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ABSTRACT

This paper focuses on the role of managerial cognition and decision making as a source of heterogeneity in firm strategies and firm performance. We link differences in managers' mental models to differences in their decision rules, strategies, and performance in a management simulation. Our results show substantial variation in mental model accuracy with more accurate mental models leading to better decision rules, better strategies, and ultimately resulting in higher performance. We find that decision makers do not need accurate mental models of the entire business environment, but accuracy in understanding key principles of the deep structure leads to superior strategies and superior performance. In decision makers' mental models, we also find evidence of superstitious beliefs and causal blind spots that undermine performance. Overall, our findings provide empirical evidence linking managers' mental models to their decision rules, strategies, and performance outcomes and, thus, help explain why managers and firms adopt different strategies and achieve different levels of competitive success.

Keywords: managerial cognition, mental models, dynamic decision making

Understanding why firms adopt different strategies is of central importance to strategy scholars and there is substantial evidence that managerial cognition is a critical determinant of strategic choices (Gavetti, 2005; Kaplan & Tripsas, 2008; Porac, Thomas, & Baden-Fuller, 1989; Reger & Huff, 1993; Simon, 1991; Walsh, 1995). Research findings show that mental models impact decision making through managers' efforts to match strategic choices to their understanding of the business environment (Barr, Stimpert, & Huff, 1992; Porac *et al.*, 1995; Tripsas & Gavetti, 2000). However, there is limited empirical evidence for the link between mental model accuracy and performance (an exception is Bourgeois, 1985). It is also unclear whether accurate mental models of the complete business environment are necessary for effective decisions and superior performance, or if only partial knowledge is required. Recent simulation-based research suggests that even partial knowledge of the business environment may dramatically improve performance (Denrell, Fang, & Levinthal, 2004; Gavetti & Levinthal, 2000), but thus far we have scarce empirical evidence. An important agenda for research into the cognitive aspects of strategy is to better understand the connection between mental models and performance outcomes and also to understand the types of deficiencies or misperceptions in decision makers' mental models that significantly degrade performance. This paper reports the results from an experimental study examining the relationships between differences in mental models, decision rules, strategies, and performance.

In the experiment, we utilize a management simulation to investigate these relationships in a controlled setting. While managerial mental models, decision rules and strategies develop in highly complex organizational decision environments, an experimental design enables better-targeted and more precise measures of constructs and testing of hypothesized causal relationships. Our analyses highlight several features of managerial cognition and strategic decision making that have not been studied in previous research. The findings show that accurate inferences about the causal relationships at work in the business environment result in superior performance outcomes and that superstitious beliefs and causal blind spots undermine effective decision-making and performance. Our results also show that decision makers do not need accurate mental models of the entire business environment, but rather an accurate understanding of the key principles of the deep structure. The findings also reveal considerable variation in the decision rules adopted. Decision makers with more accurate mental models and fewer superstitious beliefs and causal blind spots were more likely to adopt higher-performing decision rules. We also find that the different decision rules cluster into a relatively small number of distinct strategies, and that these strategies are significantly related to mental model accuracy and performance. Connecting heterogeneity in mental model accuracy to differences in decision rules and strategies contributes to our understanding about how and why strategic decisions emerge as they do and why managers adopt different strategies.

In the following sections, we start by highlighting the relevant theory and empirical findings from existing research on managerial cognition and decision making that underpin our hypotheses. In particular, we discuss research that examines variation in mental models and the links between mental models and outcomes. This is followed by a description of our methods and a discussion of the results. In the conclusion we discuss our contribution to the understanding of how differences in managerial cognition and decision making lead to differences in performance, and identify opportunities for future studies in this area.

THEORY AND HYPOTHESES

Managers have limited information processing capabilities to deal with the vast amounts of ambiguous data available for making strategic decisions. As a result, managers rely on simplified mental models of reality to organize their knowledge and make sense of the world (Cyert & March, 1963; March & Simon, 1958). Research in psychology shows that these knowledge structures impact perception, information processing, problem solving, judgment, learning, and decision making (e.g., Anderson, 1990; Johnson-Laird, 1983; Rehder, 2003). Similarly, management research provides extensive evidence that managerial mental models are heterogeneous and that these simplified representations of reality impact strategic choices (Barr *et al.*, 1992; Eden & Spender, 1998; Gavetti, 2005; Gavetti & Levinthal, 2000; Hodgkinson *et al.*, 1999; Huff, 1990; Jackson & Dutton, 1988; Kaplan & Tripsas, 2008; Porac *et al.*, 1989; Reger & Huff, 1993; Simon, 1991; Tripsas & Gavetti, 2000; Walsh, 1995). Research spanning psychology, administrative and organization theory, economics, political science, computer science and cognitive science have used a variety of terms for these knowledge structures, including: mental models, schemas, dominant logics, causal maps, cognitive maps, frames, and belief systems (Axelrod, 1976; Bettis & Prahalad, 1995; Diehl & Sterman, 1995; Hodgkinson, Maule, & Bown, 2004; Huff, 1990; Simon, 1982).

> "The psychological core of understanding… consists in your having a 'working model' of the phenomenon in your mind. If you understand inflation, a mathematical proof, the way a computer works, DNA… then you have a mental representation that serves as a model of an entity" (Johnson-Laird, 1983: 2)

Much of the strategy research examining the content of mental models has focused on how managers perceive and categorize information about their organization or competitive environment (Hodgkinson & Johnson, 1994; Jackson & Dutton, 1988; Porac *et al.*, 1995; Porac *et al.*, 1989; Reger & Huff, 1993). In contrast, there has been very little research investigating decision makers' mental models of the causal relationships in business environments and how these affect strategic choices. Recent research in psychology provides strong evidence that beliefs about cause and effect relationships are particularly important in supporting strategic decision making since they serve as the basis on which decision makers infer the consequences of their actions and guide intervention efforts to reach desired targets (Rehder, 2003). For example, solving complex strategic problems requires managers to generate options about where and how to intervene in their business by forming expectations about the possible outcomes resulting from their decisions. This process of developing strategic prescriptions relies heavily on the inferred causal relationships that make up managers' mental models about their organization and the competitive environment. Therefore, it is crucial to understand decision makers' inferences about chains of cause-effect relationships linking specific decision options to outcomes to understand how managers make strategic decisions (Levitt & March, 1988).

There has also been very little strategy research investigating the importance of accurate mental models on decision making and performance outcomes. On the one hand, Wieck speculates that "Accuracy [in mental models] is nice, but not necessary" (Weick, 1990: 6). Similarly, Sutcliffe (1994) suggests that inaccurate perceptions may lead to positive consequences for organizations if they enable managers to overcome inertial tendencies and propel them to pursue goals that might look unattainable when the environment is assessed accurately. In this line of reasoning, having an accurate mental model of the business environment may be less important than having some mental map that brings order to the world and enables incremental and adaptive action. On the other hand, an implicit assumption in much of strategy research is that successful managers have accurate mental models of the business environment and develop strategies based on these models. There is some evidence from fieldwork as well as limited empirical support that accuracy of managerial mental models of the competitive environment play an important role in firm success (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas & Gavetti, 2000). Also, decision making research finds evidence that more accurate mental models result in better judgment and choice outcomes (Gentner, Loewenstein, & Thompson, 2003). In addition, recent simulation-based work suggests more accurate mental models about the causal relationships linking actions to outcomes translate into better performance (Denrell *et al.*, 2004) and may play a central role in the discovery of superior strategic positions (Gavetti & Levinthal, 2000; Gavetti, Levinthal, & Rivkin, 2005). Overall, previous research suggests having accurate managerial mental models is important, but no prior studies have empirically tested the importance of accurate mental models about causal relationships of the business environment.

As simplifications of reality, mental models will always be incomplete and inaccurate. In the complex organizational environments in which managers typically operate, making accurate causal inferences is often very difficult. Consequently, decision makers are unlikely to construct completely accurate mental models in even a moderately complex environment. Prior research on judgment and decision-making shows that complexity – including time delays, nonlinearities, feedback effects, and stock accumulation processes – impairs the formation of accurate mental models and undermines performance (Atkins, Wood, & Rutgers, 2002; Moxnes, 1998; Paich & Sterman, 1993; Sengupta & Abdel-Hamid, 1993; Sterman, 1989a, 1989b). Prior research also provides evidence that different managers can perceive the same objective business environment differently (Barr *et al.*, 1992; Bourgeois, 1985; Tripsas & Gavetti, 2000). Therefore, we expect variation in the accuracy of decision makers' mental models as a result of their own individual, unique experiences and due to differences in their learning strategies and differing abilities to draw inferences. In addition, within this diversity we expect decision makers with more accurate mental models to make better decisions and to achieve higher performance outcomes. Of course it is certainly possible that, through good luck, vastly deficient and incorrect mental models may result in correct action in some circumstances. However, on balance, we expect more accurate mental models of the decision environment will help guide managers to focus their attention on the most relevant information and serve as a better guide for strategic decisions.

The performance effects of accurate mental models are expected to result from a better understanding of the competitive landscape and the opportunities and threats in the market. Managers with accurate beliefs about the interdependencies that exist between their firm, competitors, and the market will have a better understanding of the market drivers, the likely effects of different actions and the resources needed to ensure success in different strategic positions. They will better understand competitive reactions and time delays and therefore are less likely to abandon effective long run strategies prematurely or to remain committed to failing courses of action. In summary, we expect decision makers with more accurate mental models will have a more comprehensive understanding of the fit between different strategic options and the business environment, will formulate more effective strategies, and will be better able to understand market information and other sources of feedback compared with decision makers with less accurate mental models.

The benefits of mental model accuracy may be moderated by the complexity of the environment confronting the manager. Recent simulation-based research suggests that accurate mental models become more important in more complex decision environments (Gavetti & Levinthal, 2000). Decision makers with low quality, inaccurate mental models may still be able to achieve relatively high performance outcomes in less complex decision environments because there are fewer determinants to consider, fewer options, and the effects of decisions are more immediate and more transparent. In simple environments, accurate mental models may offer little competitive advantage as managers can quickly understand feedback and adapt strategies accordingly from the limited options available. As environments become more complex, an accurate understanding of causal relationships can contribute to the quality of choices during the formulation, implementation and evaluation of strategies, thus affording a significant competitive advantage over managers with less accurate mental models of the environment. Therefore, we also expect mental model accuracy will be more important for achieving high performance outcomes in more complex decision environments.

> H1a: More accurate mental models of the complete business environment result in higher performance outcomes.
>
> H1b: More accurate mental models of the complete business environment have a greater positive effect on performance in more complex environments.

It is also important to understand what types of misperceptions and errors in managerial mental models are most damaging for performance. There is substantial evidence that decision makers' mental models and decision heuristics suffer from a number of systematic deficiencies and biases (Camerer & Lovallo, 1999; Cyert & March, 1963; Hodgkinson *et al.*, 1999; Kahneman & Tversky, 2000; Sterman, 1989b; Zajac & Bazerman, 1991). Within this broad and multi-disciplinary literature, the stream of research on dynamic decision making focuses on causal inferences and shows that managers suffer from misperceptions of feedback between decisions and the environment (Diehl & Sterman, 1995; Moxnes, 1998; Paich & Sterman, 1993; Sengupta & Abdel-Hamid, 1993; Sterman, 1989a, 1989b). However, no prior studies have investigated how heterogeneity in mental model accuracy impacts decision making and performance outcomes, or which types of misperceptions or errors in mental models are most damaging for performance.

