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**BEHAVIOR IN BEHAVIORAL STRATEGY:
CAPTURING, MEASURING, ANALYZING**

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Measuring behavior requires techniques that can capture observed outcomes and expose underlying processes and mechanisms. In this chapter, we present a toolbox of methods: We designed experimental tasks to simulate decision environments and capture behavior. We deployed protocol analysis and text analysis to examine the underlying cognitive processes. In combination, these tools can simultaneously grasp antecedents, outcomes, processes, and mechanisms. We apply these methods to collect rich behavioral data on two key topics in strategic management: the exploration–exploitation trade-off and strategic risk-taking. This mix of methods is particularly useful to in describing actual behavior as it is, not as it should be, replacing assumptions with data and offering a finer-grained perspective of strategic decision-making.

Keywords: Experiments; Protocol Analysis; Text Analysis; Exploration-exploitation; Risk-taking

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In behavioral strategy, what constitutes “behavior” and how do we measure it? Scientists agree that actual behavior, an outcome, stems from a blend of forces: biological and neurological, psychological, economic, demographical, cultural, political and institutional, to name a few. In behavioral strategy, scholars are often interested in understanding a narrower blend, one that may include accounting for rational contemplation but also biases and heuristics, intuition, and chance (Denrell, Fang, & Liu, 2014; Hodgkinson & Healey, 2008; Tversky & Kahneman, 1975). In any field, a foremost scientific challenge is that of causality: Understanding an outcome while accounting for the forces driving it. This challenge necessitates a toolbox of methods, so that researchers can document actual behavior while peeking into the unobservable mechanisms. For instance, a choice between two options has an observable outcome, but the underlying mechanisms cannot be observed. They must be inferred.

Inferring and measuring such mechanisms is an important research challenge (Hodgkinson & Healey, 2008). It requires techniques that help the researcher collect and analyze data on decision-makers’ behavior and cognition. These can be hard to identify and interpret, so here we propose two experimental instruments, which simulate decision environments. These help us achieve both: Capturing decisional outcomes — choices in ecologically valid settings — while accounting for their predictors through qualitative and quantitative analyses.

Our instruments behaviorally capture two important topics in the field of strategic management: the tension between exploration–exploitation (March, 1991) and strategic risk-taking (Baird & Thomas, 1985). One instrument examines behavior in a canonical setting: search on a rugged landscape, consisting of peaks and valleys (Billinger, Stieglitz, & Schumacher, 2014; Kauffman & Levin, 1987; Levinthal, 1997). We created a realistic landscape that contains resources that are clustered, and asked a decision-maker to repeatedly choose along an exploitation–exploration continuum, as they do in many strategic situations (for a review, see Lavie, Stettner, & Tushman, 2010). A decision-maker may choose the familiar for a predictable gain, may attempt something completely novel

with unknown prospects — or anything in between. Whatever the choice is, the monetary consequences are real. The second instrument elicits a person's behavior when making repeated risky and, separately, ambiguous (or uncertain) decisions, both prevalent in organizational environments (DiMaggio & Powell, 1983; Zucker, 1977) and strategic decisions (Eisenhardt & Zbaracki, 1992; Kaplan, 2008; Levinthal & March, 1993; Zajac & Bazerman, 1991). The instrument presents decision-makers with choices that have real monetary consequences: A participant repeatedly chooses whether to accept a low but certain gain or a higher but less certain gain. Depending on the condition, that higher gain can be risky (probabilistic) or ambiguous (probability unknown).

In this chapter, we first give a brief review of the literature on exploration–exploitation and strategic risk-taking. We illustrate how these activities are typically measured in strategic management research, and show how our experimental instruments complement these measures. Next, we report the behaviors we observed using our instruments and elaborate on methods for grasping the underlying cognitive mechanisms. To examine these mechanisms, we used protocol analysis, a method developed by Ericsson and Simon (1984), and particularly suited for understanding cognition in strategy decisions (e.g., Laureiro-Martínez & Brusoni, 2018; Reypens & Levine, 2017). With this technique, we capture and analyze people's thought processes alongside their behavior. These processes can be expressed as text, so we employ qualitative coding but also a software-based tool to measure validated psychological, emotional, and cognitive constructs. Finally, we discuss how this unique combination of behavioral tasks, protocol analysis, and text analysis helped us uncover how decision-makers behave — and how they think they behave — supporting novel insights into taken-for-granted assumptions in strategic management.

THE TENSION BETWEEN EXPLORATION AND EXPLOITATION

The theory

In many managerial situations — R&D investments, market entry, advertising campaigns — a decision-maker chooses an action, receives feedback, and then chooses again. The choice ranges from repeating a past action in expectation of a familiar outcome (strong

exploitation) to a novel action whose outcome is largely uncertain (strong exploration). Such choices may cause a tension, for example when strategists must choose between consistency or flexibility in times of organizational change (Turner & Rindova, 2012) or when product managers decide on altering features to improve customer satisfaction (Rindova & Petkova, 2007). An optimal action is unattainable. Because probabilities are unknown and feedback is ambiguous, the situation does not lend itself to optimization, even if a decision-maker is fully rational. March (1991) referred to this challenge as the “exploration–exploitation” trade-off, where exploration is associated with “search, risk taking, play, discovery”, and exploitation with “refinement, choice, efficiency, implementation”.

An extensive stream of literature addressed how firms can cope with simultaneous pressures for exploration and exploitation (for a review, see O'Reilly & Tushman, 2013). Potential knowledge gains motivate search for new opportunities and methods, whereas inertia and the need for efficiency drive local search for existing routines and skills (Lavie & Rosenkopf, 2006). Researchers suggested that ambidexterity, the ability to balance the tension between exploration and exploitation, can result in improved outcomes such as sales growth (He & Wong, 2004) and innovation (Tushman, Smith, Wood, Westerman, & O'Reilly, 2010). Yet, this may be contingent on organizational and environmental factors such as firm size (Lavie, Kang, & Rosenkopf, 2011), top management team characteristics (W. K. Smith & Tushman, 2005), and the degree of competition (Jansen, Van Den Bosch, & Volberda, 2006).

Researchers proposed several ways in which firms can achieve such ambidexterity (O'Reilly & Tushman, 2004, 2011; Tushman & O'Reilly, 1996). Organizations can separate both activities over time and sequentially engage in exploration or exploitation (Benner & Tushman, 2003). Alternatively, exploration and exploitation activities can be structured in different organizational units (Christensen & Bower, 1996; Fang, Lee, & Schilling, 2010; O'Reilly & Tushman, 2008) or balanced between internal and external activities such as alliances and acquisitions (Lin, Yang, & Demirkan, 2007). Researchers suggest that balancing exploration and exploitation across organizational modes is more effective than

balancing these activities within a single mode (Lavie et al., 2011; Stettner & Lavie, 2014), because both activities require fundamentally different structures, strategies, and logics (Uotila, Maula, Keil, & Zahra, 2009).

