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The effect of innovation efficiency management on performance: Differences according to organizational size

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Abstract

The efficiency associated with innovation has been a frequently considered element in the literature. However, the conceptualization of this efficiency and its management is an underexplored factor. We study the way in which the different elements that conform to this efficiency are managed over time. From a dynamic efficiency analysis using data envelope analysis (DEA) and the Malmquist productivity index, we evaluate changes in efficiency and if there are differences according to firm size. Our results confirm the relevance of size in the way that firms manage their innovation efficiency and how small firms differ from larger ones in terms of efficiency management.

1 | INTRODUCTION

Innovation is considered an important and sustainable source of long-term success of organizations (Khosravi et al., 2019), but the challenges associated with innovations require oriented management. Innovation management takes into consideration a set of decisions regarding the development and renewal of a firm's offer by choosing the appropriate mix of innovations and why and how to achieve it (Onufrey & Bergek, 2021).

Following prior studies (Martínez-Alonso et al., 2020), instead of focusing independently on innovation inputs, activities or outputs, we assume that technological innovation efficiency plays a crucial role in understanding how firms achieve growth and performance. Technological innovation efficiency refers to the relative capacity to transform inputs into outputs (Cruz-Cázares et al., 2013). This approach becomes even more important as innovation is a complex, multidimensional and cross-cutting concept. In this sense, there is little empirical evidence on the process by which innovation is related to the creation of a competitive advantage (Kim et al., 2015) and, consequently, to an increase in performance (Khosravi et al., 2019). In this study, we want to delve into the idea that the relationship between innovation efficiency and performance occurs, and if it is different according to the organizational size (Khosravi et al., 2019), deepening into the research line opened by prior works such as Sullivan and Kang (1999), Damanpour (1996) or Hitt et al. (1990), among others.

Therefore, despite the existing literature, there are still many unanswered questions about how to manage innovation to achieve better performance. In this sense, this paper seeks to deepen the understanding of how innovation management can act as a potential source of competitive advantage. because, while the area of innovative inputs is much more studied, there is little research bearing in mind also the innovative capacity, that is, the ability to transform these inputs into desirable products/services. (Moon, 2013).

To achieve this objective, this paper starts from the consideration that innovation must be understood as the ability to develop a process in which the firm is able to combine the innovative inputs in which it invests with its ability to transform them into desirable products/services. Therefore, R&D expenditure policies and their ability to support continuous innovation will determine organizational performance.

The R&D expenditure policy has been one of the most discussed in aspects the literature, but the conclusions achieved offer diverse results divergent in terms of the impact on the company's performance. Although the literature differentiates between internal and external R&D expenditures, the results are yet inconclusive in terms of their impact on performance. This paper seeks to contribute to this debate and introduce the discussion about the existence of differences in such policy depending on the organizational size.

Another point to be studied is the output of such expenditures, that is, the capacity of companies to transform inputs and create new products. The literature presents various models that try to show the innovation capacity of the company, the ability to transform R&D expenditures into innovative products and the pursuit of continuous innovation. When we consider the complexity of this transformation because there are aspects that are difficult to measure, such as the implicit knowledge of the personnel involved, in the concept of 'innovation efficiency', understood as the relative capacity of a company to maximize the results of innovation (Cruz-Cázares et al., 2013,), we find the path that allows us to approach innovation as a capacity and innovation management as a dynamic process, according to the resource-based view (RBV) that we take as a frame of reference for this research. We have opted for innovative efficiency as a measure of innovative capacity, as it allows us to link R&D inputs with R&D results because it analyses the overall effect of the possible desired and undesired outcomes of the innovation process.

Furthermore, the literature has highlighted the particularities of management in SMEs versus large companies. Many studies analyse this issue in large companies; however, there is less literature available that collects the drivers of innovation practices in SMEs (Modi & Rawani, 2021).

In short, in this work, we consider innovation as the ability to develop a process that combines the policies of spending on R&D with the capacity for innovation or transformation, acting as everything to increase performance, and we raise management differences taking into account the size of the organization. Our interest focuses on the theoretical discrepancies raised, in which we will deepen our theoretical analysis.

This document is structured as follows. First, we establish the theoretical framework that will allow us to propose the hypotheses. The following section describes the sample and the methodology that will help us evaluate these hypotheses. The document continues with the results obtained and concludes with the debate and our conclusions.

2 | THEORETICAL FRAMEWORK

One important aspect related to innovation in our days is how firms deal with technological innovation efficiency (Asimakopoulos et al., 2020; Martínez-Alonso et al., 2020). However, most of the firms do operate with a limited amount of resources (Boronat-Navarro et al., 2021), and given these resource constraints, they must decide what actions to take in order to remain competitive. Thus, many authors suggest that the continuous renovation of products and processes is the key to achieving sustainable competitive advantage (Geroski, 1989).

From the perspective of efficiency, companies must achieve the highest possible volume of outputs from a given set of inputs. Although this approach has been present in the study of innovation (Cruz-Cázares et al., 2013; Manzaneque et al., 2018; Martínez-Alonso et al., 2020), it is also true that on many occasions this innovation management has been observed either from the point of view of inputs (Nguyen, Dang, et al., 2021) or from outputs (Boronat-Navarro et al., 2021). However, we can see such a process from an ambidexterity perspective, this is combining inputs and outputs policies simultaneously. Thus, we consider that 'organisational ambidexterity allows firms to integrate and mobilize different and often contradictory internal structures, activities, or processes' (Tushman & O'Reilly, 1996, p. 1337). This perspective has been omitted from the literature that has analysed innovation from an efficiency perspective. Therefore, although ambidexterity has been raised very frequently in the literature (Boronat-Navarro et al., 2021; Dranev et al., 2020), it has rarely been considered that this form of management can be employed simultaneously from the perspective of inputs and outputs (Cruz-Cázares et al., 2013).

In our case, to consider efficiency and its influence on firm performance, we consider the fact that firms must make two crucial decisions. On the one hand, companies have to decide where to spend the limited resources at their disposal. Firms must decide whether to invest in the internal development and control of the innovation process, or whether to accelerate the innovation process through external acquisition of all or part of the results (Asimakopoulos et al., 2020; Boronat-Navarro et al., 2021; Nguyen, Dang, et al., 2021), but at the same time, they must decide whether to base profitability on the continuous renovation of products and processes (Geroski, 1989), or whether to maximize profitability and exercise some control over the product rollover (Li & Yang, 2020).

2.1 | R&D Expenditure Policies

The innovative process begins when a firm decides to make a certain investment in R&D. Spescha (2019) reviews the possible relationship of R&D expenditures and firm growth. In this paper, Spescha (2019) identifies a positive relationship, in particular in smaller firms. However, this paper does not consider the effect of developing an internal R&D expenditure or an external R&D expenditure. However, this decision is more complex, as there is a need to determine the right combination of internal technology development and external technology acquisition (Nguyen, Dang, et al., 2021).

To answer these questions, some authors have suggested that successful innovative firms rely on both types of expenditures (Love et al., 2014). However, the advantages brought about by external acquisition of technology (Medda, 2020), such as speeding up technology commercialization and improving business performance (Añón Higón et al., 2018) have gained importance among firms (García-Vega & Huergo, 2019).

Wang et al. (2021) propose that internal expenditures in R&D can create a competitive advantage for a firm (Cassiman & Veugelers, 2006), but innovative firms also require technology or knowledge from external sources when developing their innovations.

Thus, performance depends on the alignment of the company's internal experience and external sources of innovation (Nguyen, Dang, et al., 2021) as a guarantee of success (Hansen, 2001), based on its learning processes and the development of its organizational competencies (Thomä & Zimmermann, 2020). This alignment or equilibrium is based on the combination, integration and acquisition of knowledge from internal and external sources, which can guarantee the generation of R&D (Hervás-Oliver et al., 2021; Medda, 2020; Thomä & Zimmermann, 2020) since overexposure to any of them can lead to worse results than those that could be obtained with an optimal combination (Ceptureanu et al., 2021; Grimpe & Kaiser, 2010). Therefore, the company will try to balance different R&D investments, that is, internal and external spending on R&D in the search for better performance (Ceptureanu et al., 2021; Wang et al., 2021).

The problem about this approach is whether firms performing simultaneously internal and external R&D expenditures achieve higher innovation performance than firms exploiting only one of the knowledge sources has received considerable attention in the literature on innovation (Wang et al., 2021), this is if firms can cope with ambidexterity in R&D sourcing.

Most of the existing studies found a complementary relationship between internal and external R&D expenditures (Asimakopoulos et al., 2020; Nguyen, Huang, et al., 2021), despite other studies found this relationship as uncomplimentary or substitutive. Thus, Laursen and Salter (2006) found substitutive relationships between both types of R&D expenditures and Alarcón and Sánchez (2013) found no complementary relationship. More recent analysis, such as that developed by Wang et al. (2021), confirmed the substitutive relationship between internal and external R&D expenditures.

When evaluating the effect on performance, it has been posed that performance depends on the alignment of the company's internal experience and external sources of innovation (Nguyen, Dang, et al., 2021) as a guarantee of success (Hansen, 2001), based on its learning processes and the development of its organizational competencies (Thomä & Zimmermann, 2020). This alignment or equilibrium is based on the combination, integration and acquisition of knowledge from internal and external sources, which can guarantee the generation of R&D. One of the key elements that has been identified as a determinant of the capacity to manage the ambidexterity of R&D expenditures is the size of the firm (Boronat-Navarro et al., 2021; Wang et al., 2021). The question is whether there are differences in internal and external R&D expenditures depending on the size of the company, being negative in SMEs and positive in large companies. This fact can be explained because smaller firms present different attitudes towards the innovation process (Triguero et al., 2013).

