The Curse of Knowledge - When Ignorance is Bliss

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Abstract

Knowledge-based views of the firm often emphasize the value of transferring best practices within organizations. Yet, in many cases, the practices that end up being transferred are not literally the 1st best solution to a problem, but only the best currently known alternative, i.e., at best, a 2nd best solution. In this paper, we ask how knowledge about a good, but not the best solution affects agents’ search and learning processes and, in turn, their performance. We conduct an experiment with a large American sample and find that participants endowed with knowledge about 2nd best solutions have a strong preference for strategies that are inferior in settings where the potential gains of finding the best solution are particularly high. As a result, we find that being ignorant to knowledge about 2nd best solutions can in many cases lead to superior choices and, consequently, to a better performance. Our results have important implications for research related to knowledge utilization, organizational search and bounded rationality.
THE CURSE OF KNOWLEDGE: WHEN IGNORANCE IS BLISS

ABSTRACT

Knowledge-based views of the firm often emphasize the value of transferring best practices within organizations. Yet, in many cases, the practices that end up being transferred are not literally the 1st best solution to a problem, but only the best currently known alternative, i.e., at best, a 2nd best solution. In this paper, we ask how knowledge about a good, but not the best solution affects agents’ search and learning processes and, in turn, their performance. We conduct an experiment with a large American sample and find that participants endowed with knowledge about 2nd best solutions have a strong preference for strategies that are inferior in settings where the potential gains of finding the best solution are particularly high. As a result, we find that being ignorant to knowledge about 2nd best solutions can in many cases lead to superior choices and, consequently, to a better performance. Our results have important implications for research related to knowledge utilization, organizational search and bounded rationality.

Keywords: Knowledge, Decision-making, Search, Bounded Rationality
Knowledge-based theories of the firm (Grant, 1996; Spender, 1996; Kogut & Zander, 1992) emphasize the value of sharing and transferring practices within organizations, in particular if the practices to be transferred are seen as “best practices” (Spender & Grant, 1996; Szulanski, 1996). Yet, more often than not, the knowledge that ends up being transferred does not literally reflect 1st best practices, or globally optimal solutions but only n-th best practices, or suboptimal solutions. In some cases, n-th best practices can be depicted as good practices, or “local peaks” (Levinthal, 1997), with satisfactory outcomes. In other cases, they may simply reflect bad practices, which can prevail and become widespread within organizations (Carroll, 1993; Meyer & Zucker, 1989; Vermeulen, 2017).

Existing research (for a review, see Meyer & Zucker, 1989; Vermeulen, 2014) has identified a variety of reasons why organizations adopt and stick to bad practices, including contagion and socialization mechanisms (Leonardi, Jackson, & Diwan, 2009; Vermeulen, 2014), the separation between research and practice (Lawler, 2007), or efforts towards legitimation (Ashford & Gibbs, 1990).

In our study, we are interested in whether there are benefits to knowledge about a good, but not the best solution. Specifically, we conduct an experiment in which participants can choose repeatedly among five different alternatives and where we provide some of these participants with information about the 2nd best solution. While theoretically this knowledge has a positive value and should, therefore, lead to a better performance, we find that this is
not always the case. Indeed, in some cases, this knowledge results in inferior choices - i.e., all else equal, participants with knowledge about the 2nd best solution make inferior choices than participants without this knowledge.

We observe this negative effect because any knowledge about a good but not the optimal, or best solution is inherently ambiguous. Take knowledge about the best solution. This knowledge is unambiguous - if you know the literal best solution to a problem, you pursue this solution. Similarly, knowledge about bad solutions is also unambiguous - if you know that a solution leads to a bad outcome you avoid this solution. However, knowledge about a good, but not the best solution is ambiguous: Should you pursue this knowledge, given that it can have a positive effect on performance (“informed exploitation”)? Or, in line with our opening quote, should you ignore this knowledge and experiment with unknown solutions (“informed exploration”)?

Obviously, which of these two fundamentally different strategies is superior depends on how much better the 1st best solution is. If the 1st best solution is much better than the 2nd best solution, it is preferable to avoid the 2nd best solution (“informed exploitation”). If the 1st best solution is only slightly better than the 2nd best solution, however, it is better to stick to the 2nd best solution (“informed exploitation”), since the potential downside of searching further outweighs the potential upside of finding a better solution. In many real world situations, however, information about the ratio between the 1st and 2nd, or other nth best solutions is not readily available because, for example, the 1st best solution has not yet been discovered.

When facing this ambiguity about their knowledge endowments, participants in our experiment reveal a strong preference for the less risky strategy of “informed exploitation”, a strategy that is inferior in settings where the potential gains of finding the optimal solution
are particularly high. As a result, these more knowledgeable participants end up making inferior choices compared to participants without this knowledge.

Our findings have important implications for theory and practice. First, we find support for claims that more knowledge is not always better (e.g., Haas and Hansen, 2005; Henderson and Clark, 1990). Specifically, we find that when the potential gains of adopting the optimal solution are particularly high, being endowed with entirely correct and unbiased knowledge does not necessarily lead to better choices. Second, we argue that access to knowledge about suboptimal practices is sufficient to explain why these practices become so widespread and persistent in organizations (Carroll, 1993; Meyer & Zucker, 1989). In particular, we find that even in the absence of information about the choices of others (Vermeulen, 2017), agents endowed with knowledge about a good, but not the best solution will often exploit this knowledge. Third, our findings lend support to the notion that uninformed agents in a particular industry may actually end up finding better solutions than their informed counterparts (e.g., Carnahan et al., 2017). Accordingly, we argue that knowledge about 2nd best solutions will often lead to strategies that make it less likely for agents to find the 1st best solution. Finally, our results address recent appeals to contrast the predictions of our formal models of search with findings from experimental research (Puranam et al., 2015). For example, studies that have looked at knowledge utilization from an experimental perspective have not yet fully addressed the conditions under which human agents switch between exploration and exploitation. Whereas past research has shown that the rate of switching between solutions decreases as a function of experience (Lea et al, 2011; Steyvers et al, 2009), we still lack studies that explain how knowledge about different solutions affects this trade-off. We contribute to this by presenting the results of an experimental study where agents balance search after being endowed with knowledge about good, but not optimal solutions.
The remainder of this paper is structured as follows: In the next section we discuss how knowledge is transferred within organizations, the persistence of bad practices and the value of knowledge about 2\textsuperscript{nd} best solutions. Next, we present our experimental setting and explain the optimal search strategy for each task. We then analyse and compare how subjects endowed with knowledge about 2\textsuperscript{nd} best solutions perform compared to uninformed subjects. Finally, we discuss our findings and the limitations of this study.

