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Revisiting the Size-R&D Productivity Relation: Introducing the Mediating Role of Decision-Making Style on the Scale and Quality of Innovative Output

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Abstract

We develop a mediation model in which firm size is proposed to affect the scale and quality of innovative output through the adoption of different decision styles during the R&D process. The aim of this study is to understand how the internal changes that firms undergo as they evolve from small to larger organizations affect R&D productivity. In so doing, we illuminate the underlying theoretical mechanism affecting two different dimensions of R&D productivity, namely the scale and quality of innovative output which have not received much attention in previous literature. Using longitudinal data of Spanish manufacturing firms we explore the validity of this mediation model. Our results show that as firms evolve in size, they increasingly emphasize analytical decision making, and consequently, large-sized firms aim for higher-quality innovations while small firms aim for a larger scale of innovative output.

Introduction

Much of the research on innovation has been aimed at settling the question of whether firm size matters for R&D productivity. Although its volume is indicative of its theoretical and practical importance, this vast literature has regarded size as a static variable, differentiating firms in a given point in time, while disregarding its dynamic nature and the internal changes that firms undergo as they evolve in size. Because firms' strategic behavior changes as they evolve from small to large organizations, we suggest adopting a dynamic view to explore the internal changes triggered by this evolution and how they ultimately affect R&D productivity. At the same time, the inconclusive nature of this literature points at the difficulty of measuring innovative output and interpreting evidence resulting from imperfect measures (Tether 1998). Many empirical studies point to a negative relation between firm size and R&D productivity (Pavit et al., 1987; Acs and Audretsch 1991; Kleinknecht et al., 1993; Cogan, 1993; Audretsch 1996; Coombs et al. 1996; Santarelli and Piergiovanni 1996), while other studies point in the opposite direction (Cohen 1995, Nooteboom 1994, Dimasi et al. 1995, Tether 1998, Laursen and Salter 2006). Yet, most studies have focused on innovation counts as measures of innovative output implicitly assuming that the quality of innovations is equally distributed across size categories, whereas only a few have used metrics capturing qualitative aspects of innovations. We question whether variations in a firm's *scale* of innovative output hold at the expense of the *quality* of such output, and suggest extending this debate beyond the firm size question and exploring how these two organizational outcomes differently relate to the internal changes undergone by firm's evolution in size.

Consistent with Winter (2006), we believe that the key to understanding organizational outcomes lies in exploring the nature of their capabilities and how these capabilities evolve. In this paper we are interested in firms' decision-making capabilities, which remain relatively understudied in the organizations literature, as a critical factor mediating the effect of firm size on R&D performance. Our contention is that evolution in size carries internal changes that affect how decisions are made, and consequently, the outcomes achieved. When organizations are small, decision makers are able to arrive at strategic choices in an unstructured, flexible, and spontaneous manner without the need for exhaustive analytical procedures to render the decision process more objectively logical in the face of investors or stakeholders. As size increases, the hindered knowledge flow and the addition of stakeholders (e.g. bondholders, employees, customers) call for an increasingly analytical decision style in order to reduce risk-taking, improve efficiency, and render the decision process more objectively logical. Through this orderly process large established firms increase control over the innovation process and reduce variance in production routines, which leads to a more efficient exploitation of existing ideas while discouraging search for new ones (Benner and Tushman 2002). As a result, evolution in size is expected to lead firms to paying less attention to the development of new products and more attention to the improvement of existing ones, thus increasing the focus on a reduced number of higher-quality innovations.

Organization research has acknowledged the importance of decision styles for organizations and shows a growing concern on how decision styles affect organizational outcomes (Eisenhardt 1989; Khatri and Ng 2000; Romme 2003; Sadler-Smith 2004; Dane and Pratt 2007). Firms increasingly spend large sums of money on analytical tools for strategic decision making, and such trend is evidenced by the exploding growth in expenditures in the information technology industries since the 1970's which now exceed two trillion dollars annually (Ryan et al. 2002). Despite the normative and theoretical importance given to analytical decision making in organizations, little is known about its effect on R&D productivity. Yet, outstanding R&D decisions are vital for getting the right product to the market at the right time. While most organizations rely to some extent on analytical tools for strategic decisions, we suggest that firms may increasingly emphasize analytical decision making depending on their size evolution. We address this gap by proposing the mediation model depicted in Figure 1.

INSERT FIGURE 1 ABOUT HERE

We contribute to the organization literature in several ways. First, we add to the debate on the sources of innovation by presenting decision style as an internal factor influencing R&D productivity. Innovation scholars have neglected the role of decision styles as a relevant determinant of innovation, and the consequences of such neglect have gone understated. Moreover, the notion that highly analytical decisions yield superior R&D outcomes, continue to shape strategic decision making in firms, and the validity of this belief has not been explored at the organizational level. Secondly, by elaborating on two different dimensions of R&D productivity, namely scale and quality, we are able to better understand the dynamics of a key organizational outcome. We realize that innovation counts, although they are representative of a firm's scale of innovative output, are poor indicators of the quality of such output. Finally, we change the way we look at firm size, not as a static characteristic of firms in a given point in time but rather as a feature that reflects evolution in organizational capabilities. We believe firm size is a construct worthy of theoretical attention, because firms of different sizes have different patterns of routine activity, different tangible and intangible assets, different repertoires of actions available to the individuals involved, and as any of these attributes change, the firm itself changes.

Theory and Hypotheses

While research on organizational evolution focuses mainly on the technological aspects of production, it also stresses the cognitive nature of the organizational structure of the firm (Nelson and Winter 1982). As a result, the evolutionary perspective has portrayed the firm as an information processing organism that has the ability to adapt and process information. This emphasis placed on cognition is crucial in a world where decision makers have different perceptions of the environment, and where acquisition of information, computation, codification, and communication are costly. In such a world, coordination can only be achieved by means of the definition of a common set of rules and codes which are shared by the members of the organization. Because incentives, information flows, and behavior differ across organizational forms, the size of firms becomes a variable of interest for understanding the cognitive structures of firms and their effect on organizational outcomes. Therefore, in this study we intend to draw on insights from decision research to better understand cognitive aspects of organizational structure.

In past research, size has been regarded as a mere organizational feature of firms at a given point in time, but not much attention has been paid to size as an indicator of organizational evolution and how it triggers internal changes that affect organizational outcomes. As firms evolve from small to large firms, they undergo changes in the flow of information, incentives, and more importantly, in the manner members arrive at judgments and decisions. This expanded conception of firm size proposed herein, as a dynamic variable which affects organizational outcomes by means of triggering specific decision styles, changes the way we look at firm size. Because it is not the size of firms *per se* but rather the internal processes activated as firms evolve in size that are proposed to influence the outcomes, understanding how decision-making capabilities change with size can help managers identify more clearly the links between organizational structure and R&D performance. Next, we review the literature exploring the link between firm size and R&D productivity, followed by an overview of the literature on decision styles.

Firm Size and R&D Productivity

Most research in R&D productivity has looked at firms' rate of innovativeness as measured by innovation counts, or innovation counts standardized by number of employees or R&D investments. Within this stream of research, many studies report an advantage in R&D productivity for large firms. Earlier explanations for this finding point at the existence of complementarities between R&D and other functional activities such as marketing or the production process (Cohen 1995), economies of scale and scope (Nooteboom 1994, Dimasi et al. 1995), cost-spreading advantages because large firms can spread R&D expenditures over their increasing output, thereby enhancing returns to R&D (Cohen and Klepper 1996), the ability to maintain a diverse portfolio of R&D projects, and better absorptive capacity of internal and external knowledge spillovers (Henderson and Cockburn 1997).

While the empirical evidence fails to generate a consensus view, several studies find that small firms in manufacturing industries introduce a larger share of innovations per employee or unit of R&D than their larger counterparts (Bound et al. 1984; Hausman et al. 1984; Pavit et al., 1987; Acs and Audretsch 1991; Kleinknecht et al., 1993; Cogan, 1993; Audretsch 1996; Coombs et al. 1996; Santarelli and Piergiovanni 1996). Supporters of this view assert that large firms are less efficient than smaller ones because of a lower marginal control and higher bureaucratic controls (Scherer and Ross 1990). According to Cohen and Klepper (1996), this result may be observed because R&D spending increases more than proportionally with size, and therefore the average cost of innovations increases, incurring a decline in R&D productivity. It is also believed that routines in large established organizations cause formalization and bureaucratization which hamper their ability to introduce innovations (Sorensen and Stuart 2000). Findings in this direction were interpreted as showing that small firms are more productive innovators than larger firms.

