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TESIS DOCTORAL

Three essays in managerial cognition and strategic decision making

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A Juana

Table of contents

General Abstract

Little is known about how managers select risky strategic actions such as the introduction of innovations, engagement in alliances, mergers, or any other strategic choice (Simon and Houghton, 2003). While the importance of firm's strategic processes has been acknowledged both theoretically and empirically, few efforts have been committed to understanding the decision paths through which managers select such risky actions and how they affect performance.

Variables related to the decision-making process, such as the type of information utilized in decision-making, and the rules for processing information have been downplayed as determinants of organizational outcomes. Decision theory has analyzed these variables mainly through neoclassical theories emphasizing rationality of agents. In the last decades, descriptive behavioral theories assuming bounded rationality of agents have surged to tackle these variables in order to explain risky actions, though little of this research deals directly with strategic management issues.

In the specific case of innovation, while most studies exploring the determinants of innovative performance have looked at organizational structures, resources and environmental characteristics, only a few studies have emphasized the influence decision making strategies on firm innovation (Simon and Houghton, 2003). Moreover, this kind of studies have focused on individual-level characteristics of key decision makers (e.g. upper echelons) as variables affecting innovation, such as age, educational background, and other socio-demographic characteristics. However, the effect of cognitive processes on firm innovation has been generally overlooked up to date.

The general lack of attention to cognitive aspects is reflected in many studies which implicitly state that decision makers are homogeneous inputs and perfect substitutes for one another taking part in the organization process. However, this neoclassical view fails to explain why organizations with similar resources, and facing similar economic environments, make significantly different decisions. Managers not only depart from the principles of classical decision theory, but are also subject to different judgmental biases when making decisions under uncertainty (March and Shapira, 1987; Hogarth, 1987). During the strategic decision-making process, managers look upon organizational and environmental factors as a base for their decisions, and act as filtering mechanisms interpreting data through their particular cognitive mechanisms. Therefore, identifying the differences in cognitive processes of managers may help explain the differences in their decisions to innovate.

In line with behavioral decision research (Hogarth, 1987; Kahneman, 2003) and other behavioral studies of organizational decision-making (Cyert and March, 1963; March and Shapira, 1987; Levinthal and March, 1993) I intend to examine the decision-making process followed by organizations by exploring the cognitive processes they follow when making strategic decisions in general. The present study will focus on the literature on heuristics and cognitive biases, and on decision making styles.

Heuristics are habitual simplifying strategies, or "rules of thumb", which people commonly use to reduce the amount of information they must consider in decision-making. Cognitive biases are systematic errors of judgment that lead to cognitive illusions which are not easily eliminated. The literature on behavioral decision-making has also recognized two fundamental styles of thinking and deciding: an analytical mode and a non-analytical mode (Kahneman, 2003). Decisions made with the analytical mode undergo computation, consultation, or evaluation of analytical data. Non-analytical decisions are intuitive, and do not make use of exhaustive data processing, and rely on heuristics, impressions, and associative or emotional tools (Kahneman, 2003). These different styles are suitable for particularly different decision environments, and exploring which one is more suitable for strategic decision processes regarding innovation is an open avenue for research.

The central contention of this thesis is that it is essential to understand non-rational[1] decision-making in order to understand why different cognitive processes may lead to different organizational decisions, behaviors and performances. I attempt to address this central theme through three essays, each one focusing on a different question and adopting a different methodology.

In **Chapter I**, I explore how different decision making styles adopted by firms during the R&D process affect innovative outcomes, and also how these decision making styles are related to the size of firms. More precisely, I 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-making styles during the R&D process. Based on the literature on cognition, I distinguish between highly-analytical and low-analytical decision making styles. Using a unique longitudinal data set from Spanish manufacturing firms in which CEO's are asked about the specific tools and procedures they use during the R&D process, I approximate firms' decision-making style and explore the validity of this mediation model. I show that that as firms increase in size, they rely more extensively on analytical decision tools for the R&D process, and consequently, highly analytical decision making leads to lower R&D productivity in terms of the

[1] The term "non-rational" is used here to describe any behavior that cannot be fitted into a rational choice model, as proposed by the neoclassical economics tradition. Also, "rationality" excludes all actions based on emotion, habits, and values.

scale of innovative output, while it leads to higher R&D productivity in terms of the quality of innovative output.

In **Chapter II**, I elaborate on a well known behavioral tendency termed “illusion of control”, which is believed to be responsible for people preferring to ‘be in charge’ themselves as opposed to others in situations involving uncertainty. Despite its recognition, there is little research exploring the conditions in which people prefer someone else to be in charge of dealing with an uncertain task. I propose source of information as a key factor affecting peoples’ tendency to prefer being in charge. Information about the focal task can be learned through experience or through a convenient description. In this chapter I present two experimental studies in which I show that illusion of control interacts with source of information in an interesting manner. While subjects that sample a lottery from experience bet higher amounts when the lottery is activated by themselves (rather than the experimenter), subjects that learn about the lottery from description bet higher amounts when the lottery is activated by the experimenter. Also, higher perceived risk from experience leads to higher illusions of control.

In **Chapter III**, I review the research on organizational learning. Recently, this stream of research has revealed the existence of “superstitious learning” in strategic decision processes. Yet, while the literature points at overconfidence as a central variable related to superstitious learning, it does not provide an explanation on why superstitious learning takes place or what individual-level processes causes it. Drawing on research in cognitive psychology, I seek to illustrate some properties which make it difficult for organizations to acquire knowledge from the strategic decisions they have previously experienced. I propose hindsight bias as a mechanism leading to superstitious learning, and other cognitive simplification heuristics related to the experience-based learning process. In this chapter I use in-depth interviews to top managers to gather information about experiential learning processes in strategic decision making in order to formulate the theoretical propositions. Managerial implications are also identified and new directions for further research are proposed.

Resumen en Castellano

Esta tesis doctoral intenta contribuir a la respuesta de la siguiente pregunta: ¿Cómo afectan las diferencias en la toma de decisiones al desempeño de las organizaciones? Al mismo tiempo, explora las diferentes fuentes de información y conocimiento que utilizan las empresas para tomar decisiones bajo incertidumbre y estudia como la adopción de diferentes fuentes de información puede afectar el comportamiento de las organizaciones. La tesis se divide en tres capítulos independientes y se utilizan tres metodologías diferentes.

En el Capítulo I, se explora cómo los diferentes estilos de toma de decisión adoptados por las empresas afectan el resultado final de los procesos de investigación y desarrollo (I+D), al mismo tiempo que se estudia la relación entre los diferentes estilos y el tamaño de las empresas Desarrollamos un modelo de mediación en el cual proponemos que el tamaño de las empresas afecta al estilo de toma de decisiones y el estilo de toma de decisiones afecta la productividad en I+D. En este caso, la medición de productividad contempla aspectos tanto de la cantidad como de la calidad del *output* innovador. Basándonos en la literatura cognitiva, distinguimos entre estilos de decisión *altamente analíticos* y *poco analíticos*. Usamos datos longitudinales de la Encuesta de Estrategias Empresariales, en la cual empresas españolas proveen información sobre el tipo de información y los procesos que utilizan durante la toma de decisiones en el proceso de I+D. Usando estos datos podemos aproximarnos a una medida del estilo de toma de decisiones de cada empresa. Se demuestra la existencia de una relación positiva entre el tamaño de la empresa y el énfasis en el estilo altamente analítico, al mismo tiempo que observamos una relación negativa entre el estilo altamente analítico y la productividad en términos de ‘cantidad’ de innovaciones, mientras que la productividad en términos de 'calidad' se relaciona positivamente.

En el Capítulo II, se desarrolla el concepto de "ilusión del control", una conducta muy investigada a la cual se atribuye la tendencia de las personas a preferir estar a cargo ellas mismas, en vez de otros, en situaciones de incertidumbre. A pesar del reconocimiento de esta tendencia, existe poca investigación que explore las condiciones en las cuales los individuos prefieren que otras personas estén a cargo situaciones de incertidumbre. En este capítulo se propone que la fuente de información por la cual los individuos aprenden sobre la tarea bajo incertidumbre, afecta la propensión de los individuos a preferir estar a cargo o no de una tarea con incertidumbre. En general la gente puede informarse acerca de una situación de incertidumbre a través de la experiencia o a través de fuentes descriptivas. Proponemos dos experimentos en los cuales se demuestra que la ilusión del control interactúa con la fuente de información de una forma muy peculiar. Mientras los individuos que se informan a través de la experiencia están dispuestos a apostar mayor cantidades cuando ellos están a cargo de activar una lotería, los individuos que se informan con información descriptiva tienden a apostar una cantidad mayor de dinero cuando otra persona está a cargo de activar la lotería. Al mismo tiempo, la mayor percepción del riesgo derivado del aprendizaje a través de la experiencia lleva a mayores niveles de ilusión del control.

En el Capítulo III, se presenta una revisión de la literatura sobre el aprendizaje organizativo. Recientemente, en la literatura del aprendizaje organizativo, se revela la tendencia un error sistemático llamado aprendizaje 'supersticioso' cuando las organizaciones aprenden de decisiones estratégicas pasadas. El principal fenómeno que se ha propuesto para explicar esta tendencia es el *overconfidence*. De todos modos, las explicaciones propuestas no explican de forma precisa los mecanismos por los cuales surgen estos errores en el aprendizaje organizativo, ni tampoco proponen causas a nivel individual que puedan ser responsables de estos errores. Utilizando la literatura sobre psicología cognitiva, ilustramos algunas de las propiedades que limitan los procesos de aprendizaje en las organizaciones cuando se trata de aprender de decisiones estratégicas pasadas. Proponemos al sesgo de retrospección (hindsight bias) como un mecanismo esencial para explicar la presencia del aprendizaje supersticioso. A través de entrevistas en profundidad a gerentes en altos cargos de organizaciones sanitarias, recopilamos información y puntos de vista para generar proposiciones teóricas sobre las causas de los errores en el aprendizaje relacionado con decisiones estratégicas. Finalmente, derivamos implicaciones prácticas y proponemos posibles extensiones de esta investigación.

CHAPTER ONE

Decision-Making Style as a Mediator between Firm Size and R&D Productivity: A Cognitive Perspective

Introduction

Although the innovation literature has shown considerable evidence that firm size affects R&D productivity (e.g., Cohen and Klepper, 1996; Tether, 1998; Benner and Tushman, 2002), the specific decision-making processes that mediate between organizational size and innovation outcomes are still not well understood (Tripsas and Gavetti, 2000). One specific gap in this causal chain is particularly important: the lack of understanding of how firms' size affects how they gather and process information for strategic decisions (Merz and Sauber, 1995; Fiegenbaum and Karnani, 1991) and, in turn, how these decision-making styles become manifested in organizational choices or courses of action (Khatri and Ng, 2000). By integrating the literatures on cognition (Dane and Pratt, 2007) and innovation, we examine the relation between R&D productivity and the adoption of different decision-making styles during the innovation process, and analyzes whether decision-making styles are related to the size of organizations.

Existing research reveals that small firms differ from large corporations in terms of the use of information (Smeltzer, Fann and Nikoliasen, 1988), planning activities (Huang, Soutar and Brown, 2002; Smith, Gannon, Grimm and Mitchell, 1988), formality of organizing (Miller, Dröge and Toulouse, 1988) and reliance on external advice (Nahavandi and Chesteen, 1988) among other aspects. While these studies are highly informative about individual management practices and their relation to firm size, they overlook the possibility of a holistic perspective in which the mix of management practices adopted by firms of different size reflects their decision-making style. Our central argument is that small and large firms possess fundamentally different styles of thinking and deciding, and these differences are likely to affect key organizational outcomes which are sensitive to decision processes. We believe that exploring the effect of decision-making style on innovative performance is important because the R&D phase is highly uncertain, entails complex search processes, requires rapid exploitation of new ideas and environmental scanning, among other difficulties, and therefore presents a scenario where the way firms organize to arrive at judgments and decisions plays a vital role.

Drawing on the literature on cognition, we define decision-making styles as the degree to which firms emphasize analytical decision making in strategic decision-processes. Decisions made in a highly-analytical manner are often slower and based on a lengthier information search as opposed to those made in a low-analytical style, and due to this variation we expect different styles to be suitable for different aspects of innovative performance. Thus, instead of focusing on a single aspect of innovative performance –as often done in innovation studies (Tether, 2000) – we distinguish between two dimensions of innovation: *scale* and *quality*. We propose a mediation model in which firms' decision-making style acts as a mediator linking the effect of firm size on these two dimensions of innovative performance. By framing this relation as a mediation model, we empirically explore (a) how firm size affects decision-making styles, (b) how decision-making styles differently affect the two dimensions of innovative performance, and finally, (c) whether firm size continues to affect the two dimensions of innovative performance after decision-making styles are accounted for.

