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INNOVATION PROBLEMS AND SEARCH FOR SOLUTIONS IN MARKETS FOR IDEAS – A SIMULATION APPROACH

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ABSTRACT

The strategy of participating in markets for ideas (MFIs) is being increasingly adopted by organisations embracing the open innovation paradigm. However, while knowledge about MFIs is growing, a complete understanding of the underlying dynamics of these markets is still lacking. This study aims at elucidating this topic by investigating the effect of the interplay between characteristics of individuals developing solutions for specific innovation problems (problem solvers), and the types of market on the performance of MFIs. The study classifies innovation problems into four typologies. Specifically, we use NK fitness landscapes to simulate the search for solutions conducted by problem solvers in several scenarios, depending on the decomposability of the innovation problems, accuracy of delineation, scientific background of the solvers, and cooperation policies of the markets. Our findings contribute to the development of the theory on search for solutions within MFIs, by revealing the characteristics of problem solvers, and the types of markets that maximise the performance of MFIs, as the quality of the best solution and the time required to elaborate on it according to specific innovation problems. Furthermore, our findings promote the formulation of guidelines for organisations using MFIs to solve their innovation problems, and for the markets' managers.

Keywords: problem solving, search process, markets for ideas, open innovation, NK fitness landscapes

1. INTRODUCTION

Organisations have recently been increasing the permeability of their boundaries to the exchange of knowledge assets with the external environment (Chesbrough, 2006b). Consistent with this trend, scholars have formalised the paradigm of open innovation, according to which 'valuable ideas can come from inside or outside the company as well' (Chesbrough, 2003: 24). Previously, organisations used to develop and exploit innovation mainly internally, by relying on their own R&D departments (Chesbrough, 2003). However, recent changes in the industrial ecosystem, such as the growing availability and mobility of skilled workers, emergence of venture capital, and improvement of suppliers' technical capabilities, have been relentlessly eroding the benefits of the closed innovation paradigm, and driving organisations to adopt a more open approach (Chesbrough, 2003; Dahlander and Gann, 2010; van de Vrande et al., 2009). However, an increasing degree of openness may provide both advantages and disadvantages, depending on how organisations face the managerial challenges of conforming to the new paradigm (Dahlander and Gann, 2010). In fact, embracing the open innovation approach causes an increasing complexity of management and organisation of innovation activities (Cassiman and Valentini, forthcoming). Thereby, strategies and practices have been developed to support organisations in effectively capturing the advantages of openness, while simultaneously lowering its risks.

Accordingly, a number of strategies have been discussed in the related literature to help organisations in pursuing the open innovation paradigm (Chesbrough, 2006b; Wang et al., 2012). Among these, an increasingly adopted approach is represented by the trading of knowledge in markets for ideas (MFIs) (Dushnitsky and Klueter, 2011; Natalicchio et al., 2014). Specifically, MFIs can be defined as marketplaces that favour the connection and exchange of knowledge assets, as solutions to specific innovation problems, among organisations looking for valuable knowledge (i.e. knowledge seekers), and problem solvers (i.e. knowledge owners). Through MFIs, organisations may broadcast their innovation problems to a wide pool of problem solvers, who may be selected according to specific criteria (Garavelli et al., 2013; Morgan and Wang, 2010). These

problem solvers, in turn, perform search processes to develop a solution that matches with the objectives of the seeking organisation, and get a reward if the solution is accepted by the same organisation.

The interest of scholars towards MFIs is constantly growing, as witnessed by the increasing number of related studies published in academic journals (Natalicchio et al., 2014). Extensive research has investigated several aspects that influence search processes conducted by problem solvers, such as formulation of innovation problems (e.g. Sieg et al., 2010; von Krogh et al., 2012), characteristics of successful solvers (e.g. Frey et al., 2011; Jeppesen and Lakhani, 2010), different types of MFIs (e.g. Chesbrough, 2006a; Garavelli et al., 2013), and features of the solutions provided (e.g. Frey et al., 2011). However, despite this increasing attention, a number of fundamental aspects remain unclear (Arora and Gambardella, 2010; Chesbrough, 2006a; Fosfuri and Giarratana, 2010; Padula et al., 2015; West et al., 2006). Hence, opening avenues for further investigations may contribute to enhancing the effectiveness of MFIs for organisations adopting open strategies to innovate. Till now very few studies have focused on the impact of interplay of MFIs' characteristics on the search processes performed by solvers, and in turn, on the related markets' performance, such as the quality of the best solutions retrieved and its speed, namely the time necessary to develop it (Afuah and Tucci, 2012; Atuahene-Gima, 2003; Macher, 2006).

Accordingly, in the present research, we aim to expand the understanding of MFIs as an open innovation strategy, by investigating how the different features of innovation problems, problem solvers, and types of MFIs interact with each other and affect the solvers' search processes, and consequently, markets' performance.

In this study, we focus on two main performance dimensions of MFIs, as the quality and speed of the best solutions provided by solvers (Afuah and Tucci, 2012; Atuahene-Gima, 2003; Macher, 2006). We expect these to be dependent on a set of distinctive features of innovation problems, solvers, and markets. Notably, innovation problems are mainly characterised by their complexity (Afuah and Tucci, 2012; Fleming, 2001; Nickerson and Zenger, 2004; Simon, 1962), which may in

turn be characterised by the degree of interaction among distinct knowledge components, and the number of components involved in the innovation problem delineation (Felin and Zenger, 2014; Jonassen, 2004; Leiblein and Macher, 2009; Simon, 1969; Sommer and Loch, 2004), which consequently affects the decomposability of the problem (Nickerson and Zenger, 2004; Simon, 1962), and the accuracy of its delineation (Funke, 1991; Leiblein and Macher, 2009), respectively. These two characteristics of innovation problems are crossed, and used for classifying them into four distinct categories: i) high-interaction and well-delineated; ii) decomposable and well-delineated; iii) high-interaction and ill-delineated; and iv) decomposable and ill-delineated. With reference to problem solvers, the relevance of having a scientific background has been included in our analysis, since this has been demonstrated to significantly influence individuals' search for solutions (Fleming and Sorenson, 2004; Gruber et al., 2013). Finally, we consider the existence of market policies that favour cooperation among solvers, thereby influencing their search for solutions (Bullinger et al., 2010; Hutter et al., 2011).

We adopted a simulation approach to analyse how these features interact with each other, and influence the solvers' search for solutions. Specifically, we selected the NK fitness landscapes approach (Kauffman, 1993), which is particularly suitable for our investigation (Davis et al., 2007). Fitness landscapes are an appropriate metaphor to describe the search processes performed by agents, allowing the analysis of the impact exerted by the concurrent effect of multiple factors (Afuah and Tucci, 2012; Fleming and Sorenson, 2004; Kavadias and Sommer, 2009; Levinthal, 1997). Simulations' results suggest the characteristics of problem solvers and markets' typologies that maximise the quality and time performance of MFIs, relative to each of the four types of innovation problems identified, hence offering both theoretical and practical contributions.

From a theoretical perspective, this study extends our comprehension of the search for solutions within MFIs to address a specific innovation problem, and consequently, our understanding of the role of MFIs in effectively supporting organisations embracing the open innovation paradigm (Arora and Gambardella, 2010). In particular, this study elucidates the simultaneous effect of

distinctive features of MFIs on market performance, which is crucial to fully comprehend how actors may benefit from different marketplaces. Regarding the practical contribution, this study provides organisations seeking solutions in MFIs and markets' managers with guidelines, allowing them to use these markets more effectively, by identifying the most suitable MFI for different types of innovation problems.

The paper is organised as follows. In the next section, we review the relevant literature on MFIs, discussing the main features of innovation problems, solvers, and types of markets. In Section 3 we develop the hypotheses guiding our analysis. In Sections 4 and 5, we present the simulation methodology, and its application to the posed problem, respectively. In Section 6, we describe and discuss the results of the simulation. Finally, the last section concludes the study by highlighting its theoretical and managerial contributions, limitations, and identifying streams of investigation as avenues for further research.

2. THEORETICAL BACKGROUND

Since Henry Chesbrough's (2003) formalisation of the open innovation paradigm, firms are increasingly opening up their boundaries to external sources of knowledge (West et al., 2014). This openness aims to benefit from ideas and solutions developed by external individuals and organisations, which may in turn be integrated within firms' innovation processes, and consequently, spur new waves of profitable outcomes (Dahlander and Gann, 2010). Scholars have discussed several different strategies through which organisations can source external knowledge, as collaborating with universities, establishing inter-firm alliances, and participating in MFIs (Chesbrough, 2006b; Wang et al., 2012). MFIs play a prominent role in favouring the adoption of the open innovation paradigm (Chesbrough, 2006a) by bridging the gap between organisations seeking external knowledge, and individuals or organisations that own that requisite knowledge (Enkel et al., 2009; Natalicchio et al., 2014). Particularly, the trade of knowledge assets is gaining increasing relevance. In fact, data from the Organisation for Economic Co-operation and

Development (OECD) (2014) reported an average annual growth of 10.1% for intellectual property (IP) transactions in the OECD area, between 2000 and 2011. Additionally, Athreye and Yang (2011), estimating the worldwide IP royalties and licensing payments in 2009, reported a value of about $180 billion, a noteworthy upturn with respect to the amount of $75 billion estimated for 2000 (Athreye and Cantwell, 2007).

