BRING THE NOISE, BUT NOT THE FUNK: DOES THE EFFECT OF PERFORMANCE MEASURE NOISE ON LEARNING DEPEND ON WHETHER THE LEARNING IS EXPERIENTIAL OR VICARIOUS?

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ABSTRACT

Performance measure noise can be a critical barrier to employees’ learning. Using an experiment, we examine whether the effects of performance measure noise on employees’ learning depends on the type of learning in which employees engage: experiential versus vicarious. We predict and find performance measure noise has a more deleterious effect on learning when such learning occurs experientially rather than vicariously. Specifically, we find experiential learners demonstrate less learning as performance measure noise increases, but vicarious learners show no such effect of performance measure noise. Collectively, our findings suggest performance measure noise and learning type play important roles in the extent to which firms realize the decision-facilitating benefits of performance measurement systems. In particular, since much of the learning in modern organizations occurs vicariously, our findings suggest performance measure noise may not be as detrimental to employees’ learning as previously thought.

Keywords: learning; performance measure noise; experiential learning; vicarious learning
I. INTRODUCTION

Using an experiment, we examine whether the effects of performance measure noise on employees’ learning depends on whether they learn from their own experiences (experiential learning) or from others’ experiences (vicarious learning). Performance measures serve an important decision-facilitating role by enhancing employees’ abilities to make better-informed decisions. In particular, performance measures facilitate learning, which we define as the process of determining which actions will be most effective in achieving the firm’s objectives. However, performance measures are often noisy because they can reflect factors beyond employee actions that affect the performance measure (e.g., economic shocks, natural disasters, random noise). Thus, performance measure noise can impede employees’ learning by making it harder for them to accurately assess the causal relationships between their actions and outcomes of interest (Ittner and Larcker 2005).

While the effect of performance measure noise on learning is a central topic in managerial accounting, this literature generally assumes learning is experiential in nature (e.g., Sprinkle 2000; Farrell, Kadous, and Towry 2008, 2012; Thornock 2016). However, employees must often learn on the job, and thus lack sufficient resources and time to fully explore, and test the effectiveness of their actions before implementing them (Campbell, Epstein, and Martinez-Jerez 2011). For example, environmental factors and/or the need for timeliness may preclude employees from fully experimenting to identify the best course of action. Luckily, employees can look to others’ experiences for additional learning opportunities. Such vicarious learning is the hallmark of formal and informal information sharing programs within firms (Banker, Chang and Kao 2002; Duhigg 2012; Li and Sandino 2018). While both experiential and vicarious learning are important in the workplace, prior accounting literature virtually ignores their differentiating features and effects.
We predict the effects of performance measure noise on employees’ learning are more deleterious when employees learn experientially rather than vicariously. We base this prediction on prior research, which demonstrates that the relative merits of experiential versus vicarious learning depend on the net effect of two countervailing forces. First, employees who learn experientially engage in more pre-action deliberations, which yields informational advantages when processing available performance measure information and identifying the next course of action (i.e., they choose an action and process data specifically tailored to the hypothesis they currently have in mind) (Markant and Gureckis 2014). In contrast, since vicarious learners are not privy to experiential learners’ pre-action deliberations, available performance measure information is not as informative, even if the vicarious learning knows what action was taken. Second, experiential learners exhibit greater myopic information processing than do vicarious learners (Merlo and Schotter 2003), creating a processing disadvantage for experiential learners. In particular, experiential learners tend to focus on and respond to more recent action-outcomes, while vicarious learners adopt a more holistic view of available information and attend to a more collective set of information.

We predict performance measure noise affects the balance of these two countervailing forces. While we are not aware of any theory or evidence suggesting performance measure noise affects the informational advantage for experiential learners, research does suggest performance measure noise affects myopic processing, the comparative disadvantage of experiential learners. Specifically, processing a larger set of information can mitigate the negative effects of performance measure noise on learning (Luft 2009). Thus, the greater tendency of experiential learners to engage in myopic processing of outcome information is more costly and negatively affects learning to a greater extent as performance measure noise increases. Because vicarious
learners are less likely to process outcome information myopically, performance measure noise affects their learning to a lesser degree.

We use an experiment to test our hypothesis. In order to conduct a clean test of our theory, we investigate our research question in a setting that, by necessity, does not map perfectly into the real-world settings in which we are most interested (Swieringa and Weick 1982; Libby, Bloomfield, and Nelson 2002). However, this research setting allows us to cleanly manipulate our independent variables of interest while holding other factors constant and minimizing potential confounds. Specifically, we adapt Merlo and Schotter’s (1999, 2003) maximization problem task, in which subjects try to learn the action that maximizes expected payoff. Expected payoff is our operationalization of the firm’s objective, so that this task operationalizes the construct of learning (determining which actions will be most effective in achieving the firm’s objectives). Subjects repeat the task multiple times and receive feedback after each iteration, from which they can learn which action maximizes their expected payoff. We manipulate the level of performance measure noise at two levels (low or high), varying the degree to which noise affects performance measure outcomes. We manipulate learning type at two levels. In the Experiential Learning condition, subjects perform the task for 36 periods, and receive outcome information after each period. In the Vicarious Learning condition, we match each subject with a subject from the Experiential Learning condition and allow the vicarious learner to observe (via his/her computer) the matched subject’s actions and outcomes for the first 35 periods. Thus, after 35 periods, the subjects within each matched pair have received the exact same information and the same opportunity to learn the payoff-maximizing action. Subjects in both learning type conditions perform the task in Period #36, and we use this single choice to assess subjects’ learning of the payoff-maximizing action.
Our results support our interaction hypothesis. Using subjects’ action-choices in Period #36, we find experiential learners exhibit less learning as performance measure noise increases, but an increase in performance measure noise does not affect learning when it occurs vicariously. Supplemental analyses suggest experiential learners process performance measure information more myopically than do vicarious learners, which hinders learning. We also find these differences can be quite profound, such that the relative benefits of vicarious learning depend on the level of performance measure noise. Specifically, we find experiential learners exhibit greater learning than do vicarious learners when performance measure noise is low, but the opposite when performance measure noise is high.

Our findings demonstrate performance measure noise and learning type play important roles in the extent to which firms realize the decision-facilitating benefits of management accounting information. Thus, our study has important implications for a wide array of settings in which any type of employee learning is a key input for firm performance (Frederickson, Peffer, and Pratt 1999; Feichter 2019). One notable setting is the development and implementation of firm strategy to control and improve financial performance. In this setting, employees implement strategy via various actions and learn about the effectiveness of these strategic actions through the firm’s strategic performance measurement system (Humphreys, Gary, and Trotman 2016). Performance measure noise can hinder such strategic learning because it inhibits learning of causal relationships between employees’ actions and outcomes of interest (Ittner and Larcker 2005). However, we demonstrate differences in learning can be exploited to mitigate the harmful effects of performance measure noise on learning, which suggests performance measure noise may not be as detrimental as previously thought.

Our study also contributes to the literature on the effects of performance measure noise on learning and performance when employees perform complex tasks (Sprinkle 2000; Farrell,
Kadous, and Towry 2008, 2012; Humphreys et al. 2016; Thornock 2016). For such tasks, relevant information about peers’ actions and outcomes may accelerate learning and help employees identify performance-enhancing actions. This is especially important in today’s complex business environment, in which trends such as job rotation programs and the expansion of job responsibilities require employees to quickly learn effective ways to perform new tasks (Lindbeck and Snower 2000). In such scenarios, our results speak to the desirability of information-sharing within the firm – either real-time or ex post – which provides employees an opportunity to learn vicariously, beyond their own experience. Our results suggest such opportunities can be especially beneficial as performance measure noise increases.

Finally, we contribute to the literature on learning (Merlo and Schotter 1999, 2003; Sprinkle 2000; Markant and Gureckis 2014). Prior research identifies two countervailing forces underlying the relative merits of experiential versus vicarious learning. Our results highlight how an important accounting variable, performance measure noise, affects the balance of these forces.

