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Regional Specialization, Competitive Pressure, and Cooperation: The Cocktail for Innovation

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Abstract: The main aim of this paper is to analyze the effect of industrial agglomeration on the degree of interorganizational cooperation and the innovative performance of firms of the electricity supply sector in Spain. For this purpose, the agglomeration coefficient in each of the 50 provinces of Spain is calculated, based on secondary data from SABI database. Subsequently, primary data are obtained from a sample of 197 companies through a structured questionnaire. In this case, the PLS-SEM technique is used. The results show that there is a positive and significant relationship between the variables analyzed. It is concluded that industrial agglomeration and cooperation are relevant external factors that boost the innovative performance of firms and that business associations foster interorganizational cooperation.

Keywords: agglomeration; cluster; specialization; cooperation; innovation; PLS-SEM; energy

JEL Classification: R12; O36; R30; L94

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1. Introduction

Innovation is a fundamental factor for economic development and favors the generation and exploitation of opportunities by companies and boosts their performance [1–3]. Its importance has increased in recent years in academia, as a fundamental factor for the survival, and competitiveness of firms [4–6]. The development of innovations requires the interaction and cooperation of multiple actors in terms of information, knowledge, and other resources in favor of particular social or economic goals [7,8]. Cooperation allows organizations to analyze the market situation, generate new ideas, and expand their knowledge base on an ongoing basis [9]. In this way, the establishment of reciprocal cooperative relationships favors the absorption of knowledge by the participating companies and its application to the development of innovations [10,11]. Thus, the exchange of knowledge with agents in the environment is essential to boost the innovative performance of firms [12,13].

Industrial agglomeration favors communication and the establishment of cooperative–competitive relationships between companies in the sector (whether direct competitors or not) that are located geographically close to each other, which reduces the costs and risks of the process and has positive effects on communication, the generation of trust, access to and creation of new knowledge, and innovative performance [14,15]. In this sense, Porter [16] highlights a driver of innovation—in addition to the intensity of local competition— as being the existence of greater opportunities for cooperation. In this regard, there are certain agents, such as business associations, that facilitate the implementation of joint innovation processes acting as intermediary entities [17,18]. Belonging to an association of entrepreneurs promotes interaction and cooperation among its members, and favors the establishment of relationships of trust, acting as a tool of cohesion and intermediation [17], which favors the acquisition and assimilation of new knowledge [19].

In this research paper we study the influence of the agglomeration of the sector on the innovative performance of firms. In addition, we analyze the mediating effect of the degree of cooperation in this relationship and the membership of an association of entrepreneurs as an antecedent variable of the degree of the cooperation of firms with entities in their environment. Specifically, the aim of this paper is to determine the effect of industrial agglomeration on the innovative performance of firms in the sector under study, and the influence of cooperation as a mediating variable in this relationship.

The analysis is carried out in two phases. In the first one, data of the electricity supply sector were extracted from the SABI database, from which the number of companies and employment in each of the 50 provinces that make up the Spanish territory were calculated. Based on this data, the degree of agglomeration of the sector in each province was calculated in relation to the national average. Subsequently, in the second phase, a theoretical model was developed based on the hypotheses put forward. A structured questionnaire was designed, composed of validated scales for the calculation of the variables included in the proposed model, and was distributed among the companies of the sector being studied, obtaining a total of 197 valid responses, and the use of the PLS-SEM method was chosen to estimate the proposed relationships. Specifically, the responses were coded and analyzed using the SmartPLS software, in its version 3.3.3, SmartPLS GmbH, Oststeinbek, Germany.

The structure of the research is the following. First, there is a review of the literature related to the studied variables and relationships, from which the research hypotheses and the nomogram of the model are proposed. Then, the methodology used is described and, later, the results of the study are set out. Finally, the results are discussed, and the conclusion drawn, emphasizing the necessity to further deepen the analysis of the effects of closeness and cooperation dynamics on innovation.

2. Literature Review

2.1. Industrial Clustering and Innovation

Although by applying logic it could be determined that the accelerated process of the globalization of the economy, the reduction in the costs of transporting goods, and the development of information and communication technologies reduce the importance of location as a driver of business performance, the reality seems to indicate that the importance of the local environment has progressively increased [20] (p.256). Thus, nowadays the choice of the environment in which to locate business activities is a key strategic decision, which determines the characteristics of external agents that can favor the generation of certain localization economies and, consequently, a comparative advantage with respect to firms in geographically dispersed locations.

According to Baldwin and Von Hippel [21], it is essential to shift the focus of innovation generation and development from within firms to an open and collaborative path, in which firms and various agents and stakeholders, especially customers, work together in the design and development of innovations. This is because the capture of ideas and knowledge by companies through interaction with different specialized agents in the environment is a potential source of valuable resources that can lead to interesting opportunities for innovation [22]. In this sense, industrial agglomeration favors the generation of cooperative–competitive environments, in which the development of the relational networks of firms is promoted, alongside the pooling of a series of complementary resources and capabilities in favor of the achievement of shared objectives [23–25].