Two related streams of research provide some guidance on the specific types of misperceptions or errors in making causal inferences that may be important in understanding the link between managerial mental models and performance. The first is research on organizational learning, which shows that experiential learning can produce superstitious beliefs about causal relationships (Denrell *et al.*, 2004; Levitt & March, 1988). The lessons of experience are drawn from a relatively small number of observations in a complex and continuously changing business environment rather than comprehensive causal knowledge (Levitt & March, 1988). Identifying which actions lead to specific outcomes is not always obvious, the causality of events is difficult to untangle, and causal inferences are typically driven by spatial and temporal contiguity leading to spurious beliefs about associations between the decisions and outcomes in complex environments (Levitt & March, 1988). Superstitious beliefs in mental models often lead to faulty diagnosis of challenges or problems, resulting in the selection of responses that do not improve and may undermine performance.

A second line of research suggests that decision makers suffer from blind spots when making strategic decisions (Zajac & Bazerman, 1991). Specifically, Zajac and Bazerman (1991) focused on blind spots about the contingent decisions of competitors. These competitive blind spots are damaging because a key component of industry analysis is identifying competitors' assumptions, initiatives, and likely responses (Porter, 1980). Given the difficulties of making accurate causal inferences in complex, dynamic settings, managers may also have blind spots about the causal relationships at work in other aspects of the business environment. Such causal blind spots might include failure to identify and understand key customer preferences, the impact of word of mouth in driving sales growth, the damaging effects of lengthy delivery delays on order cancellations, or the importance of different components of the firm's cost structure. Like superstitious beliefs, causal blind spots in managerial mental models can undermine effective decision making and performance.

Overall, misperceptions of the business environment are likely to result in inappropriate decisions and actions as challenges and problems arise. Therefore, we expect causal blind spots and superstitious beliefs in mental models will have deleterious effects on performance.

H2: The more causal blind spots and superstitious beliefs in decision makers' mental models, the lower their performance

The discussion so far has focused on the benefits of accurate mental models of the complete business environment. However, recent simulation-based research suggests that even partial knowledge of the business environment may dramatically improve performance by playing an important role in seeding and constraining the process of experiential learning (Denrell *et al.*, 2004; Gavetti & Levinthal, 2000). In search processes, even a small amount of knowledge may provide significant performance advantages by cutting down the search space and thereby reducing an otherwise lengthy random search process. This raises the question about whether accurate mental models of the entire business environment are required or if partial knowledge could result in superior performance outcomes.

Research findings on expertise provide some guidance about the performance benefits of partial knowledge. Specifically, research shows that experts have deeper, structural-level mental representations of problems, while novices typically represent problems based on detailed, situation-specific surface characteristics (Chi, Feltovich, & Glaser, 1981). Mental representations of the deep structure of a problem domain are composed of 'chunks' of knowledge about the important key principles at work (Chase & Simon, 1973; Gentner *et al.*, 2003). Mental models of the key principles enable experts to recognize common elements and patterns across a class of problems, to quickly generate and evaluate relevant options, and to systematically outperform novices whose mental models typically focus on inconsequential details rather than the deep structure. Recent strategy work has started to explore the related issue of how experienced senior executives – with rich mental models of the deep structure or architecture of a strategic problem – often draw on solutions from past experience dealing with analogous situations (Gavetti *et al.*, 2005; Gavetti & Rivkin, 2005).

Based on these strands of prior research, we expect accurate mental models of key principles of the deep structure will result in superior performance outcomes.

> H3: More accurate mental models of key principles of the deep structure of the business environment lead to higher performance outcomes

METHODS

We use an interactive, computer-based simulation of managing new product launch and lifecycle dynamics as the experimental task in our study. MBA students with no prior experience on the management simulation were invited to participate. The 63 participants included 47 male and 16 female volunteers, with an average age of 30 and an average of seven years work experience. Participants were randomly assigned to either the low complexity (n = 31) or the high complexity (n = 32) group and remained in that same group throughout the entire experiment. Participants were paid a fixed amount for their participation in the experiment. In addition, a small donation was paid to a nominated club or charity for the 43 students who also participated in the delayed-testing stage fifteen weeks later.

Task and Procedures

The management simulation task has been utilized in previous research and captures many well-established features of product lifecycle management (Paich & Sterman, 1993). In particular, the market diffusion structure (Bass, 1969; Kalish & Lilien, 1986; Mahajan, Muller, & Bass, 1995; Roberts & Urban, 1988) lies at the heart of the underlying simulation model for the task. The essence of this model is the process through which potential customers become aware of and choose to buy the product. Customer adoption increases the customer base which generates word of mouth resulting in additional sales, but also depletes the pool of potential customers. The customer base follows an s-shaped growth pattern; sales rise exponentially, then peak and decline to the rate of replacement purchases as the market saturates (Paich & Sterman, 1993). These are the principle causal relationships of the task.

Participants take on the role of Chief Executive Officer of the firm and make quarterly decisions, such as price and capacity investments, with the goal of maximizing cumulative profit from the sales of their product over a forty-quarter simulation. In the management simulation, the business environment changes as a consequence of participants' decisions and contains: a large number of interdependent variables, time delays separating decisions from their resulting impacts, some nonlinear relationships between variables, stock accumulations, and multiple feedback effects (Paich & Sterman, 1993; Sterman, 1989a). These features of the management simulation also characterize the sort of complex environment that senior managers typically operate in while making strategic decisions within their firm.

Participants completed three phases: a learning phase, an immediate testing phase, and a delayed testing phase. The learning phase and immediate testing phases were completed in an initial laboratory session in groups of 15 to 20. Each participant was seated at a separate computer and could not see other screens. The learning phase included three blocks of 40 decision trials – 120 decision trials in total – for participants to learn about and become familiar with the simulation. After each decision trial, participants received outcome feedback on their results for that trial plus their cumulative performance up to that point. This feedback was presented in both table and graphical format in order to control for the effects of feedback format (Atkins *et al.*, 2002). After each trial block (40 quarters), the simulation was reset to the same initial values and the next trial block started. The simulated outcomes could be, and were, very different from one trial block to the next since different participant decisions result in different simulated responses.

Following the learning phase, participants were asked to complete a series of questionnaires to assess their self-efficacy and mental models of the task. After completing the questionnaires, participants proceeded to the immediate testing phase, in which they completed three more blocks of 40 decision trials on the exact same version of the task. Participants were under no strict time pressure and completed each phase at their own pace. On average, the initial experimental session took three hours. Upon completing the immediate testing phase, participants left the laboratory and were paid for their participation in the study. The delayed testing phase was completed fifteen weeks later, and involved logging into the simulation from remote locations and completing three more blocks of 40 trials on the exact same version of the task. This phase was used to test the stability of the relationships proposed in all of our hypotheses.

Task Complexity

There were two levels of task complexity associated with either a monopoly market or a competitive market. In the low complexity version of the task, there were two decision variables- price and target capacity- and 19 interdependent variables in the causal structure. There was no competitor in the low complexity version of the task. In the high complexity version of the task, there were three decision variables: price, target capacity, and marketing spend. There were over

30 interdependent variables in the causal structure, including causal relationships for a competitor in the market. While it is difficult to characterize any decision as inherently strategic, the set of decisions required each quarter involve substantial capital, are made difficult by the complexity of the business environment, and have considerable potential to influence firm performance.

Measures

Performance. Performance was measured for each of the nine trial blocks by the cumulative profit at the end of the last decision trial in each block. The nine trial blocks of performance included three blocks completed during the learning phase, three blocks completed in the immediate testing phase, and three blocks completed in the delayed testing phase. The potential achievable cumulative profit was different in the high and low complexity task conditions, and therefore we divided subjects' raw performance by benchmarks for the high and low conditions. The performance benchmarks were found through a modified Powell search optimization (Powell, 1998). Marketing Spending was fixed at 5% of revenue throughout the simulation. Capacity was determined by a perfect foresight rule in which capacity always matched demand. Finally, the single price level that optimized profits over the entire simulation was computed. Note that this pricing rule is very simplistic since price does not change throughout the simulation in response to changing capacity, backlog, order demand, or any other variable in the decision environment. Therefore, the calculated cumulative profit benchmark is clearly not a global optimum for the task, but is instead simply a consistently calculated benchmark enabling comparison across the high and low complexity groups[1].

[1] We also analyzed alternative benchmarks, including a behavioral rule previously used as a benchmark on the complex version of this task (Paich and Sterman 1993). All of our statistical results are robust to these alternative benchmarks.

Mental Model Accuracy. We evaluated several methods for assessing the accuracy of decision makers' knowledge structures. We considered using the repertory grid technique (Reger & Huff, 1993), but this approach was not feasible given the number of variables in the management simulation. Over 900 response cells would have been necessary for the high complexity version of the task. We also considered facilitated interviews to develop individual causal loop diagrams (Huff, 1990; Sterman, 2000), but this approach was not practical for use in a large-sample experiment. Other scholars have used content analysis of written narratives to infer managerial mental models (Osborne, Stubbart, & Ramaprasad, 2001), but this approach did not leverage the advantage of having direct access to decision makers in our study. We also evaluated the cognitive mapping approach in which individual decision makers draw their own cognitive maps directly (Axelrod, 1976; Hodgkinson *et al.*, 1999). After a pilot test, this measurement approach was ruled out since the participants in our study were not familiar with the cognitive mapping method. There is also evidence that decision makers often have poor insight into their own decision making processes and interpretive approaches may simply capture espoused theories rather than 'theories in use' (Argyris & Schon, 1974). Instead, we devised a knowledge test using a sample of questions about the causal relationships in the management simulation for which the answers were known.

The measurement of knowledge using standardized tests is a well-developed subdiscipline of education and psychology. An individual's knowledge is measured by calculating the proportion of questions answered correctly (Borgatti & Carboni, 2007). A key advantage of our laboratory experiment is that we know the correct answers to the knowledge questions about causal relationships in the management simulation and can therefore distinguish between correct and incorrect answers. This avoids a tricky and difficult problem of measuring mental model accuracy in field settings.

One set of questions tested participants' inferences about bivariate causal relationships between pairs of variables from the management simulation. The questions covered the exhaustive set of actual relationships in each of the complexity conditions along with several items for which no relationship existed in the decision environment. Participants answered 30 items on the relationships between variables that were common to both complexity conditions. Participants in the high complexity condition answered a further 24 items relating to the additional variables and relationships in the high complexity condition. For each question, participants drew a directed influence arrow between the two variables and indicated the polarity (sign of the slope) of the relationship if they believed a causal relationship existed (Sterman, 2000). In order to complete this first set of knowledge questions, participants were provided with a complete list of variables in the management simulation. Appendix A provides a segment of the instructions along with the first three items of this first set of questions. Figure 1a and b shows diagrams of the full set of causal relationships in the low and high complexity decision environments respectively.

Insert Figure 1 Here

A second set of questions tested participants' knowledge of the relationships between a small set of variables in the management simulation and their ability to infer the dynamics of this set of variables. Each question presented the graph of one or two variables over time from the management simulation, and subjects chose from a multiple choice of answers for the evolution of another variable in the management simulation. To answer correctly, participants had to draw on their experience with the management simulation and their knowledge of the causal relationships between variables in order to determine how the dynamic behavior of the first variable or variables impacts the dynamic behavior of another variable. Appendix B provides a segment of the instructions along with one example from this set of questions. The full knowledge test is available upon request from the authors.