Exploring these relations is an important area of research for several reasons. First, while there is much evidence from laboratory experiments linking decision-making style and task performance at the individual-level (Hogarth, 1987, 2005) little is known about the impact of decision-styles on organizational-level outcomes (Khatri and Ng, 2000). Second, management teams in modern organizations of all sizes appear to have increasing information demands and this situation calls for a better understanding of how firms process and organize information (Sadler-Smith, 2004). Third, the question of whether firms should emphasize an analytical approach to strategic decision making has puzzled researchers for many years (Dane and Pratt, 2007). In parallel with this, firms increasingly spend large sums of money on analytical tools for strategic decision making, a trend that is evidenced by the explosive growth in expenditures in the information technology industries since the 1970s, which now exceed two trillion dollars annually (Ryan, Harrison and Schkade, 2002), but despite this tendency, we know little about the effect of analytically-inclined decisions on innovation. Finally, we change the way we look at firm size, not as a static characteristic of firms at a given time, but rather as a feature that reflects evolution in organizational capabilities. Firm size is a construct worthy of theoretical attention because firms of different sizes have different patterns of practices (Wally and Baum, 2003), and different repertoires of actions available to the individuals involved (Fiegenbaum and Karnani, 1991). Therefore, understanding how decision-making capabilities change with size can help managers identify the links between organizational structure and innovative productivity.

Theory and Hypotheses

Although research on innovation focuses mainly on the technological aspects of production, it also stresses the cognitive nature of the organizational structure of the firm. As a result, this perspective has portrayed the firm as an information-processing organism that has the ability to adapt (Nelson and Winter, 1982). The emphasis 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. Because information gathering and processing behaviors differ across organizational forms (Merz and Sauber, 1995), the size of firms becomes a variable of interest for understanding the cognitive styles of firms and their effect on organizational outcomes. Past research has regarded size as a mere organizational feature of firms at a given point in time, and has not paid much attention to size as an indicator of organizational evolution and to how it triggers internal changes that affect organizational outcomes. Yet, as firms become larger, they experience changes in the gathering and processing of information (Smeltzer *et al*., 1988), and, more importantly, in the manner in which members arrive at judgments and decisions (Smith *et al*., 1988). The conception of firm size proposed herein—as a dynamic variable affecting organizational outcomes by triggering specific styles of thinking and deciding—changes how 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 affect outcomes.

Next, before proposing how firm size affect decision-making styles and how decision-making styles affect innovative performance, we briefly review the literature linking firm size with R&D productivity.

Firm size and R&D productivity

Most research in R&D productivity has looked at firms' degree of innovativeness as measured by innovation counts or innovation counts standardized by the number of employees or R&D investments. In this stream of research, many studies report an advantage in R&D productivity for large firms. Earlier explanations for this finding point to 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; Dimas, Grabowski and Vernon, 1995); cost-spreading advantages because large firms can spread R&D expenditures over their increasing output and thereby enhance returns to R&D (Cohen and Klepper, 1996); the ability to maintain a diverse portfolio of R&D projects; and greater capacity to absorb internal and external knowledge spillovers (Henderson and Cockburn, 1997). Although the empirical evidence fails to generate a consensus, several studies have found that small firms in manufacturing industries introduce a larger number of innovations per employee or unit of R&D investment than their larger counterparts (Bound, Cummings, Griliches, Hall and Adam, 1984; Hausman, Hall and Grilliches, 1984; Pavitt, Robson and Townsend, 1987; Acs and Audretsch, 1991; Kleinknecht, Reijen and Smith, 1993; Santarelli and Piergiovanni, 1996). Supporters of this view assert that large firms are less R&D-productive than smaller ones because of a lower marginal control and higher bureaucratic controls (Scherer and Ross, 1990).

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 the literature hints at the possibility of an advantage for large over small firms. Dimasi *et al*. (1995) find that sales derived from product innovations were more than fivefold greater for large firms. Tether (1998), using the amount of sales derived from innovations, finds that 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 and that small companies show an even lower performance in breakthrough innovations. Although 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 on R&D and in the overall quality of the innovations they produce. However, research exploring the 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 that firms experience as they transform from small businesses to large organizations. We propose that as firm size increases, the innovation process in firms represents a conscious choice to aim for high-quality innovations as opposed to a large 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. Although a simple count of the number of innovations may approximate the scale of an organization's innovative capabilities, it ignores important qualitative aspects such as its ability to generate financial returns from investments in R&D (Narin, Noma and Perry, 1987; Schoenecker and Swanson, 2002). Although empirical evidence from previous work suggests that scale and quality of innovation 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 essay 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 that capture the monetary gains derived from innovative output. Other things being equal, a firm will be more R&D productive in scale if it produces a larger number of innovations per unit of R&D investment and will be more R&D productive in quality if its innovations 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.

Small firms tend to be more vulnerable to changing environments than larger ones, and 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 small firms frequently adopt, have explained product innovation (Vaona and Pianta, 2008) as opposed to value-oriented strategies pursued by larger firms. Similarly, product innovation has improved the survival chances of small, entrepreneurial firms through extended innovative periods when they experiment with new products (Schoonhoven, Eisenhardt and Lyman, 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, Siegel and MacMilan, 1993) as opposed to value-creating strategies adopted by large firms. In contrast, profitability measures such as return on investment and return on equity are more commonly used as metrics of success for larger firms (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 above, we suggest that size is linked to R&D productivity in the following way:

Hypothesis 1A: Firm size and R&D productivity in terms of scale of innovative output are negatively related.

Hypothesis 1B: Firm size and R&D productivity in terms of quality of innovative output are positively related.

Decision-making styles

One of the underexplored 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 styles thinking and deciding (Dane and Pratt, 2007), also referred to as cognitive strategies (Hogarth, 2005) or cognitive styles (Sadler-Smith, 2004). 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 nonanalytical style, also referred to as “intuitive,” “experiential,” or “tacit,” which is described as effortless, rapid, nonexplicit, unconscious, and producing approximate responses.

Although decision-making styles have been considered to be individual differences (Schunk and Betsch, 2005), they have also been found to depend on contextual factors (Hammond, 1996). Certain characteristics of a task, like the availability of detailed analytical information, may promote deliberate analysis, whereas others, like feedback or time pressure, may promote rapid response. Also, the notion that decision making comprises analytical and nonanalytical components is broadly accepted and relates to most people's everyday decisions (Epstein, 1994). It is important to stress that both mechanisms are simultaneously involved in most decisions. Some theorists emphasize the idea of a single continuum featuring intuitive reasoning at one extreme and analytical reasoning on the other, leaving a number of styles in between (Agor, 1989; Hammond, 1996). However, dual-process theorists have converged on the notion that analytical and intuitive styles represent two conceptually independent continuums that decision makers use simultaneously and interactively (Epstein, 1994; Hodgkinson and Sadler-Smith, 2003). Given that we cannot assess intuition per se 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-making styles excludes the possibility of testing dual-process arguments but will enable us to identify the firms' positions in the analytical continuum. Highly analytical firms will lie close to one extreme, and low-analytical firms will lie close to the opposite extreme. Under this viewpoint, firms that base their R&D decisions on numerous information tools such as detailed R&D plans, sophisticated indexes, and scientific information, among other hard data, complete a highly analytical decision process, whereas managers completing 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 based on impressions or quick associations, especially when there is no time pressure (Dane and Pratt, 2007). Yet, in the particular situation of judgments about the potential attractiveness of an invention, or the likelihood of a new product's being accepted by the public, it may not always be easy to overrule rapid judgments by analysis, because that consumes time and resources. Such decision situations require managers to engage in cognitively demanding activities (Busenitz and Barney, 1997). As a result, management teams facing R&D decisions may choose to deal with uncertainty in different ways, and the degree to which they emphasize one decision-making style or the other may cause variations in the outcomes of the R&D process.

Firm size and decision-making styles

A key distinctive feature in the management of small firms is their quicker and more nimble operation due to structural simplicity, which increases their ability to quickly respond to the dynamics of the environment. (Tushman and Romanelli, 1985). Unlike managers in large firms, managers in small firms as well as entrepreneurs manifest greater reliance on decision heuristics, which can be an effective guide to managerial decision making under conditions of uncertainty (Busenitz and Barney, 1997; Houghton, Simon, Aquino and Goldberg, 2000; Forbes, 2005). Similarly, existing research shows that small firms follow more-flexible (Fiegenbaum and Karnani, 1991), faster (Wally and Buam, 2003), and less-technocratic decision processes (Lindsay and Rue, 1980) than those followed by large firms.

In contrast, large firms tend to make decisions in a more-planned and more-formal manner (Miller *et al*., 1988) than small firms. For example, Huang *et al*. (2002) reveals that large firms planning new-product developments rely on written and explicit plans that are followed step-by-step, as opposed to small firms in which planning is often reduced to informal conversations. Another reason for a lower reliance on analytical tools is that small firms carrying out innovative activities often do so without many financial and managerial resources (Santarelli and Sterlacchini, 1990). Also, as firms increase in size, managers become subject to closer 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 information to support their decisions, which leads large corporations to adopt a highly analytical style. Therefore, in order to support their decisions and to avoid risks, managers in large corporations are likely to promote exhaustive information search, detailed planning, formal procedures, and in doing so, decision processes become more analytical. Conversely, managers in small firms may not experience 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.

In parallel with the literature on cognition, we propose that managerial configurations promoting higher decision speed, flexibility, informality, and heuristic driven decision processes are likely to reflect a rather low analytical decision-making style while configurations promoting exhaustive information search, structured planning schemes, formality, and technocratic-driven decision processes reflect high analytical decision-making styles. Because these configurations tend to vary with size, we propose the following hypothesis:

Hypothesis 2: Firms' decision-making style becomes increasingly analytical with size.

Decision-making styles and R&D productivity

Despite the escalating emphasis on analytical tools to aid decision making in firms, there is a long-standing question in management research of whether increasing emphasis on analytical decision making is synonymous of improvements in managerial action, especially in uncertain situations (Sadler-Smith, 2004). We suggest that the emphasis placed on an analytical style affects R&D through a number of mechanisms, some of which are preferable for R&D productivity from a scale and others from a quality standpoint.

Decision-Making Style and the Scale of Innovative Output. Several aspects of a highly analytical style bound the scale of innovative output. First, firms relying heavily on analytical tools for innovation-related decisions incur excessive expenditures for information acquisition to aid their decisions. These 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). Therefore, 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, currently available information is often of little help for the successful development of future opportunities (Sine, Haveman and Tolbert, 2005). The entrepreneurship literature supports the idea that entrepreneurial opportunities, such as new-product developments, often follow a messy, nonlinear, tacit, and socially complex process and that the associated outcomes can rarely be known beforehand, meaning that there is little useful pre-existing information related to finding new opportunities to exploit (Alvarez and Barney, 2005). Therefore, a highly analytical style may not be as well suited for the development of numerous new ideas as the cognitive shortcuts often used in situations characterized by information shortage, high uncertainty, and high time pressure (Baron, 1998). Third, in a situation characterized by meager information, strategic decision processes stressing sequential, systematic, and step-by-step procedures based on an exhaustive information search, are 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-making styles decrease the speed of decision processes, not only because it takes time to acquire information, but also because it takes time to analyze it. These obstacles to speedy decisions hinder the successful development of new opportunities (Eisenhardt, 1989, 1990). In a world where product life cycles are shortening, fast decision making is key to delivering new products to the market in a sustained fashion. Fourth, the reliance on analytical decision making can improve managers' perceptions of the risks involved in entrepreneurial opportunities (Keh, Foo and Lim, 2002). Managers selecting among several courses of action have to evaluate the risks of each alternative, and reluctance to examine an extensive amount of information 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 have 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 in managerial decision making that appear to reduce risk perception (Forbes, 2005; Houghton *et al.*, 2000; Busenitz and Barney, 1997). Although 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 reduce the potential number of new-product developments. Because of the above mentioned mechanisms, we claim that an analytical style is inadequate for the introduction of a consistently large number of new products.

Hypothesis 3A: The more analytical the decision-making style, the lower the R&D productivity in terms of scale.

Decision-Making Style and Quality of Innovative Output. Conversely, firms can expect to benefit from emphasizing an analytical decision-making style by developing products of higher quality at the expense of a reduced innovative output. Although approaching R&D decisions in a highly 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 lead to a better match between product and expectations in the market.

Moreover, the speed in new-product development is also likely to affect the product quality. Research on the determinants of product quality shows that rapid development can compromise the final quality of a 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 that 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 apply an effective screening process that allows canceling R&D projects that have a higher likelihood of failure, and they can chose to pursue only those projects presenting promising prospects. An increased risk perception derived from extensive analytical procedures is desirable to improve the ultimate product quality by removing potential sources of uncertainty and can certainly be worth the investments. Therefore, we propose the following hypothesis:

Hypothesis 3B: The more analytical the decision-making style, the higher the R&D productivity in terms of quality.

The mediating role of decision-making style

The way firms approach R&D decisions is proposed to be a function of the size of firms. With size, 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, and this tendency stems less from a calculated choice out of a number of known alternatives, but more from a process of sequential adaptation to new possibilities (Chesbrough and Rosenbloom, 2002).

