Int. Journal of Economics and Management **2(1):** 179 – 193 (2008) ISSN 1823 - 836X

Noise in Accounting Information: The Signal Detection Theory Perspective

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ABSTRACT

Accounting information constitutes a "noisy" representation of economic reality due to the spectrum of accounting alternatives available to meet a diversity of information needs. In the presence of noise, decision-makers can either overlook signals that truly require attention or mistake noise for signals. This paper seeks to (1) discuss how decision-makers fare in discriminating accounting signals from noise based on extant empirical findings, (2) highlight the adverse effects of noise in accounting information from the signal detection theory perspective, and (3) offer recommendations on how best to fend of the adverse influence of noise.

Keywords: Accounting Signals, Noise, Accounting Representation, Signal Detection Theory

INTRODUCTION

Accounting information is inherently "noisy"[1]. Accounting information is able to represent only some of the facets of a firm's economic reality (see Mattessich 1995; Shapiro 1997; Mattessich 2003; Mouck 2004). The presence of noise in accounting information is contingent upon the extent to which the facets of economic reality represented matches decision-makers' information needs. The greater the match between accounting representation and information needs, the

[1] Accounting information is artificially constructed and therefore has the power to reconstruct economic reality.

easier it is for decision-makers to identify the signals that require attention in the task at hand. Conversely, the greater the mismatch between accounting representation and information needs, information presented becomes "noisier" and the more difficult it is for decision-makers to see the signals.

Two key accounting summaries of a firm's economic reality, net income and net assets, have been called "noisy" signals of wealth due to the sheer number of options available in constructing the accounting numbers—e.g. LIFO versus FIFO in inventory evaluation, straight-line depreciation versus reducing balance depreciation—to meet a diversity of information needs (Mouck 2004). However, being "noisy" does not nullify the usefulness of accounting information. According to Mattessich (1995; 2003), accounting information is useful as along as decision-makers are conscious and wary of the noise within the information.

The glut of information available to a typical decision-maker in the modern organization further contributes noise to the information environment. The Internet and developments in telecommunication technologies provide a host of information channels (Farhoomand and Drury 2002; Denning 2006). From ERP systems to business intelligence tools, like On-line Analytical Processing (OLAP) systems, all have sought to provide greater access to more information for decision-making (Kumar and Hillegersberg 2000). Information glut is not simply a problem of the electronic medium. According to the American Forest and Paper Association, paper usage in business reached 1.6 trillion pages a year in the 1990s (Davenport and Beck 2000). The glut of information poses a challenge to decision-makers. It is difficult to sift out information that is relevant to the immediate task at hand, from that which must be maintained but is not currently relevant.

The presence of noise adversely affects decision-makers' performance. In "noisy" conditions, decision-makers can easily overlook problems that need to be solved. Noise can incapacitate even the most knowledgeable decision-makers. In a 2002 global survey conducted by the Fuld-Gilad-Herring Academy of Competitive Intelligence, two-thirds of the corporate strategists surveyed admitted overlooking signals of three high-impact events in the past five years (Fuld 2003). In fact, allowing problems to go unnoticed has been claimed as "all too common in the business world" (Watkins and Bazerman 2003, p. 74). The presence of noise in the information environment makes it difficult for decision-makers to see the signals. Signals are symptoms of a problem. Failing to see the signals allows the problem to go unnoticed.

The objective of this paper is to discuss, from the signal detection theory perspective, the effects of noise and how best to utilize accounting information despite the presence of noise. The signal detection theory has been widely applied and tested particularly in the realm of cognitive science and psychology to explain the effects of noise on the detection of audio and visual signals (for a synthesis of extant cognitive science and psychology literature, see Swets 1973; Swets and Pickett 1982; Swets 1996). Application of the signal detection theory in a knowledge-intensive domain like accounting—as in this paper—not only helps to validate the theory but also enriches the accounting literature.

The remainder of this paper is organized as follows. The second section provides a review of extant literature on how decision-makers fare in terms of problem detection. The third section reviews and synthesizes empirical evidence on the presence of noise in accounting information and how noise can adversely affect decision-makers' performance. The fourth section discusses, from the signal detection theory perspective, the influence of noise on problem detection and how to mitigate the adverse influence of noise. The final section concludes the discussion.