**THEORETICAL BACKGROUND**

**The Knowledge-based View of the Firm**

According to the knowledge-based view of the firm, knowledge is a critical resource for competitive advantage (e.g., Cockburn & Henderson, 1998; Cohen & Levinthal, 1990; Kogut & Zander, 1992; Grant, 1996a; Grant, 1996b; Nelson & Winter, 1982; Szulanski, 1996). The firm’s tacit knowledge resources, in particular, have been described in both cognitive and technical terms (Nonaka & Takeuchi, 1995): On the one hand it represents as a series of mental models, schemas and concepts that define the agent’s view of the organization and its environment. On the other hand, it also describes the body of technical skills necessary for different actions. Therefore, tacit knowledge is often used to reflect the value of the firm’s “know-how” and is typically mentioned in the context of operating procedures, organizational routines, or grammars of action (e.g., Cohen & BacDayan, 1994; Nelson & Winter, 1982; Pentland & Rueter, 1994). Finally, tacit knowledge is also important because it protects from imitation from outside firms, as it tends to be difficult and costly to transfer (Grant, 1996; Szulanski, 1996; Winter, 1987).

By contrast, explicit knowledge is important for competitive advantage because it helps agents make informed and better choices (Cyert & March, 1963; March, 1991; Simon, 1947). Contrary to tacit knowledge, this type of knowledge may include, for example,
explicit facts, axiomatic propositions, or important symbols, which are critical to organizational performance (Kogut & Zander, 1992; Nonaka, 1994). What is more, explicit knowledge tends to be easy to understand and is widely available (Spender, 1996). Inside organizations, agents are often exposed to explicit knowledge in the form of, for example, sales revenues, customer loyalty and retention reports, rankings and ratings, size of gross margins, or some metric about the performance of their peers. Agents may use this knowledge as a tool for performance comparisons, or decisions regarding future action.

Even though both of these knowledge resources play an important role in competitive advantage (Hannes & Fjedstad, 2000), in some cases, knowledge can be rare and socially complex (Barney, 1991; Peteraf, 1993), meaning that organizations lacking in knowledge-based capabilities will struggle, not only to transform their knowledge into competitive advantage, but also to transfer their practices (Kogut & Zander, 1992).

**Practice Transfer**

Knowledge based theories of the firm often emphasize the value of sharing and transferring practices within organizations (Grant, 1996; Spender, 1996; Kogut & Zander, 1992). The underlying idea is that transferring practices internally allows firms to build competitive advantage through the appropriation of rents from scarce internal resources (Szulanski, 1996).

Szulanski (1996) suggests that practice transfers happen in four stages: Initiation- or the events leading to the decision to transfer; Implementation- or when new practices are experimented with; Ramp-up- or the stage in which agents identify and resolve unexpected problems; and, finally Integration- or the stage in which the transferred knowledge becomes routinized. According to the author, the main challenge underlying practice transfer is to protect the knowledge bases of the firm from outside competition. However, as was
mentioned above, knowledge is also difficult and costly to transfer because practices often contain a tacit component of individual skill and collaborative social arrangement. For this reason, dynamic capabilities are critical when it comes to generating rents from an organization’s knowledge resources (DeNisi, 2003).

Unlike other intangible resources, knowledge-based capabilities are based on developing, carrying and exchanging information throughout the organization (Amit & Schoemaker, 1993) and can be seen as part of the process of collective learning (Prahalad & Hamel, 1990). Similar to tacit knowledge, these capabilities tend to be firm-specific and hard to substitute, or imitate over-time (Rugman & Verbeke, 2002) as they are directed at reconfiguring, redirecting, transforming, shaping and integrating the firm’s knowledge resources (Prahalad & Hamel, 1990). Therefore, it is not surprising that firms with inferior dynamic capabilities will face difficulties, not only in generating rents from existing knowledge bases, but also in spreading these knowledge bases throughout the organization in order to achieve a wider appropriation of rents.

However, even when the necessary knowledge resources to achieve competitive advantage exist and have, therefore, the potential to be transferred, Szulanski (1996) argues that firms will typically face three major barriers to knowledge transfer (or, “stickiness”). These barriers are the recipient’s absorptive capacity (e.g. Cohen & Levinthal, 1990), causal ambiguity (e.g., Lippman & Rumelt, 2000) and an arduous relationship between the source of knowledge and the recipient.

Absorptive capacity represents an impediment to knowledge transfer because it refers to the ability of a firm to recognize the value of new information, assimilate it and apply it to commercial ends (Cohen & Levinthal, 1990). In some cases, organizations can be said to lack absorptive capacity because they are simply unable to explore external sources of knowledge. In other cases, these sources of knowledge may be available to the organization but the
organization may still fail to retain them. In both cases, however, the absorptive capacity of a firm is largely a function of its pre-existing body of knowledge (Dierickx & Cool, 1989).

Whereas absorptive capacity reflects the recipient’s prior knowledge, causal ambiguity reflects the recipient's depth of knowledge, or irreducible uncertainty about cause-effect relationships (Lippman & Rumelt, 2000; Szulanski, 1996). In modelling capability as a production function, Lippman and Rumelt (2000) state that the difficulty in replicating a capability emanates mostly from ambiguity regarding the factors of production and how these factors interact during production. This causal ambiguity is often linked to the poorly understood idiosyncratic features of the new context in which knowledge is put to use (Szulanski, 1996; Winter, 1995). Therefore, it is not surprising that causal ambiguity regarding new practices often becomes an impediment in practice transfer.