However, firms' exploration–exploitation activities are not a simple sum game of decision-makers' actions (Knudsen & Srikanth, 2014). For this reason, a growing body of research calls for understanding the micro-foundations of exploration–exploitation to complement insights into its macro-foundations (Gavetti, 2012; Gavetti, Greve, Levinthal, & Ocasio, 2012; Gavetti, Levinthal, & Ocasio, 2007; Laureiro-Martínez, Brusoni, Canessa, & Zollo, 2015; Marino, Aversa, Mesquita, & Anand, 2015). Just like firms, decision-makers must balance exploration with exploitation. Most researchers warned about “exploitation traps”: Decision-makers persist with actions that have immediately certain returns but may be suboptimal and become obsolete (Groysberg & Lee, 2009; March, 1991). Others pointed to the danger of over-exploration, when decision-makers pay to experiment, but mistakenly continue to search even after finding a peak of high performance (Billinger et al., 2014; Levinthal & March, 1993). The question of how to maintain a balance of exploration and exploitation — behaving not too cautiously without venturing too far — is fundamental.

Thus, scholars have devoted much attention to ambidextrous decision-makers, those who can reconcile the tension between exploration and exploitation (Gibson & Birkinshaw, 2004; Jasmand, Blazevic, & de Ruyter, 2012; O'Reilly & Tushman, 2004). Ambidexterity studies have identified several personality traits and organizational factors that may affect decision-makers' ability to act in an ambidextrous way (Raisch, Birkinshaw, Probst, & Tushman, 2009). Personality traits linked to ambidexterity are a person's self-efficacy (Kauppila & Tempelaar, 2016), discipline, and passion (Andriopoulos & Lewis, 2009). Organizational factors include the role of knowledge flows (Mom, Van Den Bosch, & Volberda, 2007), networks (Lazer & Friedman, 2007; Rogan & Mors, 2014), and decision-making authority (Mom, Van Den Bosch, & Volberda, 2009).

Over the years, researchers have developed useful measures to capture various exploration–exploitation activities on the firm, team, or individual level of analysis. Table 1 samples how studies operationalized exploration–exploitation, grouped by method.

One group of studies used secondary data of firms to measure exploration–exploitation. These studies relied on patent data (e.g., Katila & Ahuja, 2002) or created indices that reflect the number of new alliance partners, the novelty of a firm’s products, or changes that are introduced (e.g., Stettner & Lavie, 2014). They often used a distinction between expenses on marketing versus R&D to denote exploration and exploitation (e.g., Lavie & Rosenkopf, 2006).

Another group of studies relied on survey methods to study exploration–exploitation at the firm- or individual-level. In these surveys, employees report perceptions of self or organizational explorative or exploitative focus. To develop scale items that reflect exploration and exploitation, researchers have drawn on March’s (1991) work. Based on interviews with managers, the authors listed 14 activities that constitute either exploration (e.g., activities requiring you to learn new knowledge or skills) or exploitation (e.g., activities of which it is clear to you how to conduct them). Survey participants were asked to self-evaluate, using a five-point scale, the extent they engage in these activities. More generally, studies referred to exploitation as opting for certainty, for example by serving existing customers, whereas exploration involves a clear departure from the existing way of doing things, for example by serving new markets. Researchers then developed scale items that reflect this distinction in their respective research setting.

Researchers also applied qualitative methods to study exploration–exploitation (e.g., Andriopoulos & Lewis, 2009; Holmqvist, 2004; Marino et al., 2015). Based on interviews or content analysis of archival documents, these researchers code behaviors or actions that involve experimentation, novelty, or risk as exploration. Behaviors or activities that involve refinement, routinization, or reproduction are coded as exploitation.

March’s (1991, pp. 74-81) seminal work on exploration–exploitation was an agent-based simulation examining learning. It began with individual decision-makers, and

exploration–exploitation was modelled as slow versus fast learning from an organizational code. Researchers have built on his work and developed simulation models to understand how individuals and organizations can balance exploration and exploitation (e.g., Fang et al., 2010). Some simulation studies model how decision-makers search on a rugged landscape, consisting of peaks and valleys (e.g., Fang & Levinthal, 2009; Knudsen & Srikanth, 2014; Lazer & Friedman, 2007). In these models, search in the local neighborhood indicates exploitation and distant search indicates exploration.

These approaches helped us understand exploration–exploitation. However, when researchers rely on secondary data, interviews, survey methods, or simulation models, they inevitably make assumptions about behavior. Thus, despite extensive research on the topic, we know little about how people actually behave in exploration–exploitation settings: How do they choose between the two? Do decision-makers pursue different exploration–exploitation paths? Is search for novel solutions influenced by individual characteristics, such as risk or ambiguity preferences?

Experimental methods offer unique advantages to address such questions. The experiments we utilize here simulate a decision environment. Rather than relying on assumed inputs and mechanisms, or asking people for their perceptions, we can observe actual behavior that has real consequence, a cornerstone of economic experiments.² The controlled environment of a laboratory reduces the risk of confounding factors and endogeneity, a perennial challenge with secondary data. Data collected in a controlled environment are more clean, precise, and objective compared to noisy real-life data or proxies that are often used in strategic management. Experiments are easier and cheaper to replicate, a crucial feature. Because of these advantages, experimental studies on exploration–exploitation have been multiplying. Here we build on these studies and present an experimental (simulational) instrument that captures how people behave in exploration–

² We use “simulational” to denote experiments in the economic tradition, which simulate a decision environment, an environment where choices have real consequences. This differs from asking participants for introspection, perceptions or intentions. Ariely and Norton (2007) eloquently summarize the differences between psychological and economic experiments.

exploitation situations. Most experimental studies operationalized exploration and exploitation as binary activities ^[10] where participants repeatedly choose between two options: either adopt a new routine (explore) or persist with an option that is currently superior (exploitation). In our instrument, participants faced a range of options along a continuum of exploration–exploitation. We examined how decision-makers behave, but also how they consider and reason, when they face exploration–exploitation continuously, with feedback, using a combination of behavioral and self-reported measures. To simultaneously capture behavioral patterns, cognitive mechanisms, and individual characteristics, we deployed a rigorous combination of quantitative and qualitative methods ^[10]