Each item on the knowledge test was scored as correct or incorrect and each participant's mental model accuracy was the percentage of items on the knowledge test answered correctly. The possible scores range from 0-1, where a score of 1 indicates perfect knowledge of the tested aspects of causal structure and dynamic behavior of small sets of variables in the decision environment. It is important to note that achieving a perfect score on the knowledge test is certainly no guarantee of success in the complex decision environment. Understanding bivariate causal relationships and correctly inferring the dynamics of small sets of interdependent variables supports the development of effective decision making in the complex system, but this remains a difficult task.

Superstitious Beliefs. Inferring a causal relationship between two variables when in reality no causal relationship exists is a superstitious belief (Levitt & March, 1988). A decision maker has a superstitious belief when a causal relationship does not exist between two variables but he/she believes a causal relationship does exist between these variables. For example, the belief that word of mouth effect increases unit costs in the simulation is an example of a superstitious belief, because word of mouth effect does not have a direct causal relationship on unit costs. We identified superstitious beliefs using the set of knowledge questions assessing participants' inferences about bivariate causal relationships between pairs of variables from the management simulation. The total number of superstitious beliefs were divided by the number of questions in each task complexity condition – 30 and 54 respectively – to normalize the values for comparison.

Causal Blind Spots. Building on the concept of blind spots identified by Zajac and Bazerman (Zajac & Bazerman, 1991), omitting a real causal relationship between two variables is a causal blind spot. A decision maker has a causal blind spot when a causal relationship actually exists between two variables but he/she does not believe there is a causal relationship between these variables. For example, the perception that the number of potential customers is not related to the price of the product is an example of a causal blind spot, because customers are price sensitive in the simulation. Lower prices enlarge the pool of potential customers who can afford and are willing to buy the product. We identified causal blind spots using the set of knowledge questions assessing participants' inferences about bivariate causal relationships between pairs of variables from the management simulation. The total number of blind spots were divided by the number of questions in each task complexity condition – 30 and 54 respectively – to normalize the values for comparison.

Mental Model Accuracy of the Deep Structure. The well-established market diffusion structure represents the key principles of the task. A total of eleven items from the knowledge test, involving questions about inferred causal relationships and dynamic behavior of small sets of variables, assess participants' knowledge of this deep structure. Appendix C provides seven example items for this measure of deep structure accuracy. The remaining four items of the deep structure accuracy measure are graphical scenario questions covering a subset of the same relationships. The example graphical scenario question in Appendix B is one of those items. Each participant's mental model accuracy of the deep structure was the percentage of these eleven items answered correctly. The possible scores range from 0-1, where a score of 1 indicates perfect knowledge of the tested aspects of the key principles of deep structure.

Control Variables

Cognitive Ability. A large body of strategy research has investigated the impact of individual and top management team characteristics on performance heterogeneity (e.g., Finkelstein & Hambrick, 1990; Hambrick & D'Aveni, 1992). One potentially important individual difference among decision makers for our study is their cognitive ability. Cognitive abilities have been shown to play a central role in problem solving, reasoning, and learning (Anderson, 1990). Participants' scores on the Graduate Management Aptitude Test (GMAT) were used as a proxy for general cognitive ability. The GMAT is widely used to assess general cognitive ability of applicants to MBA programs around the world, and is used as a selection criterion in many such programs as a reflection of the achievement and learning potential of applicants in the domain of management.

Perceived self-efficacy is an established motivational predictor of performance on complex tasks and the constituent processes, such as search, information processing and memory processes that can affect learning (Bandura, 1997). Also, complexity levels have been shown to influence the motivational reactions to tasks (Wood, Bandura, & Bailey, 1990). Therefore, self-efficacy was incorporated as a control variable to ensure that differences in performance were not solely attributable to motivational differences. Perceived self-efficacy was measured with a 10-item scale, provided in Appendix D, covering a broad range of activities involved in managing the simulated firm. The format followed the approach recommended by Bandura (1997), which has been validated in numerous empirical studies. For each item, participants first recorded whether or not they understood what was required to manage the activity - yes or no - and then recorded their confidence in their capabilities on a 10-point scale where 1 = “very low confidence” and 10 = “very high confidence.”

Mental Model Complexity. Prior research has found that the complexity of top managers’ mental models is positively related to competitive success (McNamara, Luce, & Tompson, 2002). Therefore, mental model complexity was included as a control variable. The complexity of decision makers’ mental models was measured by counting the number of inferred causal relationships in the set of knowledge questions assessing beliefs about bivariate causal relationships. Reported perceived relationships were included in the count whether or not these causal relationships were correct. In other words, this measure includes both accurate inferences of causal relationships as well as superstitious beliefs. The potential number of perceived bivariate relationships was different in the high and low complexity task conditions, and therefore we divided participants’ raw counts by the correct number of causal relationships in each condition. The result assesses the complexity of decision makers’ mental models relative to the complexity of the perfectly correct mental model. Possible scores range from 0 to values greater than 1, where a score less than 1 indicates less complexity than in the correct mental model and a score greater than 1 indicates more complexity than the correct mental model due to superstitious beliefs.

Data Analyses

The relationships proposed in Hypotheses 1-3 were tested by estimating both Ordinary Least Squares (OLS) regressions and general linear mixed models with repeated measures. In the OLS models, the dependent variable was performance at the end of either trial block six (the final trial block of the immediate testing phase) or trial block nine (the final trial block of the delayed testing phase). In the general linear mixed models with repeated measures, performance for trial blocks 4-9 in the immediate and delayed testing phases were all dependent variables, increasing the statistical power and reducing bias in the estimates. Task complexity was a between-subjects fixed effect. A first-order, auto-regressive correlation structure was specified for the repeated measures of performance across Trial Blocks. Trial Block was also included as a fixed effect. In addition, a random intercept was included for each participant. General linear mixed models provide the best linear unbiased estimates for unbalanced, correlated repeated measures data (Verbeke & Molenberghs, 2000).

RESULTS

The correlations, means, and standard deviations for the study variables are shown in Table 1. The task complexity variable was dummy coded so that 0 = low complexity and 1 = high complexity. Task complexity is negatively correlated with performance across all trial blocks and also negatively correlated with mental model accuracy. Mental model accuracy is significantly correlated with performance across all trial blocks, and there is significant variance in mental model accuracy ranging from .32-.81 with a mean of .56 and standard deviation of .11.

Insert Table 1 Here

Figure 2 illustrates mean performance and 95% confidence intervals across all nine trial blocks for the high and low complexity groups. The learning phase includes trial blocks 1-3, the immediate testing phase includes trial blocks 4-6, and the delayed testing phase includes trial blocks 7-9. Performance in both complexity conditions improves considerably from trial block 1 to trial block 3, but plateaus relatively quickly in the experiment. Performance falls slightly in the delayed testing phase, but the difference is not statistically significant. The 95% confidence intervals show there is considerable variation in performance across decision makers in the same version of the management simulation task.

Insert Figure 2 Here

Tests of Hypotheses

Models 1-3 of Table 2 test the impact of mental model accuracy of the complete business environment on performance proposed in Hypothesis 1a. Model 1 provides the OLS estimates using performance on trial block six, the last immediate testing phase trial block, as the dependent variable. In support of Hypothesis 1a, mental model accuracy is a significant predictor of performance ($b = 1.039$, $p < .05$) after controlling for task complexity, general cognitive ability, and self-efficacy. For every .01 increase in mental model accuracy (where mental model accuracy ranges from 0.00-1.00 by definition), average performance relative to benchmark increases by .01039. This is equivalent to an additional $10.4 million or $28 million in cumulative profits over the course of one complete trial block (simulation run) in the high and low complexity conditions respectively. Task complexity has a significant and negative main effect on performance ($b = -0.434$, $p < .001$), indicating that participants in the high complexity condition achieved significantly lower performance outcomes than participants in the low complexity group. General cognitive ability, self-efficacy, and mental model complexity were not significant predictors of performance.

Model 2 provides the OLS estimates using performance on trial block nine, the last delayed testing phase trial block, as the dependent variable. The results are the same as in Model 1. In fact, the effects of mental model accuracy on performance ($b = 1.668$, $p < .05$) are even stronger in the delayed testing phase than in the immediate testing phase. This indicates decision makers' mental models of the management simulation remained stable fifteen weeks after the initial laboratory session and continued to impact performance. Model 3 provides general linear mixed model estimates using repeated measures for performance on trial blocks 4-9 (all of the immediate and delayed testing phases) increasing the N to 315. Again, the results are the same as in Models 1 and 2 with a significant, positive relationship between mental model accuracy and performance ($b = 0.988$, $p < .01$) and a negative main effect of task complexity on performance ($b = -0.438$, $p < .001$)[2].

Model 4 includes the interaction of task complexity and mental model accuracy to test Hypothesis 1b. The interaction term is not significant, indicating that more accurate mental models do not have a greater positive effect on performance in more complex environments. Mental models are equally important in both low and high complexity environments and Hypothesis 1b is not supported. Overall, the results of Models 1-4 of Table 2 support Hypothesis 1a, providing empirical evidence that more accurate mental models of the complete business environment result in higher performance outcomes.

Insert Table 2 Here

Models 1-3 of Table 3 test the impact of superstitious beliefs and causal blind spots on performance proposed in Hypothesis 2. The errors in decision makers' mental models are categorized as either superstitious beliefs or causal blind spots and these two components capture the inverse of mental model accuracy. Therefore, mental model accuracy is not included as a

[2] In the interests of clarity, the fixed effects associated with each trial block and the random and repeated measures components of the models are not shown in any of our results tables. Trial block is not significant in any of our analyses due to the performance plateau which occurs after the learning phase (refer back to Figure 3). The repeated component of all models is significant, indicating that residual errors are indeed correlated by trial block. In addition, the random subject intercept is also significant in all models, indicating that performance does vary between individuals.

separate construct in these models. Also, since mental model complexity includes both correct and incorrect inferences and was not significant in prior analyses, it will be dropped from all subsequent analyses. However, all results are robust to inclusion of mental model complexity as a control variable. Model 1 provides the OLS regression estimates using performance on the sixth trial block as the dependent variable. Both superstitious beliefs ($b = -1.268$, $p < .05$) and causal blind spots ($b = -0.793$, $p < .05$) have significant negative effects on performance. To understand the relative magnitude of the effects of these errors on performance, the standardized coefficients for superstitious beliefs and causal blind spots are -.303 and -.286 respectively. The effects of these errors on performance are very similar in magnitude, with superstitious beliefs having a slightly larger negative impact. As in previous models, task complexity has a significant and negative effect on performance ($b = -0.434$, $p < .001$). General cognitive ability and self-efficacy were not significant predictors of performance.

Model 2 provides the OLS estimates using performance on trial block nine as the dependent variable. The results are the same as in Model 1 and, as in the previous analysis with mental model accuracy, the effects of superstitious beliefs ($b = -1.669$, $p < .05$) and causal blind spots ($b = -1.302$, $p < .05$) on performance are even stronger in the delayed testing phase than in the immediate testing phase. The standardized coefficients for superstitious beliefs and causal blind spots are -.318 and -.369 respectively. Again, the effects of these errors on performance are very similar in magnitude but with causal blind spots having a slightly larger negative impact on delayed testing performance. Model 3 provides general linear mixed model estimates using repeated measures for performance across trial blocks 4-9. The results are largely the same as in Models 1 and 2. Superstitious beliefs ($b = -1.111$, $p < .05$) and task complexity ($b = -0.450$, $p <$

.001) both have a significant negative impact on performance. However, causal blind spots now have only a marginally significant, negative impact on performance ($b = -0.559$, $p = .076$).