Generally, organisations may participate in MFIs to outsource internal problem-solving activities to a wide pool of individuals, with the aim of receiving valuable solutions (Afuah and Tucci, 2012; Jeppesen and Lakhani, 2010; Natalicchio et al., 2014; Poetz and Prügl, 2010; Terwiesch and Xu, 2008). This approach may be especially beneficial for organisations facing innovation problems that cannot be solved by using their existing knowledge (Jeppesen and Lakhani, 2010). Currently, companies are increasingly adopting, and getting advantages from their participation in MFIs. For instance, in a well-known case, Procter and Gamble has created a proprietary MFI, the Connect and Develop platform, through which it directly presents its innovation problems to potential problem solvers (Huston and Sakkab, 2006). Additionally, other renowned examples include General Electric (Chesbrough, 2012), IBM (Bjelland and Wood, 2008), and Dell (Bayus, 2013), which demonstrate a successful record of engaging external solvers to retrieve solutions for internal innovation problems. Furthermore, by entrusting external individuals with problem-solving activities, firms may expand their breadth of information sources, hence resulting in a higher rate of successful innovations due to an increase in the probability of retrieving highly valuable knowledge to solve internal issues (Dahlander et al., forthcoming). In other words, individuals are required to engage themselves in generating innovative solutions by performing search processes for the firm (Poetz and Prügl, 2010), thus applying fresh perspectives and cognitive frames, which in turn positively influence the problem resolution (Frey et al., 2011; Jeppesen and Lakhani, 2010). Specifically, a wide stream of scientific literature recognises the search for solutions performed by individuals, as an uncertain process of recombination of new and existing knowledge components, which could be defined as ‘any fundamental bits of knowledge or matter that inventors might use to

build inventions' (Fleming and Sorenson, 2004: 910), over a technology landscape (Fleming, 2001; Fleming and Sorenson, 2001; Henderson and Clark, 1990; Nelson and Winter, 1982). Furthermore, these solution-searching individuals are subject to cognitive and information-processing constraints (Cyert and March, 1963; Fleming, 2001), and thus they perform their search process by recombining a limited set of knowledge components at one time. Consequently, this bounded rationality assumption implies that individuals perform local search (Stuart and Podolny, 1996), generating an alternative solution in a neighbourhood of their current position over the technology landscape.

Therefore, MFIs are beneficial for organisations facing innovation problems that are not restricted to their domain of expertise (Jeppesen and Lakhani, 2010). In fact, in these cases, organisations need to perform their search for solution in a distant portion of the technology landscape. Nevertheless, by entrusting external individuals with the task of searching for solutions, MFIs could translate this distant search process into an individual's local search process (Afuah and Tucci, 2012). Consequently, while distant search is characterised by high uncertainty and risk of failure (March, 1991), by encouraging individuals to generate innovative ideas through local search, MFIs increase the effectiveness of the entire problem-solving process for the seeking organisation (Boudreau et al., 2011; Jeppesen and Lakhani, 2010; Terwiesch and Xu, 2008). However, there are some characteristics of the problem-solving process performed through MFIs that may affect the search process conducted by individuals (Afuah and Tucci, 2012), such as the characteristics of the problem itself, the agents searching for a solution, and the MFI's internal policies. In the following sections, we discuss in detail these relevant characteristics, highlighting their impact on individuals' search process, and consequently on the performance of MFIs, in terms of both quality and speed of the best solutions proposed by solvers.

2.1 Innovation problems

The characteristics of innovation problems may significantly influence how individuals search for solutions (Garcia Martinez and Walton, 2014; Jonassen, 2004; Sieg et al., 2010). Particularly, problem complexity is one of the most relevant characteristics (Afuah and Tucci, 2012; Fleming, 2001; Nickerson and Zenger, 2004; Simon, 1962), which may in turn be framed in two separate dimensions: the degree of interaction among distinct knowledge components, and the number of knowledge components involved in the delineation of the innovation problem (Felin and Zenger, 2014; Jonassen, 2004; Leiblein and Macher, 2009; Simon, 1969; Sommer and Loch, 2004).

The degree of interaction is related to the extent to which innovation problems rely on interdependent and distinct knowledge components (Afuah and Tucci, 2012; Fleming and Sorenson, 2001; Sommer and Loch, 2004). This feature has been termed as modularity (Afuah and Tucci, 2012) or decomposability of the problem (Nickerson and Zenger, 2004; Simon, 1962). Therefore, from this perspective, decomposable innovation problems are based on a low degree of interaction among knowledge components or design choices (Fleming and Sorenson, 2004; Nickerson and Zenger, 2004), while high-interaction innovation problems present a higher level of interdependence among different knowledge components (Fleming and Sorenson, 2004; Nickerson and Zenger, 2004). In particular, when independently considering this dimension, decomposable problems may be effectively solved by improving the solution choice by choice, namely through directional search, since majority of the knowledge components is independent from the others (Gavetti and Levinthal, 2000; Hsieh et al., 2007). Alternately, high-interaction problems require searchers to account for the effects of the interplay between different knowledge components when developing solutions (Fleming and Sorenson, 2001; Singh, 1997). Furthermore, a higher level of interdependence among the components enables a larger variety of combinations (Fleming and Sorenson, 2001), and increases the difficulty and uncertainty of the search (Baldwin and Clark, 2000). Hence, for this typology of problems, organisations may benefit when more individuals search independently through parallel paths (Boudreau et al., 2011; Terwiesch and Xu, 2008), since

this increases the number of approaches to face the problem, and increases the possibility of finding a valuable solution (Boudreau et al., 2011; Jeppesen and Lakhani, 2010; Terwiesch and Xu, 2008). The second dimension of complexity is represented by the number of knowledge components involved in innovation problem delineation (Felin and Zenger, 2014; Simon, 1969; Sommer and Loch, 2004). The formulation of innovation problems is a paramount step for firms participating in MFIs in order to find valuable solutions (Jeppesen and Lakhani, 2010; Jonassen, 2004; Sieg et al., 2010), since solvers rely exclusively on this information when searching for a solution (von Krogh et al., 2012). However, the delineation of an innovation problem is not an easy task. In fact, by simplifying the real problem to make it understandable by external solvers, the problem may be misrepresented, due to reasons such as the missed communication of some, especially tacit, knowledge components affecting the definition of a solution (Afuah and Tucci, 2012). The number of knowledge components revealed is directly related to how accurately firms delineate the innovation problems (Funke, 1991; Leiblein and Macher, 2009), and this in turn depends on the amount of tacit knowledge connected to the innovation problems (Afuah and Tucci, 2012). Moreover, firms may decide not to reveal some details concerning problem-related knowledge, for confidentiality reasons (Alexy et al., 2013; Sieg et al., 2010). This selective revealing of knowledge may further threaten an accurate delineation of the problem, thus generating additional biases for problem solvers. In other words, ill-delineated innovation problems may involve knowledge components that contribute to the definition of a solution, but are not effectively communicated by the firm to the solvers, and thus are unknown to them. Their presence may affect the search process performed by the solvers. Alternately, in well-delineated problems, the problem solvers are aware of the knowledge components that influence solution development.

Finally, these two dimensions of complexity discussed above may be deemed independent, but concurring to the general definition of the complexity of an innovation problem. Thereby, we identify four different typologies of innovation problems that firms may resolve through MFIs: i) high-interaction and well-delineated; ii) decomposable and well-delineated; iii) high-interaction and

ill-delineated; and iv) decomposable and ill-delineated. These typologies are representative of the innovation problems that organisations broadcast through MFIs. In fact, there is a wide range of problems that may be displayed on MFIs, from the most complex and highly rewarded Grand Challenges of X-Prize and Innocentive, to the more specific and delimited innovation problems, that may be found on a variety of MFIs, as developing a technology to detect the presence of micro-organisms in dairy products or designing a refillable package for wet wipes.

