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Location and Innovation Optimism: a Behavioral-Experimental Approach

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Abstract

Using a behavioral-experimental economics approach, this paper shows that the location of a potential innovator has an impact on her or his innovation attitude, specifically on her or his innovation optimism. Moreover, such an impact is a consequence of the way in which they can access the information about the chances of succeeding if they initiate an innovation process. Isolated innovators can learn about their success chances from external objective sources, such as market research companies or public institutions. On the other hand, when the potential innovator is located in an innovation cluster, she or he has the chance to observe innovation performance and share the experience of innovation. This work provides empirical evidence to support that innovation attitudes are significantly different in both types of location: while isolated innovators exhibit innovation pessimisms, members of innovation clusters tend to be optimistic as respect to their success chances in the innovation process.

Keywords: *Innovation, Location, Innovation optimism, Behavioral-experimental Economics, Rank-dependent utility*

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Introduction

This paper applies a behavioral-experimental approach to study the impact of localization, specifically clustering, on innovation optimism. Where a firm is located could be a key element of its success in innovation and, for this reason, it becomes essential to study the mechanisms through which clustering has an impact on innovation (Farinha et al. 2014; Schoonmaker and Carayannis 2010). As instances of this type of impact, clustering can help innovators benefit from technological spillovers or from having access to relevant information (Oerlemans et al. 2001). However, to the best of our knowledge, there is no previous work analyzing the effects of clustering in the way in which innovators can learn about their success chances and how the cognitive procedure in which such information is gained may affect their innovation behavior itself. As a first attempt to fill this gap, we study the difference between learning innovation success chances in two alternative situations: (1) as an innovator located within a cluster, which can actively observe the performance of other innovation processes launched by innovators in this very same cluster and operating in similar environmental conditions; (2) as an isolated innovator, which can only receive this information from external agents, such as market research firms or public institutions. Results show that location does have an impact on innovation optimism. Specifically, innovators that are isolated from the rest show innovation pessimism, while those belonging to an innovation cluster show a higher degree of innovation optimism.

This paper is mainly related to the literature concerning the relationship between location and innovation and the impact of the first one over the latter one (Feldman 1999; Porter 2000; Love and Roper 2001). Specifically, it is related to literature regarding the importance of prior knowledge when taking innovation decisions (Cohen and Levinthal 1990; Rogers 2010; Leiponen and Helfat 2011), as well as optimism and pessimism attitudes (Wakker 2010). The paper is also related to social cognitive theory, since it considers that knowledge acquisition can be directly related to observational learning from others within the context of social interactions in the innovation cluster (Bandura 2002; Ratten and Ratten 2007; Schiffman and Kanuk 2007). Finally, the influences of additional personal traits influencing innovative attitudes are also considered (Bäker et al. 2012; Baron 1990). Optimism is usually interpreted as seeing Bthe bright side of life^. Optimism has been tested in many different fields, from measuring optimism-pessimism from beliefs about future events (Wenglert and Rosen 2000) to attitudes toward the development of early stage breast cancer (Carver et al. 1994). In particular, optimism has been extensively studied as the source of many economic phenomena: it can affect financial and accounting decisions (Shefrin 2008; Ashton and Roberts 2005) or can distort stock returns (Barberis et al. 1998). Optimism has also been considered as an important component of utility (Brunnermeier and Parker 2004) and has been correlated with positive beliefs of future economic conditions in the novel measure of optimism developed by Puri and Robinson (2007). Finally, using a social cognitive theory and a multilevel perspective approach, Hmieleski and Baron (2009) demonstrate a negative relationship between entrepreneurs' optimism and the performance of their new ventures.