However, regardless of size, the evidence found does not show a clear relationship with future performance, and most empirical studies are related to short-term effects. Thus, to these questions must be added the dynamic and transversal nature of innovation management.

These considerations lead to the following hypotheses regarding R&D expenditure policies.

H1. The R&D expenditure policy (internal over external expenditures) has a direct, significant and positive influence on the company's performance.

2.2 | Managing outputs

The other side of innovation efficiency is related to the company's relative ability to maximize innovation results, given a certain amount of innovation inputs (Cruz-Cázares et al., 2013). Thus, together with the inputs or expenditures, particular attention must be paid to the outputs. From the point of view of efficiency, companies can try to approach the frontier of efficiency by setting the level of inputs or the level of outputs, depending on their strategy, so we must assess the viability of both points of view. Although Guan and Chen (2010), referring to R&D, state that it is difficult to improve the products and results of innovation if R&D is not increased, some studies come to the opposite conclusion (Zhong et al., 2011).

Innovation pursues the introduction of new products. However, it is difficult to maintain a continuous innovation process and firms must develop an effective product portfolio management. Effective portfolio management is vital to successful product innovation (Cooper, 1984). Portfolio management 'is about translating innovation strategy intro investment decisions on specific new-products projects' (Cooper & Sommer, 2020, p. 30). As Cooper and Sommer (2020) pointed out, portfolio management faces different challenges such as resource balancing, choosing between products and projects or the number of undergoing projects.

Overall, the transition between old and new technologies or products is far from a discrete decision (Cohen & Tripsas, 2018). It is a process that must be observed from a long-term perspective, since some firms invest considerable amounts in revitalizing the old technology, in a 'last gasp' attempt to extend its life (Adner & Snow, 2010), even identifying the links between the old and new technologies should be managed throughout a transition (Cohen & Tripsas, 2018).

Therefore, it is necessary to estimate an efficiency model as a measure of innovation that takes into account both the perspectives and limitations of previous studies. Authors such as Vega-Jurado et al. (2008) consider the launch of new products as the only result of R&D investment; however, this approach is limited. However, works such as those of Triguero et al. (2013) show persistence in continuous innovation. Its results establish that past R&D activities will condition the future supply of products, and the analysis of the company's results depends not only on the exploitation of existing skills that allow its current viability through the sale of existing products but also on the exploration that leads to the development of new products on which future profitability will be based (Koryak et al., 2018). They consider exploration to be the fundamental mechanism by which companies learn and organizational knowledge evolves (Ceptureanu et al., 2021). The issue is that we must consider both the new products and the old products that companies keep in their portfolios as a result of their innovation capacity. Some works like Rosenkopf and Nerkar (2001) conclude that they consider that the success of the old products can restrict the portfolio of new products, limiting the future options of innovation for the development inside the company. Therefore, according to this approach, companies should favour innovative over noninnovative products. For others such as Liang et al. (2014) or Dawid et al. (2020), this approach is limited and the results of the company depend not only on the exploitation of existing skills that allow its current viability through the sale of existing products. For this approach, companies must look for innovative products because of the exploration/development/innovation of their products and in the exploration/development/routinization of existing products (Mudambi & Swift, 2011). In any case, both approaches raise the reciprocal relationship between new and old products that the company keeps in its portfolio, either with a one-dimensional or two-dimensional character. The exploitation/exploration concatenation will ensure that this relationship is maintained in the long term. Thus, assuming the will to develop a continuous innovation process, the firm will assume greater dependence on sales of new products than on sales of old products. Consequently, we propose the following.

H2. The dependency on innovation (sales from an old product compared to sales from a new product) has a direct, significant and positive influence on the company's performance.

2.3 | Innovation efficiency management

Innovation efficiency can be defined as the ability to transform innovation investments into products and profits (Wang et al., 2020; Wang & Wu, 2019). Indeed, innovation is based on exploration and exploitation decisions. Tushman and O'Reilly (1996) suggested that an organization's long-term success depends on its ability to exploit its current capabilities while simultaneously exploring fundamentally new competencies. In this sense, He and Wong (2015), as well as Rosenkopf and McGrath (2011), propose that companies that are successful in terms of innovation are those that implement both exploration and exploitation strategies while maintaining a balance. However, this position is difficult to achieve as its components are linked to opposing factors (Koryak et al., 2018). To understand this perspective, we must assume that the relationship between exploration and exploitation occurs over time. Thus, the present exploration activity is a consequence of past exploration activities, and the present exploration activity will be the cause of future exploitation activities. Innovation is the engine of any activity, whether exploration or exploitation. This leads us to introduce the time dimension of innovation into our work.

However, much of the literature has not considered innovation management from an adaptive and responsive perspective. Most papers have considered the relationship between variables without attempting to evaluate or propose ways of improvement, this is to measure efficiency change over time.

In our case, we must consider that, as stated above, the capacity to manage innovation includes all the complexity and multidimensionality of the concept of innovation. To do so, we must reduce the abstraction of this capacity by finding a way to quantify and encompass its multidimensionality. It is necessary to define a way to measure innovation capability management. Although there are different alternatives for measuring innovation capacity (Saunila, 2020), we have opted for innovation efficiency as a measure of innovation capacity and changes in efficiency as innovation capacity management.

Vega-Jurado et al. (2008) proposed the existence of a link between the management of inputs and the innovative products that are achieved. However, little work has been done on the combined effect of external and internal factors on a company's innovation performance (Jiang et al., 2021). The combination of the two perspectives, inputs and outputs leads us to propose innovation efficiency will be determined by a combination of sources of innovation and the mix of products (new and old products). Therefore, companies deploy their R&D resources to make the most efficient use of these resources and enable them to gain a competitive advantage (Moon, 2013). Most studies that link efficiency and innovation have examined only the effect of innovation on overall efficiency of the company. However, there are few studies on innovative efficiency and its consequences, although this concept has begun to attract the attention of the academic community (Cruz-Cázares et al., 2013). The consideration of innovative efficiency as a measure of transformative capacity raises some research questions.

The evaluation of innovation efficiency, as aforementioned, requires identifying the determinants of both parts, the inputs of the process to be considered (Vega-Jurado et al., 2008). Although greater investments in R&D directly improve company performance without the intervention of innovation (Rodríguez & Nieto, 2015), they also do so indirectly by exposing the company to new and better resources and know-how (Jiang et al., 2021). The expected result is greater investment in R&D, a higher level of efficiency, higher levels of desirable results and lower undesirable results. This capacity is the ability to carry out the transformation of innovative inputs into an innovative output, and after what has been said before, we are going to consider investments in R&D as an input to this process. The question is whether R&D expenditure has a direct influence on performance but also indirectly through its transformation.

Faced with this dilemma, and according to Hannan and Freeman (1984), the search for this efficiency originates in specialized R&D investments since, through force of habit, firms tend to seek routine behaviours that increase efficiency motivated by learning (Nelson & Winter, 1982). However, and as has been proven, when an imbalance is created in favour of either innovative outputs (exploration) or existing outputs (exploitation), there is a negative effect on results (He & Wong, 2015; Tushman & O'Reilly, 1996). We can consider the two possibilities of conceptualizing the efficiency of innovation. Sueyoshi and Goto (2012, p. 646) proposed the analysis of efficiency by combining the two types of output unification for data envelope analysis (DEA) assessment by using a non-radial model. Thus, they suggest one unification by considering a decrease in an input vector along with a decrease in the vector of undesirable outputs. This type of unification is called natural disposability. The other unification considers an increase in an input vector but a decrease in the vector of undesirable outputs. This type of strategy is referred to as managerial disposability. Adapting this rationale to our work, we pose the question that an efficiency, which we will call *natural*, in this case, the development of new products is a unique result that the company expects from its innovative capacity. In this sense, most studies have adopted an approach that compares negative inputs with positive outputs. Cruz-Cázares et al. (2013) use the RBV to support the concept of transformation of firm resources into desirable results using internal capabilities and *managerial* efficiency in which the development of new products aims to replace existing ones.

Studies on innovation efficiency have focused almost exclusively on operational efficiency, and only a few cases have linked it to organizational outcomes and have also been approached from various perspectives (Cruz-Cázares et al., 2013). These perspectives range from the effect of inputs and outputs on a company's performance (Weerawardena et al., 2006) to the study of the long-term indirect effect of innovations achieved (García-Cabrera et al., 2021), and even some studies doubt the direct relationship (Zhong et al., 2011). Also, the empirical results of microeconomic studies of the effects on performance are still scarce and their results are not conclusive. In the work of Cruz-Cázares et al. (2013), together with Guan and Chen (2010) and Zhong et al. (2011), one of the few analyses that links innovation in efficiency with performance, they find a positive and significant effect on the performance of enterprises, since the enterprises studied were able to transform their resources efficiently. They have only contemplated natural efficiency. We consider the double perspective of efficiency, natural and managerial, thus incorporating new possibilities to the contributions of Cruz-Cázares et al. (2013), Guan and Chen (2010) or Zhong et al. (2011). Success is also measured by the combination of behaviours to renew your skills; keeping noninnovative products in your portfolio is a failure of current innovative interests, even though these could have been an innovative success in the past. Like Sueyoshi and Goto (2012), we raise this question in relation to modelling innovative efficiency. This perspective considers that companies not only produce desirable results—in this case, the addition of innovative products to their portfolio—but also undesirable results—in this case maintain existing or noninnovative products. Therefore, the question is whether both natural and managerial efficiency have a direct, significant and positive influence. Accordingly, we propose the following hypothesis.

H3. Long-term efficiency has a direct, significant and positive influence on the company's performance.