Moreover, it is also important to consider how arduous the relationship between the source and the recipient is, especially when the knowledge to be transferred has a heavy tacit component. When this is the case, a successful knowledge transfer might require numerous exchanges (Nonaka, 1994). For this reason, successful knowledge transfers tend to be associated to ease of communication (Arrow, 1974) and to the intimacy of this relationship (Marslen, 1990), with a laborious and distant relationship creating additional hardship in the transfer (Szulanski, 1996).

Furthermore, knowledge transfers from the individual to the group-level are said to depend on the development of a unique language or code, which allows members to understand who knows what and how to best coordinate organizational activities (Kogut & Zander, 1992). In this context, the challenge is often to interpret external information and encode it into new knowledge resources.

In the same vein, the view offered by Grant (1996) also suggests that the choice of coordination of knowledge (i.e., pooled, sequential, reciprocal, or team-based) is often
dependent, not on the technology itself, but on the manager’s choice. Thus, efficiency in organizations seems to be associated with maximizing the use of rules, routines and other integration mechanisms that economize on communication and knowledge transfer: Whereas in horizontal knowledge transfers this efficiency depends on finding the appropriate boundary spanners, in vertical knowledge transfers, it usually comes from relying on data-sharing and superior formal and informal structures (Kogut & Zander, 1992).

However, even when all the major barriers to practice transfers are solved by superior knowledge-based capabilities and organizing principles, many of the practices that end up being transferred are not necessarily 1st best practices (or globally optimal solutions), but only n\textsuperscript{th} best practices (or suboptimal solutions).

**Persistence of Suboptimal Practices**

The notion that our current practices are most likely only n\textsuperscript{th} best practices can be found in different streams of literature. For example, we know choices leading up to suboptimal practices may persist because, at the agent-level, these choices are typically made on the basis of a logic of consequences (March, 1994) and interpretation (Weick, 1969), rather than on a logic of computation (Simon, 1947). Accordingly, research which has examined the power of analogy in the context of strategic decisions (Gavetti, Levinthal, & Rivkin, 2005) has suggested that, sometimes, not even representations about optimal practices will guarantee that they will end up being adopted, since an early period of experimentation will often result in deviation from these representations.

Moreover, our models of search on rugged landscapes (e.g., Gavetti & Levinthal, 2000; Levinthal, 1997) explicitly indicate that because of the persistence of the effects of initial search, most organizations will fail to find the global peak, or the optimal practice and instead converge only to a local peak, or an n\textsuperscript{th} best practice. Likewise, studies that have
looked at simultaneous learning across organizational levels (Lounamaa & March, 1987) suggest that search often requires inhibiting learning in one part of the organization in order to facilitate learning in another, recurrently shifting learning from a parallel to a less efficacious sequential process, which might reduce the chances of finding optimal solutions.

What is more, the idea that the current solution is most likely not the optimal solution is also implicit in several streams of literature. Take, for example, discussions on technological progress (Butler, 1988), dominant designs and standards (Anderson & Tushman, 1990; Rosenkopf & Tushman, 1994), or benchmarking. In these and other theories, the underlying assumption is that the current solution is never the optimal solution, but only the best currently known alternative because the optimal solution has not yet been found.

Yet, even when organizations have access to better practices, retaining elements of prior practices still allows organizations to enhance their reliability (Hannan & Freeman, 1984, 1989; Levinthal, 1991) and to make clearer inferences about experimentation (Levinthal, 1991). Similarly, the value of adopting known solutions is also particularly high in the face of turbulent environments, since new solutions can quickly lose their value and become costly to implement (Posen & Levinthal, 2011).

A critical aspect in determining the adoption of an nth best practice hinges on whether the practice reflects a good practice (or, e.g., a “local peak”, Levinthal, 1997) with satisfactory outcomes or, a bad practice, with undesired outcomes (Carroll, 1993; Meyer & Zucker, 1989). Past research has examined the persistence of bad practices (Carroll, 1993; Vermeulen, 2017) and concluded that these practices are perhaps more widespread than previously thought (Meyer & Zucker, 1989).

The persistence of bad practices in organizations has been linked to factors such as the separation between research and practice (Lawler, 2007), the nature of business education (Ghoshal, 2005), impression management mechanisms (Becker & Martin, 1995) or efforts
towards legitimation (Ashford & Gibbs, 1990). Moreover, the perpetuation of these counterproductive practices has also been linked to the organization’s socialization processes. For example, Leonardi, Jackson & Diwan (2009) show that engineering students grow more committed to practices that reflect stereotypes about the profession and that they grow increasingly more resistant to practices that educators believe to be fundamental to success as an engineer. Likewise, Vermeulen (2017), in his theory of inheritance, highlights the existence of contagion mechanisms which are responsible for the adoption and survival of bad practices within organizations.

However, it is not surprising that a learning process which is fundamentally myopic (Levinthal & March, 1993), rationally bounded (Simon, 1947) and involved in ambiguity (e.g., Zollo and Singh, 2004; Zollo, 2009) will result in the adoption of suboptimal practices.

Sources of Ambiguity

Agents often face ambiguity, not only in terms of the cause-effect relationships of particular practices (i.e., causal ambiguity, as has been previously described), but also in terms of whether the “effect”, or outcome of those practice represents a success, or a failure (i.e., outcome ambiguity). Ambiguity regarding a particular practice can have a substantial impact on the choice of what knowledge is transferred and, consequently, on which practice ends up being adopted.

While causal ambiguity has been typically associated to difficulties in knowledge transfer and imitation (e.g., Lippman & Rumelt, 2000; Szulanski, 1996), outcome ambiguity has been studied in the context of corporate acquisitions (e.g., Zollo and Singh, 2004; Zollo, 2009), corporate development activities (Anand, Mulotte, & Ren, 2015), interaction and cooperation (Heidi & Miner, 1992), or technological evaluation (Johnson, Bardhi, & Dunn, 2008; Lawless & Price, 1992).
When present, ambiguity about business outcomes creates barriers to rent appropriation which, in turn, may lead to reduced competitive advantage (Reed & DeFilippi, 1990). For example, Ouchi (2014) found that bureaucracies often fail when ambiguity about outcome/performance evaluations becomes significantly greater than the ambiguity which brings about market failure, which in turn suggests that high levels of ambiguity should be kept relatively low, in order for firms to survive.

