The Effect of Causal Performance Measure Knowledge on Reducing Individuals' Discounting of Performance Measures in Profit Prediction

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July 2006

The authors are grateful to Auburn University and Indiana University for project funding. Helpful comments were provided by anonymous reviewers, Brian Ballou, Andrea Drake, Joan, Luft, Sue Ravenscroft, and Steve Salterio and participants of the AAA Ohio Region 2005 Meeting.

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ABSTRACT: Prior research suggests that both financial and nonfinancial performance measures are needed for effective prediction of long-term financial performance. However, prior research shows that individuals often discount the performance measurement information provided to them when predicting future profits or evaluating performance. One reported example of performance measure discounting is the use of common measures over unique measures. It is unclear from prior research what level of performance measure knowledge is required to affect individuals' discounting of performance measures. We examine how differences in the level of individuals' causal knowledge (i.e., strong, weak, none) regarding the relationship between the performance measure and net income affect their usage (and discounting) of the performance measure in a profit prediction task. As expected, for nonfinancial measures, the results show that individuals perceive greater predictive value in, and are more likely to use, performance measures for which they possess weak causal knowledge (i.e., directional association of performance measure relationship) as compared to measures for which they possess no causal knowledge. Contrary to expectations, the results show no difference in individuals' perceptions, or expected usage, of performance measures for which they possess strong causal knowledge (i.e., complete "story" underlying performance measure relationship) as compared to only weak causal knowledge. These findings suggest that a lack of causal knowledge regarding performance measures leads individuals to discount such measures but that discounting can be mitigated by providing individuals with relatively simple, inexpensive weak causal performance measure knowledge, such as basic statistical correlation information. The findings have implications for the level of knowledge that organizations should provide, along with the performance measures themselves, in order to reduce the likelihood that individuals unnecessarily discount otherwise predictive performance measures.

Key Words: Financial and nonfinancial performance measures, weak versus strong causal knowledge, predicting long-term financial performance, accounting knowledge.

Data Availability: Data are available from the authors upon request.

I. INTRODUCTION

Prior research suggests that both financial and nonfinancial performance measures are needed for effective prediction of long-term financial performance (Maines et al. 2002; Stivers, Covin, Hall, and Smalt 1998; Tank 1993; Measelle 1991). As a result, many companies increasingly provide individuals with large quantities of nonfinancial performance measures in addition to traditional financial performance measures (Ittner and Larcker 2003, Dempsey et al. 1997), a trend that is expected to grow well into the 21st century (White 2005). However, prior research shows that individuals often discount the performance measurement information provided to them when predicting future profits or evaluating performance. Documented examples of performance measure discounting include scenarios in which measures are captured but not used (i.e., "measurement-use gap", Stivers et al. 1998) or, more specifically, when common measures are used but unique measures are ignored (i.e., "common measures bias", Lipe and Salterio 2000).

Banker et al. (2004) finds that linking performance measures to strategy using detailed strategy maps mitigates the common measures bias.[1] Many firms create such strategy maps (Kaplan and Norton 2004) or causal models (Ittner and Larcker 2003, Rucci et al. 1998) to help individuals better understand the relationships between performance measures and earnings.[2] However, the detailed level of causal performance measure knowledge that is required to create a strategy map or causal model is very time consuming and costly to acquire. In certain situations, such a detailed level of causal knowledge might not be necessary to affect individuals' usage (i.e., reduce discounting) of the performance measures contained in the model. The purpose of this paper is to examine the level of causal knowledge that is necessary to affect individuals' use (or discounting) of performance measures in predicting future earnings.

We define performance measure discounting in a profit prediction task setting as the underweighting of one measure, relative to another measure, when both measures are equally predictive of future earnings.

We employ an experimental setting to study the effects of level of causal knowledge—strong, weak and none—and type of performance measure—nonfinancial and financial—on individuals' perception and usage of equally predictive performance measures in an earnings prediction task. [3] We define *weak* causal knowledge as merely the direction (i.e., positive or negative) of the relationship between the performance measure and earnings and *strong* causal knowledge as the causal story underlying the relationship between the performance measure and earnings. Although prior research mainly offers examples of users discounting nonfinancial performance measures, it is possible that individuals are just as likely to discount financial performance measures when they lack a certain level of causal performance measure knowledge. Therefore, we examine both types of performance measures.

Libby and Luft's (1993) model of task performance includes knowledge as an important component, along with environment, motivation and ability. Libby, Bloomfield and Nelson (2002) suggest that knowledge determines individuals' goals and how they use information to achieve their goals. Thus, these papers suggest that the knowledge individuals bring to the task can play an important role in task performance. However, the effect of variations in individuals' causal performance measure knowledge—either for financial or nonfinancial measures—on their use of such measures has received little research attention.

Prior research and firms in practice often assume or imply that detailed causal knowledge must be communicated to individuals in order to affect their judgment (Ittner and Larcker 2003). For example, Kaplan and Norton (2004) describe how many firms increasingly use strategy maps, which are graphical representations of the cause-and-effect linkages among strategic and operational objectives, in conjunction with a Balanced Scorecard to effectively communicate and implement strategy. Kaplan and Norton (2004, 9) state that, "we now realize that the strategy map . . . is as big an insight to executives as the Balanced Scorecard itself." However, the creation and communication of detailed causal performance measure knowledge, as contained in a strategy map (see Figure 1-3 in Kaplan and Norton 2004), is a costly endeavor, in terms of effort, time and money. Luft (2004) suggests that research is needed to understand the costs and benefits of providing individuals with strong causal information, including the impact on performance measure usage.

In a performance evaluation setting, Banker at el. (2004) provide evidence that evaluators of business unit managerial performance are influenced more by strategically linked measures than by non-linked measures and that this linking can mitigate the common measures bias. Specifically, Banker et al. (2004) find that when individuals understand strategy, strategically linked unique measures dominate non-linked common measures in performance evaluation. Participants in the strategy information condition were provided with a brief narrative and graphical (i.e., strategy map) information regarding the strategic business unit's strategy. Thus, participants were provided with "explicit and salient information on SBU strategy", which allowed them to "comprehend strategy and, hence, discern the strategic significance of linked measures" (Banker et al. 2004, 8).