In the specific field of innovation, innovation optimism can be defined as a bias in decision-making consisting of evaluating an innovation process as if the probabilities of succeeding were larger than they actually are, even if the objective value of such probabilities are actually known by potential innovators. Innovation optimism cannot be explained under a conventional economics approach—i.e., expected utility paradigm—were each potential innovator is modeled as a homo economicus, with perfect rationality where the only relevant element is the "content" of the information and not the way in which such information is obtained or framed. However, there are recent examples in the behavioral economic literature of how the move from a descriptive to an experiential gaining of knowledge about risk and uncertainty levels has a dramatic effect in decision-making behavior (Abdellaoui et al. 2011; Attanasi et al. 2014). In a behavioral economics framework, decision-makers can be persuaded by further reasons than objective information, as in the objective success probabilities in our specific case. Former literature has considered the limitation of information provision, given its ability to distort beliefs, as a way of achieving efficiency in decision-making processes (Brunnermeier and Parker 2004). Social cognitive theory provides with a psychological model to explain innovation optimism. In this framework, we consider that knowledge acquisition can be directly related to observing others within the context of social interactions in the innovation cluster (Bandura 2002; Ratten and Ratten 2007; Schiffman and Kanuk 2007). We also assume that potential innovators observe the innovation performing and the consequences of that behavior in their cluster and they remember the sequence of events and use this information to guide subsequent innovation behaviors. In other words, innovators do not learn new behaviors solely by trying them and either succeeding or failing, but rather by actively observing the performance in their innovation ecosystem. Social cognitive theory provides a useful framework for undertaking the task of identifying the mechanisms through which individual dispositions ultimately influence firm-level performance, for instance through the analysis of task complexity (Bolt et al. 2001), technological innovation adoption (Compeau et al. 1999), and entrepreneurial optimism (Hmieleski and Baron 2009), among others.

The decision of whether developing an innovation process or not is always made under uncertainty of the final result of this process. The key concept for the analysis of decision-making under risk and uncertainty is that of the risk attitude of the decision-maker. Under a conventional economics approach (expected utility paradigm), risk attitude is characterized by decision-maker's utility function, which determines the psychological "value" of each of the potential outcomes of the innovation process. Behavioral economics propose alternative models with a more realistic approach to the role played by probabilities in decision-making. This paper considers the rank-dependent utility model or the equivalent cumulative prospect theory in the domain of gains (Quiggin 1982; Tversky and Kahneman 1992; Wakker 2010). This model assumes that the psychological value of a probability to evaluate an innovation process—or decision weight as it is usually named—is a function of the probabilities of all the outcomes of the innovation process. As optimism is based on the shape taken by the weighting function, the estimation of such a shape cannot be carried out under conventional methods, such as surveys (as it is an unconscious process that individuals are unable to verbalize or rationalize) or with real data (as the econometric estimation requires precise inputs, difficult to obtain in non-experimental conditions. As an intermediate alternative, and as described and justified in Innovation Optimism: Definition and Measurement section, the empirical analysis in this paper follows an experimental behavioral approach.

The remainder of the paper is organized as follows: The Innovation Optimism: Definition and Measurement section defines innovation optimism and outlines a measurement methodology. The Experimental Design section describes the experimental design carried out, while the Result section collects the main results. Finally, the Discussion section gathers the conclusions from this study.

Innovation Optimism: Definition and Measurement

Within a behavioral economics framework, innovation optimism could be defined as a bias in decision-making consisting of evaluating an innovation process as if the probabilities of the best outcomes were larger than they actually are, even if the value of such probabilities are actually known by potential innovators. Social cognitive theory provides a useful theoretical framework for understanding innovation optimism and support the definition of an innovation optimism measure. Specifically, social cognitive theory suggests that the effects of personal dispositions (including optimism) are often determined by their interaction with important behavioral and environmental factors.

This section presents a formalization of this concept from a behavioral economics approach, specifically from the viewpoint of the rank-dependent utility theory. To carry out a measurement of innovation optimism attitude in this framework, data collection methodologies involving both controlled and realistic individual decision-making should be considered. Although field data are absolutely realistic, they cannot be obtained for all controlled situations required for an estimation of probability weighting functions. On the other hand, the use of questionnaires in which potential innovators face hypothetical innovation decision-making usually suffers of a lack of incentives to stylize realistically the innovation process. Behavioral-experimental economics arise as an intermediate way between field and survey data, where the appropriate economic incentives bring individuals as closer as possible to the situation where they would display their real behavior and under a controlled environment where innovation optimism—as well as other behavioral components of innovation—can be analyzed. However, there is a little behavioral-experimental evidence regarding innovation developments. In fact, there is a demand to conceal this gap (Schade 2005; Laureiro- Martínez et al. 2010; Van Rijnsoever et al. 2012). Behavioral-experimental economics have carried out studies handling some key concepts: we have learned that personal traits influence innovation (Bäker et al. 2012), that some, such as creativity, are associated to cooperation (Sikora 2014) and that innovation is linked to leadership and cooperation (Störmer and Herstatt 2014). Moreover, literature referring to clusters and localization externalities act as a proof of the impact of localization in firm performance (Porter 1998; Audretsch 1998). Nonetheless, innovation optimism and how it is affected by location have not been yet tested from a behavioral-experimental perspective.