Moreover, Ho & Keltyka (2002) studied how ambiguity aversion relates to outcomes and found that when decisions are framed as decision-making under certainty involving an ambiguous outcome, agents tend to be ambiguity prone when losing but ambiguity averse when winning. Finally, Sarin & Weber (1993) found that aversion towards ambiguity is present in both organizational and market settings and that it has the potential to induce psychological discomfort and regret in agents due to hindsight.

Ambiguity is important in the context of agent search because much of the knowledge available to agents is potentially ambiguous. If the agent has access to knowledge about the best possible practice (or globally optimal solution), this knowledge is unambiguous because there is no other course of action that can lead to a better outcome, regardless of what that outcome may be. Accordingly, the optimal search strategy for agents endowed with this knowledge is to exploit the best practice. Similarly, knowledge about the worst possible practice is unambiguous because it is sure to lead to the worst possible outcome. Therefore, the optimal search strategy for agents endowed with this knowledge is to avoid this practice and explore other alternative. However, knowledge about a good, but not the best practice is ambiguous and without further information agents will struggle to define an appropriate search strategy.

Take the example of an agent endowed with knowledge about which practice is the 2nd best practice. In this case, the agent faces not only ambiguity about the relationship
between the 2\textsuperscript{nd} best practice and its outcome (i.e., causal ambiguity), but also ambiguity about whether the outcome of the 2\textsuperscript{nd} best practice may be deemed a success (i.e., outcome ambiguity). Whereas, in this case, causal ambiguity could be addressed by obtaining additional information about the outcome of the 2\textsuperscript{nd} best practice. outcome ambiguity would be harder to address.

One way firms deal with outcome ambiguity is by defining a performance target, or aspirational level (e.g., Audia & Greve, 2006; Boyle and Shapira, 2012; Cyert and March 1963; Greve, 1998, 2003; March and Shapira, 1987, 1992; Shapira, 2017) as a baseline for success. However, even in this case, the success of a 2\textsuperscript{nd} best practice could do not be determined \textit{a priori}, i.e., without incurring the costs of experimenting with it in order to assess whether it satisfies the aspirational level. The reason why this is so is because knowing which solution is the 2\textsuperscript{nd} best does not inform about the number of solutions that satisfy that aspiration and, therefore, does not guarantee a successful outcome. In a sense, this type of information is useless in the context of strategic choice.

Moreover, when the agent is endowed with knowledge, not about which practice is the 2\textsuperscript{nd} best, but about what the outcome of the 2\textsuperscript{nd} best practice is, causal-ambiguity is no longer an issue but outcome ambiguity will still persist. In this case, outcome ambiguity will persist because the agent does not know to which practice the outcome corresponds, or, in other words, if the practice to be adopted is a best practice and, therefore, a success. Moreover, even if the agent knows that the practice is indeed not a best practice, it still faces ambiguity regarding what the outcome of the 1\textsuperscript{st} best practice might be, given that if it is much higher than the outcome of the 2\textsuperscript{nd} best practice, adopting the latter could be considered a failure.

Whereas the realization that the practice to be adopted is most likely not the 1\textsuperscript{st} best practice can, in many cases, be simply inferred, knowledge about the outcome of the 1\textsuperscript{st} best
practice is rarely available because, for example, the 1st best practice has not yet been discovered. As such, agents deal with an unavoidable ambiguity when endowed with knowledge of a good, but not the best practice.

**Search and Learning**

Organizational search is often done with some form of knowledge about the performance environment. Performance targets, or aspirational levels (Audia & Greve, 2006; Boyle and Shapira, 2012; Cyert and March 1963; Greve, 1998, 2003; March and Shapira, 1987, 1992; Shapira, 2017) are often used to balance the tradeoff between adopting a solution and learning about the value of other solutions. Whereas some research has looked at comparisons with best performers (Boyle & Shapira, 2011; Frasier-Sleyman, 1992), and other reference groups (Smith & Chae, 2017), much of the existing literature has looked at the industry average as a common reference point for search (e.g., Bromiley, 1991; Fiegenbaum & Thomas, 1988; Milliken & Lant, 1991). For example, according to classic feedback theory (Greve, 2003; Greve, 1998), if agents have expectations about the average payoff of different solutions in a given industry and their current solution falls below this industry average, agents may search until they find a solution that returns an above-average payoff. Conversely, if their performance is above the industry average, agents must decide whether to adopt this solution, or to continue searching for better solutions.

For this reason, knowledge that an n'th best solution falls below a given average, or aspiration will be associated to fundamentally different search strategies than knowledge that an n'th best solution is above this aspiration level. If a solution is below the industry average, the expected value of exploration is always positive and the best strategy is straightforward: avoid this solution and learn about the value of other solutions. While these knowledge endowments will lead to uncertainty regarding the outcomes of future choices, they will also
be less likely to lead to suboptimal strategies than knowledge that a solution is above the industry average.

Conversely, when agents are endowed with knowledge that a solution is above the industry average, they face a fundamental ambiguity about whether they should exploit their current knowledge, or whether they should try to implement the optimal solution.

In our study, agents endowed with this type of knowledge have, nonetheless, two main advantages: First, they are able to exploit an above-average solution early on if they decide against searching for the optimal solution. Second, they are more likely to find the optimal solution than agents who have no knowledge about the payoff of any solution, since ignoring the 2nd best solution automatically reduces the scope of their search.

However, these advantages do not mean that agents endowed with knowledge of 2nd best solutions will achieve a better performance. One reason why is because search can be done in multiple ways: Agents may ignore this knowledge entirely and learn about the payoff of other solutions; they may forego learning about other solutions and adopt the solution associated to positive knowledge exclusively; or, they may use a mix of these two strategies, either by exploring first and exploiting later on, or vice-versa. Yet, not only do these different strategies lead to different expected values, as those expected values will also change as a function of the distribution of payoffs of the different solutions.

