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# Causal reasoning in financial reporting and voluntary disclosure

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ABSTRACT

Causal reasoning involves understanding the cause of events that have already happened (i.e., diagnosis) as well as predicting which future events will occur (i.e., prediction). Although this type of reasoning is an important part of financial reporting and voluntary disclosure, very little research has relied on it as a basis for developing and interpreting testable research ideas. The purpose of this paper is twofold: First, we review key theories from psychology that pertain to causal reasoning. Second, we identify how these theories can be successfully used by behavioral researchers interested in financial reporting and voluntary disclosure.



## 1. Introduction

Financial professionals routinely engage in a variety of tasks that involve causal reasoning. These tasks involve understanding the cause of events that have already happened as well as predicting which future events will occur. For example, analysts must ascertain why companies beat or miss the most recent consensus forecast. Firm managers must explain historical earnings as reported to the capital markets. Investors must predict the likely future performance of companies in which they might invest. Analysts making investment recommendations for their clients must predict stock prices. Despite the prevalence of causal reasoning in financial reporting, very little research investigates these tasks using causal reasoning theories.[3]

The purpose of this paper is twofold. First, we review key theories from psychology that pertain to causal reasoning.[4] These theories apply to the two distinct components of this type of reasoning—namely, diagnosis and prediction. Diagnosis involves identifying the cause of an observed event by asking the question, "why did this event happen?" Prediction involves considering a causal event and identifying the effect or outcome that it may create in the future by asking the question, "what event will happen?" Second, we identify how these theories can be successfully used by behavioral researchers interested in financial reporting and voluntary disclosure. In particular, we not only provide short examples as we describe the theories, but also separately identify several more in-depth examples of how causal reasoning theories may be productively used in financial reporting and voluntary disclosure research.

Because they originate in psychology, the causal reasoning theories and findings that we review are largely descriptive in nature. In some cases, they demonstrate biases in how individuals engage in causal reasoning. The theories about diagnosis and prediction are distinct in

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[3] We reviewed the publications from seven journals over the 2001–2010 time period. These journals included *Accounting, Organizations and Society, Behavioral Research in Accounting, Contemporary Accounting Research, Journal of Accounting and Economics, Journal of Accounting Research, The Accounting Review,* and *Review of Accounting Studies.* Our review reveals that one percent of these published papers involved behavioral financial research using causal reasoning theories.

[4] Causal reasoning is commonly studied in philosophy and psychology. Although there is overlap between the two fields, philosophy tends to focus on what makes causal reasoning efficient and when such reasoning is done appropriately. Psychology, in contrast, addresses how individuals engage in causal reasoning, with less focus on normative issues.

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| Diagnosis | Prediction |
|---|---|
| CAUSE ← EFFECT | CAUSE → EFFECT |
| How do investors determine why analysts upgrade or downgrade their stock recommendations? | How do investors predict analyst stock recommendation changes? |
| How do investors determine whether a company's increased earnings is due to earnings management or real economic factors? | How does earnings management affect investors' earnings predictions? |
| How do analysts ascertain why companies meet, beat, or miss earnings guidance? | How do analysts anticipate the relationship between earnings guidance and earnings realizations? |
| How do investors determine the causes of fluctuations in assets and liabilities carried at fair value? | How do investors predict the effect that macroeconomic or industry developments will have on the fair value of assets and liabilities? |
| How do market participants identify the reason why some firms issue disaggregated earnings forecasts yet others issue aggregated forecasts? | How does disaggregated guidance affect predictions of future earnings? |

This figure provides a list of financial reporting questions related to either diagnosis (determining the cause from a known outcome) or prediction (determining a future outcome from a known or suspected causal belief).

**Fig. 1.** Sample Research Questions That Distinguish Between Diagnosis and Prediction.

the sense that the direction of inference differs between them. That is, diagnosis often is referred to as backward inference because individuals must reason from observed outcome to suspected cause; prediction often is termed forward inference as individuals must reason from cause to predicted outcome (Wedell, 2010). Diagnosis and prediction also are distinct in that the types of financial reporting and voluntary disclosure questions that can be answered differ between them. Fig. 1 provides examples of these questions.

Although it is useful to consider diagnosis and prediction as distinct, it also should be acknowledged that they are interrelated in at least two ways. First, because diagnosis and prediction can be viewed as two sides of the same coin (i.e., both involve causes and effects), it should not be surprising that diagnosis and prediction sometimes rely on the same psychological processes. To illustrate, reasoning with the causal cue of contiguity can occur in both diagnosis and prediction. This causal cue suggests that as the time between a cause and an outcome is shortened, the perceived connection between the cause and outcome is strengthened. For example, when diagnosing why a firm's stock price increased, a recently introduced product line may be viewed as more causal than a product line introduced months earlier. When predicting future earnings, the recently introduced product line also may be viewed as more causal, thus rendering a greater impact on the prediction than an older product line. Although not all of the psychology theories that we discuss herein are "dual purpose" as in this example (i.e., some pertain clearly to either diagnosis or prediction[5]), it is important to note that there can be overlap. Second, prediction often depends on the results of diagnosis, and vice versa. For example, if an analyst concludes that a recent increase in a company's earnings is due to transient factors, his prediction of future earnings will be different than if a persistent cause is cited as the reason for the earnings increase. As another example, if an analyst predicts high future earnings because of an expectation of high demand, his diagnosis of why those earnings subsequently met the forecast will be heavily influenced by predicted cause (i.e., high demand) and less influenced by potential alternative causes. Because of this potential interrelationship, the accuracy of diagnosis (or a prediction) can influence the quality of the resulting prediction (or diagnosis).

[5] Given the breadth and depth of many psychology theories, it is of no surprise that some theories relate only to prediction or diagnosis. For example, when explaining how an analyst makes a prediction of a company's future earnings, the researcher may be required to rely on separate theories to study how the analyst identifies the causal predictors (i.e., diagnosis) and then puts them together in some fashion for the prediction (i.e., prediction).

We believe that reviewing causal reasoning theories and identifying how they can be used by behavioral researchers in financial reporting and voluntary disclosure is important for several reasons. First, we provide insight into theories that may not be well known to behavioral researchers in financial reporting and voluntary disclosure. Much of the limited research employing causal reasoning theories in accounting was published over 15 years ago.[6] Furthermore, the existing causal reasoning research is largely outside of the financial reporting and voluntary disclosure domains, concentrated almost exclusively in managerial and auditing contexts. Because of the close match between the types of diagnosis and prediction tasks in financial reporting and voluntary disclosure contexts and the types of tasks covered by causal reasoning theories, we believe our paper will provide significant insights to financial reporting researchers.

Second, research drawing on causal reasoning theories has the potential to provide significant insights to regulators and standard setters. For example, the Securities and Exchange Commission recently stated that the management discussion and analysis (i.e., MD&A) is not fulfilling its purpose (Pozen, 2008). Although the MD&A is designed to present investors with management-provided explanations so that they can understand the past and assess the quality and future variability of a company's income and cash flows (SEC, 2003), many companies are providing only partial or boilerplate explanations. Research drawing on causal reasoning theories could address the impact of boilerplate explanations on investor judgment and how mandates to improve such explanations could facilitate investor judgment. Causal reasoning research could also address a number of projects currently under deliberation by standard setters. For example, the Financial Accounting Standards Board (FASB) recently added a disclosure project to its agenda (FASB, 2009) with the aim of establishing an overarching framework intended to make financial statement disclosures more effective, coordinated, and less redundant. Because these disclosures often involve explanations of the firm's accounting choices and methods and because they are used by investors and creditors in diagnosis and prediction tasks, research exploring current or proposed disclosures would be of use to the FASB.