While this assessment is accurate, Banker et al.'s (2004) manipulation also can be viewed as varying two different components of performance measure knowledge, either of which might affect individuals' use of performance measures. Specifically, the narrative in Banker's study (Banker et al. 2004, Exhibit 4) provided individuals with an understanding of the company's strategy, which allowed individuals to link subsequent performance measures with the company's *strategy*. However, the strategy map (Banker et al. 2004, Exhibit 4), as well as portions of the narrative, also provided individuals with a strong causal understanding (i.e., story) of how each performance measure links to *other measures*, in addition to strategy. Thus, it is possible that the difference in performance measure usage reported in their study could be due either to the linking of performance measures to strategy or to the causal linking between performance measures, or both. Also unclear from their results is whether individuals inferred the appropriate directional relationships between the performance measures in the model (i.e., neither the narrative nor the strategy map clearly states the direction—positive or negative—of each relationship) and whether directional information might affect performance measure usage. We extend prior performance measurement research, in particular Banker et al. (2004), by examining whether variations in the type of causal knowledge—either none, weak or strong—of the relationship between a performance measure and earnings affects individuals' use of that measure in predicting earnings.

Based on research involving causal mechanisms, we predict that the provision of weak causal knowledge is sufficient to reduce individuals' discounting of performance measures relative to when no knowledge of the performance measure is provided. We also predict that the provision of strong causal knowledge further reduces users' discounting of measures relative to when only weak causal knowledge is provided. As expected, the results show that, for nonfinancial measures, providing weak causal knowledge reduces discounting when compared to providing no knowledge of the performance measure. Contrary to predictions, providing strong causal knowledge does not further reduce discounting compared to providing only weak causal knowledge, for either financial or nonfinancial measures. Taken together, these results suggest that individuals' level of causal performance measure knowledge affects their perceived predictive value and usage of performance measures in predicting future earnings; however, strong causal knowledge (i.e., a complete "story" of the performance measure relationship) has no greater effect on individuals' perception of performance measures than does merely weak causal knowledge (i.e., direction of association for the performance measure relationship).

In Section II, we develop hypotheses about the type of knowledge required to reduce users' discounting of predictive performance measures. We describe the design in Section III and the results of the hypothesis tests in Section IV. In Section V, we discuss conclusions, limitations, and suggestions for future research.

II. HYPOTHESIS DEVELOPMENT

User Discounting of Predictive Performance Measures

Individuals in numerous settings attempt to predict long-term financial performance based on financial and nonfinancial performance measures. Kaplan and Norton (2001, 1996) argue that particular nonfinancial measures, such as product quality, customer satisfaction, and percentage of returning customers, should be blended with financial information to form a balanced approach to performance measurement. Consistent with this argument, recent studies (Ittner, Larcker, and Randall 2003; Riley, Pearson, and Trompeter 2003; Banker and Mashruwala 2001; Smith and Wright 2001; Nagar and Rajan 2001; Banker, Potter, and Srinivasan 2000; Ittner and Larcker 1998; Foster and Gupta 1999; Amir and Lev 1996) find evidence of a relationship between nonfinancial performance measures and financial results. The results of these studies suggest that users should perceive when both financial and nonfinancial performance measures possess predictive value of net income and, thus, should use both types of measures to predict financial performance.[4]

However, there is some evidence that nonfinancial performance measures are more likely to be discounted by users than are financial performance measures (Kaplan and Norton 1996, 1993; Eccles and Mavrinac 1995). Dempsey et al. (1997) find that analysts report that nonfinancial measures are used less frequently than financial measures, have less perceived predictive value of long-term performance than financial measures, and are harder to obtain than financial measures. Ittner, Larcker and Meyer (2003) find that weights placed on nonfinancial measures in performance evaluation are not based solely on the informativeness (ability to predict financial performance) of the measure. Rather, the weights are consistent with psychology-based predictions of quantitative, outcome-oriented financial measures that had been used in prior bonus plans. Users seem to discount the nonfinancial performance measures and rely on the financial performance measures they had used previously and about which they likely possessed more knowledge.

In addition to financial performance predictions tasks, differences in use of financial and nonfinancial performance measures have been found in performance evaluation tasks as well. For example, Lipe and Salterio (2000) employ an experiment to examine the use of generic measures (which often are financial) that are common across units and unique measures (which often are nonfinancial) that are specifically tailored to a particular unit's strategy. Their results show that, compared to common measures, unique measures are discounted by superiors evaluating the performance of subordinate unit managers. Dilla and Steinbart (2005) found similar results with participants knowledgeable about the Balanced Scorecard. While participants in the Dilla and Steinbart (2005) study use common and unique measures to a greater extent than participants in the Lipe and Salterio (2000) study, unique measures are underweighted relative to common measures for both performance evaluation and bonus allocation. However, neither study measured or manipulated superiors' knowledge of either common or unique measures. As Maines et al. (2002, 359) suggest, the results might be due to "the users' lack of framework for understanding implications of the nonfinancial measures for performance; thus, they reverted to financial measures for which they have a framework and could directly compare across divisions." Thus, it is possible that the results of Lipe and Salterio (2000) and Dilla and Steinbart (2005) are driven by a lack of sufficient knowledge for unique measures. Although our experimental task is one of financial performance prediction rather than performance evaluation, the non-use that occurs in performance evaluation is also likely to occur in financial prediction because in both tasks users must make judgments concerning the predictiveness and usefulness of different types of measures.

Weak Versus Strong Causal Performance Measure Knowledge

For the hypotheses, we dissect our definition of knowledge into weak and strong causal knowledge and examine how it affects individuals' discounting of performance measures. Weak causal knowledge, which is examined in H1, is defined as being aware of the direction in which the performance measure affects net income (i.e., whether the association is positive or negative). Strong causal knowledge, which is examined in H2, is defined as going beyond simply knowing the direction of the association between the measure and net income to include a detailed understanding of the linkages in the underlying cause-and-effect relationship (i.e., the causal mechanism) between the particular performance measure and net income. In so doing, we study the strength of causal knowledge required to affect users' perception of performance measures. There may be a threshold of knowledge necessary before users change their behavior and reduce discounting. For example, Krishnan and Booker (2002) find that investors reduce the disposition error for losses only in the presence of strong supporting arguments (i.e., a strong form was necessary to change behavior).

