

The Relationship Between Open Innovation And Innovation Persistence: A Contingency Framework

Dr. Md Shahedul Alama¹, Dr. Rod B. McNaughton²

ABSTRACT

Managers face alternatives in sourcing intellectual property and new ideas to fuel innovation. The traditional focus on in-house research is giving way to open innovation in which firms depend on external sources for technologies to use in new products and services. This article introduces a framework that identifies generic innovation pathways, how choices in one period influence later options, and likely outcomes in terms of creating innovation persistence. R&D managers will appreciate the framework as a tool that aids decision-making. The framework provides scholars with a foundation to guide future empirical research on the links between innovation form and outcome.

Keywords: open innovation; closed innovation; innovation persistence; strategic pathways.

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1. INTRODUCTION

Open innovation is increasingly replacing the traditional approach to innovation, where individual companies traditionally depended solely on in-house R&D. In the open innovation model, firms depend on external sources for the technologies they use in new products and services (Chesbrough, 2003). Technology licensing and acquisition of promising start-ups complement in-house research. However, management of open innovation is particularly challenging because of the added complexity of finding, acquiring, adapting and controlling intellectual property originating outside of the firm. A second concept - innovation persistence (Le Bas and Latham, 2006) - is gaining attention alongside open innovation. Persistence refers to the ability of a firm to remain competitive by consistently introducing innovations over several periods. As open innovation offers more technology options, this strategy has potential to help managers achieve innovation persistence.

There are multiple pathways that an R&D manager can consider while making decisions about current and future innovation. This article provides a framework that summarizes these innovation pathways and their possible contribution in achieving innovation persistence. This framework is a management tool that helps to identify contingencies in the innovation process. It elaborates the generic strategies that R&D managers can choose given a specific innovation case, and the strategic pathways that are available for innovation at time $t+1$, given a certain choice made at time t .

Before presenting the framework, we first review the emerging literature on the concepts of open innovation and innovation persistence. A description of the framework follows. The article concludes with a discussion of how the framework provides insight into the managerial challenge of choosing between strategic innovation pathways, and recommendations for further research to extend and test the framework.

1. Assistant Professor, Department of Management, School of Business and Economics, North South University, Dhaka, Bangladesh.

2. Professor and Academic Director, Centre for Innovation and Entrepreneurship, The University of Auckland Business School, Auckland, New Zealand.

2. OPEN INNOVATION AND ITS IMPLICATIONS

Chesbrough (2003) coined the term “open innovation”. In this approach, firms complement their in-house research with ideas and technologies from external sources. Technology licensing and acquiring promising start-up companies are two popular ways to tap into external sources for intellectual property and new ideas. This contrasts with the traditional practice of innovation focused on in-house research, or “closed innovation”. Chesbrough argued that companies adopt open innovation because of the increased mobility of experienced and skilled people, the difficulty of appropriating benefits of employee training, and competition from private and corporate venture capitalists that specialize in creating new firms by commercializing research. Developments like these are creating a new set of rules for managing innovation.

The concept of open innovation has links to several earlier ideas. One such concept is absorptive capacity. Cohen and Levinthal (1990) identify this as a trait of the firm that enables it to access and absorb external ideas, science, and other kinds of knowledge to use in the innovation process. This capacity helps a firm to innovate using both internal and external knowledge. Other authors identify innovative learning as interactive, cross-disciplinary and an inter-organizational phenomenon (Pavitt, 1998; Rosenberg, 1982; Von Hippel, 1988). The concept of organizational learning helps organizations to know about specific knowledge that lies outside of the boundary of the firm before they can attempt to acquire or license the technology.

The phenomenon of open innovation can also be characterized either by channels or by conduits. Owen-Smith and Powell (2004) use these two terms to describe knowledge networks. Channels imperfectly facilitate knowledge transfer and create information spillover. Both loosely connected and centrally positioned organizations benefit from this type of transfer. The other mode of knowledge transfer is analogous to a conduit that attempts to transfer knowledge selectively using legal instruments such as non-disclosure agreements, or exclusive licensing contracts.

While collaborating with others, firms choose counterparts from their own industry as well as across sectors (Eisenhardt and Schoonhoven, 1996). Owen-Smith and Powell (2004) call these cross-sector connections the “plumbing” of the market. Powell et al. (1996) characterize such diverse networks in bio-technology as the “locus of innovation”. Proving the usefulness of open innovation, Hagedoorn and Schankenraad (1994) demonstrated a positive relationship between the formation of technology partnerships and firm-level innovation. Lopez-Vegaa and Vanhaverbeke (2016) identified different searching methods that may help firms to find a suitable strategy for open innovation success. In addition, George et al. (2002) found that firms in collaboration with universities produce more patents and have lower R&D costs. Strategic alliances among firms in the biotechnology sector increase patenting rates (Shan et al., 1994; Walker et al., 1997). Stuart (2000) reports a similar result in semiconductor industries.