Method	Example measures	Example references
Secondary data	Patents Proportion of citations to patents that were not previously cited by the firm (exploration) or that were already cited (exploitation).	(Dothan & Lavie, 2016, pp. 337-338; Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001)
	New partners The proportion of new partners in a firms' alliances in each year (exploration) Prior alliance experience with a certain partner (exploitation)	(Lavie et al., 2011; Lavie & Rosenkopf, 2006; Lin et al., 2007)
	New introductions An indicator of new products, technologies, or changes introduced by firms in a certain time period. Novel introductions indicate the use of new knowledge, or exploration.	(Greve, 2007; Stettner & Lavie, 2014)
	Marketing versus R&D Alliance agreements were coded depending on whether it involved an R&D agreement; an agreement about joint marketing and service, OEM/VAR, licensing, production, or supply; or a combination of R&D and other agreements.	(Lavie et al., 2011; Lavie & Rosenkopf, 2006)
Survey	Three exploration items that reflect an organization's emphasis on innovation, variation, risk taking, experimentation, and discovery Three exploitation items that reflect an organization's emphasis on refinement, production, selection, and implementation	(Voss et al., 2008)
	Exploration scale with seven items, that include activities such as searching for new possibilities with respect to products/services and activities that are not (yet) clearly existing company policy. Exploitation scale with seven items that include activities such as activities primarily focused on achieving short-term goals and activities which clearly fit into existing company policy.	(Kauppila & Tempelaar, 2016; Mom et al., 2009)
	Exploration items that capture departure of existing knowledge and pursuit of new possibilities, products, customers, or markets. Exploitation items that captures serving existing customers or markets and building on existing knowledge or products.	(He & Wong, 2004; Jansen et al., 2006; Rogan & Mors, 2014)
Qualitative	A metric that captures to what extent solutions depart from the industry standard.	(Marino et al., 2015)

Case study or content analysis	Exploration includes actions such as experimentation, novelty, risk taking, trialing, and innovation. Exploitation includes actions such as refinement, routinization, reproduction, and fine tuning.	(Andriopoulos & Lewis, 2009; Holmqvist, 2004; Uotila et al., 2009)
Simulation	Slow versus fast learning from codified organizational norm	(Fang et al., 2010; March, 1991; Miller, Zhao, & Calantone, 2006)
	Search on rugged landscapes, typified by peaks and valleys	(Billinger et al., 2014; Fang & Levinthal, 2009; Knudsen & Srikanth, 2014; Lazer & Friedman, 2007)
Experiment	In each period, participants choose between a familiar option (exploitation) or a new one that may have a higher or lower pay-off (exploration).	(Billinger et al., 2014; Ederer & Manso, 2013; Håkonsson et al., 2016; Laureiro-Martínez et al., 2015; Van Rijnsoever, Meeus, & Donders, 2012)

Table 1. Overview of exploration–exploitation measures by method.

A behavioral measure of exploration and exploitation

For the study of exploration–exploitation decisions, we adapted Wildcat Wells, a behavioral-simulational instrument used to study communication in networks (Mason & Watts, 2012). The instrument features a lot of sand that is said to contain hidden oil fields (Figure 1), spread in a pattern of peaks and valleys, modelled as a rugged landscape (Kauffman & Levin, 1987; Levinthal, 1997). We told participants, without deception, that the oil was spread in fixed patterns, but did not tell them what the patterns are. Each participant sought to collect as much oil as possible, by deciding whether to keep drilling in a known location with unchanged performance; drill nearby a known location, where performance varied a bit; or jump far in hope of higher performance but with much uncertainty.

The instrument measures behavior by employing an induced value approach (V. L. Smith, 1976), common in experimental economics. According to it, choices are credible because they have monetary consequences, affecting the participant’s earnings. Thus, participants were paid-for-performance: Each received a show up payment plus an amount that varied in direct correlation with the amount of oil he recovered.

In the version presented here, the experiment was conducted individually. To measure exploration behavior, we calculated the search distance between consecutive drilling spots.

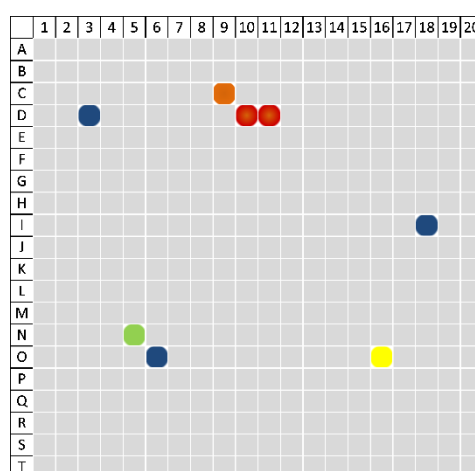


Figure 1. A measure of exploration–exploitation

The task faithfully represents the important features of an exploration–exploitation situation, as described in previous literature:

Limited resources. Participants had only limited time, so they could sample only a fraction of the entire landscape. The landscape consisted of 400 drilling spots, but participants only had 20 rounds to drill, so they could explore at most five percent of the landscape. Due to resource constraints, a trade-off naturally arose, because any resources spent on exploitation could not be spend on exploration, and vice versa. As a result, most potential spots remained untapped. This design feature is informed by situations where managers are constraint in the number of strategies they can pursue, because of constraints such as budget, time, and attention (Cyert & March, 1963; Gavetti et al., 2007; March, 1991; Turner & Rindova, 2012).

Minimal information. We only provided minimal information, so there was no map that described the terrain — a decision-maker discovered it by experiencing it. In the task, participants did not know how the oil was distributed or what the availabilities of oil were. They only knew that some of the oil reservoirs may lay closer to the surface, easier to reach, and therefore may be more profitable. Other reservoirs, we explained in the instructions, may lay deep underground, requiring more effort, and therefore may be less profitable. Some areas were completely dry. With this limited information, optimization was impossible, because the probabilities of outcomes were unknown (Alchian, 1950; Gittins, 1979). As in managerial settings, decision-makers did not have ex ante knowledge of what may be the best strategy, they could only learn through experience. In each round, each participant chose a spot to drill, received feedback, and could then choose again. Thus, participants, like managers, went through an iterative process of actions, evaluations, and reactions (Cohen, March, & Olsen, 1972; Cyert, Feigenbaum, & March, 1959; Cyert & March, 1963; March & Simon, 1958).

Valid feedback. Participants knew that the locations and sizes of oil reservoirs were set before the study began and that these were not affected by anyone's actions and did not change. Thus, the landscape offered valid feedback (March, 1991) and

served as an objective reality against which decision-makers' actions were tested (Ramoglou & Tsang, 2016).