Yet, interpretations based on innovation counts assume that the value or quality of innovations is equally distributed across size categories (Tether 1998; 2000). Few studies have attempted to approximate qualitative aspects of innovations beyond simple counts, and a careful examination of this literature hints at the possibility of an advantage for large over small-sized firms. Dimasi et al. (1995) find that sales derived from product innovations were more than fivefold greater for large than for small-sized firms. Tether (1998), using the amount of sales derived from innovations finds that, relative to their employment, large firms were three times as innovative as smaller firms. Laursen and Salter (2006) also find that larger firms have greater sales of new products than small firms, and that small companies have an even lower performance in the domain of breakthrough innovations. Correspondingly, Ziedonis (2004) finds that the number of successful patent applications granted in the U.S. significantly increase with firm size. Related to this point, others find a positive correlation between firm size and number of patents cited per new product and a negative correlation with number of new products (Katila 2002), or a greater proportion of technical personnel who are better at assessing the suitability of new practices and technologies for large firms (Deward and Dutton 1986). While it appears that small firms are more productive innovators when count metrics are used, large firms appear to be more R&D productive in terms of returns to R&D and the overall quality of the innovations they produce. However, research exploring qualitative aspects of innovation remains negligible compared to the vast literature using innovation counts, and therefore no definite conclusions can be drawn.

Nonetheless, these results suggest that firms in different size categories do not share the same objective functions concerning innovative output. A possible explanation for this divergence may lie in the internal changes undergone by firms as they transform from small business to large-sized organizations. We suggest that, as firm size increases, the innovation process within firms represents a conscious choice to aim for high-quality innovations as opposed to an increased scale of average innovations.

Two dimensions of R&D productivity: *scale* and *quality* of innovative output

Evaluating and comparing organizations' R&D productivity is a complex task because R&D processes are risky, uncertain, characterized by a long gestation period and have multiple output parameters. While a simple count of the number of innovations may approximate the scale of an organization's innovative capabilities, it ignores important aspects of R&D such as its ability to generate financial returns from investments in R&D (Narin et al. 1987; Schoenecker and Swanson 2002). The distinction between different dimensions of R&D productivity has not received much attention in previous research and may have led to confusing conclusions. Schoenecker and Swanson's (2002) survey on firm technological capability indicators, suggests that innovation counts, patent counts, or R&D spending, measure a firm's *scale* of innovative capabilities, while citation-based patent statistics, science linkages, and technological cycle time are indicative a firm's *quality* of the innovations it produces. Although some evidence from previous empirical work suggests that these dimensions are not correlated to each other (Narin *et al*. 1987; Schoenecker and Swanson 2002), the origins of this independence or the causal factors influencing each dimension remain unquestioned. In this paper, we will conceptually refer to scale as any measure of innovation counts, and we expand the extant notion of quality to include returns on R&D investments which capture the monetary gains derived from innovative output. *Ceteris paribus*, a firm will be more R&D productive in *scale* if it produces a larger amount of innovations per unit of R&D investment, and will be more R&D productive in *quality* if the innovations it introduces are able to generate more financial gains. We believe it is important to propagate this distinction not only to better understand firms' innovative activity but also to appreciate how the internal mechanisms arising in firms of different size can yield diverse outcomes.

At an early stage, when firms are small, they tend to be more vulnerable to changing environments and the expansion through increased product innovation is an essential strategy for their viability in manufacturing industries (Penrose 1980). For small firms in general, successful performance is often interpreted as growth in size, and such outcomes are often achieved through product innovation (Rao and Drazin 2002). Growth-oriented strategies, which are frequently adopted by small firms, are found to explain product innovation (Vaona and Pianta 2008) as opposed to value-oriented strategies pursued by larger firms. Similarly, product innovation has been found to improve the survival chances of small, entrepreneurial firms through extended innovative periods where they experiment with new products (Schoonhoven et al. 1990). Consequently, it is believed that survival of small firms may call for a stream of innovations to increase the scale of innovations introduced per unit of R&D investment (Siegel et al. 1993) as opposed to value-creating strategies adopted by large firms. In contrast, as firms become large, profitability measures such as return on investment and return on equity are more commonly used as metrics of success (Garnsey 1998). Because of this argument, it is suggested that large firms focus on the quality of innovations rather than on the scale of the portfolio of new products, while small firms favor the scale of innovative output. Therefore, this distinction between scale and quality can help improve our understanding of the size-R&D productivity relationship, and likewise, it will provide a starting point to analyze how decision making approaches mediate the effect of size on these two dimensions of R&D productivity. Following the arguments commented above, we suggest that size is linked to R&D productivity in the following way:

H1A: firm size and R&D productivity in terms of scale of innovative output are negatively related.

H1B: firm size and R&D productivity in terms of quality of innovative output are positively related.

Decision-making Styles

One of the under-explored but potentially critical factors influencing the relationship between firm size and the two dimensions of R&D productivity is the style in which organizations approach strategic decisions. There is a growing consensus that a useful distinction can be made between two decision styles (Allinson and Hayes 1996; Dane and Pratt 2007), also referred to as cognitive strategies (Hogarth 2005), or modes of thinking and deciding (Kahneman 2003). On the one hand, there exists an analytical style of reasoning, also called “rational” or “deliberate” which is usually described as effortful, slow, abstract, based on language, conscious, explicit, computational, and rule-governed. On the other hand, there is a non-analytical style also referred to as “intuitive”, “experiential” or “tacit”, which is described as effortless, rapid, non-explicit, unconscious, and producing approximate responses. A key distinction between these decision styles is the type and comprehensiveness of the information gathered to form judgments. For analytical judgments, the information gathering process tends to be comprehensive and hard data is usually collected, which requires effortful manipulation and timely processing. For non-analytical judgments, the data gathering process is not exhaustive and hard-data analysis is avoided, leading way to judgments which are rapid and associative, manifested by experiencing a holistic feeling, a sense of overwhelming certainty, and an awareness of a knowledge that is on the threshold of conscious perception (Hodgkinson and Sadler-Smith 2003). While decision styles have been considered as individual differences (Schunk and Betsch 2005) they have been found to mainly depend on contextual factors (Hammond 1996). Certain characteristics of a task, like availability of detailed analytical information, may promote deliberate analysis while others, like feedback or time pressure, may promote rapid response.

The notion that decision making involves analytical and non-analytical components is broadly accepted and relates to most people’s every-day decisions (Epstein 1994; Hogarth 2005). It is important to stress that both mechanisms are simultaneously involved in most decisions. Some theorists emphasize the idea of a continuum featuring “intuitive reasoning” in one extreme and “analytical reasoning” on the other, leaving a number of styles in between (Simon 1989; Hammond 1996). However, dual-process theorists have converged on the notion that analytical and intuitive styles represent two conceptually independent continuums, which decision makers use simultaneously and interactively (Epstein 1994; Hodgkinson and Sadler-Smith 2003). According to the later vision, it is possible for decision makers to approach a decision both in a highly analytical and intuitive mode simultaneously. Given that intuition *per se* cannot be assessed at the organizational level with the data available in this study, we will focus on the degree to which firms increasingly emphasize analytical decision making (defined in greater detail later). Such operationalization of decision styles excludes the possibility of testing dual-process arguments, but will enable us to identify the firms' position within the analytical continuum. Highly analytical firms will lie close to one extreme and low-analytical firms will lie close to the opposite extreme of the continuum. Under this viewpoint, managers that base their R&D decisions on numerous information tools such as detailed R&D plans, sophisticated indexes, scientific information, among other hard data, undergo a highly analytical decision process, while managers undergoing a low-analytical process move away from this end of the continuum, basing their decisions on their own subjective judgments and disregarding exhaustive information support.