As firms grow in size, this adaptation becomes more rigid, because information is filtered through a logic that is established from previous successes. Likewise, the knowledge flow diminishes, hierarchical structures become larger, and the number of stakeholders (e.g., bondholders, employees, or customers) increases. These obstacles increase the need for standardized information-sharing mechanisms that are obtained through a more-analytical decision environment. In turn, the increasingly analytical style adopted by large firms increases the perception of risks and enables decision makers to filter out potential failing R&D projects (Christensen, 1997). Through this process, large firms increase control over current innovation processes and become more efficient at exploiting existing ideas, while they are discouraged from searching new ones (Benner and Tushman, 2002). This trend, coupled with the pressure exerted by the board of directors, shareholders, and investors, leads managers to pay less attention to the development of new products and more attention to maximizing benefits from existing ones, which simultaneously promotes the use of analytical decision tools as filters. In sum, we propose that the relation between firm size and R&D productivity is mediated by decision-making style:

Hypothesis 4A: Decision-making style mediates the negative relation between firm size and R&D productivity in terms of scale.

Hypothesis 4B: Decision-making style mediates the positive relation 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 *Spanish Business Strategy Survey* (SBSS), an annual survey of 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 NACE-Rev.1 classification (National Classification of Economic Activities, revised in year 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 unique characteristic of this survey is that it has a section in which CEOs are asked about the procedures and tools 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-making styles used by firms. Contrary to other data sets, the SBSS is not restricted to the analysis of firms' technological activities and its focus goes beyond innovation-intensive firms, encompassing a more complete picture. The SBSS survey started collecting data in 1990, but the section relating to R&D decision making was included in the survey only in 1998, so our sample ranges from 1998 to 2004. Respondents to the SBSS survey were CEOs, and data were collected using direct interviewers supported by a questionnaire. Because some firms stopped providing information during the sample period for several reasons, including mergers, changes to nonindustrial activity, or shutdown of the production process, we have an unbalanced panel. In order to minimize the problems caused by missing data, only firms with at least three continuous years of data availability were selected. This results in an unbalanced panel of 614 firms, consisting of 1415 firm-year observations. The Kolmogorov-Smirnov tests on three variables from the dataset –age, number of employees, and number of innovations reported no significant differences between firms included in the analyses and those left outside. The distribution of the sample with respect to size is reasonably equitable: 42% of the firms are small (200 or fewer employees), and 58% are large. The distribution of the sample crosses the 20 industrial sectors. The chemicals, motor vehicles, machines and mechanical equipment, and food and tobacco sectors rank among the most populated sectors, which coincides with the actual distribution of Spanish manufacturing firms.

Measures

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 the number of new products developed by firm *i* in year *t*. An advantage of this measure is that, 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 from previous product lines or if they are substantial modifications from previous products. The number of new products measures not only a firm's ability to introduce new products in the market but also its ability to upgrade current ones. Also, this measure is closely related to similar measures of innovative strength such as patents (Scherer and Ross, 1990), sales growth (Scherer, 1983), and invention counts (Ahuja and Katila, 2001). The ability to produce multiple product innovations 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, is assessed by the licensing revenue obtained from 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 20 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 to generate income. On the other hand, licensing can be a great revenue model for small firms that 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 relatively quickly with little or no risks, such as going into foreign markets. Licensing can also be 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.

Antecedent Variable

$Size_{it}$. To measure the size of firms, we use the log of number of employees 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 sensitive to macroeconomic shocks.

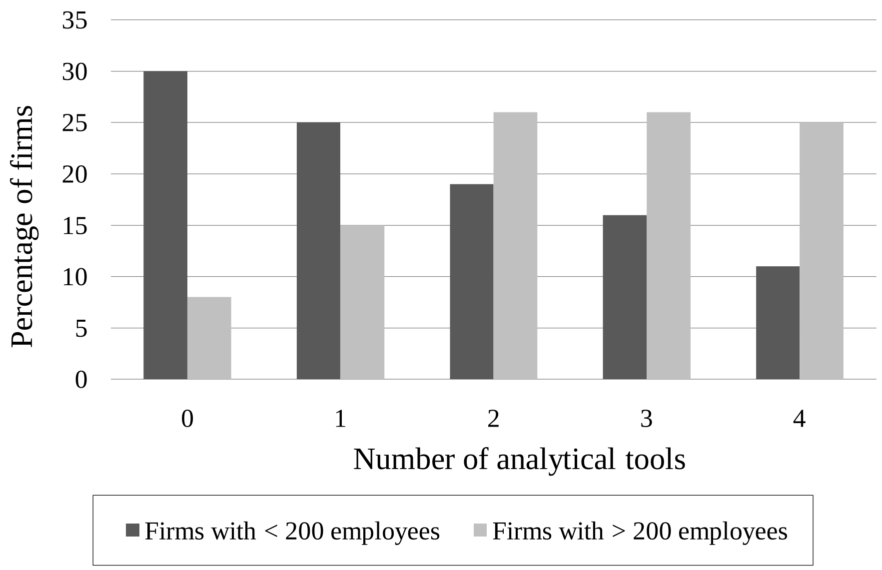
Mediator Variable

Decision-making $style_{it}$. To capture the decision-making 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 SBSS survey in which CEOs are asked to answer yes or no to a series of items, each of which 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 that 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 undertake formal planning, which entails deliberation, examination of many alternatives, and 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-art technologies augments the information pool of decision makers. This type of information is likely to be specific and not vague, meaning that it requires analytical skills to manipulate and thus use it. 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 according to the advice of experts, so firms collaborating with universities are assumed to approach decisions more analytically than those not collaborating. The fourth dummy reports whether firms evaluate the perspectives of technological opportunities during the R&D process. The evaluation of technological opportunities may reduce the uncertainty regarding R&D investments and, therefore, evaluating the potential profitability of an innovation project renders the R&D decision-making 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, and process hard data to use them successfully. 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 the fact that the composite measure is unidimensional. Because the components of composite measures need to be independent so that variation in one component does not directly drive another, we dropped two of the six initially available items that correlated strongly to other items and thus provided redundant information. The discarded items measured whether firms evaluated alternative technologies and whether they elaborated innovation indexes.

Figure 1 shows firms' reliance on analytical tools for R&D decision making according to their size. Note that most large firms rely more frequently on four or five analytical tools, whereas small firms tend to rely on zero or one. Here we can see the propensity of large firms to follow highly analytical decision making as opposed to small firms' propensity to overlook analytically intensive procedures.

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 used 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-making style versus both dimensions of R&D productivity. We split the two dependent variables by their median values into high and

Figure 1. Reliance on analytical tools by firm size



low. While firms that introduce a high number of innovations per unit of R&D investment tend to disregard analytical tools (58% of all high-scale firms use no tools), high-quality innovators present the opposite trend (54% of all high-quality innovators use three or four tools). Overall, these trends point to the possibility that the decision-making style may be driving innovation outcomes independent of firm size.

Table 1. Reliance on each analytical tool by firm size category, in % of firms

	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, in % of firms

		Scale/total R&D			Quality/total R&D	
		Low	High		Low	High
	0	17.3	58.8	**0**	24.8	6.8
Decision-making style	**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

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. We control for possible macroeconomic and business cycle shocks common to all industrial sectors, using time dummies for all the years in the sample, as well as time-invariant shocks, using industry dummies reflecting the 20 different industrial sectors. 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. By inverting the resulting correlation, increasing values indicate greater volatility rather than greater stability. Finally, to control for firm heterogeneity, we construct a presample variable according to the type of dependent variable, where in the case of *scale*, the 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, whereas in the case of *quality,* it represents the sum of the log of licensing revenue accumulated in the three years prior to the firm's entry into the sample.

Methodology

A correctly specified mediation model has to define a causal order and direction, for which temporal precedence of causal factors is essential (Mathieu, DeShon and Bergh, 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-making style, and of decision-making style on R&D productivity, for several subsequent periods. By assessing firms' size in different time periods, we avoid a static representation of size and capture the effect of firms' size evolution. 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-making style. In this step, the dependent variable is decision-making 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-making style on two dimensions of R&D productivity. In this part of the model we use distributed lags of decision-making style at times *t-1*, *t-2*, and *t-3*, while the dependent variables remain at time *t*. Because in the second stage of the model we will have two dependent variables, we will use two different econometric specifications in this stage. Finally, in the second stage of the model we also include firm size to observe how it affects R&D productivity when decision-making style is accounted for in the regressions. The firm size variable is lagged one period preceding the mediator, *t-4*, 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-making style) in the first stage and then the mediator affects the dependent variables in the second stage. We should observe that the effects of size on the dependent variables are weaker or nonexistent when the mediator is accounted for.

Model Specification

The dependent variable in the first stage, decision-making style, takes nonnegative 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 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 process. The proposed model is:

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

where D_{it} is the number of analytical tools used for decision making 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-making style.

In the second stage of the mediation model, the first dependent variable is the number of new products developed. Because this is a count outcome variable taking nonnegative integers, a regression approach for Poisson data is suitable. We specified the following regression model:

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

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-making 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-making 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 extend over a number of years; thus, we use the distributed lags approach to capture the distributed impact of decision-making style in different periods. This specification does not deal with the problem of unobserved heterogeneity, which may generate overdispersion in the data. To address this issue, we follow the Presample Panel Poisson procedure (Blundell, Griffith and Van Reenen, 1995) by including a presample variable that accounts for the stock of new-product innovations developed over the three years prior to the sample. Thus, this variable serves as a fixed effect of the firms' ability to develop new products and controls for unobservable differences across firms. In addition, following Ahuja and Katila (2001) we apply the Generalized Estimating Equations (GEE) methodology for estimating Poisson data because it accounts for remaining overdispersion and serial correlation even after we include a presample variable. 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 revenues for licensing 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. We used the transformation 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-making 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.

Results

Table 3 provides basic statistics for all the variables in the analysis. The means of our dependent variables are 2.54 for *scale* and 0.24 for *quality,* while the mean score for *decision-making style* is 2.04. Apart from the expected high correlations between variables and their respective distributed lags, we observe moderately high correlations between $logR\&D_{t-1}$ and $size_{t-1}$ (0.67), $size_{t-2}$ (0.67), $size_{t-3}$ (0.66), and $size_{t-4}$ (0.65). Robustness tests indicate that these high correlations did not affect the results of the hypothesized effects.

Table 4 shows the results for the first stage of the mediation model, where decision-making 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 3 in 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.

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 is 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 between *size* and *scale*.

In Hypothesis 2 we predicted a positive relationship between *size* and *decision-making style*. The ordered probit estimation reported in Table 4 shows the positive and significant effect of firm size on decision-making style, implying that firms become increasingly analytical in their decision-making style as they evolve in size. Model 1 shows the regression of *decision-making style* on control variables, with a pseudo-R^2 of 0.037. Models 2, 3, 4, and 5 report a positive and significant effect of the four distributed lags of *size* on *decision-making style*, which improves the overall fit, as reported by a pseudo-R^2 above 0.13. Model 6 includes the four distributed lags simultaneously and the overall effect is absorbed by the first lag, which is positive and

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

	Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Scale	2.450	18.70													
2	Quality	0.245	1.66	0.09*												
3	Size $_{t-1}$	4.340	1.49	0.07*	0.18*											
4	Size $_{t-2}$	4.327	1.49	0.07*	0.18*	0.99*										
5	Size $_{t-3}$	4.311	1.50	0.07*	0.18*	0.98*	0.99*									
6	Size $_{t-4}$	4.304	1.51	0.07*	0.18*	0.97*	0.98*	0.99*								
7	Decision-making style$_{t-1}$	0.991	1.30	0.07*	0.15*	0.53*	0.54*	0.54*	0.54*							
8	Decision-making style$_{t-2}$	0.992	1.30	0.07*	0.15*	0.53*	0.53*	0.54*	0.54*	0.83*						
9	Decision-making style$_{t-3}$	0.998	1.31	0.06*	0.14*	0.53*	0.53*	0.54*	0.54*	0.75*	0.81*					
10	Log(R&D)$_{t-1}$	11.206	2.31	0.02	0.23*	0.67*	0.67*	0.66*	0.65*	0.36*	0.37*	0.36*				
11	Log(age)	2.941	0.84	0.05*	0.12*	0.33*	0.34*	0.34*	0.35*	0.19*	0.19*	0.20*	0.22*			
12	Volatility	0.023	0.02	0.02	0.01*	-0.07*	-0.07*	-0.08*	-0.07*	-0.05*	-0.04*	-0.05*	-0.07	-0.01*		
13	Presample$_{Scale}$	7.131	47.75	0.20*	0.05*	0.10*	0.10*	0.10*	0.10*	0.08*	0.08*	0.08*	0.05	0.06*	0.01*	
14	Presample$_{quality}$	0.336	2.85	0.06*	0.72*	0.20	0.20*	0.19*	0.19*	0.18*	0.17*	0.16*	0.22	0.08*	0.00*	0.05*

* Correlations are significant at $p < 0.01$.