Weak Causal Performance Measure Knowledge

Why would weak causal knowledge change the user's perceived predictive value and usage of performance measures? Some psychology research suggests that a causal mechanism might not need to be explicitly communicated to individuals in order for a story to be inferred. For example, Buehner et al. (2003) provides experimental evidence that individuals make the mental leap from covariation to causation when they hold the conviction that (unobservable) causal powers exist in the task environment and that part of their task is to infer the unobservable causal relationships present in the environment. This condition potentially exists in a financial prediction task, such as ours, where users are given the weak causal knowledge that one measure affects net income but are not told of the underlying detailed causal mechanism connecting the measure to net income. Some research suggests that individuals might even attempt to infer a causal relationship in situations where they concede that multiple alternate interpretations of the relationship of interest are possible (Gardner 2000).

In addition, in a causal attribution task setting, Ahn et al. (1995) provide evidence that individuals "are primarily interested in searching for (causal) mechanism information." Specifically, Ahn et al. (1995) shows (Experiment 3) that when provided only with covariation information, the majority of individuals' causal attribution explanations contained a causal mechanism that was not present in the covariation information given to them in the experiment. Thus, individuals created a story to explain the information they were given. These results suggest that individuals have an apparent desire to search for causal information and suggest that performance measure users will assume an underlying causal story even when no such story is explicitly provided but weak causal knowledge is present.

In summary, in the context of a financial prediction task, the provision of weak causal knowledge is expected to serve as a cue for users to assume a causal story between the performance measure and net income even when no detailed story is explicitly communicated. Individuals are expected to assume an underlying causal mechanism even when the measures involved are sufficiently general such that they cannot accurately guess as to the actual causal story. Thus, we are not expecting that it is necessary for individuals to figure out the actual underlying detailed causal story in order for weak causal knowledge to affect their view of performance measures. Rather, we expect that simply assuming that *an* underlying causal story exists is sufficient to increase users' perceived predictive value and expected usage of the performance measure. Thus, we make the following prediction.

H1: The provision of *weak causal knowledge* regarding performance measures increases users' perceived predictive value of and expected use of performance measures as compared to the provision of *no causal knowledge* regarding performance measures.

Strong Causal Performance Measure Knowledge

It is possible that weak causal information alone is not sufficient to affect users' discounting of performance measures or does not affect users' discounting of performance measures to the same extent as does strong causal knowledge. Before users further reduce the extent to which they discount one performance measure over another, they might require detailed information regarding the causal relationship between the performance measure and net income (e.g., Krishnan and Booker 2002). Webb (2004) finds that strong links between the nonfinancial objectives and performance measures increase the manager's willingness to commit to financial goals over weak links. Thus, we expect that a detailed story will increase the perceived value and usage of performance measures as compared to weak causal information.

As discussed above, some psychology research has found that individuals infer a causal story if they believe a causal mechanism exists in the presence of only weak causal knowledge. Fugelsang and Thompson (2003) find that providing the underlying causal story about a non-obvious relationship between performance measures and net income strengthens individuals' beliefs in the relationship beyond what is expected to be assumed from the provision of only weak causal knowledge. Thus, contrary to some psychology results, their results suggest that strong causal knowledge might be needed to reduce discounting.

In addition, Broniarczyk and Alba (1994) suggest that users are reluctant to rely on predictor (e.g., performance measure) data without a conceptual connection to the criterion (e.g., future net income), such as that provided by a detailed causal story. Their results indicate that given only weak causal data, individuals tend to rely on prior beliefs; but if given strong causal knowledge, individuals rely on the relationships in the data when predicting quality estimates. In addition, Luft and Shields (2001) find that the lagged link between performance measures and future profits is more transparent to individuals with nonfinancial performance measures than to individuals with financial measures because nonfinancial performance measures activate a link to a causal story that financial measures do not activate. Based on these findings, we predict that individuals with strong causal knowledge of performance measures (i.e., the underlying detailed causal story) view such measures as being more predictive of future financial performance and more useful in predicting future financial performance than individuals with only weak causal knowledge of such measures.

H2: The provision of *strong causal knowledge* regarding performance measures increases users' perceived predictive value of and expected use of performance measures as compared to the provision of *weak causal knowledge* regarding performance measures.

III. RESEARCH METHOD

Design and Participants

The experiment manipulates knowledge (none, weak causal, or strong causal) and type of performance measure (financial or nonfinancial) in a 3 x 2 between-subjects design. Participants were randomly assigned to one of the six experimental conditions. The type of performance measure is a between-subjects manipulation, such that each participant is presented only with two nonfinancial performance measures or two financial performance measures. This manipulation enables us to determine whether the change in perceived predictive value and expected usage is due solely to the differences in performance measure knowledge or also to the performance measure label as either financial or nonfinancial. While we do not predict differences due to the type of measure, given the prior literature's focus on nonfinancial data, we examine whether users approach the two types of measures differently. Thus, the same data are presented for the financial and nonfinancial conditions.

Also, performance measure knowledge is a between-subject manipulation, such that each participant is presented with either strong causal knowledge, weak causal knowledge, or no knowledge concerning one performance measure and no knowledge concerning the other performance measure. For each participant, the difference in perceived predictive value between the two measures is calculated and compared across conditions. This within-subject aspect of the design controls for individuals' inherent differences in perceived value for the manipulated performance measures, thereby isolating the incremental effect of providing either weak causal or strong causal knowledge, above no knowledge, on individuals' perceived value and use of the measures.

The sample consisted of 127 undergraduate business, Masters of Accountancy and MBA students at a large midwestern university. Participants were informed that they would receive a fixed amount of $7 for completing the approximately 45-minute managerial simulation plus a bonus of up to $8 based on the accuracy of their responses. Participants returned at a later time to collect their pay, which was adjusted for the grand mean so that participants in the no knowledge conditions were not at a disadvantage. The average earnings were $11.25.