Managers often use analytical tools to "double-check" judgments derived from impressions or quick associations, especially when there is no time pressure. Yet, in the particular situation of judgments about the potential attractiveness of an invention, or the likelihood of a new product being accepted by the public, rapid judgments may not always be easy to overrule by analysis, because it consumes time and resources. Such decision situations require managers to engage in cognitively demanding activities (Busenitz and Barney 1997). While most operating decisions by managers appear to entail little uncertainty (e.g., selection of inventory level or accounting method), R&D decisions are highly uncertain because decision makers must analyze their own organization, the environment, make predictions about future states of the environment and their competitors, among other difficulties. As a result, managers facing R&D decisions may choose to deal with uncertainty in different ways, either by acquiring vast amounts of information tools or by disregarding analysis. Therefore, the degree to which decision makers emphasize one decision style or the other may cause variations in the outcomes of the R&D process. A key proposition of this study is that firms' reliance on one style or the other relates to their size evolution.

Firm Size and Decision-making Styles

A key distinctive feature in the management of small firms is the tendency to disregard analytical mechanisms. In contrast to managers in large firms who rely extensively on analytical procedures, entrepreneurs in small firms manifest greater reliance on shortcuts often referred to as decision heuristics, which can be an effective guide to managerial decision making under conditions of uncertainty and complexity (Busenitz and Barney 1997; Houghton et al. 2000; Forbes 2005). Relatedly, Lindsay and Rue (1980) suggest that small firms follow a less technocratic decision approach as compared with large firms. This view coincides with descriptions of top-managers in large corporations, who are usually regarded as risk averse and as following structured analytical processes to arrive at decisions.

Large firms tend to make decisions in a more planned and structured manner than small firms (Busenitz and Barney 1997), thus, decision makers in large firms have to gather as much information as possible to make strategic decisions. Apart from developing formal plans, firms can rely on several decision-making tools to render the R&D process more analytical, such as acquiring scientific information, collaborating with universities, or evaluating technological perspectives, among other sources of information. In this same vein, evidence presented by Huang et al. (2002) reveals that small firms planning new product developments tend to be less formal than large firms, since their strategic planning is often reduced to informal conversations, as opposed to written and explicit plans which are followed step-by-step in large corporations.

Moreover, small firms' limited budgets force them to deal with uncertainty differently than large firms. When firms are small and carry out innovative activities, they often do so without many financial and managerial resources and, in particular, without formalized methods (Santarelli and Sterlacchini, 1990). As a result, smaller firms are forced to rely less extensively on analytical tools than larger firms to cope with the uncertainty in strategic decision making. Also, as firms turn into large organizations, managers increasingly become subject to close monitoring by the firm's board of directors, shareholders, and institutional investors who expect decision making to be based on justifiable arguments. Therefore, managers are likely to search for objective pieces of information to support their decisions, which leads large corporations to adopt a highly-analytical style. Conversely, managers in small firms may not undergo this type of pressure and have more freedom to make key decisions based on personalized judgments, without having to acquire expensive information to back their decisions. This implies that reliance on an analytical decision-making style is linked to the evolution of firm size. We propose the following hypothesis:

H2: Decision style becomes increasingly analytical with firm size.

Decision Styles and R&D Productivity

The importance of decision making for the R&D process is attested by a shift in the notion of R&D, which is increasingly seen as a strategic decision-making process of vital relevance to firms. It is therefore straightforward to expect that differences in the way decisions are made may generate variations in R&D productivity. The emphasis placed on an analytical style affects R&D productivity through a number of mechanisms, some of which are preferable for R&D productivity from a *scale* and others from a *quality* standpoint.

Decision style and the scale of innovative output. Several aspects of a highly-analytical style, as opposed to a low-analytical one, bound the scale of innovative output. First, firms relying heavily on analytical tools for innovation-related decisions incur excessive expenditures on information acquisition to aid their decisions. These information tools considerably increase the costs of the R&D process without necessarily incrementing the amount of innovation in the same proportion (Cohen and Klepper 1996). Substantial investments in analytical tools can be seen as fixed costs that are incurred every time an R&D project is pursued, and this posits a constraint on the number of R&D projects that an organization can support.

Second, in addition to inflating the costs of the R&D process, it is suggested that currently available information is often of little help for the successful development of future opportunities (Sine et al. 2005). The effectiveness of decision making is contingent upon the usefulness of the data gathered to form judgments. In this line, the entrepreneurship literature supports that entrepreneurial opportunities, such as new product developments, often follow a messy, non-linear, tacit and socially complex process, and that the associated outcomes can rarely be known ex ante, meaning that there is little useful preexisting information related to exploiting new opportunities (Alvarez and Barney 2005). This implies that managers in charge of innovation-related decision may often take cognitive shortcuts as a response to the conditions associated with the task of innovating, such as information shortage, high uncertainty and high time pressure (Baron 1998). Therefore, a highly analytical style may not be as well suited as low-analytical decision making to tasks such as R&D problems that involve a high level of uncertainty.

Third, in a situation characterized by meager information, analytical decision making, which stresses sequential, systematic, and step-by-step approaches to strategic decisions, often demonstrate to be time consuming. Eisenhardt (1990) observed that executives who were able to keep their organizations on pace with the rate of change in their operating environments were likely to discard analytical procedures as a primary basis for making key strategic decisions. In contrast, decision makers who were less effective and slower tended to emphasize formal, technocratic approaches to decision making. Analytical decision styles decreases decision-making speed not only because it takes time to acquire information but also because it takes time to analyze it. These obstacles to decision speed deter the successful exploitation of new opportunities (Eisenhardt 1989; 1990). In a world where product life-cycles are shortening at a fast pace, fast decision making is key to delivering new products to the market.

Fourth, the reliance on analytical tools for decision making can enhance the perception of the risks involved in R&D decisions. Managers selecting among several alternative courses of action have to evaluate the risks entailed by each alternative, and the reluctance to examine an extensive array of information pieces may lead to underestimating potential risks. Several studies have emphasized the importance of lowered risk perception as a catalyst of engagement in risky actions, such as first-moving behavior (Lieberman and Montgomery 1998), innovation or even new venture creation (Simon and Houghton 1999). Studies examining on-the-field decisions regarding product innovation found that managers disregarding analytical mechanisms have a lower perception of risks involved in strategic decisions and consequently present a higher commitment to innovation (Simon and Houghton 2003).

Scholars in this field have evaluated the presence of heuristics and biases such as overconfidence (Forbes 2005), illusion of control (Houghton et al. 2000), representativeness (Busenitz and Barney 1997), and other behavioral regularities in managerial decision making which appear to reduce risk perception. While a highly analytical style can lead to an enhanced assessment of risks, it keeps decision makers from easily engaging in various R&D projects and can consequently reduces the potential number of new product developments. Because of the mechanisms discussed in this section, we claim that an analytical style is inadequate for the introduction of a consistently large number of new products.

H3A: The more analytical the decision style, the lower the R&D productivity in terms of scale.

Decision style and the quality of innovative output. Conversely, firms can expect to benefit from emphasizing an analytical decision style by developing products of higher quality at the expense of a reduced innovative output. Undertaking R&D decisions in a highly analytical manner can have several advantages in terms of the quality of the innovative output. Although approaching R&D decisions in an analytical manner is costly, it ensures a more comprehensive information set from which to draw more accurate inferences. Useful preexisting information related to exploiting new opportunities is rarely available (Alvarez and Barney 2005), but constant investments in information search and extensive market analyses can ultimately provide some sort of advantage to firms. The better insight gained by acquiring and analyzing information related to a specific R&D project can improve the assessment of potential new products and can lead to a better match between product and expectations in the market.

The speed in new product development is likely to affect the product quality. Research on the determinants of product quality sustains that rapid development can compromise the final quality of new product (Crawford, 1992). Increased decision speed is associated with time pressure and, when taken to extreme situations, might call for excessive shortcuts in the decision-making process which in turn lead to narrow sets of alternatives and diminish the chances of selecting the optimal alternative. Thus, slow decision making can promote higher quality output.

At the same time, by having a fine-grained perception of the risks, analytical decision makers can undergo an effective screening process which allows canceling R&D projects that have a higher likelihood of failure, and can chose to pursue only those projects presenting promising prospects. An increased risk perception derived from extensive analytical procedures is desirable in order to improve the ultimate product quality by removing potential sources of uncertainty, and can certainly be worth the investments.

H3B: The more analytical the decision style, the higher the R&D productivity in terms of quality.