II. BACKGROUND AND HYPOTHESIS

Learning and Performance Measure Noise

We define learning as the process of determining which actions will be most effective in achieving the firm’s objectives. Learning can take various forms and occurs at all levels of the firm in various contexts. For example, customer service employees learn over time the best methods for dealing with customers. Likewise, production employees learn how to complete tasks that enhance effectiveness and efficiency (produce quality products, reduce waste). At higher levels of the firm, employees learn about the effectiveness of their actions when implementing the firm’s strategy (making capital investments, identifying strategic tactics), and managing subordinate employees (learning subordinates’ strengths and weaknesses, their responses to different evaluation and compensation practices).
To facilitate employees’ learning, firms rely on performance measurement systems, which provide information useful for evaluating performance, identifying opportunities for improvement, and adapting (Ittner and Larcker 2005). The usefulness of these systems spans the entire firm and helps employees make better-informed decisions. That is, performance measurement systems serve an important decision-facilitating role (Demski and Feltham 1976).

We consider scenarios in which employees are interested in learning about the outcomes of implementing an action (performance effects), but performance measures are noisy in that the outcomes are a function of the employee’s action and other, uncontrollable factors. In such scenarios, performance measure noise is a critical barrier to learning (Ittner and Larcker 2005). Specifically, performance measure noise undermines the usefulness of outcome-based performance measures because noise makes it more difficult for employees to learn about the effectiveness of their actions by observing the effect such actions have on the outcome. For example, suppose an airline’s objective is to improve customer satisfaction, and the airline measures customer satisfaction using customers’ responses to a satisfaction survey. To the extent that customers’ responses are affected by uncontrollable factors like weather delays, the customer satisfaction measure is noisy, and employees may draw erroneous conclusions about the effectiveness of actions taken to achieve the firm’s objective. Likewise, suppose a firm introduces a loyalty rewards program to improve customer retention and loyalty (measured by number of repeat customers). Uncontrollable factors, such as an economy-wide increase in demand, may inflate the number of repeat customers and prevent employees from drawing correct conclusions about the effects of the loyalty program on customer retention and loyalty. Finally, suppose a firm initiates a sales contest to boost salesperson effort and performance. Uncontrollable factors, such as raw material outages caused by supplier labor disputes, may
negatively affect sales and hinder employees’ ability to learn about the effect of the contest on effort and performance.¹

Notably, the prior literature on performance measure noise and learning has focused on experiential learning, i.e., learning from one’s own experiences (Sprinkle 2000; Farrell, Kadous, and Towry 2008, 2012; Humphreys et al. 2016; Thornock 2016). For example, Sprinkle (2000) finds incentive pay accelerates discovery of action choices that increase performance, and Thornock (2016) finds the lag between action choices and outcome information affects learning.

However, experiential learning can be limited because employees often lack sufficient time and resources to fully explore and examine the full range of possible actions (Campbell et al. 2011). Fortunately, employees have other sources of information, as they can look to others’ experiences for additional learning opportunities. Such vicarious learning can be valuable for employees’ learning (Ittner and Larcker 2005). For instance, Duhigg (2012) describes an anecdote about Alcoa Corporation, in which weekly reports shared through the company’s intranet not only helped plant managers better understand the company’s strategy emphasizing worker safety, but also spurred learning regarding input pricing and other important operational issues.²

Despite its importance, relatively little accounting research considers the effects of vicarious learning on employees’ learning (one exception is Choi, Hecht, Tafkov and Towry 2012, 2013).

¹ Broadly speaking, performance measures can be noisy due to (1) uncontrollable factors, (2) imperfections in the measurement process, and/or (3) construct validity, whereby performance measures imperfectly represent an underlying construct of interest. Regarding (3), while prior research on strategy surrogation explores this type of performance measure noise (Choi, Hecht, and Tayler 2012, 2013), it is beyond the scope of the current study. The other two forms of performance measure noise are similar, but distinct (Luft 2009). We focus on (1) in this study, given its importance in learning settings (Dye 2004; Luft 2009). This focus is consistent with prior research on performance measure noise (Feltham and Xie 1994; Gibbs, Merchant, Van der Stede, and Vargus 2004).

² For example, TGI Friday’s introduced its “$10 endless appetizers” promotion in a few, selected locations in the summer of 2014. Based on the data collected from these locations, the restaurant made the promotion permanent in all locations in early 2017. When this happened, managers of locations that were not part of the initial promotion had no first-hand experience with the promotion. Instead, these managers had to learn vicariously from the experience of those involved in the initial promotion to figure out how to implement the promotion at their locations.
(2016), who study vicarious learning in isolation and find observing a peer employee’s positive versus negative outcome affects vicarious learners’ focus on performance measures versus strategic constructs. To help fill that gap, we investigate whether the previously documented negative effects of performance measure noise on learning differs for experiential versus vicarious learners. In the next subsection, we develop theory to predict the effects of performance measure noise on learning depend on learning type, such that performance measure noise negatively affects learning to a greater extent when employees learn experientially rather than vicariously.

**Hypothesis**

Research highlights two countervailing forces that explain differences in the processes used by experiential versus vicarious learners. A comparative advantage of experiential learners is they find the content of performance measure outcome information to be more relevant than do vicarious learners (Markant and Gureckis 2014), creating an informational advantage for experiential learners. Specifically, experiential learning involves a hypothesis-dependent sampling process, in which the experiential learner chooses an action and processes data specifically tailored to the hypothesis s/he currently has in mind. For example, consider an employee who identifies and implements a customer rewards program as a strategic initiative (hypothesizes the program increases customer satisfaction). Then, the employee evaluates customer satisfaction survey information collected throughout the year to determine whether the program was successful (tests the hypothesis). As a result of this process, employees who learn

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3 Although we draw inspiration from real-world examples like Alcoa in which employees may learn experientially and vicariously, we do not study the relative merits of learning experientially versus learning both ways. Rather, given the lack of extant (accounting) research on different learning types, particularly as it relates to the harmful effects of performance measure noise on learning, we take a more modest approach and examine whether the effects of performance measure noise on learning extend to settings in which employees learn vicariously. As noted in Section V, studying the effects of performance measure noise in settings in which employees may learn using both types is a potentially fruitful opportunity for future research.
experientially engage in more pre-action deliberations, which yields informational advantages when processing available outcome information and identifying the next course of action, such as continuing the customer reward program or considering another initiative. In contrast, since employees engaged in vicarious learning are typically not privy to the experiential learner’s hypothesis-oriented, pre-action considerations, available outcome information is not as informative, even if the vicarious learner knows what initiative was chosen. In other words, an experiential learner knows what hypothesis is being tested and why, while a vicarious learner does not. A vicarious learner “must make sense of what happens to come along, to find the significant groupings in the flow of events to which he is exposed and over which he has only partial control” (Bruner, Goodnow, and Austin 1956, 126).

In contrast, a comparative disadvantage of experiential learners is they exhibit greater myopic processing of performance measure information than individuals engaged in vicarious learning. Specifically, experiential learners focus on and respond to a subset of performance measure information (e.g., customer satisfaction surveys from the most recent fiscal quarter), rather than attend to a collective set of performance measure information (e.g., customer satisfaction surveys for the entire fiscal year).4

Research across disciplines report evidence consistent with experiential learners exhibiting a greater propensity for myopic processing. Psychology research on construal level theory finds less psychological distance leads individuals provided with a temporal dataset to make forecasts that emphasize more recent trends in the data over the global trends reflected in the entire dataset (Henderson, Fujita, Trope, and Liberman 2006). Construal level theory asserts

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4 Consistent with prior research on learning, we use myopia to refer to focusing on a narrow set of information rather than on a broader set of information. Thus, we distinguish our conceptualization of myopia from research on managerial myopia (Stein 1988, 1989; Porter 1992), which describes the tendency for employees to take actions that maximize short-term outcomes at the expense of long-term outcomes.
less psychological distance promotes concrete, low-level representations of events and outcomes that emphasize highly context-specific details, while greater psychological distance promotes more abstract, high-level representations of events and outcomes, which are more schematic and decontextualized (Liberman, Trope, and Stephan 2007; Trope and Liberman 2010). Thus, when making forecasts using a temporal dataset (e.g., predicting future stock prices using historical stock price data), less psychological distance leads individuals to extrapolate using trends in recent datapoints (e.g., stock price movements during the most recent fiscal quarter) and not the general trends suggested by the collective set of data (e.g., stock price movements over the past 1-2 years). In our setting, we expect that experiential learning reduces psychological distance compared to vicarious learning due to the direct, first-hand experience with actions and associated outcomes. Given this decreased psychological distance – and the accompanying tendency to maintain concrete, low-level representations of events and outcomes – employees engaged in experiential learning are more likely than employees engaged in vicarious learning to narrow their focus on subsets of data, even when a more complete dataset is available.5