Experimental Procedure

The experiment began by providing participants with a one-page description of the fictitious S&F company, which manufactures ice cream. Participants then were provided with a brief narrative about S&F's performance measures. The contents of the narrative varied depending upon the experimental condition. After reading the narrative, all participants were provided with the same financial report containing the results for each of two performance measures and net income for the past six quarters. Participants were allowed to refer back to their narrative and the financial report as they completed the task.

Participants were told to assume that the relationships present in the six quarters of data were to persist in the future. Participants then responded to a series of questions to measure the dependent variables.[5] After the experiment, participants completed an exit questionnaire, which gathered data regarding manipulation checks, participants' initial beliefs of the relationship between net income and each performance measure and demographics.

Independent Variables

The independent variables are knowledge (none, weak causal, strong causal) and type of performance measure (financial, nonfinancial). The information in the narrative was varied to provide different levels of performance measure knowledge. In each condition, participants were provided with two performance measures and for one (either Sponsorships or Composite Index) of the two measures, no additional information was provided in any of the six conditions. The narrative varied the performance measure knowledge provided about the second performance measure (either Promotions or Average Degrees – see Appendix A). Thus, no additional information about the second performance measure was provided in the "no knowledge" condition. In the "weak causal knowledge" condition, the information included only the direction of the relationship between the second measure and net income. In the "strong causal knowledge" condition, the information included the direction of the relationship between the second measure and net income and an explanation of how that measure affected net income.

There was no mention in any of the narratives as to the magnitude of the relationship between the performance measure and net income. Thus, participants could draw their own conclusions as to the perceived value of each performance measure and the parameter estimate of each performance measure. Thus, the six experimental conditions are as follows: no financial narrative, no nonfinancial narrative, weak causal financial narrative, weak causal nonfinancial narrative, strong causal financial narrative, and strong causal nonfinancial narrative.

The two financial performance measures are Promotions and Sponsorships and the two nonfinancial performance measures are Average Degrees and Composite Index. The lack of specificity in the performance measure labels helped ensure that participants could not accurately infer the relationship between net income and the performance measure. Pilot studies revealed that examples of typical financial measures, such as Direct Materials, were familiar to all participants and, as such, manipulations of Direct Materials were not successful. Performance measure knowledge manipulations were successful with the measures chosen as described in Section IV.

For each condition, both performance measures had positive relationships with net income. Figure 2 (Panel A) shows the normative predictive values for the data set. The experiment was designed such that each measure has the same predictive value (i.e., parameter value) of $500. Thus, if differences in causal knowledge do not play a significant role in profit prediction, then participants should use the two measures equally. Also, it is important to note that the experiment is designed such that both performance measures are necessary to accurately predict net income. Thus, if knowledge (or lack of knowledge) influences the participant to ignore or discount a measure, then the participant is not correctly utilizing the performance measures. In so doing, we ensure that any difference in measures' perceived predictive value are due to differences in users' performance measure knowledge and not to actual differences in predictive value.

[INSERT FIGURE 1 ABOUT HERE]

Dependent Variables

The three dependent variables include participants' perception of how predictive each performance measure is of future net income, their indication of how frequently they would use each performance measure to predict future net income and the amount of money they would spend to purchase each performance measure if the measure were not provided internally. Using a 7-point Likert scale (1=not at all predictive, 7=very predictive), participants indicated their perception of how predictive each performance measure is of future net income. Also, using a 7-

point Likert scale (1=never use, 7=use very frequently), participants indicated how frequently they would use each measure to predict future net income. Finally, participants allocated $100 among the four measures to indicate the amount they would spend to purchase each measure.

In testing H1 and H2, we examine the change in the dependent variables across performance measure knowledge conditions to examine the effect of each knowledge type on users' perception of performance measures. Each dependent variable is measured as the difference in the participant's response between the measure about which knowledge is provided (either Promotions or Average Degrees) and the measure about which no knowledge is provided (either Sponsorships or Composite Index). Therefore, PVDIF is a within-subject measure that captures the difference in perceived predictive value between the performance measure for which users' knowledge is manipulated (either strong causal, weak causal or none) and the performance measure for which users have no knowledge (i.e., no knowledge is manipulated for this measure). The three dependent variables used to test the hypotheses are: PVDIF (difference in perceived predictive value), FUDIF (difference in expected frequency of use), and MSDIF (difference in the amount of money spent to purchase).

We employ the output from an OLS multiple regression to define the predictive value of the two performance measures in our data set. Figure 1 (Panel B) contains the performance measurement and net income data employed in the experiment. We use raw, unscaled regression weights to define the measures' predictive value because of their straightforward interpretability. The use of unscaled regression weights is justified because of the lack of multicollinearity between the measures and the minimal differences in the measures' means and standard deviations (Cooksey 1996, 162).

IV. RESULTS

H1: The Effect of Weak Causal Knowledge on the Discounting of Performance Measures

Hypothesis 1 predicts that the provision of weak causal knowledge of performance measures increases users' perceived predictive value and expected frequency of use of such measures as compared to the provision of no causal knowledge of performance measures. Table 1 displays the descriptive statistics for the three dependent variables, PVDIF, FUDIF and MSDIF.

[INSERT TABLE 1 ABOUT HERE]

Hypothesis 1 does not predict differences between financial and nonfinancial performance measure types. ANOVA results in Panel A of Tables 2, 3, and 4 show no main effect for PMTYPE for any of the dependent variables of H1 and H2. As such, financial and nonfinancial responses were collapsed to test the pre-planned comparisons for H1 and H2. Panel A of Table 2 presents the ANOVA results with PVDIF as the dependent variable. The results show a marginally significant main effect for KNOWLEDGE ($F = 21.60$; one-tailed $p = .06$) and a marginally significant interaction effect ($F = 1.83$; one-tailed $p = .082$). Panel B of Table 2 presents the results of the specific pre-planned two-cell knowledge comparison predicted in H1, specifically between weak causal and none. A positive PVDIF indicates that users perceive a greater predictive value for the performance measure about which their knowledge is manipulated than for the performance measure about which they have no knowledge.[6] As predicted in H1, PVDIF is significantly greater with weak causal (.691) knowledge than with no knowledge (-0.047) ($t = -1.89$; one-tailed $p = .031$). Thus, users perceive a greater predictive value for (or discount to a lesser extent) the performance measure for which they have weak causal knowledge as compared to the performance measure for which they have no causal knowledge.