The Mediating Role of Decision Style

The way firms approach R&D decisions is proposed to be a function of an evolutionary process within the firm. As firms evolve from small organizational units to larger corporations, they incur changes in patterns of routine activities, in information processing, and in other repertoires of actions related to strategic decision making. Through this process, firms change the stresses on outcomes of innovation from scale to quality. Managers in small firms are able to arrive at strategic decisions in a more unstructured, flexible, fast and spontaneous manner that leads to a rapid development of new ideas, favoring innovation. In this stage, there is an initial hypothesis of how to arrive at a final product, rather than a fully elaborated strategic plan. This tendency stems less from a calculated choice from a number of known alternatives, but more from a process of sequential adaptation to new possibilities (Chesbrough and Rosenbloom 2002).

As firms increase in size, this adaptation becomes more rigid, as information is filtered through a logic that is established from previous successes. Likewise, the knowledge flow diminishes, hierarchical structures become larger, and the amount of stakeholders (e.g. bondholders, employees, or customers) increases. These obstacles increase the need for standardized information sharing mechanisms which are obtained through more analytical decision-environment. In turn, the increasingly analytical style adopted by large firms increases the perception of risks and enable decision makers to filter out potential failing R&D projects (Christensen 1997). This trend, coupled with the pressure exerted by the board of directors, shareholders and investors, leads managers to require less attention to the development of new products and more attention to the existing one, which simultaneously promote the use of analytical decision-tools as filters. Therefore, the different decision styles arise as a result of firms' evolution in size and consequently influence whether firms innovate in scale or in quality.

In summary, we propose that the relationship between firm size and R&D productivity is mediated by decision style. As a result we believe that part of the variability in R&D productivity usually captured by size should be attributed to decision style. By isolating the effect of decision-style we may observe that the remaining effect of size on R&D productivity decreases. Our last hypothesis is:

H4A: Decision style mediates the link between firm size and R&D productivity in terms of scale.

H4B: Decision style mediates the link between firm size and R&D productivity in terms of quality.

Data and Methodology

Sample and data

In our empirical analysis we use longitudinal data from the 'Encuesta sobre Estrategias Empresariales' (ESEE, Survey of Business Strategies), an annual survey which refers to a representative sample of Spanish manufacturing firms conducted by the Spanish Ministry of Industry, Tourism and Commerce. Firms in the sample represent 20 industrial sectors according to the CNAE-93 classification (National Classification of Economic Activities, 1993). Because only companies in manufacturing sectors were surveyed, the industrial background is fairly comparable, and results may be generalizable to a wide range of industrial sectors. A characteristic of the data set is that newly created firms have been added annually with the same sampling criteria as in the base year and exiting firms have been recorded in the sample of firms surveyed each year. Because some firms stopped providing information during the sample period for several reasons, including mergers, changes to non-industrial activity, or production process shut down, we have an unbalanced panel with 1415 firm-year observations. A second characteristic is that the survey has a section in which CEOs are asked about the procedures and tools they used for decision making during the R&D process, which is crucial to this study and serves as the basis for capturing the different decision styles used by firms. The ESEE survey started collecting data in 1990 with an average response rate of 92%, but the section relating to R&D decision making, was included in the survey only in 1998, so our sample ranges from 1998 to 2005. Respondents of the ESEE survey were CEOs and data were collected using direct interviewers supported by a questionnaire. The distribution of the sample with respect to size is reasonably equitable, where 42 percent of the firms are small and 58 percent are large. The threshold used to distinguish small from large firms is 200 employees as suggested by the Spanish Ministry of Industry, Tourism and Commerce. The distribution of the sample across the 20 industrial sectors. The 'chemicals', 'motor vehicles', 'machines and mechanical equipment', and 'food and tobacco' sectors rank among the most populated sectors, and such distribution resembles the actual distribution of Spanish manufacturing firms. Finally, Figure 2 shows firms' reliance on analytical tools for R&D decision-making according to their size. Note that most large firms rely with a higher frequency on four or five analytical tools, while the tendency for small firms is to rely on zero or less than two. From this graph we can see the propensity of large firms to follow highly-analytical decision making as opposed to small firms' propensity to disregard analytically-intensive decision procedures.

INSERT FIGURE 2 ABOUT HERE

Measures

Modeling R&D productivity and measuring firms' decision style present a key operational challenge for testing our hypotheses. In particular, we need to identify empirical measures that approximate the degree to which firms become increasingly analytical in their decision making, and the scale and quality of innovative output. Because we are going to control for total R&D expenditures in the regression analyses, each of the dependent variables in our models will feature one of the dimensions of innovative output. Therefore, the analyses will report the effect of the antecedent, mediator, and control variables on the scale and quality of innovative output conditional on the amount invested in R&D

Dependent Variables.

Scale$_{it}$: The variable accounting for the quantitative aspect of innovative output, *Scale*$_{it}$, is measured by new product development frequency of firms, that is, by the number of new products developed by firm *i* in year *t*. New products as a measure of innovation *scale*, has both significant strengths and weaknesses. First, in our data the number of new products developed is directly related to inventiveness: they are recognized as "new products" only if they are completely different to previous product lines or if they have suffered substantial modifications from previous products. The number of new products not only measures a firm's ability to introduce new products in the market but also its ability to upgrade current ones. Survey results to top R&D executives suggest that the most common way of assessing a competitors' innovative strength is by their ability to develop new products (Schoenecker and Swanson, 2002). Second, this measure is closely related to similar measures of innovative strength such as patents (Scherer and Ross 1990; Ahuja and Katila 2001), sales growth (Scherer 1983), and invention counts (Achilladelis et al. 1987). The ability to produce multiple product innovations in a given period is critical in high-velocity environments and is considered a key indicator of innovative performance (Schoonhoven et al. 1990).

Quality$_{it}$: The dependent variable approximating the quality of the innovative output in the sense of "returns-on-R&D-investments", *Quality*$_{it}$, is assessed by the licensing revenue obtained from product innovations by firm *i* in year *t*. For many industries, licensing revenue is the primary reason for their innovation activity and the growth in licensing revenue has increased substantially over the past twenty years (Arora and Fosfuri 2003). On the one hand, large companies usually have a technology group that handles all their licensing activities, and therefore have an incentive to use licensing as an outlet to generate income. On the other hand, licensing can be a great revenue model for small firms which usually do not have the resources to enter or effectively compete in their target markets, or where their technology is applicable to a number of industries. Licensing of new ideas can enable firms to enter new markets with little or no risks relatively quickly, like going into foreign markets. Licensing can also provide an advantage to firms by providing an opportunity to establish industry standards and to deter entry (Gallini 1984). Through cross-licensing, firms can gain greater freedom to develop new products and compete in new markets without worrying about potential litigation. Additional incentives to licensing include the selection of competitors (Rockett 1990). Arora and Fosfuri (2003) suggest that licensing activity in the product market limits the negative impact of competitors' licenses, while increasing total revenues of firms. Sales derived from new products stands as a potential alternative measure for the quality of innovation, but may not be as appropriate as the measure considered in this study because it varies depending on other factors unrelated to the actual product's quality, like the firm's sales and marketing power, size of market share, or monopoly power (Cohen 1995). The amount of sales of new products reflects other functional capabilities of firms and not necessarily the quality of the R&D output. In this respect, licensing revenue acts as a proxy for the quality of the innovative output without including additional noise as new product sales.

Mediator variable

Decision style$_{it}$: To capture the decision style of firms by the degree to which firm *i* relies on analytical tools for R&D decision-making purposes at time *t*, we built a composite measure using four items. Data were gathered from a section of the ESEE survey in which CEOs are asked to answer 'yes' or 'no' to a series of items where each one represents a different tool or procedure used during the R&D process. Because composite measures quantify complex concepts more adequately than single indicators, we selected four of these items from a total of six available, and added them up with equal weighting to create a rank-ordering variable which approximates the continuum-like nature of the analytical construct. This measure takes a minimum value of zero and a maximum of four. Firms with the maximum score are assumed to follow a highly analytical style and as firms move away from the maximum score they are assumed to become less analytically oriented for R&D decision making.