2.2 Problem solvers participating in MFIs

Inventors, entrepreneurs, and research organisations usually represent the offer side in MFIs, and operate as solvers of firms' innovation problems (Arora and Gambardella, 2010; Natalicchio et al., 2014). The extant literature suggests that individuals are the most represented category of problem solvers within MFIs (Jeppesen and Lakhani, 2010; Terwiesch and Xu, 2008). Generally, individuals participating in MFIs are not selected according to a specific characteristic, which may differ according to their cultural and professional background (Garavelli et al., 2013; Jeppesen and Lakhani, 2010). In this study, we focus on the relevance of the background of solvers, by highlighting how this influences their search processes, together with the characteristics of innovation problems, and markets' typologies. Specifically, several studies have discussed that having a scientific background may support individuals in developing valuable solutions (e.g. Fleming and Sorenson, 2004; Furukawa and Goto, 2006; Gruber et al., 2013). In particular, Fleming and Sorenson (2004: 911) pointed out that 'scientific knowledge […] provides inventors with the equivalent of a map', thus allowing a better comprehension of the phenomena at the base of a specific problem. Accordingly, this means that the cognitive capabilities of problem solvers endowed with scientific knowledge are more developed as compared to solvers without scientific training (Fleming and Sorenson, 2004). Specifically, in MFIs we may identify scientists and non-scientists as common problem solvers (Jeppesen and Lakhani, 2010). Scientists tend to be less rationally bounded than other solvers (Siggelkow and Rivkin, 2006), and accordingly, they can

assess more simultaneous changes of their solutions at once (Rivkin and Siggelkow, 2003; Siggelkow and Rivkin, 2006). Hence, science may provide solvers with theoretical guidance, resulting in an upturn of the search process' effectiveness (Fabrizio, 2009; Fleming, 2002; Fleming and Sorenson, 2004; Gruber et al., 2013; Nelson, 1982). Moreover, science may also provide tests to easily scan different design alternatives (Nelson, 1982), which further improves the effectiveness of the search for solutions. Furthermore, Gruber et al. (2013) noticed that having a scientific background is likely to increase the learning abilities of individuals, by facilitating the assimilation of distant technological knowledge. Thus, there is a difference in how scientists and other common problem solvers perform their search. In fact, the relevance of solvers' scientific background has been revealed in actual examples, as shown in the study by Jeppesen and Lakhani (2010), who observed that 65% of InnoCentive's problem solvers who submitted solutions that are eventually acquired by organisations, held a Ph.D. degree, suggesting the existence of a scientific background.

2.3 Types of market

MFIs may adopt policies and rules aimed at promoting the creation of problem solvers' communities, by which they may interact and collaborate with peers to co-create solutions (Bullinger et al., 2010; Garavelli et al., 2013; Hutter et al., 2011; Rullani and Haefliger, 2013). Therefore, solvers are both competitors, because they submit solutions independently and in competition with others, and co-operators, being keen to offer and receive suggestions to improve the quality of their submissions. In such a co-opetitive environment (Brandenburger and Nalebuff, 1996), problem solvers are stimulated to engage in social interaction, by sharing thoughts and comments on others' solutions. Consequently, knowledge and information are spread among solvers who therefore, benefit from cross-learning, and may improve the average quality of their solutions (Hutter et al., 2011). In fact, by offering feedback, observations, analyses, and criticisms, co-opetitors provide problem solvers with fresh perspectives that could help improve their solutions (Majchrzak and Malhotra, 2013). Bullinger et al. (2010) suggested a U-shaped relation between the

innovativeness of submitted solutions, and the extent of solvers' cooperative behaviour. Though solvers' cooperative behaviour provides advantages in terms of cross-learning and solutions' refining, an MFI may favour the competitive orientation of problem solvers. This is accomplished by reducing collaboration opportunities, in the attempt to leverage the intrinsic motivation of solvers, who become focused on their work, and by striving to provide the best idea may develop creative and high quality solutions (Boudreau et al., 2011; Bullinger et al., 2010; Frey et al., 2011). Accordingly, the co-opetitive or competitive nature of MFIs is another relevant characteristic that may significantly influence solvers' search, and eventually, the performance of these marketplaces.

3. RESEARCH HYPOTHESES

In the previous section, we showed that the characteristics of innovation problems, problem solvers, and types of markets may influence the search for solution process, and consequently, the performance of MFIs, such as the quality and speed of the best solution retrieved (Atuahene-Gima, 2003; Macher, 2006). Moreover, the interplay between the abovementioned features may generate unexpected and counterintuitive effects that should be investigated to increase our understanding about the search process conducted by solvers in MFIs. Currently, a wide array of MFIs presenting different features is available to firms facing innovation problems (e.g. Garavelli et al., 2013). Generally, firms may decide to broadcast their innovation problems in a specific MFI according to their characteristics, with the aim of maximising the quality of the best solution retrieved or minimising the time required to develop it. Thereby, in the following sections, consistent with our research question, we analyse the search for solution processes from the innovation problem perspective. Specifically, based on the two main characteristics of innovation problems, their decomposability (Afuah and Tucci, 2012; Nickerson and Zenger, 2004; Simon, 1962), and accuracy of delineation (Afuah and Tucci, 2012; Funke, 1991; Leiblein and Macher, 2009), we identify four types of problems. For each problem type we develop hypotheses discussing the impact of the

interplay between the characteristics of problem solvers and types of market on the related performance of MFIs.

3.1 High-interaction and well-delineated innovation problems

Quality of solutions

This typology of innovation problems is characterised by significant interdependencies among the knowledge components involved in solution development, which are however, all known to the problem solvers. For such problems, many local optimal solutions, which are represented by local peaks in the technology landscape, are available (Levinthal, 1997; Macher, 2006), and problem solvers may easily reach one of them (Levinthal, 1997). However, solvers with a scientific background search in a different way as compared to solvers without a scientific background, since the former are endowed with greater foresight due to the knowledge of the phenomena underlying a problem (Fleming and Sorenson, 2004). This knowledge drives them towards attaining higher quality solutions (Felin and Zenger, 2014). Furthermore, coupled with a clear understanding of all the knowledge components relevant to the problem, a scientific background allows solvers to leverage their cognitive capabilities in solution development. Having a scientific background is particularly relevant for this typology of problems (Hsieh et al., 2007), since the high degree of interaction among knowledge components increases the uncertainty of the search process (Baldwin and Clark, 2000; Nickerson and Zenger, 2004). This uncertainty could be mitigated by a greater foresight of the technology landscape, as provided by science (Fleming and Sorenson, 2004). In addition, having a scientific background makes cooperation among problem solvers unnecessary or even detrimental. In fact, complete understanding of the knowledge components involved allows a solver to perform her search across all possibilities without requiring suggestions or feedback from others (Hsieh et al., 2007). Accordingly, we can pose the following hypothesis:

H1a: Highest quality solutions for high-interaction and well-delineated innovation problems are provided when the MFI is populated by problem solvers with a scientific background operating in a competitive environment.

Speed of solutions

In co-opetitive MFIs, problem solvers may decide to collaborate with peers, but this strategy requires investment of time and energy for the creation and sustenance of collaborative relationships (McFadyen and Cannella, 2004). Thus, co-opetitive problem solvers invest their resources both in developing their individual solutions, and in collaborating with other solvers. Moreover, the outcome of collaborations is often uncertain; hence, the effort of solvers, in terms of time, may not be repaid (Bullinger et al., 2010). Alternately, in competitive markets, problem solvers employ their time exclusively in developing solutions (Bullinger et al., 2010), increasing the speed to reach a local optimal solution. In addition, for high-interaction and well-delineated innovation problems, solvers may find local optimal solutions in time, which they can further modify only by exploiting cognitive capabilities, which is characteristic of a scientific background (Billinger et al., 2014; Fleming and Sorenson, 2004). Therefore, problem solvers without a scientific background may promptly develop a solution that cannot be additionally improved, and consequently, decide to submit. Thus, even though the quality of solutions may be lower than the quality of those developed by scientists, the common solvers' submissions may be comparatively faster. From this reasoning, we can pose the following hypothesis:

H1b: Speediest solutions for high-interaction and well-delineated innovation problems are provided when the MFI is populated by problem solvers without a scientific background operating in a competitive environment.

3.2 Decomposable and well-delineated innovation problems

Quality of solutions

Decomposable and well-delineated problems present few interdependencies, where all the knowledge components relevant to solution development are known to problem solvers. For these problems, simple directional search for providing solutions is a favoured strategy (Felin and Zenger, 2014; Gavetti and Levinthal, 2000; Hsieh et al., 2007; Nickerson and Zenger, 2004). Thus, the cognitive capabilities characteristic of problem solvers with a scientific background may add little advantage to develop a valuable solution, and result as being redundant (Fleming and Sorenson, 2004; Hsieh et al., 2007). Accordingly, we do not expect a significant difference in quality performance between MFIs populated by scientists and non-scientists. Additionally, competition among solvers may generate higher-quality solutions than collaboration, since it does not deflect problem solvers from their path to the solution search, but instead supports them in performing directional search (Nickerson and Zenger, 2004). Therefore, we can state the following hypothesis:

H2a: Highest quality solutions for decomposable and well-delineated innovation problems are provided when the search for solutions is performed by problem solvers operating in a competitive environment, irrespective of their scientific background.