Open innovation is pursued by an increasing number of companies. Chesbrough argued that corporate R&D managers no longer just direct the few researchers who are employed by the company; rather they are now responsible for managing the universal set of researchers who are working in the industry in the same and related fields. The first step in managing externally located researchers is awareness of ongoing developments and recognition of possible opportunities. Firms may capitalize on an opportunity that arises from outside research through technology licensing and start-up acquisition. Similarly, firms also license their technology to others in cases where the technology is not a good fit with their current business model or capabilities.

The traditional paradigm of closed innovation focuses on internal sources of ideas and technologies to solve problems. A firm may or may not use a technology developed within the firm depending on its fit with firm’s current business model. Such unused technologies would end up “on-the-shelf”, perhaps with an expectation

that they might become useful in the future. Similarly, when a firm that follows the traditional path to innovation needs a new technology, it relies on internal R&D to develop the technology. The firm must wait while the technology is being developed internally, and as a result, the firm to miss the market opportunity.

In an era of open innovation, managers are concerned with how to make products in a timely manner at the lowest cost. These two objectives often oppose each other. An externally developed technology may be available immediately, but the cost of acquiring it could be higher than waiting for an internally developed technology. Technology availability and sourcing costs need to be balanced with the timing and likely payback from pursuing an opportunity. Chesbrough (2003, 50) describes this as follows – “You would like to use as much of the surrounding knowledge as necessary to get the knowledge you need on a timely basis”. One interpretation of this statement is that a firm would usually create knowledge only if it is otherwise unavailable in the market. If another firm already has the knowledge, it might be quicker and less costly to acquire the knowledge from external source. Though the focus is often on technology licensing and start-up acquisition, there are many other ways to access external knowledge. For example, a firm could help to fund a university researcher, hire a graduate student of a professor whose specialization is in the area, or develop an R&D alliance with another firm or research organization.

By using all the sources of knowledge for innovation, firms can try to ensure that they consistently and continuously develop new products that satisfy the evolving needs of their customers. When a firm uses an open innovation strategy, decision making about which direction to proceed can be very challenging. Before describing a framework to help managers address this problem, we first describe an outcome, persistent innovation, which can help firms achieve a sustainable competitive advantage.

3. INNOVATION PERSISTENCE

An important source of competitive advantage is the capability to innovate persistently and efficiently. Le Bas & Latham (2006) define innovation persistence as occurring when a firm that has innovated during a given period also innovates in the following period. Deschryvere (2014) found that open innovation helps SMEs to achieve innovation persistence. Martínez-Ros and Labeaga (2009) and Clausen et al. (2011) both examined the effect of different innovation strategies and their role in firms’ achievement of innovation persistence. The firm may pursue an open innovation strategy to achieve innovation persistence at the lowest possible cost using a suitable strategy or method to execute open innovation.

Le Bas and Latham (2006, 2-4) characterized eight situations in which a firm may innovate persistently, sporadically, or not at all. They use two 2 x 2 matrices to illustrate their eight cases. Figure 1 is our extension of their categorization to a 3 x 3 case where the firm may innovate in field i or field j or not innovate in period t and t+1. Nine possible cases are shown in Figure 1.

Figure 1: Scenarios to capture firm’s innovation activities in two different technological fields (i and j) during two time periods (t and t+1)

Firm’s Action in Period t+1	Firm’s Action in Period t		
	Innovate in Field i	Innovate in Field j	Do not innovate
Innovate in Field i	Case 1	Case 4	Case 7
Innovate in Field j	Case 2	Case 5	Case 8
Do not innovate	Case 3	Case 6	Case 9

Source: Adapted from two figures in Le Bas and Latham (2006).

Case 1 describes the scenario where the firm innovates in the same technological field (i) during both periods of t and t+1. Case 2 represents innovation in two different technological fields i and j during two periods (t and t+1). In Case 3 the firm does not innovate during the next period (t+1) after innovating in technological field i during time period t. Similarly, Cases 4 through 6 represent similar actions but reverse combinations of technological fields. In Case 7, the firm does not innovate during period t, but it does innovate in the technological field i during the next period (t+1). Case 8 represents a scenario where the firm does not innovate during period t, but it innovates in technological field j during the next period. Finally, Case 9 represents a scenario where the firm does not innovate during both time periods (t and t+1).

Among these combinations, Cases 1, 2, 4 and 5 represent persistent innovation if only two periods are considered. Of these, Cases 2 and 4 represent “lateral entry” since the technological field changes between the two consecutive periods. Cases 3, 6, 7 and 8 represent scenarios with sporadic innovation. Case 9 represents a scenario where no innovation has occurred, describing the case of technological sterility (Le Bas and Latham, 2006).

While this representation of nine scenarios provides insight into the variety of innovation outcomes, it does not expose the interactions between technological invention and user need that underlie successful product or service innovation. For an innovation to become successful there must be a business model that connects a technology to an expressed or implicit user need.