The first item captures whether firms formally establish an R&D committee and a detailed R&D plan to guide their R&D process. Firms establishing a formal R&D plan and committee are likely to undergo formal planning, which entails deliberation, examination of many alternatives, selection of an optimal strategy, and therefore resembles an analytical approach to decision making. The second dummy measures whether firms acquire scientific information to improve their R&D projects. Scientific information such as exhaustive research reports or insights about state-of-the-arts technologies, augment the information pool of decision makers. This type of information is likely to be specific and not vague, meaning that it requires analytical skills for it to be manipulated and thus used. The third dummy variable reports whether firms collaborate with universities. Collaborating with universities may reduce the firm's risk in the development process of a new product, and may enhance the firm's final decisions due to the advice of experts, so firms collaborating with universities are assumed to approach decisions more analytically than those not collaborating. The fourth dummy repots whether firms evaluate the perspectives of technological opportunities during the R&D process. The evaluation of technological opportunities may serve to reduce the uncertainty regarding R&D investments and, therefore, evaluating the potential profitability of an innovation project renders the R&D decision process more analytical. All these items point in the same direction, so that the presence or use of any of these procedures renders the R&D process more analytical in that firms need to make use of analytical skills, devote time and cognitive efforts, process hard data, in order to successfully utilize them. A reasonably high Cronbach's alpha (.76) confirmed the internal consistency of this construct, and an exploratory factor analysis revealed that a single factor underlies the four items (only one factor with an eigenvalue greater than one), supporting that the composite measure is uni-dimensional. Because the components of composite measures need to be independent so that variation in one component does not directly drive another, we dropped two out of the six initially available items because they correlated extremely high to other items, and thus provided redundant information. The discarded items measured whether firms evaluate alternative technologies and whether firms elaborate innovation indexes.

Table 1 shows the breakdown of the percentage of firms using each decision tool. The most commonly used tool is the formation of an R&D committee (70%), and the least relied upon is scientific information (45%). For the four items, large firms have a higher frequency of use than smaller ones. Table 2 presents a tabulation of decision style versus both dimensions of R&D productivity. We split the two dependent variables by its median value into "high" and "low. While firms that introduce a high number on innovations per unit of R&D investment tend to disregard analytical tools (58% of all high-scale firms use 0 tools), high-quality innovators present the opposite trend (54% of all high-quality innovators use 3 or 4 tools). Overall, these trends point at the possibility that the decision style may be driving innovation outcomes independent of firm size.

INSERT TABLE 1 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

Antecedent Variable

Logemployees$_{it}$: To measure the size of firms we use the log of number of employees (*Logemployees*), instead of other commonly used measures such as log of sales which highly correlates with other control variables like R&D expenditures. This measure of size is more stable across time than other measures based on sales which are more volatile and sensible to macroeconomic shocks.

Control Variables

Because we are interested in R&D productivity, we control for R&D expenditures of firms lagged one period, so variations in the scale and quality of innovative output are conditional on R&D expenditures. R&D expenditure is also regarded as a proxy for the accumulation for absorptive capacity (Cohen and Levinthal 1990). We control for possible macroeconomic and business cycle shocks common to all industrial sectors using time dummies for the years 1998-2005, as well as time invariant shocks using industry dummies reflecting the 20 different industrial sectors as defined by the CNAE-93 classification. We include firm age measured by the log of age, which controls for the experience of firms. We also control for environmental volatility in the product market following Sorenson's (2003) approach. This measure uses the correlation in sales from period *t* to period *t-1*. Product sales represent relatively stable attributes, so consumers should consume the same products from one period to the next if they prefer the same attributes, meaning that a high correlation between periods reflects low volatility while low correlation signals higher volatility. Finally, to control for firm heterogeneity we construct a presample variable according to the type of dependent variable, where in the case of *Scale* presample variable represents the sum of product innovations obtained by a firm in the three years prior to the firm's entry into the sample, while in the case of *Quality* represents the sum of licensing revenue accumulated in the three years prior to the firm's entry into the sample.

Methodology

A panel data design was used to test the hypotheses. Because we are testing a mediation model, the hypothesized antecedent, mediator, and dependent variables must not be coincident in time. As MacKinnon et al. (2007, page 604) note, "Longitudinal data allow a researcher to examine many aspects of a mediation model that are unavailable in cross-sectional data, such as whether an effect is stable across time and whether there is evidence for one of the important conditions of causality, temporal precedence". A correctly specified mediation model then has to define a causal order and direction, for which temporal precedence of causal factors is essential (Mathieu and DeShon 2008). To account for temporal precedence of variables, we follow a "distributed lags" procedure (Ahuja and Lampert 2001). The distributed lags enable us to assess the time pattern of the effects of firm size on decision style, and of decision style on R&D productivity, for several subsequent periods. Also, the distributed lags grasp the evolution of firm size. By assessing firms' size in different time periods, we avoid a static representation of size, and capture the effect of firms' size evolution both on the mediator and dependent variables. Nonetheless, the distributed lags may be statistically inconsequential in any one period (Ahuja and Katila 2001) because their net impact is likely to be distributed over several periods.

We develop a mediation model in two stages. First, we test whether firm size causally affects decision style. In this step, the dependent variable is decision style at time *t*, and as explanatory variables we include distributed lags of size at times *t-1*, *t-2*, *t-3* and *t-4*. The second stage of the mediation model reports the effect of decision style on R&D productivity. In this part of the model we use distributed lags of decision style at times *t-1*, *t-2*, and *t-3*, while the dependent variables capturing R&D productivity remain at time *t*. Note that in the second stage of the model we will have two dependent variables reflecting both dimensions of R&D productivity, thus, we will use two different econometric specifications in this stage. Also note that instead of constructing the R&D productivity variables as a ratio of innovative output to R&D input, which is intuitively the most direct way of providing a productivity measure, we rather move the denominator of this ratio, R&D expenditure, to the right-hand side of the equation. In this way, the regression analysis will report the effect of decision styles on the scale and quality of innovative output conditional on the amount invested in R&D. Finally, in the second stage of the model we also include firm size to observe how it affects R&D productivity when decision style is accounted for in the regressions. The firm size variable is lagged one period preceding the mediator, *t-4*, in order to maintain temporal precedence of causal factors. To establish mediation, we follow Baron's and Kenny's (1986) steps, by which size must affect the mediator (decision style) in the first stage; then the mediator affects the dependent variables in the second stage, and we should observe that the effects of size on the dependent variables is weaker or non-existent when the mediator is accounted for.

Model specification and econometric issues

We now describe the econometric approach for the two stages of our mediation model. The dependent variable in the first stage is decision style, as measured by the number of analytical tools used by firms for decision making during the R&D process, and takes non-negative integer values from zero to four. Because the assumptions of the linear regression model do not hold with this type of data, an ordered probit regression approach is appropriate since the dependent variable is a count outcome bounded at value four. An ordered probit approach is the preferred way to capture the ordinal ranking of the dependent variable (McKelvey and Zavoina 1975), and in this case our variable ranks the degree to which firms emphasize analytical decision making during the R&D where zero means non-analytical decision style and four entails highly-analytical decision style. The proposed model is:

$$D_{it} = S_{it-1}\beta_1 + S_{it-2}\beta_2 + S_{it-3}\beta_3 + S_{it-4}\beta_4 + X_{it-1}\gamma \qquad (1)$$

Where D_{it} is the number of analytical tools used for decision making during the R&D process by firm *i* in year *t*, $S_{it-year}$ is the vector of lags for firm size in years *t-1*, *t-2*, *t-3* and *t-4*, and X_{it-1} is the vector of controls affecting decision style.

In the second stage of the mediation model we approximate R&D productivity in terms of *scale* by the number of new products developed. Because this is a count outcome variable taking non-negative integers, a regression approach for Poisson data is suitable. We specified the following regression model:

$$P_{it} = \exp(S_{it-4} + D_{it-1}\beta_1 + D_{it-2}\beta_2 + D_{it-3}\beta_3 + X_{it-1}\gamma) \qquad (2)$$

where P_{it} is the number of new products obtained by firm *i* in year *t*, S_{it-4} is the size of firms in *t-4*, $D_{it-year}$ is the lagged vector of decision style variables for years *t-1* to *t-3*, and X_{it-1} is a vector of control variables affecting P_{it}. This specification implies that the scale of new products introduced by any firm in any given year is randomly distributed following a Poisson process, where S_{it-4}, the covariate vectors X_{it-1} and decision style at *t-1*, *t-2*, and *t-3* determine the mean of this process. We assume that the impact of using analytical tools is likely to be felt over a number of years, thus, we use the distributed lags approach to capture the distributed impact of decision style in different periods. In simple terms, R&D productivity's *scale* of any firm during the year 2003 is potentially influenced by the use of analytical tools during the periods 2002, 2001, and 2000. In sensitivity tests (results available from the authors), we used two and four lags and results remained stable.