Speed of solutions

Developing solutions for this typology of innovation problems is a straightforward process that brings towards few local optimal solutions (Levinthal, 1997). Although they do not provide significant gains in terms of quality, as discussed above, solvers with a scientific background may solve the innovation problem in a timely manner. In fact, in their search process, they are guided by science, and accordingly, are driven towards the shortest path to valuable solution development (Fleming and Sorenson, 2004). Furthermore, since directional search is a favoured strategy to develop a solution in this case (Felin and Zenger, 2014; Gavetti and Levinthal, 2000; Hsieh et al.,

2007; Nickerson and Zenger, 2004), collaborations may not be needed to comply with the seeking organisation's time constraints. In fact, collaboration may be irrelevant and costly for solvers, due to the time and resources that are required to render it effective (Fleming, 2002; McFadyen and Cannella, 2004). Accordingly, we can develop the following hypothesis:

H2b: Speediest solutions for decomposable and well-delineated innovation problems are provided when the MFI is populated by problem solvers with a scientific background operating in a competitive environment.

3.3 High-interaction and ill-delineated innovation problems

Quality of solutions

As mentioned above, problem solvers having a scientific background may perform their search for solutions more effectively than common solvers when dealing with high-interaction innovation problems (Fleming and Sorenson, 2004; Hsieh et al., 2007). This holds true for ill-delineated innovation problems as well. In fact, relying on scientific knowledge, problem solvers may build a theory (Fleming and Sorenson, 2004) to overcome the difficulties arising from incomplete understanding of the knowledge components influencing solution development (Felin and Zenger, 2014; Macher, 2006), and consequently be guided towards the highest quality solution. Additionally, being ill-delineated, none of the solvers has a clear picture of the problem. Therefore, cooperation with other solvers may result in feedback and suggestions, which is useful to get a clearer understanding of the issue, and eventually improving the quality of the solution (Hutter et al., 2011; Majchrzak and Malhotra, 2013) by supporting solvers' recombinant search (Fleming, 2002). According to the above reasoning, we can pose the following hypothesis:

H3a: Highest quality solutions for high-interaction and ill-delineated innovation problems are provided when the MFI is populated by problem solvers with a scientific background operating in a co-opetitive environment.

Speed of solutions

For such typology of innovation problems, many optimal solutions are available. Hence, performing local search allows solvers to find a local optimal solution promptly (Levinthal, 1997; Rivkin, 2000). Thereby, if an organisation is interested in finding a prompt solution to high-interaction and ill-delineated problems, it should involve a pool of problem solvers without scientific background. In fact, while scientists may exploit their cognitive capabilities to develop a higher quality solution (Fleming and Sorenson, 2004), their search strategy may require more time to develop a solution. Therefore, problem solvers without a scientific background may provide a solution faster. Furthermore, as stated earlier, adopting a cooperative behaviour may delay the solution submission that exceeds the advantages of co-opetition (McFadyen and Cannella, 2004). Following this reasoning, we can pose that:

H3b: Speediest solutions for high-interaction and ill-delineated innovation problems are provided when the MFI is populated by problem solvers without a scientific background operating in a competitive environment.

3.4 Decomposable and ill-delineated innovation problems

Quality of solutions

This typology of innovation problems is characterised by few local optimal solutions (Levinthal, 1997; Rivkin, 2000). However, the search for these solutions is not straightforward, since not all the relevant knowledge components to develop a valuable solution are accurately delineated by the organisation facing the problem. Thus, a proper search strategy must be adopted by problem

solvers. In particular, directional search may not be a suitable strategy due to the lack of complete understanding about the actual innovation problem (Macher, 2006). Alternately, exploiting scientific knowledge in the search process may not procure remarkable results. In fact, scientists may add marginal value to the solution search process for this typology of innovation problems, since the technology landscape is quite smooth but not completely defined (Fleming and Sorenson, 2004). Hence, we do not expect a significant difference in terms of quality performance between MFIs where the search is performed by scientists, and MFIs in which the search is instead conducted by common solvers. Moreover, the main issue of this typology of problems concerns the undefined knowledge components that shall be considered to improve the quality of the solutions submitted (Felin and Zenger, 2014; Macher, 2006; Sommer and Loch, 2004). Therefore, to overcome these issues, cooperation among problem solvers is necessary, who through feedback and suggestions, may identify unknown relevant knowledge components (Hutter et al., 2011; Majchrzak and Malhotra, 2013), and perform recombinant search to deliver a high-quality solution (Fleming, 2002). Therefore, we can state that:

H4a: Highest quality solutions for decomposable and ill-delineated innovation problems are provided when the search for solutions is performed by problem solvers operating in a co-opetitive environment, irrespective of their scientific background.

Speed of solutions

When firms aim at obtaining quick solutions for this type of innovation problem, it is more beneficial to participate in an MFI populated by problem solvers without a scientific background. Scientists would use their cognitive capabilities to develop a valuable solution (Macher, 2006); however, in the specific case of ill-delineated innovation problems, this may require longer time as compared to that required by common solvers to complete their search process. In fact, problem solvers without a scientific background may adopt the directional search strategy to develop a local

optimal solution promptly, which cannot be improved further (Levinthal, 1997). Additionally, as mentioned above, for this problem cooperation may be detrimental for solvers, since it would require a significant amount of time to obtain results appreciated by the organisation seeking a solution (Fleming, 2002; McFadyen and Cannella, 2004). Based on this reasoning, we can pose the following hypothesis:

H4b: Speediest solutions for decomposable and ill-delineated innovation problems are provided when the MFI is populated by problem solvers without a scientific background operating in a competitive environment.

4. METHODOLOGY

As previously discussed, the understanding of the main dynamics of MFIs, and their effective contribution to firms' open innovation strategies still presents some gaps, despite the growing body of literature (Arora and Gambardella, 2010; Natalicchio et al., 2014). Therefore, being this topic in its early development phase, studies that contribute to the theory may be beneficial for both scholars and practitioners. For MFIs, so far, academic studies have mostly developed simple theory, defined as 'underdeveloped theory that has only few constructs and related propositions with modest empirical or analytic grounding' (Davis et al., 2007: 482). Under these circumstances, the need for more solid theoretical development makes simulation a useful research methodology (Davis et al., 2007; Rivkin, 2000; Rudolph and Repenning, 2002).

Additionally, the existing literature showed that few studies dealt with highly granular data (e.g. Boudreau et al., 2011; Jeppesen and Lakhani, 2010), it being very difficult to conduct extensive research on disaggregated data from real MFIs. The reasons for this are manifold. First, it is difficult to collect data. Second, confidentiality issues are particularly relevant in this field (Dushnitsky and Klueter, 2011). Finally, often MFIs' managers do not build databases that include data on innovation problems and related solutions, and characteristics of organisations and

individuals. Therefore, the use of simulation is an appropriate methodology to provide an effective answer to the research question underlying this study (Davis et al., 2007). Furthermore, it is significant to note that simulation methods may be helpful to develop theory, and generate influential understanding (e.g. March, 1991). Specifically, in this study, we focus on problem-solving activities within MFIs, and according to Newell and Simon (1961), computer simulation is one of the best methods to analyse individuals' problem solving behaviour.

In particular, we applied simulation with NK fitness landscapes, as introduced by Kauffman (1993). In fact, we are interested in understanding how problem solvers search for and provide solutions to an innovation problem, and evaluate performance indicators, such as the quality and speed of the best solutions submitted (Afuah and Tucci, 2012; Atuahene-Gima, 2003; Macher, 2006), under different scenarios. Hence, consistent with the aim of this study, NK fitness landscapes represent a particularly suitable choice, since these may well describe the technological landscape where individuals perform their search for solving problems or develop new inventions (e.g. Afuah and Tucci, 2012; Fleming and Sorenson, 2004; Gavetti and Levinthal, 2000; Kavadias and Sommer, 2009). Since the formalisation of NK fitness landscapes by Kauffman (1993), the first study that applied this model to management literature was conducted by Levinthal (1997). From this seminal work, an increasing body of literature in management has utilised NK fitness landscapes (e.g. Ethiraj and Levinthal, 2004; Gavetti and Levinthal, 2000; Rivkin and Siggelkow, 2007; Siggelkow and Levinthal, 2005; Siggelkow and Rivkin, 2006). Specifically, NK fitness landscapes are often used to represent and analyse search processes. For instance, Gavetti and Levinthal (2000) applied the model to understand the differences in cognitive and experiential search by individuals. Siggelkow and Rivkin (2006) used NK fitness landscapes to analyse how the outcomes of search in multilevel organisations are influenced by the level of exploration of single business units. Further, Kavadias and Sommer (2009) in their study about the effectiveness of brainstorming represented the search for solutions through NK fitness landscapes. Finally, regarding the open innovation literature, NK fitness landscapes were recently used by Afuah and Tucci (2012) to investigate the

circumstances under which crowdsourcing would be a suitable option for organisations facing innovation problems.