Moreover, productive specialization is one of the essential externalities derived from industrial agglomeration [26], which favors the technical specialization of processes and knowledge, not only of those companies dedicated to the industry in question, but also of those others that perform complementary activities [27]. In this sense, collaboration between various specialized economic agents, belonging to a given geographical area, increases the likelihood of the success of the innovation development processes undertaken by firms [28–30].

In addition, the exchange of knowledge between these specialized agents located geographically close to each other avoids duplication of efforts for the development of new knowledge and innovations [15]. Based on the above, the following hypothesis is proposed:

Hypothesis 1 (+): *There is a positive and significant relationship between the degree of agglomeration of the sector and the innovative performance of firms.*

2.2. Business Associations and Interorganizational Cooperation

According to Mejía-Villa, Tanco, and San Martín [19], the role of business associations as stimulators of innovation has been scarcely studied, despite the particularities conferred by their associative nature, which do not pursue lucrative purposes but simply defend the interests of their members and promote their positioning in the market, as well as enhance the dissemination of knowledge and the innovation capacity of their associates.

Business associations act as the promoters of collaborative innovation [19]. They are non-profit organizations [17] that usually bring together a large part of the entrepreneurs of a specific sector and region, in the first instance, exercising a certain degree of cohesion among them, in that their membership of the association is due to very similar motives and/or needs.

According to Nonaka and Konno [31], through continuous interaction at different levels between individuals and the sharing of their individual experiences, knowledge, and visions in a specific environment and time, the right conditions are established for the generation of trust, ideas, and new knowledge, as well as their development and integration. This can lead to the adoption of efficient, effective, and innovative solutions to their common problems. The effective development of open innovation processes requires that the communication channels work smoothly, as well as the existence of trust between the different individuals or agents involved in the process [32].

In this regard, socialization is an essential element for the generation of trust and the exchange and combination of ideas, information, and knowledge, especially tacit knowledge [33,34]. The latter is rooted in the experiences, aspirations, and values of individuals, which makes its dissemination difficult, although through continuous interaction between individuals in a specific place and time, its transfer can be promoted [31].

Zheng [35] concluded that various characteristics of the relational networks established by firms with agents in their environment, such as the strength of ties, trust, and shared norms and vision, can influence their ability to develop innovations. However, it is necessary to combine the agglomeration approach with other tools to accelerate results in terms of cooperation and innovation [36]. In this respect, business associations act as intermediary agents, favoring continuous interaction between entities with complementary resources and capabilities.

According to Sun, Zhang, and Zhang [37], the density of relational networks and the intensity of cooperation have a positive effect on the innovative performance of participants. Thus, they can influence the quality and quantity of cooperation agreements established by the company with agents in the environment and the transmission of tacit knowledge, especially among entities belonging to the association itself. Based on the above, the following hypothesis is proposed:

Hypothesis 2 (+): *There is a positive and significant relationship between active membership in a business association and the degree of cooperation of firms with surrounding agents.*

2.3. Industrial Clustering, Cooperation and Innovation

In today's knowledge society, access to external sources of valuable information and knowledge is essential for the survival of firms [38,39]. According to Audretsch, Hülsbeck, and Lehmann [40], collaborative networks contribute to the increased competitiveness of countries and regions through the pooling of resources and capabilities for the joint development of innovations.

Intangible resources based on knowledge drive the creation of value by companies [41] and favor their constant adaptation to current dynamic environments, in which it is difficult to make reliable forecasts [42]. This flexibility, in turn, facilitates access to new technologies and knowledge, as well as their assimilation and exploitation [43].

Geographical proximity does not automatically imply the establishment of cooperation agreements between entities located in a given region [44]. Interorganizational learning and the joint development of innovations seems to require, in addition to physical proximity, the existence of social and cognitive proximity between specialized economic agents located geographically close, which allows them to communicate effectively [45–47]. In this respect, industrial agglomeration implies the existence of a large number of entities that, in addition to being located geographically close, are specialized in a main industry, which can have a positive impact on social and cognitive proximity.

This can favor the membership of certain specialized social networks that, according to Alguezaui and Filieri [48], allows firms to access a wide set of valuable resources and capabilities shared by their members, especially new knowledge, which is an essential factor in the development of innovations.

Industrial agglomeration fosters the generation of a favorable environment for inter-firm cooperation [49]. The geographical proximity derived from industrial agglomeration fosters the generation of links between economic agents belonging to a main industry, and boosts the strength of relationships, trust, the existence of shared values, and the efficiency and effectiveness with which knowledge is transferred [50–52].

Thus, the interaction between individuals derived from collaboration with external agents allows firms to increase their knowledge base and establish mutually beneficial relationships [53–55]. By making constant efforts in this area, collective learning dynamics are generated that drive the development of innovations [56–58]. In particular, the effective exploitation of external knowledge sources has a positive effect on the innovative performance of firms [59].