[INSERT TABLES 2, 3, and 4 ABOUT HERE]

Panel A of Table 3 presents the ANOVA results with FUDIF as the dependent variable. The results show a significant main effect for KNOWLEDGE (F = 2.46; one-tailed p = .044). Panel B of Table 3 presents the results of the specific pre-planned two-cell knowledge comparison predicted in H1, specifically between weak causal and none. Also, as predicted in H1, FUDIF is significantly greater with weak causal knowledge (.667) than with no knowledge (-0.093) (t = -1.67; one-tailed p = .05).

Finally, Panel A of Table 4 presents the ANOVA results with MSDIF as the dependent variable. The results show a marginally significant main effect for knowledge (F = 2.18; one-tailed p = .058). The results of the specific pre-planned two-cell knowledge comparison, specifically between weak causal and none, reveal the expected difference between these two conditions. Again, as predicted in H1, a marginally significant t-test reveals that MSDIF is greater with weak causal knowledge (10.83) than with no knowledge (-0.93) (t = -1.50; one-tailed p = .069). Taken together, the results suggest that users discount to a lesser extent (i.e., perceive greater predictive value for, are more likely to use and spend more money to purchase) the performance measure for which they have weak causal knowledge as compared to the performance measure for which they have no causal knowledge. Thus, H1 is supported.

Supplemental Analysis: H1

Although no differences were predicted between nonfinancial and financial performance measures for H1 or H2, descriptive statistics (see Table 1) suggest that such differences might be present.[7] Thus, further analysis was conducted by comparing across knowledge conditions within each performance measure type (i.e., for nonfinancial and financial measures separately). With respect to H1, PVDIF (t = -2.38; one-tailed p = .01), FUDIF (t = -1.96; one-tailed p = .03), and MSDIF (t = -1.49; one-tailed p = .07) are significant between the weak and no causal knowledge conditions for nonfinancial performance measures. However, PVDIF (t = -0.10; one-tailed p = .46), FUDIF (t = -0.09; one-tailed p = .46), and MSDIF (t = -0.57; one-tailed p = .28) are not significant between the weak and no causal knowledge conditions for financial performance measures. It is possible that in the no causal knowledge conditions (i.e., knowledge not manipulated), participants with financial measures nonetheless had a weak story in mind for Promotions (which is manipulated in the weak and strong financial conditions), but that participants with nonfinancial measures had no such weak story in mind for Average Degrees (which is manipulated in the weak and strong nonfinancial conditions).[8] Thus, providing weak causal knowledge, as compared to no causal knowledge, has a significant impact for nonfinancial measures but not for financial measures.

H2: The Effect of Strong Causal Knowledge on the Discounting of Performance Measures

Hypothesis 2 predicts that the provision of strong causal knowledge of performance measures increases users' perceived predictive value and expected use of such measures, as compared to the provision of weak causal knowledge of performance measures. Panel B of Table 2 presents the PVDIF results for the specific pre-planned two-cell comparison predicted in H2, specifically between the strong causal and weak causal knowledge conditions. Contrary to H2, the results show no difference in PVDIF between strong and weak causal knowledge (t = 0.31; one-tailed p = .378). Similarly, Panel B of Tables 3 and 4 shows no difference in FUDIF (t = -.34; one-tailed p = .367) and MSDIF (t = -.44; one-tailed p = .33), respectively, between the strong and weak causal knowledge conditions for performance measures. Similar to H1, a supplementary analysis was conducted. However, this analysis revealed no differences between weak and strong causal knowledge for either financial or nonfinancial performance measure type.[9] Thus, contrary to expectations, providing users with strong causal knowledge about performance measures, either financial or nonfinancial, does *not* reduce the extent to which they discount such measures as compared to performance measures about which they possess only weak causal knowledge.

Manipulation Checks

Participants answered four [five] questions on a 5-point Likert-scale (1 = strongly disagree, 5 = strongly agree) to determine if they understood what information about the financial [nonfinancial] performance measures was and was not provided in their narrative. Appendix B presents these nine questions. As H1 and H2 make no distinction between financial and nonfinancial performance measures, the questions were combined to test for a main effect of knowledge type (i.e., weak causal vs. strong causal). One-way ANOVA results for the summed manipulation score shows a main effect for knowledge type ($F = 24.22$; one-tailed $p < .001$). T-test results show a significant difference ($t = 2.18$; $p = .032$) between no causal knowledge (mean = 13.24; standard deviation = 3.41) and weak causal knowledge (mean = 14.69; standard deviation = 2.70). Thus, participants in the weak causal condition reported greater knowledge about the underlying causal relationships between the performance measures than did participants in the no causal condition. Also, t-test results show a significant difference ($t = 4.76$; one-tailed $p < .001$) between weak causal knowledge and strong causal knowledge (mean = 18.38; standard deviation = 4.24). Thus, participants in the strong causal condition reported greater knowledge about the underlying causal relationships between the performance measures than did participants in the weak causal condition. Therefore, the results of the manipulation checks indicate that performance measure knowledge was successfully manipulated across the three knowledge conditions.

Work experience, accounting and statistics courses, GPA, GMAT and SAT scores, and gender were analyzed as potential covariates. None of these control variables affected the results of the hypothesis tests.

V. CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

Recent accounting studies find some evidence of a relationship between nonfinancial performance measures and financial results and support the call for firms to present, both internally and externally, more information on nonfinancial indicators of future financial performance. Yet, other studies report that nonfinancial performance measures are used significantly less than financial performance measures and often are perceived as having significantly less predictive value of future financial performance than financial performance measures. This apparent contradiction likely is explained by several factors. We examine the role played by one such factor—causal performance measure knowledge—on individuals' propensity to discount normatively predictive performance measures in a profit prediction task.