H3a. Long-term natural efficiency has a direct, significant and positive influence on the company's performance.

H3b. Long-term managerial efficiency has a direct, significant and positive influence on company performance.

Considering the delayed effect of innovation on performance that has been overlooked on numerous occasions (Guan et al., 2006), or the focus has been on short-term effects on company performance (Agarwal & Sambamurthy, 2002), we pose that the innovative efficiency is determined by the company's ability to manage appropriately over the long term. The time perspective is important because as long as innovative efficiency is maintained or improved, the company will continue to innovate in the future. New products would attract new investment and lead to new product launches in the future. Despite these positive linear trajectories, the company could react to negative results by changing both its R&D expenditure policies and its mix of new and existing products, as few companies can maintain their levels of innovation (Geroski et al., 1997). Existing empirical evidence on this point shows an inverted relationship in U with the sale of new products (Grimpe & Kaiser, 2010). However, we must consider that for firms to manage their innovative capacity, they must consider the two efficiencies, the natural and the managerial efficiency. These considerations lead us to the following hypotheses about the innovation capacity.

H4. Changes in natural efficiency have a direct, significant and positive influence on the performance of the company.

H5. Changes in managerial efficiency have a direct, significant and positive influence on company performance.

The question is whether R&D expenses have a significant and positive influence on the company's future performance, which will be lower in SMEs than in large companies. In terms of heterogeneity, we propose that the size of the company is a discriminatory criterion that leads to different innovation management (Wang et al., 2021). Although authors such as Song et al. (2007) or Chiesa and Frattini (2009) argue that the possession of greater resources does not guarantee the achievement of superior performance, we believe that this assertion is due to the static and punctual vision of innovation. If we consider investments in R&D, both internal and external, as a source of knowledge (Rosenkopf & Nerkar, 2001), not only does the combination and integration of these sources drive learning processes and the development of organizational skills but also their acquisition. Companies must decide how they want to use and renew their skills, and they must choose a particular combination of knowledge to compete in markets (Dierickx & Cool, 1989). In SMEs, the search for equilibrium and budgetary limitations for the innovation process poses the problem that having to focus on one or another type of source, that is, for this type of company, internal spending on R&D are extremes of the same continuum and has a one-dimensional character. In large companies, R&D expenditure policies are two-dimensional. In this sense, Boronat-Navarro et al. (2021) found that larger organizations achieve better results from ambidexterity, in particular with those that have competitive intelligence routines. However, what may be better for SMEs is still an unanswered question.

There are also many references in the literature on the effect of firm size on innovation (Damanpour, 1996; Hitt et al., 1990; Sullivan & Kang, 1999; Wade, 1996). As for the availability of resources in innovation, where large firms are concerned, the results in this respect are contradictory (Sullivan & Kang, 1999); negative results that may derive from the lack of flexibility associated with the innovation process (Manda & Uzsoy, 2021); and inconclusive results (Aiken et al., 1980; Martínez-Ros & Labeaga, 2002; Smart et al., 2021). It is plausible to think then when associating SMEs to a lesser availability of resources, the results are negative and positive when associating them a greater capacity of adaptation or use of technological resources thanks to their flexibility, assumption of risks and creativity (Koberg et al., 2003). We must also consider that SMEs often have insufficient production or distribution capacity to support both types of products in their portfolio and are forced to decide between new and old products, with a clear tendency towards the former. From a Penosian perspective, the availability of resources for larger firms and their potentially greater access to slack resources (Agustí et al., 2021) could help them to maintain both types of products, as they enjoy greater access to resources and can generate capabilities that could lead to greater economies of scale (Cockburn & Henderson, 2001). There are recent studies, such as Hsieh et al. (2020), which find that in large companies, belonging to highly competitive industries such as aerospace and defence, innovation capacity does not seem to have a clear impact on company results. The conclusion is that it is not precisely a company in excellent financial shape that is the most efficient, and vice versa. These findings are explained, on the one hand, by the excessive dependence and support of financial leverage, in terms of resources, but most especially by affirming the need to seek a balance between innovation capacity and company performance. Therefore, we suggest that the results could be conditioned by the size of the firms, which highlights the need for a more detailed study taking this aspect into account.

H6. Long-term natural efficiency in SMEs has a direct, significant and positive influence on performance lower than that of large enterprises.

H7. Long-term managerial efficiency in SMEs has a direct, significant and positive influence on performance greater than in large enterprises.

H8. Changes in SMEs innovation capacity differ from those observed in large enterprises.

Our hypothesis can be represented as can be seen in Figure 1.

3 | DATA AND SAMPLE

To test the hypothesis of this study, we collected information from the Technological Innovation Panel of Spain (PITEC). This is a statistical instrument designed to monitor the technological innovation activities of Spanish companies. Using these panel data enabled us to study changes over time and observe the heterogeneity of the decisions adopted by companies, avoiding the limitations of previous studies (Cruz-Cázares et al., 2010; Tidd & Bessant, 2009). We studied the period 2008–2011, which is consistent with this perspective. Although the choice of a single country is a limitation, it avoids the problem of information asymmetry that could arise in a multinational study (Gao & Chou, 2015; Seru, 2014). Innovation was measured for the period 2008–2010, while the results were associated with the year 2011.

The selected database includes firms associated with innovative processes. However, the companies selected for the analysis were the result of a data depuration process in which we excluded firms that, although they were considered technology companies, had shown no activity or had too few events to comply with the requirements of the DEA analysis. Our requirements were that the firms be private companies. Second, given that the study covers the period of economic crisis 2008–2014, we excluded firms whose activities had been affected by the crisis (merger, closure or sale). Third, they should not have been affected by employment events such as staff transfers, employment regulation, absorption, changes in the reference unit or activity. These preliminary selection filters are in accordance with the DEA methodology and sensitive to values that were lost in the observations. The final sample consisted of 104 firms, of which 50 had a total turnover

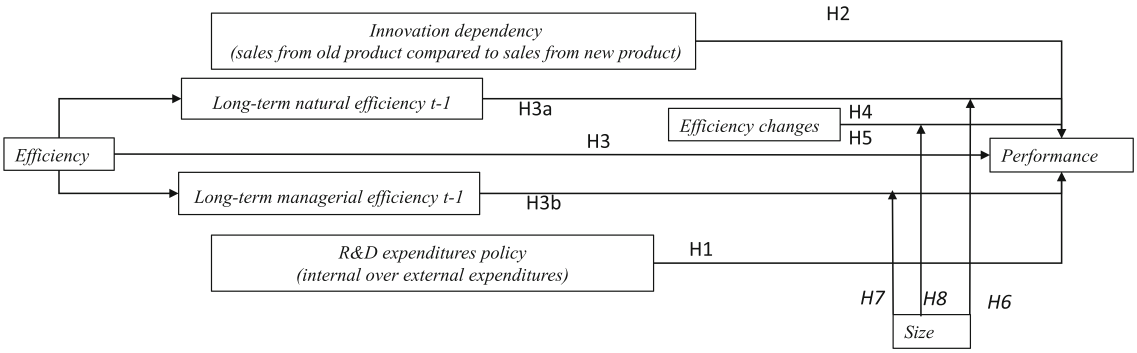

FIGURE 1 Proposed model and hypothesis

of more than 43 million euros, according to the EU threshold between SMEs and large companies, and 54 were SMEs.

As discussed before, innovation is a complex and uncertain process (Bunduchi et al., 2011), which has led to the creation of a vast number of measurements and indicators for the process (see, e.g., Brenner & Broekel, 2011; Fritsch & Slavtchev, 2007; Guan & Chen, 2010). Bearing in mind our purpose, we must consider not only innovation-related inputs but also the innovation-related outputs they should lead to (Cruz-Cázares et al., 2013).

As discussed in our theoretical framework, there is a strong consensus on inputs in the study of R&D expenditure, measuring them in absolute terms (O'Regan et al., 2006), relative (Hitt et al., 1997) or in terms of human resources associated with this activity (J. Wang & Hwang, 2007). Thus, we have used R&D expenditures as input. It should be noted that this creates difficulties that might affect the calculation of the efficiency of an innovative process. Studies into R&D spending have approached the subject from different perspectives, focusing either on the need to choose between internal or external R&D expenditure (Freeman, 1987; Kline & Rosenberg, 1986; Nelson, 1993) or on the added value given to internal R&D spending by external expenditure (Pisano, 1990; Rosenberg, 1990; Ulset, 1996). Considering that our study aims to understand the importance of the search for or exploitation of the processes, we have therefore introduced the relationship between internal and external innovation expenditure, and we have taken advantage of the information contained in the database regarding both sources of expenses in R&D during the period 2008–2010. We have created the external expenditure in R&D divided by the internal expenditure in R&D (EXT/INT) to evaluate such an equilibrium.

Regarding the output, many studies view patents as a positive result (Gao & Chou, 2015; Lee et al., 2010; J. Wang & Hwang, 2007; Zhong et al., 2011). However, while patents are an important measure of innovation production (Kelly et al., 2021), the decision to acquire a patent does not guarantee the success of innovative processes of a firm. Another option was to consider innovative products that show the results of the firm's dynamic capabilities. The ability to generate this type of product demonstrates, on the one hand, the exploitation of existing competencies and, on the other, the exploration of new competencies that must be sought out and developed to be able to adapt to the continuous changes that occur in a dynamic environment (Levinthal & March, 1993; McGrath, 2001).