Although studies linked to the analysis of the so-called "New Economic Geography" provide certain theoretical explanations in this regard [60], at present there is still some confusion when trying to determine which of the positive externalities generated by industrial agglomeration favor the development of firms and their innovative performance [61]. Thus, this paper proposes that cooperation is one of the main factors derived from industrial agglomeration that favors the innovative performance of firms. Based on this, the following hypothesis is proposed.

Hypothesis 3 (+): *The degree of cooperation of firms with surrounding agents mediates the relationship between the degree of agglomeration of the sector and the innovative performance of firms.*

3. Methodology

3.1. Population and Sample

The population being studied is made up of the companies belonging to the electricity supply sector in Spain. According to the "Sistema de Análisis de Balances Ibéricos (SABI)" database, the number of active companies in Spain for the year 2019 is 13,339.

The sample is comprised of 197 companies in the sector, located in different regions of Spain. Although this sector only employs 2% of the total number of workers in Spain, its activity generates 13.3% of the gross added value, which positions it as the second most important sector, being only surpassed by the "Food, beverages and tobacco" sector, as well as presenting the highest average productivity per employee (449,800 euros) (According to the data issued by the National Statistics Institute for the financial year 2017: https://www.ine.es/, accessed on 3 February 2022).

3.2. Data Collection and Measurement of Variables

The data used to test the hypotheses come from both primary and secondary sources. In relation to the former, the data were obtained through the design and distribution of a questionnaire to the companies in the population under study (The questionnaire is described in detail in Appendix A). A total of 11,757 emails were sent out, addressed to the companies' management staff, as they were considered to have a broad knowledge of the general functioning of the organization, as well as of the main decision-making bodies. The tools used for the design and distribution of the questionnaire were "Qualtrics" and "Microsoft Outlook" software, version January 2021, Qualtrics, Washington, DC, USA, respectively.

The questionnaire distribution process covered a period of 4 months, specifically from September to December 2020, during which, in addition to the initial mailing, several reminders were sent out, as well as telephone calls to encourage participants to collaborate with the research. After analyzing the completed questionnaires to determine their statistical validity, and after discarding any that were not considered valid (for different reasons, such as the existence of a large number of missing values, the presence of response patterns or a high number of single-value responses), a sample of 197 valid responses was collected. Hair, Hult, Ringle, and Sarstedt [62] establish, through their "minimum R^2" method, that for a minimum R^2 value of the model equal to 0.500 and a maximum number of predictors of 2, the minimum sample size is 33 cases.

Regarding the secondary sources, we used the SABI database to determine the degree of agglomeration of companies and employment in the sector, as it allows us to determine the exact number of employees per company, as well as the number of companies per province, which increases the precision of the study. Due to the peculiarities inherent to the territorial organization of Spain, we decided to take the province as the territorial delimitation. In this way, the fifty provinces and the autonomous cities of Ceuta and Melilla were considered.

Innovative performance (dependent variable): A 7-point Likert-type scale with 13 items was used to measure this reflective variable. Specifically, validated scales of 5, 4, 3, and 1 items were used to measure the innovative performance of product, process, marketing, and management, respectively, based on the works of Prajogo and Ahmed [63] and Škerlavaj, Song, and Lee [64].

Degree of agglomeration of the sector (independent variable): This formative variable determines the degree of concentration of the sector under study in each of the regions. The geographical concentration of firms is measured in different ways in the agglomeration literature. Some studies use the density of firms in each specific industry and geographical area [65–67], while others use employment data [68,69]. In this paper, both indicators were used to calculate this construct. This type of coefficient has been widely used in many empirical works related to the study of clusters. Although they are simple indicators, they make it possible to determine in a clear and comprehensible way the regional distribution of companies and employees belonging to a given sector or industry. As territorial units of analysis we used the 50 provinces and 2 autonomous cities of Spain. Once the territorial division was established, the degree of regional concentration of employment and companies in the sector was analyzed in relation to the national average, by using the following coefficient

$$AC = (a{:}b){:}(c{:}d) \tag{1}$$

where AC: agglomeration coefficient. a: Sector units at regional level. b: Total units at regional level. c: Sector units at national level. d: Total units at national level [65–69].

This coefficient should be interpreted as follows. Regions that present a value greater than 1 have a degree of concentration of employees and/or companies in the sector that is greater than the national average. The higher the value of the coefficient, the greater the degree of concentration in the region in question.

Cooperation (mediating variable): Firms mainly have access to new knowledge through internal development or from external sources [70]. In this line, several authors highlight the role of cooperation with accessible external sources as a tool that allows the generation of ideas and knowledge sharing and, consequently, favors the increase of the knowledge base of the participating companies [71–73]. Thus, it is proposed that the degree of cooperation between firms and the different nodes of their network of relationships can be favored by belonging to a business association. This paper proposes that cooperation mediates the relationship between the degree of agglomeration of the sector and the innovative performance of firms. This reflective variable refers to the extent to which firms cooperate with the main stakeholders in their environment (competing firms, suppliers, customers, universities, technology centers, and other entities). It was measured by means of a Likert-type scale of 7 points and 6 items, which was elaborated based on the work of Claver-Cortés, Marco-Lajara, and Manresa-Marhuenda [74].