Economics research on learning more directly suggests experiential learning leads to greater myopic processing than vicarious learning. Specifically, Merlo and Schotter (2003) conduct a multi-period experiment in which subjects are tasked with identifying an optimal (payoff-maximizing) strategy in a setting where performance measures contain noise (though the authors hold performance measure noise constant). They find experiential learners are less successful than are vicarious learners at identifying the optimal strategy due to “reinforcement

5 Gioia and Manz (1985) characterize vicarious learning as a process whereby individuals develop a cognitive representation, or script, of the observed behavior. These scripts can vary from episodic scripts (concrete representations of specific observations and experiences) to generalized scripts (abstract representations that span multiple observations and experiences). Gioia and Manz (1985) do not compare experiential and vicarious learning, but the evidence from research on construal level theory suggests experiential (vicarious) learners are more likely to develop episodic (generalized) scripts. See Section V for additional discussion.
learning.” Specifically, experiential learners appear to simply react to period-by-period information (playing the same strategy if the prior period’s payoff was relatively high, and switching to a new strategy if the prior period’s payoff was relatively low). Importantly, reinforcement learning simply reinforces the choices that are actually made, and not the hypothetical choices that could have been made, but were not. In contrast, vicarious learners, who, as observers find themselves in a more abstract situation, are more likely to consider not only the choices that are actually made (by experiential learners), but also the hypothetical choices that could have been made and the payoffs resulting from such hypothetical choices (Camerer and Ho 1999).

The extent to which learning type moderates the effects of performance measure noise on learning is determined by the net effect of experiential learners’ comparative informational advantage and myopic processing disadvantage. We are not aware of any theory or evidence to predict experiential learners’ information advantage (their understanding of why they chose a particular action) diminishes as performance measure noise increases. However, theory suggests the negative effects of performance measure noise on learning and decision-making are reduced when employees process a larger set of information (Luft 2009). Thus, experiential learners’ greater tendency to engage in myopic processing of performance measure information becomes more costly and has a greater negative effect on learning as performance measure noise increases. In contrast, vicarious learners do not exhibit such effects to the same degree because their more holistic – as opposed to myopic – processing of performance measure information leaves them less susceptible than experiential learners to the effects of performance measure noise.

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6 Casas-Arce, Lourenço, and Martínez-Jerez (2017) conduct a three-month field experiment with home repair professionals (who act as experiential learners) in which the authors manipulate feedback frequency (weekly or monthly) and level of detail (detailed or aggregated). They find evidence consistent with myopic processing. Specifically, the professionals behave like “local thinkers” (Gennaioli and Shleifer 2010) in that they overweight the information contained in the most recent feedback report, thereby disregarding information from previous reports.
noise. This discussion leads to the following prediction of an interaction between performance measure noise and learning type:7

**Hypothesis:** The effect of performance measure noise on learning depends on the type of learning, such that the negative effect of an increase in performance measure noise will be greater for experiential learners than for vicarious learners.

### III. EXPERIMENTAL DESIGN

**Overview**

We conducted an experiment with 72 subjects recruited from a large public university in the southeastern United States. On average, subjects were 20.1 years old, and 58 percent were female. We manipulated both performance measure noise (low vs. high) and learning type (experiential vs. vicarious) between subjects. Each experimental session involved 36 periods and lasted approximately 100 minutes. Subjects’ payoffs were denominated in the experimental currency, *Lira*, and we converted *Lira* to US dollars at a rate of $0.016 ($0.0125) per *Lira* in the Low Noise (High Noise) condition. We used different exchange rates to hold constant expected pay across conditions. Prior to administering any experimental sessions, we obtained approval from the Institutional Review Board of the university where we conducted the experiment.

**Task Description**

We adapted Merlo and Schotter’s (2003) computerized decision-making task.8 We informed subjects they would compete against a computer (the Paired Computer) in individual

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7 Our hypothesis focuses on how learning type moderates the effects of performance measure noise on learning, and thus, our theory does not allow us to develop a prediction about whether one type of learning is more effective (ordinally) than the other type as performance measure noise increases. However, our experimental design allows us to examine this issue, and we report related results in Section IV.

8 Our design differs from Merlo and Schotter’s (2003) in several ways. Most notably, we manipulate performance measure noise at two levels. Merlo and Schotter (2003) manipulate learning type while holding performance measure noise constant. Therefore, their study does not inform how learning type interacts with performance measure noise to affect learning.
tournaments for 36 periods.\(^9\) In each period, winning subjects earned a prize of 29 Lira, and losing subjects earned a prize of 17.2 Lira. In the event of a tie, subjects earned either 29 or 17.2 Lira, each with 50 percent probability.

We informed subjects the prizes in each period would be allocated by comparing the subject’s and the Paired Computer’s Total Number. Winning (losing) subjects in each period were those subjects whose Total Number was larger (smaller) than the Paired Computer’s Total Number. A subject’s Total Number is the sum of two components: the Decision Number and the Random Number. In each period, subjects performing the task chose a Decision Number, \(e\), between 0 and 100 (inclusive). Subjects were also assigned a Random Number, \(e\), which was selected from the uniformly distributed range \([-a, +a]\). Subjects received a new Random Number each period, but were not informed what this number was until the end of the period. We informed subjects the Paired Computer’s Total Number would be calculated in the same way as the subjects’ Total Number. To strengthen our inferences about subjects’ learning, for each performance measure noise condition, we randomly generated two sets of 36 Random Numbers in advance of the experiment sessions, and assigned one set of Random Numbers to all subjects and the other set to the Paired Computer. Thus, within each performance measure noise condition, all parameters other than the chosen Decision Number were the same for all subjects and their Paired Computers in each period.

As described in the instructions, subjects’ payoffs in each period were calculated as their prize (29 or 17.2 Lira) less their Decision Cost, which was equal to \(e^2/250\). Figure 1 displays the Decision Cost table that was available to all subjects throughout the entire experimental session.

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\(^9\) Merlo and Schotter’s (2003) study involved 76 periods. We included fewer rounds to avoid fatigue effects on subjects’ behavior, as a 76-period session was projected to last about 3 hours. We are not aware of any theory suggesting the number of periods interacts with learning type and/or performance measure noise to affect learning.
We elected to pay subjects in each period in order to model a setting in which managers “learn on the job” (i.e., task performance while learning is important for more than just learning’s sake).

In addition to paying subjects in each period, we structured the payoffs such that in Period #36, subjects had the opportunity to earn 35 times more than in each of the previous 35 periods. We made this experimental design choice to encourage subjects to take the task seriously and to motivate them to use Periods #1-35 to learn the Decision Number that maximizes their expected payoffs in Period #36 (and from the experiment overall). We informed subjects in all conditions of this payoff structure across periods.

At the end of each period, subjects received outcome information that included their Decision Number, Random Number, and Total Number for the period, the same information for the Paired Computer, and their payoff for the period (see Figure 2 for a sample screenshot). To maintain control over the information available to subjects, we did not allow them to access outcome information from past periods. Allowing subjects to do so would inhibit our ability to cleanly observe and compare the effects of learning type in our study because different behaviors in accessing outcome information of past periods likely leads to differences in information available to subjects. Further, an option to access histories would weaken our learning type manipulation and introduce a potential confound, as experiential learners could learn experientially “in the moment,” but learn vicariously by passively reviewing past outcomes. This would make it difficult to discern whether any differences in learning we observe across conditions are due to differences in learning type or because we exposed subjects to both types of learning versus only one type of learning.

Notably, the Paired Computer chose 37 (12) as its Decision Number in the Low Noise (High Noise) condition in every period, and we informed all subjects of the Paired Computer’s pre-determined Decision Number choices. Thus, although the experimental setting involves a
competition between subjects and the Paired Computer, informing subjects of the Paired Computer’s pre-determined Decision Number choices effectively changes the setting from a two-player game to a one-player optimization problem. We discuss the derivation of the Paired Computer’s Decision Number choices later in this section and in the Appendix.

The payoff function described above highlights the key trade-off that is at the heart of what subjects are trying to learn in our experiment. Specifically, choosing a higher Decision Number increases the subject’s probability of winning the larger prize, but is also more costly. Thus, subjects are trying to learn the Decision Number that maximizes their expected payoffs, and they do so using information about actual Decision Number choices and the resulting actual payoffs, which is a noisy outcome measure because the actual payoffs are affected by the Random Number (a random, uncontrollable factor). In summary, we use this abstract setting to operationalize the construct of learning, such that participants work to determine which action (the Decision Number) is most effective at achieving firm objectives (expected payoffs), using a noisy performance measure (actual payoffs).