Causal reasoning research also has the potential to provide significant insights to preparers and users of financial reports and voluntary disclosures. For example, such research could explore how analysts can improve their predictions of earnings. Although analysts' training emphasizes that both diagnosis and prediction are important when analyzing a company, training materials often lack meaningful discussion of how diagnosis is linked to prediction, or vice versa. Specifically, these sources typically instruct analysts to understand a firm's industry and strategy to aid in prediction (forecasting) tasks, with significantly less (and in some cases, no) focus on the pitfalls or reasoning errors commonly encountered during diagnosis.[7] In sum, causal reasoning theories can speak to a number of important issues in the financial reporting and voluntary disclosure domains.[8]

Our paper is distinct from prior papers, in particular that of Koonce and Mercer (2005). The primary purpose of their paper was to educate archival researchers in how psychology theories, as compared to economic theories, can provide different and/or more-specific predictions in financial accounting research. The purpose of our paper is different. That is, our objective is not to compare economic theories with psychology theories. Rather, we provide insights into how causal reasoning theories from psychology can provide important insights into financial reporting and voluntary disclosure issues. These causal reasoning theories address diagnosis and prediction tasks—tasks which are pervasive in financial reporting and voluntary disclosure settings. In addition, because Koonce and Mercer (2005) provided an overview of a variety of theories from psychology, they largely focused on theories other than those involving causal reasoning (e.g., expertise theory, prospect theory). Even their limited discussion of theories within the causal reasoning domain was not centered on the ideas of diagnosis and prediction. Because of the importance of diagnosis and prediction in financial reporting and voluntary disclosure, we believe that the wealth of descriptive psychology research provides a profitable source of theories for researchers to draw on. Indeed, insights in this paper could not be gleaned from prior accounting papers, including Koonce and Mercer (2005).

This paper is organized as follows. Section 2 provides a brief overview of causal reasoning including prediction and diagnosis. This section also discusses how causal reasoning is different from other psychological processes. Section 3 lays out theories that address diagnosis, while Section 4 provides a summary of prediction theories. Section 5 discusses the interrelationship between prediction and diagnosis. Section 6 offers concluding remarks.

[6] Although relatively low numbers of causal reasoning papers existed several decades ago, there nevertheless has still been a decline since that time. One possible reason is that most behavioral seminars in accounting PhD programs cover recently published papers. To the extent that these papers do not rely on causal reasoning theories, then students are not trained in these theories. Our informal review of the syllabi in accounting PhD programs suggests the validity of this idea. Another possible reason is that the type of research questions has shifted from that previous time (e.g., from mostly behavioral auditing research to more behavioral financial research).

[7] To be specific, we reviewed four leading financial statement analysis textbooks. While these books make some reference to the linkage between diagnosis and prediction (e.g., all indicate that an industry and strategy analysis should be performed prior to forecasting), the examples and instructions for forecasting future earnings focus on tools like industry averages and recent trends rather than underlying causes of past performance. The textbooks do not explicitly cover concepts such as sufficiency and necessity, cues to causality (e.g., contiguity/temporal proximity), wishful thinking, or a variety of other topics covered in this paper.

[8] We purposely do not make any statements regarding whether the causal reasoning theories we discuss herein are better than alternative theories (e.g., economic theories). We believe that such statements are difficult to make because psychology theories and theories from other domains often are complementary (Koonce & Mercer, 2005). For example, understanding how investors view explanations about bad news from firm managers is likely a joint function of insights from economic theory (litigation risk concerns, Skinner, 1994) and causal reasoning theory (attribution theory, Kelley, 1967). Neither theory is better than the other; rather, both are important. Our goal in this paper is provide researchers with insights into psychology theories on causal reasoning, perhaps allowing them to view familiar problems from a new perspective.

## 2. Causal reasoning in financial reporting

Most decisions made by investors, analysts, firm managers, and other preparers/users of financial reports are the outcome of a complex process that usually is comprised of two different kinds of reasoning: looking backward to understand the past and looking forward to predict the future. Thinking backward is diagnostic in nature. It involves looking for patterns, making links between events that may seem unconnected, and testing possible chains of causation to explain an event. Thinking forward is distinctly different, as it involves starting from a belief about a suspected cause and predicting a potential outcome or event. Although prediction can be judgmental (the focus of most psychology research), it also may utilize mathematical techniques. In either case, the decision maker must identify the causal predictors and then weight them either judgmentally or statistically to make the prediction.

Given this fairly broad description of diagnosis and prediction, one might conclude that all of the judgments and decisions that pertain to the financial reporting process involve some kind of causal reasoning. Such a conclusion would be erroneous, however, as causal reasoning is but one type of cognitive processing that individuals can use to solve problems. For example, prospect theory describes how individuals make choices between alternatives that have uncertain future outcomes (Kahneman & Tversky, 1979). The theory does not rely on causal reasoning per se, but rather is based on the idea that people make choices based on whether the alternatives are framed as gains or losses and on the underlying uncertainty associated with the alternatives. Causal reasoning involves determining cause–effect relationships between events. Prediction and diagnosis tasks require individuals to have an understanding of these relationships in order to make judgments. Thus, causal reasoning theories are well suited for research in financial reporting and voluntary disclosure.

The causal reasoning theories we describe in next two sections are organized along the lines of diagnosis and prediction. Fig. 2 provides a summary of these theories. As noted previously, although these two causal reasoning processes are clearly distinct, in some cases they rely on the same psychological theories. Fig. 2 reflects our opinions regarding which theories are applicable to diagnosis, prediction, or both diagnosis and prediction. Because our goal in the next two sections of the paper is to describe the theories in general, we limit the remainder of our discussion of these "dual purpose" theories to either diagnosis or prediction.

| THEORIES ONLY RELATED TO DIAGNOSIS | THEORIES ONLY RELATED TO PREDICTION |
|---|---|
| Attribution theory (3.1)<br>Correspondent inference theory (3.1.1)<br>Covariation theory (3.1.2)<br>Fundamental attribution error (3.1.3)<br>Actor-observer bias (3.1.3)<br>Counterfactual reasoning theory (3.2) | Statistical prediction (4.1)<br>Heuristics (4.3)<br>Regression to the mean (4.3.4)<br>Desirability bias (4.3.5)<br>Construal level theory (4.4) |
| **THEORIES PERTAINING TO BOTH DIAGNOSIS AND PREDICTION** | |
| False-consensus effect (3.1.3)<br>Cues-to-causality (4.2)<br>Heuristics (4.3)<br>Representativeness (4.3.1)<br>Availability (4.3.2)<br>Confirmation bias (4.3.3) | |

This figure lists the causal reasoning theories described within this paper. The section of the paper where we discuss each theory is included in brackets. Each theory applies to either diagnosis, prediction or both diagnosis and prediction.

**Fig. 2.** Causal Reasoning Theories.

## 3. Diagnosis

### 3.1. Attribution theory

Attribution theory is a psychology theory that addresses how individuals generate explanations for events. These explanations are typically referred to as attributions, because they pertain to how individuals attribute, or diagnose, the cause of an event that has already occurred. In general, this theory is not focused on whether individuals can identify the *true* cause of events, but rather on how individuals identify the *judged or suspected* causes of events. Some of the research in this area, however, does address whether an individual's attribution judgments are normatively correct (Fischhoff, 1976).

Because of its breadth and descriptive appeal, attribution theory is arguably the most applicable theory to those financial reporting situations where an event or outcome has occurred and the investor (or other individual) is attempting to discern the reason *why*. As described below, there are a number of sub-theories within the attribution theory realm, along with a number of commonly observed behaviors documented in each of those subfields.

In general, there are two categories of attributions that individuals may make – dispositional (i.e., personal) and situational. For example, if a company has reported decreasing earnings over several years, investors may render a dispositional attribution and ascribe that performance decline to an ineffective CEO. Alternatively, they may render a situational attribution and credit the performance to a worsening economy. This distinction between the two types of attributions is critical, as it may determine whether a manager is punished or rewarded. That is, a good outcome (e.g., increased earnings) attributable to a firm manager's actions is likely to be rewarded. In contrast, a good outcome attributable to the environment is less likely to be rewarded.

Attribution theory is sub-divided into two areas, largely corresponding to whether individuals are attempting to make attributions based on a single instance of an outcome or multiple instances of an outcome. We consider each in turn.

#### 3.1.1. Correspondent inference theory

Turning first to the single instance of an outcome, a subtheory within the attribution literature, termed correspondent inference theory, addresses how individuals make an attribution in these situations (Gilbert, 1998; Jones & Davis, 1965). To make an attribution from a single occurrence of an outcome or event, individuals typically rely on three factors—choice, expectations, and intent. First, behavior that is freely chosen is generally attributed to the person more than if that same behavior was coerced. Second, behavior that is expected is generally attributed more to the person than behavior that is unexpected.[9] Third, individuals consider the intended consequences of someone's behavior. Behavior that produces many desirable outcomes does not reveal a person's specific motives as clearly as actions that produce only a single desirable outcome. For example, one would be more uncertain as to why a CEO stays on a job that is in a desirable city, is highly paying, and is in an important field as compared to a CEO who stays on the job in an undesirable city and in a lackluster field but is highly paid.