Association (antecedent variable): According to Dalziel [17], associations are non-profit entities that bring together a high proportion of entrepreneurs in each sector and region. These associations defend the interests of their members and promote cooperation among them. Likewise, membership and participation in the association can favor the generation of relationships of trust between members, which in turn can influence their willingness to cooperate in a wide range of areas, pooling their resources and capabilities to achieve shared objectives. Association was established as an antecedent variable of cooperation. This reflective variable was measured by means of a 7-point Likert-type scale with 3 items, reflecting membership or not of an association and the type of participation, active or passive, of the associates.

3.3. Analysis Technique

To test the hypotheses, structural equation modelling (SEM) was used; specifically, the second-generation multivariate analysis technique of partial least squares (PLS), which according to Hair, Sarstedt, Pieper, and Ringle [75], has gained great relevance in recent years among researchers in the field of strategic management of the company.

For this purpose, the SmartPLS software, version 3.3.3 was used [76]. According to Hair, Hult, Ringle, Sarstedt, Castillo Apraiz, Cepeda Carrión, and Roldán [77], it is a suitable technique for predictive analytics, especially in the field of social sciences. In addition, it allows us to test models of linear relationships between variables, including those of a latent nature.

The PLS-SEM technique uses the maximization of the explained variance of the observable and unobservable variables to estimate the parameters of the established model [78]. According to these authors, due to the above, this technique is particularly suitable for research in the field of social sciences. It has been evidenced that the PLS-SEM method obtains greater flexibility and robustness than traditional approaches [79].

This method of analysis has been chosen for different reasons. Fundamentally, because the study is predictive in nature, making it suitable for the use of the PLS-SEM technique [80]. In addition, it is an efficient tool for the estimation of complex models, which allows working with relatively small sample sizes, and with data that do not follow a specific distribution [77].

Finally, the proposed model includes second-order latent variables, and the PLS technique allows us to efficiently estimate this type of multidimensional model [81].

4. Data Analysis and Results

4.1. Data Analysis and Results

The results of the first phase of analysis, relating to the distribution of the sector in Spain, are presented in Table 1 below. Specifically, the values corresponding to the degree of agglomeration of the sector (companies and employment) at the provincial level, in comparison with the national average, are shown. The distribution of the sample according to the degree of agglomeration of the sector in the province in which they are located, in relation to the national average, is also shown.

Table 1. Distribution of the sample in relation to the degree of agglomeration of the sector under study, in absolute and relative values.

Coefficient	Degree of Agglomeration of the Region	Number of Firms of the Sample	Percentage of the Sample
Employees	Higher than the national average	114 companies	57.87%
	Lower than the national average	83 companies	42.13%
Companies	Higher than the national average	112 companies	56.85%
	Lower than the national average	85 companies	43.15%

Table 2 details the distribution of the population of companies compared to the sample in relative terms, according to their location or not, in a region that presents agglomeration of firms or employment in the sector, in comparison with the national average.

Table 2. Comparison of the distribution of the population and the sample in relation to the degree of agglomeration of the sector under study, in relative values.

Coefficient	Degree of Agglomeration of the Region	Percentage of the Population	Percentage of the Sample
Employees	Higher than the national average	66.09%	57.87%
	Lower than the national average	33.91%	42.13%
Companies	Higher than the national average	66.62%	56.85%
	Lower than the national average	33.38%	43.15%

Table 3 shows brief descriptive statistics of the data obtained in the questionnaire.

Table 3. Descriptive statistic of the data obtained in the questionnaire.

	Mean	Min	Max	S.D.
Cooperation	4.396	1	7	1.726
Association	1.868	1	3	0.776
I.P.	4.809	1	7	1.590
D.A.S.	1.086	0.059	4.743	0.928

Note: D.A.S.: Degree of agglomeration of the sector. I.P.: Innovative performance. S.D.: Standard deviation.

Finally, Figures 1 and 2 show in detail the agglomeration coefficient of the sector under study in each of the provinces, in relation to the number of companies and employment, respectively. To facilitate its reading, a color range has been established, which varies from dark red, for levels of agglomeration much lower than the national average, to dark green, for high levels of agglomeration. The other colors indicate intermediate levels.