PROBLEM-SOLVING, PROBLEM-DETECTION AND DECISION-MAKING PROCESS

Simon (1960) described decision making as a three-step process. First, the problem has to be identified. Second, alternative courses of action are designed to solve the problem. Third, upon evaluation of the alternative courses of action, the preferred alternative is selected and implemented.

The three steps of the decision making process are related. The problem identified affects the alternative courses of action generated. The set of alternatives generated, in turn, affects the selection made. For instance, let us assume that high labour cost involved in the manufacturing of a company's product lines has been identified as the cause of poor profitability. Thus, high labour cost has been identified as a problem. Decision-makers need to generate alternative courses of action, such as process automation, relocation of manufacturing plant to a geographical area that offers cheaper labour, etc. Upon evaluation of these alternatives, the most appropriate one is selected and implemented. However, if decline in the demand for the company's most popular product has been identified as the problem that causes poor profitability instead, decision-makers need to generate a different set of alternatives, such as product innovation, geographical expansion, etc. Next, a selection is made based on this set of alternatives.

The first step of the decision-making process, i.e. problem detection, is critical. Performance of the two subsequent steps depends on it. The examples illustrated in the previous paragraph have shown how identification of two different problems—high labour cost and decline in product demand—results in the pursuit of two different courses of actions. Let us assume that high labour cost is, in fact, not a problem. However, it has been identified as a problem that needs to be solved. Hence, regardless of the chosen course of actions (process automation, relocation of manufacturing plant to a geographical area that offers cheaper labour, etc.), the real problem—i.e. decline in product demand—remains unsolved because it was not identified. Thus, decision making performance is adversely affected by not identifying the real problem.

Simon (1960) contended that assessing decision making performance based on the final step alone is inappropriate. This is because performance at each of the three steps contributes towards overall decision making performance. Nevertheless, the extant literature has largely focused on the final step, i.e. problem-solving.

Problem-solving

Research from a variety of scientific and professional disciplines, ranging from physics and medicine to management accounting and auditing, have examined how best to solve problems efficiently and effectively (Chi, Feltovich et al., 1981; Vessey 1991; Hassebrock, Johnson et al., 1993; Umanath and Vessey 1994; Vessey 1994; Vera-Munoz, Jr et al., 2001; Kadous and Sedor 2004; Hammersley 2006). These studies implicitly assumed that the correct problems have been identified. They are primarily interested in how to facilitate the problem-solving process; how to facilitate understanding of the problem at hand and how to enable decision-makers to acquire and process information in a manner that ensures efficient and effective implementation of the last two steps in the decision-making process – generation and evaluation of alternative solutions, and selection and implementation of the most appropriate solution.

Few studies have demonstrated that encouraging decision-makers to concentrate on problem-solving is not without its drawbacks. Focusing on problem-solving adversely affects performance at the first step of the decision-making process – i.e. problem-detection (see Sanderson 1990; Sanderson and Murtagh 1990; Besnard, Greathead et al., 2004). In an attempt to help improve efficiency and effectiveness in problem-solving, decision-makers' scope of information acquired and processed is limited. Information relevant to the problem decision-makers are attempting to solve tends to be overemphasized. Other information tends to be ignored. In the event that the problem decision-makers are attempting to solve is, in fact, not a problem, such limited scope of information processed offers little assistance in unraveling this.

Concentrating on solving the problem at hand can lead decision-makers to overlook other problems. This is because decision-makers' primary concern is to understand and solve the problem at hand. Information acquisition and processing are directed towards this purpose. Even when decision-makers encounter signals, i.e. symptoms, of other problems, they have a tendency to divert their attention away from such signals (Sanderson and Murtagh 1990). When solving the problem at hand takes precedence, decision-makers fail to perceive the significance of the signals of other problems. Instead, such signals are dismissed as noise.

Problem-detection in the accounting domain

The first step of the decision making process—i.e. problem-detection—has most commonly been examined in auditing. This is because of the very nature of auditing decision making. Like medical doctors, auditors are regarded as diagnosticians (Libby 1985). Auditors frequently encounter various signals in clients' accounts. Having to detect the problems causing these signals (i.e. symptoms) is an auditor's day-to-day task.