As expected, the results suggest that providing weak causal knowledge reduces individuals' discounting of performance measures as compared to when no causal knowledge is provided. Interestingly, the effect is significant for nonfinancial measures but not for financial measures even though the same data set was used for both types of performance measures. It is possible that in the absence of knowledge manipulation participants were better able to create a causal story for the financial measures than for the nonfinancial measures, thereby eliminating the effect of providing weak causal knowledge for financial performance measures. Contrary to predictions, providing strong causal knowledge does not further reduce discounting compared to when only weak causal knowledge is provided. These combined results provide preliminary empirical evidence as to the depth of knowledge required by individuals to reduce their discounting of normatively predictive performance measures.

The results have potential implications both for organizations' performance measurement systems and for future accounting research involving performance measurement. Given that generating and providing employees with strong causal performance measure knowledge is costly for organizations in terms of time and money, this study contributes important insights as to the level of knowledge required to reduce individuals' discounting of performance measures. For example, the result that weak causal knowledge reduces individuals' discounting of performance measures suggests that organizations might benefit from taking various steps to provide individuals with weak causal knowledge regarding key performance measures beyond just making the measures more available. For instance, decreasing the cost to analysts or other interested external stakeholders of obtaining performance measures (e.g., through voluntary firm disclosure, press releases, corporate sustainability reports, etc.) or making performance measures easier for employees to obtain (e.g., by providing them on performance evaluation reports, such as Balanced Scorecards, etc.) might need to be augmented with some level of causal performance measure knowledge to increase the likelihood of their subsequent use. To a large extent, organizations determine the type of performance measure knowledge most individuals possess by the way in which they present such information. At a minimum, organizations likely know the direction of the association between performance measures and earnings and, thus, are able to provide individuals with this weak causal knowledge by informing them that a given measure affects earnings in a positive or negative manner.

The finding that individuals' causal performance measure knowledge affects how they view performance measures has implications for future accounting research involving nonfinancial performance measurement. For example, future research should consider that although individuals' decisions as to which performance measures to use or not use for accurate predictions should be based on the measures' predictive value, such decisions appear to be significantly influenced by whether or not individuals possess at least weak causal knowledge regarding the performance measure. More specifically, future research might examine the specific conditions under which providing strong causal knowledge reduces discounting of performance measures to a greater extent than providing only weak causal knowledge. Such research would build upon the current study's results of reducing discounting by offering insights of when strong causal knowledge reduces performance measure discounting. For example, providing individuals with strong causal performance measure knowledge, as is required in developing a causal model (Ittner and Larcker 2003) or a strategy map (Kaplan and Norton 2004), is costly to organizations because it requires them to spend considerable resources generating and communicating the underlying causal mechanism (or story) to individuals.

Contrary to assumptions and implications made in prior performance measurement research, our study suggests that it might not be necessary for organizations to expend more effort in generating and communicating a strong causal story for every performance measure in predicting future profits. Future research is necessary to understand exactly which tasks and task conditions benefit from strong causal performance measure knowledge. Understanding how causal performance measure knowledge reduces individuals' discounting of normatively predictive measures might help lead to the generation of tools to debias performance evaluation and other uses of performance measurement data, such as the financial prediction task setting examined in the current study (e.g., Roberts, Albright, and Hibbets 2004).

Also, future research might extend this study by examining whether additional factors, besides the level of causal knowledge, affect individuals' perception and use of financial and nonfinancial performance measures in predicting future profits. Finally, future research might examine how individuals' reported perceptions of performance measures' predictive values translate into more or less accurate estimates of predictive value. Such work could help determine whether increased knowledge leads to increased accuracy in estimating the predictive value of performance measures.

This study is subject to several limitations. First, the generalizability of the results might be affected by the stylized nature of the experimental narrative, which successfully manipulated individuals' level of financial or nonfinancial performance measure knowledge using one page of dialogue. Successful communication of causal performance measure knowledge to individuals in practice might prove to be more or less difficult than in this experimental setting (Jensen and Meckling 1992). Second, the experiment utilized student participants. However, the Masters of Accountancy and MBA students represent typical users of performance measures in reality, such as employees, investors and auditors, and behaved no differently than the undergraduate participants. Finally, although potentially significant in reality, the cost of obtaining accurate causal performance measure knowledge is not examined in this study. The effect of knowledge on individuals' view of performance measures might differ if the provided knowledge is inaccurate.

Endnotes

[1] Roberts et al. (2004) find that the common measures bias in a performance evaluation task can be mitigated by reducing the cognitive demands placed on evaluators, which they accomplish by disaggregating the steps involved in performing a balanced scorecard evaluation. However, we focus on whether the level of individuals' causal knowledge, rather than on the level of task disaggregation, affects their use of performance measures. Also, we focus on the task of financial prediction rather than performance evaluation.

[2] For example, Ittner and Larcker (2003) report that approximately 30% of their 157 survey companies develop detailed causal models that link nonfinancial performance measures to long-term economic performance.

[3] As examined in this study, knowledge pertains only to information *about* the performance measure's relationship to earnings, rather than to information concerning *how to use* the performance measure in a given task. In other words, this study is not examining whether "better knowledge leads to better decisions in a given task setting", but instead whether different types of causal knowledge about the performance measure differentially affect how individuals perceive normatively equally predictive performance measures.

[4] We define the predictive value of a performance measure as the measure's absolute parameter value, which is the change (increase or decrease) in net income that results from a one-unit increase in the performance measure (Cooksey 1996, 162). Therefore, a performance measure with a $500 parameter value has a greater predictive value than a performance measure with a $250 parameter value.

[5] The order in which data was collected for the dependent variables varied randomly to ensure that task order did not affect participants' responses.

[6] However, in the none condition, the sign of PVDIF has little meaning other than to show whether, in the absence of any knowledge manipulation for Average Degrees (or Promotions in the financial condition), participants perceived greater predictive value for Average Degrees (positive PVDIF) or Composite Index (negative PVDIF). The same statement also pertains to FUDIF and MSDIF, as well as for the financial performance measure condition.