Successful innovation management should also lead to a relatively high propensity for factors that enable innovation to continue, and activities in one stage will affect the next, so that the process of innovation will be characterized by the exploitation and exploration of knowledge (Fritsch & Slavtchev, 2007). For this reason, we use the sale of innovative products in a period as an output of the innovative process. We agree with Helfat and Raubitschek (2000) that the product portfolio serves as a platform for future product sequences and this platform requires the combination of knowledge and capabilities. This in turn creates an opportunity for competitive advantage through the strategic linking of these products, which requires a complex combination of activities and knowledge appropriate for each stage of the value chain.

In the perspective of continuous innovation, the predominance of old products can be considered undesirable output. These outputs are the result of the exploitation of previously innovative knowledge and capabilities that do not require a radical redesign, but simply an improvement in processes (Sanders & Linderman, 2014). These are adaptive behaviours that cannot be given up; they are the product of the areas of the firm's competencies but restrict its options for the future (Dierickx & Cool, 1989). To evaluate both types of output, we have examined the sales of old products divided by the sales obtained from products that are innovative (OLD/NEW), either for the company or for the market, as the reflection of the dependency on innovation.

Jointly with these variables we have introduced the relationship to the a group of firms (GROUP) and the other expenses as control variables for our models (OEXP).

4 | METHODOLOGY

Our investigation follows a two-step process. First, in a preliminary stage, we determine the levels of efficiency, as a measure of innovation capacity, considering the complexity and uncertainty of innovative inputs and outputs, as described by Moon (2013). This requires the application of a data envelopment analysis (DEA) (Chang & Lo, 2005; Murthi et al., 1997; Zahra & Nielsen, 2002). Second, to test our hypothesis, we used a regression study to evaluate the influence of the constructs developed in the preliminary phase on organizational performance.

DEA is a linear programming technique that measures the relative efficiency of the business units when the efficiency frontier is non-linear. This methodology allows us to identify performance directly as an efficiency outcome, giving an objective evaluation of the efficiency of the innovation process. Unlike previous studies, which have focused on a single type of output (Cruz-Cázares et al., 2013), we consider efficiency to require the adoption of perspectives that allow negative outputs to be introduced (Dyson & Shale, 2010; Glover & Sueyoshi, 2009). DEA allows us to consider as a positive outcome only the sale of new products from which we will deduct the natural efficiency and also allows us to introduce, together with the sale of new products, a negative outcome, the sales of old products or existing products, giving rise to managerial efficiency.

In this case, we examined the input and output of the innovation process at an early stage during the 2008–2011 period, using a bootstrap of the intertemporal DEA. We will use a step-by-step DEA that combines annual efficiencies. The DEA model (the 2009 efficiency level) is based on the input internal expenses 2009, external expenses 2009, for sales new products 2008, sales old products 2008, for total sales volume for the year 2009 (sales new products 2009, sales old products 2009). We will operate in the same way to obtain the efficiency of 2010. Using these models, we can observe the efficiency of the two stages, DEA1 and DEA2. A new DEA3 analysis allows us to combine both levels of efficiency that lead to efficiency in the period 2009–2011, as can be seen in Figure 2.

The approach for our analysis is based on the work of Sueyoshi and Goto (2012 and 2014), and our modifications are detailed in Appendix A. By taking this approach, we assume that firms will adopt a strategy that considers that an increase in the input vector will decrease the bad output vector and increase the good output vector as far as possible (Sueyoshi & Goto, 2012). Mathematically, these assertions can be expressed axiomatically: We might consider $X \in R_m^+$ as an input vector, $G \in R_s^+$ as a desirable output vector and $B \in R_h^+$ as an undesirable output vector.

This concept is referred to in the literature as managerial disposability and can be defined by the following vectors of production factors.

$$P^m(X) = \left\{ (G,B); G \le \sum_{j=1}^{n} G_j \lambda_j; B \ge \sum_{j=1}^{n} B_j \lambda_j; X \le \sum_{j=1}^{n} X_j \lambda_j; \lambda_j \ge 0, j = 1, \dots, n \right\}.$$

Adhering to the requirements of the DEA methodology, we estimated a frontier model, DEA bootstrap, for the period. Efficiency scores range from 0 to 1 and the difference between the score achieved and unity is the percentage of inefficiency (EFF).

The DEA methodology allows us to disaggregate efficiency into natural efficiency (NATEFF), which considers only those outputs good for the system, in our case the sale of new products resulting each year from the innovation processes carried out in the previous period, and in managerial efficiency (MANEFF), which contemplates efficiency taking into account the negative outputs of the process.

We now need to extend these concepts into a time period using the measurement of the Malmquist index (IM) (Sueyoshi & Goto, 2014; C. H. Wang et al., 2012). CCR deterministic model named after the developments of Charnes et al. (1978). The IM represents the progress in efficiency from one period to another according to the movements at the border, defined by the distances of the functions, capturing the changes in efficiency in a period t as companies approach or move away from the efficient border of period $t-1$. The MI values show whether their value is 1 that companies have maintained the level of efficiency, whether it is less than 1 that they have become inefficient, and if it is greater than 1 that they have grown in efficiency. The IM with frontier crossover between the two periods can be reorganized as follows. Accordingly, we have created IMNAT for the natural efficiency and IMMAN for the managerial efficiency.

$$\mathrm{IM}_{t-1}^{t} = \sqrt{\frac{\mathrm{UEM}_{t-1}}{\mathrm{IUEM}_{t-1 \to t-1\&t}} \frac{\mathrm{UEM}_{t}}{\mathrm{IUEM}_{t \to t-1\&t}}}.$$

4.1 | Stage II: The influence of variables on performance

In this phase, we will link to the overall performance of the company, in our case to the total sales volume in 2011. We will further segment the sample into small and large companies according to whether the total sales established by the EU (43 million €).

The next step was to test our hypotheses. We will test the relationship of innovative capacity to this performance, in line with studies by Zahra and Nielsen (2002) and Chang and Lo (2005). To achieve this, we use OLS regression analysis to establish the causal relationship between sales for 2011 and our independent variables, R&D expenditure policies, innovative capacity and innovation dependency.

The strategy for the regressions was sequential, that is, we depart from the simplest model and introduce the variables according to the sequence of the hypothesis established. Thus, we first evaluate the possible effect of the inputs and outputs on performance, leaving out of the model the efficiency of the firms. The same sequence of regressions will apply for subsamples, small and large companies.

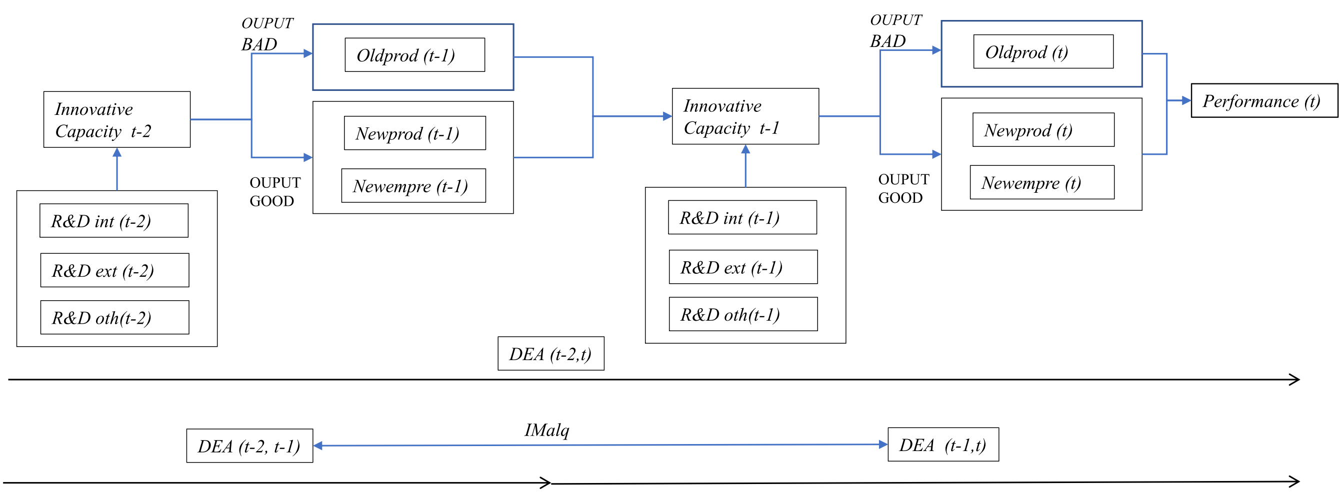

FIGURE 2 Evaluation of innovative capacity on performance [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Efficiency descriptive statistics

	N	Min.	Max.	Mean	SD
Eficiencia-Good_ Natural_DEA1	107.00	0.80	1.00	0.99	0.03
Eficiencia-Good_managerial_DEA1	107.00	0.64	1.00	0.69	0.10
Eficiencia-Good_DUO_DEA1	107.00	0.46	1.00	0.66	0.06
Eficiencia-Good_ Natural_DEA2	107.00	0.71	1.00	0.99	0.04
Eficiencia-Good_managerial_DEA2	107.00	0.64	1.00	0.86	0.12
Eficiencia-Good_DUO_DEA2	107.00	0.60	1.00	0.84	0.13
Eficiencia-Good_ Natural_DEA3	107.00	0.73	1.00	0.98	0.04
Eficiencia-Good_managerial_DEA3	107.00	0.79	1.00	0.96	0.06
Eficiencia-Good_DUO_DEA3	107.00	0.62	1.00	0.92	0.09

5 | RESULTS

Following the requirements of the DEA methodology, we estimate a three-frontier model: a first model for the DEA bootstrap for the period 08_09 for DEA1, a second for the period 09_10 for DEA2 and a third complete model covering the previous two periods and DEA3 for the period 08-10. Efficiency scores range from 0 to 1 the difference between the score achieved and the unity is the percentage of inefficiency. Moreover, and in order to test our hypothesis, the DEA methodology allows us to disaggregate efficiency into natural efficiency, which considers only those outputs good for the system, in our case the sale of new products resulting each year from the innovation processes carried out in the previous period, and in managerial efficiency that contemplates efficiency taking into account the negative outputs of the process. Table 1 shows descriptive statistics and reflects the mean, median and standard deviation of efficiency scores (EFF), both total efficiency and DUO, as well as natural and managerial efficiencies.