**Experimental Manipulations**

We manipulated performance measure noise at two levels by varying the range of possible Random Numbers. In the Low Noise condition, we informed subjects the range of the Random Number was [-20, +20], inclusive (i.e., \( a = 20 \)). In the High Noise condition, we informed subjects the range of the Random Number was [-60, +60], inclusive (i.e., \( a = 60 \)). Thus, in the High Noise condition, the Random Number had a greater effect on the subjects’ Total Number, which increased the likelihood of inaccurate inferences about the Decision Number that maximizes expected payoffs.

We manipulated learning type via the role subjects played during the first 35 periods. Subjects in the Experiential Learning condition performed the task (i.e., chose the Decision
Number) for the first 35 periods. In the Vicarious Learning condition, each subject was randomly matched with a subject from the Experiential Learning condition, and observed the latter’s end-of-period information in each of the first 35 periods (the same end-of-period screen shown in Figure 1). We held the pairings constant over the first 35 periods, but subjects did not know the identity of their match. To hold compensation constant across learning type conditions, subjects in the Vicarious Learning condition received the same payoffs as their matched subject from the Experiential Learning condition in the first 35 periods.

In Period #36, all subjects chose their own Decision Number. Thus, in this final period, subjects in the Experiential Learning condition performed the task just as they did in the first 35 periods, while subjects in the Vicarious Learning condition no longer observed their matched subject and instead performed the task themselves. All subjects received information about all 36 periods during the instructions phase of the experimental session. To ensure subjects understood the setting, the instructions provided information for both Experiential Learning and Vicarious Learning conditions to all subjects, and subjects did not know their assigned learning type until after completing a quiz on the information contained in the instructions.

**Dependent Measures**

We now discuss our primary dependent measure, *Learning*. Typically, measuring learning involves comparing early- and late-stage knowledge (e.g., comparing subjects’ Decision Number choices in Periods #1 and #36). However, this approach is not possible with subjects in the Vicarious Learning condition as they do not choose a Decision Number until the final period. Importantly, this is not a limitation of our experimental design because subjects’ initial knowledge in both learning type conditions is expected to be equalized via random assignment. Therefore, we assess learning by examining the deviation of the chosen Decision Number from
the payoff-maximizing Decision Number in Period #36 only, as this deviation acts as a sufficient statistic for what subjects learned over the previous 35 periods (Merlo and Schotter 2003).

To create our primary dependent measure, Learning, we calculate the absolute difference between subjects’ Decision Number in Period #36 and the Decision Number that maximizes their expected payoffs. To improve interpretability, we use the negative of this absolute difference, such that larger (i.e., less negative) values of Learning indicate more learning. We also collected data in the post-experimental questionnaire related to subjects’ consideration of outcome information to explore the extent to which subjects processed performance measure information myopically and whether such myopic processing affects learning.

Session Timeline

We conducted each session in a computer lab using z-tree software (Fischbacher 2007). At the start of each session, subjects read instructions detailing the experiment, and the instructions were then read aloud by the administrator. Then, subjects completed a short quiz to ensure their understanding. The experiment did not begin until all subjects had correctly answered all questions. Next, subjects engaged in their role for 36 periods. After Period #36, subjects completed a post-experimental questionnaire eliciting process-related and demographic information, and were paid. Subjects earned an average of $23.09 for their participation in the experiment, including a $5 show-up payment.

Additional Discussion of Experimental Design

Several features of our design warrant further discussion. First, we used a relatively abstract setting and task rather than a contextually-rich experiment involving a firm objective and related performance measurement system. An abstract setting helps mitigate the effects of subjects’ pre-existing beliefs about the effectiveness of an action for achieving the firm’s objectives and/or the appropriateness of the performance measures. Such beliefs could preclude a
clean manipulation of learning type and performance measure noise. Moreover, our setting and task is appropriate for testing our hypothesis for several reasons: (i) the task involves learning because identifying the Decision Number that maximizes subjects’ expected payoffs is a non-trivial process, (ii) the Decision Number that maximizes subjects’ expected payoffs serves as a theoretical benchmark against which we can compare subjects’ Decision Number choices to measure their learning, and (iii) the task includes features we can readily change to manipulate our variables of interest without introducing potential theory-oriented confounds.

Second, we explicitly informed subjects of the Paired Computer’s pre-determined Decision Number choices. This information serves as a useful cue to guide subjects’ Decision Number choices, with two important implications. One, this cue “reins in” (but does not limit) the significant number of initial options available to subjects. That is, there were 101 possible Decision Number choices, but only 35 periods in which to explore these options. While subjects could make whatever choices they wished, the static nature of the Paired Computer’s Decision Number highlights a particular point within this range. Two, some subjects could interpret the static nature of the Paired Computer’s Decision Number as a signal of optimality. Importantly, all subjects have an equal opportunity to consider this interpretation and choose the same Decision Number. Ultimately, our setting is one in which an optimal choice exists, and there is a potential signal of what that choice is. These features work against finding our hypothesized interaction, and so differences in learning exhibited by subjects in our setting likely generalize to settings in which the optimal choice is more difficult to identify.

Third, according to prior research that has used the same underlying experimental task as ours (e.g., Bull, Schotter, and Weigelt 1987; Schotter and Weigelt 1992; Merlo and Schotter 1999, 2003), the Decision Number that maximizes subjects’ expected payoffs in each period, $e^*$,
is equal to \[(29 – 17.2) \times 250]/4a\). We summarize the derivation of \(e^*\) in the Appendix.\(^{10}\) Given our manipulation of performance measure noise, \(e^*\) is 37 in the Low Noise condition and 12 in the High Noise condition. Notably, this solution is “symmetric” in that if we had two human subjects competing against each other in our experiment, the optimal choice for both players is to choose \(e^*\). In order to manipulate performance measure noise, but still hold constant that the Paired Computer was playing the optimal choice, it was necessary to allow different values of \(e^*\) across our Low Noise and High Noise conditions. Importantly, we do not expect this difference to create inferential difficulties because this difference in \(e^*\) between our Low Noise and High Noise conditions does not explain the hypothesized interaction between learning type and performance measure noise. However, we do consider this difference further in analyses reported in Section IV.

Finally, as part of our learning type manipulation, subjects in the Vicarious Learning condition simply observed the end-of-period information of their matched subject from the Experiential Learning condition in each of the first 35 periods, and did not perform another task. Thus, subjects in the Vicarious Learning condition could potentially be less distracted than subjects in the Experiential Learning condition, particularly during the first 35 periods. Relatedly, subjects in the Vicarious Learning condition may feel less decision fatigue than subjects in the Experiential Learning condition since subjects in the former condition only make one decision while those in the latter condition make 36 decisions. If our theory predicted a simple main effect of learning type, these differences between learning type conditions could introduce potential alternate explanations for our results. However, such differences are unlikely

\(^{10}\) The derivation of \(e^*\) treats the Random Number, \(\varepsilon\), as a continuous variable. If \(\varepsilon\) is treated as a discrete variable, then the Decision Number that maximizes expected payoffs, given that the Paired Computer is choosing 37 (12) in the Low (High) Noise condition, is 36 (12) in the Low (High) Noise condition. We find inferentially similar results if we adjust \textit{Learning} for this possibility. We thank Zach King and Tim Shields for highlighting this point.
to explain our results because our theory predicts an interaction, such that the effects of performance measure noise depend on learning type. As discussed in Section IV, the pattern of our results allows us to rule out these alternate explanations for our findings.

**IV. RESULTS**

**Descriptive Statistics**

Table 1 reports descriptive statistics for *Learning* and other dependent measures based on responses from the post-experimental questionnaire. Table 1 also reports subjects’ Decision Number choices in Period #36. Figure 3 graphically displays *Learning* by condition. In the following sub-sections, we report hypothesis test results and various additional analyses related to our theory. Since neither age nor gender differs across conditions (two-tailed p > 0.10 for both variables), we ignore these variables in the analyses reported below.