Problem detection—the first step of the decision-making process—has received less attention in other accounting contexts, in comparison with the auditing context. For instance, variance analysis is a classic management accounting technique used to identify problems by comparing actual performance with some targeted level of performance. Actual performance that is below a targeted level constitutes a signal, i.e. symptom of a problem. A variety of variance analysis techniques have been introduced to assess the various aspects of a firm's performance (for examples, see Ramsey 1999; Emsley 2001; Mitchell and Thomas 2005). Nevertheless, few studies have empirically investigated how the various techniques fare in terms of facilitating problem-detection (Emsley 2001). Further, Emsley (2000) contended that management accounting texts tend to elaborate the calculation of variances in great detail, but offer little advice on how to identify the problems that have generated the variances.

In short, there is a paucity of research examining the first step of the decision making process, i.e. problem-detection. Yet, the presence of noise in accounting information complicates the task of having to detect problems. How noise can hinder decision-makers' performance in terms of problem-detection is detailed in the following section.

NOISE IN ACCOUNTING INFORMATION

Descriptive studies have demonstrated that accounting information is "noisy" (Mattessich 1995; Shapiro 1997; Mattessich 2003; Mouck 2004). This is because the extent to which accounting information is able to represent economic reality is constrained by pragmatic factors, such as cost-benefit tradeoffs (Shapiro 1997). Even when accounting information can be presented in a manner that fully reflects economic reality, such an effort has to be abandoned if the costs involved are not justifiable. In other words, noise is inherent in accounting information. Yet, many decision-makers are dependent on accounting numbers to keep them informed of business performance and in ensuring problems that need to be solved are quickly identified.

Empirical evidence indicates that having to discriminate signals from noise in accounting information is not easy. For instance, Buchheit (2003; 2004) manipulated capacity cost information (reporting versus not reporting capacity cost information) in two studies. In practice, the reason for providing capacity cost information is to assist decision-makers in the evaluation of how effective resources are being utilized. In his first study, Buchheit (2003) found that participants cut unused capacity resources indiscriminately when provided with capacity cost information. Even in the event that unused capacity is not a problem, participants still responded in a similar manner; minimizing unused capacity resources. In his second study, Buchheit (2004) found that participants adjusted selling prices in response to changes in sunk costs; participants were responding to noise.

In addition to noise inherent in accounting information, the manner in which information is presented can also inadvertently produce noise. More specifically, decision-makers have been found to succumb to the influence of noise introduced as a result of the sequence in which information is presented (Tuttle, Coller et al., 1997; Ahlawat 1999; Arnold, Collier et al., 2000; Monroe and Ng 2000; Trotman and Wright 2000). Information last encountered is perceived as more relevant, which is a recency effect. Decision-makers' performance is adversely affected when such perception is incorrect; noise is misinterpreted as signals.

In sum, the extant literature suggests that decision-makers have difficulties discriminating signals from noise. This is true particularly when the facets of economic reality relevant to the tasks at hand are not explicitly represented and thus can result in the misinterpretation of noise as signals. Yet, decision-makers need to recognize the signals that suggest the presence of a problem before they are able to respond to the problem. When decision-makers fail to differentiate between signal and noise, they do not even know that a problem exists.

SIGNAL DETECTION THEORY PERSPECTIVE OF PROBLEM-DETECTION

In order to detect a problem, decision-makers need to examine the information provided. They need to determine whether there are signals, i.e. symptoms, which indicate the presence of a problem. Next, decision-makers need to respond either "yes", a problem exists, or "no", a problem does not exist. In short, decision-makers need to distinguish between two classes of event. They need to distinguish signals from noise - whether a problem exists.

Various decision-making tasks involve distinguishing between two classes of events. Examples of such tasks are detection of errors and misstatements in audit clients' accounts (whether there are errors and misstatements or not) and fraud detection (whether fraud exists or not). Such tasks are not restricted to the accounting domain. They are all around us, from detection of flaws in manufactured products and malfunctions in nuclear power plants to weather forecasting and detection of diseases in people (see Swets 1996).

Signal detection theory has been widely applied in explaining performance of tasks that involve distinguishing between two classes of events. The theory has been tested and validated across various research disciplines, from tone and light detection in psychology to fraud detection in business and management (for more information, see Brown 1981; Blocher, Moffie et al., 1986; for more information, see Swets 1996; Klein, Goodhue et al., 1997; Karim and Siegel 1998; Sprinkle and Tubbs 1998; McGrew and Bilotta 2000; Barkan 2002; Raslear and Coplen 2004; Ramsay and Tubbs 2005). The theory is used to explain problem-detection performance.