In particular, we argue that the ratio between the payoff of the 1st and the 2nd best solution is critical in determining the adequate search strategy and that, for this reason, agents who are endowed with knowledge of 2nd best solutions may end up implementing strategies that have a negative effect on performance. In contrast, uninformed agents must always initiate search by exploring unknown solutions and since their best strategy is to stick to a solution as long as its payoff clears a performance target, they may, in many cases, achieve a better performance than other informed agents.
As such, knowledge of 2nd best solutions is particularly helpful when agents can make reasonable assumptions about the distribution of payoffs of existing solutions. For example, in contexts in which the distribution of payoffs may vary considerably and where the ratio between the 1st and the 2nd best solution may be particularly high, adopting the 2nd best solution will most likely result in high opportunity costs. Conversely, in contexts in which the distribution of payoffs is less variable and where the ratio between the 1st and 2nd best solution is low, not adopting the 2nd best solution will most likely result in high exploration costs.

It is also worth noting that we are not the first to suggest that more knowledge is not always better. For example, Haas and Hansen (2005) argue that utilizing knowledge to complete sales bids for consulting projects can actually have a negative impact on performance. Similarly, Henderson and Clark (1990) posit that prior knowledge can actually blind decision-making and that it may “not only not be useful, but may actually handicap the firm” (p.13). Finally, Carnahan et al. (2017) also suggest that founders who are not endowed with pre-entry industry knowledge may end up finding better solutions than their informed counterparts. In these and other related studies, however, the definition of knowledge is less restrictive than in our study, as it may involve agents endowed with incorrect, or outdated beliefs. As a result, it is not surprising that knowledge can have negative implications for performance. However we are interested in whether knowledge about a good, but not the best solution always helps performance, even in cases in which the agents’ knowledge endowments are entirely correct and unbiased.

Furthermore, studies that have looked at knowledge utilization from an experimental perspective have not yet fully addressed the conditions under which human agents switch between exploration and exploitation (Puranam et al., 2015). Whereas some studies have shown that the rate of switching between solutions decreases as a function of experience (Lea
et al, 2011; Steyvers et al, 2009), we still lack studies that explain how knowledge about different solutions affects this trade-off. In our study, we look at agents searching while endowed with two types of knowledge: when they know that a solution is above the average, but not whether this solution is the optimal or only an n\textsuperscript{th} best solution; and, when they know that a solution is above average and that it is not the optimal, but only an n\textsuperscript{th} best solution, i.e., the 2\textsuperscript{nd} best solution.

In the next section, we analytically determine the best strategy for these different scenarios and compare its expected value to the performance of human subjects in our experimental setting. We then analyse these strategies in light of different payoff distributions and discuss its implications for theory and research.

METHOD

We employ an experiment in order to investigate how human subjects approach search when they are endowed with knowledge about 2\textsuperscript{nd} best solutions. Even though experiments are known to mitigate some of the endogeneity issues that are typically raised in the management and organizations literature (e.g., Highhouse, 2009), they are also known to suffer from validity concerns. A question that is frequently raised by researchers is the extent to which effects found in the laboratory are still observable in the real world. In our experiments, we address these external validity issues by taking two measures: First, we depart from the traditional experimental population of university students and deliberately broaden the demographic spectrum of our sample by recruiting subjects from Amazon Mechanical Turk; a platform which has been used frequently in the past for experimental research (e.g., Eriksson & Simpson, 2010; Mason & Suri, 2012; Paolacci, Chandler, and Ipeirotis, 2010; Smith & Chae, 2017). Second, we devise a sufficiently abstract task (in the vein of Billinger,
Stieglitz & Schumacher, 2014, 2016), with the goal of capturing the most basic mechanisms of knowledge utilization in the context of strategic decision-making.

Yet another concern of experimental research is the extent to which it minimizes measurement error, or the effects of confounding variables. In order to address these internal validity issues, we design an experimental task where participants may only reach an above-average performance (i.e., a better performance than by random choice) by utilizing the task-specific knowledge that we endow them with, therefore guaranteeing that our final results are not contaminated by any external sources of knowledge. At the same time, demand effects, as in the case of social desirability (e.g., Fisher, 1993; Nederhof, 1985) are also controlled for, given that the entire experiment is conducted remotely and without the presence of a researcher. In order to do so, we ran a series of pre-test experiments with variations in the instructions provided, as well as a series of interpretation questions, which allow us to be reasonably confident about our participants’ understanding of the task.

Furthermore, we rule out the hypothesis that subjects may not be making optimal use of their knowledge because they have limited cognitive capacity to recall the information provided or their past choices. To this end, we display relevant information throughout the tasks, such as the treatment information (i.e., information about the performance target and payoff of the treatment solution), the payoff of prior choices, or the number of times a subject made a particular choice. What is more, we rule out any order effects that might arise from the use of the same payoffs in a within-subjects design by utilizing scaled versions of these values across the different experimental tasks and by randomizing the order of solutions anew for each participant and condition. Finally, as discussed in the section above, we control for the possibility that knowledge may have become obsolete or misleading, given that we always treat our subjects with accurate and unbiased knowledge.
The Experiment

The experiment follows a within-subjects design with random assignment to treatment- and control-group and is conducted over the internet, in the participant’s own computer. Before the experimental tasks we ask our subjects to read a set of instructions about the choices they are about to make and to answer a series of questions regarding these instructions. Here, a rule is imposed to stop participants from progressing to the experimental task (and hence, from reaching the final sample), in case at least one of these questions is incorrectly answered.

The subjects who make it to the next stage face a simple task. The underlying task of the experiment is a sequential choice problem (two periods) between five solutions with different values. Initially, these values are unknown to the participants. Participants are only informed that the average value across all solutions is (for example) zero and that they can only learn about the payoff of their solutions by choosing them. Once a particular choice is made, its payoff is revealed. There is no noise or ambiguity about this information - if, for example, the choice with a payoff of 8.8 is selected, the participants are informed that their choice has a payoff of 8.8. Our participants are also informed about this fact (but, as suggested by the results of this experiment, not all participants had trust in this information).

Beyond a fixed participation fee, which corresponds to around 15% of the participants’ potential payment, incentives are directly tied to the payoff of each participant’s choices in the experimental tasks. Table 1 shows the distributions used to calculate subjects’ bonuses.

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Control-group. Figure 1 shows the information presented to subjects in the control-group. We provide subjects in the control-group only with knowledge about the average payoff of all solutions.