The decision of whether developing an innovation process or not is always made under uncertainty of the final result of this process. Despite of the high impact that creativity, innovation experience, technical expertise, and other more controllable aspects of the innovation process may have on its result, there is always a random component that finally determines the success level of an innovation in terms of patent value, company profits, etc. For the sake of simplicity and in order to establish a simple formal definition of innovation optimism, let us consider that the impacts of the nonrandom components of the innovation process are known by the decision-maker and that the results of such a process can be described as a series of potential outcomes (for instance, value of the patents generated by the innovation process) $x_1 > x_2 > \cdots > x_n$ where outcome x_i takes place with a probability p_i.

In decision making under risk, assuming that each decision-maker knows the probabilities of each potential outcome, she or he will launch the innovation process in these cases where the utility of the investment required to finance innovation is lower that the expected utility of the innovation process. Formally, if I denotes the innovation investment and $IJ(x)$ the utility of an outcome x, the innovation process will launch if and only if $IJ(I) < \sum_{i=1}^{n} p_i U(x_i)$. It is well known that, in this paradigm, a decision maker is risk-averse (respectively risk-seeking) if her or his utility function is concave (respectively convex). Notice that, in expected utility models, the value of an outcome does not coincide with the outcome (in general $IJ(x) \neq x$) meanwhile the psychological value of each probability p_i is always this very same probability p_i which is used in the valuation of the decision to start the innovation process with no additional transformation.

Rank-dependent utility, however, allows for formalization and quantification of the psychological phenomenon of innovation optimism, and modeling its relation with other key aspects of innovation such as location. A rank—or more intuitively a good-news probability—for any potential outcome x of the innovation process is defined as the probability of the innovation process yielding an outcome strictly larger than x. Formally, $rank(x) = \sum_{x_i > x}[prob(x_i)]$. Ranks are numbers between 0 and 1, where 0 (respectively 1) is the rank associated to the best (respectively the worst) possible outcome that can be obtained through the innovation process. Let us define $x_{n+1} = -\infty$. Then, the probability of outcome x_i can be written as $p_i = rank(x_{i+1}) - rank(x_i)$ for $i = 1, \dots, n$.

A weighting function is a non-decreasing application $w: [0,1] \to [0,1]$ that transforms ranks into ranks. Given a weighting function w, the decision weight of outcome $x_i$is defined as $\pi_i = w\big(rank(x_{i+1})\big) - w\big(rank(x_i)\big)$. Notice that if the weighting function is the identity, i.e. $w(p) = p$, then the decision weights are positive numbers lower than one, *but* they are not required to add up to one. Decision weights are related to the slope of the weighting function: the steeper the weighting function is, the larger the difference between $w(rank(x_{i+1}))$ and $w(rank(x_i)$ and then the larger corresponding decision weight π_i.

Under rank-dependent utility, a potential innovator with utility function $U(x)$ and weighting function $w(p)$ will launch an innovation project if and only if $IJ(I) < \sum_{i=1}^{n} \pi_i U(x_i)$.