This theory is potentially useful in understanding important financial reporting questions because the issues of choice, expectations, and intent are central to this domain. For example, the choice issue could be central in understanding how investors view companies' actions in light of mandatory versus voluntary accounting standards. This theory suggests that investors would generally attribute a firm's voluntary adoption of fair value accounting for employee stock options as more related to something about the firm's managers (e.g., their forthcomingness) than if they were required by mandatory accounting standards to use fair value measurement. The theory also suggests that a firm's choice to voluntarily use the direct method for their statement of cash flows would be more informative about the firm than if that method was required.[10]

#### 3.1.2. Covariation theory

In some cases, individuals have multiple instances of an outcome to draw on to make an attribution for a currently observed outcome or event. In these cases, another subtheory within the attribution literature is applicable. Specifically, covariation theory best describes individual behavior in these multiple-instance situations (Kelley, 1967; Shaklee, 1983). The basic premise of covariation theory is that for something to be the cause of an observed behavior, the cause must be present when the behavior occurs and must be absent when it does not occur. This idea often is captured in a standard contingency table format, as shown in Fig. 3, where a cause is either present or absent and an outcome also is either present or absent. These four combinations of causes and outcomes constitute the four cells of the contingency table.

A complete causal assessment requires that all four cells of the contingency table be evaluated (Lipe, 1991). To illustrate, consider a credit analyst who is determining why a specific firm defaulted on a loan. In theory, the analyst would categorize all firms into one of two outcome categories (i.e., those that have or have not defaulted on a loan). He also would categorize them based on whether they have exceeded a certain debt-to-equity ratio—the suspected cause of defaulting on a loan. To the extent that there are relatively large numbers of instances in Cells A and D and relatively few instances in Cells B and C, the analyst would conclude that a high debt-to-equity ratio is

[9] Expectancy violation theory also makes predictions in this situation (Burgoon & Burgoon, 2001). In particular, it posits that unexpected behavior will result in greater cognitive processing and information search. However, the theory is silent on whether the individual will use causal reasoning in the expanded processing and search efforts.

[10] Signaling theory also indicates that a *voluntary* (versus mandatory) disclosure provides information separate from the content of the disclosure itself (Bhattacharya & Ritter, 1983). Accordingly, this example highlights how causal reasoning theories may suggest similar effects as theories from economics. As explained by Koonce and Mercer (2005), though, the two areas often differ in their explanation of the process behind the effect.

| | | Outcome | |
|---|---|---|---|
| | | *Present* | *Absent* |
| Cause | *Present* | A | B |
| | *Absent* | C | D |

This figure illustrates the standard contingency table often used in the context of causal reasoning. This table can be used to examine the relationship between a suspected cause and an outcome. Instances when the suspected cause is present and the outcome is present would be included in cell A. If the suspected cause exists but the outcome is absent, the occurrence would be included in cell B. Similar logic is used when considering an occurrence where the suspected cause is absent but the outcome is either present or absent—these occurrences are included in cells C and D, respectively.

**Fig. 3.** Contingency Table.

likely an explanatory cause. Of course, individuals rarely have the time or inclination to tally the number of instances of causes and outcomes into contingency tables. The effects of this failure to "think" in terms of covariation likely explains why auditors have difficulty judging how often events co-occur (Waller & Felix, 1987).[11]

Covariation theory indicates that individuals will gather information regarding how another individual's behavior covaries, or changes, across time, place, and individuals. This information will allow the individual to make an attribution about the cause of the observed behavior (Hilton, Smith, & Kim, 1995). Three types of information are useful in making the aforementioned determination—consensus, distinctiveness, and consistency. Consensus information provides data about the behavior of others—that is, are they behaving similarly or dissimilarly to the person being judged. Consistency information provides data about how the individual being judged behaves in similar situations at other times. Finally, distinctiveness information provides data on how the individual being judged behaves in different situations.

According to the theory, when these three sources of information combine into one of two distinct patterns, a clear attribution can be made (Kelley, 1967). A dispositional attribution is likely to be made when consensus and distinctiveness of the other's behavior is low but its consistency is high. In contrast, a situational attribution is likely if all three are high.[12] Because firm managers and analysts regularly provide financial information to the markets across time and under various situations, this theory is quite applicable to financial reporting. For example, if an analyst is consistently recommending a particular stock, a potential investor trying to ascertain why the analyst made the recommendation could seek out distinctiveness and consensus information. That is, does this analyst recommend all stocks regardless of circumstance, or is this behavior distinctive? Moreover, do other analysts also recommend the stock? If the behavior is high in distinctiveness and consensus, then the potential investor attributes the recommendation to a situational cause, such as a very strong company being evaluated. If others are not recommending the stock and this analyst always recommends all stocks, then the investor would attribute the reason for the analyst's recommendation to something about him (i.e., dispositional attribution) such as his incentives to curry favor with management.

While research has shown that individuals do tend to make attributions in accordance with the tenets of correspondent inference theory and covariation theory, there are certainly situations where they take shortcuts. Time is limited for most individuals and so engaging in an analysis of consensus, distinctiveness, and consistency information is not always possible. In some cases, individuals may lack the needed information. As a result, the use of cognitive shortcuts is employed and this can frequently lead to error, as explained below.

### 3.1.3. Attribution errors

The false-consensus effect is the tendency for individuals to overestimate the extent to which others share their opinions, attributes, and behaviors (Gilovich, 1990; Ross, Greene, & House, 1977). This tendency is particularly strong when the actual percentage of others who agree is low. For example, a firm CEO may erroneously believe that market participants agree with him when he tells them that the company will increase earnings over the next 3 years. Individuals exhibit the false-consensus effect partly because they tend to notice (notice much less) when similar others agree (do not agree) with their conclusions (Mullen, Dovidio, Johnson, & Cooper, 1992). Because the

[11] Novick and Cheng (2004) offer an alternative to covariation theory. Specifically, in their causal-power theory, they argue that people not only use covariation information but also supplement it with other information to form causal inferences. Specifically, they maintain that individuals judge a potential cause by how well (i.e., the magnitude of) other available information combines with that potential cause to produce or prevent the effect under consideration.

[12] When consistency is low, it is not possible to make a clear dispositional or situational attribution.

false-consensus effect is partly caused by an availability bias (see Section 4.3.2 of the paper), it is of no surprise that this bias occurs even when unsubstantiated by statistical data, leading to the perception of a consensus that does not exist (Slovic, Fischhoff, & Lichtenstein, 1982).

Taking shortcuts when making attributions may also lead to the fundamental attribution error (Gilbert, Krull, & Malone, 1990; Ross, 1977). When individuals explain the behavior of others, they tend to overestimate the role of personal factors and overlook the impact of the situation. For example, investors observing a firm CEO explaining why his company's earnings will grow over the next 3 years may underestimate the influence of pressures on the CEO to keep his job and high pay (i.e., situational factors). That is, investors may overestimate the role of CEO's ability to grow the company in the fashion indicated by his statements.

Interestingly, while people tend to make personal attributions for the behavior of others, they tend to make situational attributions for their own behavior. This effect is termed the actor–observer bias (Jones & Nisbett, 1972; Malle, 2006). Drawing on the previous disclosure example, a manager who overestimates future growth is more likely to blame a missed forecast on macroeconomic circumstances than on his overconfidence.[13] Such behavior may suggest that the attributions made by managers in press and other releases are unlikely to align completely with the attributions made by the financial press and Wall Street. Although prior financial research has documented that managers of public (versus private) firms offer more self-serving attributions (Aerts, 2005; also see Lee, Peterson, & Tiedens, 2004), it has not studied the actor–observer bias.

### 3.2. Counterfactual reasoning theory

Counterfactual reasoning theory is closely related to attribution theory (Spellman & Ndiaye, 2007). Counterfactual reasoning refers to the attempt to understand the cause of an outcome or event by engaging in "what if" or "if only" thinking. For example, "if only the company had properly disposed of its hazardous waste, its stock price would not have recently plummeted." Counterfactual reasoning does not occur for every outcome that an individual experiences. Such thinking is more likely when events are seen as abnormal versus normal, when negative rather than positive events occur, when they occur early in a chain of events, when the individual is personally involved, and when the outcome is controllable or changeable (McEleney & Byrne, 2006; Roese & Olson, 1995). A recent experimental study tests whether counterfactuals can influence investors' judgments concerning firm managers who use derivatives to manage risks (Koonce, Lipe, & McAnally, 2008).

