showed similar results and realized that working outside the production unit has a significant opportunity cost in the participation of agricultural innovation activities in Ireland. Additionally, Sauer and Zilberman (2012) exhibited that income outside the production unit had a negative effect on the adoption of innovations among dairy cattle producers in Denmark.

The results of the study show that the size of the extension groups (p = 0.1214) is not a determining factor in the agricultural innovation index. However, the positive sign of the coefficient shows that an increase in the size of the groups could positively affect agricultural innovation among small producers.

The findings reveal that a results-oriented public policy on agricultural innovation with a target population focused on small producers could use selection criteria centered on farm size, investment in productive assets of the production unit, and education of the beneficiaries. This proposal is explained below:

First, a government action aimed at improving agricultural innovation should be designed based on a criterion of greater inclusion in terms of education. The model showed that producers with more formal education are more likely to improve their conditions as a result of their participation in the rural extensionist policy. However, the innovation model should be adjusted to allow less educated producers to use their own knowledge, much of it ancestral, to acquire, synthesize, take advantage of new knowledge, and apply it to solve problems in their production units and improve the adoption of agricultural innovations.

Second, a policy initiative to improve access to credit and increase the asset level of producers would facilitate agricultural innovation. Ideally, innovation policy should be targeted to those producers with a minimum investment in productive assets, which is positively related to innovation adoption rates, according to the findings of this research.

CONCLUSIONS

The study enabled the establishment of a measure of the degree of agricultural innovation among small rural producers in Mexico, taking into account multiple factors that account for this phenomenon. A very low level of innovation was found, which is mainly explained by the producers' actions, which are characterized by individual behavior, resulting in low integration for production and marketing.

Similarly, the article presented an econometric model for analyzing agricultural innovation based on a continuous response variable, unlike other models that use limited dependent variables, mainly dichotomous variables. The results showed the greater importance of the variables education, level of productive assets of the production unit, and farm size for improving agricultural innovation among small rural producers in Mexico.

Finally, the results show that for small farmers, the size of the production unit is negatively related to the agricultural innovation index, suggesting that providing small farmers with rural advisory services can boost the generation of knowledge aimed at increasing their production. However, more efficient farmer-to-farmer partnership mechanisms are needed to improve access to credit and markets and ensure the welfare of farm households by increasing their profitability and income.

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