Example (adapted from Wakker 2010). Let us consider an innovation process with four potential outcomes $x_1 > x_2 > x_3 > x_4$ with identical probabilities $p_1 = p_2 = p_3 = p_4 = 0.25$. Let us assume that the weighting function for a potential innovator is given by $w(p) = p^{0.5}$. Then, the decision weights for each outcome will be given by $\pi_1 = w\big(rank(x_2)\big) - w\big(rank(x_1)\big) = 0.25^{0.5} - 0^{0.5} = 0.50, \pi_2 = 0.21, \pi_3 = 0.16$ and $\pi_3 = 0.13$. Notice that, although the probabilities of all four outcomes are identical, the potential innovator makes the decision of launching the innovation considering that the decision weight (subjective probability) of the best outcome $x_1$is $\pi_1 = 0.50 > 0.25 = p_1$ and the decision weight for the worst outcome x_4 is $\pi_4 = 0.13 < 0.25 = p_4$. Even if the potential innovator knows the actual probabilities of succeeding in the innovation process, she or he behaves as if the probability of succeeding was higher that it actually is and if the probability of not succeeding was lower than it actually is. In other word, she or he is exhibiting innovation optimism. Notice that this phenomenon cannot be explained under conventional expected utility paradigm, where potential innovator always makes decision with the actual values of the probabilities, in this example 0.25 for each outcome.

Recall that ranks are good-news probabilities, i.e., a small rank means that the probability of getting a better outcome is small and the corresponding outcome is quite good. In other words, the lower the rank, the better the outcome. Let us consider that w is concave, as in Fig. 1a. In this case, the slope of the weighting function is decreasing and the decision weights corresponding to the lower ranks—where the weighting function is steeper—are larger to those corresponding to the higher ranks. In other words, a potential innovator with a concave weighting function will exhibit innovation optimism, since she or he will make the decision of launching the innovation process overweighting the better outcomes and underweighting the worse ones.

The approach to innovation optimism through the concavity of the weighting function allows for the definition of an innovation optimism index able to quantify the optimism level of a potential innovator. Although never applied to the specific field of innovation optimism, the economic behavioral literature presents different alternatives to define an optimism index for abstract general decision-making under risk. A common approach is to consider the shapes of both the utility and probability weighting functions (Wakker 2010). In these cases, and similarly to the well-known risk-aversion index in the conventional expected utility theory, the optimism index could be defined in terms of the curvature of these functions using a parametrical approach. Even quite useful for theoretical analysis, this approach presents relevant difficulties and the result is very sensitive to the selection of the parametrical families to be used for utility and probability weighting estimations. However, for applied empirical analysis, filtering out the probability weighting component and the application of nonparametric estimation methods may provide with better indexes of the motivational optimism and pessimism (Epstein 2008). This is the approach followed in this paper.

The innovation optimism index Ω is defined as $\Omega = 2(A_o - A_p)$ where A_o is the area under the weighting curve and over the diagonal and A_p is the area under the diagonal and over the weighting curve. Notice that if the weighting function is concave and the subjects exhibit innovation optimism, then $\Omega > 0$. If the weighting curve is convex and the subject pessimistic, then $\Omega < 0$. The maximum (respectively minimum) value of the index is obtained when a subject assigns decision weight 1 to the best (respectively worst) outcome. In this case $A_o = 0.5$ and $A_p = 0$ ($A_o = 0$ and $A_p = 0.5$ respectively) and $\Omega = 1$ (respectively $\Omega = -1$). These cases are presented in Fig.2.

Experimental Design

In this paper, the impact of location in the innovation optimism is tested by means of a behavioral economics experiment. In this experiment, potential innovators elicit the maximum level of investment that they will make in order to launch a series of 12 innovation processes in two different treatments. Each treatment stylizes the way of gaining information about the potential outcomes of the innovation process associated to a location pattern: in the first treatment the innovator is isolated and cannot observe the performance of any other innovators, while in the second one the potential innovator is located in an innovation cluster and she or he is able to observe the outcomes of identical innovation processes implemented by the other members of the cluster. The main difference between treatments is that in the isolated innovator treatment the information of the likelihood of each innovation outcome is obtained descriptively from an external objective source (market research company, public institutions, etc.) and in the innovation information cluster this information comes from an active experiential observation of the results of the innovation processes launched by other members of the cluster. For the sake of simplicity, and following Abdellaoui et al. (2011), we consider 12 innovation processes with only two potential outcomes: high (success) and low (non-success), as presented in Table 1. Since Abdellaoui et al. (2011) determines that there are no order effects between descriptive and experienced treatments, our experiment follows a within approach where the same subjects elicit maximum innovation investments for both treatments in a fixed order.