The literature often equates the existence of technology with an innovation opportunity. However, the mere invention of a technology does not allow a firm to benefit from it. The innovator must find a way to appropriate the benefits of the investment in R&D; i.e., a business model will be needed to generate revenue. This can be through the market for a new product or service in which the technology is embedded, or the market for the technology itself (i.e., the inventor licenses or sells the technology for use by another firm).

An ongoing debate is whether a market need drives a technological innovation or whether a technological innovation informs the stakeholders to give rise to a market need (Von Tunzelman, 1995). We proceed with the assumption that both are possible. Some products are the result of market pull while technology push inspires others (Chidamber and Kon, 1994). Branzei and Vertinsky (2006) look at product innovation from dynamic capabilities perspective. Although they do not explicitly use the term of Open Innovation as coined by Chesbrough, the study explores the same phenomenon. Using Cohen and Levinthal (1990), Eisenhardt and Martin (2000) and Zahra and George (2002) as their theoretical foundation, Branzei and Vertinsky identify dynamic capabilities that the firm uses to: “acquire and assimilate external knowledge, transform it into novel, unique competencies and ideas, and then harvest these ideas by first generating and then effectively commercializing new or improved products (Branzei & Vertinsky, 2006, p. 79)”. In some cases, both market and technological forces shape a product or a service idea. It is important to have as much information as possible about customers, market needs and available technologies to decide how hard to push a technology and likely willingness of customers to adopt the product or the service. In this connection, firms will be benefited if they work on developing their market scanning capability (Alam et. al. 2013a) and technology scanning capability (Alam et. al. 2013b). In pursuit of the “best” strategy, managers may use open innovation or closed innovation or more suitably, a mix of both on a contingent basis keeping cost and other factors in mind.

An innovation may use an existing technology to meet an implicit customer need (i.e., create a new product or service using existing technology), or a new technology to meet an explicit customer need (i.e. re-create an existing product or service using new technology), or a new technology to meet an implicit customer need (i.e., create a new product or service using new technology). Figure 1 does not deal with these varying situations. In

addition, there might be more than one player involved in the process of realization of a given innovation. This aspect of the innovation process is also absent in Figure 1. To facilitate a better understanding of the innovation process and to capture the interactions between technological field and customer need, a new framework is proposed in the following section.

4. A FRAMEWORK TO MANAGE INNOVATION TO ACHIEVE PERSISTENCE

The proposed framework looks at the innovation effort of a single focal firm and illustrates the alternatives that management faces with respect to the innovation process. For a successful innovation, a confluence of resources must happen. These resources are many, but we consider only two – a technology and a trademark. We also simplify the situation by assuming technologies under consideration are patented (and that a firm may choose to license a technology to other firms if it wishes). Thus, a firm owns a technology (i.e., owns patent for it) and controls its use. We use the concept of “trademark” to indicate a product or a service that fulfills a user need. For our analysis, we consider a single trademark to map to a single user need (not vice versa) and a firm owns each of the trademarks.

A technology patent and a trademark are usually the two intellectual properties needed to create a successful innovation. From ownership perspective, these two resources may come from a single owner or two owners may contribute the two resources. When two owners contribute to the creation of a single innovation, it would be an instance of open innovation. Off course, we simplify the scenario by assuming that there would be only one technology (patent) used to implement an innovation. Even given our simplifying assumption, there are several ways in which open innovation can occur. Figure 2 and Figure 3 together present our framework.

Technology i and technology j are not substitutes. However, a new technology k may replace either of them. Trademark x and trademark y represent two responses to user needs and are owned by two different firms. The firms do not hold exclusive right to serve these two markets (i.e., no monopoly market situation exists). Therefore, a new trademark z could replace either of the trademarks (x or y) through market competition. The new trademark could also address a new user need. For the purpose of our discussion, we assume that at time t, technology i and trademark x are owned by the same firm, while technology j and trademark y are owned by other different firms. In Figure 3, the new technology k and the new trademark z are owned by the firm that also owns technology i and trademark x.

Before going into the details of the specific innovation situations, it is important to emphasize that this framework captures the possible pathways through which an existing firm may innovate, either by using a new trademark with a new or existing technology or by changing the way an existing trademark uses a new or existing technology. This framework captures the strategic choices that the firm’s management can consider by identifying the scenarios when a firm may choose open innovation.

Figure 2 shows interaction between two technologies (i and j) and two trademarks (x and y) at period t. The two technologies belong to different firms. Similarly, the two trademarks belong to different firms. The firm under consideration owns technology i and trademark x. Technology j may be owned by another firm or by any other entity (e.g., a university or private research lab). The second product or service (trademark y) is owned by a different firm. Some useful insight can be gained by looking at the four cases in Figure 2 from the perspective of the firm that owns technology i and trademark x.

Figure 2: Time t: two firms own two separate technologies and two separate trademarks creating four innovation cases (A, B, C and D)

Trademarks at time period t	Patents at time period t	
	Technology (i)	Technology (j)
Trademark (x)	Case A Type: CI	Case C Type: OI
Trademark (y)	Case B Type: OI	Case D Type: OI

Note: OI = Open Innovation; CI = Closed Innovation.