When individuals engage in counterfactual thinking, they typically conduct one of two types of causal simulations to test the accuracy of their causal reasoning. First, they can ask themselves the following question: Would the outcome have occurred if the suspected cause had not? This statement corresponds to Cell C in the contingency table presented earlier (Fig. 3) and provides critical information about the *necessity* of the cause (McGill, 1998). That is, "would the company's stock price have plummeted if they had not disposed of their hazardous waste improperly?" When engaging in counterfactual thinking, individuals may also ask the question, "given that the suspected cause has occurred, will the outcome always occur?" This statement provides information about the *sufficiency* of the cause and corresponds to Cell B in the contingency table. That is, "will improper disposal of hazardous waste always cause the company's stock price to plummet?"[14] In both of these lines of reasoning, the causal strength of the suspected cause is assessed via a causal simulation (Kahneman & Tversky, 1982).[15]

One major determinant of the use of counterfactual reasoning is whether the outcome being observed results from action or inaction (Ritov & Baron, 1990). Counterfactuals are more likely to be generated when firm managers take actions (rather than fail to take actions). Moreover, blame and credit are more likely to be given in circumstances involving action (Baron & Ritov, 1994). The result of this effect, often termed the omission bias, is that evaluations of actions are more extreme than evaluations of inactions. Analysts and investors may be subject to omission bias when judging the credibility or competence of managers, as well as future firm performance. For example, initiating an unnecessary restructuring plan that subsequently leads to poor performance could be judged as worse than failing to initiate a necessary restructuring plan with the same results. Similarly, analysts and investors may attribute less blame for a negative earnings surprise to a manager who fails to revise his prior earnings forecast downwards than to a manager who revises his prior forecast upwards, holding negative earnings surprise constant.

Although counterfactual reasoning is beneficial as it helps individuals understand the potential causal relationship between a cause and an outcome, it also may lead to reasoning errors. Research has shown that individuals making causal judgments tend to unevenly weight the cells of the contingency table. Specifically, they tend to rely most heavily on Cell A followed by Cell B, Cell C, and finally Cell D (Mandel & Lehman, 1998). As a result, individuals

[13] The actor–observer bias is well documented phenomena when considering negative events. However, there is mixed evidence for the bias with positive events (Malle, 2006). For example, when a firm's financial performance exceeds expectations, management may attribute the performance to their actions to increase their reputation and future compensation. Therefore, while the actor–observer bias would predict more situational attributions for every outcome, self-serving tendencies often lead to more dispositional attributions when positive outcomes occur.

[14] In an auditing context, Anderson and Koonce (1998) test how well auditors can evaluate the sufficiency of a cause (in their case, a management-provided explanation for a financial statement fluctuation). Their results show that only when auditors quantify the implications of the cause can they accurately assess sufficiency.

[15] On a related note, how individuals tally the instances in a contingency table can be another source of reasoning errors. That is, how many instances need be tallied for the contingency table to be useful for attributing causality? Because all situations are unique in some fashion, how likely is it that individuals use the same judgment rules in tallying the instances? Is feedback available for verifying the placement of instances within the table? Issues such as these make learning from experience difficult (Einhorn, 1980).

are prone to making an incorrect conclusion about the cause of an outcome because they stop searching for other pertinent facts once a sufficient cause is identified—that is, once Cells A and B are examined (Shaklee and Fischhoff, 1982).

While the above discussion addresses *when* counterfactual reasoning is likely to occur and the manner of such reasoning, other research identifies the *content* of counterfactuals that are likely to be generated. There are generally three types of counterfactuals that can be produced (Roese & Olson, 1995). First, counterfactuals may be upward (downward)—that is, describing alternatives that are better (worse) than the actual outcome. Second, counterfactuals may be additive (subtractive)—that is, describing the addition (deletion) of new causes. Third, counterfactuals may be internal (external)—that is, focusing on actions of the person (others). Not surprisingly, the consequences of counterfactual reasoning are varied depending on factors, such as the type of counterfactual generated (Alicke, Buckingham, Zell, & Davis, 2008).

Firm managers likely engage in counterfactual reasoning quite frequently. Firms are required to explain the causes of their past performance in the management discussion and analysis section of their annual reports (SEC, 2003). In many cases, they do so by describing how financial statement results would have been different under various "if only" circumstances. For example, some firms report what their revenues would have been assuming that (i.e., if only) currency exchange rates had remained constant throughout the year. In these cases, firms are comparing Cells A and C of the contingency table. Press releases also contain instances of counterfactual reasoning. For example, firms that present pro forma earnings because they disagree with current accounting rules arguably are engaging in counterfactual reasoning. Specifically, firms that adjust the reported earnings for research and development costs and or stock-based compensation are implicitly providing an alternative "if only accounting rules were different, our earnings would better represent our underlying economics" scenario.

### 3.3. Future research examples

With this overview of causal reasoning theories related to diagnosis, we provide two examples of how these theories could be used in future research in financial reporting and voluntary disclosure.

#### 3.3.1. Diagnosis—management explanations for past performance

Firms routinely provide explanations of their past performance in both mandatory and voluntary disclosure venues. In terms of mandatory reporting, firms are required by GAAP to disclose financial results in their quarterly and annual SEC filings as well as explanations for those financial results in the report's management discussion and analysis (MD&A) section. A natural question relates to how investors evaluate the content of these disclosures. This question is particularly important as much of the archival disclosure literature has focused on the determinants and consequences of the amount (and not content) of disclosure (e.g., Miller, 2002). One exception is Li (2008) who examines the readability of annual reports, finding that companies with easier-to-read financial reports have more-persistent earnings. His study touched on an intriguing angle of causal reasoning—that is, for profitable firms, a higher frequency of causation words (e.g., because) in the financial reports is associated with less persistent earnings. This finding is of interest because these types of words could imply any number of causal statements by firm managers—either favorable or unfavorable.

The causal reasoning theories that we have reviewed suggest some possible ideas as to the types of causal statements that firm managers may make and, thus, the market's reaction to them. For example, do firm managers tend to provide situational attributions for their firm's poor performance and attribute competitors' performance to dispositional (i.e., firm) factors (cf. Bettman & Weitz, 1983)? While this tendency might suggest that the market would react favorably to firms (i.e., by viewing the problem outside of the control of management), is it possible that the market understands the actor–observer bias described earlier in the paper and, thus, reacts unfavorably. Exploring the interaction between the statements that firms make in their MD&A and behavioral tendencies on the part of those who observe them is a largely untapped, area for future research.

Such research is particularly important in light of another behavioral tendency that may actually work against market participants fully adjusting for any self-serving tendencies on the part of firms. Specifically, the fundamental attribution error (or correspondence bias) is widely known and leads to predictable errors when attributing the cause of another's behavior to dispositional versus situational factors (Gilbert & Malone, 1995). Indeed, this error suggests that market participants may *not* fully undo the effects of the actor–observer bias noted above. Rather, they may over-rely on self-serving statements made by firm managers when explaining past firm performance. Investigating the fundamental attribution error seems particularly intriguing when firm managers provide information via press releases and conference calls. Those venues often communicate more timely information to market participants than financial reports. Moreover, conference calls arguably provide more information about emotion and tone than do press releases (Mayew & Venkatachalam, 2009), perhaps increasing the opportunity to observe the fundamental attribution error. It is surprising that such a robust and significant human error remains untested in financial reporting and voluntary disclosure.

#### 3.3.2. Diagnosis—analysts' explanations of firm/manager behavior

Analysts must understand why actual earnings meet, exceed, or fall short of previous forecasts (e.g., Burgstahler & Dichev, 1997). Just as management analyzes and communicates the reasons behind missing/beating earnings benchmarks, so too do analysts. Accordingly, an analysis of analyst reports may provide evidence concerning whether analysts engage in counterfactual reasoning, particularly in cases when a firm misses earnings forecasts. Counterfactual reasoning theory has not been widely used

in the financial reporting and voluntary disclosure domains despite its importance to causal reasoning. To our knowledge, no systematic analysis regarding the types of counterfactuals that are used within company disclosures has been performed.