The experiment provides with the elicitation of maximum investments for 960 different innovation processes from 40 subjects and was carried out at LINEEX, Laboratory for Research in Experimental Economics of the University of Valencia, during December 2014.

In the experiment, subjects were explained that they were going to decide whether to develop or not a new product for a given market. Carrying out this development implied an investment cost and products might face a favorable scenario, with a successful outcome, or an unfavorable scenario.

The running of the experiment consisted in two different phases and the filling of a sociodemographic questionnaire. In the first phase, subjects would operate in 12 different and independent markets with 12 different products, one for each market. Since each market had different conditions: different competitors, prices, customers, etc., each one was characterized by different probabilities of facing the favorable and unfavorable scenario and different outcomes for each case. A market research firm provided the probabilities of facing each one of the two states, and probabilities and outcomes were both known for the subjects. Their decision was how much they are willing to invest in order to develop that particular product. In other words, subjects revealed their willingness to innovate in different localizations.

In order to obtain this critical level of investment, subjects were provided a budget, which corresponded with the highest outcome, i.e., the result in case innovation was successful. Participants elicited the maximum investment level following a bisection method (Abdellaoui et al. 2011). To this end, and for each market, subjects were asked the question "Would you develop this product for X ECU[1]s?" a total of six times with six different prices. Investment levels were not random. The investment level in the first question was exactly the mid-value between the lowest and the highest possible outcome. For example, if the developed product could achieve a profit of 0 ECUs (unfavorable scenario) or 200 ECUs (favorable scenario), the first question would be: "Would you develop this product for 100 ECUs?". If the subject answered "No", this meant this required investment was too high. Hence, a lower investment level would be proposed in the next question, in particular, the mid-value between the low outcome and the refused invested level, in this example 50 ECUs. If, for instance, in this case, the subject answered "Yes", this would imply that 50 ECUs was an investment level which the subject would make to develop this product, but 100 ECUs were too high. The next question would be the mid-value between 50 ECUs and 100 ECUs, 75 ECUs. Therefore, following this bisection process, the price was being bounded question after question, and after six questions it was not greater than a 4 ECUs interval. We consider that the subject is indifferent between investing the central value of the last interval or actually launching the innovation process.

To guarantee that investment decisions are made under realistic incentives, we follow a BDM mechanism (Wakker and Deneffe 1996) to decide if subjects actually make the investment (reducing her or his initial endowment) and launch the process. Specifically, once the maximum investment level was elicited (as the lowest value from the final interval), a random investment level was determined, i.e., the market required investment level. If subject's maximum investment level was lower than what the market required investment level, she or he would not carry out the product development, and would keep his entire initial budget. However, if subject's maximum investment level was equal or greater than what the market required investment level, the subject would innovate and develop the product, paying the market price. Randomness would determine whether the product finally faced the favorable or unfavorable scenario. This mechanism is widely used in the economic experimental literature, since the dominant strategy for a subject is to elicit her or his maximum investment honestly.

The second phase was similar to the first one. The only difference was how participants got to know the probabilities for each outcome. In the first phase, a market research firm eased this information descriptively, but in this second phase, subjects experienced these probabilities. Subjects belonged to a business park where other similar firms operated, and they could observe whether these firms had innovated or not in the

[1] ECU=experimental currency units, that is the currency used at Lineex. At the end of the experiment, ECU were Exchange to actual Euros at a rate of 30 ECUs=1 Euro.

previous phase, and if this innovation had been successful. After a period of observation, subjects had to make the same decisions as before, in the same markets (presented in a different order), but with unknown probabilities.

A market from each phase was randomly picked out and played. Benefits in case of developing the product were the initial budget discounting the market investment requirement, plus the outcome corresponding to one of the two possible scenarios. If the participant's willingness to innovate was lower than what the market required, he would keep his initial budget.

Results

The methodology to estimate the innovation optimism level for each individual has been adapted from Abdellaoui et al. (2011). As in this paper, potential innovators are asked the maximum amount that they would invest to launch 12 different innovation processes with two potential outcomes: success and non-success. Innovators know the value of these outcomes, but the information of the probability of success is provided in a different way in the isolated innovator treatment (actual probability) and innovation cluster treatment (observation of the outcome obtained by those member of the innovation cluster that have actually launched the same innovation process).