Any of the cases in period t may represent one of the three possible situations during an earlier state (i.e., period t-1, not shown). It could be an entry point for the firm during time period t; it could be a status quo situation when compared with the earlier period; or it could be reached from a different state through innovation during the earlier period, irrespective of the situation during the earlier period (t-1). These four cases represent four distinct situations for the firm in question during time period t.

In both Figure 2 and Figure 3, Case A represents a situation when the firm employs its own technology i in a product or service using trademark x it owns. In other words, both the resources used in the creation of the innovation are coming from the same owner. This is a case of closed innovation. The challenge for the manager of the firm in this situation is to maintain market share and possibly increase it. A firm in this situation may face two risks: a decline in the use of technology i and/or user need for the product or the service using trademark x being replaced by other trademarks.

Case B represents a situation where the firm rents the patent for technology i to a different firm to be used in a product or service using trademark y and it earns revenue from licensing fee. Here, the two resources needed to create the innovation are coming from two different owners. This is a case of open innovation. The focal firm shares the risk of introducing an innovation to marketplace with another firm. At the same time, it gives away some profit potential. This case also represents an opportunity for a new product or service development effort where the firm could potentially use a new trademark to replace the product or service using trademark y. In addition, the firm faces a threat since the owner of trademark y may choose to use other technologies in its product or service resulting in loss for the focal firm as it would lose the revenue stream from licensing technology i.

Case C represents a situation where the firm incurs a licensing cost for technology j which it does not own but uses in its product or service using trademark x through a licensing arrangement. Like Case B, the two resources needed to create the innovation come from two different sources. Thus, it is an example of open innovation. This case also represents an opportunity for the focal firm to develop a new technology on its own that will be used along with trademark x. The alternative technology could have better performance and/or lower cost, making it an attractive choice to replace technology j.

Case D represents an untapped market opportunity for the focal firm. Another firm has used trademark y in a product or a service using technology j owned by another entity. The focal firm is not involved in this market in any way. Given enough resources and strategic fit, the focal firm could decide to engage this market later.

Figure 3 captures the possible scenarios during the next time period t+1, where the four cases shown in Figure 2 might persist (i.e., maintain status-quo) or one of the additional five cases (E, F, G, H or A') might evolve through new innovation action. In Figure 3, the new technology k and the new trademark z are owned by the firm that also owns technology i and trademark x. Case E, G and A' evolve because of a closed innovation strategy. Case F and Case H evolve because of an open innovation strategy.

In Case E, the focal firm uses its existing technology *i* to create a product or a service using new trademark *z* after a successful product or service development effort. This situation could help to avoid a risk of Case A (i.e., product or service using trademark *x* becoming obsolete). The firm could also develop a product or a service using new trademark *z* to benefit from the opportunity that was available in Case B (i.e., to increase its revenue by moving from a technology licensing business model to a business model in which it uses its own technology to develop the new product or service using its own trademark). Whether moving from Case A or Case B, the firm must go through a successful new product or service development exercise to reach Case E. In the first scenario (moving from Case A to Case E), the firm stays in the closed innovation paradigm. However, in the second scenario (moving from Case B to Case E), the firm moves from open innovation to a closed innovation situation.

Figure 3: Time *t*+1: the two firms may continue to hold their previous positions and/or create an innovation to move to one of the new cases (Cases E, F, G, H, A')

Trademarks at time period <i>t</i> +1	Patents at time period <i>t</i> +1		
	Technology (<i>i</i>)	Technology (<i>j</i>)	New Technology (<i>k</i>)
Trademark (<i>x</i>)	Case A	Case C	Case G Type: CI
Trademark (<i>y</i>)	Case B	Case D	Case H Type: OI
New Trademark (<i>z</i>)	Case E Type: CI	Case F Type: OI	Case A' Type: CI

Note: OI = Open Innovation; CI = Closed Innovation.

In order to realize Case F, the focal firm must develop a new product or a new service using a new trademark *z* while the firm licenses technology *j* for use. This could happen in order to avoid the risk of changing user need in Case C or to enter an untapped market represented in Case D. Both these scenarios are cases of open innovation.

Case G could evolve if the focal firm develops a new technology to avoid paying licensing fee for a technology that was being used in trademark *x* in Case C. The focal firm starts using its own technology *k* in its existing product or service using trademark *x*. In this case, the firm moves from open innovation to a closed innovation scenario. This new technology *k* could have similar or better performance compared to technology *j*. Case G could also evolve because of moving from Case A. In this situation, the firm would try to avoid a risk present in Case A (i.e., declining demand for technology *i*). In this scenario, as the firm itself develops the new technology *k*, it remains an example of closed innovation.

Case H arises when the focal firm develops a new technology *k* and rents it to other firm so the other firm can use the technology in its existing product or service that uses trademark *y*. This could happen because of a move from either Case B or Case D. This case could become reality if the technology *k* has better performance, so the other firm replaces technology *i* with technology *k*. Alternatively in this case, the focal firm could engage the untapped market in Case D through technology licensing. Case H represents open innovation.