Four possible outcomes of problem-detection

In detecting problems, decision-makers can reach four possible decision outcomes. There are two correct decision outcomes. In signal detection theory, the two correct decision outcomes are known as *hits* and *correct negatives*. A *hit* is a correct conclusion regarding the existence of a problem; decision-makers correctly conclude that a problem exists. A *correct negative* is a correct conclusion regarding the absence of a problem; decision-makers correctly conclude that a problem does not exist.

Decision-makers can also reach two incorrect decision outcomes. The two incorrect outcomes are known as *false alarms* and *misses* in signal detection theory. A *false alarm* is a mistake, i.e. a wrong conclusion is made regarding the existence of a problem; decision-makers incorrectly conclude that a problem exists, when a problem does not exist. A *miss* is a mistake, i.e. a wrong conclusion is made regarding the absence of a problem; decision-makers incorrectly conclude that a problem does not exist, when a problem does exists. The four possible outcomes described above are summarized in Table 1.

Table 1 Four possible decision outcomes of a problem-detection task

		Decision-makers' response	
		Yes (Problem exists)	No (Problem does not exist)
Reality	Problem	*Hits* P(Yes/Problem)	*Misses* P(No/Problem)
	No Problem	*False Alarms* P(Yes/No-problem)	*Correct Negatives* P(No/No-Problem)

Key: P denotes probability

Problem-detection in the accounting domain

Signal detection theory was first applied in psychology to explain performance in terms of tone and light detection (see Swets and Pickett 1982; see Swets 1996). In psychology research, signals are explicit. For example, using the theory to explain tone detection, a signal refers to a specific loudness or pitch of a tone, which an individual is required to detect. In light detection, a signal refers to a specific brightness or colour of a light, which an individual is required to detect. In tone and light detection, it is clear exactly what to detect. Furthermore, an individual needs to account for only one signal – either a specific loudness or pitch of a tone, or a specific brightness or colour of a light.

However, having to detect problems in a knowledge-intensive domain like accounting is not as straightforward. The signals that decision-makers need to take into consideration in deciding whether a problem exists are not as explicit and well-defined as those in tone and light detection. Multiple information cues have to be taken into consideration. Knowledge is required to identify the relevant information, which consists of multiple information cues, and infer whether there are any signals, i.e. symptoms of a problem.

Decision-makers also need to be wary of irrelevant information as it contains noise only. Recall that noise is capable of not only obscuring signals but also diverting decision-makers' attention away from the signals. The presence of noise has been acknowledged in the psychology literature from the 1940s (see Swets 1996).

Applying signal detection theory to problem detection, noise is information without any signal that indicates the presence of a problem. Noise is irrelevant information in the background that makes it difficult for decision-makers to see the signals as well as information that diverts decision-makers' attention away from the signals. Signals are information that enables decision-makers to determine the presence of a problem. Consistent with signal detection theory, signals and noise can be represented using two probability distributions.

Figure 1 illustrates the two probability distributions. The noise distribution represents the probability of a state where only noise is present. The signal distribution represents the probability of a state where signals are added to noise. Decision-makers determine whether a problem exists by setting a decision threshold. The decision threshold is represented by the dotted vertical line situated between the two distributions. Decision-makers will decide that a problem exists when information examined is perceived as greater than the decision threshold. In contrast, when information examined is perceived as below the threshold, decision-makers will decide that a problem does not exist.

For the signal distribution, the area under the distribution and to the right of the decision threshold equals the probability of decision-makers making the right decision by responding "yes" when a problem does exist, *hit* rate [P (Yes/Problem)]