Table 4. First stage of mediation - ordered probit regression predicting decision-making style

	Decision-making style					
	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	yes	yes	yes	Yes	yes	yes
Pseudo-R^2	0.037	0.137	0.136	0.136	0.135	0.141
N	1415	1415	1415	1415	1415	1415

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two tailed)

significant. Because there is temporal precedence between *size* and *decision-making style*, a causal and directional link can be established between the two variables. This result supports Hypothesis 2 and establishes the first step mediation. Note also that the magnitude of the effect is strongest for *size* in period *t-1* and diminishes as lags become more distant in time.

In Hypothesis 3A we predicted a negative relationship between *decision-making style* and *scale*. In Model 2 in Table 6, the distributed lags of *decision-making style* 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-making style* and *quality*. Model 5 in Table 5 presents the distributed lags of *decision-making styles* and shows statistical significance in the second lag, but not in the remaining ones, which affects *quality* in a positive direction. This positive link provides modest support for Hypothesis 3B and suggests that firms employing highly analytical decision making have higher chances of introducing innovations of above-average quality and that investments in analytical tools for decision making should therefore be expected to increase the

Table 5. Second stage of mediation

	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-making style t-1		0.112***	0.109***		0.019	0.019
		[0.010]	[0.011]		[0.045]	[0.045]
Decision-making style t-2		-0.040***	-0.032**		0.100*	0.102*
		[0.009]	[0.011]		[0.040]	[0.042]
Decision-making 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	yes	yes	yes	yes	Yes	yes
Year controls	yes	yes	yes	yes	Yes	yes
R^2				0.177	0.246	0.247
Chi-squared	8546.08	7817.19	8370.3	604.27	70.8	71.20
N	1415	1415	1415	1415	1415	1415

† p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001 (two tailed)

quality, though not the quantity, of the innovative output. Finally, hypotheses 4A and 4B predict that *decision-making style* mediates the effect of *size* on *scale* and *quality* respectively. Model 3 includes *size* together with the distributed lags of *decision-making style,* and we observe that the effect of *size* is mediated by *decision-making style*, as the magnitude of *size* decreases from -0.254 in Model 1 to -0.229 in Model 3 once we account for decision-making style. This mediation, however, is partial because *size* still significantly affects the dependent variable. Conversely, in Model 6, once *size* and *decision-making style* are included together, the effect of *size* becomes insignificant and the second lag of *decision-making 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, as the variability that was previously explained by *size* becomes absorbed by *decision-making style*. 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 (results available from the authors).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 has a significant role only 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 *scale* and insignificant for *quality*.

Discussion and Conclusion

One of the contributions of our study is to bring to light the previously underplayed construct of decision-making style as a key factor influencing innovative output and to demonstrate that as firms evolve in size, they experience changes in their decision-making style that 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-making 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.

A key contribution of our study is to show how firms' decision-making style affects organizational-level outcomes. After controlling for industry and time effects, we demonstrate that different decision-making 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 increasing the 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 innovative output at the expense of its quality. The divergent effects of decision-making styles reported in this study question the long-standing view held by strategists who picture the task of intelligent management as necessarily facilitating analytically rational action (Levinthal and March, 1993) while outlining the conditions under which nonanalytical approaches may be desirable.

Our results shed light on 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 trade-off puts forth the more-difficult question 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 fusion call for a 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 that reflects changes in organizational structure, but more importantly, changes in firms' cognition. As organizations increase in size, they change the cognitive lenses through which they view strategic decisions, and this change is accomplished 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 behaviors change with size, helps explain why size affects innovation. Because firm size *per se* is not solely accountable for variations in R&D productivity, further research may be needed to revisit the theoretical relevance of firm size and to better clarify how it affects organizational outcomes. Firm size is not a variable that 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 create spin-offs, spin outs, and skunk works to downsize their R&D business units. In this way, the behavior of such business units may resemble that of small firms. Rather than focusing on size, managers should try to influence the way R&D decisions are approached, as it is a decisive factor affecting innovation.

The importance of decision-making styles in the R&D process points to 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 but should emphasize a rather low-analytical approach when a quick succession of multiple new products is needed. 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. Therefore, 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. Moreover, heavy investments in state-of-the-art analytical tools to aid strategic decision-making processes may not always be desirable. This type of investment may be adequate for firms in a determined market position and in a specific stage of their life cycle in which improvements in profit margins of current products is more important than the development of additional new products.

The prevalent assumption that analytical decisions yield choices superior to those coming from informal, low-analytical processes is questionable. Although this assumption may hold true in determined circumstances, it has led research to underplay the relevance of other sources of knowledge, such as intuition, out-of-the-box creativity, or even “gut feelings,” which have proven to be relevant for performance (Damasio, 1994). In contrast, consistent with evolutionary arguments depicting organizations as evolving and bounded-rational units that seek adaptation (Nelson and Winter, 1982), we suggest that the process of innovation should not be conceived necessarily as a rational-analytical production process, but rather a process encompassing both analytical and nonanalytical 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 of our findings. Another limitation is that the variable used to capture decision-making style may not fully represent the essence of the construct. The construct of decision-making style could be better captured through psychometric techniques applied to top management teams. Other improvements involve drawing on insights from behavioral decision-making research to assess more accurately the type of cognitive characteristics that distinguish managers in successfully innovative firms.

Although this study helps to address several issues regarding innovation-related decision making, it raises several others. A natural question arising from this study is whether the absence of analytical judgment implies higher reliance on intuitive judgment 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. Agor (1989) argues that managers often rely on intuition after engaging in analytical thinking, to synthesize and integrate the judgments derived from the analysis. Conversely, Shapiro and Spence (1997) suggest that nonanalytical judgments should occur first, and thorough analytical judgments should follow to corroborate firsthand impressions or intuitions.

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

Conclusions

This study demonstrates that organizational decision-making style matters: It proves to be an important factor for understanding R&D productivity. We have stressed throughout that the way organizations approach decision making during the R&D process is dependent on firm size and that the choice of decision-making style ultimately affects the scale and quality of the innovative output. Highly analytical decision making leads firms to emphasize the quality of innovation, whereas low-analytical decision making leads to emphasizing the quantity of innovations. In making this point, we tried to fit this study into the literature linking firm size with innovation, and have expanded the debate by including the mediating role of decision-making 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 organization research and decision-making research and call for further efforts to bridge these complementary areas.

CHAPTER 2

I will do it better than you because I have done it before:

How experience breeds illusion of control

Introduction

People tend to believe they exert control over outcomes that are outside their span of control (Langer, 1975). One way in which this illusion is manifested is by people's tendency to prefer being 'in charge' themselves as opposed to others, even in situations governed by chance. This pervasive illusion of control is particularly relevant in processes that are highly influenced by complex and unknown phenomena in which individuals exert little or no control. For example, the performance of a security in the stock market, the outcome of complex strategic management decisions, the result of radical innovation activities. To illustrate the relevance of this illusion, consider a manager responsible for a firm's financial investments, would she invest the firm's funds herself or would she delegate the task to a fund manager? Would the amount invested differ depending on who is in charge of the operation? Moreover, would her decision depend on her experience in financial investments? Research suggests that feelings of control lead individuals to exaggerate their subjective probability of success, which in turn lead them to prefer to be in control, even in purely random tasks (Langer, 1975; Koehler, Gibbs, and Hogarth, 1994). In a number of studies, Langer (1975) showed that people prefer to choose their own lottery ticket instead of having one chosen for them. Similarly, Fellner, Güth and Maciejovsky (2004) report a tendency for people to prefer their individually chosen portfolio in favor of an equally good alternative chosen by another person. This general finding is robust over different dependent measures, including willingness to bet, willingness to trade an item, reports of confidence over outcomes, among others (e.g., Burger & Cooper, 1979; McKenna, 1993; Wortman, 1975).

Yet, there are domains in which people consistently underestimate their performance relative to others' (Kruger, 1999; Moore & Kim, 2003; Windschitl, Kruger, & Simms, 2003) suggesting that they may not always prefer to be in charge of uncertain tasks. In a study by Benartzi and Thaler (2002), in which participants were faced with the task of investing in pension funds resulting from a self-selected portfolio, an average portfolio, and a professional portfolio, the majority of participants preferred the average and professional portfolios to the self-selected one.

An underexplored but potentially critical factor influencing people's assessments of their influence over outcomes is their experience. Referring to the previous example, it is reasonable to expect that experience in financial investing will lead the manager to prefer being in charge of the process, while the lack of experience may lead her to delegate the task. Recent studies have documented the impact of experience on decisions. Findings suggest that when participants learn about risky prospects from experience their choices are dramatically different than when they learn about these prospects from convenient descriptions (Hertwig, Erev, Barron & Weber, 2004; Weber, Shafir & Blais, 2004). Because the conditions that facilitate illusory control vary depending on the context and particularly on the contexts of information acquisition, we propose that illusion of control is affected by the source of information (experience vs. description) influencing risk-taking behavior. This study focuses on the interaction between experience-based learning and the illusion of control, two phenomena that often cause people to have a naïve perception of the world they live in.

We experimentally assess the influence of source of information on the willingness to bet on a random event and its interaction with person in charge (self or other). We consider two scenarios: a scenario where people learn about a lottery from description, that is, observing the possible outcomes and likelihoods of those outcomes; and a scenario where people learn about a lottery from experience, that is, by sampling from an urn with replacement. These scenarios are replicated both in a situation where the participant is in charge executing the lottery, and in a situation where someone else is in charge of executing the lottery.

Theory and hypotheses

Several scenarios have been identified where illusion of control is expected (Langer, 1975), where it is not expected (Alloy & Abramson, 1979) and where it may be reversed (Thompson, 1999; Martin, Abramson & Alloy, 1984). Illusion of control is expected in situations characterized by personal involvement, familiarity, foreknowledge of the desired outcome, and success at the task (Langer, 1975; Thompson, 1999), among people with nondepressed mood (Alloy & Abramson, 1979) and in need for control (Biner, Angle, Park, Mellinger, & Barber, 1995). When there is feedback highlighting failure and negative moods, the illusion of control is not expected (Alloy & Abramson, 1979). By contrast, Martin et al. (1984) found that depressed participants tended to overestimate someone else's control over a non-contingent outcome, and also that females judged others to have a high degree of control over a random task, thus suggesting a reversed illusion of control. Although a large body of research has been conducted on illusion of control, little is known about how this bias interacts with experience. We delineate three competing hypotheses. The first, a default hypothesis, is that people believe they exert no control over a purely random process. Although there is evidence of illusion of control taking place in several contexts, we propose this hypothesis because the interaction of illusion of control and experience has not been explored before.

A second hypothesis is related to the finding that involvement with a task facilitates illusions of control. According to Langer (1975) people engage in illusions of control because they confuse luck for skill. This confusion is likely to happen when chance situations have characteristics of skill-based situations. For example, familiarity and involvement are characteristics that may favor ones chances in a skill task but will grant no advantage in a purely random task. Thus, illusion of control is observed when people have the chance to practice the task, increasing the degree of involvement with such task (Matute, 1996; Thompson et al., 1998) and when participants have more time to think about the task (Langer, 1975), among several other situations. Because the conditions that facilitate the illusion of control vary depending on the context and particularly on the contexts of information acquisition, this hypothesis proposes that illusion of control will be observed both in the experience and description condition, but will be higher in the experience condition. More precisely, we suggest that people will confuse chance with skill leading to a higher willingness to pay to play the lottery when they are in charge of executing the lottery, but the illusory control of subjects acquiring information through experience will be higher than for subjects acquiring descriptive information.

A third hypothesis is based on the assertion that people tend to judge themselves better than average on easy tasks and worse than average on difficult tasks (Kruger & Burrus, 2004; Kruger, Windschitl, Burrus, Fessel, & Chambers, 2008). Findings suggest that people have more information about themselves than about others, so when their own performance is exceptional (either good or bad), they assume that others' will be less exceptional. Therefore, they believe that they are above average on tasks in which they have performed well and below average on tasks in which they have performed poorly. Additional support for this hypothesis is the finding that the above-average effect tends to occur in domains in which absolute skills are high but a below-average effect tends to occur in domains in which absolute skills are low (Kruger, 1999). We propose that learning from experience increases involvement with the task and this highlights the misperception that skills influence outcomes, making the task appear easier than what it actually is. By contrast, learning about a random task from description highlights its random nature, which in turn emphasizes the irrelevance of skills, making the task appear difficult. This third hypothesis, therefore, predicts that people will prefer to be in charge of the task when they learn about it from experience, and prefer somebody else to be in charge of the task when they learn about it from description. More precisely, source of information and person in charge interact in such way that when people learn from experience they are willing to pay more to play the lottery if they are in charge of execution, but when they learn from description they are willing to pay more if someone else is in charge of lottery execution.

We report two studies that investigated how source of information interacts with person in charge. In the two studies, illusion of control was assessed by asking participants to report their willingness to pay to play a lottery following the traditional Becker, de Groot and Marschak (1964) which has been shown to elicit incentive compatible responses. This willingness to pay was contrasted for the cases when the participants were in charge of activating a random task to the cases when the experimenter was in charge to activating it.