Case A' represents an innovation for the focal firm where the new technology *k* is used to develop a new product or a new service using its new trademark *z*. According to our assumptions, the same firm owns both the technology *k* and the trademark *z*. Therefore, it represents a case of closed innovation, like Case A.

5. IMPLICATIONS AND EXTENSION OF THE FRAMEWORK

Let us focus on the open innovation issues within the restrictions of our initial assumptions. At period t, four cases represent all the possible scenarios. Out of these four, Case A is a closed innovation situation; Case B, Case C and Case D are open innovation situations. From the situations during period t described in Figure 2, if the management of the firm is only worried about what it is doing during the next time period t+1 (i.e., not considering what others are doing on either the technology or the user need), the possibilities are presented in Figure 3. Here Cases E, G and A' represent closed innovation situations where the firm could move using their own resources. Cases F and H represent open innovation scenarios for the firm where it does not look beyond its already established relationships with other players. When there are more varieties in the environment, it is likely that cases F and H would offer more opportunities for the incumbent firm to benefit using open innovation.

Figure 3 illustrates several pathways through which managers in incumbent firms may use an open innovation strategy to innovate. The choices are limited since we have assumed that both the new technology k and new trademark z are owned by the focal firm (i.e., the same firm owns technology i and trademark x as in case A). However, if we add to this assumption (i.e., if we add a new technology k' and new trademark z' which are owned by other firms), there would be additional choices to consider. Figure 4 shows the extended framework with relaxed restrictions.

Even with the restricted assumptions, open innovation offers two strategic options for managers in the focal firm to consider. If the firm considers what others are doing in the marketplace as shown in Figure 4, there arises several new scenarios. In Figure 4, technology k' represents all other new technologies being developed by other players and trademark z' represents all other new trademarks being used by other players to develop a new product or a new service. In the extended framework, Case E' and Case G' describe two additional open innovation situations where the focal firm is directly involved. Case F' and Case H' represent new development resulting from open innovation efforts in other firms where the focal firm is not engaged.

These cases are important to be aware of since they represent market dynamics in competitive fields, which may have implications for the firm (e.g., product or service using trademark z' in Case F' may replace product or service using trademark x in Case C or technology k' in Case H' may replace technology i in Case B). Aside from the four new cases (E', F', G', H') in time period t+1 that evolve as a result of a lateral movement from situations in time period t, there are other situations (B', C' and D') involving other firms in time period t+1 that may develop irrespective of anything that existed during time period t.

Figure 4: The initial cases (A, B, C, D) during period t is replicated during period t+1 (A', B', C', D'); with possibilities of other situations (E', F', G', H')

Trademark at time period t+1	Patents in Technological Fields at time period t+1			
	Technology (i)	Technology (j)	New Technology (k)	New Technology (k')
Trademark (x)	Case A	Case C	Case G Type: CI	Case G' Type: OI
Trademark (y)	Case B	Case D	Case H Type: OI	Case H' Type: OI
New Trademark (z)	Case E Type: CI	Case F Type: OI	Case A' Type: CI	Case C' Type: OI
New Trademark(z')	Case E' Type: OI	Case F' Type: OI	Case B' Type: OI	Case D' Type: OI

Note: OI = Open Innovation; CI = Closed Innovation.

From a different perspective, Figure 4 illustrates the start of a new quadrant (Cases A', B', C', D') in time period t+1 that is similar to the initial four cases (A, B, C, D) during period t. However, these four new cases could happen irrespective of what existed during the earlier period. In addition, there are two more quadrants through lateral movements from the cases presented in Figure 2. These lateral movements could happen either on the technology axis or on the trademark axis. The new technology quadrant (cases G, H, G' H') results by keeping the trademarks from period t intact but changing the underlying technologies. The new trademark quadrant (cases E, E', F, F') results by keeping the technologies from period t intact but changing the trademarks. Another new quadrant (Cases A', B', C', D') results from changes in both the technologies and trademarks that existed during period t.

As indicated in Table 1, the strategic pathways involving open innovation offer both challenges and opportunities for the focal firm. Some outcomes are readily understandable as indicated in the table as either “Desired” or “Not desired”. However, there are many other possibilities, which are indicated as “Neutral” since the actual implication of these movements would depend on the context of the focal firm and many other competitive and environmental factors not considered in this article.