Rugged landscape. The landscape was rugged, so outcomes were correlated in space (Kauffman & Levin, 1987; Levinthal & March, 1993). We instructed participants that the oil reservoirs stretched over an area in a pattern, so that the amount of oil in one spot may be related to the amount of oil in its neighboring spots. We also showed an example of how a natural resource, such as those “lakes of oil”, can be distributed in a pattern. The pattern was shown by colors: An identical color meant that the same amount is available; different colors meant different levels of availability (Figure 1). So, participants knew that they could expect similar outcomes if they stayed in nearby regions. But, if they wanted to discover novel outcomes, they had to experiment and search across the landscape. As in managerial situations, breakthrough discoveries required a more extensive search than incremental improvements (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001).

Exploration and exploitation as two ends of continuum. As proposed by Lavie et al. (2010), we represented exploration—exploitation as two ends of a continuum rather than binary choices or separate activities. Some studies considered exploration or exploitation as a binary choice (e.g., Håkonsson et al., 2016; Laureiro-Martínez et al., 2015; Van Rijnsoever et al., 2012), but this design choice may not fully reflect the range of choices in-between pure exploitation and exploration. Some studies also measured exploration and exploitation as orthogonal activities on separate scales (e.g., Jasmand et al., 2012; Kauppila & Tempelaar, 2016; Mom et al., 2009), potentially underestimating the inherent trade-off between both activities. While the tension between exploration and exploitation may be reconciled, for example by separating both activities over time, it does not take away the inherent trade-off that arises when decision-makers need to allocate limited resources to either exploration or exploitation. We therefore consider exploration and exploitation as two ends of a single continuum, since it closely reflects the tension individuals face when making exploration—exploitation decisions.

Managerial serendipity. Participants were not bound to begin exploration at a specific point. Instead, they could choose to begin wherever desired. This feature reflects some of the serendipity of managerial decision-making (Denrell et al., 2014; Sidney G. Winter, 2012). Information accumulated only with experience, so initial steps were necessarily random. Because of this design feature, individuals necessarily went through a process of blind variation, where actions were initially guided by trial and error (Campbell, 1974). Most likely, we would observe different responses had we required participants to start at the point of lowest performance, in which any move would necessarily result in improved performance.

STRATEGIC RISK-TAKING

The theory

Risk plays a central role in strategic decision-making. Imagine a situation where a manager must choose between spending on advertising for a staple product, expecting a certain return, or investing in additional features. Market studies project that advertising will increase consumers' willingness to pay by five percent; additional features will increase it by ten percent, but with a 50 percent probability. What would the manager choose? Even if it involves known probabilities and no major exploratory option, such a decision requires a choice on the exploration–exploitation continuum. The outcome will affect performance, so strategy researchers have long aimed to understand the antecedents of strategic risk-taking.

Scholarly interest in decisions under risk decisions dates at least back to Frank Knight (1921), who distinguishes between risky situations, in which the probability distribution is known, and ambiguous and uncertain ones, in which it is absent, as in our setting (also see, Ellsberg, 1961). Management scholars first developed conceptual models of strategic risk-taking. In 1985, including industrial, organizational and decision-maker variables. In 1998, Wiseman and Gomez-Meija (1998) and March and Shapira (1987) found that managers do not interpret risk by assessing probabilities of possible outcomes. Rather, the authors suggest that performance targets guide managers' decisions. found that managers do not interpret risk by assessing probabilities of possible outcomes. Rather, the authors suggest that performance targets guide managers' decisions.

Since then, much research on risk examined how different types of incentives affect risk-taking behavior of managers or executives, such as equity-based compensation or stock options (e.g., Wright, Kroll, Krug, & Pettus, 2007). Another stream of literature considers the effects of CEO characteristics, such as social class background (e.g., Kish-Gephart & Campbell, 2015), hubris (e.g., Li & Tang, 2010), and celebrity status (e.g., Cho, Arthurs, Townsend, Miller, & Barden, 2016). In absence of direct data on CEO behaviors, these studies naturally rely on archival data and use various proxies for risk-taking such as a firm's research and development expenditures, capital expenditures, the value of the firm's long-term debt, size of acquisition premiums, or a combination thereof. While these measures may capture aggregate firm-level actions, they fall short of identifying the actual risk choices of individuals.

To this end, studies have used experimental methods to capture strategic risk-taking and its antecedents. For example, Chng and Wang (2015) used a decision-making task, where managers are presented with hypothetical scenarios and are asked to make several business decisions. In such experiments, participants are asked to allocate a budget to different projects that vary in terms of risk and rewards. Risk-taking is then measured as the amount of money spent on a risky investment. In these scenarios, probabilities of success or failure of choosing the risky strategies are presented to participants.

As scholar have recognized early, some life decisions are risky, such as whether to buy a lottery ticket, but many are ambiguous or uncertain. This is true in most organizational and strategic settings: A probability distribution of outcomes is unavailable. For this reason, our instrument separately measures preferences for risk and ambiguity (better known as uncertainty).

A behavioral measure of risk and ambiguity

Decision-making research, in psychology and economics, shows that individuals have different preferences for risk. These affect a range of behaviors, such as saving money, buying insurance, choosing to smoke, or changing jobs.

Building on a measure from an impactful study in neuroeconomics (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005), we developed a web-based instrument, which measures risk and ambiguity preferences separately and behaviorally, again — by simulating a decision environment where choices have real consequences. The instrument reflects the distinction between risk and uncertainty (Knight, 1921) by asking participants to choose between combinations of certain payments, payments with some known probability (i.e., risky payments), and payments with unknown probability (i.e., ambiguous or uncertain payments).

We presented a deck of cards composed of red and blue cards. Each participant then chose between accepting a certain but low reward — or betting on the color of a card in hope of receiving an uncertain but higher reward. If participants chose to bet, they only received a reward if the color they chose matched the color of a randomly drawn card. In the risk treatment, the proportion of blue and red cards in the card deck was known, so participants could calculate the probability of receiving a higher reward. In the ambiguity treatment, the proportions were unknown, so probabilities were incalculable and so was expected value. Participants made 24 risky and 24 ambiguous choices, in a random order.

Based on the proportion of risky and uncertain bets, we developed a risk and ambiguity profile for each participant. Participants' earnings in this experiment were determined by their choice in one randomly drawn round.