Insert Table 3 Here

Models 1-3 of Table 4 test the impact of accurate mental models of the deep structure on performance proposed in Hypothesis 3. Model 1 provides the OLS regression estimates using performance on the sixth trial block as the dependent variable. Deep structure accuracy has a significant positive impact on performance ($b = 0.596$, $p < .05$) indicating that decision makers' do not need an accurate mental model of the complete business environment, but rather accurate mental models of key principles of the deep structure. For every .01 increase in deep structure accuracy (where deep structure accuracy ranges from 0.00-1.00 by definition), average performance relative to benchmark increases by .00596. This is equivalent to an additional $6 million or $16.7 million in cumulative profits over the course of one complete trial block (simulation run) in the high and low complexity conditions respectively. As in previous models, task complexity has a significant and negative effect on performance ($b = -0.442$, $p < .001$). General cognitive ability and self-efficacy were not significant predictors of performance. Model 2 provides the OLS estimates using performance on trial block nine as the dependent variable. The results are the same as in Model 1 and, as in the previous analysis with mental model accuracy, the effects of deep structure accuracy on performance ($b = 1.178$, $p < .01$) are even stronger in the delayed testing phase than in the immediate testing phase. Model 3 provides general linear mixed model estimates using repeated measures for performance across trial blocks 4-9. The results are the same as in Models 1 and 2 with a significant and positive impact of deep structure accuracy on performance ($b = 0.555$, $p < .05$) and a negative effect of task complexity on performance ($b = -0.446$, $p < .001$).

Insert Table 4 Here

Decision Rules and Strategies

In order to further investigate the mechanisms linking mental models and performance, we performed supplementary analyses of participants' decisions and strategies. In the face of complexity, decision makers adopt satisficing rules of thumb and heuristics that are intended to be consistent with their simplified mental models of the business environment (Cyert & March, 1963; Levitt & March, 1988; March & Simon, 1958; Simon, 1991). Mental models encompass beliefs about what information decision makers consider most relevant in a given situation and how much weight to give to different pieces of information when making decisions. Decisions resulting in favorable outcomes are repeated when the same situation is encountered again and, in due course, this leads to the development of rules of thumb for making decisions that managers have seen in the past (Cyert & March, 1963; Levitt & March, 1988). Over time, these decision rules are likely to be executed more and more automatically, without high levels of cognitive effort or conscious processing (Argyris & Schon, 1974).

Research shows that linear models of decision making often provide good higher-level representations of underlying processes (Camerer, 1981; Cyert & March, 1963; Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Levitt & March, 1988). Supported by post experiment interviews, analysis of participants' experimental logs, and the decision rules identified in previous research for this new product launch experimental task (Paich & Sterman, 1993), we identified linear decision rules for pricing and capacity investment decisions for each participant.

Participants' capacity investment decisions involved estimating future demand by extrapolating current demand using the recent growth rate, and then making adjustments to balance capacity with expected future demand. Capacity adjustments do not happen instantaneously in most organizational settings or in our management simulation. Instead, decision makers set a target capacity level and after a time delay the actual level of production capacity approaches this target value. This time delay in combination with the requirement for accurate expectations with respect to future demand, makes the capacity investment decision dynamically complex (Sterman *et al.*, 2007; Zajac & Bazerman, 1991). Equation 1 shows the form in which participants' capacity decision rules were estimated, where C* is target capacity, D is actual demand, g is fractional demand growth over the last two quarters, B is Backlog, C is Capacity, the subscript *t* is time, and the subscript *t*-1 is the current time lagged by one period. We estimated parameters for the intercept *c* and the information weights a_0, a_1, and a_2.

$$\log(C_t^*) = c + a_0 \log(D_{t-1}) + a_1 \log(1 + g_{t-1}) + a_2 \log(B_t / C_t) + \varepsilon_1 \qquad (1)$$

Participants' pricing decisions involved a markup from unit variable cost, with margin over cost driven by the ratio of demand to capacity. This markup pricing rule is consistent with behavioral pricing rules documented in organizations from a wide range of competitive environments (Cyert & March, 1963). Equation 2 shows the form in which this pricing decision rule was estimated, where P is price, UVC is unit variable cost, B is Backlog, C is Capacity, the subscript *t* is time, and the subscript *t*-1 is the current time lagged by one period. We estimated parameters for the intercept b_0 and the information weights b_1 and b_2.

$$\log(P_t) = b_0 + b_1 \log(UVC_{t-1}) + b_2 \log(B_t / C_t) + \varepsilon_2 \qquad (2)$$

The information weights for the capacity and pricing decision rules were estimated separately for each trial block for each participant using Prais-Winsten regressions to correct for first-order autocorrelation (Camerer, 1981; Einhorn *et al.*, 1979). The results indicate that the decision rules capture the majority of the variance in participants' decisions in both complexity conditions. The mean R^2's for the high and low complexity conditions are 0.75 and 0.85 respectively for the Target Capacity rule, and 0.97 and 0.92 for the Price rule. For the capacity and pricing decision rules, we also computed the optimal information weights maximizing cumulative profit[3]. These should in no way be construed as the global optimal decision rules for the management simulation since the rules only incorporate a handful of information cues in accordance with the information processing constraints of boundedly rational decision makers. The optimal information weights for these rules were used to calculate how far participants' information weights deviated from the optimal values[4].

We estimated general linear mixed models with repeated measures to investigate the relationships between mental models and decision rules using deviation from the optimal information weights across trial blocks 4-9 as the dependent variable. Larger deviations indicate less effective decision rules and Models 1-3 of Table 5 show the results[5]. Model 1 shows that mental model accuracy of the complete business environment has a significant impact ($b = -3.398$, $p < .001$), with more accurate mental models reducing the deviation from optimal information weights. Task complexity also has a significant impact ($b = 2.640$, $p < .001$) indicating participants' decision rules in the high complexity condition deviate more from the optimal information weights than participants in the low complexity group. Model 2 shows that more superstitious beliefs ($b = 3.472$, $p < .01$) and causal blind spots ($b = 2.839$, $p < .01$) result

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[3] The optimal information weights were computed using the Powell algorithm with random multiple starts over more than ten million simulations.

[4] For this calculation, the deviations were adjusted by a weighting factor to account for the sensitivity of performance to each information cue and then the absolute differences summed across all information cues in both decision rules.

[5] A total of twelve cases–out of 315 total repeated measures cases–were identified as extreme outliers across multiple information weights and removed for the analysis.

in less effective decision rules with significantly larger deviations from the optimally computed weights. Model 3 shows that more accurate mental models of the deep structure result in more effective decision rules with significantly smaller deviations from the optimally computed information weights ($b = -2.140$, $p < .01$). Overall, these results provide strong evidence of the powerful connection between mental models and decision making.

Insert Table 5 Here

Further analysis of participants' pricing and capacity decision rules, show rapid stabilization of the information weights for both rules. Establishing these links shows one more mechanism connecting mental models and performance variation. The evolution of decision rules were tested using ANOVA contrasts comparing the information weights between trial blocks with the data pooled across participants and analyzed separately for each level of complexity. For the capacity investment decision rules, there are some significant differences between information weights on the first four trial blocks. However, there are no significant differences between information weights in all subsequent trial blocks of the immediate testing phase. In the pricing decision rule, there are no significant differences between information weights throughout all trial blocks of the learning and immediate testing phases. These results provide evidence that participants formed decision rules rapidly and largely stabilized the information weights for these rules by the end of the fourth trial block with little adjustment thereafter. This speedy stabilization of the decision rules helps explain why average performance plateaus so rapidly.

Our analysis of decision rules shows a great deal of variation in participants' information weights. To the extent that there are distinctive patterns of decision rules, this could be evidence of different high-level policies or strategies. Recent strategy research suggests different configurations of specific choice and decision sets lie below the surface of higher-level policies and overarching strategies (Gavetti *et al.*, 2005). Managers and firms vary in terms of the overall strategies they adopt. For example, a firm that adopts a pricing rule to capture market share by dropping price as unit cost decrease over time (e.g., due to learning curve effects) and a capacity investment rule that rapidly expands capacity to fulfill demand could be characterized as adopting a "Get-big-fast cost leadership" strategy (Sterman *et al.*, 2007). Different patterns of decision rules could similarly represent other generic strategies such as a premium price, niche strategy, as well as many other mixed strategies (Porter, 1980). These strategies may be the result of either rational ex ante planning or emergent behavior. Identifying different strategies by examining the observed patterns in decision rules is necessarily exploratory, but enables us to investigate heterogeneity in strategies and the relationships between mental models and strategies.

We used two-stage cluster analysis of the information weights to explore patterns in the decision rules. The first stage involved hierarchical analysis to identify outliers and centroid means, followed by K-Means nonhierarchical analysis to identify distinctive strategies (Ketchen Jr & Shook, 1996)[6]. As shown in Table 6, this analysis identified five distinct strategies for the low complexity task condition and four distinct strategies for the high complexity task condition. These strategies capture the range of observed patterns in the pricing and capacity investment decision rules. For example, the Tenacious Build and Hold strategy in the low complexity task combined building capacity to an initial forecast – as indicated by the large intercept for capacity

[6] The analyses were run separately for each task complexity condition. Multiple clustering algorithms were employed in both stages and the cluster results were robust to using different distance algorithms for identifying clusters.

investment – along with reducing price as unit costs fall – as indicated by a relatively large cue weight for unit cost. Figure 3 illustrates the different patterns of capacity investment decisions associated with the four distinct strategies in the high complexity decision environment. Similarly, Figure 4 illustrates the different patterns of pricing decisions associated with the five distinct strategies in the low complexity decision environment.

Insert Table 6 Here

Insert Figure 3 and Figure 4 Here

ANOVA shows there are significant differences in both mental model accuracy ($F = 5.372$, $p < .01$) and performance ($F = 14.745$, $p < .001$) between the four distinctive strategies in the high complexity decision environment. There are also significant differences in performance ($F = 3.064$, $p < .05$) and marginally significant differences in mental model accuracy ($F = 2.300$, $p = .06$) between the five distinctive strategies in the low complexity decision environment. Establishing these differences shows an additional mechanism connecting mental models and performance variation; the accuracy of decision makers' mental models impacts the strategies they adopt and there are significant performance differences between the different strategies.

We also ran the complete set of pairwise tests of the differences in mental model accuracy and performance across the various strategies. The results show that there are significant differences in performance between each of the four high complexity strategies (all p values $< .01$) and that the Rapid Response strategy is associated with significantly higher mental model accuracy than each of the other three strategies (all p values $< .01$). There are no significant differences in mental model accuracy between the other three strategies in the high complexity condition. In the low complexity condition, the Aggressive strategy is associated with significantly higher mental model accuracy than the Hold Your Horses strategy ($p < .01$) and the Slow Going strategy ($p < .05$). The Aggressive strategy is also associated with significantly higher performance than all four other strategies (all p values < .05), while the Premium Price strategy is associated with significantly lower performance than all four other strategies in the low complexity condition (all p values < .05). These results show that decision makers with the most accurate mental models adopt the best strategies and achieve superior performance under both complexity conditions. However, at lower levels of mental model accuracy the connection between mental model accuracy, the strategies adopted and performance outcomes achieved are not as straightforward. These findings suggest there may be threshold effects relating mental models to the selection of higher-level strategies. It is important to highlight that research shows that the superior strategy in this new product lifecycle simulation depends on features of the decision environment such as the length of time delays in adjusting capacity and variation in competitor responses (Sterman *et al.*, 2007). Therefore, we are not suggesting that the highest performing strategies in the management simulation are in any way the ‘best’ strategies for firms to adopt when launching new products and managing the lifecycle. Instead, we emphasize that these results demonstrate there are links between decision makers’ mental models and the different strategies they adopt, and connect heterogeneity in mental model accuracy, decision rules, and strategies to variation in performance outcomes.