This specification does not deal with the problem of unobserved heterogeneity which is the possibility that unmeasured characteristics of firms may account for the observed variance. It is likely that firms included in the sample have substantially different innovative capabilities (Ahuja and Katila 2001), and such heterogeneity may cause estimation problems if it is not accounted for in the specification. The main problem generated by unobserved heterogeneity is overdispersion in the data. To address this issue we follow the Presample Panel Poisson procedure (Blundell et al. 1995) by including a presample variable which accounts for the stock of new product innovations developed over the three years prior to the sample. Thus, this instrumental variable serves as a fixed-effect of the firms' ability to develop new products, and provides a basis for controlling unobservable differences across firms. In addition, we apply the Generalized Estimating Equations (GEE) methodology for estimating Poisson data because it accounts for remaining overdispersion and serial correlation even after including a presample variable (Ahuja and Katila 2001). The beta and standard errors estimated through GEE are consistent. Moreover, we correct for possible violations of the independence assumption of the independent variable by specifying an exchangeable correlation matrix, which assumes interdependence of subsequent observations of the dependent variable through time without imposing a specific type of correlation (Diggle, Heagerty, Liang and Zeger 2002).

Examination of the reported licensing revenues figures indicated significant skewness, so we transformed this measure using the natural log transformation $Quality_{it}$ = ln(1+ $licensing\ revenue_{it}$). In regression analysis, high skewness can increase the risk of Type I and Type II errors (Greene 1999), and the natural log transformation has been proven to eliminate this problem. The transformation was used because the untransformed variable can naturally take value zero and the natural log of zero is undefined. We used Feasible Generalized Least Squares (Greene 1999) which allows for estimating parameters in the presence of autocorrelation and heteroskedasticity. Finally, we report results with robust or White-Huber standard errors. The model is as follows:

$$Q_{it} = S_{it-4} + D_{it-1}\beta_1 + D_{it-2}\beta_2 + D_{it-3}\beta_3 + X_{it-1}\gamma \qquad (3)$$

where Q_{it} is the log of licensing revenue of firm *i* in year *t*, S_{it-4} is the size of firms in *t-4*, $D_{it-year}$ is the lagged vector of decision style variables for years *t-1* to *t-3*, and X_{it-1} is a vector of control variables affecting Q_{it}. We also include a presample variable accounting for the accumulated licensing revenue from three years previous to the inclusion in the sample. This specification only differs from the previous one in the dependent variable and in the presample variable, while the remaining regressors are the same.

Results

Table 3 provides basic statistics for all the variables used in the analysis. The means of our dependent variables are 4.98 for *Scale* and 0.54 for *Quality*, while the mean score for *Decision style* is 2.04. Apart from the expected high correlations between variables and their respective distributed lags, such as for *Size* and *Decision style*, we observe moderately high correlations between $LogR\&D_{t-1}$ and $Size_{t-1}$ (0.64), $Size_{t-1}$ (0.65), $Size_{t-3}$ (0.64), and $Size_{t-4}$ (0.63). Robustness tests indicate that the results of the hypothesized effects were unaffected by these high correlations.

INSERT TABLE 3 ABOUT HERE

Table 4 shows the results for the first stage of the mediation model where decision style is regressed against firm size. Table 5 reports the second part of the mediation model, where the two dimensions of R&D productivity serve as dependent variables. Models 1, 2, and 3in Table 5 show the presample panel regression using GEE Poisson estimators, and Models 4, 5, and 6 report the presample panel regressions with GLS estimators.

INSERT TABLE 4 ABOUT HERE

INSERT TABLE 5 ABOUT HERE

In Hypothesis 1A we predicted a negative relationship between firm size and R&D productivity in terms of scale. The coefficient for *Size* reported in Model 1 in Table 5, shows a negative and significant effect on *Scale*. This result indicates support for Hypothesis 1A and provides additional evidence for the often observed relation between firm size and declining new product development. Hypothesis 1B predicted a positive relationship between firm size and R&D productivity in terms of quality. Model 4 shows that *Size* has a positive and significant effect on *Quality*, meaning that the innovative output of large firms is of higher quality in terms of return-to-investments than that of smaller firms. This finding supports Hypothesis 1B and goes in line with our initial statement about the possibility that the hypothesized negative relation between new product development and size holds at the expense of the quality of the innovations developed. Note however, that the relationship between *Size* and *Quality* is not as strong as that with *Scale*.

In Hypothesis 2 we predicted a positive relationship between *Size* and *Decision style*. The ordered probit estimation reported in Table 4 shows the positive and significant effect of firm size on decision style, implying that firms become increasingly analytical in their decision style as they evolve in size. Model 1 shows the regression of *Decision style* on control variables, with a pseudo-R^2 of 0.03. Models 2, 3, 4, and 5, report a positive and significant effect of the four distributed lags of *Size* on *Decision style*, which improves the overall fit as reported by a pseudo-R^2 of 0.13. Model 6 includes the four distributed lags simultaneously and the overall effect is absorbed by the first lag which is positive and significant. Because there is temporal precedence between the *Size* and *Decision style*, a causal and directional link can be established between the two variables. This result supports Hypothesis 2 and establishes the first step in the mediation process. Note also that the magnitude of the effect is strongest for Size in period *t-1* and it diminishes as lags become more distant in time.

In Hypothesis 3A we predicted a negative relationship between *Decision style* and *Scale*. In Model 2 in Table 6, the distributed lags of *Decision style* are entered and present an overall negative effect on *Scale*, since the sum of the lags is negative. The negative effect of distributed lags is persistent in Model 3, thus, Hypothesis 3A is supported. Hypothesis 3B suggested a positive relationship between *Decision style* and *Quality*. Model 5 in Table 5 presents the distributed lags of *Decision styles* and shows statistical significance in the second lag but not on the remaining ones, which affects *Quality* in a positive direction. This positive link provides modest support for Hypothesis 3B and suggests that firms undergoing highly analytical decision making have higher chances of introducing innovations of above-average quality, and investments in analytical tools for decision making should therefore be expected to increase the quality, while not the quantity, of the innovative output. Finally, hypotheses 4A and 4B predict that *Decision style* mediates the effect of *Size* on *Scale* and *Quality* respectively. Model 3 includes *Size* together with the distributed lags of *Decision style* and we observe that the effect of *Size* is mediated by *Decision style*, since the magnitude of *Size* decreases from -0.194 in Model 1 to -0.175 in Model 3 once we account for decision style. This mediation however, is partial because *Size* still significantly affects the dependent variable. Contrarily, in Model 6, once *Size* and *Decision style* are included together, the effect of *Size* becomes insignificant and the second lag of *Decision style* consistently remains positive and significant. In this case, mediation is full because *Size* no longer affects *Quality* once the mediator variable is accounted for. These findings support Hypothesis 4A and Hypothesis 4B since the variability that was previously explained by *Size* becomes absorbed by *Decision style*.

The controls do not report surprising results. *Log(R&D)* has a positive and significant effect on both dependent variables throughout every model, although the effect appears to be much stronger for *Scale* than for *Quality*. Overall, *Log(age)* shows a positive and consistently significant effect on both dependent variables. While $Presample_{quality}$ is one of the strongest correlates in the *Quality* regressions, $Presample_{scale}$ does not play a prominent role in explaining new product development, and only has a significant role in Model 2, where it has a negative sign. Finally, *Volatility* seems to have a negative effect on the dependent variables, but it is robustly significant for the case of *Scale* and insignificant for *Quality*.

Discussion and Conclusion

One of the contributions of our research is to bring to light the previously underplayed construct of decision style as a key factor influencing innovative output, and demonstrate that as firms evolve in size, they undergo changes in their decision style which affect the scale and quality of innovative output. In line with our arguments, we find a marked causal relation between firm size as measured by the number of employees and decision style. As firms increase in size they tend to rely more extensively on analytical decision tools to aid their decision making during the R&D process. For robustness, we also tested the hypotheses using the log of sales as a metric of size, and the analyses yield consistent results in all the steps of the mediation model[1].