The 12 innovation decisions faced in each location pattern are presented in Table 1. Innovation processes 1 to 7 and 8 to 12 are used to estimate the utility function and the decision weights for each agent, respectively. For each process i, the central point of the last interval obtained in the bisection procedure, I_i is considered as the maximum amount that the agent would invest to start the innovation process and she or he would be indifferent between obtaining I_i for sure or launching the process. In other words, for each decision and agent $U(I_i) = \pi_{i,1}[U(x)_{i,1}] + \pi_{i,2}[U(x)_{i,2}]$.

Recent works (e.g., Abdellaoui et al. 2008) suggest using a power function as a parametric specification for utility. Following this approach, let us consider that $U(x) = x^{\alpha}$. Notice that this function is concave if $\alpha < 1$, linear if $\alpha = 1$ and convex if $\alpha > 1$. Under this assumption, for innovation processes $i = 1, 2, \dots, 7$ in treatment 1, we have that $I_i = [w(0.25)x_{i,1}^{\alpha} + (1 - w(0.25)x_{i,2}^{\alpha}$ and, for each subject $w(0.25)$ and α is significantly different for the potential innovators in each location (p value=0.00 for the t test of equality of average values).

The weighting function for each agent can now be estimated using the maximum investments that this agent would pay to launch innovation processes $i = 8, \dots, 12$ and the value of α already obtained. For the treatment of isolated innovators, we have that $U(I_i) = \pi_{i,1}\left[U(x)_{i,1}\right] + \pi_{i,2}\left[U(x)_{i,2}\right]$ or $w(p_i) = \left(\frac{I_i}{200}\right)^{\alpha}$ and a similar result holds for the treatment of the innovation cluster, replacing p_t by the experienced (observed) proportion of successful subjects located in the innovation cluster and that have actually launched the innovation process.[2] The results of the estimation of the weighting function for each location are shown in Table 3 and Fig. 3. As also shown in Table 3, weighting functions are significantly different in all the cases but the smallest probability 0.05.

[2] *For treatment 2, the experienced probability of success is different for each subject. According to the methodology in Abdellaoui et al. (2011), linear interpolation has been applied to recover the values of the weighting functions in 0.05, 0.25, 0.50, 0.75, and 0.95.*

Figure 4 presents the weighting functions (median values) for isolated innovators and innovation clusters. Weighting function is convex for these isolated innovators. However, it is concave in the case of subjects located in an innovation cluster that obtain their information from active direct observation of the success rate of the other members located in the same cluster. In other words, the observation of the results of the innovation processes in the innovation cluster where the subject is located seems to generate innovation optimism.

The innovation optimism index defined in Innovation Optimism: Definition and Measurement section allows for a measurement of the magnitude of this effect, as shown in Table 4. A *t* test for paired samples shows that the innovation optimism index is significantly different in both locations (p value=0.00). Moreover, the index is positive for subjects in the innovation cluster and negative for isolated innovators: in other word, innovation attitude changes from pessimism to optimisms when information on the chances of the innovation process is not objectively provided by external sources but experientially observed from the performance of the members of the innovation cluster.

Discussion

Using a behavioral-experimental economics approach, this paper shows that the location of a potential innovator has an impact on her or his innovation attitude, specifically on her or his innovation optimism. Moreover, such an impact is a consequence of the way in which they can access the information about the chances of succeeding if they initiate an innovation process. Isolated innovators can learn about their success chances from external objective sources, such as market research companies or public institutions. On the other hand, when the potential innovator is located in an innovation cluster, she or he has the chance to observe innovation performance and share the experience of innovation. This work provides empirical evidence to support that innovation attitudes are significantly different in both types of location: while isolated innovators exhibit innovation pessimism, members of innovation clusters tend to be optimistic as respect to their success chances in the innovation process. In other ways, our behavioral analysis shows that a shared experience within the cluster increases innovation optimism. However, an open question that is not answered in this paper is if this increment in innovation optimism would be efficient with respect to the results of the processes started by the members of the cluster: although the location in the cluster increases innovation optimism and makes subject more active to start new innovation processes, optimism generates a decision bias that distorts the actual values of success probabilities when they are transformed into decision weights and used to compare the return of the innovation process with the required innovation investment. Then, location in the cluster may generate the implementation of innovation activities that should be precluded by a more realistic and rational risk analysis.