Assuming that analysts do engage in counterfactual reasoning and document this type of thinking in their reports, important additional questions include determining whether analysts have a tendency to mentally undo management actions or environmental conditions by asking whether the outcome would have occurred absent these factors. While management may have an incentive to perform such an analysis using environmental factors when bad outcomes occur, analysts may be more prone to engage in counterfactual reasoning using management actions. This tendency may be greater for analysts who have fewer incentives to curry favor with managers or generate retail investor trade. If research were to document such differences, it might suggest that analysts without such incentives are more likely to assign blame (in the form of lower stock price estimates and recommendations) to those firms that miss their earnings estimates or having declining earnings.

Because of their role as information intermediaries (Schipper, 1991), analysts may be prone to tallying information about many firms within an industry. As a result, an important question is whether they evaluate firms in light of the tenets of covariation theory. For example, do analysts consider information about consensus, consistency, and distinctiveness in an attempt to understand the behavior of a particular firm? Although there are numerous types of information that analysts could track over firms, time, and contexts, firms' financial reporting choices are among the most important. Some accounting standards allow a choice as to how to measure financial statement elements, such as whether to use amortized cost or fair value in measuring financial instruments (FASB, 2007). Thus, an analyst observing a firm that consistently chooses fair value accounting for all of its financial instruments will evaluate the reason for that behavior in light of what other firms do. If most other firms do not elect fair value measurement, then the analyst is likely to attribute the firm's behavior to a dispositional cause, such as wanting to be forthcoming about the value of its instruments. In contrast, if all other firms also consistently choose fair value accounting, then the analyst is less likely to make that same attribution. Future research could profitably explore these (as well as other) ideas pertaining to diagnosis.

## 4. Prediction

Prediction is essentially the "opposite" of diagnosis. That is, prediction starts with a belief about a known or suspected cause and anticipates the unknown effect or outcome (whereas diagnosis starts with a known outcome and moves to a suspected cause). Fig. 1 illustrates the distinction. Prediction can occur after an individual has rendered a diagnosis. Alternatively, it can occur without a preceding diagnosis (Einhorn & Hogarth, 1982). For example, an analyst who observes an unusual increase in a company's earnings ascertains whether the cause is something persistent (i.e., new product introduction) or something more transient (i.e., one-time sale of property). Here, the diagnosis of the cause of the earnings increase can influence prediction as different causes have different implications for the future (Soffer & Soffer, 2003). In other cases, though, financial professionals do not have information about previous diagnoses or choose to ignore it. For example, an analyst may decide that because of changing economic circumstances, his prior diagnoses are now irrelevant for current predictions.

### 4.1. Statistical prediction

Statistical prediction is what often comes to mind when thinking about forecasting the future. A number of studies in various domains (e.g., college success, parole violation, medical diagnosis, bankruptcy) focus on the issue of whether trained experts' judgmental predictions are better than statistically derived, weighted averages of the relevant predictors. Results reveal that the statistical method provides more accurate predictions (Meehl, 1954; Sawyer, 1996). This superiority of statistical combination can occur even when the individual making the prediction has more information than that available to the statistical model. The practical implication of this research has been that in many prediction situations, the experts should be asked what predictors (i.e., factors that work to produce the outcome being predicted) to use, but a mechanical prediction model should combine the information to make the prediction.

Further research in this area shows that the statistical models even outperform human prediction when the weights on the predictors are not set to optimal levels (i.e., to maximize prediction accuracy) (Dawes, 1979). Unit weighting schemes, where each predictor variable is standardized and weighted +1 or −1 depending on direction, often provide the most-accurate prediction performance. Indeed, the signs on the coefficients are much more important than the specific numerical weights.

Despite the superiority of statistical models over human prediction, the overall level of prediction accuracy tends to be fairly poor (Einhorn, 1972). Stated differently, much of the future is not easily predictable. As a result, individuals tend to believe that if a statistical model does not predict well, something else may do better. Often this "something else" is judgmental (i.e., human) prediction, which, as previously stated, generally fails to outperform statistical models. Recent work in managerial accounting corroborates this result by showing how individuals sub-optimally weight performance measures when determining how employees should be evaluated (Krishnan, Luft, & Shields, 2005).

Judgmental prediction appears to be a frequent means by which investors and analysts derive forecasts of earnings. A review of financial statement analysis textbooks and anecdotal evidence indicates that the prior year numbers are the starting point for developing a financial forecast. The investor or analyst then identifies potential factors that may change the forecasted numbers (i.e., causes) and judgmentally derives the forecast. Indeed,

prior research suggests that analysts do not use sophisticated models to generate forecasts or valuations, but rather rely on simple heuristics (Bradshaw, 2004; Bradshaw, Richardson, & Sloan, 2001).[16]

### 4.2. Cues-to-causality

When making predictions, individuals frequently use predictors that are aptly named cues-to-causality. These predictors include covariation, ordering, similarity and contiguity (Einhorn & Hogarth, 1986). They allow individuals to assess the logic and strength of a potential cause–effect relationship, thereby facilitating prediction. When multiple cues point to a similar relationship between a cause and effect, the assessor's certainty and judged strength of that causal relationship increases.

*Covariation* refers to the idea that the more frequently a cause leads to an effect (and, likewise, the more frequently the absence of the cause leads to no effect), the more probable it is that the cause actually produces the effect. This relationship is illustrated in a standard contingency table, as shown in Fig. 3. When making predictions, financial professionals determine the extent to which events did or can coincide in determining the strength of the cause–effect relationship between the events. Consider an automotive analyst who believes that each financial incentive program offered to car buyers coincides with increasing firm sales. That financial incentives and increasing sales tend to occur together is a significant cue-to-causality; therefore, the introduction of new incentives will likely influence that analyst's predictions. This idea has been documented in managerial accounting. There, accountants make better decisions when they consider the covariation between each possible project and future firm value (Vera-Muñoz, Shackell, & Buehner, 2007).

Because causes logically must precede effects, the *ordering* of these two factors can provide important evidence for prediction (Greville and Buehner, 2007). For example, an airline analyst observes an increase in fuel prices. As a result, he predicts that this increase (i.e., cause) will result in higher costs in the future. The analyst's prediction stems from his knowledge about the relationship between fuel prices and subsequent operating costs. Not only do these two events correlate but they also occur in a specific sequence. The ordering cue aids in the analyst's prediction of future operating costs. When two events coincide but do not consistently occur in the cause–effect order, the likelihood of a causal relationship diminishes.

The *similarity* between the cause and effect is another important cue-to-causality. Similarity often is gauged by how comparable causes and effects are in terms of their strength (Einhorn & Hogarth, 1986). For example, when a company invests a large amount of money over a long period of time into research and development for a new product, investors likely expect that investment to result in large profits over a long time period. The strength of the cause (i.e. large investment in research and development) is a cue used to predict the effect size (i.e. large profits over many years).

*Contiguity* of events is another important cue-to-causality. This cue generally refers to how temporally close the cause and outcome are. In general, individuals expect outcomes to occur shortly after the causal event and in close proximity to the causal event. Time-lagged regularities are harder to think about because the number of potentially intervening (i.e., alternative) causes that must be considered increases. For example, predicting how future earnings will be affected by a new product introduction is arguably easier for investors than predicting how future earnings will be affected by new research and development efforts which often take years to come to fruition. Further, it can be difficult to use current financial measures when making investment decisions since financial outcomes are often delayed (Kelly, 2007). In particular, managers within companies that utilize intangible assets have difficulty using financial measures for prediction as the time between the investment and earnings realization is often long.

The cues of covariation, ordering, similarity and contiguity provide systematic means for individuals to make causal predictions.[17] The stronger the cues, the more likely it is that a causal link can be established between events. As this causal link is strengthened, the events provide greater power and reliability in predicting future events. In some cases, though, individuals may err in their use of these causality cues, either because of time constraints or because they believe that their reasoning leads to "good enough" judgments and decisions (Gigerenzer, Todd, and the ABC Group, 1999). We discuss such errors below.

### 4.3. Heuristics

Traditional models of rationality have tended to view individuals as possessing limitless knowledge and time. In many situations, individuals rely on simple rules of thumb, or heuristics, which speed up the causal reasoning process. These heuristics are acquired over a lifetime of experience and are very efficient. However, as described below, they sometimes reduce the accuracy of predictions (Tversky & Kahneman, 1974).