5. MODEL

The first conceptualisation of a fitness landscape was made by Wright (1932) in the field of genetics. Fitness landscapes were used to link *N* genes (or attributes) of an organism, which are represented by *N* dimensions of the landscape, to an overall fitness level. Extending Wright's research, Kauffman (1993) elaborated the NK fitness landscapes in the context of population genetics, towards the end of the 20th century. Organisms can be described from their genotype, which is the sequence of their genes. The idea behind the model was that each gene of an organism contributes to its overall fitness. However, interactions may exist among genes. Thus, the contribution of a gene to the overall fitness may depend on its allele, which is the form of a gene, and those of other genes that interact with it. Therefore, the overall fitness of an organism is determined by the alleles of its genes.

Two parameters are identified in Kauffman's formalisation of NK fitness landscapes: the number of attributes that determine the fitness of an organism (*N*), and the number of interactions of each attribute with others (*K*). Generally, in studies conducted through NK fitness landscapes, it is assumed that each attribute can assume two values (e.g. Gavetti and Levinthal, 2000; Levinthal, 1997; Siggelkow and Rivkin, 2006). Consequently, there are 2^N different possible configurations for an organism in a landscape. Considering a generic attribute having the value a_i, its contribution to the fitness is randomly generated from a uniform distribution ranging from zero to one, and depends on both a_i itself, and the value of those attributes that interact with it, represented by the vector $\boldsymbol{a}_{-i}$. Hence, the contribution to the fitness of a generic attribute is determined as follows:

$$f_i = c_i(a_i, \boldsymbol{a}_{-i})$$

Furthermore, since the contribution of each attribute depends on its value and on the value of *K* different attributes, it can assume 2^{K+1} different values. Therefore, the overall fitness *f* of a configuration is calculated by averaging the different contributions, as follows:

$$f = \frac{\sum_{i=1}^{N} c_i(a_i, \boldsymbol{a}_{-i})}{N}$$

The parameter *K* acts on the shape of the landscape (Levinthal, 1997). In fact, Kauffman (1993) showed that low interaction among attributes, denoted by a low value of *K*, generates a relatively smooth landscape, with few peaks representing local maxima. Alternately, when interaction is high, that is, when *K* assumes a higher value, with an upper limit of *N-1*, the landscape is relatively rugged, and characterised by many peaks.

During the simulation, agents may modify their attributes' configuration to reach others characterised by a higher fitness value, a process known as 'adaptive walk' (Kauffman, 1993). Usually, due to their bounded rationality (Cyert and March, 1963; Fleming, 2001), agents may change a subset of their attributes at every instant. Thus, they perform a search for new configurations in their neighbourhood, which may be more or less broad according to the search radius of the agents (Siggelkow and Rivkin, 2006). When agents cannot find a configuration with a higher fitness in their neighbourhood, they stop, since they have reached a local maximum (Levinthal, 1997; Rivkin and Siggelkow, 2003). However, in some cases they may also perform a 'long-jump' (Kauffman, 1993), and move towards a completely different configuration, which they may adopt if its fitness is higher as compared to the previous one.

5.1 Model specification

The model simulates the process of search for solutions conducted by solvers, in response to a specific innovation problem, by assuming that solvers may combine a definite set of knowledge components according to different configurations to generate their solutions (Fleming and Sorenson, 2004). In our study, we assume that each knowledge component may be exploited (or

not) in the solution development, without considering other options. Thus, it is possible to have two values for each knowledge component, one, if the solver uses the component, and zero otherwise. Although this assumption is common in related literature, the model can be extended to have an arbitrarily finite number of values for each knowledge component without changing its qualitative properties (Gavetti and Levinthal, 2000). We fixed the size of the vector of knowledge components N equal to 15, implying that these 15 specific components are available to solvers to develop a solution. The size of the vector of knowledge components has been selected from the data presented by Rivkin and Siggelkow (2007) in their work, where the authors reported the values of N and K concerning actual examples of products or design. In the various examples, N varies from 13 to 111. Innovation problems usually broadcasted in MFIs are quite defined and limited (Sieg et al., 2010; von Krogh et al., 2012). Thus, we referred to values relative to products such as 'Automobile break system' and 'Automobile climate control systems', comparable with the objects of real innovation problems, whose N varies from 13 to 16. Hence, the value of 15 may be considered a reasonable choice. Furthermore, we also adopted different sizes of the knowledge vector (N=14 and N=16), but the results remain confirmed.

At the beginning of the simulation, problem solvers are randomly generated. Therefore, they begin their search process with a random starting solution, having an initial fitness value (f), which represents the quality of their solution, as the degree to which the solution they propose may solve the innovation problem (Atuahene-Gima, 2003). At each instant, solvers may modify their solutions by using (or not) a knowledge component. Consequently, solvers may shift towards another solution configuration, in the attempt to reach a higher fitness value, i.e. a solution of higher quality. We assumed that problem solvers know the neighbourhood of their solution, and that they may shift towards the first solution of higher quality they find (Levinthal, 1997; Rivkin, 2000). In addition, we also hypothesised that solvers self-select their solution at each instant. Specifically, if they evaluate the quality of their current solution as not satisfying, they may stop their search efforts without submitting any solution, similar to actual MFIs (Jeppesen and Lakhani, 2010). In terms of

modelling, we set that agents withdraw if their solution's fitness is less than half of the best solution's fitness at that instant.

In this study, we identified four relevant and different features of innovation problems, solvers, and markets, that directly and concurrently influence the search process carried out by solvers, consistent with the discussion provided in the previous sections. For each characteristic, we consider two alternatives, according to the scheme reported in Table 1.

Characteristics of innovation problems		**Characteristics of markets**	**Characteristics of problem solvers**
High-interaction vs. Decomposable	Well-delineated vs. Ill-delineated	Co-opetitive vs. Competitive	Scientific background vs. Non-scientific background

Table 1: Characteristics included in the model.

Submitted solutions shall comply with the requests of the innovation problem (Sieg et al., 2010). Specifically, we analysed two characteristics of innovation problems. The first one referred to its decomposability, conceived as the degree of interaction among different knowledge components on which it relies (Afuah and Tucci, 2012; Nickerson and Zenger, 2004). NK fitness landscapes are particularly suitable to model interactions among different attributes through the parameter K (Davis et al., 2007; Levinthal, 1997; Rivkin and Siggelkow, 2007). In particular, two different values of K were assumed in order to simulate decomposable and high-interaction innovation problems. For decomposable problems, we assumed that they carry a minimum degree of interaction among knowledge components (Nickerson and Zenger, 2004), which means that every component interacts with a different one. Thus, we modelled these problems posing K=1. Alternately, to represent high-interaction innovation problems, we excluded the full interaction hypothesis (i.e. $K=N-1$). In MFIs, problems are refined by simplifying them as much as possible, in order to allow solvers to provide valuable solutions (Sieg et al., 2010), while being careful to avoid

extreme simplification that could lead to misrepresentation (Afuah and Tucci, 2012). Moreover, with reference to the data reported by Rivkin and Siggelkow (2007), for values of *N* similar to those we selected, *K* is set between 1.5 and 4, hence indicating that each knowledge component interacts with less than a third of the other components. Thereby, we modelled a high-interaction innovation problem as a more extreme case, and accordingly, we set the value of *K* equal to six, i.e. slightly less than half the value assumed by *N*. In addition, findings do not change by varying the value of *K* (*K*=5, and *K*=7).

The other modelled characteristic of innovation problems was represented by the number of knowledge components involved in problem delineation (Felin and Zenger, 2014; Simon, 1969; Sommer and Loch, 2004). This feature was included in the model by expanding or limiting the solvers' search scope. In particular, we assumed that in well-delineated innovation problems all knowledge components significant to solution development are explicit to the problem solvers. Therefore, solvers' search process can be performed by involving all the relevant knowledge components. Alternately, in ill-delineated problems not all knowledge components that are significant to the definition of a solution are communicated to the solvers. Thus, problem solvers narrow the breadth of their search to a limited number of components. Accordingly, we assumed that an ill-delineated innovation problem allows solvers to develop a solution based on a subset of six knowledge components.