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Treatment-group. In one of our treatment-groups, participants are told what solution is the 2nd best solution and what its payoff is. In another treatment-group participants are simply informed about the payoff of the 2nd best solution, but not whether it is the 2nd best.

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Insert Figure 2 & 3 about here
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Research participants. We recruited a large sample of American, MTurk Workers in two waves (N = 736, N = 712). In total, we obtained 1448 participants, between the ages of 18 and 76 years old (M = 36.5, SD = 11.6). The majority of respondents (59.1%) were female, and 71.3% of the total sample reported that they had participated in the study to earn some additional money, whereas 13.1% revealed that taking Mechanical Turk Human Intelligence Tasks (HITs) represented their primary source of income. Furthermore, subjects also reported an average of three years of higher education studies by the time of the experiment.
**Optimal Strategy in Experimental Task**

Consider that for two periods in time $t$ subjects must choose from a set of five solutions $N$, and that the performance environment can be described by the payoffs $P$ to these solutions, i.e., $P_n = [p_1, \ldots, p_N]$. When subjects are endowed with knowledge that a particular solution $n$ is the $1^{\text{st}}$ best solution, i.e., that $P_n = \max(p_1, \ldots, p_n)$, exploration has no value and the optimal use of this knowledge is straightforward: adopt the $1^{\text{st}}$ best solution in both periods and obtain a safe reward $r_j = 2p_1$, where $r$ corresponds to the cumulative payoff of agent $j$ and $p_1$ to the payoff of the $1^{\text{st}}$ best solution.

However, when subjects are endowed only with knowledge about the payoff of the $2^{\text{nd}}$ best solution ($p_2$), the optimal search strategy is less evident. In this case, subjects face a dilemma because the optimal use of knowledge about $p_2$ depends on the distribution of payoffs, and this is rarely known. For example, as Figure 4 illustrates, when the distribution of payoffs is not fat-tailed, i.e., when the ratio $c = p_1/p_2$ is low, the optimal strategy is to exploit $p_2$ in both periods and to obtain a safe reward $r_j = 2p_2$. Conversely, when the distribution of payoffs is fat-tailed, i.e., when the ratio $c$ is high, the optimal strategy is not to exploit $p_2$ in both periods, but to learn about the payoff of alternative solutions in $t_2$ with the goal of finding a better solution: If a participant finds $p_1$ in $t_1$, the participant can then exploit $p_1$ again in $t_2$; if not, the participant can always fall back on $p_2$ and exploit it in $t_2$, instead. When employed correctly, this strategy has an expected value of $E[r_j] = \frac{1}{4} (2p_2 + p_1)$.
In cases in which subjects do not know the payoff of any particular solution but have information about the average payoff of solutions, the optimal search strategy depends on an initial period of exploration: if the payoff of the solution adopted in $t_1$ is above the average, the optimal strategy is to adopt that solution again in $t_2$; if, instead, the payoff of the solution adopted in $t_1$ falls below the average, the optimal strategy is to adopt a different solution in $t_2$; a strategy with an overall expected value of $E[r_j] = \frac{1}{4} (p_1 + p_2)$.

While the optimal strategy for cases in which agents do not know $p_2$ is dominated by a strategy of using knowledge of $p_2$ to find the $p_1$, not knowing $p_2$ also comes with the benefit of not having to face the ambiguity of determining the correct strategy and, consequently, the likelihood of adopting an inferior one. In addition to this, since agents who do not know $p_2$ do not face any ambiguity about the optimal strategy, they are not affected by the value of the ratio $c$. Thus, to the extent that a large share of agents endowed with knowledge of $p_2$ opts for an exploitation strategy when the ratio $c$ is high, having no knowledge about $p_2$ may lead to a higher performance than being endowed with this knowledge.

Moreover, not all types of knowledge are equally valuable. For example, being endowed only with knowledge that a particular solution $n$ is the 2$^{nd}$ best solution does not help agents determine the optimal strategy. This is because knowing that a particular solution is the 2$^{nd}$ best does not inform about how many solutions are below or above the average payoff. For example, in some cases, there might be only one solution below the average payoff, and being endowed with knowledge about the 2$^{nd}$ best solution would not be synonymous with being endowed with knowledge about an above-average solution. By implication, this knowledge would not allow the agent to formulate a search strategy aimed at achieving an above-average performance.

Finally, we highlight that since the performance environment is stable in this setting, risk does not play a role in the choice between solutions. In other words, agents’ choice
cannot be explained by their propensity to choose between, for example, a solution with a safe payoff, or a solution with an expected value equivalent to that payoff. Likewise, the distribution of negative choices, both in number and in value, is not important for the subjects’ decision-making processes. In this case, the simple strategy of searching when a solution falls below the average, or exploiting otherwise offers the same expected value, regardless of the distribution of negative solutions.

In the section below, we analyse the strategies that our sample employed when facing a similar task and what implications these strategies have for performance.

RESULTS

The Value of Knowledge

In our experiments, we are interested in how knowledge about $p_2$ affects subjects’ performance in this search problem. Specifically, we are interested in how this performance compares to the performance of uninformed agents.

In Figure 5, on the y-axis, we plot the average performance difference (of the sum of payoffs of the subjects choices in $t_1$ and $t_2$) between subjects with knowledge about $p_2$ (treatment-groups) and without this knowledge (control). We do report the performance difference for two different ratios as $c = 7.3$ (left) and $c = 88$ (right).

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Insert Figure 5 about here

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With a relatively low ratio $c$, being endowed with knowledge about $p_2$ has a significant positive performance effect: it helps subjects make choices that are better than
those of uniformed subjects. If, however, the ratio $c$ becomes high, subjects with knowledge of $p_2$ make worse choices than uninformed ones. As such, despite the fact that the knowledge we endow subjects with is totally accurate, it can become a liability, depending on the distribution of payoffs.

Furthermore, we find that when the ratio $c$ between the 1st and 2nd best solution is low, knowing which solution is $p_2$ is critical for performance. This is so because in cases in which the distribution of payoffs does not have a long tail, strategies that involve exploitation of $p_2$ have a high expected value. Accordingly, when agents know that a particular solution is $p_2$ they will adopt this solution more often and, in turn, achieve a better performance than if they are ignorant to this knowledge ($M_{Treatment 1} = 1.9, M_{Control} = 0.9, t(1884.9) = 3.3, p < 0.001$).