Table 1: Strategic pathways and their possible outcomes

Movement Direction	Strategic Implications	Outcome Type
Case A »» Case G	Update of technology	Neutral
Case A »» Case G'	Incur technology licensing cost	Not desired
Case A »» Case E	Update of trademark / Reuse of technology	Neutral / Desired
Case A »» Case E'	Move from revenue model to licensing model	Neutral
Case B »» Case H	Update of technology	Neutral
Case B »» Case H'	Loss of licensing revenue	Not desired
Case B »» Case E	Move from licensing model to revenue model	Neutral
Case B »» Case E'	Update of trademark / Reuse of technology	Neutral / Desired
Case C »» Case G	Save technology licensing cost	Desired
Case C »» Case G'	Update of technology	Neutral
Case C »» Case F	Update of trademark / Reuse of technology	Neutral / Desired
Case C »» Case F'	Loss of market share	Not Desired
Case D »» Case H	Untapped to income from technology licensing	Desired
Case D »» Case H'	Untapped to untapped	Neutral
Case D »» Case F	Untapped to technology licensing	Desired
Case D »» Case F'	Untapped to untapped	Neutral

6. CONCLUSION AND FUTURE RESEARCH

The innovation management framework presented in this article illustrates the number of innovation pathways that a manager may consider at the strategic level in order to achieve innovation persistence. The available choices during a given period may or may not depend on the innovation situation of the firm during the previous period. Based on the market situation, internal resources and other external factors, managers would choose one of the strategic pathways available. A key benefit of this framework is that it captures the interaction between technology field and user need that was absent in previous framework proposed by Le Bas & Latham (2006).

The contingency framework with its extension (described in Figure 2, Figure 3 and Figure 4) also captures the specific outcomes from each of the possible strategic pathways shown in Table 1. Some of the outcomes are desirable or some are not desirable, however, others are less clear as to their implications. These “neutral”

strategic pathways are more interesting to examine, as they are potentially more challenging for R&D managers. For example, Lakemond et al. (2016) examines how knowledge matching and project management play role in defining success of inbound open innovation. Managing open innovation networks carefully and community engagement can play promising role in open innovation success (Randhawa et al. 2016) and thereby help firms to achieve innovation persistence. Also, the success of technological innovation that is the main focus of this article is greatly influenced by the ongoing organizational innovation in the firms (Sapprasert and Clausen 2012). One of the weaknesses of this contingency framework is that it does not capture any such contextual situations (among many other possible situations) of individual firms. This additional information is required to assess whether the outcomes labeled “neutral” in the framework are desirable or not. Examining these neutral transitions with more theoretical analysis as well as with historical data of product and service development would be promising avenues of future research.

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AUTHOR'S BIOGRAPHY

Md Shahedul Alam is assistant professor in the Department of Management in School of Business and Economics at North South University. He obtained his PhD in Management Sciences from University of Waterloo in Ontario, Canada and completed his MSEE degree from Texas Tech University. He completed his bachelors from Bangladesh University of Engineering and Technology, Dhaka. Dr. Alam is involved in multiple outreach training activities offered by NSU to women entrepreneurs in collaboration with several local and international partners. In personal capacity, he also advises startups and mentors budding entrepreneurs. Prior to joining North South University, Dr. Alam has taught at University of Waterloo, McMaster University, Royal Military College of Canada and Wilfrid Laurier University in Canada and at Presidency University in Bangladesh.

Rod B. McNaughton is professor of entrepreneurship and academic director of the Centre for Innovation and Entrepreneurship at the University of Auckland School of Business. He has extensive experience developing entrepreneurial ecosystems and helping start-ups launch and grow gained as both an educator and advisor. An internationally recognized thought leader on entrepreneurship issues, Rod's scholarly research, focused on the rapid internationalization of knowledge-intensive new ventures, is published in more than 100 refereed journal articles and books. Prior to joining the University of Auckland, Rod was the Eyton Chair in Entrepreneurship and Director of the Conrad School of Entrepreneurship and Business at the University of Waterloo, which is widely recognized as Canada's most innovative university. He received his PhD in Marketing from Lancaster University, and his PhD in Economic Geography from Western University.

DETECTING EARNING MANIPULATION IN A DEVELOPING ECONOMY: AN EMPIRICAL STUDY USING BENEISH M-SCORE MODEL

Ms. Shirin Sharmin¹, Mr. Ashraful Arefin², Mohammad Arman³, PhD, FRM

ABSTRACT

Manipulation of financial statements entails the intentional and often ill-motivated manoeuvring of financial records towards a pre-determined target. In such cases, motivations include achieving budgetary targets and rewarding senior managers with generous rewards – a classic instance of conflict of interests. Such manipulations have lately become increasingly frequent and severe in Bangladesh. In this backdrop, the concerned board of directors is looking for improved surveillance techniques to better prevent and/or, detect and investigate possible financial frauds. In their quest for proactive approach against manipulation of financial statements, the board of directors look for warning signs and the present empirical study provides a profile of a company that is likely to manipulate its financial statements. In this study, data from 2016-2017 financial reports were utilized that correspond to 105 companies, excluding banks, non-banking financial institutions, insurance companies, and mutual funds listed at the Dhaka Stock Exchange (DSE) and the likelihood of accounting manipulation was quantified applying Beneish M-score model. It revealed that the maximum M-score was 7.06 and the minimum was -8.98, where higher scores indicate increased likelihood of accounting manipulation. Using a cut-off point of -1.78, twenty five companies were found to be suspected of accounting manipulation, while using a cut-off point of -2.22, fifty seven companies were found to be likely manipulator. Later a logistic model was developed to relate the likelihood of accounting manipulation to several company specific variables that were not explicitly considered in the Beneish M-score model. The findings are likely to benefit analysis of profiles of companies prone to accounting manipulation and thus could contribute to better corporate governance practices in emerging economies such as Bangladesh.