This paper has theoretical, methodological, and management-policy implications. From a theoretical viewpoint, we show that pertaining to an innovation cluster and the observation of the performance of other innovators generates an increment of the decision weights associated to the best outcomes and produces a psychological feeling of optimism, which reduces the risk-aversion of potential innovators and enhances innovation. In other words, members of innovation clusters are keener to launch innovation processes than isolated innovators, even when the objective success chances are the same. Then the way in which information flows within an innovation cluster arises as one of the mechanisms through which localization has an impact on innovation.

From a methodological viewpoint, this paper contributes to fill the gap of behavioral-experimental works in innovation. Moreover, it shows that a behavioral economic approach helps to explain innovation behaviors and attitudes—specifically optimism—that are beyond of the scope of the conventional non-behavioral models based in the expected utility approach to model the uncertainty component underlying any innovation process. We also present a methodology to quantify innovation optimism by applying rank dependent utility and an econometric methodology to define and compute an innovation optimism index.

From a management-policy viewpoint, the results support the hypothesis that promoting innovation clusters and the sharing of the information among the members of the cluster could be an effective strategy to promote innovation through the enhancement of innovation optimism. Finally, this analysis opens a series of new questions that should be covered in future research. In particular, the mechanisms through which the observation of innovation performance increases optimism should be clarified, discriminating between the impact of the proportion of the members of the cluster that actually innovate (herding effect) and the impact of the proportion of innovator actually succeeding in their innovation processes (experienced probability effect). The experimental design in this paper does not allow distinguishing between the impacts of these two key behavioral effects. As a last topic for future research, the impact of location in a cluster on the performance of launched innovation projects should also be considered in future behavioral-experimental studies of innovation.

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Figures and Tables

Figure 1. Innovation attitude generated by the weighting function.

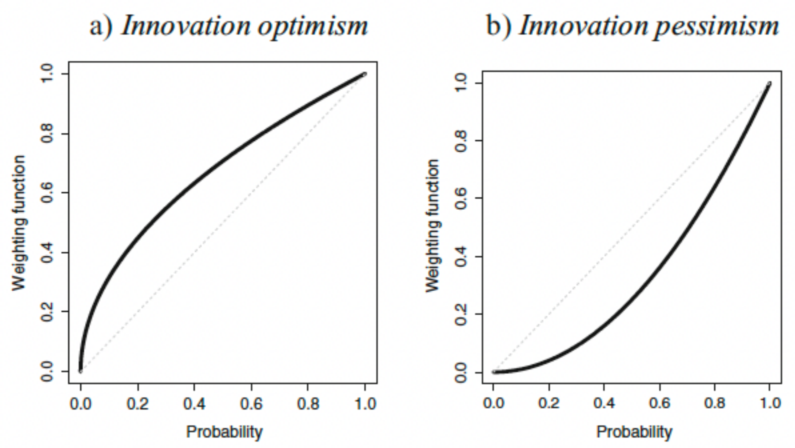

Figure 2. Extreme innovation attitudes generated by the weighting function.

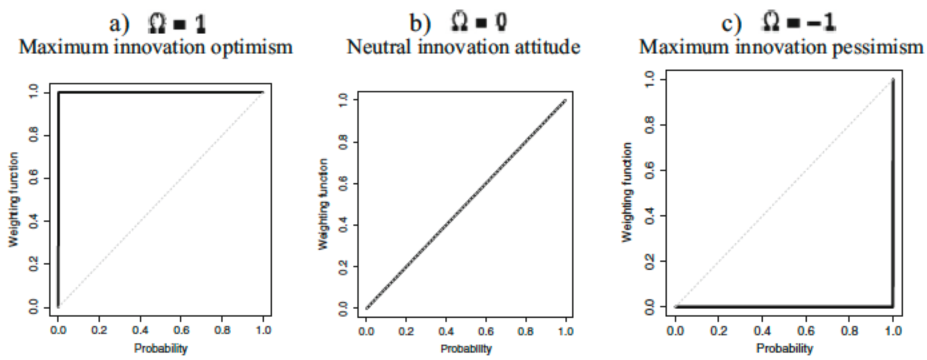

Table 1. innovation processes to elicit the corresponding maximum investment to launch the innovation process (Abdellaoui et al. 2011).