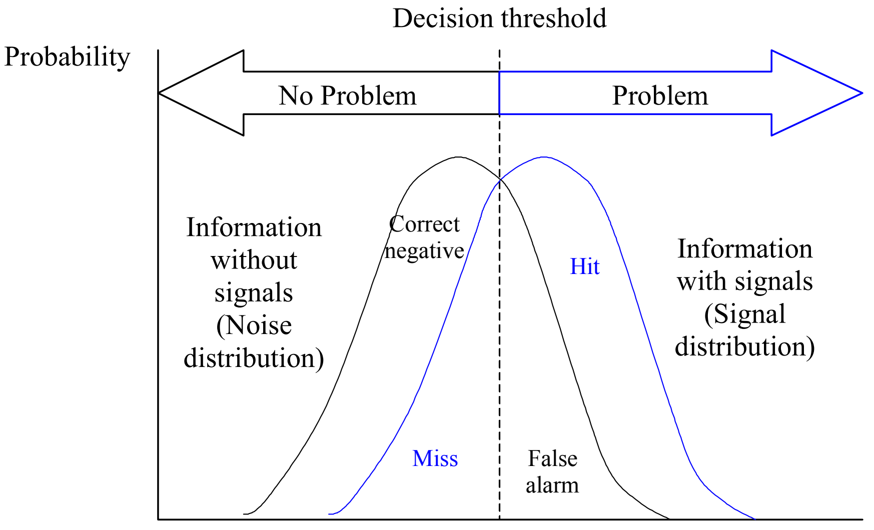

Figure 1 Signal and noise distribution

(see Figure 1). The area under the signal distribution and to the left of the decision threshold equals the probability of decision-makers making a mistake by responding "no" when a problem does exist, *miss* rate [P (No/Problem)].

As for the noise distribution, the area under the distribution and to the left of the decision threshold equals the probability of decision-makers making the right decision by responding "no" when a problem does not exist, *correct negative* rate [P (No/No-problem)] (see Figure 1). The area under the noise distribution and to the right of the decision threshold equals the probability of decision-makers making a mistake by responding "yes" when a problem does not exist, *false alarm* rate [P (Yes/No-problem)].

When information examined contains strong signals that suggest the presence of a problem, such information is perceived by decision-makers as being near the right hand side of the signal distribution. Decision-makers are able to reliably identify the problem, *hit*. On the other hand, information with no hint of a problem at all is perceived as being near the left hand side of the noise distribution. Decision-makers are able to reliably dismiss such information as noise; they are able to reliably conclude that a problem does not exist, *correct negative*.

However, decision-makers are not always able to reliably decide whether a problem exists. In this case, information examined is perceived as being in the overlapping portion of the two distributions. It is difficult to differentiate between signal and noise. Signals can easily be misconstrued as noise and thus dismissed.

This results in mistakes, i.e. *misses.* Conversely, noise can also be easily misconstrued as signals and thus results in *false alarms*.

How to mitigate the adverse influence of noise

Applying signal detection theory, there are two ways to improve problem-detection performance. First, decision-makers can adjust their decision threshold. Setting of the decision threshold is determined by the cost-benefit tradeoffs associated with detecting the correct problems. Neutral decision-makers set their decision threshold at a point where the two distributions—i.e. signal and noise distribution—intersect (see Figure 1). At this point, decision-makers are not biased towards responding "yes" or "no" upon examining information provided. If decision-makers set their decision threshold to the left of this point, decision-makers are biased towards responding "yes"; a problem exists. Even weak signals result in a decision of "yes". Alternatively, if decision-makers set the decision threshold to the right of the "neutral" point, decision-makers are biased towards responding "no"; a problem does not exist. In this case, decision-makers dismiss all except the strongest signals.

In order to improve *hit* rate, decision-makers can relax their decision threshold by setting it to the left of the "neutral" point. However, the side effect is even the weakest signals trigger the "yes" response; a problem exists. This helps to improve not only *hit* rate, but also *false alarm* rate. In short, relaxing the decision threshold helps to increase the detection of both correct and incorrect problems.

The second way to improve problem-detection performance is to reduce the overlap between the signal and noise distribution. As mentioned earlier, when information examined is perceived as being in the overlapping portion of the two distributions, decision-makers are unable to reliably decide whether a problem exists. Problems are not easily discriminable. Problem discriminability refers to the extent to which a problem can be distinguished in the presence of noise. The greater the overlap between the signal and noise distribution, problems become less discriminable. Conversely, the smaller the overlap, the more discriminable problems become.