From these results, we observe that managerial efficiency has lower average values than natural efficiency in both periods. This in general, and noting that duo efficiency has increased in the study period, has been done mainly via input.

Once the efficiencies generated by the DEAs have been obtained, our research continues through the analysis of regressions for the corroboration of our hypotheses.

From the OLS regressions (see Table 2), we can observe that H1 and H2 cannot be confirmed for the total sample. However, efficiency seems to play a crucial role in performance ($\beta = -4.814$, $p < .001$) confirming H3. When decomposing efficiency, in which we have used DEA3 for the full period (Model 4), it can be seen that the significance of both relationships is significant ($\beta = -6.449$, $p < .001$ for natural and $\beta = -2.826$, $p < .01$ for managerial). With these results, we confirm H3a and H3b.

When we include changes in efficiency level (IM, calculated on DEA1 and DEA2) (Model 5), it can be seen that efficiencies remain significant, but only changes in managerial efficiency exert a low but significant effect on performance ($\beta = 4.229\text{E-}5$, $p < .05$).

However, we proposed a theoretical effect associated with resource availability; this is related to the size of the company. Consequently, we split the sample into two according to the 43-million criteria. € established by the EU.

The results obtained for each subsample respond to H6, H7 and H8 are shown in Tables 3 and 4. In models from 6 to 15, it can be seen that the results for each of the subsamples. In the group comparison, performed with SPSS ver. 26, the regressions presented significant results at the $p < .001$ level in the ANOVA. In both subsamples, efficiency (Models 8 and 13) appeared to be significant ($\beta = -9.080$, $p < .001$ for SMEs and $\beta = -1.420$, $p < .005$ for larger firms).

When decomposing the efficiency in both samples, for SMEs, being efficient remains important for performance, as can be seen in Models 10 and 15 ($\beta = -16.548$, $p < .001$ for natural), while for bigger firms, this is not so important (non-significant effect for managerial and natural).

However, the IM associated with natural efficiency is significant for SMEs ($\beta = .135$, $p < .01$) (Model 10), but the Malmquist associated with natural efficiency showed a small but significant effect. It is interesting to remark that when the IM is introduced in the regressions, the significance of the managerial efficiency becomes non-significant in the bigger companies sample (Model 15), while both efficiencies remain significant for SMEs. Regarding the effects of changes, in both subsamples, it is the IM associated with the natural efficiency that exerts a significant effect on performance, despite it being more significant for big companies, while the effect presents a higher coefficient for SMEs.

These results confirm H6 and H7, since both effects are significant for SMEs while they are not for large companies, but they do not fully confirm hypothesis H8.

5.1 | Decomposition of the Malmquist Productivity Index

As our results are not fully significant, and following some authors (Orea, 2002) that have criticized the IM, observing that it does not provide an accurate measure of productivity change because it ignores the potential contribution of scale economies to productivity change. The DEA methodology defines the technological frontier in a given period, reflecting the firms that use the available resources in

TABLE 2 OLS regression for the whole sample

	Model 1				Model 2				Model 3				Model 4			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	7.266	0.213	.000		7.257	0.223	.000		11.861	0.593	.000		16.447	1.532	.000	
GROUP	0.279	0.137	.044	1.023	0.279	0.139	.047	1.031	0.142	0.110	.199	1.056	0.159	0.122	.195	1.060
OEXP	0.370	0.213	.086	1.023	0.375	0.216	.085	1.029	0.231	0.170	.178	1.041	0.297	0.188	.117	1.044
OLD/NEW					0.000	0.001	.798	1.011	8.89E-02	0.001	.931	1.013	8.56E-02	0.001	.940	1.018
EXT/INT					0.033	0.166	.845	1.010	0.033	0.130	.799	1.010	−0.004	0.144	.979	1.016
EFF									−4.814	0.592	.000	1.034				
NATEFF													−6.499	1.303	.000	1.049
MANEFF													−2.826	1.038	.008	1.051

	Model 5			
	Coef	SE	Sig.	FIV
(Constant)	15.696	1.841	.000	
GROUP	0.136	0.123	.287	1.103
OEXP	0.256	0.193	.189	1.053
OLD/NEW	0.000	0.001	.714	1.022
EXT/INT	0.032	0.148	.813	1.020
NATEFF	−6.405	1.518	.000	1.355
MANEFF	−2.203	1.097	.047	1.118
IMNAT	1.916E-05	0.000	.444	1.392
IMMAN	4.229E-05	0.000	.017	1.059

TABLE 3 OLS regression for the SME sample

	Model 6				Model 7				Model 8				Model 9			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	7.111	0.147	.000		7.108	0.163	.000		16.007	1.165	.000		27.795	4.246	.000	
GROUP	0.151	0.12	.211	1.011	0.148	0.123	.233	1.027	0.033	0.086	.699	1.059	0.048	0.104	.644	1.115
OEXP	0.047	0.152	.757	1.011	0.051	0.157	.747	1.051	−0.083	0.11	.454	1.078	0.004	0.128	.977	1.056
OLD/NEW					0.000	0.001	.831	1.019	0.000	0.001	.642	1.029	−0.00006748	0.001	.92	1.033
EXT/INT					0.013	0.182	.941	1.051	0.114	0.126	.37	1.062	0.051	0.148	.73	1.056
EFF									−9.08	1.183	.000	1.081				
NATEFF													−15.837	4.214	.000	1.109
MANEFF													−4.964	1.539	.002	1.046

	Model 10			
	Coef	SE	Sig.	FIV
(Constant)	24.843	3.968	.000	
GROUP	0.102	0.098	.304	1.150
OEXP	0.003	0.119	.983	1.059
OLD/NEW	0.000	0.001	.466	1.038
EXT/INT	0.124	0.144	.395	1.160
NATEFF	−16.548	3.923	.000	1.110
MANEFF	−1.588	1.476	.287	1.112
IMNAT	0.135	0.047	.006	1.182
IMMAN	0.000	0.000	.569	1.114

TABLE 4 OLS regression for the sample of big companies

	Model 11				Model 12				Model 13				Model 14			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	8.079	0.288	.000		8.130	0.289	.000		9.320	0.577	.000		1.08	1.381	.000	
GROUP	0.005	0.133	.972	1.097	−0.039	0.135	.775	1.144	−0.041	0.128	.748	1.144	−0.049	0.132	.714	1.156
OEXP	0.192	0.276	.49	1.097	0.168	0.277	.548	1.118	0.204	0.264	.445	1.122	0.116	0.278	.679	1.182
OLD/NEW					0.004	0.004	.371	1.055	0.004	0.004	.288	1.059	0.004	0.004	.306	1.164
EXT/INT					−0.197	0.137	.155	1.075	−0.184	0.13	.166	1.077	−0.209	0.133	.124	1.078
EFF									−1.420	0.605	.023	1.012				
NATEFF													−2.202	1.073	.046	1.017
MANEFF													0.221	0.952	.818	1.189

	Model 15			
	Coef	SE	Sig.	FIV
(Constant)	7.560	1.642	.000	
GROUP	−0.065	0.136	.638	1.230
OEXP	−0.030	0.281	.917	1.210
OLD/NEW	0.001	0.005	.873	1.289
EXT/INT	−0.160	0.135	.244	1.100
NATEFF	−0.843	1.237	.499	1.348
MANEFF	1.606	1.008	.119	1.330
IMNAT	4.325E-05	0.000	.026	1.424
IMMAN	1.521E-05	0.000	.283	1.245

TABLE 5 Malquimst index descriptives for SMEs

		IMNAT	IMCUP-NAT	IMFRON-NAT	IMESC-NAT	IMMAN	IMCUP-MAN	IMFRON-MAN	IMESC-MAN
N	Valid	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00
	Lost	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean		1.74	8.44	1.89	45,761.81	407.84	153,379.28	29.20	106.46
Mode		1.00	1.00	1.00	0.000[b]	1.252[b]	1.00	0.000[b]	0.000[b]
SD		0.95	19.01	4.32	337,192.17	801.51	609,930.68	81.80	134.21
Asymmetry		1.95	3.45	4.68	7.55	1.91	5.16	4.79	1.40
Std. error asymmetric		0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32
Kurtosis		3.96	11.46	23.03	56.99	2.89	29.13	27.27	1.13
Std. error kurtosis		0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Percentiles	25.00	1.07[a]	0.98[a]	0.25[a]	0.67[a]	2.90[a]	4.55[a]	0.14[a]	0.87[a]
	50.00	1.37	1.76	0.99	1.11	4.97	15.72	0.63	50.77
	75.00	1.95	5.43	1.25	2.18	22.00	101.92	7.67	162.82

[a]Percentiles are calculated from pooled data.
[b]There are multiple modes. The smallest value is displayed.