Yet, when the ratio between the 1st and 2nd best solution is high, knowing which solution is $p_2$ can actually have a negative effect on performance. Because the distribution of payoffs has a longer tail, the expected value of strategies that involve exploration is higher than the expected value of strategies that involve only exploitation. We find that when this is the case, subjects will achieve a worse performance than if they did not have this knowledge ($M_{Treatment 1} = 3.5, M_{Control} = 4.5, t(1829.2) = -2, p < 0.04$).

At the same time, we look at the performance of subjects who know only $p_2$, but not whether this solution is the 1st, 2nd, 3rd, or even 4th best solution. Even though we find a small performance advantage for the case in which the payoff distribution does not have a long tail, we did not find this difference to be significantly better than the performance of the control group ($M_{Treatment 2} = 1.2, M_{Control} = 0.9, t(1731.6) = 0.8, p = 0.42$), in this case, because participants did not employ enough strategies that involve exploitation of $p_2$.

Conversely, when we look at the case in which the ratio between the 1st and 2nd best solution is high, we find a negative performance effect of knowledge. Even though participants endowed with this knowledge exploited $p_2$ marginally less in $t_1$ and $t_2$ ($M_{Treatment 2}$
= 31.7%, \( M_{\text{Treatment 1}} = 36.5\%, z = 3.5, p = 0.06 \), and in \( t_1 \) alone (\( M_{\text{Treatment 2}} = 19.2\%, M_{\text{Treatment 1}} = 23.2\%, z = 3.2, p = 0.07 \)), they did not invest more in strategies that involve keeping \( p_2 \) as a fallback option for early exploration (\( M_{\text{Treatment 2}} = 14.6\%, M_{\text{Treatment 1}} = 14.4\%, z = 0.0, p = 0.97 \), but explored different solutions instead, in both periods (\( M_{\text{Treatment 2}} = 29.7\%, M_{\text{Treatment 1}} = 21.9\%, z = 11.4, p < 0.001 \)). As a result, the negative effect of knowledge is stronger when subjects are endowed only with knowledge about the payoff of \( p_2 \), than when they are endowed also with knowledge that a particular solution is an \( n^{\text{th}} \) best solution.

**How Knowledge Affects Choice and Search Behavior**

As outlined above, there are two (potentially) rational strategies on how to optimally use knowledge about \( p_2 \) and, which of the two strategies is rational depends on the ratio \( c \). For low ratios, it is optimal to use this knowledge to exploit \( p_2 \) in both periods (“informed exploitation”). For high ratios, it is optimal to try to find \( p_1 \) in \( t_1 \) and, if unsuccessful, fall back on \( p_2 \) in \( t_2 \) (“informed exploration”). For uninformed participants (control-group), in contrast, the optimal strategy is to keep on exploring if \( t_1 \)’s solution is below average and to exploit if \( t_1 \)’s solution is above the average (“uninformed search”).

In Figure 6, we plot the share of participants (y-axis) who adopted any of these rational strategy in this choice problem.

The figure shows that uninformed subjects are more likely to adopt a rational strategy than informed subjects (70% vs. 50%). In this case, the share of rational subjects, as well as
the share of informed exploiters/explorers is unaffected by the ratio. This is not surprising, considering that subjects do not know what the ratio is *a priori*. Yet, it has important consequences for performance. While for a low ratio $c$, informed exploitation is optimal, when the ratio $c$ is high, informed exploitation quickly becomes an inferior strategy and informed exploration becomes a more relevant and superior strategy. This inferiority also explains why for high ratios $c$, uninformed search can lead to better results than informed search.

However, we caution that these results are only a conservative estimate. In the real world, the actual share of informed exploiters is likely higher than in our study. Recall that “informed exploitation” is a risk-free strategy, while “informed exploration” is risky by nature, given its high variance in outcomes. Moreover, we must take into consideration the low incentives and stakes involved in this experiment, which mean that subjects might have acted in a more explorative manner than in the real world.

**Finding Optimal Solutions**

Finally, we look at how being endowed with knowledge about 2nd best solutions affects finding the best, or optimal solution. We expected that, as more subjects in the treatment groups exploited their knowledge endowments, the less likely they would be to find the optimal solution. Figure 7 shows the proportion of participants who found the optimal solution, by experimental condition.

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Insert Figure 7 about here

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Our results indicate that because most subjects in the treatment-group employed strategies that involved some degree of exploitation of \( p_2 \), they were actually less likely to find the optimal solution than subjects in the control-group. Furthermore, we did not register any differences in the proportion of subjects who found the optimal solution in the two different experiments.

**DISCUSSION**

Knowledge is often portrayed as a critical resource (e.g., Grant, 1996; Kogut & Zander, 1992; Szulanski, 1996). This idea is not only broadly reflected in the evolutionary and strategic management literatures (e.g., Cockburn & Henderson, 1998; Cohen & Levinthal, 1990; Kogut & Zander, 1992; Grant, 1996a; Grant, 1996b; Nelson & Winter, 1982; Szulanski, 1996), as it is also reflected in behavioral and decision-making research, where knowledge is known to play a critical role in allowing boundedly rational actors to make informed, and better decisions (e.g., Cyert & March, 1964; March, 1991; Simon, 1947, Gavetti & Levinthal, 2005, Posen & Levinthal, 2011). In the past, superior knowledge bases have been associated to higher firm performance (Garvin, 1998; Senge, 1990), higher strategic flexibility and a quicker reaction to environmental change (Grant, 1996b; Volberda, 1996). Yet, thus far, our understanding of the micro-mechanisms of knowledge utilization and the way in which they remain linked to the persistence of bad practices remains very limited.

The current work examines how organizational search and, consequently, performance is affected by knowledge about 2\(^{nd}\) best solutions. Our experiment indicates that in, for example, entrepreneurial settings, where the payoff of 1\(^{st}\) best solutions may be much higher than the payoff of 2\(^{nd}\) best solutions, adopting 2\(^{nd}\) best solutions will likely lead to high opportunity costs, whereas in, for example, managerial settings, where the distribution of
payoffs is likely constrained by the organization, failing to adopt the 2nd best solution will be associated to high exploration costs.