**Hypothesis Test**

Our hypothesis predicts an interaction between performance measure noise and learning type, such that the effects of an increase in performance measure noise are more harmful when learning occurs experientially rather than vicariously. To test our hypothesis, we conduct regressions using *Learning* as the dependent variable. As noted earlier, *Learning* is the negative of the absolute difference between subjects’ Decision Number in Period #36 and the Decision Number that maximizes subjects’ expected payoff, which is 37 (12) in the Low (High) Noise condition. For this and all subsequent analyses, we cluster the data by matched pairs of experiential and vicarious learners. The need to cluster the data by pair precludes the use of more traditional statistical methods for analyzing the data (e.g., ANOVA).

The first regression model shown in Table 2 includes all four conditions (Model (1)). The independent variables are an indicator variable for performance measure noise equal to 0 (1) for the Low (High) Noise condition, an indicator variable for learning type equal to 0 (1) for the
Experiential (Vicarious) Learning condition, and the interaction of these two variables. Given the coding of the independent variables and *Learning*, our hypothesis predicts a positive coefficient on the interaction term. Consistent with our hypothesis, we find a statistically significant interaction (one-tailed p < 0.01).

We follow up on this initial result and conduct two regressions testing the simple effects of performance measure noise separately within the Experiential Learning and Vicarious Learning conditions (Models (2) and (3), respectively, in Table 2). In the Experiential Learning condition, we find an increase in performance measure noise has a negative effect on subjects’ *Learning* (one-tailed p < 0.01). However, in the Vicarious Learning condition, an increase in performance measure noise has no effect on subjects’ *Learning* (two-tailed p = 0.46). These results are also consistent with our hypothesis.

Because the Decision Number that maximizes expected payoff differs between the Low Noise and High Noise conditions, we also test whether our hypothesis test results are robust to considering this difference. Specifically, we repeat our hypothesis test using the *Average Percentage of Learning* as the dependent variable. We compute this measure as *Learning* divided by the Decision Number that maximizes subjects’ expected payoff, which is 37 (12) in the Low (High) Noise condition. Consistent with our hypothesis, we find a statistically significant positive interaction term coefficient (coefficient = 0.83, one-tailed p < 0.01) indicating the effects of an increase in performance measure noise are more harmful when learning occurs experientially than vicariously, even after accounting for the difference between noise conditions in the Decision Number that maximizes expected payoffs. In addition, simple effect analyses show an increase in performance measure noise has a negative effect on subjects’ *Average Percentage of Learning* in both the Experiential Learning condition (-12.31% vs. -120.37%, t =
5.78, one-tailed p < 0.01) and the Vicarious Learning condition (-17.57% vs. -42.13%, t = 2.52, two-tailed p = 0.02).

**Supplemental Analyses: Myopic Processing of Information**

In this subsection, we report analyses related to myopic processing, which is the theoretical basis for our predicted interaction effect on performance. Specifically, we analyze the following issues: (i) How much information do experiential learners use at any given time? (ii) How much information do experiential and vicarious learners consider in Period #36? (iii) Does myopic processing affect learning?  

**How Much Information Do Experiential Learners Use at Any Given Time?**

Since experiential learners choose a Decision Number in every period, we are able to assess how much information experiential learners consider at any given time. Specifically, we regress the Decision Number chosen by each subject in the Experiential Learning condition in each period \( t \) on his or her Decision Number choices in periods \( t-1 \) through \( t-5 \), payoffs in periods \( t-1 \) through \( t-5 \), and indicator variables equal to 0 (1) for losing (winning) a tournament in each of periods \( t-1 \) through \( t-5 \). If experiential learners process information myopically, then we would expect they would not consider end-of-period information from more than a few periods back when choosing a Decision Number in period \( t \). In the regression, we also include a local estimate of the sign of the slope of the payoff function as one of the independent variables, calculated as \( \text{Slope}_{i, t} \equiv \text{sign} \left[ (\text{payoff}_{i, t-1} - \text{payoff}_{i, t-2})/(\text{Decision Number}_{i, t-1} - \text{Decision Number}_{i, t-2}) \right] \) for each subject \( i \) in period \( t \). This local estimate captures the extent to which experiential

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11 Despite their shared history, matched pairs of experiential and vicarious learners behaved different in Period #36, which likely reflects differences in how they processed performance measure information. Specifically, conditional on observing the same information in Periods #1-35, the correlation between experiential and vicarious learners’ Decision Number choices in Period #36 is only 0.40 (two-tailed p = 0.10) in the Low Noise condition and 0.33 (two-tailed p = 0.18) in the High Noise condition.
learners use their Decision Number choices and payoffs from prior periods to identify the Decision Number that maximizes their expected payoffs (Merlo and Schotter 1999).

Table 3 presents the regression results. In the pooled regression (Model 1), we find a statistically significant positive coefficient for experiential learners’ Decision Number choices in period $t-1$ (two-tailed $p < 0.01$), a statistically significant positive coefficient for their payoffs in period $t-1$ (two-tailed $p = 0.01$), and a statistically significant negative coefficient for the winning a tournament in period $t-1$ (two-tailed $p = 0.01$). We also find a marginally significant positive coefficient for experiential learners’ Decision Number choice in period $t-2$ (two-tailed $p = 0.06$). All other coefficients in Model 1 are not statistically significant.

These results suggest experiential learners considered, at most, information from the preceding two periods when choosing their Decision Number. The negative coefficient for winning a tournament suggests experiential learners simply reacted to their last period outcome by increasing (decreasing) their Decision Number if they lost (won) the last tournament. Finally, the statistically insignificant coefficient for the local estimate of the sign of the slope of the payoff function (two-tailed $p = 0.43$) suggests experiential learners were not trying to identify the Decision Number that maximizes their expected payoffs.\(^{12}\)

Figure 4 provides additional evidence regarding experiential learners’ myopic processing. Specifically, Figure 4 graphically presents Learning by experiential learners across all 36 periods. If experiential learners’ processing of information reflects their cumulative, and not simply their most recent, experience, then we should observe a clear, positive trend in Learning.

\(^{12}\) In Models 2 and 3, we report the regression results for the Low Noise and High Noise conditions, respectively. We find relatively similar results, though some statistically significant coefficients in Model 1 (the pooled regression) are no longer statistically significant in Models 2 or 3. We do not find any statistically significant coefficients in Models 2 or 3 that were not statistically significant in Model 1. Thus, broadly speaking, the results in Models 2 and 3 are consistent with those of Model 1, and suggest experiential learners chose their Decision Numbers in a myopic fashion.
by experiential learners over time. However, consistent with the regression results reported above, the pattern of Learning by experiential learners over time presented in Figure 4 does not suggest experiential learners in either the Low Noise (Panel A) or the High Noise (Panel B) condition exhibit greater learning over time.

**How Much Information Do Experiential and Vicarious Learners Consider in Period #36?**

To examine differences in how experiential and vicarious learners processed performance measure information, we capture subjects’ focus on end-of-period information via a post-experimental question. For this question, subjects select a statement that most accurately describes the amount of information (number of periods) they considered when choosing their Decision Number in Period #36.

Figure 5 presents the frequency with which subjects in the Experiential Learning and Vicarious Learning conditions chose each response option. While 56 percent of experiential learners indicated they focused on the information received from the last period or from the last three periods, only 11 percent of vicarious learners did so. Less than half – 44 percent – of the experiential learners indicated they considered information from the last 10 periods or from all periods. In contrast, a vast majority – 89 percent – of the vicarious learners indicated they considered information from the last 10 periods or from all periods. In fact, 72 percent of vicarious learners indicated they considered information from all periods. A Mann-Whitney U test confirms vicarious learners considered a larger set of information than did experiential learners ($z = -3.98$, one-tailed $p < 0.01$, not tabulated).

We also find experiential learners exhibit a greater tendency to process information myopically using responses to two other questions from the post-experimental questionnaire. Specifically, subjects indicate how useful they found information from (i) Period #35, and (ii) Periods #1-34. Subjects respond to each question using a seven-point scale with endpoints of 1
(not at all useful) to 7 (very useful). We ask about information from Period #35 separately from Periods #1-34 to better capture potential differences in perceived usefulness of information immediately preceding Period #36, when all subjects would perform the task. Our theory predicts experiential learners would find Period #35 information more useful than would vicarious learners because of their greater tendency to process information myopically, but vicarious learners would find information from Periods #1-34 more useful than would experiential learners because they are more likely to engage in a holistic processing of information. Table 1 presents descriptive statistics of subjects’ responses to these two questions.