To study the impact of the background of problem solvers on the search process, we examined the role of their scientific skills. Accordingly, we analysed the solvers' background by focusing on its scientific nature, which has been proved to significantly influence their search strategies (e.g. Fleming and Sorenson, 2004; Gruber et al., 2013). To model this feature, we posited that science provides scientist solvers with a broader representation of the solution neighbourhood as compared to common solvers, allowing for the relaxation of the bounded rationality hypothesis (Fabrizio, 2009; Fleming and Sorenson, 2004; Gruber et al., 2013). Accordingly, we acted on the search radius, defined as the largest number of simultaneous changes to single knowledge components that

may be undertaken by the solvers (Siggelkow and Rivkin, 2006). Therefore, we assumed that problem solvers with a scientific background might search in a larger neighbourhood (search radius equal to two) as compared to solvers without scientific skills (search radius equal to one).

Finally, we modelled a characteristic of MFIs, such as their policy about competition and/or cooperation among problem solvers. MFIs, in fact, may allow individuals to discuss and share ideas about a particular innovation problem, hence fostering the adoption of both cooperative and competitive behaviour (Bullinger et al., 2010). In order to simulate co-opetitive MFIs, we randomly assigned solvers a propensity to collaborate. In fact, although MFIs may make available tools and instruments to collaborate, individuals may also have a purely competitive behaviour. At each instant, collaborative solvers may seek suggestions from other solvers. In this case, they have to find other collaborative solvers willing to cooperate by providing suggestions. In our model, a suggestion means that a problem solver could copy a random subset of the solution configuration of another collaborative solver. Then, the former evaluates the fitness of the new configuration, and if this is higher than the previous one, she moves to the new configuration, otherwise stops. In other words, a collaborative individual may adopt the choice of using (or not) some knowledge components in her solution configuration by copying the choices made by another collaborative solver. The new solution is then adopted by the solver if its quality is higher than that of the previous solution developed by her, otherwise the solution is dropped. On the other hand, competitive MFIs were simulated by forcing the solvers to perform their search independently, without the possibility of collaborating with others.

Based on all the variables discussed above, 16 different scenarios were generated (see Table A.1 in Appendix). Finally, we evaluated the market performance for each scenario. Specifically, we first assessed the quality of the best idea submitted, namely the maximum fitness. We used the maximum fitness since it is deemed more important than the average fitness in MFIs. In fact, it is preferred to have a single outstanding idea over several good ideas (Terwiesch and Xu, 2008). Furthermore, we also considered the number of instants necessary to reach the best idea. This

information is useful to understand the differences among the simulated scenarios in terms of readiness to provide solutions. In some cases, especially for decomposable innovation problems, various solvers may concurrently develop the highest quality solution, though in different time periods. In these situations, there may be ambiguity concerning the value of the time performance indicator. Thus, here we assumed the shortest number of periods as the time performance indicator to develop the highest quality solution. For instance, if the highest quality solution was developed by three solvers, in four, three, and seven periods, respectively, we considered three as the value of the time performance indicator.

6. RESULTS AND DISCUSSION

According to Table 2, for each typology of innovation problems, we modelled four scenarios. For each scenario we in turn performed 300 simulations, and calculated the quality and time performance of the markets as the fitness level of the best solution and the time (number of periods) needed to develop it, respectively. For each simulation, we generated 25 problem solvers that performed their search for ideas within 25 periods. Although the number of solvers may seem low, this is a good approximation of real MFIs. InnoCentive's figures show that each innovation problem averagely receives about 20 submissions of solutions[1]. Nevertheless, we included in our model the possibility that problem solvers self-select their solution, and withdraw without submitting any. In addition, solvers can submit their solutions within a limited interval of time. The results of simulation, accordingly, showed that problem solvers always reach a local peak within 25 time instants in competitive MFIs, hence supporting our assumption. We could not apply this argument to co-opetitive MFIs, due to the hypothesis that solvers in these markets may look for collaboration at each instant of time. However, we observed that increasing the number of periods does not significantly affect co-opetitive MFIs' performance.

[1] InnoCentive. Facts & Stats. InnoCentive website, http://www.innocentive.com/aboutinnocentive/facts-stats (accessed March 4th, 2015)

Totally, we simulated 120,000 search processes in different scenarios, and results of the simulations were averaged by scenario (see Table 2). We applied the Student's *t*-test to compare performance results of different scenarios (see Tables A.2a and A.2b in Appendix). Since our study adopts the innovation problems perspective, we tested the market performance of scenarios belonging to the same typology of innovation problems. Therefore, comparisons of the performance across different typologies are not reported in Tables A.2a and A.2b.

Hypothesis 1a posits that highest quality solutions for high-interaction and well-delineated innovation problems are provided by individuals with a scientific background operating in a competitive MFI. Our results partially support this hypothesis by showing that engaging a pool of problem solvers with a scientific background is effective to increase the average quality of the best solution. However, we found that the type of market does not have a significant influence. We may interpret this finding considering that, for this type of innovation problem, the co-operation with other scientists may be redundant for solution development, since the solvers' knowledge background, as well as their search strategies may be similar, and they cannot exploit the benefits of knowledge diversity (Taylor and Greve, 2006). Hypothesis 1b states that speediest solutions for high-interaction and well-delineated innovation problems are retrieved when solvers do not have a scientific background, and the MFI is competitive. This hypothesis is supported by our results ($p<0.10$). Therefore, as hypothesised, common problem solvers in a competitive environment may develop a solution faster, since they devote their whole time to the search process, and find a local optimal solution promptly (Billinger et al., 2014), without having scientific knowledge.

Regarding decomposable and well-delineated innovation problems, Hypothesis 2a suggests that highest quality solutions are obtained when the market is competitive, irrespective of the background of problem solvers. Our analysis does not support this hypothesis, showing that there is no statistically significant difference between solutions developed in competitive and co-opetitive MFIs, as well as between MFIs populated by scientists or common solvers. Results show that the solution development for this type of innovation problem is effective by simply pursuing directional

Number of scenario	Decomposable vs. High-interaction	Well-delineated vs. Ill-delineated	Co-opetitive vs. Competitive	Scientific background vs. Non-scientific background	Quality of the best solution[2]	Number of periods to develop the best solution[2]
1	High-interaction	Well-delineated	Co-opetitive	Scientific	0.787 (0.022)	9.04 (6.56)
2	High-interaction	Well-delineated	Co-opetitive	Non scientific	0.774 (0.024)	10.02 (7.85)
3	High-interaction	Well-delineated	Competitive	Scientific	0.788 (0.023)	6.06 (2.39)
4	High-interaction	Well-delineated	Competitive	Non scientific	0.776 (0.023)	5.81 (2.31)
5	Decomposable	Well-delineated	Co-opetitive	Scientific	0.713 (0.045)	5.02 (1.50)
6	Decomposable	Well-delineated	Co-opetitive	Non scientific	0.712 (0.046)	5.49 (3.57)
7	Decomposable	Well-delineated	Competitive	Scientific	0.712 (0.047)	4.58 (1.24)
8	Decomposable	Well-delineated	Competitive	Non scientific	0.713 (0.046)	4.61 (1.51)
9	High-interaction	Ill-delineated	Co-opetitive	Scientific	0.737 (0.025)	10.41 (9.57)
10	High-interaction	Ill-delineated	Co-opetitive	Non scientific	0.727 (0.026)	9.52 (9.59)
11	High-interaction	Ill-delineated	Competitive	Scientific	0.733 (0.024)	3.64 (1.71)
12	High-interaction	Ill-delineated	Competitive	Non scientific	0.727 (0.026)	3.26 (1.70)
13	Decomposable	Ill-delineated	Co-opetitive	Scientific	0.678 (0.050)	10.04 (9.39)
14	Decomposable	Ill-delineated	Co-opetitive	Non scientific	0.682 (0.046)	10.24 (9.91)
15	Decomposable	Ill-delineated	Competitive	Scientific	0.679 (0.048)	3.75 (1.82)
16	Decomposable	Ill-delineated	Competitive	Non scientific	0.681 (0.046)	3.12 (1.36)

Table 2: Results of simulations (standard deviations are in brackets).

[2] Each result is an average over 300 landscapes.

search (Felin and Zenger, 2014; Hsieh et al., 2007). Thus, the role of science and the possibility of cooperation are negligible for increasing the quality of the best solution, since common solvers may autonomously find the path towards the highest quality solution (Hsieh et al., 2007). In turn, Hypothesis 2b assumes that speediest solutions are obtained when solvers are scientists developing a solution in a competitive MFI. The statistical analysis showed partial support for this hypothesis. In fact, we found that solutions are provided faster in competitive MFIs as compared to co-opetitive MFIs ($p<0.001$). There is, however, no statistical support to accept a positive effect of solvers' scientific background on time performance. Additionally, we may interpret this finding by considering that the science-guided search for solutions to decomposable and well-defined innovation problems does not provide speedier solutions than the directional search conducted by common solvers.