Innovation process (i)	1	2	3	4	5	6	7	8	9	10	11	12
Success ($x_{1,1}$)	100	200	200	50	150	200	200	200	200	200	200	200
Non-success ($x_{1,2}$)	0	50	100	0	100	150	0	0	0	0	0	0
Probability of success (p_i)	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.05	0.25	0.50	0.75	0.95

Table 2. Estimation of α by location.

	Isolated innovator	Innovation cluster
Median	1.68	0.81
Average	2.67	1.34
Standard deviation	2.28	1.29

Table 3. Estimation of $w(p_i)$ by location

Isolated innovators	$w(0.05)$	$w(0.25)$	$w(0.50)$	$w(0.75)$	$w(0.95)$
Median	0.06	0.17	0.37	0.67	0.89
Average	0.01	0.23	0.44	0.62	0.77
Standard deviation	0.18	0.25	0.30	0.29	0.25
Innovation cluster	$w(0.05)$	$w(0.25)$	$w(0.50)$	$w(0.75)$	$w(0.95)$
Median	0.08	0.30	0.72	0.91	0.95
Average	0.10	0.42	0.64	0.80	0.93
Standard deviation	0.10	0.30	0.26	0.23	0.10
p value (t test)	0.36	0.00	0.01	0.03	0.00

Figure 3. Distribution of estimated weighting function by location.

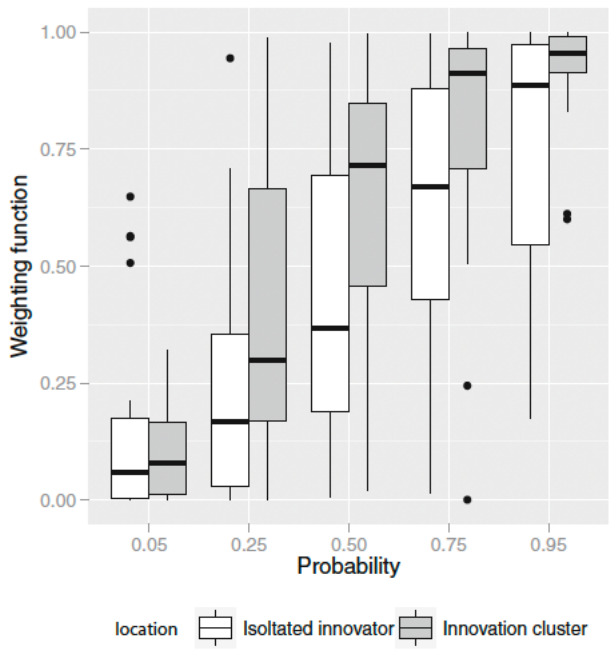

Figure 4. Median values of the weighting function by location (Continuous line=innovation cluster/dashed line=isolated innovator).

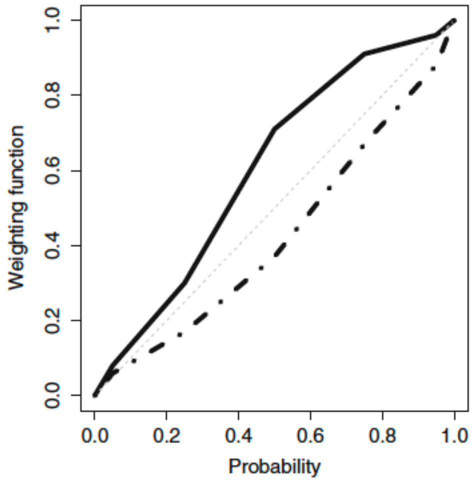

Table 4. Descriptive statistics of the estimation of Ω by location.

	Isolated innovator	Innovation cluster
Median	−0.12	0.20
Average	−0.11	0.18
Standard deviation	0.39	0.34