[7] Descriptive statistics are not affected by outliers based on results of tests with SPSS.

[8] Such ex post analysis is in agreement with Webb (2004), Fugelsang and Thompson (2003), and Broniarczyk and Alba (1994). In these studies, the "weak" link was unavailable to people because it was not provided and could not be determined by participants from the variable names or if provided, the link was not plausible to participants.

[9] With respect to H2, neither the nonfinancial nor financial measures were significant between weak and strong causal knowledge conditions. Specifically for the nonfinancial condition, PVDIF ($t = 1.17$; one-tailed $p = .13$), FUDIF ($t = 0.20$; one-tailed $p = .42$), and MSDIF ($t = -0.31$; one-tailed $p = .38$) were not significant. For the financial condition, PVDIF ($t = -0.85$; one-tailed $p = .20$), FUDIF ($t = -0.80$; one-tailed $p = .21$), and MSDIF ($t = -0.31$; one-tailed $p = .38$) were not significant.

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Figure 1
Experimental Parameters

Panel A: Performance Measure Information

PERFORMANCE MEASURE	TYPE	NORMATIVE PREDICTIVE VALUE[a]
Promotions	Financial	+$500
Sponsorship	Financial	+$500
Composite Index	Nonfinancial	+$500
Avg. Degrees of Temperature Below Margin	Nonfinancial	+$500

Panel B: Net Income Function

Quarter	Fixed Costs	Promotions OR Composite Index (X_1)	Sponsorships OR Average Degrees Below Margin (X_2)	Error	Net Income[b]
March 2001	$100,000	90	70	$2,500	$182,500
June 2001	$100,000	70	45	-$2,500	$155,000
Sept 2001	$100,000	60	50	$1,500	$156,500
Dec 2001	$100,000	80	65	-$1,500	$171,000
March 2002	$100,000	40	60	$2,000	$152,000
June 2002	$100,000	50	80	-$2,000	$163,000

[a] Normative predictive value is defined as the raw, unstandardized regression coefficient output from an OLS multiple regression analysis (Cooksey 1996, 162).

[b] The function used to generate NET INCOME (and the OLS estimate of the function) is: = $100,000 + 500X_1$ + 500X_2$ + error; the error term is independent, has a mean of 0 and is uniformly distributed.
R^2 = .963

Table 1: Descriptive Statistics

Panel A: Differences in Perceived Predictive Value: PVDIF

		KNOWLEDGE None	Weak Causal	Strong Causal	Row Totals
PM TYPE	Financial [a]	.381[b] (1.50) [21]	.429 (1.69) [21]	.857 (1.59) [21]	.556 (1.58) [63]
	Nonfinancial	-.455 (1.87) [22]	.952 (2.01) [21]	.286 (1.68) [21]	.250 (1.92) [64]
	Column Totals	-.047 (1.73) [43]	.691 (1.85) [42]	.571 (1.64) [42]	.402 (1.76) [127]

Panel B: Differences in Frequency of Use: FUDIF

		KNOWLEDGE None	Weak Causal	Strong Causal	Row Totals
PM TYPE	Financial	.333 (1.53) [21]	.381 (1.80) [21]	.833 (1.85) [21]	.516 (1.72) [63]
	Nonfinancial	-.500 (2.09) [22]	.952 (2.75) [21]	.810 (1.83) [21]	.406 (2.31) [64]
	Column Totals	-.0930 (1.86) [43]	.667 (2.31) [42]	.821 (1.82) [42]	.461 (2.03) [127]

Panel C: Differences in Money Spent: MSDIF

		KNOWLEDGE None	Weak Causal	Strong Causal	Row Totals
PM TYPE	Financial	7.14 (29.73) [21]	13.33 (39.44) [21]	16.76 (31.89) [21]	12.41 (33.63) [63]
	Nonfinancial	-8.64 (36.03) [22]	8.33 (38.74) [21]	11.67 (30.71) [21]	3.59 (35.92) [64]
	Column Totals	-.930 (33.67) [43]	10.83 (38.70) [42]	14.21 (31.03) [42]	7.97 (34.95) [127]

[a] PMTYPE = performance measure type; KNOWLEDGE = knowledge of performance measure.
[b] Cells contain means, (standard deviations), and the [number of observations].

Table 2
Difference in Perceived Predictive Value: PVDIF[a]
Results of ANOVA and Pre-Planned Comparisons

Panel A – ANOVA:

Factor	Sum of Squares	df	Mean Square	F-stat	One-tail p-value
PM Type[b]	2.75	1	2.75	0.92	.170
Knowledge[c]	12.98	2	6.49	21.60	.060
PM Type x Knowledge	10.98	2	5.49	1.83	.082
Explained	27.16	5	5.43	1.81	.058
Residual	363.36	121	3.00		

Panel B – Pre-planned Comparisons to Test H1 and H2: PVDIF

Mean Comparison Between:		**t-stat.**[e]	**p-value**
Weak Causal .691[d] (1.85) [42]	None -.047 (1.73) [43]	-1.89	.031
Strong Causal .571 (1.64) [42]	Weak Causal .691 (1.85) [42]	0.31	.378

[a] PVDIF =
Nonfinancial: perceived predictive value of Avg. Degrees - perceived predictive value of Composite Index;
Financial: perceived predictive value of Promotions – perceived predictive value of Sponsorships
[b] PM Type = Financial and Nonfinancial
[c] Knowledge = None, weak causal, strong causal.
[d] Cells contain means, (standard deviations), and [number of observations].
[e] One-tailed test.