Hypothesis 3a states that highest quality solutions for high-interaction and ill-delineated innovation problems are provided by solvers with a scientific background performing their search in a co-opetitive MFI. Our results fully support this hypothesis ($p<0.05$). Therefore, cooperation between solvers and scientific skills supports solvers in facing the difficulties of innovation problems characterised by high degree of interaction among not fully identified knowledge components (Felin and Zenger, 2014; Hutter et al., 2011). Regarding the same typology of problems, Hypothesis 3b posits that speediest solutions are obtained when MFIs are populated by solvers without a scientific background, and governed by competitive mechanisms. The statistical analysis confirms this hypothesis ($p<0.01$), thereby highlighting the advantages of directional and autonomous search when firms are interested in timely retrieval solutions.

Finally, Hypothesis 4a assumes that highest quality solutions for decomposable and ill-delineated innovation problems are developed when MFIs are co-opetitive, irrespective of the background of the solvers. This hypothesis is not confirmed by the statistical analysis. Both the background of solvers and the cooperation policy of MFI do not influence the quality of the best solutions retrieved for this problem type. In this case, even though full details about knowledge components that may

influence the solution development are not provided to solvers, performing an independent search is sufficient to provide the highest quality solution (Hsieh et al., 2007). Further, having scientific capabilities does not generate appreciable improvements. Considering time performance, Hypothesis 4b poses that speediest solutions are obtained when solvers do not have a scientific background, and operate in a competitive MFI. Our results support this hypothesis ($p<0.001$), and confirm that common solvers are able to provide timely solutions to firms facing a decomposable and ill-delineated innovation problem. This occurs especially when they are not involved in cooperative activities that may require time to be carried out (McFadyen and Cannella, 2004). Results of the simulations are depicted in Figure 1, grouped by performance of interest and innovation problem, while the main findings are summarised in Table 3.

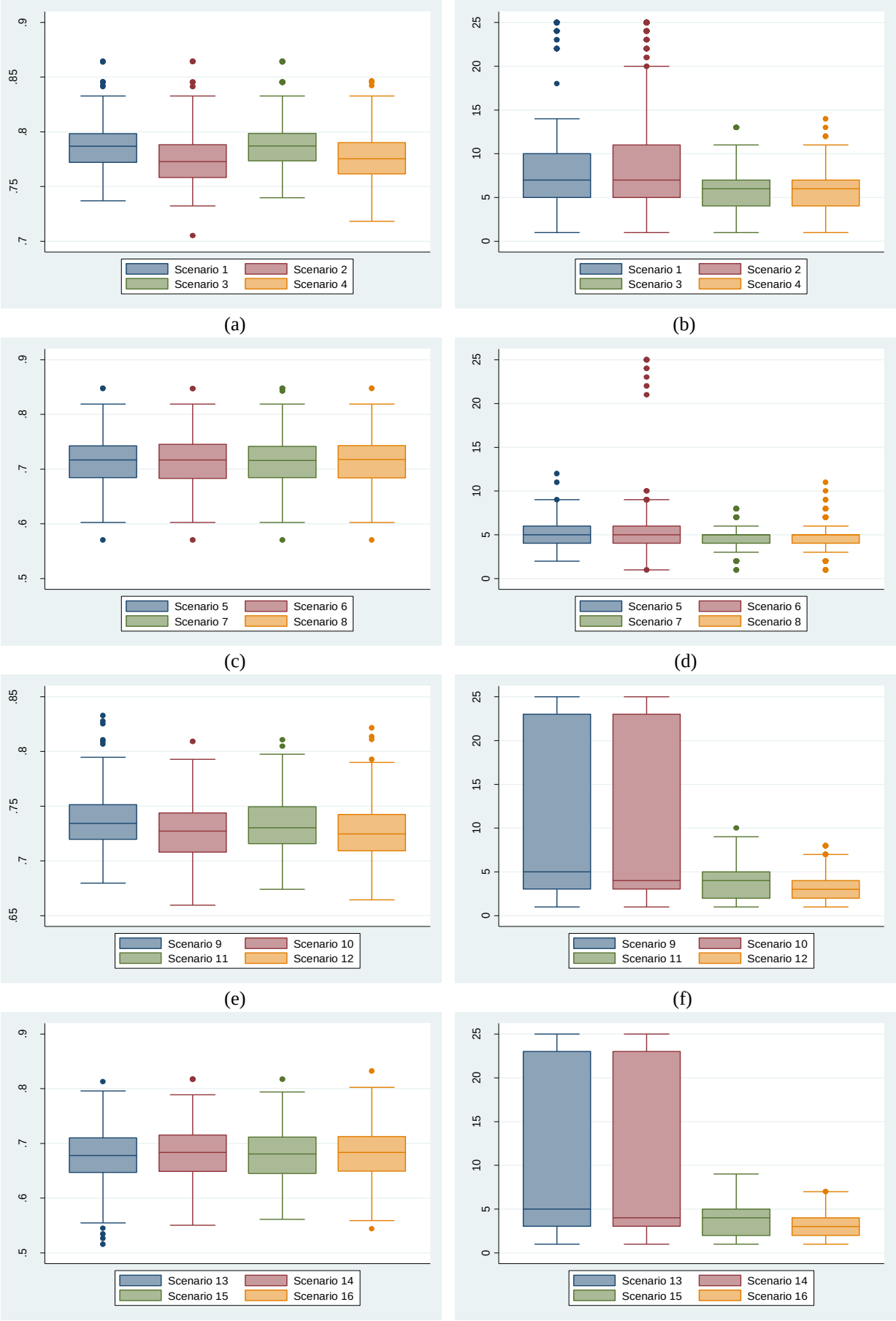

Figure 1: Performance results of the 16 scenarios.

Innovation Problem	Quality performance	Time performance
High-interaction and well-delineated	Best results for MFIs populated by problem solvers with a scientific background	Best results for MFIs populated by problem solvers without a scientific background operating in a competitive environment
Decomposable and well-delineated	No statistically significant differences between MFIs populated by problem solvers with or without a scientific background and between competitive and co-opetitive environments	Best results for MFIs populated by problem solvers operating in a competitive environment
High-interaction and ill-delineated	Best results for MFIs populated by problem solvers with a scientific background operating in a co-opetitive environment	Best results for MFIs populated by problem solvers without a scientific background operating in a competitive environment
Decomposable and ill-delineated	No statistically significant differences between MFIs populated by problem solvers with or without a scientific background and between competitive and co-opetitive environments	Best results for MFIs populated by problem solvers without a scientific background operating in a competitive environment

Table 3: Summary of results.

7. CONCLUSIONS

Several strategies may be pursued by organisations to increase the permeability of their boundaries in order to exchange knowledge with the external environment (Chesbrough, 2006b; Wang et al., 2012; West et al., 2006). In particular, MFIs are becoming increasingly important to organisations adopting the open innovation paradigm (Chesbrough, 2006b), since these markets allow them to acquire knowledge assets from the external environment (Arora and Gambardella, 2010; Dushnitsky and Klueter, 2011; Fosfuri and Giarratana, 2010). In this study, we further elucidate the potential role of MFIs for innovating organisations. Specifically, distinguishing four different types of innovation problems, we analysed the characteristics of problem solvers and types of markets that provide the highest quality of submitted solutions and minimise their development time, by simulating the search process carried out by solvers through NK fitness landscapes. This simulation model is particularly suitable to investigate search processes, as revealed by several previous studies (e.g. Afuah and Tucci, 2012; Gavetti and Levinthal, 2000; Kavadias and Sommer, 2009; Siggelkow and Rivkin, 2006). Thus, we modelled four different characteristics that influence the search process, including high-interaction vs. decomposable and well-defined vs. ill-defined nature of innovation problems, scientific skills characterising solvers' background, and cooperation policies of the markets. By relying on the two characteristics of innovation problems, four different typologies were identified. For each of these typologies, we simulated different scenarios in order to understand which types of problem solvers and markets offer the best performance, in terms of quality and speed.

Our results showed that the interplay between the background of problem solvers and the cooperation policy of MFIs influences the quality of the best solution retrieved for high-interaction innovation problems. However, we also observed that for both well- and ill-delineated decomposable innovation problems, having a scientific background and allowing for cooperation do not sensibly increase the quality performance. Thus, for these types of innovation problems, it is possible to develop the highest quality solutions through simple directional search, due to the

smoothness of the relative landscape. The other investigated performance was the time required to develop the best solutions. Additionally in this case, relevance of the concurrent effects of the characteristics of problem solvers and markets cooperation policies is confirmed for the different innovation problems. Nevertheless, a general trend emerges for the time performance. In fact, competition among solvers provides speediest results for the four problem types under investigation. This may be understandable by considering that establishing an effective collaboration is not a trivial process, and requires a significant time effort. Accordingly, while collaborations may provide advantages for the quality performance, as in the case of high-interaction and ill-delineated innovation problems, it results as being detrimental for the time performance.