Figure 2 illustrates the signal and noise distribution with a smaller overlapping portion compared with that of Figure 1. Compared with figure 1, the area under the signal distribution and to the right of the decision threshold is larger. At a given decision threshold, there is a higher likelihood of identifying the correct problems (*hits*). On the other hand, the area under the signal distribution and to the left of the decision threshold is smaller. The likelihood of making a mistake by responding "no" when a problem exists (*miss*) is also lower. Similarly, the area under the noise distribution and to the left of the decision threshold is larger as well. Hence, the likelihood of making the correct decision by responding "no"

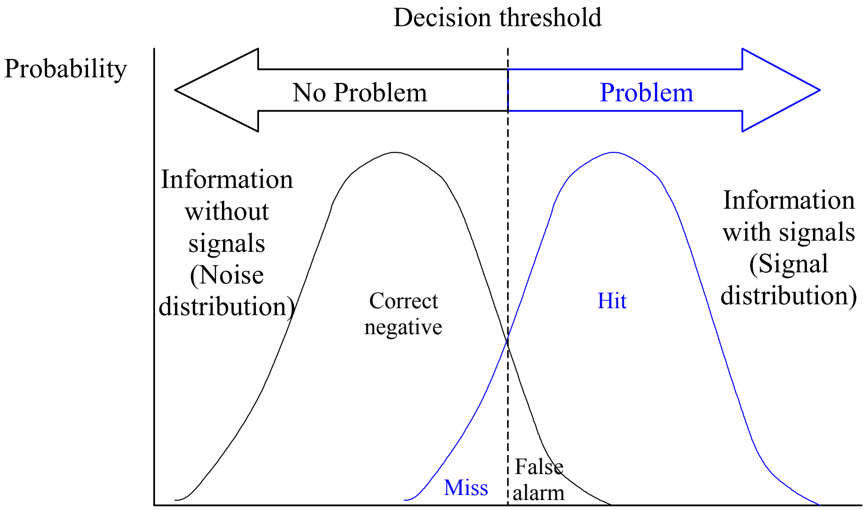

Figure 2 Signal and noise distribution at a higher level of problem discriminability

when a problem does not exist (*correct negative*) is higher. Conversely, the area under the noise distribution and to the right of the decision threshold is smaller. This suggests a lower likelihood of making a mistake by responding "yes" when a problem does not exist (*false alarm*).

Unlike relaxing the decision threshold, improving problem-detection performance by reducing the overlap between the signal and noise distribution does not have the side effect of a corresponding increase in the *false alarm* rate. In fact, it helps to reduce the *false alarm* rate. Reduced overlap between the two distributions enhances the signals. Thus, decision-makers are better able to discriminate signals from noise. In this manner, problems become more discriminable. Decision-makers are in a better position to reliably identify problems and are less likely to make mistakes by identifying the wrong problems, *false alarms*.

DISCUSSION AND CONCLUSION

"*Why didn't we see this coming?*" is a question that no decision-makers want to ask yet many find it impossible to avoid (Fuld 2003). Accounting information is "noisy". Noise obscures signals resulting in overlooked problems—i.e. *misses*—or detection of the wrong problems—i.e. *false alarms*. However, the adverse effect of noise can be mitigated by making problems more discriminable.

Extant literature suggests that accounting knowledge is able to mitigate the adverse influence of noise by making problems more discriminable. More specifically, empirical evidence suggests that knowledgeable decision-makers are less likely to succumb to the adverse effect of noise in accounting information (Simnett 1996; Hunton and McEwen 1997; Shelton 1999). Compared with their less knowledgeable counterparts, knowledgeable decision-makers are in a better position to discriminate between information that is relevant and irrelevant. In this manner, knowledgeable decision-makers are better able to dismiss irrelevant information and thus noise. Knowledge also enables decision-makers to correctly infer from the relevant information whether accounting signals exists, which in turn, makes problems more discriminable. The resultant more-discriminable-problems pave the way for the detection of the correct problems, i.e. *hits*.

In light of the mitigating effect that knowledge has on the adverse influence of noise in accounting information, Mattessich (1995; 2003) called for the assumptions underlying accounting information to be disclosed to decision-makers. The aim of disclosing the underlying accounting assumptions is to educate decision-makers of the limitations and thus noise in accounting information. Decision-makers who are equipped with the knowledge of the presence of noise in accounting information are in a better position to fend of the hostile effect of noise. Besides the disclosure of the underlying accounting assumptions, future research can consider exploring other avenues to better equip and enable decision-makers to make use of accounting information despite the presence of noise.

ACKNOWLEDGEMENTS

This paper is part and parcel of the author's PhD dissertation (a copy of the dissertation is available at the University of Melbourne as well as Universiti Putra Malaysia's library). The author acknowledges the assistance of her PhD supervisory committee—i.e. Associate Professor Michael Davern and Associate Professor Axel Schulz—particularly at the early stage of theory development.

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