As a prelude to that discussion, though, it is important to briefly discuss the baseline employed to identify *when* human prediction involves biases. Modern probability theory, including Bayesian updating, is the most-frequently used normative model to identify bias. This framework requires that individuals making predictions must identify all possible outcomes and the probabilities associated with each. Such identification often can be represented by decision trees in which possible outcomes are identified along with their associated probabilities. Then using axioms of probability theory (Edwards, Miles, & Winterfeldt, 2007; Winkler, 2003), individuals can judge the likelihood of various potential, multi-stage outcomes. If new information is obtained, they can then update their probability

[16] Similar findings have been reporting in auditing, where auditors tend to set simple expectations for current-year account balances often using the current year's unaudited book values (McDaniel & Kinney, 1995).

[17] Research in managerial accounting (Brown, 1985, 1987) investigated how similarity, temporal order, and covariation were used in a diagnosis task—namely, managerial accountants making causal judgments about labor variances.

assessments in light of the logic of Bayes' theorem. The decision theoretic perspective works best when objective probabilities are available, such as in games of chance (e.g., throwing dice), or in well-defined empirical situations where statistical frequencies can be obtained (e.g., number of days of sunshine in Florida). It works more poorly in situations where all outcomes cannot be identified and/or well-defined or agreed-upon probabilities are not available. Because the latter situations arguably are typical in most financial reporting situations, decision theory seems to be less applicable in this context. However, the insights from prior research involving well-defined outcomes and probabilities are useful in understanding how judgment in less-structured contexts occurs.

#### 4.3.1. Representativeness

One commonly used heuristic is the representativeness heuristic. When people use this heuristic, they are relying on similarity to make their predictions. Although similarity is a logical cue-to-causality, it sometimes leads individuals to see causal structure when none exists. For example, gamblers believe that when a roulette wheel has a run of three or more reds, they should then bet black as they are sure to win because "black is due" (Tversky & Kahneman, 1974). That is, they judge the roulette sequences as causally related when, in fact, they are independent. This thinking is sometimes referred to as the gamblers' fallacy (Boynton, 2003; Kahneman & Tversky, 1972).

Representativeness also leads people to over-rely on superficial similarities between different situations in predicting outcomes of those situations (Spina et al., 2010). This type of representative thinking can lead to overly optimistic predictions. For example, in the late 1990s, firms that added "dot-com" to their name experienced a significant increase in stock prices (i.e., predictions of high success) even though the probabilities of success for internet startups were fairly low (Cooper, 2001). Most of these firms eventually collapsed, suggesting that perhaps the initial stock price run-up was because the firms' future successes were being judged based on how representative each was of a typical successful internet startup. Research reveals that auditors are also prone to the representativeness heuristic (Frederick & Libby, 1986; Joyce & Biddle, 1981).

Seeing a causal relationship where it is not (or where it is not as strong as it is judged) is frequently bolstered by what is commonly called "scenario thinking." This type of thinking occurs when an individual mentally simulates how potential or actual causes could lead to potential outcomes. Psychology research indicates that individuals seek out this type of information as opposed to information regarding covariation of events (Ahn, Kalish, Medin, & Gelman, 1995). In building the mental simulation, people assimilate the available evidence to create a story involving the cause and outcome.[18] This story, in turn, increases the believability of the outcome, often beyond that which could be sustained by a logical analysis of the probabilities involved in each component of the story (Kahneman & Lovallo, 1993). Perhaps it comes as no surprise that good trial attorneys use stories to win their cases. Research in accounting shows that scenario thinking causes financial analysts to make more optimistic financial forecasts (Sedor, 2002) and auditors to increase their agreement with client-provided explanations (Koonce, 1992).

#### 4.3.2. Availability

Because good stories are often etched into memories, they can lead to yet another bias in causal reasoning. When individuals make a prediction based on how easily related information comes to mind (rather than assessing the underlying probabilities), they are relying on what is termed the availability heuristic. Essentially, this heuristic operates on the notion that "if you can think of it, it must be common or frequent." Extensive media coverage in the financial reporting domain may fuel the tendency to rely on the availability heuristic.

While this heuristic can lead to normatively correct predictions, it often causes individuals to misestimate the likelihood of certain outcomes (see Libby, 1985 in auditing). For example, investors and analysts were likely very guarded with respect to their assessments of technology stocks following the market crash in 2001. The overvaluation of technology stocks was very available in memory and, thus, judged as likely to occur again, even though such effects logically may not repeat. The consideration of alternative perspectives can reduce this tendency. Specifically, analysts are noted to issue less optimistic forecasts when they are explicitly asked to generate alternatives causes for the forecast (Kadous, Krische, & Sedor, 2006; also see Heiman, 1990, in auditing). Presumably, when analysts are asked to provide alternatives, these alternatives seem more likely and thus influence the analysts' forecasts.

#### 4.3.3. Confirmation bias

Confirmation bias refers to a type of selective thinking whereby individuals tend to notice and to look for what confirms their beliefs, and to ignore, not look for, or undervalue the relevance of what contradicts their beliefs (Klayman & Ha, 1987; Swann & Read, 1981). In the context of cues-to-causality, individuals tend to focus on Cell A of the standard contingency table (Mandel & Lehman, 1998). That is, they overly focus on instances where a cause is present *and* the effect occurs. For example, if investors believe that the stock market reacts negatively to certain government policies, they will take note of instances in which policy changes correspond to price decreases, but will be inattentive to instances in which policy changes correspond to stock price increases (or may even re-interpret the data in those instances).

Numerous studies have demonstrated that people generally give an excessive amount of value to confirmatory information, that is, to positive or supportive data. The most likely reason for the excessive influence of confirmatory information is that it is easier to think about (Gilovich, 1993). It is much easier to see how data supports a position than it is to see how it contradicts the position. Successes

[18] Some psychologists have made the argument that virtually all of our knowledge is stored in the form of scenarios (Schank & Abelson, 1995). Their idea is that experience is a temporal sequence of events, and so naturally individuals tend to use that time-sequence as a way to summarize the past (diagnosis) and anticipate the future (prediction).

are often unambiguous or data are easily massaged to count as successes, while greater effort is required to interpret negative events as unsuccessful (or sufficiently negative). The tendency to give more attention and weight to the positive and the confirmatory has been shown to influence memory. When digging into our memories for data relevant to a position, we are more likely to recall data that confirms the position (Hope, Memon, & McGeorge, 2004).

#### 4.3.4. Ignoring regression to the mean

Regression to the mean is a statistical phenomenon in which high or low performance tends to be followed by more average performance (Secrist, 1933). This effect occurs whenever an individual has a nonrandom sample from a population and a cause–effect relationship that is not fully explanatory at all times (i.e., not a perfect predictor and measurement error in the two variables). If the cause and the effect are *perfectly* correlated, there will be no regression to the mean. But this is unlikely to ever occur in most real-world settings, including financial reporting situations (see De Bondt & Thaler, 1989). Almost all measures have some degree of unreliability, and relationships between measures will not be perfect. As a result, there will be regression to the mean between these two measures, given asymmetrically sampled subgroups.

Ignoring the powerful force of regression to the mean causes individuals to incorrectly rely on causal factors in prediction. For example, Tom Peter and Robert Waterman wrote a best-selling booked entitled *In Search of Excellence*. They selected 43 exceptional companies and described what they viewed as the causal factors making them exceptional. But a follow-up article by Business Week 5 years later revealed that over one-third of the original companies were in financial difficulty or bankrupt (example taken from Hastie & Dawes, 2010). Not surprisingly, these companies regressed to the population mean of all companies.

#### 4.3.5. Desirability bias

The desirability bias is the tendency for individuals to predict that current conditions are more likely to lead to desirable than undesirable outcomes. Indeed, most predict that good events are more likely to happen to them and bad events more likely to happen to others (Krizan, Miller, & Johar, 2010; Weinstein, 1980). This bias occurs because individuals use and interpret facts, reports, events, and perceptions according to what they would like to be the case rather than according to the actual evidence. This bias, sometimes referred to as unrealistic optimism or wishful thinking, is particularly interesting as often people fail to recognize that others engage in the same tendency (Seybert & Bloomfield, 2009).