DISCUSSION

Our results provide empirical evidence for the links between mental models, decision rules, strategies, and performance outcomes, and help explain why some managers and not others adopt strategies that are ultimately associated with competitive success. In our study, there was substantial variation in the accuracy of decision makers' mental models and also in performance. While it is certainly true that perfect mental models are not necessary to reach high performance outcomes (Sutcliffe, 1994; Weick, 1990), our findings show that on balance, decision makers with more accurate mental models of the causal relationships at work in the entire business environment achieve higher performance outcomes. Further, this relationship not only remained stable but grew stronger between the immediate and delayed testing phases, providing evidence that decision makers' mental models of the experimental task were not ephemeral. Our results are consistent with the limited prior empirical research findings about the importance of accurate mental models (Barr *et al.*, 1992; Bourgeois, 1985), and extend prior work by providing systematic evidence connecting differences in mental models of causal relationships with performance heterogeneity.

We also investigated which types of misperceptions and errors in mental models are most damaging for performance by testing the impact of superstitious beliefs and causal blind spots. Our results show that both types of inference errors significantly degrade performance, but that superstitious beliefs undermine performance more than causal blind spots. These results provide empirical support for prior theoretical research in organizational learning and behavioral decision analysis extolling the prevalence and dangers of superstitious learning (Levitt & March, 1988) and blind spots (Zajac & Bazerman, 1991). Our findings also broaden the concept of competitor blind spots (Zajac & Bazerman, 1991) to include causal blind spots about other important features of the decision environment. This has important implications for management research and practice. For example, participants in our experiment–similar to managers in many real product lifecycle situations–repeatedly made decisions that resulted in industry overcapacity. Competitive blind spots alone do not explain these persistent decision errors since half of our participants were in the low complexity condition as monopoly producers. Causal blind spots and superstitious beliefs in decision makers' mental models about market diffusion and capacity adjustment dynamics played a prominent role in these repeated boom and bust cycles.

Our findings also show that decision makers do not need to have accurate mental models of the complete business environment. Similarly, more complex mental models that include a larger number of incorrect cause-effect inferences do not enhance performance above simpler, high-quality mental models. Specifically, we find that accurate mental models about the key principles of the deep structure are sufficient for achieving superior performance outcomes. These results support recent theoretical work in strategy positing the benefits of partial knowledge (Denrell *et al.*, 2004; Gavetti & Levinthal, 2000). These findings are also consistent with prior research showing that experts with richer cognitive representations of the deep structure of problems outperform novices whose mental models typically focus on surface characteristics and details (Chi *et al.*, 1981; Gentner *et al.*, 2003). An important implication is that managers do not need to develop perfect and complete mental models of dynamic and complex business environments, but they must be capable of learning the key principles.

Our analyses also demonstrate there is considerable variation in the decision rules participants adopt, and that more accurate mental models, fewer superstitious beliefs, fewer causal blind spots, and deep structure accuracy lead to more effective decision rules. These findings extend the body of work identifying the detrimental mean effects of decision biases and heuristics (e.g., Kahneman & Tversky, 2000; Sterman, 1989b; Zajac & Bazerman, 1991) by accumulating evidence of heterogeneity in decision rules and connecting these differences to mental model accuracy. To our knowledge, this is the first study to empirically test the relationship between mental model accuracy and decision rules.

We also find that decision rules stabilize rapidly and that decision makers only make incremental adjustments in their information weights after the fourth trial block, which explains why performance plateaus far below the potential achievable level. Rapid stabilization of decision rules is consistent with psychology research on complex problem solving that finds actors learning a new task or solving a novel complex problem quickly automate decision and action rules once they reach functional, satisficing, levels of performance (Anderson, 1982; Ericsson, Krampe, & Tesch-Romer, 1993). Our findings are also consistent with a wide range of management research showing that managers typically interpret information to reinforce their current mental model rather than challenge and update their beliefs (Argyris, 1999; Barr *et al.*, 1992) and that in the face of complexity many firms reach suboptimal decision configuration “sticking points” from which they do not move (Rivken, 2000; Rivkin & Siggelkow, 2003). In addition, we also find a number of distinctive strategies or patterns in participants’ decision rules. There are significant differences in mental model accuracy across these different strategies, and these different strategies account for significant variation in performance. These findings help us understand observed variation in managerial cognition and decision making processes that underlie the origins of successful strategies.

Limitations and Future Research

Experimental findings linking diversity in mental models, decision rules, and strategies to performance heterogeneity are not conclusive evidence of these links in competitive environments. External validity is a common concern with experimental studies and ultimately can only be addressed through accumulating a stream of both experimental studies and field research replicating and extending our findings. However, recent meta-analyses comparing effect sizes from lab studies and field research reveals a correlation of .73-.97 suggesting a high degree of generalizability from lab to field (Anderson, Lindsay, & Bushman, 1999; Cohen-Charash & Spector, 2001). In addition, in the design of our study, we made choices that we believe contribute to the potential external validity of our findings. Specifically, dynamic decision making experiments using complex management simulations incorporating feedback, time delays, stock accumulations, and nonlinearities more closely approximate the decision making environments of senior managers than the experimental tasks typically employed in psychological and judgment and decision making research. The product lifecycle simulation represents a real world context where the strategic phenomenon of boom and bust is prevalent and the underlying causal model is well-established (Bass, 1969; Paich & Sterman, 1993; Roberts & Urban, 1988). In addition, decision makers in our studies had access to the same sort of information, through quarterly management reports about their simulated firm, that managers use in making similar decisions in real organizations (e.g., financial and operational reports).

Set against the potential limits to the external validity of our findings are the rigorous internal validity claims afforded by our experimental design, which enabled us to measure attributes of decision makers' mental models, such as accuracy of causal inferences, that are notoriously difficult to measure in the field due to uncertainty about the objective cause-effect relationships. We were also able to manipulate decision environment complexity in a controlled setting and rigorously test the causal impacts on mental model accuracy, decision rules, and performance.

Future research should assess the generalizability of our findings by testing these relationships both in the field and in laboratory experiments across a variety of management contexts and decision makers. Recent developments in measuring knowledge in the field may provide opportunities to accurately estimate knowledge levels in domains where the objectively right answers are not known a priori (Borgatti & Carboni, 2007). Prior research also suggests possible ways to operationalize decision environment complexity in field settings (Sutherland, 1980), potentially providing a path for exploring the impact of complexity on mental models, strategic decisions, and performance in the field.

Our study also focused on individual decision makers and does not explore the enactment process in organizations where teams of executives come together to make decisions in a social context. Firm strategies and decisions are the product of a socio-political process embedded in an organizational context involving multiple actors (Chattopadhyay *et al.*, 1999; Kaplan, Forthcoming). However, ultimately it is individuals whose mental models form the substance of such collective deliberations. We believe that isolating the cognitive aspects of decision making enables us to build solid microfoundations before we extend the scope to include social processes.

Our results suggest that addressing deficiencies in mental model accuracy will help improve performance outcomes. Fortunately, knowledge gaps are subject to remedial action. We believe learning laboratories using simulation models of common management challenges represent one promising approach to developing high-quality mental models of the deep structures (Gary, Dosi, & Lovallo, 2008). Recent advances in interactive modeling and simulation tools provide an effective means for representing the causal structure of business and social systems and to learn about these complex, dynamic environments through simulation (Sterman, 2000). More work is also needed to isolate the small set of enduring causal relationships underpinning a wide range of management problems and challenges. Research is also needed on interventions to develop reflection and deframing skills helping managers question their own mental models and decision rules in an ongoing way. Such skills may prevent managers and firms from prematurely locking into inaccurate mental models and decision rules (Rivkin & Siggelkow, 2003; Tripsas & Gavetti, 2000).

There are also opportunities for further research examining heterogeneity in decision rules connecting high-level policies and strategies with decision making processes on the front lines (Cyert & March, 1963; Simon, 1982). Research on decision errors and biases has primarily focused on identifying the mean or modal effects of specific types of errors (Camerer & Lovallo, 1999; Kahneman & Tversky, 2000; Paich & Sterman, 1993; Zajac & Bazerman, 1991). More work is needed to understand the heterogeneity in decision rules and heuristics and how differences in decision rules impact performance. This is particularly important for strategy scholars trying to explain heterogeneity in strategies and performance among firms. More research is also needed on the formation of decision rules and the links to mental models to help us better understand the origins of strategy.

Understanding that differences in mental model accuracy explain why individual decision makers adopt different strategies associated with different levels of competitive success is an important step forward, and provides a number of opportunities for future research examining the cognitive aspects of strategy and identifying mechanisms to support better strategic thinking and decision making.

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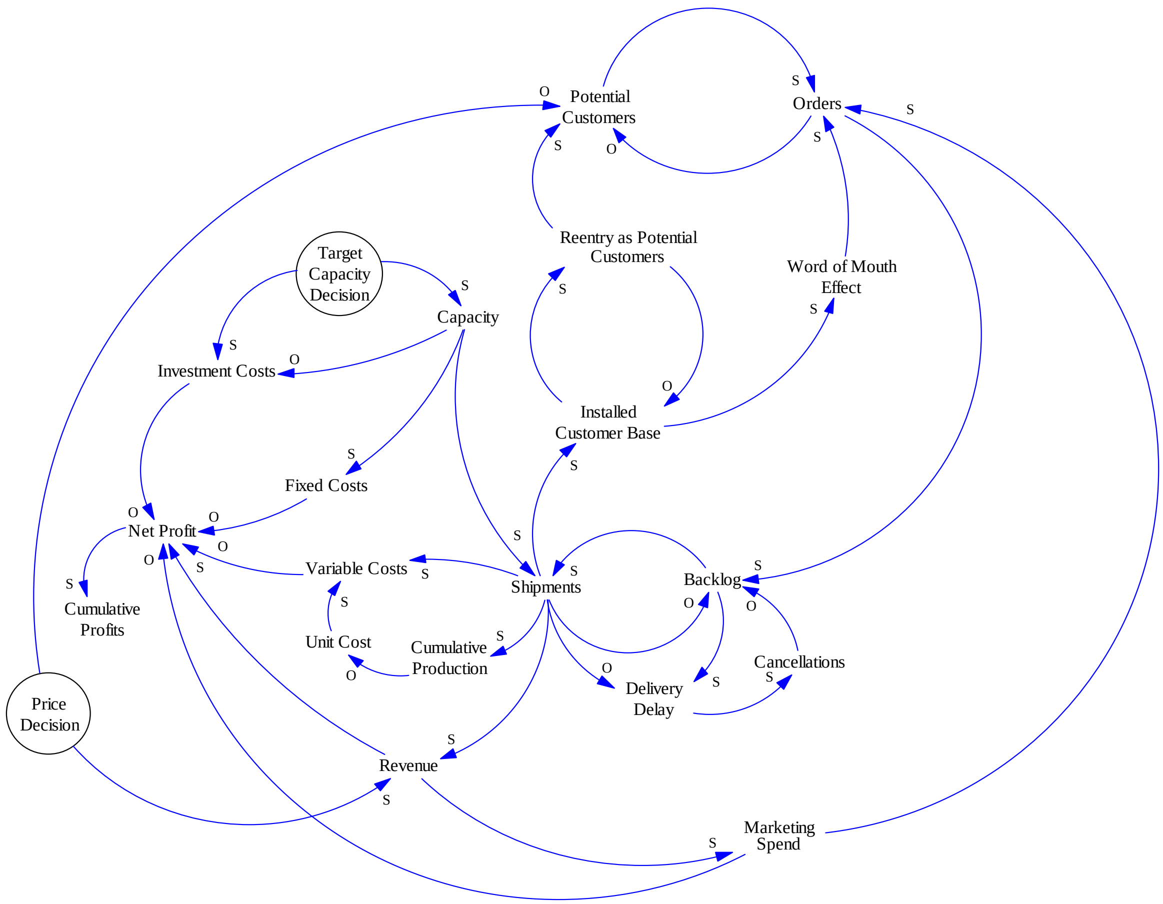