We find evidence consistent with our theory. Regarding information from Period #35, a regression with subjects’ responses as the dependent variable and an indicator variable equal to 0 (1) for the Experiential (Vicarious) Learning condition as the independent variable reveals subjects in the Experiential Learning condition found Period #35 information to be more useful than subjects in the Vicarious Learning condition (4.98 vs. 4.47, t = 1.35, one-tailed p = 0.09, not tabulated). However, in a similar regression with subjects’ ratings of the usefulness of Periods #1-34 as the dependent variable, we find the opposite is true for Periods #1-34 (5.81 vs. 5.14, t = 3.03, one-tailed p = 0.01, not tabulated). This pattern of results is consistent with experiential learners processing information more myopically than vicarious learners.13

**Does Myopic Processing Affect Learning?**

---

13 Immediately after choosing a Decision Number in Period #36, but before learning the outcome for that period, subjects indicate the extent to which they were confident that the Decision Number they chose in Period #36 maximizes their expected payoffs, using a seven-point scale with endpoints of 1 (not at all confident) and 7 (very confident). In a regression with responses as the dependent variable, and an indicator variable for performance measure noise, an indicator variable for learning type, and the interaction of these two variables as the independent variables, we do not find any statistically significant differences across conditions in subjects’ confidence levels (all two-tailed p-values > 0.20, not tabulated).
Collectively, the results from these supplemental analyses suggest experiential learners exhibit a greater propensity to engage in myopic processing of performance measure information than vicarious learners. Notably, this myopic processing proved especially detrimental to learning in our setting. Specifically, we measure the extent to which subjects process information myopically by taking the difference between subjects’ ratings of the usefulness of information from Periods #1-34 and the usefulness of information from Period #35. Larger (more positive) values of this difference measure indicate less myopic processing of information. Thus, we expect this difference measure to be positively associated with Learning. A regression of Learning on this difference measure reveals a positive coefficient (coefficient = 1.04, t = 1.67, one-tailed p = 0.05, not tabulated), consistent with greater myopic processing of information leading to less learning.

Alternate Explanations

In this subsection, we address two potential alternate explanations for our results. A potential alternate explanation for experiential learners’ greater focus on end-of-period information from more recent periods (as described earlier) is they have already fully absorbed the end-of-period information from earlier periods. That is, experiential learners may have successfully incorporated information from early periods into their Decision Number strategy. Our results do not support this alternate explanation. Specifically, recall Figure 4 shows Learning by experiential learners does not improve over time, which suggests experiential learners’ processing of information does not reflect their cumulative experience, but simply their most recent experience. Moreover, if experiential learners did, in fact, incorporate information from earlier periods into their Decision Number strategy, then they would demonstrate greater learning than vicarious learners in both the Low Noise and High Noise conditions. However,
within the High Noise condition, we find *Learning is lower* for experiential learners (see analyses reported in the next subsection).

Task difficulty is another potential alternate explanation for our results. Specifically, while vicarious learners could focus on maximizing their expected payoffs in Period #36, experiential learners had to worry about maximizing their expected payoffs across all 36 periods, which could have been especially challenging in the High Noise condition. We reject this alternate explanation for three reasons. First, in the post-experimental questionnaire, subjects provide their assessments of task difficulty using a seven-point scale with endpoints of 1 (very easy) and 7 (very difficult), and we find perceptions of task difficulty do not differ across conditions (all two-tailed p-values > 0.10, not tabulated). Second, we repeat our hypothesis test after including this task difficulty measure and all two- and three-way interaction terms, and we find inferentially similar results; neither the task difficulty measure nor any of the related interaction terms are statistically significant (all two-tailed p-values > 0.20, not tabulated). Finally, in the post-experimental questionnaire, subjects also indicate how much effort they devoted to maximizing expected earnings, using a seven-point scale with endpoints of 1 (very low) and 7 (very high). Experiential learners indicate expending greater effort ($t = 4.43$, $p < 0.01$), but responses do not vary across noise conditions. Nevertheless, we repeat our hypothesis test after including this effort measure and all two- and three-way interactions. Neither the effort measure nor any of the related interactions term are statistically significant (all two-tailed p-values > 0.20, not tabulated).\(^{14}\)

\(^{14}\) We also capture feelings of control in the post-experimental questionnaire. First, subjects indicate the extent to which they felt in control of how they performed the task in Period #36. Second, subjects indicate the extent to which they felt in control of influencing their overall pay. Subjects respond to both questions using a seven-point scale with endpoints of 1 (Strongly Disagree) and 7 (Strongly Agree). A factor analysis using responses to these two questions reveals only one factor with an eigenvalue greater than 1 (explains 84.61 percent of the variance in responses). We retain this factor and use the resulting factor score as our measure of subjects’ feelings of control. We performed a regression with this factor score as the dependent variable, and an indicator variable for
Simple Effects of Learning Type

While not the primary focus of our study, our design allows us to compare the simple effects of learning type within performance measure noise conditions. Within the Low Noise condition, we find Learning is marginally greater in the Experiential Learning condition than in the Vicarious Learning condition (two-tailed p = 0.10). In contrast, within the High Noise condition, we find Learning is lower in the Experiential Learning condition than in the Vicarious Learning condition (two-tailed p < 0.01). This finding is quite notable, because it suggests the differential effects of performance measure noise on experiential versus vicarious learners can be so profound as to “flip” the relative benefits of the two learning types. Combined with our main hypothesis tests, these analyses collectively suggest that, depending on the level of performance measure noise, vicarious learning may be either superior to or inferior to experiential learning.

V. CONCLUSION

We examine the interactive effects of performance measure noise and learning type on learning. We predict and find an increase in performance measure noise has a more deleterious effect on learning when such learning occurs experientially rather than vicariously. Supplemental analyses suggest experiential learners process performance measure outcome information more

\[ t = 4.65, \text{two-tailed } p < 0.01 \]

In particular, experiential learners felt more in control than vicarious learners, likely because the former could actually choose a Decision Number in all 36 periods. Importantly, feelings of control do not appear to be driving our hypothesis test results. Specifically, we find inferentially similar results when we repeat our hypothesis test after including the factor score measure of control and all related interaction terms.

\[ D = 0.72, p < 0.01 \]

In the Low Noise condition, the experiential learner exhibited greater learning in 10 out of 18 pairs, exhibited the same amount of learning in 5 pairs, and exhibited less learning in 3 pairs. However, in the High Noise condition, the experiential learner exhibited greater learning in only 1 out of 18 pairs, exhibited the same amount of learning in 2 pairs, and exhibited less learning in 15 pairs. A Kolmogorov-Smirnov test comparing these distributions across the noise conditions indicates the two distributions are significantly different (D = 0.72, p < 0.01).
myopically than do vicarious learners, which hinders learning. Collectively, our findings suggest performance measure noise and learning type play important roles in the extent to which firms realize the decision-facilitating benefits of strategic performance measurement systems. Specifically, the difference between “feedback” (information about one’s experience) and “data” (information about someone else’s experience) is an important distinction that affects learning by helping to mitigate the harmful effects of performance measure noise on learning. As a result, performance measure noise may not be as detrimental to learning as previously thought.

This insight has important implications for academics, as we extend prior accounting literature to highlight the relative benefits of different learning types, and when these benefits arise. Our results also have implications for practice, as they highlight when opportunities for vicarious learning yield the greatest benefit, thereby allowing firms to manage the tradeoff balancing costly information-sharing mechanisms that enable vicarious learning with the benefits that accrue from such opportunities. The use of a firm’s strategic performance measurement system to facilitate employees’ strategic learning (learning about the effectiveness of strategic actions) is one real-world setting in which the insights of our study are particularly valuable. In particular, given the complexity of strategy-related decision-making (Humphreys et al. 2016), vicarious learning may enhance employees’ strategic learning more than experiential learning.

The limitations of our study offer opportunities for future research. For example, future research could use a different experimental design to measure myopic processing in a more objective and direct manner rather than rely on subjects’ post-experimental responses. Relatedly, we do not directly capture experiential and vicarious learners’ cognitive representations (scripts, schemas, etc.) of the decision-making task in our experiment (Gioia and Manz 1985). Future research could confirm whether experiential (vicarious) learners are more likely to develop episodic (generalized) mental representations. To the extent that this occurs, an interesting
avenue for future research is whether encouraging experiential learner to adopt a third-party perspective – which could facilitate a generalized script – would improve their decision-making. Also, while our participants make a single decision in each period, employees often make multiple decisions in a single period and/or rely on information about multiple measures (Humphreys et al. 2016). Future research could examine whether our results generalize to such settings. Beyond our study’s limitations, other future research opportunities include whether our results generalize to other forms of performance measure noise (e.g., measurement error, construct representation) and whether the opportunity to learn both experientially and vicariously) influences learning.
REFERENCES


APPENDIX

As discussed in Section III, we adapt Merlo and Schotter’s (2003) computerized decision-making task. This task builds on Bull et al.’s (1987) analytical model of a symmetric rank-order tournament with two players. In this Appendix, we summarize relevant features of Bull et al.’s model and the derivation of \( e^* \) within our experimental setting.