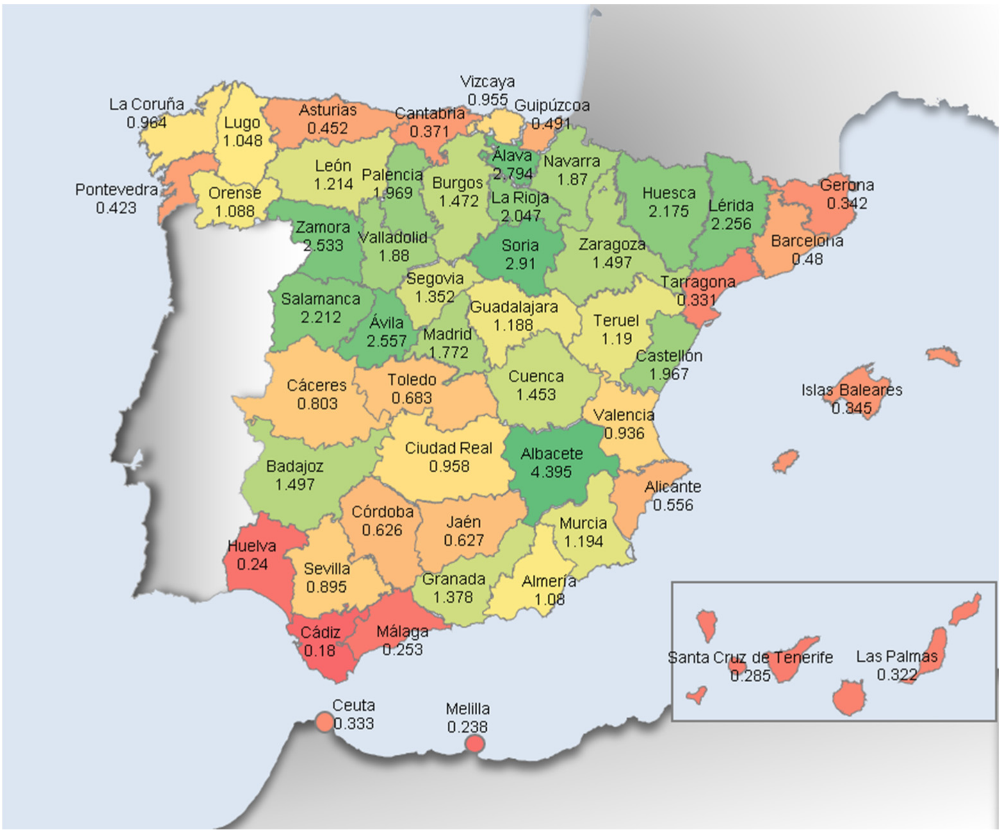

Figure 1. Degree of agglomeration of companies in the sector at the provincial level in Spain.

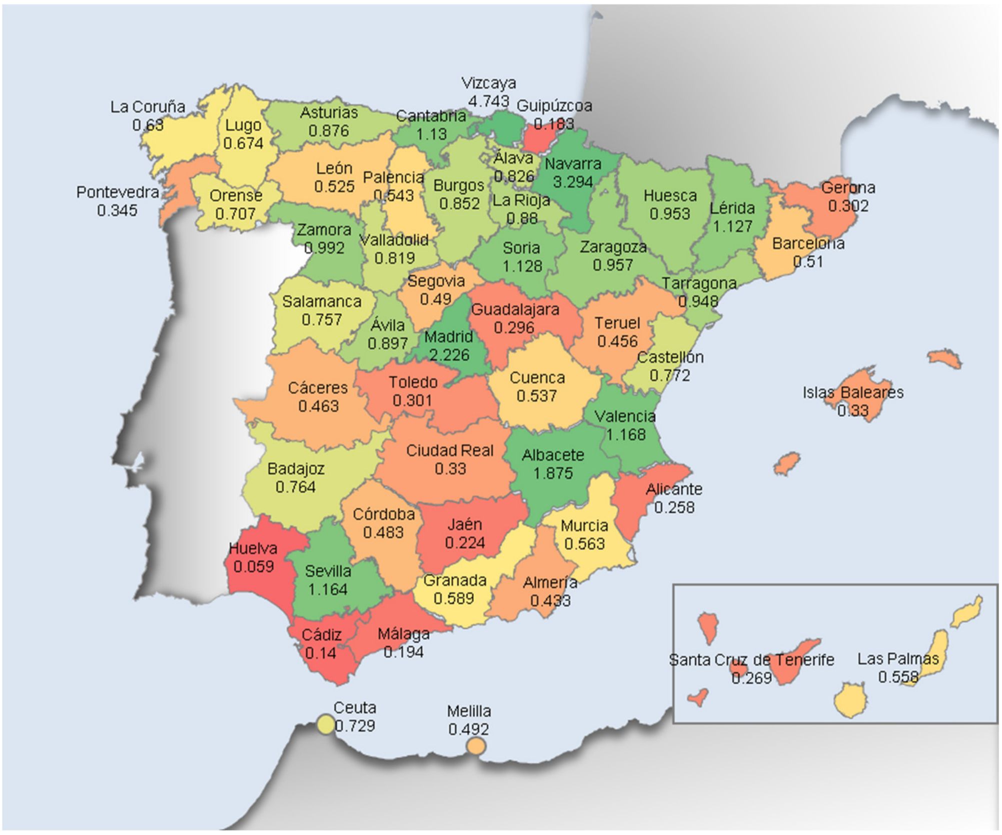

Figure 2. Degree of agglomeration of employment in the sector at the provincial level in Spain.