Keywords: manipulation of financial statements, Dhaka Stock Exchange (DSE), Beneish M-score.

INTRODUCTION

Fraudulent financial reporting stems mostly from mostly ill-motivated manoeuvring of financial records and such instances abound in both developed and developing economies. Earning manipulations have lately become increasingly frequent as well as sophisticated in emerging economies like Bangladesh. Lack of development in capital market could be attributed to the regulator, Securities and Exchange Commission (SEC) that may have failed to detect possible earning manipulators at the entry level, i.e., Initial Public Offering (IPO) or, at a later stage. Analysis on possible earning manipulation of companies and ways to detect those early could safeguard investors' interest. The primary objective of the current study is to profile companies prone to earning manipulation and thus help regulators such as SEC with vigilant evaluation of the quality of financial reports.

Before beginning any financial analysis, an analyst must clarify the purpose, context, and perspective first. General steps in this regard include developing an understanding of the company as well as its industry, which is followed by learning about management. Identifying significant accounting areas comes next and comparison the company's financial statements, disclosures, and accounting policies follow accordingly. Such

1. VP (Investments), LR Global Bangladesh Asset Management Company Ltd. ssharmin@lrglobalbd.com

2. Lecturer (adjunct), School of Business & Economics, North South University, Dhaka ashraful.arefin@northsouth.edu

3. Assistant Professor, School of Business & Economics, North South University, Dhaka mohammad.arman@northsouth.edu

comparison could be in the context of the company's historical record (time series analysis). Also, comparison could be drawn in the context of peer or, competitor companies (cross sectional analysis) by means of ratio analysis. While evaluating the quality of the financial reports, the analysts look for warnings signs of possible issues. Companies that operate in multiple sector – segments by geography or, by product, the analysis becomes more challenging since accounting line items may be shifted resulting in one segment showing strong performance while the consolidated results worsen. In addition to the qualitative steps described above, at the final stage of evaluation of financial reporting quality, the analyst could apply quantitative tools and techniques. Beneish M-score model is one such empirical model that gained popularity recently, esp. in the context of the developed nations (Beneish, 1999). The current study employs Beneish M-score model to ascertain quality of financial reporting and then profiles the companies prone to reporting manipulation via econometric model such as linear and discrete regression models. Such a two-step approach esp. in the context of a developing nation's capital market renders uniqueness to the study.

LITERATURE REVIEW

The Beneish model was developed by Professor Messod Daniel Beneish, who formulated several analytical ratios and variables in order to detect the possible occurrence of financial fraud. He proposed an eight variable model that utilizes data from financial statements of companies and produce a 'M-score' that shows the degree of earning manipulation. Over the years numerous analysts in industry and researchers in academia have applied the model to perform post facto analysis of corporate scandals in order to shedding more light to the dark world of earning manipulation. Bhabani and Amponsah (2017) enlisted the studies that used M-score while analyzing major corporate scandals involving earning manipulation and those include Impink's (2010) analysis of WorldCom scandal, Omar's (2014) analysis of Megan Media Holdings Berhad (MMHB) scandal, and Mahama's (2015) scrutiny of Enron Corporation. Drabkova (2014) found out that the Altman Z-score model (Altman, 1968) and Beneish models were superior compared to other quantitative models in detecting financial reporting frauds. Additionally, studies conducted by Ofori (2016), Aris et al (2013), and Warshavsky (2012) etc. advocated the use of Beneish model as a quantitative tool to evaluate prospects of manipulating earnings. However, other studies questioned the use of Beneish model as an ultimate detector of fraud. Cynthia (2005) argued that the Beneish model could not consistently discover problems in fraud in financial reporting. Ugochukwu and Azubuike (2013) showed that the traditional eight variable-model could not effectively evaluate the quality of financial statements. Amoa-Gyarteng (2014), opted for Altman Z-score model over Beneish model due to the former's efficiency in predicting bankruptcy and detecting FFR at Anglogoldashanti. The Beneish model has eight variables and these are found from information from financial statements (Beneish, 1999). The model is as follows:

$$\text{M-score} = -4.84 + 0.92 \cdot \text{DRSI} + 0.528 \cdot \text{GMI} + 0.404 \cdot \text{AQI} + 0.892 \cdot \text{SGI} + 0.115 \cdot \text{DEPI} - 0.172 \cdot \text{SGAI} + 4.679 \cdot \text{TATA} - 0.327 \cdot \text{LVGI}$$