Figure 1a Causal relationships of the low complexity task[7]

[7] The arrows linking variables are defined formally as follows (Sterman, 2000):

$$x \xrightarrow{S} y \Rightarrow \frac{\partial y}{\partial x} > 0 \quad and \quad x \xrightarrow{O} y \Rightarrow \frac{\partial y}{\partial x} < 0$$

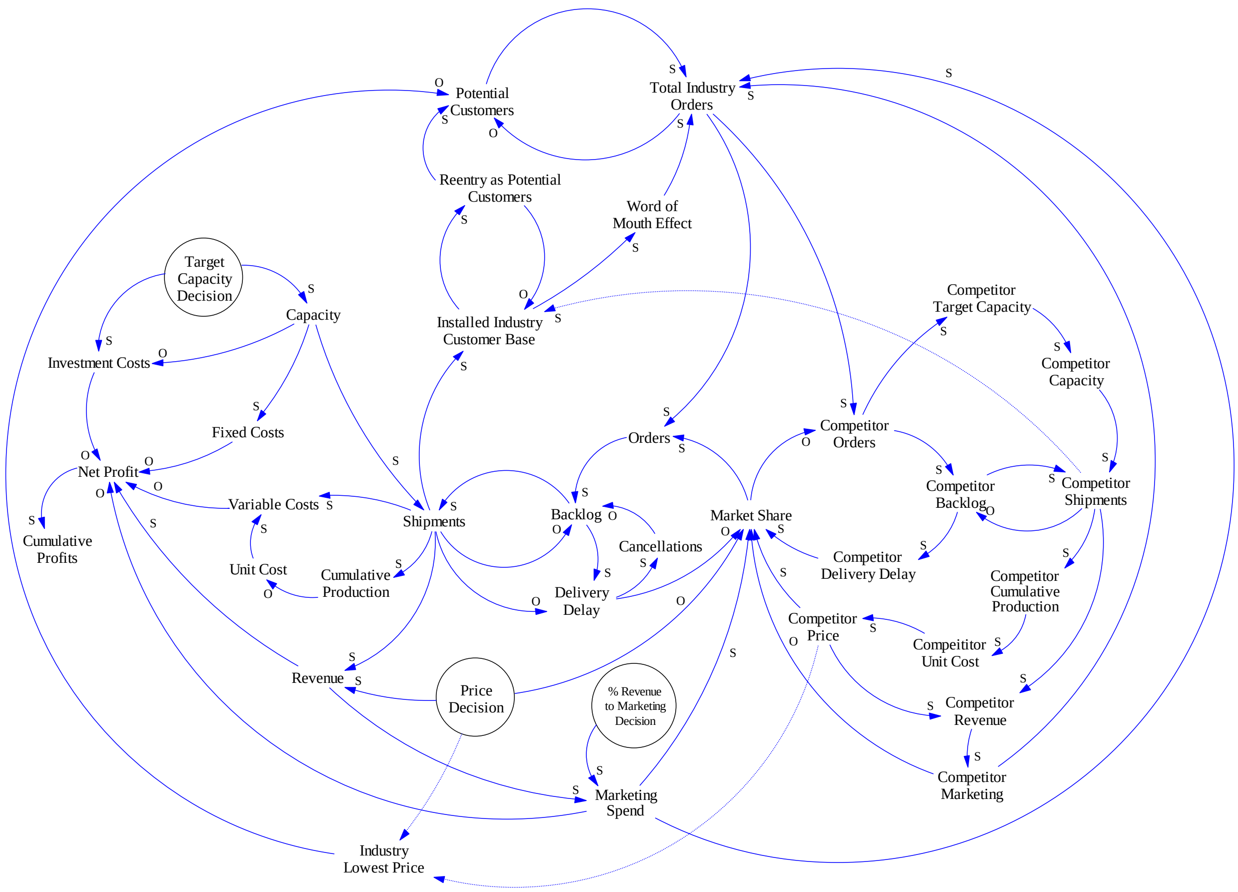


Figure 1b Causal relationships of the high complexity task

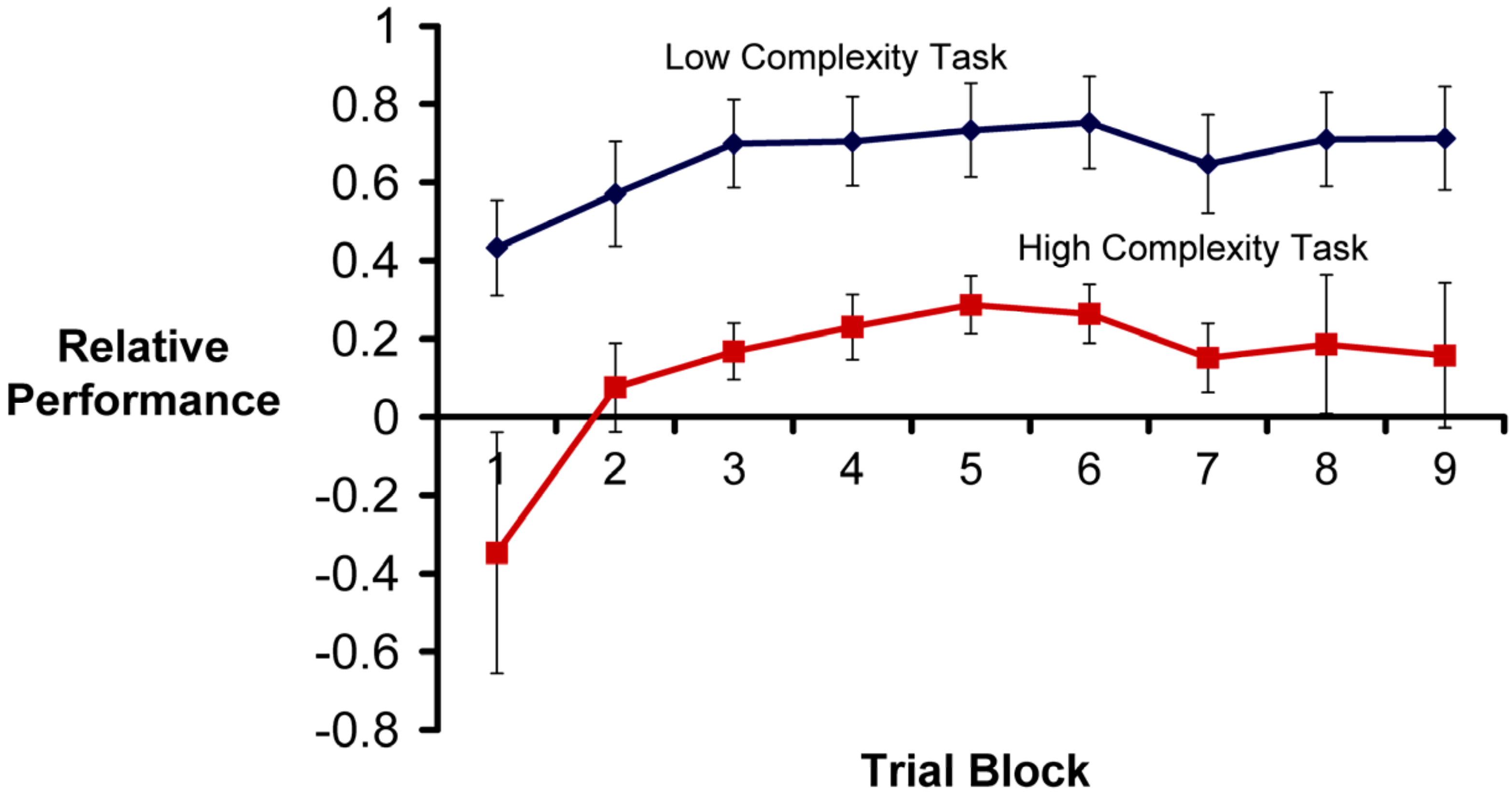


Figure 2 Mean performance relative to benchmark and 95% confidence intervals for low and high complexity groups across all nine trial blocks

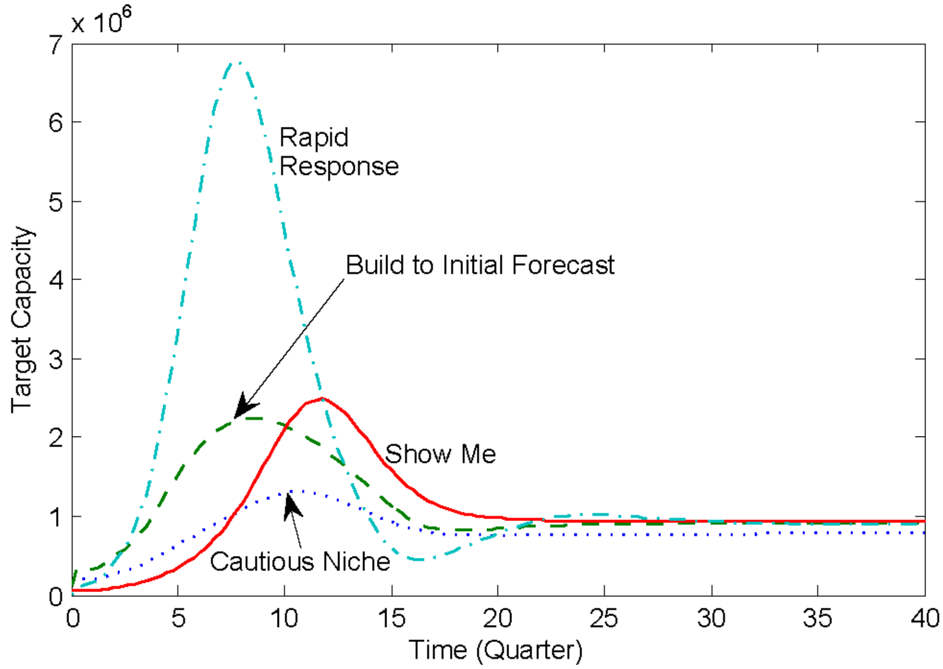


Figure 3 Different patterns of target capacity decisions for the four high complexity strategies