A key contribution of our study is to show how firms' choice of decision style affects innovative output. After controlling for industry and time effects, we demonstrate that different decision styles are adequate for different purposes. A highly-analytical approach to R&D decisions hinders the introduction of numerous new products, presumably because it is time consuming, requires substantial fixed costs for every research project, and restrains creativity by means of an increased perception of risks. In turn, it leads to a reduced output of higher quality. A low-analytical approach is fast, consumes few resources, and does not filter out highly risky projects, which leads to an increased quantity of the innovative output at the expense of its quality. This divergent effect of decision style reported in this study questions the longstanding view held by strategists who picture the task of intelligent management necessarily as that facilitating analytically rational action (Levinthal and March 1993), while it outlines the conditions under which non-analytical decision-making may be desirable.

Our results shed light onto the size-R&D productivity dilemma by showing that firm size can be positively or negatively related to R&D productivity depending on the dimension we assess. Smaller firms are better than large firms at developing more new products per unit of R&D investment but this advantage is eclipsed by the lower quality of their innovative output. This tradeoff puts forth the more difficult question of whether scale is preferable to quality and under what circumstances. Although we may be tempted to conclude that the quality of the innovative output should always matter the most, current trends such as globalization, reduced product-cycle times, increasing competition, and technology

[1] Results are available from the authors

fusion, call for higher speed of introduction of new products and for an ability to generate many subsequent products at a fast pace, and in such situations quality could play a secondary role.

Throughout the development of the mediation model we have conceptualized size as a dynamic variable which reflects changes in organizational structure, but more importantly, changes in cognitive mechanisms adopted by firms. As organizations evolve in size, they have proved to change their cognitive lenses through which they approach strategic decisions, and this change is done through the acquisition of specific decision-aiding tools and procedures that make the R&D process increasingly analytical.

Implications

The fact that firms' decision-making behavior changes with size, has a clear theoretical implication for future research on innovation which is the need to control for differences in decision-making practices and to diminish the theoretical importance of firm size. Because firm size *per se* is not solely accountable for variations in R&D productivity, we thus expect it to become a construct of less importance in future research. Firm size is not a variable which managers are able to freely change in the short term. At most, managers in small firms can target a determined growth in size per year, and in large firms they can perform spin offs, spin outs, skunk works to downsize their R&D business units and in this way, such business units may resemble the behavior of small firms. Rather than focusing on size, managers should pay attention to the way R&D decision making is approached, since it is a decisive factor affecting R&D productivity.

The importance of decision styles in the R&D process point at the strategic relevance of key decision makers in charge of managing and shaping the decision-making processes in manufacturing firms. Our results suggest that managers must emphasize analytical decision making when improvements in the quality of the innovative output are needed, and should emphasize a rather low-analytical approach when a quick succession of multiple new products is needed. For managers, a key implication of our study is that firms should 'think small' if they believe that innovation scale is their concern, and should 'think large' if they pursue higher-quality innovation. Relatedly, because the quality of innovations is often hard to measure, managers may try to impose a target number of innovations in their strategic plans, but they should be aware of the potential problems of posing innovation targets. According to our results, large firms using a highly analytical approach to R&D may not be able to produce a large number of high-quality innovations, so in such cases, imposing a given number of innovations as a target may be ineffective. This implies that firms should make a choice of the dimension of R&D productivity they want to pursue, because quality and quantity appear to be mutually exclusive dimensions and the quality of innovations comes at the expense of a large quantity of innovations. Moreover, heavy investments in state-of-the-arts analytical tools to aid strategic decision-making processes may not always be desirable. Managers should bear in mind that this type of investments are adequate for firms placed in a determined market position and in a specific stage of their life-cycle, in which improvements in profit margins of current products is substantially more important than the development of additional new products.

Related to this point, is the questionable but prevalent assumption about managerial decision making sustaining that analytical decisions yield superior choices than those coming from informal, low-analytical processes. While this assumption may hold true in determined circumstances, it has led research in this field to neglect the relevance of other sources of knowledge such as intuitions, out-of-the-box creativity, or even 'gut feelings', which have proven to be relevant for task performance (Damasio 1994). Contrary to this view, and consistent with evolutionary arguments depicting organizations as evolving and bounded-rational units which seek adaptation through routine-driven behaviors (Nelson and Winter 1982), we suggest that the process of innovation should not be conceived necessarily as a rational-analytical production process, and rather as a process encompassing both analytical and non-analytical factors.

Limitations and further research

Some limitations of this study include the measurement of the dependent variables. Although there are no perfect measurements for the scale and quality of innovations, other measures such as patent counts, or citation-based patent counts could be used to re-examine our hypotheses and test the validity to our findings. Another limitation is that the variable used to grasp decision style may not fully capture the essence of the construct. The decision style construct could be better grasped through psychometric techniques applied to top management teams. An individual-level approach using a sample of top-managers would also bring interesting insights to this debate. Other improvements involve drawing on insights from behavioral decision research to assess more accurately the type of cognitive characteristics that distinguish managers in successfully innovative firms. It is possible that the presence of specific decision heuristics or biases explain the ease with which some firms devote resources to innovation.

While this study helps to address several issues regarding innovation-related decision making, it raises several other. A natural question arising from this study is whether the absence of analytical judgment implies higher reliance on intuitive judgments or whether these two thinking modes are independent in organizational decision making. If intuition is believed to play an important role in strategic decisions, how could intuition be measured at the organizational level? This greater question opens up an avenue for future research on organizational decision making. It is also important to order the time sequence of the two types of decision making. Shapiro and Spence (1997) suggest that non-analytical judgments should occur first, and then thorough analytical judgments should follow to corroborate first-hand impressions or intuitions. Conversely, Agor (1986) argues that managers often rely on intuition after engaging in analytical thinking, for synthesizing and integrating the judgments derived from the analysis.

In this study we have focused on key internal factors of innovation and have not considered how external factors of innovation could interact with the size or decision style of firms in determining innovative output. One variable of interest which was included as a control in this study, environmental uncertainty, has proved to affect innovative output, but we do not know whether larger or more analytically-oriented firms are better suited in high volatile environments for innovation purposes. Extending this study to include the moderating effect of external determinants of innovation poses an interesting avenue of future research.

Conclusions

In conclusion, this study demonstrates that organizational decision style matters: it proves to be an important factor for understanding R&D productivity. We have emphasized throughout the paper that the way organizations approach decision making during the R&D process is dependent on the evolution of firm size and that such choice of decision style ultimately affects the scale and quality of the innovative output produced by firms. High analytical decision making leads firms to emphasize the quality innovation while low-analytical decision making leads to emphasizing the quantity of innovations. In making this point, we tried to fit this study in the literature that explores the role of firm size on innovation and have expanded this debate by including the mediating role of decision style and by distinguishing two dimensions of R&D productivity. To wrap up, we suggest that further research on how decision-making styles affect the strategic behavior of firms is needed not only for theory development but also to increase organizational scholars' attention to other sources of knowledge apart from analytical procedures, that can help organizations form judgments in complex situations. We hope this study helps reduce the gap between organizational research and decision-making research, and call for further efforts to bridge these complementary areas.