Study 1

Methods

The experiment is a 2x2 between-subject design. Participants are assigned to one of four conditions that differ in whether they learn about a lottery from description or experience and whether the lottery is played by themselves or by the experimenter (self-draw or experimenter-draw). Participants performed two tasks: a simple choice problem designed to earn game money and an inference task in which participants state their willingness to pay (WTP) to play a lottery. We use WTP to capture the differences in magnitude of individuals' commitment to a risky task depending on the source of information and person in charge of executing the task.

Participants

Eighty-six volunteers served as paid participants in this study. The sample was largely male (61%), and the proportion of male to female participants was evenly distributed among the four conditions. Participants were undergraduate students from various backgrounds at Universitat Pompeu Fabra, Spain.

Apparatus and procedure

The experiment was run in a computerized laboratory in eight successive sessions with a median of eleven participants in each session. Participants entered the laboratory and sat in front of a computer screen for the first task, which did not vary across conditions. The first task involved a one-shot choice between 10€ for sure and 12€ with 30% probability or 0€ otherwise. The objective of this task is two-fold. On the one hand, by having participants earn their game money, we reduce the influence of a house-money effect on risk-taking behavior. On the other hand, by setting a riskless option of 10€ objectively –and exaggeratedly—more favorable than a risky option of 12€, we expect to have most participants move to the second task with constant earnings and therefore constant reference points which facilitates the analysis.

The second task involved expressing the WTP to play a lottery that pays 10€ with probability 0.9 and 0€ otherwise. This task differs from previous tasks used in studies of illusion of control because it involves high probability of winning, whereas most tasks used in other studies involved small probability of winning. In previous studies, control is revealed by people overestimating their probability of winning, while in the current task, control would be revealed by an underestimation of the probability of not gaining 10€. The reason to make the positive gain so probable is that emphasis on success has shown to increase the illusions of control (Langer and Roth, 1975).

The procedure to elicit the WTP followed the traditional Becker, de Groot and Marschak (1964) method for incentive compatibility. In this method, participants are asked to express their maximum WTP for a risky lottery. Their WTP is then compared to the price of the lottery, which is a random number between the highest and lowest outcomes of the risky lottery. If the stated WTP is higher than or equal to the randomly drawn price, the participant pays the price and plays the lottery. Otherwise the participant pays nothing and does not play the lottery.

After the first task, the experimenter calls the attention of all participants and shows them ten lottery tickets priced from 1€[2] to 10€. The experimenter then shuffles the tickets and asks for a volunteer to select one ticket at random and sign its back without looking at its price. All participants become aware that one ticket was drawn at random but none knows its price.

The second task of the experiment is done individually in the experimenter's office, which is located inside the laboratory but in a separate room. For each participant in the four conditions, the experimenter reads aloud the following instructions:

[2] Though the lottery's lowest payoff was 0€, we used 1€ as the lowest ticket price to avoid confusion with the possible zero-cost of the lottery. This change does not alter the incentive compatibility in the Becker-deGroot-Marschak method.

> “You have won 10€ (0€ or 12€) in the first part of the experiment. This money is yours. Now, the experiment consists of the following game, the bag that you see on the table has tokens inside, these can be red or black. The game consists of withdrawing one token from the bag without looking. If the token withdrawn is red, the university will pay you 10€, while if the token is black the university will pay you nothing. To play this lottery it is necessary to purchase a ticket, but you do not know the price of the ticket. In fact, you saw the price drawn at random by a volunteer in the first part of the experiment. Your task is to offer the amount that you would be willing to pay to purchase a ticket to play the lottery. If your offer is higher than or equal to its price, you will pay the price and play the lottery. Otherwise, you will not be able to play the lottery. Before expressing your willingness to pay …”

In the rest of the experiment, instructions differed across conditions. In the description condition, the instructions followed:

> “… I will show you the content of the bag.” The experimenter empties the content of the bag on top of the table and reveals 9 red tokens and 1 black.

In the experience condition, the instructions followed:

> “… I will let you play the game as many times as you like, but without monetary remuneration. The goal is that you learn about the content of the bag such that you can estimate the amount that you are willing to pay to play the game for real money. You can withdraw as many tokens as you like, one by one, always letting the experimenter put the token back in the bag before you

draw again. You must tell the experimenter when you have sampled enough".

The participants then sampled the lottery as much as they wanted.

After the participants had seen the content of the bag (description) and sampled the lottery sufficiently (experience), they answered in a written form, one of the two following questions provided also in a written form:

> <u>Self-draw (DS condition):</u> "¿How much are you willing to pay for a ticket to play this game, taking into account that *you* will draw the token out of the bag?"
>
> <u>Experimenter-draw (DE condition):</u> "¿How much are you willing to pay for a ticket to play this game, taking into account that *the experimenter* will draw the token out of the bag?"

The materials used in the experiment were casino tokens and a dark brown bag that did not allow participants to see the tokens inside. Lottery tickets were designed in essay to resemble real lottery tickets. A laboratory assistant recorded all experimental results.

Compensation

Participants did not receive a show-up fee but were paid for the payoffs in the first and second task. When the participant's WTP in the second task was lower than the random price of the lottery, the compensation was equal to the payoff in the first task. Otherwise, the compensation was the payoff of the first task minus the random price plus the payoff of the lottery. The mean compensation was 12.10€.

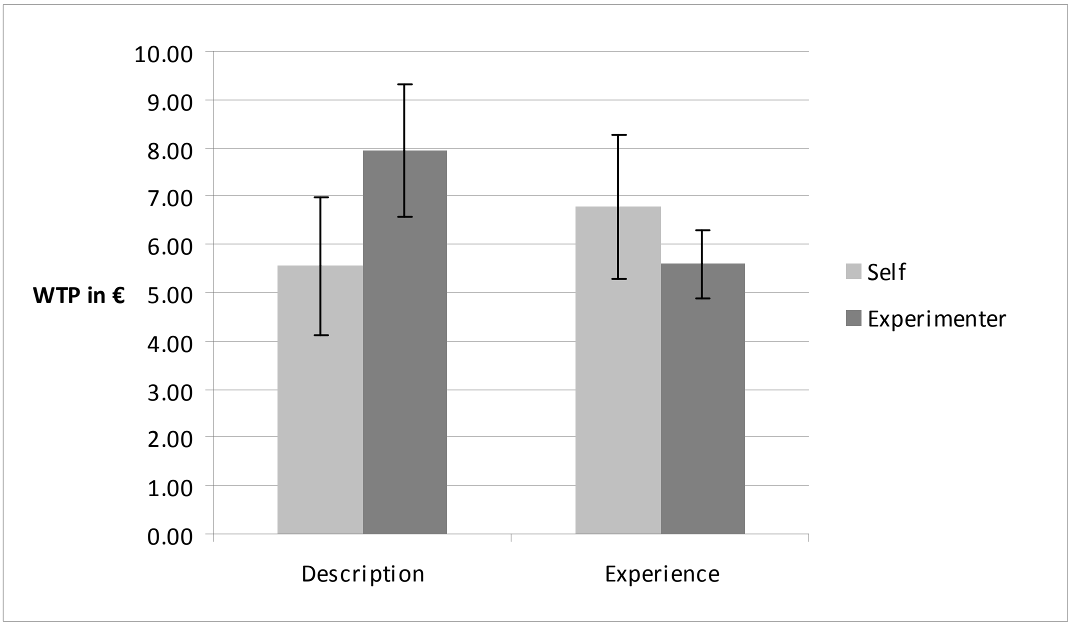
Results

As expected, 83 participants chose the safe 10€-option in the first task, while three participants chose the risky lottery and obtained 0€. These participants were removed from the analysis as their WTP was elicited from a different reference point than the majority of participants. The final sample consisted of 83 participants: 20 participants in the DE condition, 20 in DS, 22 in EE, and 21 in ES.

ANOVA results show a significant interaction between source of knowledge and person in charge, $F(1, 83) = 66.04$, $p = .002$. The analysis showed no significant main effect for person in charge, $F(1, 83) = 14.73$, $p = .138$, or for the source of knowledge, $F(1, 83) = 15.04$, $p = .134$. Figure 1 shows that in the description condition, participants were, on average, willing to pay a significantly higher amount to play the lottery when the token was drawn by the experimenter (7.95€; SD = 2.76) than when it was drawn by themselves (5.55€; SD = 2.84). The opposite is observed in the experience condition, where participants were willing to pay a mean of 6.76€ (SD = 2.98) when the token was drawn by themselves and a mean of 5.59€ (SD = 1.44) when the token was drawn by the experimenter.

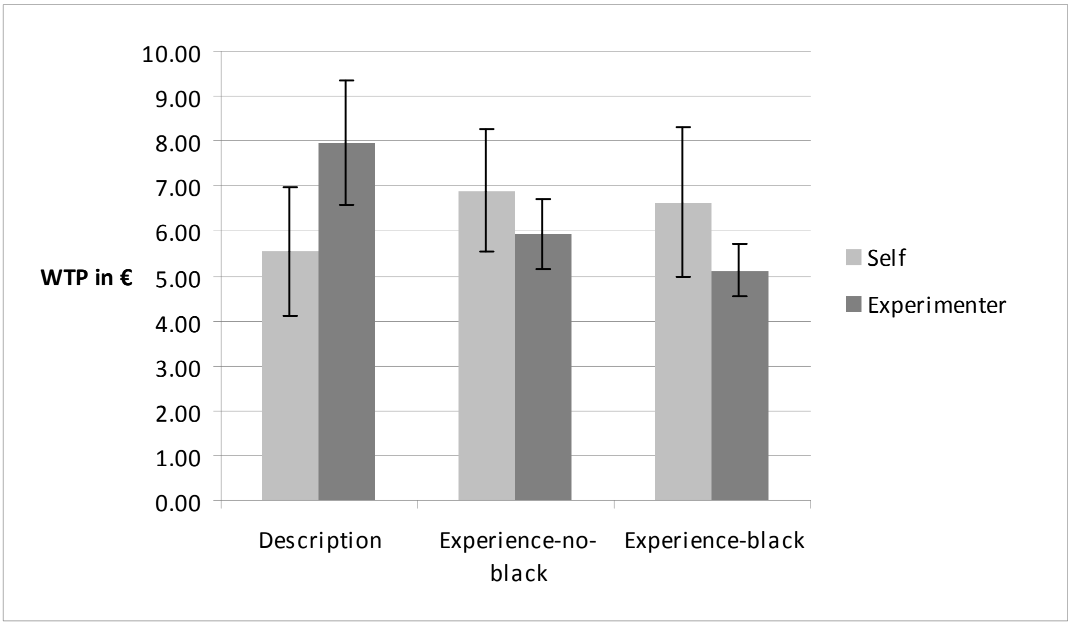
Results from Study 1 disconfirm the first and second hypothesis and favor the third hypothesis. Participants that learned about the lottery from experience became involved with the task, and results suggest that participants perceived the task easier for them than for the experimenter. Moreover, participants in the experience condition revealed illusion of control across different observed probability. When participants in the experience condition were separated into those that observed the black token more often than expected and those that observed the black token less often than expected, results are similar. This finding, shown in figure 2 suggests that the driver of the effect is not the observed probability but the source of information.

Figure 1: Study 1: WTP for a lottery that pays 10€ with p=0.90 and 0€ otherwise.



Note: Error bars indicate standard deviation.

Figure 2. Study 1: WTP for a lottery in samples of different observed probabilities



Note: Error bars indicate standard deviation.

Is this pattern of results driven by the attractiveness of the lottery? An alternative explanation of current results is that this highly attractive lottery breeds illusion of control in experience because the black token is underweighted (Hertwig et al, 2004), and favors the reverse effect in description because the black token is overweighted. Relating this assumption to the general observation that people tend to attribute causality to personal factors for good outcomes and to others for bad outcomes (Miller & Ross, 1975), then participants in the experience condition would prefer to be in charge of playing the lottery to benefit from the likely gain, whereas participants in the description condition would prefer the experimenter to be in charge as the bad outcome is overweighted. To rule out this alternative hypothesis we designed study 2, which follows the same method and procedure as study 1 and involves a less attractive lottery, one in which failure is more frequent than success.

Study 2

This study was aimed at testing whether the attractiveness of the lottery used in Study 1 drove the pattern of results. Therefore, Study 2 was a replication of Study 1 with identical method, materials and procedure, excepting for one major variation. The lottery used involved a 10% chance to win 10€ and 0€ otherwise. Therefore, this time, the bag contained 9 black tokens that paid 0€ and one red token that paid 10€.

Participants

Eighty-six volunteers served as paid participants. There were 21 participants in the DE condition, 23 in DS, 21 in EE, and 1 in ES. The sample was 52% female, and the proportion of male to female participants was evenly distributed among the four conditions. Participants were undergraduate students from various backgrounds at Universitat Pompeu Fabra, Spain.

Compensation

As in study 1, participants did not receive a show-up fee but were paid for the payoffs in the first and second task. The mean compensation was 9.80 €.