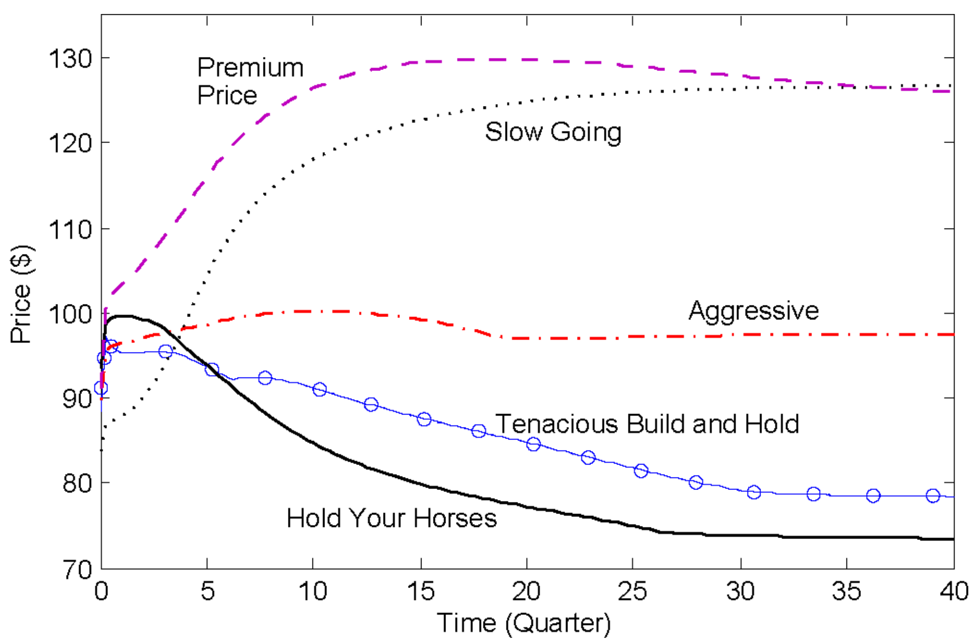


Figure 4 Different patterns of pricing decisions for the five strategies in the low complexity task

Table 1 Correlations, means and standard deviations for study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. GMAT	1																
2. Task complexity	.019	1															
3. Performance 1	.173	-.501**	1														
4. Performance 2	.101	-.578**	.428**	1													
5. Performance 3	.025	-.707**	.453**	.741**	1												
6. Performance 4	.116	-.646**	.471**	.724**	.869**	1											
7. Performance 5	.132	-.626**	.498**	.736**	.846**	.922**	1										
8. Performance 6	.078	-.664**	.509**	.750**	.828**	.869**	.903**	1									
9. Performance 7	-.020	-.682**	.420**	.550**	.582**	.625**	.613**	.687**	1								
10. Performance 8	.127	-.617**	.390*	.581**	.655**	.703**	.658**	.737**	.781**	1							
11. Performance 9	.138	-.608**	.459**	.537**	.592**	.618**	.626**	.709**	.847**	.790**	1						
12. Self-efficacy	.137	-.328**	.266*	.283*	.248*	.291*	.266*	.281*	.347*	.400**	.326*	1					
13. Mental model accuracy	.365**	-.330**	.307*	.433**	.384**	.370**	.387**	.442**	.373*	.480**	.530**	.226	1				
14. Mental mod complexity	.108	-.284*	.180	.225	.154	.083	.125	.194	.279	.257	.367*	.302*	.408**	1			
15. Superstitious beliefs	-.236	-.129	.014	-.015	-.057	-.134	-.073	-.034	.027	-.055	-.026	.133	-.222	.735**	1		
16. Causal blind spots	-.108	.397**	-.235	-.353**	-.304*	-.216	-.278*	-.366**	-.332*	-.364*	-.444**	-.319*	-.613**	-.903**	-.540**	1	
17. Deep structure accuracy	.402**	-.269*	.402*	.249*	.263*	.273*	.299*	.387**	.361*	.556**	.496**	.283*	.769**	.309*	-.176	-.417**	1
Total																	
Mean	642.22	.51	.04	.32	.43	.46	.51	.51	.43	.49	.47	5.66	.56	.84	.20	.18	.39
Std. Deviation	54.30	.50	.78	.43	.38	.37	.36	.37	.37	.43	.46	1.28	.11	.19	.09	.13	.14
N	63	63	63	63	63	63	62	62	43	42	43	63	63	63	63	63	63
Low Complexity																	
Mean	641.19		.43	.57	.70	.71	.73	.75	.65	.71	.71	6.08	.60	.89	.21	.13	.43
Std. Deviation	56.72		.34	.38	.32	.32	.34	.33	.32	.30	.33	1.23	.10	.14	.09	.09	.14
N	31		31	31	31	31	31	31	24	24	24	31	31	31	31	31	31
High Complexity																	
Mean	643.22		-.34	.08	.17	.23	.29	.26	.15	.19	.16	5.25	.53	.79	.19	.24	.36
Std. Deviation	52.73		.89	.33	.21	.24	.21	.21	.20	.38	.41	1.20	.10	.21	.10	.15	.14
N	32		32	32	32	32	31	31	19	18	19	32	32	32	32	32	32

** p< 0.01, 2-tailed.
* p< 0.05, 2-tailed.

Table 2 Impact of mental model accuracy of the complete business environment on performance

Variables	Model 1[a]	Model 2	Model 3[b]	Model 4
Intercept	0.321	-0.091	0.168	0.098
	(0.437)	(0.624)	(0.371)	(0.405)
Task Complexity	-0.434***	-0.432**	-0.438***	-0.439***
	(0.078)	(0.128)	(0.067)	(0.067)
Self-efficacy	0.016	0.011	0.020	0.020
	(0.030)	(0.045)	(0.025)	(0.025)
GMAT (cognitive ability)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Mental Model Complexity	-0.263	-0.038	-0.269	-0.286
	(0.216)	(0.364)	(0.185)	(0.190)
Mental Model Accuracy	1.039*	1.668*	0.988**	1.123*
	(0.392)	(0.619)	(0.335)	(0.456)
MentalModAcc X				-0.263
Task_Complexity				(0.593)
Adjusted R^2	0.470	0.434		
F	11.81	7.442		
Observations	61	42	315	315
Number of Parameters	5	5	14	15
-2 Restricted Log Likelihood			-7.041	-8.023
Akaike's Inf. Criterion (AIC)			-1.041	-2.023
Schwarz's Bayesian (BIC)			10.111	9.118

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

a Models 1 and 2 use Performance on the 6th and 9th trial block, respectively, as the DV and are:

$$Perf = B_0 Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 MentalModComplex + B_5 MentalModAcc + e$$

b Models 3 and 4 use Performance on the 4-9 trial blocks as the repeated measures DV and are:

$$Perf_{it} = B_0 Intercept_i + B_1 TaskComplexity_i + B_2 SelfEff_i + B_3 GMAT_i + B_4 MentalModComplex_i + B_5 MentalModAcc_i + B_6 MentalModAcc\_X\_TaskComplexity_i + B_7 TrialBlk_{it} + e_{it}$$

Table 3 Impact of superstitious beliefs and causal blind spots on performance

Variables	Model 1[a]	Model 2	Model 3[b,c]
Intercept	1.140*	1.278	0.821
	(0.529)	(0.808)	(0.455)
Task Complexity	-0.434***	-0.457***	-0.450***
	(0.078)	(0.132)	(0.068)
Self-efficacy	0.010	0.008	0.017
	(0.029)	(0.045)	(0.026)
GMAT (cognitive ability)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Superstitious Beliefs	-1.268*	-1.669*	-1.111*
	(0.504)	(0.774)	(0.423)
Causal Blind Spots	-0.793*	-1.302*	-0.559
	(0.357)	(0.571)	(0.310)
Adjusted R^2	0.471	0.411	
F	11.849***	6.868***	
Observations	61	42	315
Number of Parameters	5	5	14
-2 Restricted Log Likelihood			-6.529
Akaike's Inf. Criterion (AIC)			-0.529
Schwarz's Bayesian (BIC)			10.622

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

a Models 1 and 2 use Performance on the 6th and 9th trial block, respectively, as the DV and are:

$$Perf = B_0Intercept + B_1TaskComplexity + B_2SelfEff + B_3GMAT + B_4Superstitious + B_5BlindSpots + e$$

b Model 3 uses Performance on the 4-9 trial blocks as the repeated measures DV and is:

$$Perf_{it} = B_0Intercept_i + B_1TaskComplexity_i + B_2SelfEff_i + B_3GMAT_i + B_4Superstitious_i + B_5BlindSpots_i + B_6TrialBlk_{it} + e_{it}$$

c We also tested the interactions between superstitious beliefs and task complexity and also causal blind spots and task complexity. The interaction terms were not significant in any of the models and our results were robust to these changes.

Table 4 Impact of mental model accuracy of the deep structure on performance

Variables	Model 1[a]	Model 2	Model 3[b]
Intercept	0.480	0.428	0.305
	(0.440)	(0.624)	(0.377)
Task Complexity	-0.442***	-0.471***	-0.446***
	(0.076)	(0.121)	(0.066)
Self-efficacy	0.004	-0.005	0.008
	(0.030)	(0.044)	(0.026)
GMAT (cognitive ability)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Deep Structure Accuracy	0.596*	1.178**	0.555*
	(0.286)	(0.417)	(0.245)
Adjusted R^2	0.454	0.443	
F	13.704***	9.36***	
Observations	61	42	315
Number of Parameters	4	4	13
-2 Restricted Log Likelihood			-4.479
Akaike's Inf. Criterion (AIC)			1.521
Schwarz's Bayesian (BIC)			12.682

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

a Models 1 and 2 use Performance on the 6th and 9th trial block, respectively, as the DV and are:

$$Perf = B_0 Intercept + B_1 TaskComplexity + B_2 SelfEff + B_3 GMAT + B_4 DeepStrucAcc + e$$

b Model 3 uses Performance on the 4-9 trial blocks as the repeated measures DV and is:

$$Perf_{it} = B_0 Intercept_i + B_1 TaskComplexity_i + B_2 SelfEff_i + B_3 GMAT_i + B_4 MDeepStrucAcc_i + B_5 TrialBlk_{it} + e_{it}$$

Table 5 Impact of mental model accuracy on deviation from optimal information weights

Variables	Model 1[a]	Model 2[b]	Model 3[c]
Intercept	3.170**	0.210	2.182*
	(1.004)	(1.299)	(1.068)
Task Complexity	2.640***	2.681***	2.736***
	(0.190)	(0.195)	(0.189)
Self-efficacy	-0.062	-0.055	-0.041
	(0.068)	(0.072)	(0.072)
GMAT (cognitive ability)	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)
Mental Model Accuracy	-3.398***		
	(0.883)		
Superstitious Beliefs		3.472**	
		(1.232)	
Causal Blind Spots		2.839**	
		(0.881)	
Deep Structure Accuracy			-2.140**
			(0.702)
Observations	297	297	297
Number of Parameters	13	14	13
-2 Restricted Log Likelihood	767.896	768.317	772.923
Akaike's Inf. Criterion (AIC)	773.896	774.317	778.923
Schwarz's Bayesian (BIC)	784.874	785.285	789.901

Notes:
Unstandardized coefficients with standard errors in parentheses
* p < .05; ** p < .01; *** p < .001

All models use Deviation from Optimal Information Weights on trial blocks 4-9 as the Dependent Variable

a Model 1 is:

$$\text{Deviation\_from\_Opt\_Weights}_{it} = B_0\text{Intercept}_i + B_1\text{TaskComplexity}_i + B_2\text{SelfEff}_i + B_3\text{GMAT}_i + B_4\text{MentalModAcc}_i + B_5\text{TrialBlk}_{it} + e_{it}$$

b Model 2 is:

$$\text{Deviation\_from\_Opt\_Weights}_{it} = B_0\text{Intercept}_i + B_1\text{TaskComplexity}_i + B_2\text{SelfEff}_i + B_3\text{GMAT}_i + B_4\text{Superstitious}_i + B_5\text{BlindSpots}_i + B_6\text{TrialBlk}_{it} + e_{it}$$

c Model 3 is:

$$\text{Deviation\_from\_Opt\_Weights}_{it} = B_0\text{Intercept}_i + B_1\text{TaskComplexity}_i + B_2\text{SelfEff}_i + B_3\text{GMAT}_i + B_4\text{MDeepStrucAcc}_i + B_5\text{TrialBlk}_{it} + e_{it}$$