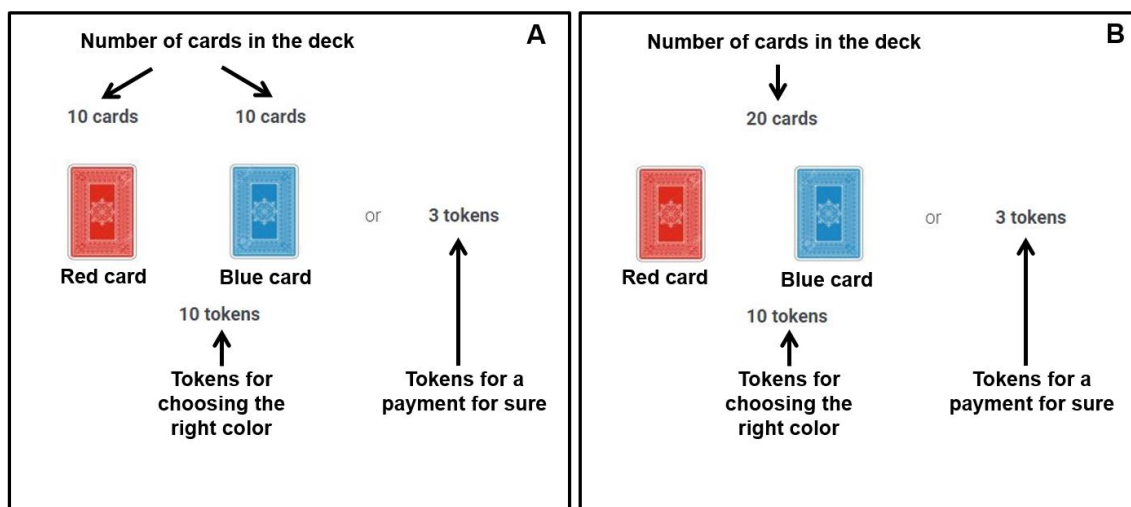


Figure 2. A measure of risk (left) and ambiguity (right).

EXPERIMENTAL PROCEDURE

We recruited 57 participants, almost all graduate students. At first blush, the use of student participants appears to hinder generalizability. But studies that compared student versus managerial behavior found few differences between how the two populations, even in complicated decision-making tasks such as forecasting (Bolton, Ockenfels, & Thonemann, 2012). Two large reviews have recently concluded that there are no systematic differences between the behavior of students and managers in many cognitive functions (Fréchette, 2015, 2016). This is not entirely surprising: Today's students are tomorrow's managers.

We conducted the experiment one-on-one with individual participants. When a participant entered the room, she was randomly assigned to begin either with the risk/ambiguity or the exploration task. Participants completed the risk/ambiguity task using a laptop. To complete the exploration task, participants were asked to stand in front of a board depicting the landscape and read the instructions. When finished, each participant answered comprehension questions. If at least one question was wrong, we referred the participant back to the instructions and allowed her to change her answers. If a participant failed the comprehension questions twice, she was dismissed.

During the exploration task, we requested participants to verbalize their thought processes as they emerged during the experiment, as per protocol analysis guidelines (Ericsson & Simon, 1984). With their consent, we audio recorded these verbal reports. Before participants started, we gave them a short exercise and asked them to think out loud as they were looking around the room. We then gave participants a marker that they could place on any location in the landscape. After they decided where to drill and placed the marker there, the experimenter revealed the outcome.

As participants made their drilling decisions, we probed them to think out loud. Following Ericsson and Simon's (1984) guidelines, we regularly asked them to share their thoughts or say whatever was going through their mind. After the exploration task, participants answered a short questionnaire to measure their confidence and action bias as they were conducting the experiment (see Appendix for measures). We controlled for these

measures, since participants that are more confident and inclined to take action during the experiment, are likely to be biased towards exploration.

All participants were paid for their performance. The experiments were reviewed and approved by the Institutional Review Board.

ANALYZING BEHAVIORAL AND SELF-REPORTED DATA

Behavioral data

We quantitatively analyzed 1140 exploration–exploitation decisions and 2736 choices between certain and risky or ambiguous outcomes. Our dataset also included measures of participants’ action bias, confidence, and general demographics.

We first created a measure for each participant’s exploration–exploitation behavior. We calculated the search distance between two consecutive drilling spots a participant chose. Large search distances indicate long jumps on the landscape or exploration, small search distances indicate search in the local neighborhood or exploitation. We then mapped participants’ search distances over time (Figure 3). By large, five different patterns emerge. Some patterns reveal high peaks (e.g., participants no. 16, 21, 46), indicating frequent jumps across the landscape. Other patterns also show peaks, but lower and less frequent ones (e.g., 10, 28, 95). Some patterns show only a strong peak in the early rounds (e.g., 12, 27, 73). Others show the opposite: only in the end there is a peak (e.g., 15, 32, 63). Some patterns are completely flat (e.g., 11, 57, 75), indicating that these participants only searched around the local neighborhood of previous drilling spots. These different search patterns reveal that participants not only differ in how much they explore, but also in when they choose to explore.