4.2. Model Evaluation

The model under analysis includes multidimensional constructs that, according to [82], are composed of different related dimensions that can be analyzed as a single theoretical concept. According to Van Riel, Henseler, Kemény, and Sasovova [83], a first analysis should be performed to obtain the scores of the first-order latent variables, which will be used in the subsequent analysis to model the second-order constructs. PLS is an effective tool for process [84]. Ringle, Sarstedt, and Straub [85] state that this two-stage process, commonly used in social science research, allows the second-order construct to be established in an endogenous way within the structural model.

The results obtained after evaluating the research model using PLS-SEM, which, according to Hair et al. [77], should be carried out in two stages, the first corresponding to the measurement model and the second to the structural model, which are presented below. The final models, both saturated and estimated, present a good fit, as they have a standardized root mean square residual [SRMSR] value of $0.057 < 0.08$ [86].

4.2.1. Evaluation of the Formative and Reflective Measurement Models

When evaluating measurement models, different criteria must be followed depending on the type of construct involved, formative or reflective [77]. For the evaluation of the formative model (degree of sector agglomeration), a single item representing the essence of the latent variable that formative indicators seek to measure is used [87]. In this first step, which is also called "redundancy analysis" [88] and determines the convergent validity of the model, the degree of correlation between the different measures of the same construct is assessed by using different indicators. For this, the formative latent variable is used as an exogenous variable, which acts as a predictor of another endogenous construct that uses other indicators of a reflective nature.

Although, generally, the use of individual indicators is not recommended when using the PLS technique, in the case of redundancy analysis it is appropriate, since its objective is not to capture the total content of the construct but simply its fundamental elements, to have a standard of comparison [77].

Thus, this item, called "PSecGDP", indicates the percentage share of the sector under study of the GDP at the provincial level (For its calculation, secondary data obtained from the SABI database and the National Statistics Institute (INE) are used). According to Hair et al. [77], the value of the path coefficient between the two constructs should be greater than 0.7 and the value of R^2 greater than 0.5. The path coefficient between both formative and reflective indicators takes the value $0.916 > 0.8$, and the R^2 amounts to $0.839 > 0.5$, which means that the formative measurement model meets the convergent validity criterion.

The degree of collinearity of the formative indicators is significantly lower than the critical values set, as the VIF value amounts to $1.192 < 3$ [89]. Finally, the significance and relevance of the formative indicators are assessed.

After running the bootstrapping process, in full mode and 5,000 random subsamples, it was found that both the weights and the external loadings of the formative indicators have significantly different values from zero, both in relative terms (External weights: L1 = 0.583 (Employment agglomeration coefficient); L2 = 0.612 (Agglomeration coefficient of the companies)) and in absolute terms (External loadings: L1 = 0.828; L2 = 0.846), which indicates that their contribution to the construct is high.

To evaluate the reflective model, internal consistency and convergent and discriminant validity must be analyzed [77]. According to these authors, in the first case, three methods are used: Cronbach's alpha (Tends to underestimate internal consistency reliability) (α), composite reliability (Tends to overestimate internal consistency reliability) (ρc) and Dijkstra–Henseler's rho (It is considered a measure of consistent reliability) (ρA).

As can be seen in Table 4, all values are significantly higher than 0.7 [77,88,90]. To confirm convergent validity, the measurement is performed by assessing the reliability of the indicators, that is, the size of the external loadings (λ) and the average variance extracted

(AVE), which refers to the total mean value of the loadings of the indicators belonging to the same construct squared [77]. Furthermore, it is observed that the value of the external loadings is greater than 0.707, and the AVE > 0.5, so this criterion is also met [77,91].

Table 4. Assessment of internal consistency and convergent validity.

Variables	**Cronbach's Alpha**	**Rho_A**	**Composite Reliability**	**Average Variance Extracted**
Association	1 indicator	1 indicator	1 indicator	1 indicator
Cooperation	0.885	0.885	0.913	0.638
I.P.	0.847	0.851	0.897	0.686
External Loads (λ)				
	Cooperation		Innovative Performance	
COOP customers	0.859			
COOP competitors	0.787			
COOP Tech. centers	0.713			
COOP others	0.756			
COOP suppliers	0.828			
COOP universities	0.841			
I.P. management			0.810	
I.P. marketing			0.786	
I.P. process			0.857	
I.P. product			0.858	

Note: COOP: Cooperation. Tech.: Technology. I.P.: Innovative performance.

Traditionally, two methods are used: cross-loading analysis and the Fornell and Larcker method. Although both criteria are fulfilled, according to [91], these methods have certain shortcomings that affect the detection of discriminant validity problems. These authors determine that the heterotrait–monotrait ratio (HTMT) is a more effective tool for this purpose.