7.1 Theoretical contributions

This study provides a number of theoretical contributions. First, we contribute to the literature on problem solving (Afuah and Tucci, 2012; Jonassen, 2004; Nelson and Winter, 1982; Nickerson and Zenger, 2004; Simon, 1962), by investigating the outcomes of the search processes conducted by individuals to provide a solution to a particular innovation problem, under defined hypotheses. Specifically, for different types of innovation problems, we analysed the effects of the interplay between the characteristics of problem solvers and market policies on the critical performance of MFIs. Further, we also proposed a taxonomy of innovation problems based on two main dimensions, the degree of interaction among distinct knowledge components, and the number of knowledge components involved in the delineation of the problem (Felin and Zenger, 2014; Jonassen, 2004; Leiblein and Macher, 2009; Simon, 1969; Sommer and Loch, 2004).

Second, we further increased our understanding of MFIs (Arora and Gambardella, 2010; Jeppesen and Lakhani, 2010; Natalicchio et al., 2014; Poetz and Prügl, 2010), by studying the scenarios that offer the highest results in terms of market performance for different innovation problems. In addition, we included in our analysis some scarcely examined aspects, such as the role of

cooperation between problem solvers in MFIs, which despite its potential importance (e.g. Bullinger et al., 2010; Hutter et al., 2011), has received limited attention.

Third, we also extend the literature on open innovation by analysing the role of MFIs for innovating organisations (Chesbrough, 2006a; Natalicchio et al., 2014; West et al., 2006), and discussing how to increase the effectiveness of this strategy to meet organisations' goals.

Finally, from a methodological point of view, we showed an application of the NK fitness landscape models to the search process performed by solvers in an MFI (see also Afuah and Tucci, 2012). In this sense, we contribute to promote the use of these simulation models to answer research questions regarding the adoption of the open innovation paradigm. Moreover, we also proposed some methods to model specific characteristics of innovation problems, solvers, and collaboration policies.

7.2 Managerial contributions

From a managerial point of view, our findings promote the formulation of guidelines for stakeholders in MFIs, particularly for organisations looking for solutions to their innovation problems through MFIs, and for markets' managers. In fact, our results support organisations in selecting the specific MFI in which they should participate to effectively find solutions for their internal problems, according to the two considered performance indicators. Additionally, by showing our results from the two perspectives of quality and time, we analyse two different needs of organisations, since there may be cases in which time to receive solutions, though of acceptable quality, is paramount for them, and other situations where the quality of the received solutions assumes a fundamental role. We addressed these two different needs, thus providing a substantial practical contribution. Moreover, our findings also advice MFIs' managers about how to set the best conditions to be effective, according to organisations' specific innovation problems, and the market performance they want to favour. For instance, managers may decide to address a high-interaction and well-delineated innovation problem to a pool of problem solvers with a relevant scientific

background, to maximise the probabilities of getting a high-quality solution. Thus, they may increase the positive impact of MFIs for organisations embracing the open innovation paradigm, by being more proactive with respect to their objectives.

7.3 Limitations and further research

This study has some limitations that may open avenues for further research. First, we used random patterns of interaction among knowledge components in the simulation. In fact, we did not specify the interacting knowledge components, since we kept the innovation problems at a conceptual level. However, it may be interesting to refer to the interaction patterns of real innovation problems to better understand if this influences the outcome of the simulation. Second, fitness in the presented model is calculated by averaging the contributions of the considered knowledge components, as it generally occurs when using NK fitness landscapes (e.g. Gavetti and Levinthal, 2000; Kauffman, 1993; Levinthal, 1997). However, in real situations, different knowledge components might not equally contribute to the quality of the submitted solutions. Therefore, further studies may consider this aspect by offering alternative methodologies to calculate the fitness of solutions. Third, we modelled collaboration by considering that a problem solver gives suggestions to another solver, who in turn receives the suggestion and accepts it if the fitness of her solution improves. While this is a clear example of collaboration, further analyses could involve different hypotheses to model alternative collaborative behaviour among problem solvers as, for instance, the co-creation of solutions. Fourth, we assumed that all the solvers begin their search process from the first instant of time. In MFIs, solvers may start their search at any instant of time during the period available to submit ideas. Considering this aspect may contribute to increase the suitability of the model in real situations. Finally, motivations of solvers play an important role in the participation in MFIs (e.g. Boudreau et al., 2011; Frey et al., 2011; Garcia Martinez and Walton, 2014; Garcia Martinez, 2015). Motivated solvers may devote more effort in the search for ideas and solutions, for example

by increasing the pace of search or starting parallel search processes. Modelling this feature may provide further interesting insights about the effectiveness of MFIs.

APPENDIX A

N	Decomposable vs. High-interaction	Well-delineated vs. Ill-delineated	Co-opetitive vs. Competitive	Scientific background vs. Non-scientific background
1	High-interaction	Well-delineated	Co-opetitive	Scientific
2	High-interaction	Well-delineated	Co-opetitive	Non scientific
3	High-interaction	Well-delineated	Competitive	Scientific
4	High-interaction	Well-delineated	Competitive	Non scientific
5	Decomposable	Well-delineated	Co-opetitive	Scientific
6	Decomposable	Well-delineated	Co-opetitive	Non scientific
7	Decomposable	Well-delineated	Competitive	Scientific
8	Decomposable	Well-delineated	Competitive	Non scientific
9	High-interaction	Ill-delineated	Co-opetitive	Scientific
10	High-interaction	Ill-delineated	Co-opetitive	Non scientific
11	High-interaction	Ill-delineated	Competitive	Scientific
12	High-interaction	Ill-delineated	Competitive	Non scientific
13	Decomposable	Ill-delineated	Co-opetitive	Scientific
14	Decomposable	Ill-delineated	Co-opetitive	Non scientific
15	Decomposable	Ill-delineated	Competitive	Scientific
16	Decomposable	Ill-delineated	Competitive	Non scientific

Table A.1: List of scenarios

Innovation Problem	Scenario	Quality performance	3	1	4	2	9	11	12	10	8	5	6	7	14	16	15	13
High-interaction and Well-delineated	3	0.788 (0.023)	-	0.54	6.39	7.30												
	1	0.787 (0.022)		-	5.99	6.92												
	4	0.776 (0.023)			-	1.04												
	2	0.774 (0.024)				-												
High-interaction and Ill-delineated	9	0.737 (0.025)					-	2.00	4.80	4.80								
	11	0.733 (0.024)						-	2.94	2.94								
	12	0.727 (0.026)							-	0								
	10	0.727 (0.026)								-								
Decomposable and Well-delineated	8	0.713 (0.046)									-	0	0.27	0.26				
	5	0.713 (0.045)										-	0.27	0.27				
	6	0.712 (0.046)											-	0				
	7	0.712 (0.047)												-				
Decomposable and Ill-delineated	14	0.682 (0.046)													-	0.27	0.78	1.02
	16	0.681 (0.046)														-	0.52	0.76
	15	0.679 (0.048)															-	0.25
	13	0.678 (0.050)																-

Table A.2a: *t*-test values for quality performance (standard deviations are in brackets).

Innovation Problem	Scenario	Time performance	16	15	13	14	12	11	10	9	7	8	5	6	4	3	1	2
Decomposable and Ill-delineated	16	3.12 (1.36)	-	-4.80	-12.63	-12.33												
	15	3.75 (1.82)			-11.39	-11.16												
	13	10.04 (9.39)				-0.25												
	14	10.24 (9.91)				-												
High-interaction and Ill-delineated	12	3.26 (1.70)					-	-2.73	-11.13	-12.74								
	11	3.64 (1.71)						-	-10.46	-12.06								
	10	9.52 (9.59)							-	-1.14								
	9	10.41 (9.57)								-								
Decomposable and Well-delineated	7	4.58 (1.24)									-	-0.27	-3.92	-4.17				
	8	4.61 (1.51)											-3.34	-3.93				
	5	5.02 (1.50)												-2.10				
	6	5.49 (3.57)												-				
High-interaction and Ill-delineated	4	5.81 (2.31)													-	-1.30	-8.04	-8.91
	3	6.06 (2.39)															-7.39	-8.36
	1	9.04 (6.56)																-1.66
	2	10.02 (7.85)																-

Table A.2b: *t*-test values for time performance (standard deviations are in brackets).

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