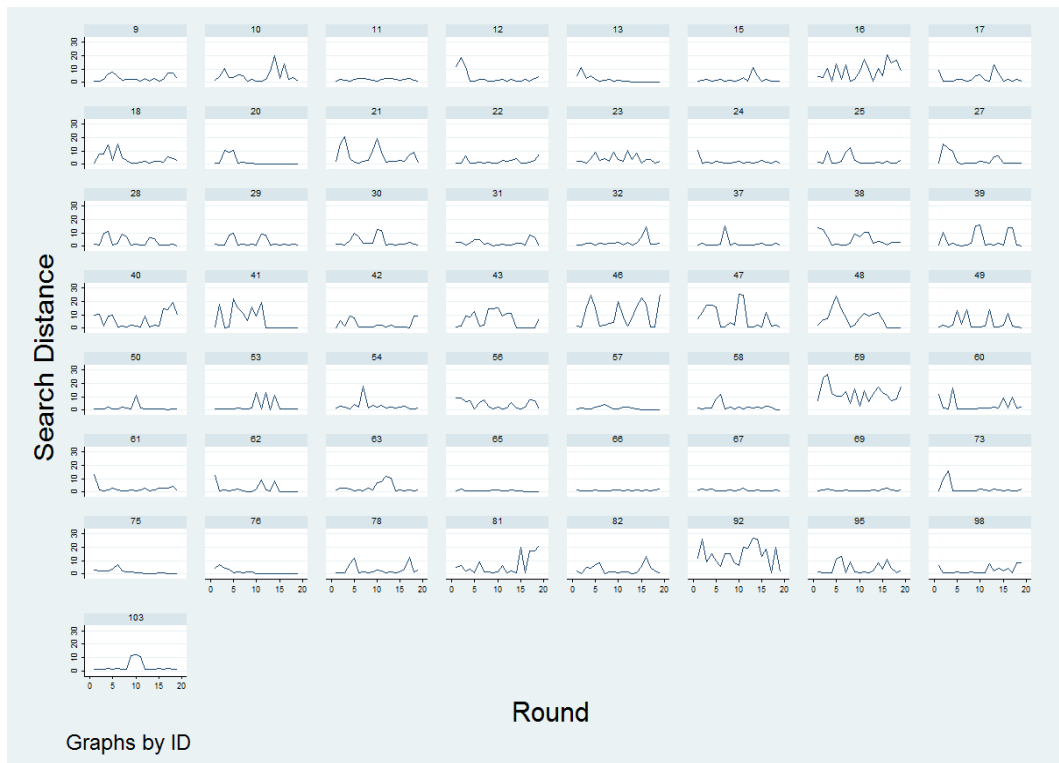


Figure 3. Individual participants' search patterns over time.

Based on participants' repeated choices between certain and risky or ambiguous payoffs in the card task, we created a score for each participant. The score reflects the percentage of times a participant preferred the certain outcome over the risky or ambiguous one. Choices for certainty in the risk and ambiguity treatment were somewhat correlated (correlation of 0.5091). Figure 4 shows this correlation. The figure also shows that more people opted for certainty in risky situations than in ambiguous situations (right lower quadrant versus left upper quadrant). Those that preferred certainty under ambiguity almost all also preferred certainty under risk (right upper quadrant). Some preferred certainty under risk, but were comfortable with ambiguity (right lower quadrant). Most people that were comfortable under ambiguity were also comfortable under risk (left lower quadrant).

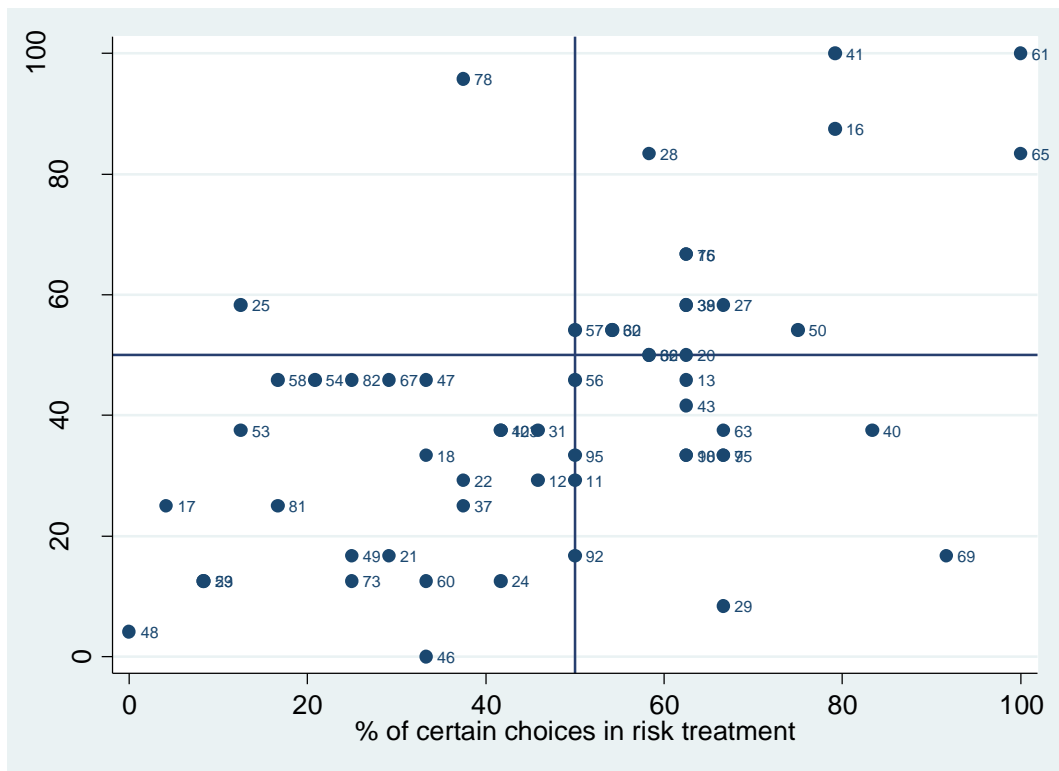


Figure 4. The percentage of certain choices participants made in the risk treatment (x axis) and ambiguity treatment (y axis).

Self-reported data

Next to the quantitative behavioral data, we collected qualitative data on participants' thought processes during the exploration task. We first transcribed the 57 audio recordings and then manually coded each verbal report with the qualitative analysis software NVivo (QSR International, 2012). Our coding followed the process of open, axial, and selective coding as recommended by qualitative researchers (Miles & Huberman, 1984; Strauss & Corbin, 1990). We first openly coded the transcripts. During this phase, we labelled words and passages as close to the data as possible. Then, we used axial coding. In this step, we grouped codes into higher-level constructs. For example, the open codes "stay in the same cluster", "change directions", "stay around profitable area" were grouped into the higher-order category "stay close". Finally, we applied selective coding and grouped axial codes into core behaviors. These were "exploit", "explore", "exploit and explore".

Figure 5 represents our inductively created coding map, where the box sizes represent the relative frequency of each of the axial and selective codes. The figure shows that about

half of the codes were linked to exploitation. From the other half of the codes, the majority referred to strictly exploration. The remaining codes indicated the tension between exploitation and exploration.

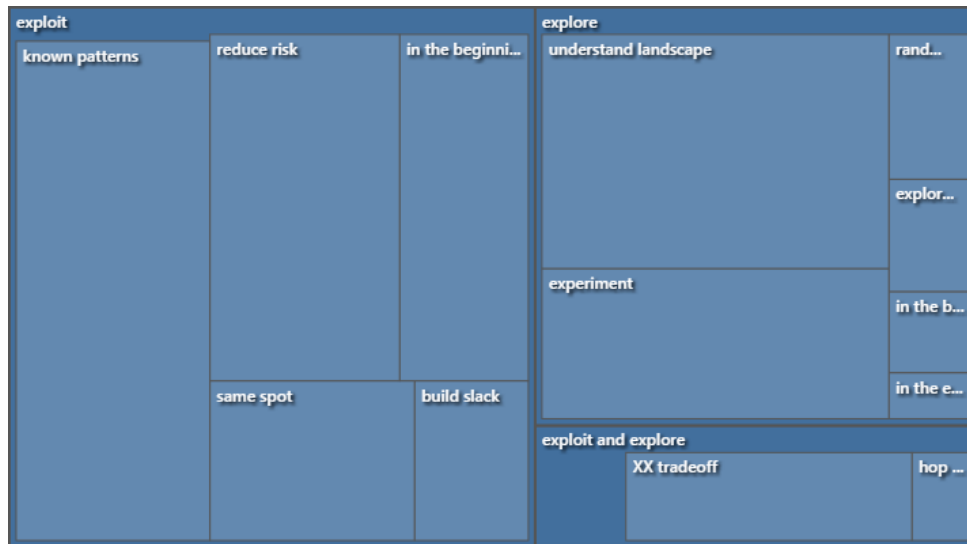


Figure 5. A visual coding map of selective codes (e.g., exploit) and axial codes (e.g., known patterns).