In the model, two identical players, \( i \) and \( j \), compete over two prizes, \( M \) and \( m \), with \( M > m \). Let \( x \) denote the prize, and \( e \) denote a player’s effort. Because the tournament involves two identical players, we specify variables in this Appendix for only player \( i \), and note the same specifications apply to player \( j \). Player \( i \) has a utility function that is separable in the utility of the prize and the disutility of effort:

\[
U_i(x, e) = u(x) - c(e)
\]

where \( u(\cdot) \) is a linear function, and \( c(\cdot) \) is a convex function. Player \( i \)’s performance measure, \( y \), is a function of the player’s effort and a noise term:

\[
y_i = f(e_i) + \varepsilon_i
\]

where the noise term is independently realized for each player. Player \( i \) wins the prize \( M \) if \( y_i > y_j \), and wins \( m \) if \( y_i < y_j \). Let \( p(e_i, e_j) \) denote the probability player \( i \) wins the bigger prize, \( M \).

Then, player \( i \)’s expected payoff is:

\[
E\pi_i(e_i, e_j) = p(e_i, e_j) u(M) + [1 - p(e_i, e_j)] u(m) - c(e_i)
\]

Consistent with Merlo and Schotter (2003), we adopt the following variable specifications:

\[
U_i(x, e) = x - e^2/k
\]

\[
y_i = e_i + \varepsilon_i
\]

where \( k > 0 \), \( \varepsilon_i \) is drawn from the set \([-a, +a]\) based on a uniform distribution, with \( a > 0 \), and \( e_i \) lies between 0 and 100 (inclusive).
Given these specifications, the optimal effort choice, \( e^* \), is as follows:

\[
e^* = \frac{(M - m)k}{4a}
\]

In our experiment, we set \( M = 29 \) Lira, \( m = 17.2 \) Lira, \( k = 250 \), and set \( a = 20 \) (\( a = 60 \)) in the Low Noise (High Noise) condition. Based on these parameters, the Decision Number that maximizes subjects’ expected payoffs is \( e^* = 37 \) (12) in the Low Noise (High Noise) condition. Because the tournament is symmetric, the Nash equilibrium strategy is for both players to choose \( e^* \) according to the equation above. In our experiment, we replace one player with a computer programmed to always choose \( e^* \).
The Decision Cost table shows the Decision Cost for each possible Decision Number. The higher the Decision Number, the higher the Decision Cost. All subjects have access to the table throughout the experimental session.
Figure 2 presents a screenshot of the screen subjects saw at the end of each period from the Low Noise condition. At the end of each period, subjects received a summary of their chosen Decision Number, Random Number, and Total Number. Subjects also received corresponding information about the Paired Computer, and their payoff for the period. In Periods #1-35, the summary information regarding subjects’ Total Number was presented under the heading “Matched Group A Participant” for subjects in the Vicarious Learning condition, and under the heading “You” for subjects in the Experiential Learning condition. In Period #36, this summary information was presented under the heading “You” in both learning type conditions because all subjects performed the task in Period #36. In the Low Noise condition, the Paired Computer always chose 37 as its Decision Number (as shown in Figure 2). In the High Noise condition, the Paired Computer always chose 12 as its Decision Number.
Performance Measure Noise is manipulated between-subjects at two levels. In the Low Noise condition, subjects received a Random Number, which is selected from the range [-20, +20] based on a uniform distribution. In the High Noise condition, subjects received a Random Number, which is selected from the range [-60, +60] based on a uniform distribution.

Learning Type is manipulated between-subjects at two levels. In the Experiential Learning condition, subjects performed the task for 36 periods. In the Vicarious Learning condition, subjects were matched with another subject in the Experiential Learning condition. Subjects in the Vicarious Learning condition observed (via their computer) their matched subject’s Decision Number choices and outcomes for the first 35 periods, and then performed the task themselves in Period #36.

Learning is the inverse of the absolute difference between subjects’ Decision Number in Period #36 and the Decision Number that maximizes subjects’ expected payoff, which is 37 (12) in the Low Noise (High Noise) condition. Larger (less negative) values of this measure indicate greater learning.
FIGURE 4
Learning by Experiential Learners Over Time

Panel A: Low Noise Condition
FIGURE 4 (continued)

Panel B: High Noise Condition

Figure 4 presents a graph of Learning by experiential learners in the Low Noise (Panel A) and High Noise (Panel B) conditions. In the Low Noise condition, subjects received a Random Number, which is selected from the range [-20, +20] based on a uniform distribution. In the High Noise condition, subjects received a Random Number, which is selected from the range [-60, +60] based on a uniform distribution. Learning is the inverse of the absolute difference between subjects’ Decision Number choice and the Decision Number that maximizes subjects’ expected payoff, which is 37 (12) in the Low Noise (High Noise) condition. Larger (less negative) values of this measure indicate greater learning.
In the post-experimental questionnaire, subjects answered the following question: The following four statements describe different strategies regarding how much feedback you could have considered when choosing your Decision Number in Period #36. Which statement most accurately describes how you actually chose your Decision Number in Period #36? Response options include a) I considered only the feedback received from the last period, b) I considered the feedback received from the last three periods, c) I considered the feedback received from the last 10 periods, and d) I considered the feedback received from all periods so far.

Learning Type is manipulated between-subjects at two levels. In the Experiential Learning condition, subjects performed the task for 36 periods. In the Vicarious Learning condition, subjects were matched with another subject in the Experiential Learning condition. Subjects in the Vicarious Learning condition observed (via their computer) their matched subject’s Decision Number choices and outcomes for the first 35 periods, and then performed the task themselves in Period #36.
TABLE 1
Descriptive Statistics – Mean (Standard Deviation)

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<th>Experiential Learningb</th>
<th>Vicarious Learningb</th>
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<td>High Noisea</td>
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<td></td>
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a **Performance Measure Noise** is manipulated between-subjects at two levels. In the Low Noise condition, subjects received a Random Number, which was selected from the range [-20, +20] based on a uniform distribution. In the High Noise condition, subjects received a Random Number, which was selected from the range [-60, +60] based on a uniform distribution.

b **Learning Type** is manipulated between-subjects at two levels. In the Experiential Learning condition, subjects performed the task for 36 periods. In the Vicarious Learning condition, subjects were matched with another subject in the Experiential Learning condition. Subjects in the Vicarious Learning condition observed (via their computer) their matched subject’s Decision Number choices and outcomes for the first 35 periods, and then performed the task themselves in Period #36.

c **Learning** is the negative of the absolute difference between subjects’ Decision Number in Period #36 and the Decision Number that maximizes subjects’ expected payoff, which is 37 (12) in the Low Noise (High Noise) condition. Larger (i.e., less negative) values of this measure indicate greater learning.

d **Decision Number** is the subject’s Decision Number choice in Period #36 (the final period). In Period #36 all subjects individually chose a Decision Number.
TABLE 1 (continued)

° Feedback Usefulness (Periods #1-34) is subjects’ responses to the following question from the post-experimental questionnaire: How useful did you find the feedback you received in Periods #1-34 (outcome report you received at the end of Periods #1-34)? Subjects respond using a seven-point Likert scale with endpoints of 1 (not at all useful) and 7 (very useful).