Our experiment also indicates that subjects are more likely to secure an above-average payoff early on when they know that they are dealing with 2nd best solutions, compared to when they do not know whether a solution is the optimal, or only an nth best solution. Conversely, when subjects know only that the payoff of the current solution is above the average, they are more likely to take this knowledge as negative and explore other, unknown solutions.

What is more, we find that being endowed with knowledge about 2nd best solutions does not seem to induce any fundamental differences in the proportion of subjects who use this knowledge to engage in a strategy of “informed exploitation”. Moreover, we find that subjects do not predominantly employ a strategy that looks for a better solution early on and that uses knowledge about the 2nd best solution as a fall back for this initial exploration; a strategy which always has a higher expected value than guaranteeing an above-target payoff early on, and later exploring an unknown alternative.

The results of these two experiments also lend support to the intuition that, in many industries, newcomers without pre-entry knowledge often end up finding better solutions than incumbents who possess some form of knowledge about existing solutions (e.g., Carnahan et al., working paper): If an agent initiates search with knowledge about the 2nd best solution, the chances of the agent adopting that solution are higher than the chances of the agent looking for the optimal solution, even if the agent is theoretically more likely to do so than if it did not possess that knowledge.

From a managerial perspective, it is also important to understand how micro-level behavior affects organizational-level phenomena (e.g., Gavetti, 2005, 2012; Gibson et al, 2004; Lubatkin et al., 2006; O‘Reilly and Tushman, 2011). Recent research has paid attention
to this need. For example, in a recent fMRI study, Laureiro-Martinez et al. (2014) reveal that while exploration of new knowledge is associated to the activation of brain regions responsible for attentional control, exploitation of existing knowledge is in turn associated to reward-seeking brain regions, leading to a stronger activation, in anticipation of safe, predictable rewards. Furthermore, in a distinct experimental study of search in rugged landscapes, Billinger, Stieglitz and Schumacher (2014) show strong evidence for a behavioral model of adaptive search, by demonstrating that success narrows down search to the neighborhood of the status quo, while failure promotes gradually more exploratory search. We contribute to this conceptual and empirical puzzle by providing a better understanding of how organizational search and, consequently, performance are affected by agent’s knowledge of $n^{th}$ best solutions. Taken together, these findings help us better understand why agents have either been known to over-exploit suboptimal solutions (e.g., Levinthal & March, 1993), or to be too risk-averse to engage in exploratory behavior (e.g., Denrell & March, 2001; March, 1996; Nohria & Gulati, 1996).

**LIMITATIONS**

One important blind spot of this work is the fact that these results haven’t yet been replicated in other contexts, such as in actual organizational environments, or in more traditional laboratory settings. Indeed, we still do not know whether the search behavior we observe might be affected by the introduction of additional factors, such as a higher number of solutions or the stakes involved in real-life contexts. For that reason, we recommend that these results be taken and interpreted conservatively.

Moreover, we should note that the choice for a total of five available solutions in our experiment was made on the basis of practical reasons. In this case, a total of five solutions allows us to have a performance target (i.e., the average), a 1$^{st}$ best, or optimal, solution and
an n\textsuperscript{th} best solution above this performance target, but below the 1\textsuperscript{st} best solution (i.e., the 2\textsuperscript{nd} best solution). Nevertheless, we ended up testing a scenario in which the n\textsuperscript{th} best solution is always represented as being the 2\textsuperscript{nd} best solution, even if in some cases, our subjects were not aware of this. For this reason, we suggest that future studies focus on decisions made on the basis of other n\textsuperscript{th} best solutions.

**CONCLUSION**

We set out to study whether knowledge of 2\textsuperscript{nd} best solutions can have a positive effect on agents’ search and learning processes and in turn, on organizational performance. Our results indicate that when agents have knowledge about 2\textsuperscript{nd} best solutions, their search strategies may actually hurt performance, even if their knowledge endowments are entirely correct and unbiased. In particular, we find that agents have a strong preference for the less risky strategy of “informed exploitation”, which is inferior in settings where the potential gains of finding the optimal solution are quite high. As a result, these more knowledgeable participants make inferior choices compared to participants without this knowledge. These results have important implications for research and practice, especially in light of the fact that ignoring knowledge is difficult (e.g., Camerer, Loewenstein, & Weber, 1989; Heath & Heath, 2006) and that even bad solutions may persist and spread inside organizations (Carroll, 1993; Meyer & Zucker, 1989; Vermeulen, 2014).
REFERENCES


TABLE 1

Payoff Distributions Used to Calculate Incentives

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<tr>
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<th>Distribution 2</th>
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<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; Best</td>
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<td>+14.8</td>
</tr>
<tr>
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<td>+7.2</td>
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</tr>
<tr>
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<tr>
<td>5&lt;sup&gt;th&lt;/sup&gt; Best</td>
<td>-6</td>
<td>0</td>
</tr>
</tbody>
</table>

Note. The two payoff distributions were randomly assigned to each task.
FIGURE 1
Screenshot of the Experimental Task - Information Provided to the Control-group

The average value of solutions in this task is 0

FIGURE 2
Screenshot of the Experimental Task - Information Provided to Treatment-group 1

The average payoff of solutions in this task is 6
Solution 2 is the second best solution and has a payoff of 7.2
FIGURE 3
Screenshot of the Experimental Task - Information Provided to Treatment-group 2

Choice 1

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Solution</th>
<th>Payoff</th>
<th>Times Chosen</th>
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<td>?</td>
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<tr>
<td>Times Chosen</td>
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</tr>
</tbody>
</table>

The average payoff of solutions in this task is 6
Solution 4 has a payoff of 7.2

FIGURE 4
Performance of Different Strategies To Use Knowledge Endowments

- ignore knowledge about 2nd best
- explore and fall back
- exploit
FIGURE 5
Performance Effect of Knowledge

FIGURE 6
Share of Participants Who Adopt a Rational Strategy
FIGURE 7

Share of Participants Who Find the Optimal Solution With and Without Outcome Ambiguity