Based on the manual coding of participants’ verbal reports, we distilled several processes and drivers of exploration and exploitation emerged. Table 2 reports illustrative quotes related to exploration and exploitation. For example, the verbal reports revealed that when people *exploited*, they followed existing patterns and stayed close to previously discovered spots. When people *explored*, they were often guided by random choices. Some chose arbitrary drilling locations, for example based on their lucky numbers. Whereas some were strictly focused on finding the maximum outcome and viewed unsuccessful exploration as wasted chances, others were exploring for the fun of experimenting.

Exploitation

I am just going around the same lines, considering there were a lot of barrels there (participant 15)

I think I am going to use the option of re-drilling in the same area, so that is [in coordinates] O-15. I’m going to re-drill in the same area one more time O-14. Yea one more time, O-14. (participant 49)

The safest bet right now I think would be K-13. Alright, so I am just going to exploit the potential of this place over here (participant 66)

We can keep drilling in the same spot which means that I can earn the same amount of oil, I would like to go with H-11. So that my points increase, I would again go with I-11 (participant 16)

Exploration

I'm going to try a random pattern and understand first how large I can go, so something completely random (participant 43)

Now let me try to find a different pattern to see if I can get something better or something equal in a different area (participant 81)

Now I just want to give it a try, I just need to know whether 1000 is the maximum availability or if there is anything more, so I'm just giving it a random try (participant 10)

Now let me try going south and see what we got, just for an experiment and let me pick J-10 (participant 23)

Table 2. Example quotes related to exploitation and exploration.

To complement manual coding, we used a text analysis software, Linguistic Word Inquiry Count (LIWC, Pennebaker, Booth, Boyd, & Francis, 2015). The software analyzes each document on pre-defined categories such as emotions or cognitive processes and indicates how this document scores on each of these categories (Pennebaker, Boyd, Jordan, & Blackburn, 2015). To calculate such a score, the developers created a dictionary of words that reflect a certain category. For example, the category “achievement” contains 213 words such as “win, success, better”. Along with other categories such as “power” and “reward” it is grouped in a higher order category “drives”. The category “cognitive processes” includes 797 words and contains sub-categories such as “causation”, “discrepancy”, “differentiation”, “insight” and “tentative”. Since the software’s development in 2001, the categories have been extensively validated in different populations of writers and speakers such as CEOs and students (e.g., Nadkarni & Chen, 2014; Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014). To analyze text documents, the software compares the words and stems in the documents with the words in the software’s dictionary of words and categories. The software then calculates a score that represents the percentage of words in a document that belongs to a specific category, controlling for text length.

Figure 6 shows the mean LIWC scores per category. As can be expected given the experimental setting, participants’ verbal reports score high on words that reflect a present focus (e.g., now, is) or relativity words that reflect space (e.g., down, next), motion (e.g., go), or time (e.g. until). On average, around 15 percent of the words participants used reflect cognitive processes (e.g., think, wonder, because, know). Of the cognitive processes, those that reflect tentative words were most common (e.g., maybe, perhaps), followed by insight

(e.g., think, know), differentiation (e.g., but, else), discrepancy (e.g., should, would), and causation (e.g., because, effect). Words that express certainty represent a small minority (0.61 percent).

Participants' verbal reports also reveal a reliance on affective processes. Participants' mostly used words that revealed positive emotions (e.g., love, nice, sweet). To a lesser extent their verbal reports contained negative emotions such as risk and sadness. The LIWC scores also show that some participants' choices were driven by finding the maximum amount of oil. This is illustrated by drives such as rewards (e.g., take, price, benefit), achievement (e.g., win, success, better), and power (e.g., superior).