According to Kline [92], the value of the HTMT ratio should be less than 0.85. Table 5 shows that the model largely meets this requirement.

Table 5. Evaluation of discriminant validity.

Heterotrait–Monotrait Ratio (HTMT)			
	Association	Cooperation	I.P.
Association			
Cooperation	0.631		
I.P.	0.522	0.744	

Note: I.P.: Innovative performance.

4.2.2. Evaluation of the Structural Model

The evaluation of the structural model allows us to determine the predictive capacity of the model and the type of relationships existing between the different latent variables that compose it and, consequently, to test the hypotheses put forward in the theoretical framework.

To this end, according to Hair et al. [77] the following elements must be analyzed: the significance level and relevance of the relationships, the value of the coefficients of determination (R^2), collinearity, effect size f^2, and predictive relevance (Q^2).

Figure 3 shows the nomogram, where the path coefficients obtained by running the bootstrapping process in full mode and 5000 random subsamples can be observed. Tables 6 and 7 show data corresponding to the direct and indirect effects, respectively.

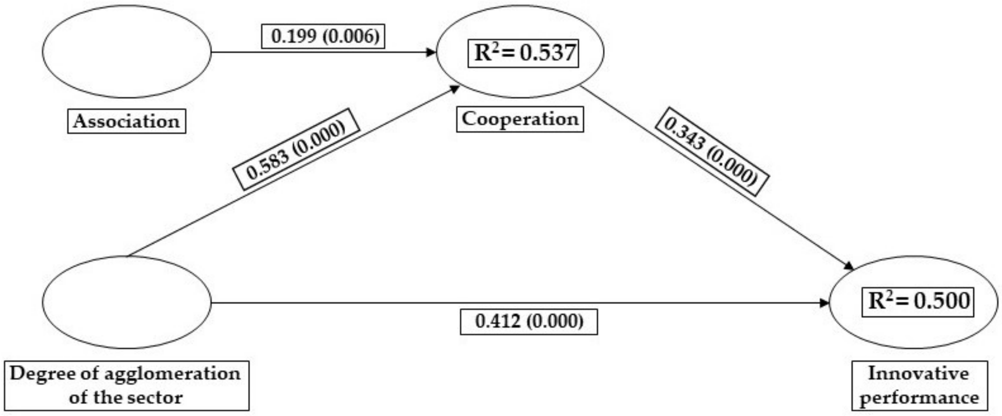

Figure 3. Path coefficients and significance levels of the proposed model.

Table 6. Summary of direct effects.

Structural Path	Coef. (β)	S.D.	*p*-Values	t0.005. 4999	99% C.I.	Results
D.A.S. -> Cooperation	0.583 **	0.066	0.000	8.808	[0.426–0.739]	
D.A.S. -> I.P.	0.412 **	0.081	0.000	4.991	[0.211–0.596]	H1 (+) ✓
Association -> Cooperation	0.199 **	0.076	0.006	2.640	[0.017–0.363]	H2 (+) ✓
Cooperation -> I.P.	0.343 **	0.094	0.000	3.646	[0.124–0.558]	

Note: C.I.: Confidence interval. D.A.S.: Degree of agglomeration of the sector. I.P.: Innovative performance. Coef.: Coefficient. S.D.: Standard deviation. ** Statistically significant at 1%.

Table 7. Summary of indirect effects.

Total Effect of D.A.S. on I.P.		Direct Effect of D.A.S. on I.P.		Indirect Effect of D.A.S. on I.P.			Results
Coef. (β)	t0.005, 4999	Coef. (β)	t0.005, 4999	Estimate	t0.005, 4999	C.I. 99%	
0.612 **	14.241	0.412 **	4.991	0.200	3.028	[0.067–0.371]	H3 (+) ✓

Note: C.I.: Confidence interval. D.A.S.: Degree of agglomeration of the sector. I.P.: Innovative performance. Coef: Coefficient. ** Statistically significant at 1%.

When analyzing the data, it is observed that there is no collinearity, as all VIF values are less than three [89]. There is a positive and significant direct effect of the degree of industry agglomeration on the innovative performance of firms [0.412, p = 0.000]. In addition, there is a positive and significant indirect effect produced by the mediation of the variable "Cooperation" [0.200, p = 0.000]. The proposed model explains 53.7% and 50.8% of the variance of the constructs "Cooperation" and "Innovative Performance", respectively.

Furthermore, the contribution of the exogenous construct "Degree of industry agglomeration" to the R^2 value of the endogenous latent variables "Cooperation" and "Innovative Performance" (f^2) is large [0.397] and median [0.167], in this order, based on the values proposed by [93]. In turn, the contribution of the exogenous construct "Cooperation" to the R^2 value of the endogenous latent variable "Innovative Performance" is median [0.115]. The data point to the existence of a direct and positive effect of belonging to an association on the degree of cooperation of firms [0.199, p =0.006], although the contribution of the exogenous construct "Association" on the endogenous latent variable "Cooperation" is small [93].