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Tables and Figures

Figure 1 Conceptual Model of the Mediating Role of Decision Style

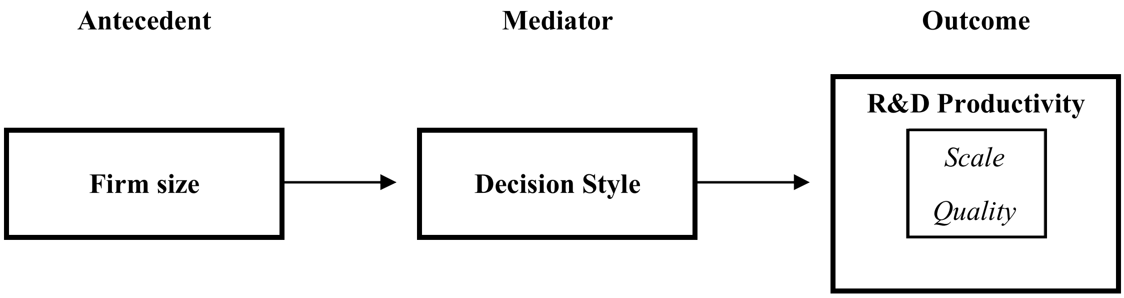

Figure 2 Reliance on Analytical Tools by Firm Size

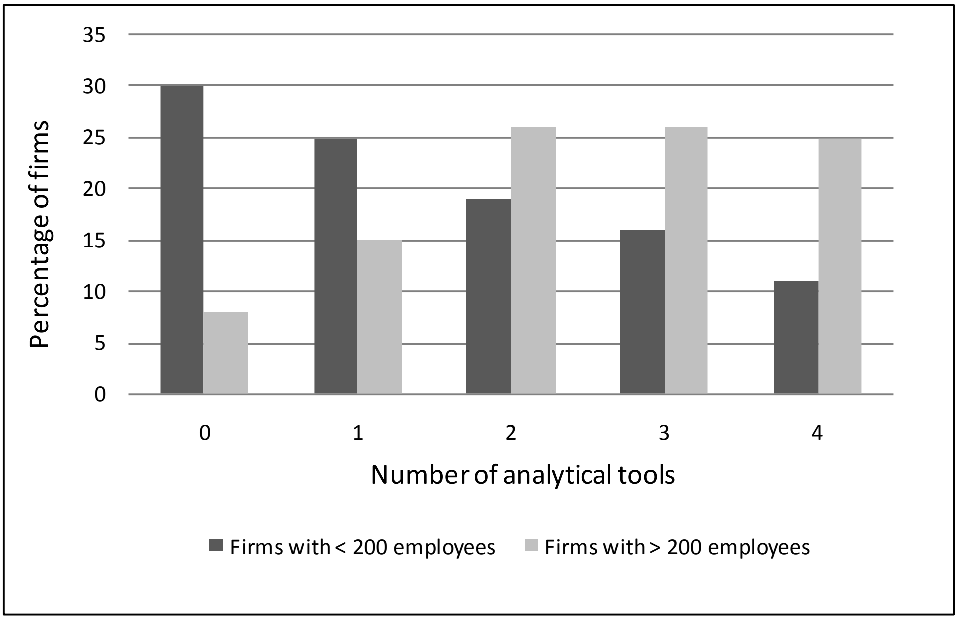

Table 3. Means, standard deviations, minimum and maximum values and correlations for all variables

	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*Scale*	4.98	32.51														
2	*Quality*	0.54	2.49	-0.019													
3	*Size* $_{t-1}$	5.41	1.35	-0.107*	0.179*												
4	*Size* $_{t-2}$	5.39	1.35	-0.110*	0.180*	0.989*											
5	*Size* $_{t-3}$	5.36	1.36	-0.122*	0.183*	0.981*	0.989*										
6	*Size* $_{t-4}$	4.29	1.54	-0.116*	0.183*	0.974*	0.981*	0.989*									
7	*Decision style*	2.04	1.37	-0.172*	0.156*	0.535*	0.535*	0.534*	0.534*								
8	*Decision style* $_{t-1}$	2.17	1.32	-0.138*	0.147*	0.535*	0.538*	0.538*	0.537*	0.735*							
9	*Decision style* $_{t-2}$	2.09	1.35	-0.136*	0.151*	0.533*	0.535*	0.539*	0.539*	0.765*	0.732*						
10	*Decision style* $_{t-3}$	2.02	1.37	-0.117*	0.141*	0.533*	0.534*	0.535*	0.540*	0.705*	0.752*	0.712*					
11	*Log(R&D)* $_{t-1}$	11.28	2.32	-0.250*	0.160*	0.638*	0.647*	0.642*	0.633*	0.356*	0.370*	0.365*	0.371*				
12	*Log(age)*	3.21	0.84	-0.056*	0.110*	0.397*	0.397*	0.393*	0.386*	0.190*	0.1940*	0.194*	0.195*	0.209*			
13	*Volatility*	0.02	0.02	0.050*	0.012	-0.074*	-0.074*	-0.077*	-0.072*	-0.043*	-0.051*	-0.044*	-0.046*	-0.047*	-0.007		
14	*Presample* $_{Scale}$	14.79	84.41	0.119*	0.048*	0.097*	0.095*	0.095*	0.095*	0.084*	0.084*	0.081*	0.079*	0.046*	0.059*	0.013	
15	*Presample* $_{quality}$	26,343.59	201,951.40	-0.016	0.389*	0.145*	0.146*	0.148*	0.150*	0.121*	0.119*	0.118*	0.117*	0.228*	0.065*	0.017*	0.003

* correlations are significant at the 99% confidence level (alpha=0.01)

Table 1 – Percentage of reliance on each analytical tool by firm size category

	R&D committee	Scientific info.	University	Perspective tech.
> 200 employees	82%	57%	63%	62%
< 200 employees	53%	29%	30%	47%
All firms	70%	45%	49%	56%

Table 2 - Distribution of analytical tools by each dimension of R&D productivity

		Scale/total R&D			***Quality/total R&D***	
		Low	**High**		**Low**	**High**
Decision Style	**0**	17.3%	58.8%	**0**	24.8%	6.8%
	1	18.6%	20.6%	**1**	22.6%	19.4%
	2	22.1%	11.8%	**2**	20.1%	19.7%
	3	23%	8.8%	**3**	18.3%	36.7%
	4	19%	0.0%	**4**	14.2%	17.3%
		100%	100%		100%	100%

Table 4 - First stage of mediation - Ordered probit regression predicting decision style

	Decision style					
Variable	1	2	3	4	5	6
size t-1		0.441***				0.426***
		[0.008]				[0.064]
size t-2			0.439***			0.063
			[0.136]			[0.087]
size t-3				0.434***		-0.049
				[0.008]		[0.077]
size t-4					0.431***	0.006
					[0.009]	[0.057]
Industry controls (20 sectors)	Yes	Yes	Yes	Yes	Yes	Yes
Year controls (1998-2004)	Yes	Yes	Yes	Yes	Yes	Yes
pseudo-R2	0.037	0.137	0.136	0.136	0.135	0.141
n	1415	1415	1415	1415	1415	1415

***p<0.001; **p<0.01; *p<0.05; †p<0.1

Table 5 - Second stage of mediation model

	GEE presample Poisson regression			GLS presample regression		
	Scale (number of product innovations)			*Quality (log of licensing revenue)*		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
size t-4	-0.254***		-0.229***	0.070*		-0.007
	[0.016]		[0.016]	[0.035]		[0.083]
Decision style t-1		0.112***	0.109***		0.019	0.019
		[0.010]	[0.011]		[0.045]	[0.045]
Decision style t-2		-0.040***	-0.032**		0.100*	0.102*
		[0.009]	[0.011]		[0.040]	[0.042]
Decision style t-3		-0.086***	-0.077***		-0.058	-0.058
		[0.011]	[0.012]		[0.057]	[0.059]
log(R&D) t-1	0.334***	0.220***	0.315***	0.083***	0.091*	0.094†
	[0.010]	[0.008]	[0.010]	[0.023]	[0.046]	[0.050]
Log(age)	0.177***	0.160***	0.196***	0.092*	0.213**	0.216**
	[0.020]	[0.018]	[0.020]	[0.0437]	[0.076]	[0.081]
Presample	0.0001	-0.0002**	-0.0001	0.003***	0.004***	0.005***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
Volatility	-4.752***	-4.000***	-4.25***	1.050	-0.526	-0.557
	[0.955]	[0.846]	[0.940]	[1.427]	[2.212]	[-2.216]
Intercept	-5.806***	-5.591***	-5.865***	-0.537	-1.640**	-1.771**
	[1.052]	[0.979]	[1.093]	[0.467]	[0.502]	[0.577]
Industry controls (20 sectors)	Yes	Yes	Yes	Yes	Yes	Yes
Year controls (1998-2004)	Yes	Yes	Yes	Yes	Yes	Yes
R2				0.177	0.246	0.247
Chi-squared	8546.08	7817.19	8370.3	604.27	70.8	71.20
N	1415	1415	1415	1014	1014	1014

***p<0.001; **p<0.01; *p<0.05; †p<0.1

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