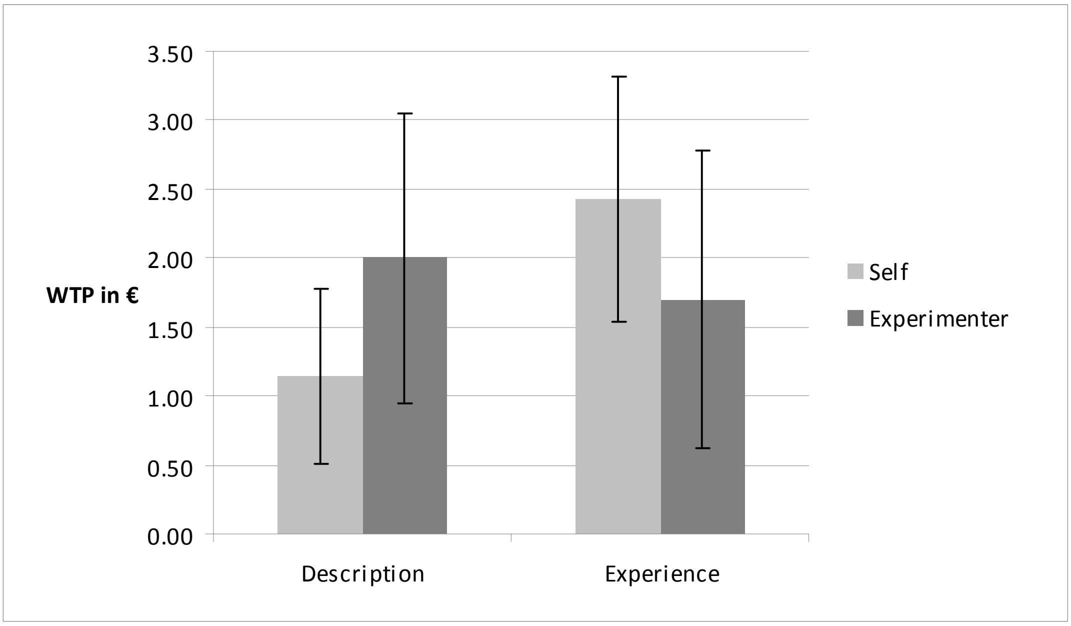
Results

Results suggest that the attractiveness of the lottery does not drive the interaction between source of knowledge and person in charge. ANOVA results confirm the pattern observed in Study 1. The interaction between source of information and person in charge is significant, $F(1, 86)= 11.47$, $p=.054$. The main effects for illusion of control (as reflected by person in charge) and information source are not significant. Figure 3 displays the same pattern as Figure 1 although the amounts participants are willing to pay are notably smaller as a consequence of the less attractive lottery. In the description condition, participants were, on average, willing to pay a higher amount to play the lottery when the token was drawn by the experimenter (2€; SD = 2.10) than when it was drawn by themselves (1.30€; SD = 1.46). The opposite is observed in the experience condition, where participants were willing to pay a mean of 2.43€ (SD = 1.78) when the token was drawn by themselves and a mean of 1.67€ (SD = 2.11) when the token was drawn by the experimenter.

Small samples in the experience condition

One commonly observed finding in the literature of experience-based choice is that people draw small samples, even when sampling is costless. For example, Hertwig et al (2004) found, for a binary choice task, a sample median of 15 observations per problem (7 per lottery). Weber et al. (2004) found similar results. In our study 1, the mean sample size was 5.16 draws (SD = 1.82) and the median was 5, while in study 2 the mean sample size was 7.21 (SD = 2.59)

Figure 3. Study 2: WTP for a lottery that pays 10€ with p=0.10 and 0€ otherwise.



Note: Error bars indicate standard deviation.

and the median 7. It is important to highlight that the task in studies 1 and 2 is not a choice task, where small samples may amplify the differences and render choice simpler (Hertwig & Pleskac, 2008). In the current context, small samples are objectively misleading. The relevance of this result is emphasized as participants sampled from only one lottery, and not from many lotteries as in previous studies (e.g. more than 12 lotteries in Hertwig et al's analysis of 6 problems).

The significant difference between sample sizes in study 1 and 2 ($t = 4.37$, $p < .001$, $N = 42$) reflects the different search patterns of participants as a function of the attractiveness of the lottery. In the attractive lottery, participants drew smaller samples possibly because they encountered the desired outcome more frequently, whereas in the unattractive lottery participants persisted in their search for a desired outcome.

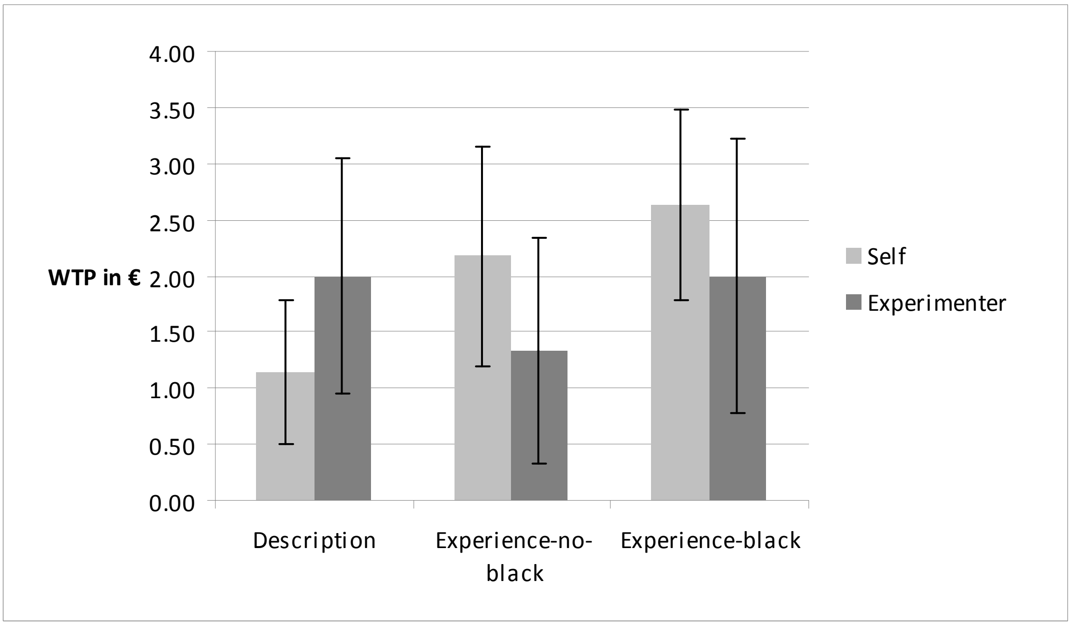
One important aspect of the current sampling design is that it resembles a realistic sampling process. In this case, sampling was not as costless as in previous studies where draws were done by clicking on a button in a computer screen (e.g. Hertwig et al., 2004; Hau et al., 2008; Rakow et al., 2008). The process of sampling in this study involved participants putting their hand in a bag and pulling out a token. The experimenter would then get the token back from the participant, put it back in the bag and shake the bag to shuffle the tokens, to start the process again. Therefore, the process of sampling may have appeared more costly than in previous studies, which could have limited sample size. Yet, it should be born in mind that, if sampling tends to be more costly outside the laboratory than in an experimental setting, we suspect that sample sizes of real-world phenomena would then be trivial.

Insensitivity to observed probabilities

Additional evidence for the interaction between experience and illusion of control can be found in the analysis of different observed probabilities. Results from studies 1 and 2 reveal participants' insensitivity to observed probabilities. Figures 3 and 4 break down the experience condition between participants that observed the rare token (the black token in study 1 and the red token in study 2) more frequently than expected by its objective probability and participants that observed the rare token less frequently than expected. In Study 1, 23 of the 43 participants in the experience condition never encountered the black token that paid 0€ (hereafter, the experience-no-black condition) while 20 participants encountered it at least once. Since all participants that encountered the black token (hereafter experience-black condition) sampled less than 10 times, the chance of getting the black token was overrepresented in their samples. The mean observed probability of participants in the experience-black condition was 0.24 (N = 20, SD = 0.10) and 0 of those in the experience-no-black. Yet, WTP to play the lottery was strikingly similar between these two groups (see Figure 2). Although the overall WTP did not change significantly, higher perceived risk led to a more marked illusion of control, as reflected by a higher WTP difference between those in charge of executing the lottery and those that were not in charge. Notably, as the risk of getting the black token increased, participants were more willing to draw the token themselves.

Insensitivity to probabilities can also be seen by comparing the results produced by the participants in the description condition, who saw a 0.10 probability of 0€, and the results produced by the participants in the experience-no-black condition, who saw a 0 probability of 0€. The pooled WTP for the description condition is a mean of 6.75€ (N = 40, SD = 3.01) and the pooled WTP for the experience-no-black condition is 6.35€ (N = 2.65, SD = 2.14). Identical results can be observed in Study 2. The pooled WTP for the description condition is a mean of 1.57€ (N = 42, SD = 1.77) and the pooled WTP for the participants in the experience condition that never encounter the red token (experience-no-red) is 2.08€ (N =41, SD = 1.98).

Fig. 4. Study 2: WTP for a lottery in samples of different observed probabilities



Note: Error bars indicate standard deviation.

General discussion

This research examined how people's illusion of control interacts with experience. Two studies reported herein found that participants that learned about a lottery from experience were willing to pay higher amounts to play the lottery when they activated the random event than when the experimenter did. Conversely, the two studies revealed that participants that learned about the lottery from a convenient description paid higher amounts to play the lottery when the experimenter activates the random event than when they activate it themselves. Interestingly, this pattern of results was robust to the attractiveness of the lottery as well as to marked differences in perceived risk.

The seminal work by Langer (1975) introduced the idea of an illusion of control that predicts that people prefer to be in charge of tasks that produce random outcomes. Results from our study suggest a reverse illusion of control in scenarios where the random nature of the task is described rather than experienced. It is important to bear in mind that a reverse illusion of control still considers that a certain degree of control can be exerted over random outcomes, thus implying a cognitive bias. The difference, however, is that the carrier of control is not oneself but other. This idea has been developed in the context of learned helplessness (Alloy & Abrahamson, 1982), which suggests that in certain contexts, people perceive lack of control over outcomes. This condition has been associated to clinical depression (Selingman, 1975). In fact, previous studies on depressed participants had already provided evidence of a reverse illusion of control (Martin et al, 1984). In this study, we provide an alternative explanation based on a social factor interacting with the source of information: people perceive themselves worse than average on tasks perceived as difficult, and a key factor explaining varying perceptions of task difficulty is the source of information.

There are many consequential economic and social situations with the key characteristics of our experiments. Both studies 1 and 2 serve as metaphors for a situation in which a manager is responsible for investing its firm’s funds on the stock market. We learned that experience will influence the decision on whether to delegate the task. A fund manager with experience will avoid delegating the task even though she is aware that outcomes depend on random fluctuations of the market (Makridakis et al, 2008). If she is forced to delegate the task, for external reasons, she will invest less than what she would invest if she was in charge.

Another example is the decision of who should drive a car in a selected route that, as most car journeys, involves a small risk of an accident. A person may prefer to drive the car on a route that she has done repeatedly, whereas the same driver may prefer somebody else to drive in a new route that has to be assessed from a descriptive map.

Our findings add evidence to the notion that the way people learn about a probabilistic event affects the risk they are willing to take (Hertwig et al, 2004: Weber et al, 2004). In addition, our findings suggest that the risk people are willing to take depend, to a significant extent to the interaction between the source of knowledge and the person to in charge of executing the task.

CHAPTER THREE

Learning from past strategic decisions:

Hindsight bias as a source of superstitious learning

Introduction

Large-scale strategic decisions are rare, complex, made in ambiguous environments, and governed by causal and outcome ambiguity (Zollo, 2009). Examples of such decisions are major acquisitions and mergers, major organizational change programs, important repositioning of products, or any other significant strategic decision occurring a few times in the life-span of an organization. Organization scholars agree that in such situations rational analysis and deduction are likely to be difficult to apply (March, 2006), and instead, knowledge gained from prior decisions is likely to be retrieved as a source of valuable information (March, Sproull and Tamuz, 1991; Gavetti, Levinthal and Rivkin, 2005). This idea has caused an interest in how feedback from the performance of previous decisions affects the likelihood of different types of strategic actions (March, 1991; Greve, 1998).

While the belief that strategic decisions are well-served by experiential learning is strongly rooted among managers and management scholars, research in behavioral disciplines suggest that learning from experience comes at the cost of numerous biases which may outweigh the benefits of the competences developed through the accumulation of experience (Bukszar and Connolly, 1988; March, 2006). Surprisingly, despite the relevance of learning processes in strategic decision making, little is known about the mechanisms that lead to such imperfections.

A major problem in learning from past strategic decisions has to do with the possibility of "superstitious learning", which is the gap between managers' beliefs about the causes of strategic outcomes and the actual causes (Levitt and March, 1988; Zollo, 2009). A leading explanation for why superstitious learning occurs, points at overconfidence effects spurred by experience accumulation, which are often strong enough to overtake the competence building process generated by the stock of experience (Zollo, 2009).