It seems reasonable to assume that managers, analysts, and investors are likely to fall victim to wishful thinking when making predictions. For example, managers may issue optimistic forecasts despite the presence of certain factors that could lead to missing those forecasts. Nevertheless, they may truly believe that the company will experience abnormally positive performance. Before the recent financial meltdown, most bankers probably did not envision that the loans they were making would lead to the problems that did ensue.

### 4.4. Construal level theory

The time horizon of prediction also has been shown to influence behavior. Different types of causal factors are used depending on whether a prediction is being made for the short-run or the long-run (Trope & Liberman, 2003). Specifically, individuals tend to construe distant-future events at an abstract level and near-future events at a more concrete, detailed level. For example, a firm may think of "financing an acquisition" in the distant future (e.g., 3–5 years out), but think about this same event more concretely (e.g., "issuing equity to acquire a target company in the oil industry") in the near-term (Sagristano, Trope, & Liberman, 2002). The key to construal theory is that people are more likely to think about a distant future situation in terms of broad knowledge instead of specifics, *even if* specific information is available.

This theory has obvious applicability to prediction. Specifically, predictions regarding distant-future events will be based on high-level construals of events (e.g., desirability of outcomes), whereas predictions of near-term events are based on low-level construals (e.g., feasibility of outcomes). Ordinarily, people will have less information and are therefore likely to make less-accurate predictions for the distant (versus the near) future. However, because higher level construals contain less contextual features (which tend to undermine confidence in one's predictions), predictions for the distant future often are made with greater confidence than predictions for the near-term.

### 4.5. Examples of future research

With this overview of theories pertaining to prediction, we provide examples of how these theories could be used in future research on financial reporting and voluntary disclosure.

#### 4.5.1. Prediction—management forecasts

Management forecasts of future earnings are often accompanied by causal explanations. Archival research by Baginski, Hassell, and Kimbrough (2004) documents the importance of studying these causal explanations and their content. Specifically, they find that the stock price reaction to earnings forecasts is greater when they are accompanied by causal explanations, suggesting the role that they play in shaping the market's expectation of the future. Additional research could build on their findings by studying the content of these explanations, as proffered below.

One interesting direction for future research is to explore whether the explanations provided by firm managers along with their earnings forecasts depend on the time horizon of the forecasts. According to construal level theory, managers are likely to consider more concrete causal relationships in the near-term than in the longer horizon where more abstract ideas are likely to be considered. Because detailed information about distant-future events is often less available than information about events that will occur in the near-term, it might appear logical that firm

managers behave in the fashion prescribed by construal level theory. On the other hand, companies typically consider longer-term plans and goals and, thus, may have access to more-detailed information about the future. Thus, whether firm managers fall prey to the effects of construal level theory is an interesting avenue for research. Such investigations may lend additional insights into the general finding that forecasts are more optimistic at longer horizons (e.g., Cowen, Groysberg, & Healy, 2006; Hart & Hugon, 2010).

On a related note, even if firm managers do not fall prey to the effects of construal theory, future research could explore whether firm managers *publicly* disclose more abstract information with their longer-term earnings forecasts to the public markets. That is, even if firm managers have more-detailed information available, they may choose to not disclose it.

The manner in which market participants evaluate management's causal arguments that accompany their forecasts is another natural direction for future research. Do investors generate mental simulations or "stories" around the causal arguments provided by management, in an attempt to judge the veracity of forecasted earnings? Or, alternatively, do they use a reasoning process that involves the representativeness heuristic? It is possible that market participants over-rely on the degree to which management's forecast is representative of a typical situation rather than engaging in a causal analysis. For example, forecasts that include decreases in R&D expenses may be more representative (and, thus, judged more predictive) when economic times are difficult than when prosperous, because few companies would cut R&D when resources are plentiful. As a result, investors might judge earnings increases driven by decreases in R&D expense as more likely in difficult times as compared to prosperous times.[19]

#### 4.5.2. Prediction—analysts' forecasts of future earnings

Analysts regularly forecast earnings and stock prices for the companies that they follow. Prior research finds that analysts are more optimistic at longer forecast horizons. This result has been attributed to management walkdown (Dechow, Sloan, & Soliman, 2004) and also analysts' incentives to generate trading commissions for their brokerages (Jackson, 2005). While construal level theory could certainly apply in this case, other theories also could be pertinent to this empirical finding. For example, analysts could be affected by confirmation bias (cf. Thayer, 2009). Many finance and accounting studies assume that market participants, including analysts, use all relevant information when forming judgments about companies. Such behavior would imply that these participants systematically consider all four cells of a standard contingency table—that is, they consider when a particular causal factor, like an organizational restructuring or a new advertising campaign, will lead to increased earnings and when it will not (see Fig. 3, Cells A and B, respectively). They also should consider Cells C and D where the cause is absent, yet earnings subsequently increase or do not increase. Whether analysts consider each of these cells—important steps for complete causal analysis—is an empirical question. The theory behind confirmation bias would suggest that analysts primarily consider Cell A which only bolsters their belief in the strength of the causal relationship underlying their forecast or stock recommendation. However, this possibility should be validated by research.

Considerable empirical evidence exists for many market anomalies but little research investigates their effects on the judgments of experts, such as analysts. For example, the market appears to over-extrapolate from past firm growth and from accruals contained in earnings (Fairfield, Whisenant, & Yohn, 2003; Sloan, 1996). As a result, subsequent market returns are abnormally low for high growth and high accrual firms. Drawing on the theories discussed in this paper, it is possible that these anomalies are attributable to the market's failure to recognize that these extreme firm characteristics are due, at least in part, to the randomness of the measures and will thus exhibit regression to the mean in future periods. This failure on the part of market participants, such as analysts, could lead to a misdiagnosis of past firm performance (attributing positive or negative news to an incorrect cause rather than mere chance) and a poor prediction of future firm performance. Research could explore this possibility and also identify the situations where analysts are more or less likely to anticipate regression to the mean for individual firms or within specific industries. Research examining these conditions could ultimately help analysts improve their forecast accuracy.

## 5. The intersection of diagnosis and prediction

The preceding sections have described causal reasoning theories within the contexts of prediction and diagnosis. The examples presented therein rested on the assumption that the prediction or diagnosis task "stood alone" and did not depend on a previous diagnosis or prediction. Although such an assumption is appropriate in some cases, it is also possible that these causal reasoning processes are related, as we explain below.

There are two ways in which diagnosis and prediction could be interrelated. First, because diagnosis and prediction can be viewed as two sides of the same coin (i.e., both involve causes and effects), it should not be surprising that in some cases, they involve the same psychological processes.[20] For example, investors may rely on covariation information when determining why actual earnings exceeded the consensus forecast *and* when making a prediction of future earnings. What is particularly intriguing is that existing studies investigate covariation in either a

[19] This discussion suggests that perhaps some causal reasoning theories may be more applicable for the generation (versus evaluation) of causes. In general, we believe that the theories we discuss are applicable to both the generation and evaluation of potential causes. As such, they are suitable to answering research questions where potential causes must be generated by the decision maker and where they are already available to the decision maker.

[20] An extreme point of view, held by some, is that this occurs because diagnosis and prediction are one and the same. Interestingly, though, the limited research on this idea provides contradictory insights (Medin, Coley, Storms, & Hayes, 2003; Wedell, 2010).

diagnosis or prediction context. They *rarely* simultaneously compare the effects of one theory for *both* diagnosis and prediction tasks. As a result, there is virtually no evidence regarding whether causal reasoning processes (and the biases and errors that sometimes occur) are similar or different between the two types of tasks. To illustrate, consider the availability heuristic. Recall that the use of availability in causal reasoning occurs when individuals make judgments based on how easily related information comes to mind (rather than assessing the underlying probabilities). This heuristic can occur in prediction, for example, when analysts judge the likelihood of a company going bankrupt based on the number of other company bankruptcies that come to mind. It also can occur in diagnosis. An analyst who is determining the cause of an unexpected rise in sales may judge the likelihood of several causes based on how quickly and readily they come to mind. In both cases, the analyst's judgments and decisions—either prediction or diagnosis—are likely biased because availability was used as a causal reasoning shortcut. However, to our knowledge, no research has examined whether the degree of bias is similar in diagnosis versus prediction.