TABLE 6 Malquimst index descriptives for big firms

		IMNAT	IMCUP-NAT	IMFRON-NAT	IMESC-NAT	IMMAN	IMCUP-MAN	IMFRON-MAN	IMESC-MAN
N	Valid	50.000	50.000	50.000	50.000	50.000	50.000	50.000	50.000
	Lost	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mean		1122.273	23,524,293.435	6.767	2069.196	1339.934	412,781.859	28.834	68.682
Mode		1.000[a]	1.000	0.000[a]	0.000	1.000[a]	1.000	0.000[a]	0.000[a]
SD		3914.915	115,830,606.080	38.710	7344.934	4894.282	2,916,541.033	99.627	98.814
Asymmetry		4.060	6.148	6.892	5.075	4.192	7.071	5.023	2.072
Std. error asymetric		0.337	0.337	0.337	0.337	0.337	0.337	0.337	0.337
Kurtosis		17.115	39.713	48.145	28.626	17.741	50.000	27.761	4.104
Std. error kurtosis		0.662	0.662	0.662	0.662	0.662	0.662	0.662	0.662
Percentiles	25.000	1.975	1.679	0.062	0.088	6.421	4.156	0.251	5.003
	50.000	4.600	23.516	0.222	0.321	14.721	14.214	0.999	20.512
	75.000	8.162	158.504	1.003	2.156	36.812	94.468	6.688	96.828

[a]Percentiles are calculated from pooled data.
[b]There are multiple modes. The smallest value is displayed.

the most efficient way in the period or, in other words, defines the best-practice firms, that is, those that produce the maximum amount of output possible given the inputs used in period t, based on the observations of the sample in that period.

The distance between the production points of the other firms and the technological frontier makes it possible to obtain measures of their technical inefficiency. In DEA, the use of Malmquist indices, which show the rate of change in technical efficiency between periods, is considered since they reflect the rates between an index of change in the quantity of outputs and an index of change in the quantities of inputs in different periods. However, the IM can be calculated using non-parametric techniques (DEA) (Färe et al., 1992) or parametric frontier approaches (Fuentes et al., 2001). Following the process depicted by Orea (2002) and Lee et al. (2011), we decompose the IM into three different indexes: the 'catching-up' efficiency, the scale and the frontier indices.

The Malmquist 'catching-up' efficiency index (IMCUP) can be considered the rate of change that is observed when the distance in period t between the firm's efficiency in t and the frontier in t is different from the distance in period $t+1$ between the firm's efficiency in $t+1$ and the frontier in $t+1$. The IM frontier efficiency (IMFRON) refers to the rates of change that are observed from changes in the

TABLE 7 OLS regression for the Malmquist index decomposition

	MODEL 16				MODEL 17				MODEL 18				MODEL 19			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	7.266	0.213	.000		7.257	0.223	.000		16.447	1.532	.000		15.880	1.529	.000	
GROUP	0.279	0.137	.044	1.023	0.279	0.139	.047	1.031	0.159	0.122	.195	1.060	0.216	0.119	.073	1.107
OEXP	0.370	0.213	.086	1.023	0.375	0.216	.085	1.029	0.297	0.188	.117	1.044	0.213	0.182	.246	1.074
OLD/NEW					0.000	0.001	.798	1.011	8.56E-02	0.001	.940	1.018	0.000	0.001	.886	1.032
EXT/INT					0.033	0.166	.845	1.010	−0.004	0.144	.979	1.016	0.144	0.152	.347	1.245
NATEFF									−6.499	1.303	.000	1.049	−6.165	1.262	.000	1.078
MANEFF									−2.826	1.038	.008	1.051	−2.463	1.057	.022	1.193
IMCUP-NAT													1.93E-06	0.000	.006	1.019
IMFRON-NAT													−0.001	0.002	.658	1.185
IMESC-NAT													5.00E-05	0.000	.821	1.019
IMCUP-MAN													−4.22E-06	0.000	.875	1.030
IMFRON-MAN													9.82E-02	0.001	.881	1.205
IMESC-MAN													−0.001	0.001	.022	1.421

TABLE 8 OLS regression for the Malmquist index decomposition in SMEs

	Model 20				Model 21				Model 22				Model 23			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	7.111	0.147	.000		7.108	0.163	.000		27.795	4.246	.000		29.128	4.207	.000	
GROUP	0.151	0.120	.211	1.011	0.148	0.123	.233	1.027	0.048	0.104	.644	1.115	0.144	0.107	.187	1.290
OEXP	0.047	0.152	.757	1.011	0.051	0.157	.747	1.051	0.004	0.128	.977	1.056	−0.124	0.133	.359	1.246
OLD/NEW					0.000	0.001	.831	1.019	−6.75E-02	0.001	.920	1.033	−0.001	0.001	.369	2.802
EXT/INT					0.013	0.182	.941	1.051	0.051	0.148	.730	1.056	0.063	0.194	.749	1.965
NATEFF									−15.837	4.214	.000	1.109	−16.575	4.109	.000	1.145
MANEFF									−4.964	1.539	.002	1.046	−5.511	1.656	.002	1.315
IMCUP-NAT													0.005	0.003	.106	1.560
IMFRON-NAT													0.022	0.017	.208	3.222
IMESC-NAT													1.00E-04	0.000	.504	1.436
IMCUP-MAN													−1.71E-04	0.000	.066	1.744
IMFRON-MAN													0.000	0.001	.787	1.751
IMESC-MAN													0.000	0.000	.503	2.020

TABLE 9 OLS regression for the Malmquist index decomposition in big firms

	Model 24				Model 25				Model 26				Model 27			
	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV	Coef	SE	Sig.	FIV
(Constant)	8.079	0.288	.000		8.130	0.289	.000		10.080	1.381	.000		9.806	1.248	.000	
GROUP	0.005	0.133	.972	1.097	−0.039	0.135	.775	1.144	−0.049	0.132	.714	1.156	−0.099	0.120	.414	1.360
OEXP	0.192	0.276	.490	1.097	0.168	0.277	.548	1.118	0.116	0.278	.679	1.182	0.022	0.236	.925	1.224
OLD/NEW					0.004	0.004	.371	1.055	0.004	0.004	.306	1.164	0.001	0.004	.799	1.368
EXT/INT					−0.197	0.137	.155	1.075	−0.209	0.133	.124	1.078	−0.037	0.126	.770	1.379
NATEFF									−2.202	1.073	.046	1.017	−2.081	0.921	.030	1.070
MANEFF									0.221	0.952	.818	1.189	0.583	0.889	.516	1.481
IMCUP-NAT													1.14E-06	0.000	.016	1.049
IMFRON-NAT													0.001	0.002	.567	1.340
IMESC-NAT													1.17E-02	0.000	.134	1.203
IMCUP-MAN													−3.16E-05	0.000	.094	1.096
IMFRON-MAN													0.000	0.001	.831	1.348
IMESC-MAN													−0.002	0.001	.006	1.513

frontier between the periods considered. Finally, the Malmquist scale index (IMESC) is related to the changes in efficiency that result from a proportional change in all inputs. All these indices were calculated from both the managerial and natural perspectives.

The results obtained from the Malmquist indices are described in Tables 5 and 6. The data presented show how some of the observed firms stand out for drastic changes in their efficiencies as can be seen by the mean, mode and standard deviation. Although from these results we can draw some conclusions.

Thus, it is worth noting for small companies that the descriptive variables show values close to 1, except for the managerial and natural IMFRON, with values close to 0, which allows us to affirm that in the period under study the efficiency frontier has suffered a contraction, more pronounced in the managerial frontier.

In the case of large companies (Table 7), we also observe a change in the frontiers, although in this case the contraction is greater in the natural frontier IM than in the managerial frontier. In this case, it also can be observed a decrease in the natural IMESC.

The positive change in both the natural and managerial IMCUP in both types of firms shows how, in general, firms, as a consequence of their own technological improvement, are better positioned in relation to the firms considered more efficient than in the previous period and are moving towards the technological frontier.

The inclusion of this decomposition in the regressions offers interesting results on the effects of different efficiency management decisions on firm performance (Tables 7–9).

Therefore, for the whole sample, IMCUP-NAT ($\beta = -1.93\text{E-}06$, $p < .01$) and IMESC-MAN ($\beta = -.001$, $p < .05$) present significant effect on performance jointly with the two efficiencies. However, these efficiencies seem to be due to the presence of large samples; as when we split the sample in two, for SMEs the different Malmquist indices do not present significant effects.

6 | DISCUSSION AND CONCLUSIONS

This study is based on a two-fold objective. First, we have tried to demonstrate the need to adopt complex approaches that recognize the true nature of innovation, and second, we have specifically examined the value of efficiency in the innovation process, as proposed in previous works (Cruz-Cázares et al., 2013). To this end, we have incorporated advances in efficiency analysis methodology (Manzaneque et al., 2018; Martínez-Alonso et al., 2020), such as the use of radial models (Sueyoshi & Goto, 2012). The use of this methodology has allowed us to consider the management of innovative efficiency from a dynamic perspective, as suggested in the literature. The results obtained with these techniques allow us to propose relationships that may seem contradictory in the literature on the study of efficiency, such as the negative relationship between managerial efficiency and performance measured by firm sales.

However, our results do not answer all these questions despite offering interesting clues for future research. What we can see from the results obtained is that beyond the introduction of measures of input or output (Manzaneque et al., 2018), researcher should consider the management of innovation carried out by firms over time. This is in line with dynamic approaches to resource management and capabilities that confirm that it is not the possession but the value derived from innovation that can explain the performance of firms and the need for adaptation when facing transformations (Onufrey & Bergek, 2021).

In terms of R&D expenditure policies, after our results, we assume that the company must seek alignment or balance in the combination, integration and acquisition of knowledge from internal and external sources (Añón Higón et al., 2018; García-Vega & Huergo, 2019; Spescha, 2019). Our results also show different attitudes in R&D expenditures in line with previous research (Añón-Higón et al., 2018; Triguero et al., 2013). Therefore, a possible equifinality can be assumed by the lack of effect of the different expenditure policies analysed. This aspect will require research in the future.