In this paper we propose another mechanism to help explain superstitious learning, namely, the hindsight bias. Studies by cognitive psychologists show that when individuals retrieve information from the past, they incur hindsight bias, which refers to the tendency for people to see an event as more likely *after* the event has occurred than *prior* to the event (Fischhoff, 1975). In hindsight, people tend to exaggerate their predictive capacity of events which have already taken place (Hoffrage and Pohl, 2003; Musch and Wagner, 2007). The main argument is that judgments made in hindsight about the probability of success of previous decisions are likely to be strongly biased towards actual outcomes, and this leads to biased codification of the cause-effect relation linking past strategic decisions and realized outcomes. Moreover, we elaborate on the heuristic mechanisms that may be responsible for such bias.

We use a grounded theory approach to explore how managers use the information from previous experiences in strategic decisions to formulate new decisions. Through ten in-depth interviews to top-managers in the health industry we gather information to build theoretical propositions. Because experiential learning has been studied in decisions made with high frequency (e.g. learning curves literature), the contribution of this article is to further understand experiential learning in the context of rare strategic decisions. By shedding light on the micro-processes followed by decision makers when learning from experience, we identify some of the limitations of managerial cognition in strategic decision making.

We begin by exploring experiential learning and its relevance in strategy formulation. Then, we elaborate on superstitious learning. Following, we briefly review the literature o hindsight bias, and provide propositions on how it affects strategic decisions and how it can help explain superstitious learning. Throughout the development of propositions we provide insights from interviews to top managers. We conclude with a discussion and concluding remarks.

Theoretical Background

The Role of Experiential Learning in Strategic Decision Making

The growing importance of experiential learning in decision making is evidenced by its central position in organizational decision theory (Cyert and March, 1963; March, 1994; Gavetti and Levinthal, 2000; Greve, 2003; Gavetti, Levinthal and Rivkin, 2005; March, 2006), and by the burgeoning interest in cognitive psychology (Hertwig, Fanselow, and Hoffrage, 2003; Hertwig *et al.*, 2004; Erev and Barron, 2005). In organization research, ideas of experience-based processes have been used to understand action, change, and the development of knowledge in organizations (March, 1994). In this literature, the use of past experiences as a source of knowledge is usually proposed as an alternative to analytical decision processes, since strategic rationality appears to demand greater stability in preferences and higher cognitive capabilities compared to what can be sustained in reality (Levinthal and March, 1993).

Approaches to decision making stressing the importance of deductive reasoning and analytical choice in the strategy-making process, have been criticized for their inadequacy in complex scenarios of highly interactive variables where deductive rationality is least able to provide effective decisions (Simon, 1955; Levinthal and March, 1993; March, 2006). As a reaction to models of calculative rationality, theories stemming from behavioral disciplines have emerged to provide alternative explanations about how decision makers approach strategic decisions. Many studies in this field point to the importance of experiential learning as the key element aiding strategic choice (Cohen and Sproull, 1996; Gavetti and Levinthal, 2000; Greve, 2003). The underlying idea is that organizations learn from feedback-based reinforcement processes and thus increase organizational intelligence (Levitt and March, 1988; Gavetti and Levinthal, 2000; Denrell and March, 2001; March, 2006). Reinforcement processes are those in which the propensity to adopt certain procedures depends on the feedback from past outcomes and where more successful procedures are more likely to survive than less successful ones (Nelson and Winter, 1982; Greve, 2003). The proponents of this view believe that such processes are beneficial because they allow firms to discover effective competitive positions in novel environments (Gavetti *et al.*, 2005).

Nonetheless, organizations often depend on simplified interpretations of past events and on judgmental heuristics, which reflect the systematic limitations of decision makers' cognitive and memory capabilities (Kahneman and Tversky, 2000). Learning processes are less reliable in situations when feedback is limited and difficult to interpret — as it is frequently the case in strategic decision situations — and therefore, such task environments exacerbate the identification of links between decisions and observed outcomes (Denrell, Fang and Levinthal, 2004). Yet, it is precisely in those decision situations where information about the environment is most ambiguous that top managers have to rely on interpretations of past events.

Superstitious learning from strategic decisions

In addition to the fact that strategic decisions are infrequent, task dissimilarity between strategic decisions, noise, ambiguity, temporal delays, and environmental changes, further decrease the usefulness of feedback (Levinthal and Rerup, 2006; March, 2006). In these settings people become remarkably insensitive to determining whether outcomes should be attributed to their skill or to other uncontrollable factors (Hogarth, 1987; Friedland, 2006), which in turn promotes superstitious learning. According to Levitt and March's (1988) seminal paper, superstitious learning is defined as a situation in which "the subjective experience of learning is compelling, but the connections between actions and outcomes are misspecified". For example, when managers observe that their decision to introduce a radical new technology is followed by utmost success, they tend to overlook the infinity of factors that brought about such success and attribute it to few factors such as managerial foresight, effective predictions about the state of the environment, reliable information regarding consumer behavior, among others. In fact, only a low percentage of radical innovations turn out to be great successes, and even within the same firm, strategic decisions based on the predictions from the same management team and same reliable information sources may produce disturbingly different outcomes. The consequences of superstitious learning is the overestimation of managers' influence over uncertain processes and misleading understanding of the underlying causes of success. We sustain that a central mechanism explaining superstitious learning is 'hindsight bias' which we review in the next section.

Judgments made in hindsight

The accuracy of judgments based on information from past experiences also depends on the way decision makers construct their memory. Cognitive psychologists claim that our memory of the past is not a memory of the uncertainties of the past, but rather a reconstruction of past events based on the outcomes we have observed. The knowledge that an event has occurred seems to reshape memory (Hogarth, 1987), and with hindsight, we tend to exaggerate what we had known in foresight (Hoffrage and Pohl, 2003).

This effect, called the "hindsight bias", is the inclination to see past events as being predictable and reasonable to expect. Several experiments are found in the literature in which people are presented with outcome knowledge and, as a consequence, tend to falsely believe that they would have predicted the outcome of such event (Hoffrage and Pohl, 2003). This bias has been identified in a variety of experimental tasks (Fischhoff, 1982), including confidence judgments in the outcome of events, choices between alternatives, and estimations of quantities; as well as in a variety of domains outside the laboratory, such as political events (Pennington, 1981), medical diagnosis (Arkes, Wortmann, Saville, and Harkness, 1981), outcomes of scientific experiments (Slovic and Fischhoff, 1977), economic decisions (Bukszar and Connolly, 1988), and general knowledge (Hell, Gigerenzer, Gauggel, Mall, & Müller, 1988). It is a robust phenomenon which is hard to eliminate and that can be easily demonstrated (Fischhoff, 1982; Christensen-Szalanski and Willham, 1991). Besides, this effect has proved more pronounced when people have little experience in a task or decision (Christensen-Szalanski and Willham, 1991; Musch and Wagner, 2007), which is particularly relevant for strategic decisions.

In the context of strategic decisions, there is only one study looking at this effect, and it is tested in an experimental setting. In this experiment by Bukszar and Connolly (1988), three groups of advanced strategy students in an MBA program were given a strategy case regarding a pharmaceutical firm's expansion to another country. The three groups were asked for an analysis of the potential success or failure of this strategic decision in terms of return on investment (ROI) after a two-year period, based on detailed information provided in the case. The three groups differed in the following way: the first group had no outcome information (control group); the second group had a report saying that the firm generated a ROI of 36 percent after the two year period (high-outcome condition), and the third group had a report saying that the firm generated a ROI of 4 percent after the two year period (low-outcome condition). The groups which were provided outcome information were instructed to ignore it, and to base their predictions on the descriptive information. Results showed that the participants were unable to ignore outcome information in spite of being specifically warned to do so. The predicted ROI were significantly different between groups and were biased toward the outcome information they had observed, while the control group predicted a value in between the others. Moreover, students in the high-outcome condition tended to see the strategic decision as less risky and more attractive than those in the low-outcome condition.

Hindsight bias plays a key role in judgments of sequential events. Second judgments are less independent than what managers would like to believe, and this can have considerable consequences when the initial judgment is poor. Consider the example of a physician who is asked a second opinion on a diagnosis but is aware of the first diagnose, or a researcher who is asked to review a manuscript but knows the results of previous reviews (Pohl, 2004). Similarly, managers that have to decide whether to follow a given course of action may be biased to decide according to past knowledge of the outcome of similar decisions.

Correspondingly, consider the example of a manager who retrieves a past decision and attempts to evaluate the quality of the decision process that was followed for such decision. It would be inadequate to take into consideration information that was not (and could not possibly be) available at the moment the decision was made, as happens with realized outcomes. In the presence of hindsight bias, a manager evaluating past decisions may conclude that decisions resulting in positive outcomes were caused by better decision processes than those that resulted in negative ones (Hawkins and Hastie, 1990).

When managers are aware of the result of past strategic decisions, negative outcomes are confidently judged as caused by poor decisions (Clapham and Schwenk, 1991), although these decisions were probably judged as adequate at the time they were made. The consequence of this distortion is the illusion of “creeping determinism” (Fischhoff, 1975), as if the environment was characterized by being predictable and where causal links between decisions and outcomes are evident and easily established. Therefore this distortion leads to judging past events as having been inevitable and to overestimating the likelihood of success of strategic decisions when top managers are aware that similar decisions have proved successful in the past. To shed some light on the possibility of hindsight bias as a cause of superstitious learning in strategic decision making, we set out to interview a group of managers to draw information on how they assess past strategic decisions.

Semi-structured interviews to top managers

The data for this research consists of semi-structured interviews with top-managers in several organizations in the health industry. All of them form public or private hospital, or clinics. A total of 10 interviewees participated in the study. Because we are interested in gathering information about strategic decision processes and experience, participant selection criteria were based on: (1) level of seniority, and (2) hierarchy within the company, because only top managers with enough experience in their firms’ strategy formulation are likely to convey valid information regarding these issues. The mean age of participants is 43.7, and their experience in the industry was on average 16 years. There were a total of 6 men and 4 women. The length of the interviews ranged from approximately 40 to 60 minutes. The interview questions were open-ended and intended to elicit participants’ views about their organization’s strategy making processes, strategy evaluation and the use of experiential information. The interviews were tape recorded and transcribed to enhance the reliability of the analysis. In total there were 67 pages of interview text.

Because the nature of this study is exploratory, the data gathered in these interviews is not used for statistical testing but rather for building theoretical propositions. We begin by asking interviewees their general conception of strategy formulation and strategic decisions, to examine whether their vision of strategy coincides with its corresponding academic notion. Then, we moved on to ask questions about learning from past strategic decisions, evaluation of past strategy, handling information from past decisions, and experiential learning in general.

Managerial perspectives on strategy and hindsight judgments

Earlier studies (see March and Shapira, 1987, for a review) report a substantial gap between manager's and academics' understanding of managerial risk-taking and managerial action. Therefore, before asking specifically about the role of experience in strategic decision making, we asked each manager to define the term 'strategic decision' in order to start the interview with a shared understanding of the term and to explore the particular perspectives of participants. There was a consensus among all the participants by which they regarded strategic decisions as radically different from routine, operational decisions made every day. Among all the definitions, there was a common notion of strategic decisions as involving "uncertainty", "risk", "change", as a "time consuming process", made in "unclear scenarios", and with a "tremendous impact on the organization". Some managers recalled concepts related to the fuzziness involved in strategic decisions, such as "tricky", "hazy", or "inherently problematic" decisions. Lastly, another group recalled concepts relating to the way these decision processes are conducted, saying that strategic decisions are made "always by teams and never individually", made by "directive committees", "over a long period of time, and in a sequential manner". One of the most representative answers was the following:

> "I think of strategic decisions as those important decisions implying structural changes, reorganization, or repositioning of our whole organization. […] Of course they are rare and only take place once in a while, but when we have to deal with these situations we focus all our attention and resources on that particular decision process to make sure we eliminate all potential risks. We believe you can't assume risks in strategic decisions. We bring our best people, consult experts, and meditate the final decision progressively, little by little."

In general, the notion of strategic decision was surprisingly similar to the notion developed in the academic literature. In this particular sample, the common understanding of strategy assures that the feedback from questions regarding strategy assessment is valid and that it refers to the same shared concept of strategic decisions.

The next set of open-ended questions was aimed at understanding the type of information that decision makers consult for strategic decisions. Nine out of ten interviewees reported some kind of experience-based information. Among the terms recalled, the most frequent were "we consult experts with experience in the specific type of decision we are facing", "we talk to experienced people", "we make use of lessons learned from our own decisions made in the past", "our department keeps track of past strategic decision processes". Also, eight out of ten interviewees declared that their organization keeps a "record" or "memoire" of important decisions, which is kept in an archive and is often consulted. An illustrative example of managers' reliance on experience for strategy formulation is the following:

> "We try to monitor the environment and analyze as much data as we can. But that's only one part of the picture. Then, we bring in the people with experience in our firm, and they take a look at the numbers and data analyses. The bottom line is that these people have been 'there before' and are aware of the potential risks we face in these large-impact endeavors. They've learned the lesson from past strategic decisions. […] I myself take into account my own experience, and think back to similar situations and

> recall what I did right, what I did wrong. You always look at the past in these situations trying to avoid previous mistakes."