In one of the very few studies on this point, Fernbach, Darlow, and Sloman (2010) show that the magnitude of a causal reasoning bias that exists in diagnosis is not the same as in prediction. They examined the well-known finding that individuals tend to not consider a sufficient number of potential alternative causes. Their study showed that medical professionals neglected alternative causes to a greater extent when reasoning from cause to effect (i.e., prediction) as compared to reasoning from effect to cause (i.e., diagnosis).[21] The lack of similar studies in other areas suggests that there are interesting opportunities for further research, both from a basic and an applied perspective, on how these two causal reasoning processes may produce more biased judgments in prediction or diagnosis.

The second way in which prediction and diagnosis are related is that prediction often depends on a preceding diagnosis, and diagnosis often depends on a preceding prediction. Given the time-series nature of financial reporting—where predictions are made, actual realizations occur, and the process starts over again—this interrelationship seems particularly important. For example, an analyst who concludes that a past earnings increase is due to a one-time transaction is likely to make a lower prediction of future earnings than the analyst who attributes that increase to a new product line (i.e., to a persistent cause). In a similar way, an analyst who predicts earnings to fall short of expectations because of a particular reason (e.g., poor economy) is likely to diagnose an actual shortfall in earnings as being due to that predicted reason, rather than other potential reasons.

Once again, the psychology research on this type of interrelationship between prediction and diagnosis is quite limited. Almost all of the research examines either diagnosis or prediction, and not both within the same study. Perhaps unsurprisingly, though, the limited research that addresses both indicates that there are carryover effects. Epstude and Roese (2008) show how this carryover can be beneficial. They document that engaging in counterfactual reasoning to test the veracity of a potential cause of an event (e.g., "if only I had not taken the busy freeway, I would not have been late to my appointment") can improve predictions about the future (e.g., "I will not take the busy freeway if I do not want to be late"). Establishing those financial reporting situations where the carryover both is and is *not* beneficial are important directions for future research. That is, errors made in a preceding diagnosis or prediction may be amplified or double-counted when a subsequent prediction or diagnosis occurs. For example, an analyst who relies on availability and, thus, makes an erroneous diagnosis of a company's past performance may then again have a tendency to rely on availability when predicting future earnings, furthering the potential error in judgment.

### 5.1. Examples of future research

With this overview of the linkages between prediction and diagnosis, we provide several examples of how these theories could be used in future research in financial reporting and voluntary disclosure. Given the paucity of causal reasoning research in general, however, it seems fruitful for future research in financial reporting and voluntary disclosure to initially focus on research issues related to diagnosis or prediction alone. Once an improved understanding of each of these causal reasoning processes is attained, then research exploring issues related to their intersection would be the natural next step.

#### 5.1.1. Differential impact of causal reasoning on prediction versus diagnosis

As noted, very little research has explored how the effects of a particular causal reasoning theory might "behave" differently in prediction versus diagnosis. To illustrate, recall the previous discussion about the representativeness heuristic. Research documents that individuals often form stories that follow familiar sequences of events to make predictions, and do not rely on the probabilities associated with that sequence of events. In other words, these individuals may utilize prototypical scenarios at the expense of accuracy. Thus, an interesting research question is whether the use of the representativeness heuristic is similar between diagnosis and prediction. It is possible that this heuristic would have a smaller effect in the diagnosis setting. For example, it may be relatively easy for an investor to imagine that a troubled company could hire a star CEO and then exhibit a great turnaround, because there are famous stories of such turnarounds. Of course, the same could be true for diagnosis – if a troubled company exhibits a turnaround after hiring a new CEO, investors may assume the CEO was the primary factor in the turnaround (since it matches the prototypical story). However, there is a key difference between these two scenarios. In the prediction scenario, evidence contrary to the prototypical story may not be available (as the predicted event has not yet occurred). In contrast, in the diagnosis scenario, other evidence already exists (e.g., increasing

[21] This finding leads to yet another intriguing idea for future research—that is, can the bias be reduced if the prediction task is reframed as a diagnosis problem?

consumer demand for the company's products, more favorable contracts with suppliers, etc.) that may suggest that the CEO was not the primary factor in the turnaround. If such information is considered by the investor, less biased judgments may emerge in diagnosis tasks as compared to prediction tasks.

As another idea for future research, consider the confirmation bias. Recall that this bias occurs when individuals tend to notice and more heavily weight information that confirms their prior beliefs. A natural question is whether the size of this effect is greater in prediction (where the outcome has not yet occurred) or in diagnosis (where the outcome has occurred). One might think that the bias would be greater in prediction tasks as the outcome (e.g., the actual earnings realization) has not yet become available. However, significant research in the area of motivated reasoning (Kunda, 1990) suggests it may occur as strongly in diagnosis. There, people who are highly motivated to maintain their beliefs may re-interpret evidence in a way that supports their prior beliefs, particularly when they are able to construct reasonable justifications. The actor–observer effect, discussed previously, may be a manifestation of this type of motivated reasoning. That is, the type of diagnostic attribution may clearly depend on one's perspective and, therefore, prior beliefs.

*5.1.2. The effects of diagnosis on prediction and vice versa*

Financial reporting appears particularly well suited for investigation of how diagnosis might influence prediction and vice versa. That is, the sequential, time-series nature of many tasks within financial reporting makes this a natural setting to study this interrelationship. The presence of market forces adds an additional layer of interest (and complexity) to the interrelationship between prediction and diagnosis, as it is possible that those market forces may temper any initial errors.

To illustrate how research could explore this interrelationship, recall our earlier discussion of the actor–observer bias and consider a situation where a firm reports earnings that miss (i.e., fall below) the consensus forecast. Not only will management typically provide a diagnostic explanation for the earnings number, but analysts will likely also make their own diagnosis. According to the theory behind the actor–observer bias, the firm manager has an incentive to attribute or diagnose the cause as related to outside factors (e.g., unexpected weakness in the economy). In contrast, the analyst is more likely to attribute the missed forecast to a weak CEO (i.e., an internal, or personal, attribution). If such forces were at work, a natural follow-on research question relates to how the analyst's prediction for next-period's earnings would be influenced by the manager's own attribution for firm performance. Does the analyst consider only his/her diagnosis for the missed forecast in making a prediction for the future? To what extent does the manager's attribution influence the analyst? Research that addresses the interrelationship between diagnosis and prediction could explore this interesting question.

Another common finding in the psychology literature is the false-consensus effect, also discussed previously in this paper. Here, firm managers would likely overestimate the extent to which analysts and investors share their opinions about the company's past performance. If documented within the financial reporting domain, a natural next question would be how this effect influences the manager's own forecasts of future earnings. In other words, is the manager insensitive to a lack of consensus which may be revealed in analyst reports and/or selling behavior? Do those firm managers behave in the same fashion as if the relevant market participants fully agreed with his diagnosis of the company's past performance?

While these two examples illustrate two research opportunities regarding the influence diagnosis on prediction, research also could explore the opposite relationship—namely, the influence of prediction on subsequent diagnosis. Consider our previous discussion on the desirability bias. This bias occurs when individuals predict that current conditions are more likely to lead to desirable than undesirable outcomes. Firm managers may be susceptible to this bias when making predictions of their firm's future performance (i.e., forecasting earnings or stock prices). An interesting follow-on question is how their diagnosis and subsequent predictions are affected by a prior optimistic prediction that is not achieved. Do firm managers "true up" their rosy perspectives once a backward-looking diagnosis of bad news is revealed, or does their prior prediction interfere with that subsequent evaluation? For example, a manager predicting that a new product launch will lead to increased earnings may be more likely to diagnose a subsequent earnings decrease as attributable to macroeconomic circumstances and not to the failure of the product. Had the manager not made a causal linkage between the product and earnings in the initial prediction, perhaps a more evenhanded diagnosis could be performed. Taken one step further, would the resulting incorrect diagnosis then lead the manager to make yet more optimistic future predictions about the product?

## 6. Conclusion

In this paper, we accomplish two objectives. First, we review key theories from psychology that pertain to causal reasoning. These theories apply to the two distinct components of this type of reasoning—namely, diagnosis and prediction. Second, our paper provides insight into theories that may not be well known to current behavioral researchers in financial reporting and voluntary disclosure. Use of these theories is important as research drawing on causal reasoning has the potential to provide significant insights to preparers and users of financial reports and voluntary disclosures as well as standard setters and regulators. That is, we believe that there are significant opportunities to advance our understanding of important issues in financial reporting and voluntary disclosure using these theories given the close match between the types of diagnosis and prediction tasks in financial reporting and voluntary disclosure contexts and the types of tasks covered by causal reasoning theories.

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