The role played by the size of the firm is noteworthy (Mazzarol et al., 2010). Thus, from our results, we must insist on the role played by the amount of available resources. However, this does not mean that smaller firms are inefficient but that the policies they must use in order to achieve such efficiency differ from those used by bigger firms. Indeed, it is the management of efficiency that, and over the efficiency level itself, contributes to the increase of the performance of firms. This is, in our opinion, one of the key contributions of this paper. Thus, only continuous improvement of efficiency will determine a better performance, and efficiency is what orients the different input and output innovation policies into a possible competitive advantage.

Our results contribute to previous works (Cassiman & Veugelers, 2006; Grimpe & Kaiser, 2010), in the evaluation of the different expenditure policies (Nguyen, Dang, et al., 2021). Indeed, they allow for the combination of possible contradicting effects such as what Song et al. (2007) or Chiesa and Frattini (2009) argued, proposing that the possession of greater resources does not guarantee the achievement of superior performance.

We also reinforce the need to adopt efficiency-based innovation analysis (Cruz-Cázares et al., 2013; Stadler, 2011), by using DEA. However, we advance previous work as we incorporate the continuous innovation policy that has been suggested by many authors (Khosravi et al., 2019; Martínez-Alonso et al., 2020), by establishing a possible negative outcome of this innovative capacity. Thus, we reflect the possibility of considering negative the non-replacement of existing products/services by the new products/services generated by the innovation. This aspect was not considered by prior research (Boronat-Navarro et al., 2021; Cruz-Cázares et al., 2013; Martínez-Alonso et al., 2020; Vega-Jurado et al., 2008) and reinforces the idea of product portfolio management (Cooper & Sommer, 2020).

Our work presents the following contributions. For the academic community, we give another example of the interest in using a technique that has until now focused on the analysis of efficiency in certain specific fields of management. The result is the application of an approach that until now has been applied only under the consideration of inputs as negative and results as positive, and we have included the possibility of a negative result. These techniques allow evolution over time to be evaluated, and on the other hand, they enable several types of output with opposing values to be included, which we see in the composition of the product portfolio. As we have said from the outset, the innovative approach is complex and should be studied in such a way as to adhere as closely as possible to this reality.

For managers, we find that, although size is a relevant aspect in innovation management, innovative efficiency is crucial to firm performance independently of firm size. The ability to keep track of innovation (frontier in our analysis) reveals the need to monitor the evolution of the industry. However, the constant renewal of products and the continuous introduction of new products on the market reduce organizational performance, being necessary to develop a balanced strategy between new and old products. These issues are particularly important in small companies. The limited amount of resources is a constraining and fundamental characteristic of these firms; however, they must pursue a continuous upgrading in innovative efficiency to improve organizational performance. Therefore, the negative effect of innovation observed in these firms highlights the need to efficiently manage the product portfolio and the product rollover. The substitution of new products for old ones is a key and decisive factor (Li & Yang, 2020), and this is beyond the predominance of one type over the other.

In the case of large companies, the management of innovation differs. Thus, portfolio management has less weight, with a possible management more focused on a traditional efficiency perspective that puts emphasis on investing in R&D to introduce new ones, since they have a greater endowment of resources that allow combining both policies. This affects not only market performance but also production systems (Manda & Uzsoy, 2021).

We have also shown that the many contradictions found in the review of the literature on innovation management can be understood differently depending on whether it is an SME or a large company. Although for all types of companies the management of innovation as an isolated process is influenced by R&D expenditure policies, that is, the volume of investment made in R&D fundamentally, and secondly, it is influenced by the intention that the innovative process be considered efficient when it is oriented towards substituting existing products/services, innovation cannot be seen in isolation, as its results will be linked to the results of past innovations. In SMEs, this innovative efficiency of replacing existing products/services with new products/services has negative implications for performance. This efficiency has a much smaller impact on large companies.

Geroski et al. (1997) posed that few companies can maintain their levels of innovation in this regard, to say that SMEs should not maintain the level of innovation because it would detract from their performance, which will depend on the exploitation of their past innovations. However, large companies must maintain their levels of innovation because it adds to their performance. In other words, while SMEs, in order to improve their performance, have to balance exploration and exploitation, and this will be their source of competitive advantage (Arora & Gambardella, 1990; Hansen, 2001; Veugelers, 1997), because these companies are limited by their R&D investment capacity and their productive capacity, in large companies, improving their performance must be explored because this is their source of competitive advantage, mainly because innovation increases their knowledge base and improves learning. This is the main consequence for management that can be taken from this study.

Our article contains certain limitations that must be addressed to advance our understanding of innovative efficiency. Our sample focuses on firms that are considered to be innovative and uses a somewhat limited time period. We accept that sales of innovative products have a delay that is nothing but fixed and therefore suggest a study that uses models with broader time scales. Similarly, the use of panels that are not controlled by the research team requires the use of proxies that could create a degree of distortion in some of the results. Therefore, increasing the number of variables considered in the efficiency evaluation might produce results that produce a richer interpretation than those presented in this study. Finally, continuous advances in the DEA methodology require an almost constant review of the different studies to refine the results and their possible consequences. These limitations point to future research lines based on this work that will lead to improved recommendations in relation to how firms should manage innovation.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from National Institute of Statistics (www.ine.es). Restrictions apply to the availability of these data, which were used under license for this study. Analysis processes and results are available from the authors.

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APPENDIX A

A.1 | Natural and managerial efficiency

$$P^n(X)=\left\{(G,B);G\le\sum_{j=1}^{n}G_j\lambda_j;B\ge\sum_{j=1}^{n}B_j\lambda_j;X\ge\sum_{j=1}^{n}X_j\lambda_j;\lambda_j\ge0,j=1,\ldots,n\right\},$$

$$P^m(X)=\left\{(G,B);G\le\sum_{j=1}^{n}G_j\lambda_j;B\ge\sum_{j=1}^{n}B_j\lambda_j;X\le\sum_{j=1}^{n}X_j\lambda_j;\lambda_j\ge0,j=1,\ldots,n\right\}.$$

In our DEA model (Sueyoshi & Goto, 2012), each jth DMU $j=1,\ldots,n$, uses inputs $X_j=(x_{1j},\ldots,x_{mj})^T$ and generates desirable outputs, represented by $G_j=(g_{1j},\ldots,g_{sj})^T$, and undesirable outputs, represented by $B_j=(b_{1j},\ldots,b_{hj})^T$. Furthermore, $d_i^x, i=1,\ldots,m, d_r^g, r=1,\ldots,s$, and $d_f^b, f=1,\ldots,h$ represent slack variables related to inputs and desirable and undesirable outputs, respectively. $\lambda=(\lambda_1,\ldots,\lambda_n)^T$ are unknown structural or intensity variables, which are used for connecting the input and output vectors via a convex combination. R is the range resolute throughout the upper and lower bounds of inputs, desirable outputs and undesirable outputs and is expressed by following expressions:

$$R_i^x=(m+s+h)^{-1}\left(\max\{x_{ij}|j=1,\ldots,n\}-\min\{x_{ij}|j=1,\ldots,n\}\right)^{-1},$$

$$R_r^g=(m+s+h)^{-1}\left(\max\{g_{rj}|j=1,\ldots,n\}-\min\{g_{rj}|j=1,\ldots,n\}\right)^{-1},$$

$$R_f^b=(m+s+h)^{-1}\left(\max\{b_{fj}|j=1,\ldots,n\}-\min\{b_{fj}|j=1,\ldots,n\}\right)^{-1}.$$

The managerial efficiency of the kth DMU is evaluated by the following radial model:

$$\begin{aligned}
&\operatorname{Max}\xi+\varepsilon\left[\textstyle\sum_{i=1}^{m}R_i^x d_i^x+\sum_{r=1}^{s}R_r^g d_r^g+\sum_{f=1}^{h}R_f^b d_f^b\right]\\
&s.t.\textstyle\sum_{j=1}^{n}x_{ij}\lambda_j+(-1)^o d_i^x=x_{ik}\quad(i=1,\ldots,m),\\
&\quad\textstyle\sum_{j=1}^{n}g_{rj}\lambda_j-d_r^g-\xi g_{rk}=g_{rk}\quad(r=1,\ldots,s),\\
&\quad\textstyle\sum_{j=1}^{n}b_{fj}\lambda_j+d_f^b+\xi b_{fk}=b_{fk}\quad(f=1,\ldots,h),\\
&\textstyle\sum_{j=1}^{n}\lambda_j=1,\\
&\lambda_j\ge0\,(j=1,\ldots,n),d_i^x\ge0\,(i=1,\ldots,m),\\
&d_r^g\ge0\,(r=1,\ldots,s),d_f^b\ge0\,(f=1,\ldots,h)\ \textit{and}\\
&\qquad\xi:\textit{unrestricted}.
\end{aligned}\tag{A1}$$

Its solution provides the necessary efficiency scores, measured by

$$\theta^*=1-\left[\xi^*+\varepsilon\left(\textstyle\sum_{i=1}^{m}R_i^x d_i^{x*}+\sum_{r=1}^{s}R_r^g d_r^{g*}+\sum_{f=1}^{h}R_f^b d_f^{b*}\right)\right],\tag{A2}$$

being $o=1$ to managerial efficiency and $o=0$ to natural efficiency.