† Feedback Usefulness (Period #35) is subjects’ responses to the following question from the post-experimental questionnaire: How useful did you find the feedback you received immediately before the final period (outcome report you received at the end of Period #35)? Subjects respond using a seven-point Likert scale with endpoints of 1 (not at all useful) and 7 (very useful).
### TABLE 2
Test of Hypothesis

<table>
<thead>
<tr>
<th>Learning&lt;sup&gt;a&lt;/sup&gt; All Conditions Model (1)</th>
<th>Learning&lt;sup&gt;a&lt;/sup&gt; Experiential Learning&lt;sup&gt;c&lt;/sup&gt; Model (2)</th>
<th>Learning&lt;sup&gt;a&lt;/sup&gt; Vicarious Learning&lt;sup&gt;c&lt;/sup&gt; Model (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Measure</td>
<td>-9.89</td>
<td>-9.89</td>
</tr>
<tr>
<td>Noise&lt;sup&gt;b&lt;/sup&gt;</td>
<td>(2.48)</td>
<td>(2.46)</td>
</tr>
<tr>
<td>(0 = low; 1 = high)</td>
<td>[-3.99][&lt; 0.01]</td>
<td>[-4.02][&lt; 0.01]&lt;sup&gt;‡&lt;/sup&gt;</td>
</tr>
<tr>
<td>Learning Type&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-1.94</td>
<td></td>
</tr>
<tr>
<td>(0 = experiential; 1 = vicarious)</td>
<td>(1.12)</td>
<td></td>
</tr>
<tr>
<td>Performance Measure</td>
<td>11.33</td>
<td></td>
</tr>
<tr>
<td>Noise x Learning Type</td>
<td>(2.49)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.56</td>
<td>-4.56</td>
</tr>
<tr>
<td></td>
<td>(1.07)</td>
<td>(1.06)</td>
</tr>
<tr>
<td></td>
<td>[-4.25][&lt; 0.01]</td>
<td>[-4.28][&lt; 0.01]</td>
</tr>
<tr>
<td>N</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.28</td>
<td>0.32</td>
</tr>
<tr>
<td>N</td>
<td>72</td>
<td>36</td>
</tr>
</tbody>
</table>

The table reports the regression coefficient, (standard error), [t-statistic], and {p-value}, respectively. Reported p-values denoted with a ‡ are one-tailed.

<sup>a</sup> Learning is the negative of the absolute difference between subjects' Decision Number in Period #36 and the Decision Number that maximizes subjects' expected payoff, which is 37 (12) in the Low Noise (High Noise) condition in Period #36. Larger (i.e., less negative) values of this measure indicate greater learning.

<sup>b</sup> Performance Measure Noise is manipulated between-subjects at two levels. In the Low Noise condition, subjects received a Random Number, which is selected from the range [-20, +20] based on a uniform distribution. In the High Noise condition, subjects received a Random Number, which is selected from the range [-60, +60] based on a uniform distribution.
Learning Type is manipulated between-subjects at two levels. In the Experiential Learning condition, subjects performed the task for 36 periods. In the Vicarious Learning condition, subjects were matched with another subject in the Experiential Learning condition. Subjects in the Vicarious Learning condition observed (via their computer) their matched subject’s Decision Number choices and outcomes for the first 35 periods, and then performed the task themselves in Period #36.
### TABLE 3
Myopic Processing (Experiential Learners)\textsuperscript{a,b}

<table>
<thead>
<tr>
<th></th>
<th>Both Conditions Model (1)\textsuperscript{c}</th>
<th>Low Noise Model (2)\textsuperscript{c}</th>
<th>High Noise Model (3)\textsuperscript{c}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision Number \textsubscript{t-1}</td>
<td>0.60*** (0.09)</td>
<td>0.53** (0.15)</td>
<td>0.62*** (0.12)</td>
</tr>
<tr>
<td>Decision Number \textsubscript{t-2}</td>
<td>0.20* (0.10)</td>
<td>0.16 (0.19)</td>
<td>0.21* (0.11)</td>
</tr>
<tr>
<td>Decision Number \textsubscript{t-3}</td>
<td>0.12 (0.10)</td>
<td>0.01 (0.18)</td>
<td>0.20 (0.12)</td>
</tr>
<tr>
<td>Decision Number \textsubscript{t-4}</td>
<td>0.59 (0.09)</td>
<td>0.07 (0.14)</td>
<td>0.07 (0.11)</td>
</tr>
<tr>
<td>Decision Number \textsubscript{t-5}</td>
<td>0.14 (0.08)</td>
<td>0.13 (0.10)</td>
<td>0.09 (0.12)</td>
</tr>
<tr>
<td>Payoff \textsubscript{t-1}</td>
<td>1.03** (0.38)</td>
<td>0.73 (0.47)</td>
<td>1.12* (0.57)</td>
</tr>
<tr>
<td>Payoff \textsubscript{t-2}</td>
<td>0.21 (0.27)</td>
<td>0.19 (0.47)</td>
<td>0.21 (0.30)</td>
</tr>
<tr>
<td>Payoff \textsubscript{t-3}</td>
<td>0.12 (0.30)</td>
<td>-0.44 (0.49)</td>
<td>0.47 (0.35)</td>
</tr>
<tr>
<td>Payoff \textsubscript{t-4}</td>
<td>-0.19 (0.31)</td>
<td>0.31 (0.30)</td>
<td>-0.37 (0.43)</td>
</tr>
<tr>
<td>Payoff \textsubscript{t-5}</td>
<td>0.07 (0.34)</td>
<td>-0.10 (0.30)</td>
<td>0.07 (0.54)</td>
</tr>
<tr>
<td>Win \textsubscript{t-1}</td>
<td>-12.53** (4.41)</td>
<td>-6.73 (5.82)</td>
<td>-14.66** (6.49)</td>
</tr>
<tr>
<td>Win \textsubscript{t-2}</td>
<td>-4.06 (3.38)</td>
<td>-2.78 (5.58)</td>
<td>-4.83 (4.16)</td>
</tr>
<tr>
<td>Win \textsubscript{t-3}</td>
<td>-0.89 (3.70)</td>
<td>6.75 (6.14)</td>
<td>-5.44 (3.91)</td>
</tr>
<tr>
<td>Win \textsubscript{t-4}</td>
<td>2.34 (3.52)</td>
<td>-2.73 (3.60)</td>
<td>4.92 (5.20)</td>
</tr>
<tr>
<td>Win \textsubscript{t-5}</td>
<td>-0.81 (4.05)</td>
<td>1.94 (3.54)</td>
<td>-0.73 (6.64)</td>
</tr>
<tr>
<td>Slope</td>
<td>0.41 (0.51)</td>
<td>0.11 (0.54)</td>
<td>0.51 (0.80)</td>
</tr>
<tr>
<td>Constant</td>
<td>-19.56** (7.35)</td>
<td>-7.56 (10.91)</td>
<td>-23.66** (10.17)</td>
</tr>
<tr>
<td>R\textsuperscript{2}</td>
<td>0.48</td>
<td>0.44</td>
<td>0.46</td>
</tr>
<tr>
<td>N</td>
<td>1,102</td>
<td>555</td>
<td>547</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Indicates significance at the 0.1 level (two-tailed).
\textsuperscript{b} Indicates significance at the 0.05 level (two-tailed).
\textsuperscript{c} Indicates significance at the 0.01 level (two-tailed).
We regress the Decision Number chosen by subjects in the Experiential Learning condition in each period \( t \) on their Decision Number choices in periods \( t-1 \) through \( t-5 \), payoffs in periods \( t-1 \) through \( t-5 \), and indicator variables equal to 0 (1) for losing (winning) a tournament in each of periods \( t-1 \) through \( t-5 \). The independent variables also include a local estimate of the sign of the slope of the payoff function, calculated as \( \text{Slope}_{i,t} \equiv \text{sign} \left[ \frac{\text{payoff}_{i,t-1} - \text{payoff}_{i,t-2}}{\text{Decision Number}_{i,t-1} - \text{Decision Number}_{i,t-2}} \right] \) for each subject \( i \) in period \( t \). Reported statistics are the coefficient (standard error). ***, **, * indicate statistical significance at the 1%, 5% and 10% level (two-tailed), respectively.

In the Experiential Learning condition, subjects performed the task for 36 periods. In the Vicarious Learning condition, subjects were matched with another subject in the Experiential Learning condition. Subjects in the Vicarious Learning condition observed (via their computer) their matched subject’s Decision Number choices and outcomes for the first 35 periods, and then performed the task themselves in Period #36.

In the Low Noise condition, subjects received a Random Number, which is selected from the range [-20, +20] based on a uniform distribution. In the High Noise condition, subjects received a Random Number, which is selected from the range [-60, +60] based on a uniform distribution. In Model (1), we report the results of the pooled regression combining both performance measure noise conditions. In Models (2) and (3), we report the regression results for the Low Noise and High Noise conditions, respectively.