Finally, the values of the endogenous variables' "cooperation" and "innovative performance" have Q^2 values 0.335 and 0.341, respectively, which indicates that the model has a moderate predictive relevance on the mentioned variables, in accordance with the values established by Hair, Risher, Sarstedt, and Ringle [94]. Based on these data, the three hypotheses are confirmed:

✓ **H1 (+):** *There is a positive and significant relationship between the degree of agglomeration of the sector and the innovative performance of firms.*

✓ **H2 (+):** *There is a positive and significant relationship between active membership in a business association and the degree of cooperation of firms with surrounding agents.*

✓ **H3 (+):** *The degree of cooperation of firms with surrounding agents mediates the relationship between the degree of agglomeration of the sector and the innovative performance of firms.*

5. Conclusions

This paper contributes to the existing literature on the analysis of positive externalities derived from industrial agglomeration, particularly those related to cooperation and the innovative performance of firms. The three hypotheses are confirmed, thus establishing a positive and significant relationship between the variables of the proposed model. Based on these findings, three main conclusions are established. First, the positive externalities derived from industrial agglomeration boost the innovative performance of firms. Second, cooperation between specialized entities is established as an important positive externality derived from industrial agglomeration, which has a positive effect on the innovative performance of firms. Finally, business associations foster cooperation, especially among their associates, and act as representative entities that facilitate the establishment of agreements at the superstructure level.

Collaboration with external actors in knowledge sharing and the development of collaborative innovation processes increases the chances of superior innovative performance [95]. However, firms should carefully select the partners with whom they cooperate, as this is an element that directly influences the outcomes of partnerships [96]. In this regard, belonging to a region with a high degree of agglomeration in each sector implies a high degree of specialization of the linked firms [27].

Thus, industrial agglomeration derives from the existence of specialized entities located geographically close, which translates into the availability of potentially valuable partners with which to establish cooperation agreements. In addition, business associations play an intermediary role that favors cooperation at different levels. In this context, continuous interaction with specialized industry players boosts the innovative performance of firms [97].

The results obtained in this study highlight the importance of location and cooperation as drivers of firms' innovative performance. The environment in which they are located can provide opportunities for access to potential sources of valuable resources and capabilities, especially new knowledge. Therefore, despite globalization and the accelerated development of information and communication technologies in recent decades, and especially in recent years, there are certain elements associated with geographical and cognitive proximity that favor the effective transfer of knowledge and the innovative performance of companies. For this reason, it is necessary to continue to study industrial agglomeration in depth as a tool for regional economic development and competitiveness.

In relation to the limitations of the work, it is worth highlighting the eminently external focus of the study. Thus, in future work it would be interesting to incorporate the influence of the internal factors of the companies in the study of the determinants of their innovative performance. In particular, it would be interesting to incorporate the absorptive capacity of firms, which could influence the degree to which firms benefit from collaboration with external agents [98].

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Appendix A

Concept	Items	Definition	Measurement
Cooperation	Coop1	Degree to which your company cooperates with its customers.	Likert scale (−3 = Far inferior relative to my competitors; +3 = Far superior relative to my competitors).
	Coop2	Extent to which your company cooperates with its suppliers.	
	Coop3	Degree to which your company cooperates with its competitors.	
	Coop4	Extent to which your company cooperates with universities.	
	Coop5	Extent to which your company cooperates with technology centers.	
	Coop6	Extent to which your company cooperates with other types of institutions.	
Association	Asoc1	Yes, and actively participates.	Single election.
	Asoc2	Yes, but it does NOT actively participate.	
	Asoc3	No.	
Innovative performance	DI1	Degree of novelty of our new products.	Likert scale (−3 = Far inferior relative to my competitors; +3 = Far superior relative to my competitors).
	DI2	Use of the latest technological innovations in the new products developed by my company.	
	DI3	Speed of new product development.	
	DI4	Number of new products introduced by my company in the market.	
	DI5	Number of our new products that are new to the market (they are the first to be launched on the market).	
	DI6	Level of technological competitiveness of my company.	
	DI7	Speed with which the latest technological innovations are adopted in our processes.	
	DI8	Degree to which the technology used in our processes is up to date or new.	
	DI9	Pace of updating our processes, techniques, and technologies.	
	DI10	In my company, the development of new distribution channels for products and services is an ongoing process.	Likert scale (−3 = Strongly disagree; +3 = Strongly agree).
	DI11	In my company, customer suggestions or complaints are handled with urgency and attention.	
	DI12	My company develops better marketing innovations than its competitors.	
	DI13	My company constantly emphasizes and introduces management innovations.	

Concept	Items	Definition	Measurement
Size	TM	Company size.	Number of employees as of 31 December 2020
Age	ANT	Seniority of the company.	Years elapsed between the date of incorporation and fiscal year 2020

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