A.2 | Malmquist Index

"Natural disposability": The Malmquist index (Sueyoshi & Goto, 2014), with frontier shift between two periods may be specified using the following expression:

$$INC_{t-1}^{t}=\sqrt{\frac{\text{UEN}_{t-1}}{\text{IUEN}_{t-1\to t-1\&t}}\frac{\text{UEN}_t}{\text{IUEN}_{t\to t-1\&t}}}.$$

The degree of unified efficiency UEN_t of the kth DMU in the t period is measured by the following model under natural disposability:

$$(\text{P1})\ \operatorname{Max}\xi+\varepsilon\left[\sum_{i=1}^{m}R_i^x d_i^x+\sum_{r=1}^{s}R_r^g d_r^g+\sum_{f=1}^{h}R_f^b d_f^b\right]$$

$$s.t.\sum_{j\in J_t}x_{ijt}\lambda_{jt}+d_i^x=x_{ikt};\ \forall k\in J_t;\ i=1,\ldots,m$$

$$\sum_{j\in J_t}g_{rjt}\lambda_{jt}-d_r^g-\xi g_{rkt}=g_{rkt};\ \forall k\in J_t;\ r=1,\ldots,s$$

$$\sum_{j\in J_t}b_{fjt}\lambda_{jt}+d_f^b+\xi b_{fkt}=b_{fkt};\ \forall k\in J_t;\ f=1,\ldots,h$$

$$\lambda_{jt}\ge0;\ j=1,\ldots,n;t=2,\ldots,T;\xi\,\text{no restringido};d_i^x\ge0;i=1,\ldots,m$$

$$d_r^g\ge0;r=1,\ldots,s;d_f^b\ge0;\ f=1,\ldots,h,$$

where $R_i^x=(m+s+h)^{-1}\left(\max\{x_{ij};j\in J_{t-1}\cup J_t\}-\min\{x_{ij};j\in J_{t-1}\cup J_t\}\right)^{-1}$; $R_r^g=(m+s+h)^{-1}\left(\max\{g_{rj};j\in J_{t-1}\cup J_t\}-\min\{g_{rj};j\in J_{t-1}\cup J_t\}\right)^{-1}$; $R_f^b=(m+s+h)^{-1}\left(\max\{b_{fj};j\in J_{t-1}\cup J_t\}-\min\{b_{fj};j\in J_{t-1}\cup J_t\}\right)^{-1}$.

The degree of UEN_{kt} of the kth DMU in the t period is determined by

$$\text{UEN}_{kt}=1-\left[\xi+\varepsilon\left(\sum_{i=1}^{m}R_i^x d_i^x+\sum_{r=1}^{s}R_r^g d_r^g+\sum_{f=1}^{h}R_f^b d_f^b\right)\right].$$

The degree of UEN_{t-1} with respect to the kth DMU in the period $t-1$ is measured by replacing t with $t-1$ in the Model (P1).

The degree of $\text{IUEN}_{t-1\to t-1\&t}$ with respect to the kth DMU between two periods is determined by the following model:

$$(\text{P2})\ \operatorname{Max}\xi+\varepsilon\left[\sum_{i=1}^{m}R_i^x d_i^x+\sum_{r=1}^{s}R_r^g d_r^g+\sum_{f=1}^{h}R_f^b d_f^b\right]$$

$$s.t.\sum_{j\in J_{t-1\&t}}x_{ijt-1}\lambda_{jt-1\&t}+d_i^x=x_{ikt-1};\ \forall k\in J_{t-1};\ i=1,\ldots,m$$

$$\sum_{j\in J_{t-1\&t}}g_{rjt-1}\lambda_{jt-1\&t}-d_r^g-\xi g_{rkt}=g_{rkt-1};\ \forall k\in J_{t-1};\ r=1,\ldots,s$$

$$\sum_{j\in J_{t-1\&t}}b_{fjt-1}\lambda_{jt-1\&t}+d_f^b+\xi b_{fkt}=b_{fkt-1};\ \forall k\in J_{t-1};\ f=1,\ldots,h$$

$$\lambda_{jt-1\&t} \geq 0;\ j=1,\ldots,n; t=2,\ldots,T; \xi \text{ no restringido}; d_i^x \geq 0; i=1,\ldots,m$$

$$d_r^g \geq 0; r=1,\ldots,s; d_f^b \geq 0;\ f=1,\ldots,h.$$

The degree of $\text{IUEN}_{t \to t-1\&t}$ with respect to the kth DMU between two periods is determined by the following model:

$$(\text{P3})\ \text{Max}\, \xi + \varepsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right]$$

$$s.t. \sum_{j \in J_{t-1\&t}} x_{ijt}\, \lambda_{jt} + d_i^x = x_{ikt};\ \forall k \in J_t;\ i=1,\ldots,m$$

$$\sum_{j \in J_{t-1\&t}} g_{rjt}\, \lambda_{jt} - d_r^g\ -\ \xi\, g_{rkt}\ = g_{rkt};\ \forall k \in J_t;\ r=1,\ldots,s$$

$$\sum_{j \in J_{t-1\&t}} b_{fjt}\, \lambda_{jt} + d_f^b +\ \xi\, b_{fkt}\ = b_{fkt};\ \forall k \in J_t;\ f=1,\ldots,h$$

$$\lambda_{jt} \geq 0;\ j=1,\ldots,n; t=2,\ldots,T; \xi \text{ no restringido}; d_i^x \geq 0; i=1,\ldots,m$$

$$d_r^g \geq 0; r=1,\ldots,s; d_f^b \geq 0;\ f=1,\ldots,h.$$

"Managerial disposability": The Malmquist index with frontier shift between two periods may be represented as follows:

$$IMNC_{t-1}^{t} = \sqrt{\frac{\text{UEM}_{t-1}}{\text{IUEM}_{t-1 \to t-1\&t}} \frac{\text{UEM}_{t}}{\text{IUEM}_{t \to t-1\&t}}}.$$

The degree of UEM_t of the kth DMU in the t period is measured by the following model:

$$(\text{P4})\ \text{Max}\, \xi + \varepsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right]$$

$$s.t. \sum_{j \in J_t} x_{ijt}\, \lambda_{jt} - d_i^x = x_{ikt};\ \forall k \in J_t;\ i=1,\ldots,m$$

$$\sum_{j \in J_t} g_{rjt}\, \lambda_{jt} - d_r^g\ -\ \xi\, g_{rkt}\ = g_{rkt};\ \forall k \in J_t;\ r=1,\ldots,s$$

$$\sum_{j \in J_t} b_{fjt}\, \lambda_{jt} + d_f^b +\ \xi\, b_{fkt}\ = b_{fkt};\ \forall k \in J_t;\ f=1,\ldots,h$$

$$\lambda_{jt} \geq 0;\ j=1,\ldots,n; t=2,\ldots,T; \xi \text{ no restringido}; d_i^x \geq 0; i=1,\ldots,m$$

$$d_r^g \geq 0; r=1,\ldots,s; d_f^b \geq 0;\ f=1,\ldots,h.$$

The degree of UEM_{kt} with respect to the kth DMU in the t period is determined by

$$\text{UEM}_{kt} = 1 - \left[\xi + \varepsilon \left(\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right) \right].$$

The degree of UEM_{t-1} with respect to the kth DMU in the $t-1$ period is measured by replacing t with $t-1$ in the Model (P4).

The degree of $\text{IUEM}_{t-1 \to t-1\&t}$ of the kth DMU in the $t-1$ period is determined by the following model:

$$(\text{P5})\ \text{Max}\, \xi + \varepsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right]$$

$$s.t. \sum_{j \in J_{t-1\&t}} x_{ijt-1\&t}\, \lambda_{jt-1\&t} - d_i^x = x_{ikt-1};\ \forall k \in J_{t-1};\ i=1,\ldots,m$$

$$\sum_{j \in J_{t-1\&t}} g_{rjt-1\&t}\, \lambda_{jt-1\&t} - d_r^g\ -\ \xi\, g_{rkt}\ = g_{rkt-1};\ \forall k \in J_{t-1};\ r=1,\ldots,s$$

$$\sum_{j \in J_{t-1\&t}} b_{fjt-1\&t}\, \lambda_{jt-1\&t} + d_f^b +\ \xi\, b_{fkt}\ = b_{fkt-1};\ \forall k \in J_{t-1};\ f=1,\ldots,h$$

$$\lambda_{jt-1\&t} \geq 0;\ j=1,\ldots,n; t=2,\ldots,T; \xi \text{ no restringido}; d_i^x \geq 0; i=1,\ldots,m$$

$$d_r^g \geq 0; r=1,\ldots,s; d_f^b \geq 0;\ f=1,\ldots,h.$$

The degree of $\text{IUEM}_{t \to t-1\&t}$ of the kth DMU in the t period is determined by the following model:

$$(\text{P6})\ \text{Max}\, \xi + \varepsilon \left[\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \right]$$

$$s.t. \sum_{j \in J_{t-1\&t}} x_{ijt-1\&t}\, \lambda_{jt-1\&t} + d_i^x = x_{ikt};\ \forall k \in J_t;\ i=1,\ldots,m$$

$$\sum_{j \in J_{t-1\&t}} g_{rjt-1\&t}\, \lambda_{jt-1\&t} - d_r^g\ -\ \xi\, g_{rkt}\ = g_{rkt};\ \forall k \in J_t;\ r=1,\ldots,s$$

$$\sum_{j \in J_{t-1\&t}} b_{fjt-1\&t}\, \lambda_{jt-1\&t} + d_f^b +\ \xi\, b_{fkt}\ = b_{fkt};\ \forall k \in J_t;\ f=1,\ldots,h$$

$$\lambda_{jt-1\&t} \geq 0;\ j=1,\ldots,n; t=2,\ldots,T; \xi \text{ no restringido}; d_i^x \geq 0; i=1,\ldots,m$$

$$d_r^g \geq 0; r=1,\ldots,s; d_f^b \geq 0;\ f=1,\ldots,h.$$