Table 3
Difference in Expected Frequency of Use: FUDIF [a]
Results of ANOVA and Pre-Planned Comparisons

Panel A - 3 x 2 ANOVA:

Factor	Sum of Squares	Df	Mean Square	F-stat	One-tail p-value
PM Type[b]	0.29	1	0.29	0.07	.395
Knowledge[c]	19.97	2	9.98	2.46	.044
PM Type x Knowledge	10.57	2	5.29	1.31	.137
Explained	31.33	5	6.26	1.55	.090
Residual	489.98	121	4.05		

Panel B – Pre-planned Comparisons to Test H1 and H2: FUDIF

Mean Comparison Between:		t-stat.[e]	p-value
Weak Causal .667[d] (2.31) [42]	None -.093 (1.86) [43]	-1.67	.050
Strong Causal .821 (1.82) [42]	Weak Causal .667 (2.31) [42]	-0.34	.367

[a] FUDIF =
Nonfinancial: frequency of use of Avg. Degrees – frequency of use of Composite Index;
Financial: frequency of use of Promotions – frequency of use of Sponsorships
[b] PM Type = Financial and Nonfinancial
[c] Knowledge = None, weak causal, strong causal.
[d] Cells contain means, (standard deviations), and [number of observations].
[e] One-tailed test.

Table 4
Difference in Dollars Spent to Purchase: MSDIF [a]
Results of ANOVA and Pre-Planned Comparisons

Panel A - 3 x 2 ANOVA:

Factor	Sum of Squares	df	Mean Square	F-stat	One-tail p-value
PM Type[b]	2361	1	2361	1.97	.082
Knowledge[c]	5246	2	2623	2.18	.058
PM Type x Knowledge	818	2	409	0.34	.356
Explained	8598	5	1720	1.43	.108
Residual	145281	121	1200		

Panel B – Pre-planned Comparisons to Test H1 and H2: MSDIF

Mean Comparison Between:		t-stat.[e]	p-value
Weak Causal 10.83[d] (38.70) [42]	None -0.93 (33.67) [43]	-1.50	.069
Strong Causal 14.21 (31.03) [42]	Weak Causal 10.83 (38.70) [42]	-0.44	.330

[a] MSDIF =
Nonfinancial: money spent of Avg. Degrees – money spent of Composite Index;
Financial: money spent of Promotions – money spent of Sponsorships
[b] PM Type = Financial and Nonfinancial
[c] Knowledge = None, weak causal, strong causal.
[d] Cells contain means, (standard deviations), and [number of observations].
[e] One-tailed test.

APPENDIX A

EXPERIMENTAL NARRATIVES:

Panel A: Weak Causal Financial

S&F has performed extensive analyses to understand the relationships between Net Income and one of its financial measures: Promotions. The findings are presented below.

S&F knows that the dollars spent on Promotions positively affects Net Income. Thus, all else equal, Net Income increases (decreases) from one quarter to the next as the dollars spent on Promotions increases (decreases) from one quarter to the next.

Panel B: Strong Causal Financial

S&F has performed extensive analyses to understand the relationships between Net Income and one of its financial measures: Promotions. The findings are presented below.

S&F manages its promotions through advertising and product placements. Promotions, such as advertising in local newspapers and fliers, has proven to be an effective mechanism for quickly attracting consumers. As the dollars spent on Promotions increase, revenues increase. As a result, S&F knows that the dollars spent on Promotions positively affects Net Income. Thus, all else equal, Net Income increases (decreases) from one quarter to the next as the dollars spent on Promotions increases (decreases) from one quarter to the next.

Panel C: Weak Causal Nonfinancial

S&F has performed extensive analyses to understand the relationships between Net Income and one of its nonfinancial measures: Average Degrees of Temperature Below Margin. The findings are presented below.

S&F knows that Average Degrees of Temperature Below Margin positively affects Net Income. Thus, all else equal, Net Income increases (decreases) from one quarter to the next as the Average Degrees of Temperature Below Margin increases (decreases) from one quarter to the next.

APPENDIX A - continued

Panel D: Strong Causal Nonfinancial

S&F has performed extensive analyses to understand the relationships between Net Income and one of its nonfinancial measures: Average Degrees of Temperature Below Margin. The findings are presented below.

A mix of ingredients is poured into a tank where it is blended and pasteurized. The mix then is pumped into the freezing tank where it is partially frozen. Once the ice cream is partially frozen and packaged into containers, it is stored in the hardening room. An area of concern to S&F management is performance in the hardening room. There have been problems in the past with temperature controls allowing the temperature to rise above the desired maximum margin temperature. As the temperature in the hardening room rises above the maximum margin temperature, it creates excess moisture and results in stale product. The stale product must be written-off, which increases the cost of goods sold expense. However, as the temperature in the hardening room falls below the maximum margin temperature, less excess moisture is created and, therefore, less stale product is generated. As a result, production workers monitor temperature and moisture levels and provide a summary measure to management. The summary measure, referred to as the Average Degrees of Temperature Below Margin, is the average number of degrees the temperature in the hardening room is below the desired maximum margin temperature. Falling below the maximum margin temperature decreases the amount of excess moisture, thereby decreasing the amount of stale product that must be written off. Therefore, the greater the average temperature below the maximum, the less the amount of stale product that must be written-off and the greater the Net Income. As a result, S&F knows that Average Degrees of Temperature Below Margin positively affects Net Income. Thus, all else equal, Net Income increases (decreases) from one quarter to the next as the Average Degrees of Temperature Below Margin increases (decreases) from one quarter to the next.

Appendix B
Manipulation Check Questions

Based on the S&F company information you read earlier, please indicate to what extent you agree or disagree that each of the following statements was provided in the company information.

(For all questions, the following scale was used:)[a]

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

1) As dollars spent on Promotions increases, revenues increase. (FINANCIAL)

2) S&F manages its promotions through advertising and product placements. (FINANCIAL)

3) The dollars spent on Promotions ($) positively affects Net Income. (FINANCIAL)

4) Promotions has proven to be an effective mechanism for quickly attracting consumers. (FINANCIAL)

5) Ingredients are poured into a tank where they are blended and pasteurized. (NONFINANCIAL)

6) Falling below the maximum margin temperature decreases the amount of excess moisture, thereby decreasing the amount of stale product that must be written off. (NONFINANCIAL)

7) The stale product must be written-off, which increases the cost of goods sold expense. (NONFINANCIAL)

8) Net Income increases as the Avg. Degrees of Temp. Below Margin increases. (NONFINANCIAL)

9) Avg. Degrees of Temp. Below Margin positively affects Net Income. (NONFINANCIAL)

[a] Information in ( ) did not appear on the exit questionnaire.