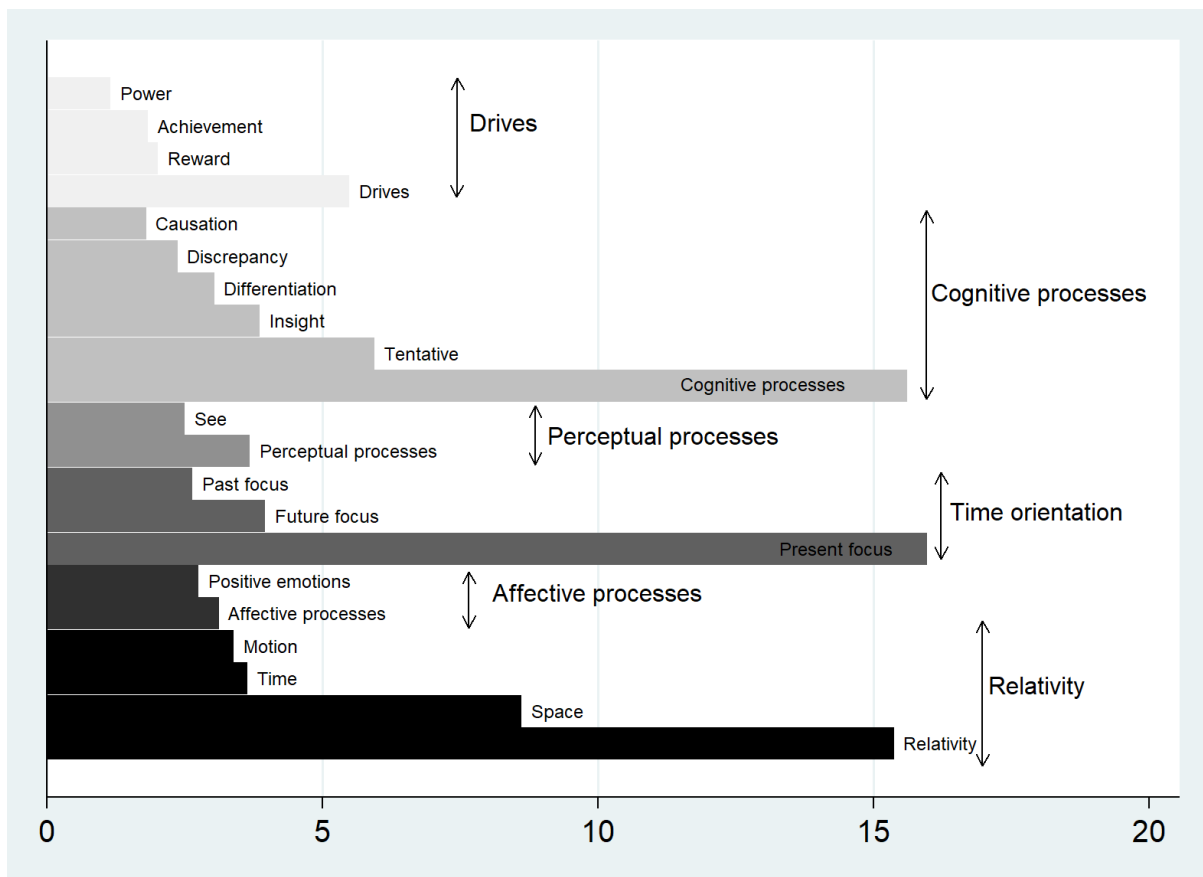


Figure 6. Mean scores of LIWC categories. From top to bottom: Drives (power, achievement, reward); Cognitive processes (causation, discrepancy, differentiation, insight, tentative); Perceptual processes (see, hear, feel); Time orientation (past, present, future focus); Affective processes (positive emotions, negative emotions); Relativity (motion, time, space).

DISCUSSION

In this chapter, we described instruments to examine the exploration–exploitation tension and risk-taking. Both topics have been studied extensively, but mostly using methods that rely on assumptions about behavior. The instruments we presented can help narrow the gap,

by supplementing assumptions with evidence. We used a combination of methods: experimental tasks, protocol analysis, and text analysis. By triangulating qualitative and quantitative data of actual behavior and thought processes, several insights emerge.

With our mix of methods, we can uncover how intuitive and emotional drivers underlie behavior. March (1991) acknowledged this intuitive component, when he associated exploration with play in his seminal work. Yet, empirical work that followed this seminal piece mostly considers exploration as a directed, strategic choice, often measured using archival data on patents, R&D investments, or the choice of alliance partners. While such measures may capture the search, risk taking, and discovery aspects of exploration as defined by March (1991), they do not fully capture the playful, intuitive mechanisms that also drive exploration. Next to these intuitive mechanisms, our proposed methods can also grasp emotions. Drawing on substantial research in psychology, management researchers call for studying emotions in organizational settings (Huy, 2012) and consider it an important, still unfolding field of discovery (Ashkanasy, Humphrey, & Huy, 2017). We used the text analysis software LIWC to identify the emotions that may play a role, based on decision-makers' verbal reports of their thought processes.

By studying people's decision-making processes and uncovering underlying mechanisms, we can discover subtleties in taken-for-granted assumptions. As Raisch et al. (2009) note, a common assumption in firm-level or team-level studies on exploration–exploitation is that decision-makers simply switch between the two, for example when such activities are split over organizational units. Studies on the individual level do acknowledge there are differences in how decision-makers choose between exploration and exploitation (e.g., Jasmand et al., 2012; Kauppila & Tempelaar, 2016; Mom et al., 2007, 2009). These researchers, among others, suggest that not everyone is equally able to balance the two, which is why they seek to identify the context factors or personality traits shared by decision-makers who do balance exploration with exploitation. Yet, these studies seem to assume that there is a homogenous group of ambidextrous decision-makers who mentally process the tension between exploration and exploitation in the same way. Our instruments and

methods can directly test these assumptions, by enabling a closer look into people's behavior and thought processes as they face the tension between exploration and exploitation over time.

Through the rigorous design of experimental instruments, we can capture related, but distinct concepts, offering a finer-grained perspective of strategic decision-making. Following Knight (1921), we created an instrument that distinguishes between risk and uncertainty. Given the prevalence of ambiguous situations in management, experimental studies on the antecedents of strategic risk-taking may also include decision-making under uncertainty, without presenting the probabilities of success or failure of certain strategies. Since not all decision-makers may respond equally to risky or ambiguous situations, antecedents of strategic risk-taking may have different effects when decision-makers decide under ambiguity.

The micro-level insights that emerge using our toolbox of methods can advance our understanding of macro-level phenomena. When solely focusing on macro outcomes, important micro-level differences may dilute. Such a focus on outcomes, without considering underlying decision-making processes, may be shortsighted. For example, several features of the organizational context that have been suggested to support exploration at the team or firm level, may have different effects on individual organizational members depending on their decision-making processes. These individual-level differences in turn can influence the balance between exploration and exploitation at the team and organizational level.

Here we focused on individual-level processes, but there is value in looking beyond them: organizational search often involves interaction and collaboration (Levine & Prietula, 2012, 2014). And interacting with others raises questions of emotions and team processes (e.g., Håkonsson et al., 2016), interpersonal power and trust (e.g., Schilke & Huang, Forthcoming; Schilke, Reimann, & Cook, 2015). The plot is further twisted by a variety of situational conditions that can affect search, such as the diversity of counterparts involved. Research has shown that even seemingly unrelated features, such as the ethnicity of others,

can affect how an individual processes information and this the search outcome (Levine et al., 2014; Levine & Stark, 2015).

To understand exploration–exploitation, at any level of analysis, it is important to consider underlying decision-making mechanism (Baer, Dirks, & Nickerson, 2013; Teece, 2007; Sidney G Winter, 2013). By shedding light on these mechanisms, our understanding of the microfoundations of strategy can be advanced.

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APPENDIX

Confidence

Five-point Likert scale: 1 = not at all, 5 = to a very great extent.

1. When making drilling decisions, I was confident
2. I knew from the start which areas contain the most oil
3. It was easy to figure out where the oil was
4. I did not know how the oil reservoirs were distributed (Reverse)
5. It was easy to know when I found the most profitable drilling spot

Action Bias

1. Five-point Likert scale: 1 = not at all, 5 = to a very great extent.
2. It was hard to decide between drilling in the same spot or choosing a new one
(Reverse)
3. I felt conflict when thinking about drilling in the same spot
4. It was very easy for me to choose moving to a different drilling spot
5. I felt compelled to drill in a different spot each round