This example illustrates the relevance of past actions on current strategy formulation. When participants started to talk about experience or prior strategic decisions, we used this moment to ask them about retrospective evaluations of past strategic decisions. The question was simply 'how do you evaluate the quality of a strategic decision made in the past?'. The answers to this question given by the ten interviewees converged to the same idea: they look at the outcome of the strategic decision to judge its quality. For seven out of the ten managers the first response to the question pointed to "results obtained", "outcome" or "success" of the strategic decision. A representative example of interviewees answering in this line is the following:

> "I look at the results obtained from that particular strategic decision. If the decision turned out to be a big success, then we think of that as a high quality decision. Later on, those strategies are recalled as good examples in future strategic processes. Strategic failures are certainly caused by bad-quality planning, […] (as if) something went wrong in the decision process, or some information was neglected".

Two other managers regarded this question as an obvious issue and did not hesitate to claim that "we just need to see the outcome of the decision, that's obvious", or "we check the overall results obtained from that decision, in terms of financial or economic performance, and that's it". Only two managers in the whole sample offered as a first response factors unrelated to decision outcomes, namely situational factors like "the environmental uncertainty at the time the decision was made". One of them clearly illustrates the psychological effects of hindsight bias in the following way:

> "To assess a strategic decision made in the past we first try to evaluate the context in which the decision was made, the information we had, and other variables present at that time. Still, even though we know the decision was made under specific conditions and that it was probably the adequate decision at that point, we end up looking at the outcomes. It's hard not to

> focus on the outcomes. Especially when the outcomes are not what you expected; then it is hard not to compare the actual outcomes with the potential outcome of an alternative course of action".

This simplified interpretation of strategic actions not only suggests superstitious learning effects, but also a tendency to code unsuccessful strategic decisions as necessarily caused by poor decision processes and success as caused by flawless decisions. In accordance with this tendency to judge strategic decisions by their outcomes and not by the decision process, what may have been a high-quality strategy according to the facts available at the time may be incorrectly criticized and a good decision-maker may be unfairly punished. Overall, the perspectives of the ten interviewees show that managers use retrospective evaluations of past strategic decisions in order to make new strategic decisions. However, all the evidence suggests that managers not only are incapable of ignoring outcomes of strategic decisions to evaluate the quality of the process which lead to such decisions, but rather they use outcome information as a central estimator of the quality of such decision. This is a clear example of hindsight bias. The fact that managers establish a direct relationship between the observed outcome of a strategic decision and the quality of the decision process reflects a misleading understanding of the causal links between driving strategic outcomes, and leads to superstitious learning. Managers observing successful outcomes superstitiously learn that the decision processes underlying such successes are necessarily high-quality decisions, whereas failures are necessarily caused by poor decision processes. Although this may be the case in some cases, it is certainly not always true, and when samples from experience are small, this biased causal link leads to superstitious learning. Moreover, this leads to an underestimation of the risks involved in decisions coded as 'good' decisions, derived from an increased confidence in past successes. We therefore suggest the following propositions:

Proposition 1A: Hindsight bias in evaluations of past strategic decisions leads to superstitious learning.

Proposition 1B: Retrospective evaluations of past strategic decisions lead to confusing misfortune (or unpredictable forces) for managerial incompetence, and fortune for managerial competence.

Proposition 1C: Hindsight bias in evaluations of past strategic decisions leads to exaggerating the predictability of future strategic situations.

Judging by availability of observed outcomes

People, as well as most organizations, use samples of observed outcomes to construct beliefs about the outcomes that may follow choices in future situations. Through this heuristic mechanism, organizational members attempt to deduct patterns from what they observe and underplay other potential alternative outcomes (March *et al*., 1991). As it is difficult to establish causal relations between rare strategic decisions and corresponding outcomes, organizations tend to pay greater attention on observed outcomes and neglect the importance of any alternative outcomes that did not take place.

However, to learn effectively from past strategic decisions, not only must observed outcomes be taken into account, but also the alternative hypothetical outcomes that have not occurred must be considered if the success likelihood of future decisions is to be assessed accurately (March *et al*., 1991; Hogarth and Einhorn, 1992). This is particularly relevant for strategic decisions, where the causal paths between competence and performance at a task are difficult to specify due to high causal complexity and the influence of environmental impredictability, which implies that actual outcomes may not necessarily represent the most likely outcome from the decision made (Powell, Lovallo and Caringal, 2006). By only incorporating outcome-related knowledge to the mental representation of a novel decision situation, managers cannot envisage outcomes other than those observed in the past, and this may lead them to underestimate the risks of unprecedented events. This reinforcement process exaggerates the likelihood of what has actually happened and underestimates the likelihood of what might have happened (March, 2006).

Behavioral decision research suggests that people often estimate the likelihood of events by retrieving examples from memory, and in doing so the evaluation of frequencies or probabilities of an event often depend upon the ease of recall of such an event (Tversky and Kahneman, 1974; Raghubir and Menon, 2005). This “availability heuristic” is an effective tool to assess the probabilities of occurrence of an event in stable environments with frequent feedback. However, when events are selectively stored in memory and are therefore systematically easier to remember, the availability heuristic leads to biased likelihood judgments, where easily remembered events are perceived as having a greater probability of occurrence. Therefore, since only observed outcomes become readily available in the organization’s memory while non-occurrences are discarded, managers retrieving past decisions for likelihood judgments of possible outcomes may form estimates that are biased towards observed outcomes. This logic points at the availability heuristic as a potential explanation for hindsight bias in evaluations of past strategy.

We asked our interviewees to recall and describe a strategic decision made in the past. Every single manager easily recalled a successful strategic process while none recalled a failure. Among the examples, managers mentioned “redesigning the clinic building to incorporate new functional areas, and to accommodate existing services in order to provide a more flexible yet efficient service overall”, “changing the existing payroll scheme to a performance-pay system, which requires new contracts, changes in the schedules of most employees and incorporation of new staff", or "the introduction of a new technologies in the sterilization service which implied the restructuring of the whole service, leading to layoffs and incorporation of qualified staff", all of which resulted in successful improvements of organizational performance. These answers suggest that not only observed outcomes are given more importance than non-occurrences, but also successes are more salient in memory than failures. Related to this point, one of the interviewees reported that:

> "When looking backwards for lessons from past strategy I tend to focus on big successes. I tend to analyze past strategic decisions depending on the salience of their impact; if the impact of a decision was great and salient I consider it as a useful example to learn from it. May be in the future a similar situation may come up, and knowing that a specific strategy worked out well, makes me feel more prepared for facing similar situations in the future".

Because successful outcomes appear to be easier to recall and become more readily available than failures, the consequence of judgments by availability is that the perceived probability of success of strategic processes that were stored in memory as 'successful' is higher than for events remembered as 'failure' (Tversky and Kahneman, 1974; MacLeod and Campbell, 1992). This tendency has direct implications for strategic decision making. When successes in risky strategic decisions (e.g., the successful introduction of radical innovations) are over-represented in the pool of experiential knowledge while failures are under-represented, managers may gain excessive confidence in their strategic decision making abilities. We therefore suggest the propositions.

Proposition 2A: Retrospective evaluations of past strategic decisions are biased towards observed outcomes because memories from the past are retrieved following the availability *heuristic, through which actual occurrences are easily recalled while non-occurrences are neglected.*

Proposition 2B: Retrospective evaluations of past strategic decisions are overly optimistic because successful outcomes are more readily available than failures in the organization's memory.

Proposition 2C: Hindsight bias in the evaluation of past strategic decisions is partly caused by the availability heuristic.

Discussion and concluding remarks

Individuals are well equipped for learning from experience when they experience multiple trials and get accurate feedback (Hogarth, 2001). For example, managers learn that a certain production process is better than other because, after repeating both processes several times, they consistently observe that one process outperforms the other. Conversely, when tasks do not have this structure because the context is novel, ambiguous, and the feedback received from such tasks is limited and unclear, learning from the past becomes challenging. Yet, managers cope with this type of situations in the same way as they do with those more frequently encountered. The result of this poor learning process is superstitious learning. Even if managers acquire competence through experiencing rare strategic decision processes, they often learn the wrong lesson and induce misleading causal relations between decisions and outcomes.

Throughout the paper we claimed that a key factor explaining superstitious learning is the robust and commonly observed hindsight bias. Once managers know that an outcome has occurred their perceived likelihood of that event increases. Therefore, managers tend to believe that this relative inevitability was apparent before the event. Another problem with hindsight bias has to do with reward and punishment structures. As noted by Fischhoff (1975), “when second guessed by a hindsightful observer, his misfortune appears to have been incompetence, or worse.” Judging the competence of a management team based on the outcomes achieved in rare strategic decisions may lead to rewarding people who have been lucky or happened to achieve a successful outcome for unknown causes outside their control, and may punish competent managers in situations where misfortune or unpredictable events played a major role. One way to help solve this problem is by rewarding managers for the quality in the decision process (e.g. alternatives considered, exhaustiveness of information search, reliance on external advice, proper assessment of the risks involved, etc.) and not solely on outcomes.

In the last part of the paper we elaborated on the tendency to over-rely on observed outcomes. Individuals tend to learn from what they observe but not necessarily from what they do not observe. This form of logic is common among managers and is widely implemented by most business schools, where the case method is precisely intended to give students a base from which to draw useful examples for future similar situations they may face (Gavetti *et al.*, 2005). This behavior can have the advantage of rapid adaptation in unchanging environments with frequent feedback, but the disadvantage is that valid learning often requires knowing things that have not been observed (Hogarth, 2001). Giving excessive importance to observed outcomes while disregarding the non-occurrences of possible alternative outcomes can prompt managers to underestimate the risks involved in strategic decisions. Top managers tend to use their sample of past experiences as unbiased estimators of the chances of success in similar future decisions. This poses a problem because the stored memories of past experiences overweight the presence of successes while they also underrepresent less desirable events. Through this process, strategies that turned out successfully, irrespective of their quality, are stored in the organizations memory and become readily available for future retrieval. In this way, this biased construction of common beliefs is stored in the form of causal links between decisions and outcomes and become incorporated in the organization's set of beliefs.

Whereas in our every-day life, simplifications in the reconstruction of memory may be a useful mechanism to help cope with the excessive amount of information found in the environment, it can have a great impact in novel and complex contexts where the possibility of accurately predicting outcomes is low or nonexistent. Nonetheless, reshaping our understanding of the world in terms of what has already been seen to happen can also be a beneficial adaptive behavior. The disadvantages of biased memory reconstruction are probably outweighted by the benefits of adaptive learning (Pohl, 2004). Memory has a limited capacity, and it is important to store events in a coherent way that allows recall. Environmental conditions render the identification of useful relations arduous, and it is therefore economical to concentrate and remember the relations that work and forget those that did not (Hogarth, 1987).

A key difference in the ability to learn correctly from experience is the extent to which individuals engage in counterfactual thinking (Baron, 1999). When people reflect on the past events that are available in their memory, they often think not only of the events that actually happened but also about how those events might have happened differently (Walsh and Byrne, 2004). This is done by mentally undoing the aspects of the decision process that led to the observed outcome.

One way of increasing the amount of alternative outcomes available in a manager's pool of knowledge is to imagine how past decisions could have produced different (yet possible) outcomes. By increasing the number of alternatives retrieved from past decisions, counterfactual thinking provides a better understanding of the process that underlies the observed cause-effect relation (Morris and Moore, 2000). The ability of managers to extensively retrieve relevant information cues from the past and conceive different alternative scenarios can reduce the degree to which judgments are biased toward easily available information. In this respect, research on entrepreneurial activities in organizations suggests that entrepreneurial managers are less likely than other managers to engage in counterfactual thinking and therefore more likely to perceive situations as more favorable (e.g. less risky) to them (Baron, 1999). This means that failure to engage in counterfactual thinking may lead to risk-taking as a consequence of overlooking potential negative events. In sum, counterfactual thinking can improve outcome and frequency judgments by increasing the set of available alternatives retrieved from past experiences.

Managerial risk taking is crucial for a firm's strategy and, consequently, for its performance (Simon and Houghton, 2003; Hambrick 2007). Becoming aware of the heuristic mechanisms that lead to biases in experiential learning can enhance organizational strategy formulation by reducing unnecessary risk-taking. The theories of competitive advantage implicitly assume that managers have a significant degree of foresight about the emergence of strategic advantages (Ahuja, Coff and Lee, 2005). While this article challenges this view, we sustain however that managers can present a competitive advantage when they understand the limits of managerial foresight and the nature of adaptive learning.

We realize that this article has limitations. The propositions suggested, although potentially testable, require intrusive access to individual-level information from managers which is usually hard to obtain (Hambrick, 2007). Moreover, several individual-level (e.g. managers' background, years of tenure, motivational differences) and environmental-level variables (e.g. environmental complexity) may moderate the effect of heuristic decision making on decision biases, so we are aware that a more comprehensive model would benefit from such controls. Opportunities for future research in this line also include an examination of organizational outcomes as a function of the presence — and degree — of the cognitive biases arising in the experiential learning process. This type of research may be served by simulation techniques, since acquiring individual-level data is often a restriction.

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