Table 6 Distinct strategies identified in the high and low complexity task conditions

Strategies	Description	N[a]	Perf[b]	Mental Model Acc[c]	Capacity Invest. Decision Rule[d] Intercept	Orders	Growth	Backlog/ Capacity	Pricing Decision Rule[e] Intercept	Cost	Backlog/ Capacity
Low Complexity Strategies											
[1] Tenacious Build & Hold	Build capacity to initial forecast and maintain position while reducing price	59	0.74	0.60	12.78	0.10	0.05	0.27	2.34	0.57	0.05
[2] Slow Going	Slow and cautious capacity investment with high price	47	0.72	0.62	11.87	0.09	0.04	0.18	7.18	-0.66	0.02
[3] Aggressive	Responsive capacity adj. to market demand while maintaining fixed price	28	0.92	0.64	7.28	0.48	0.38	0.53	4.51	0.02	0.02
[4] Hold Your Horses	Capacity investment lags demand with aggressive price cutting	40	0.74	0.56	5.04	0.65	-0.13	-0.03	2.19	0.60	0.03
[5] Premium Price	Charge price premium and avoid excess capacity by following demand	68	0.55	0.60	6.46	0.51	-0.10	0.01	5.83	-0.28	0.05
High Complexity Strategies											
[1] Cautious Niche	Raise margin when excess demand & cautious capacity expansion	62	0.16	0.50	8.69	0.33	0.04	0.08	-1.45	1.47	0.05
[2] Build to Initial Forecast	Build capacity to initial forecast and maintain constant margin	77	0.30	0.53	11.72	0.14	0.24	0.42	0.74	0.88	0.01
[3] Show Me	Invest in capacity only after seeing demand & drop prices as unit costs fall	76	0.02	0.52	2.35	0.79	0.02	-0.06	0.35	0.97	-0.01
[4] Rapid Response	Aggressive capacity adj. to match demand and drop prices as unit costs fall	16	0.49	0.62	10.13	0.23	1.22	1.62	0.73	0.88	0.00

Notes:
a Number of decision makers adopting each strategy over trial blocks 1-9

b Mean performance across trial blocks 4-9 for each strategy

c Mean mental model accuracy across trial blocks 4-9 for each strategy

d Mean information weights (cluster centroids) for the capacity investment decision rule for each strategy over trial blocks 1-9

d Mean information weights (cluster centroids) for the pricing decision rule for each strategy over trial blocks 1-9

Appendix A: Segment from the first set of knowledge questions about bivariate causal relationships

$$X \xrightarrow{S} Y$$

This arrow indicates that an increase in X results in an increase in Y above what it would have been (all else equal). On the other hand, a decrease in X results in a decrease in Y below what it would have been (all else equal). X and Y move in the SAME direction.

$$X \xrightarrow{O} Y$$

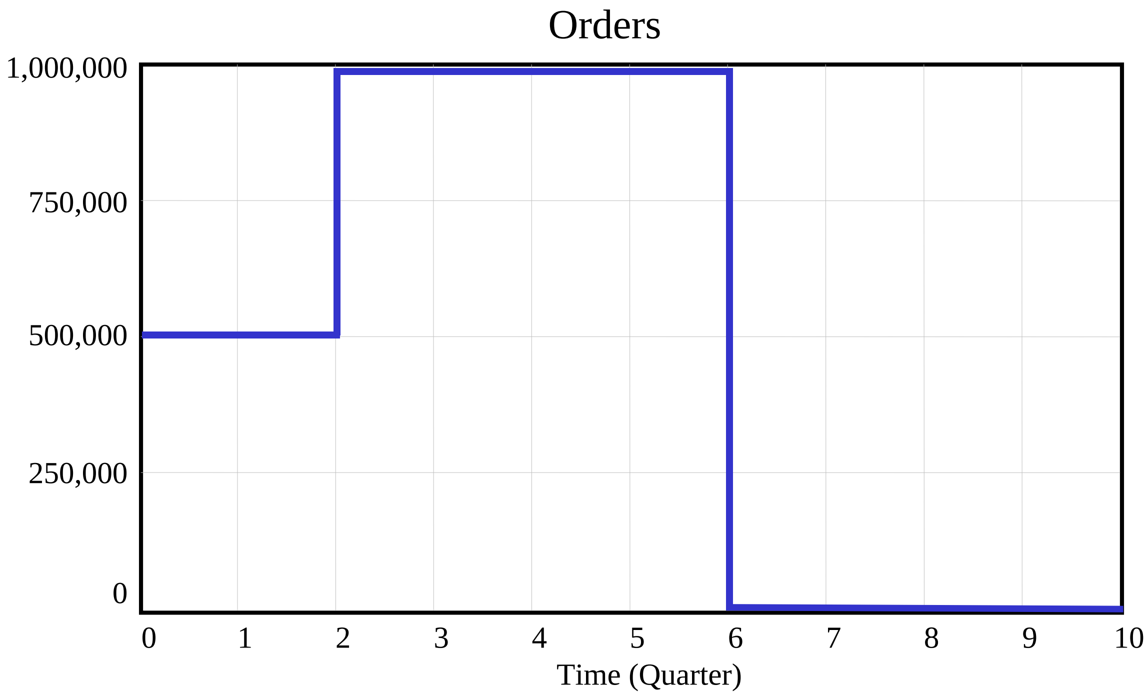
In contrast, this arrow indicates X and Y move in the OPPOSITE direction. For example, an increase in X results in a decrease in Y below what it would have been (all else equal). On the other hand, a decrease in X results in an increase in Y above what it would have been (all else equal).

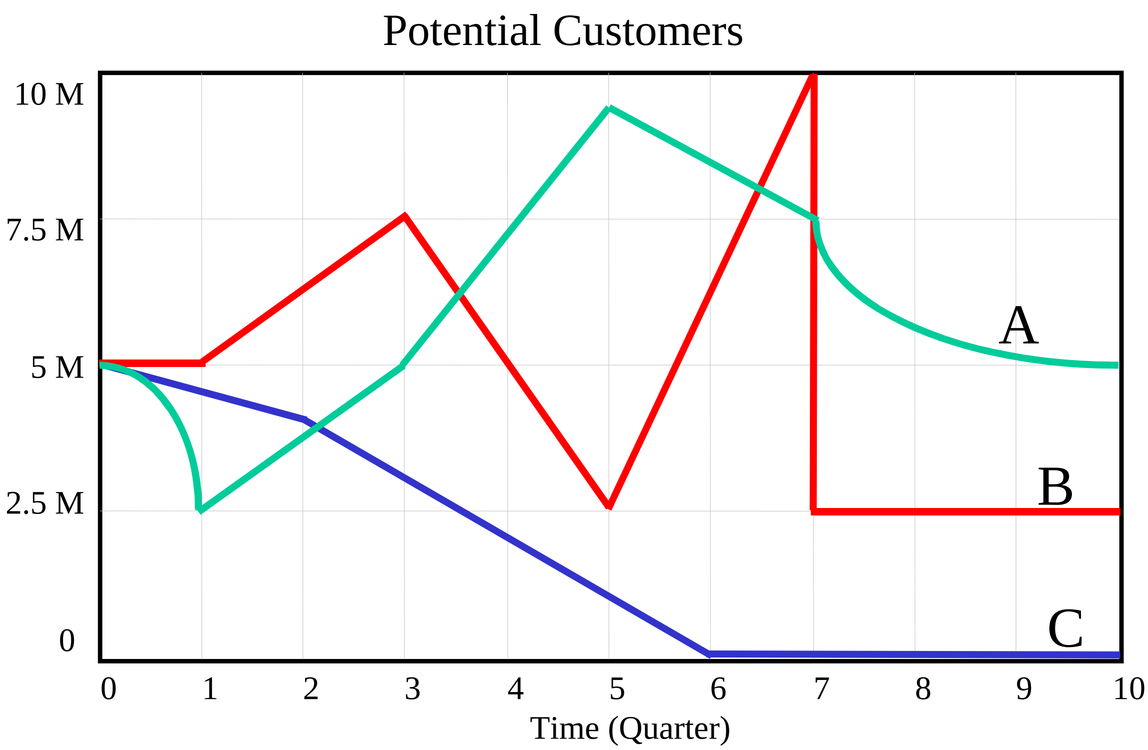
Think about the relationships between these variables that you believe are embedded in the simulator. Relying only on your experience with the simulated firm, draw the appropriate influence arrow(s) for each variable pair and indicate whether the causal influence is in the same or opposite direction using an ‘S’ or ‘O’ at the end of the arrow. Identify any cases in which there is two-way dependency between the variables by drawing the appropriate arrows representing the two-way loop of influence. Focus only on direct relationships and ignore any intervening variables that may result in indirect influence arrows. If there is no direct relationship between the variable pair, write ‘NONE’ between the two variables. If you do not have any idea about the correct answer, then write ‘Do Not Know’ instead of guessing randomly.

1.	Orders	Backlog
2.	Shipments	Backlog
3.	Backlog	Delivery Delay

Appendix B: Example graphical scenario question from the second set of knowledge questions

Using the time path of Total Industry Orders provided in the top graph below, select the letter of the appropriate time path for Industry Potential Customers on the bottom graph. Circle D if none of the lines in the bottom graph show the correct time path. Assume the initial value of industry Potential Customers is 5 million at Time 0. Also assume that no other variables affect industry Potential Customers over this time horizon.





Answer: A) B) C) D) None of the Above

Appendix C: Example questions assessing deep structure accuracy

The following are seven example items about bivariate causal relationships used to measure deep structure accuracy. See Appendix A for the instructions participants were given for answering these questions. Also note that these questions were randomly placed throughout the knowledge test and therefore the numbers along the left side of the table below do not reflect the order of the questions in the full knowledge test. The remaining four items of the deep structure accuracy measure are graphical scenario questions covering a subset of the same relationships. The example graphical scenario question in Appendix B is one of those items.

1.	Potential Customers	Orders
2.	Potential Customers	Reentry as Potential Customers
3.	Potential Customers	Price
4.	Installed Customer Base	Shipments
5.	Installed Customer Base	Reentry as Potential Customer s
6.	Installed Customer Base	Word of Mouth Effect
7.	Orders	Word of Mouth Effect

Appendix D: Items measuring perceived self-efficacy on the simulation

Listed below are activities that often have to be completed during the Management Simulation.

In the column headed *Can Do*, place a check (√) alongside an activity if you believe you had some understanding of what was required, even if you could not do it very well.

If you believe that you had no understanding of how to manage an activity, place a cross (X) in the *Can Do* column and write a zero (0) in the *Confidence* Column.

For each of the tasks checked (√) as *Can Do*, indicate in the *Confidence* column how confident you are that you could effectively manage the activity described. Use the following scale to record your answers in the *Confidence* column.

1	2	3	4	5	6	7	8	9	10
Very Little confidence				Moderate confidence					Total confidence

	Can Do	**Confidence**
1. Setting appropriate price levels	_______	_______
2. Setting appropriate target capacity levels	_______	_______
3. Meeting customer demand (orders)	_______	_______
4. Consistently increasing cumulative profits	_______	_______
5. Controlling the backlog of orders	_______	_______
6. Controlling delivery delays	_______	_______
7. Consistently increasing revenue	_______	_______
8. Increasing customers orders	_______	_______
9. Controlling total costs	_______	_______
10. Managing the overall simulation	_______	_______