Where,

- M-score = Score indicating probability of earnings manipulation
- DSR (days sales receivable index) = $(\text{Receivablest}/\text{Salest})/(\text{Receivablest-1}/\text{Salest-1})$.
The receivable days of the current and prior year are compared with the objective of revealing inflated revenue and change here could be indicative of inappropriate revenue recognition.
- GMI (gross margin index) = $\text{Gross margint-1}/\text{Gross margint}$.
A company with poor growth potential is more likely to manipulate and deterioration in margins could prompt companies to manipulate earnings.
- AQI (asset quality index) = $[1 - (\text{PPEt} + \text{CAt})/\text{TAt}]/[1 - (\text{PPEt-1} + \text{CAt-1})/\text{TAt-1}]$, where PPE is property, plant, and equipment; CA is current assets; and TA is total assets.
Change in the percentage of assets other than in PPE and CA could indicate excessive expenditure capitalization. AQI greater than 1 means the entity has either increased its intangibles or cost deferral,

which may indicate signs of earning manipulation.

- SGI (sales growth index) = $\text{Sales}_t / \text{Sales}_{t-1}$.

It measures current sales versus prior year and it may reveal company's intention to manage the perception of continuing growth by manipulating sales and earnings.

- DEPI (depreciation index) = $\text{Depreciation rate}_t - 1 / \text{Depreciation rate}_t$,

where $\text{Depreciation rate} = \text{Depreciation} / (\text{Depreciation} + \text{PPE})$.

Declining depreciation rates could indicate understated depreciation as a means of manipulating earnings.

- SGAI (sales, general, and administrative expenses index) = $(\text{SGA}_t / \text{Sales}_t) / (\text{SGA}_{t-1} / \text{Sales}_{t-1})$.

It compares current SG&A expenses with that of prior year and an increase in fixed SGA expenses may hint at decreasing administrative and marketing efficiency, which could result in companies' earning manipulation.

- TATA = Total Accruals to Total Assets.

Higher accruals can indicate earnings manipulation and thus this ratio signals to the extent management is involved in earning manipulation.

- LEVI (leverage index) = $\text{Leverage}_t / \text{Leverage}_{t-1}$, where Leverage is calculated as the ratio of debt to assets. Increasing leverage could influence companies to manipulate earnings.

Beneish (1999) developed the model in a way to make sure that the M-score is a normally distributed random variable with a mean of 0 and a standard deviation of 1.0. Higher M-scores (i.e., less negative numbers) indicate an increased probability of earnings manipulation. In order to classify the companies as potential manipulators, Beneish (1999) proposed that the cut-off value of M-score should be -1.78. Thus any score more than -1.78 would indicate a company more likely to be an earning manipulator. However, a cut-off score of -2.22 has also been proposed, which means a company that scores more than -2.22 is more likely to be an earning manipulator. Finally, it should be noted that Beneish M-Score is a probabilistic model and it cannot detect companies that manipulate their earnings with 100% accuracy.

METHODOLOGY

The current study utilized data from companies listed at Dhaka Stock Exchange and accordingly the M-scores were calculated using Beneish M-score. Later, a multiple linear regression (MLR) model was also developed using SPSS with the probability of earning manipulation (as obtained from M-score using cumulative normal table) as the dependent variables. The independent variables were extracted from companies' financial statements and those had not been used in Beneish model. Multiple linear regression is a popular statistical technique used to analyze relationship between a single dependent variable continuous in nature, here the probability of earning manipulation, and several independent or, predictor variables. These predictor variables are weighted by the MLR procedure to ensure maximal prediction and the weights indicate relative contributions of the predictor variables to the overall forecasting. Additionally, the weights, also called the coefficients, facilitate interpretation as to the impact of each variable in the process of forecasting.

Further, a binomial logistic regression model was developed using SPSS with the dependent variable to be whether the company is a likely earning manipulator or, not; companies with M-scores greater than -2.22 were classified as likely manipulators. The independent variables included data not already included in the Beneish model. Logistic regression is a special form of regression where the dependent variable is a discrete variable, not a continuous one. In this study we developed a binary logistic model where the dependent variable is a dichotomous one having values of 1 and 0 (1 if the company is a likely manipulator of financial statements; 0 other wise). The interpretation is similar to linear regression, although few differences exist.

DATA COLLECTION

The data to be fed into the Beneish model were collected from annual reports of companies listed in the Dhaka Stock Exchange (DSE). Beneish M-score model was primarily developed in the context of developed nations and studies concerning application of this model mostly center on those nations. Therefore, this study was conducted in the context of a developing nation such as Bangladesh’s capital market. Although more than 500 companies are listed in DSE, not all the companies have their data available via annual reports in company websites. Also, banks and non-banking financial institutions were excluded from analysis due to the fact that Beneish M-score model cannot readily be applied to financial companies. Finally, a total of 104 companies’ data corresponding to year 2016-2017 were collected and subsequently analyzed. Table 1 shows descriptive statistics of the variables available for modeling using M-score. Evidently, such a selection process renders convenience at the cost of selection bias. This is because companies that are prone to earning manipulation may not be listed at all to avoid disclosure. Also, a number of listed companies do not have financial statements available to public despite the mandate and these companies, if included, in the study could prove to be more likely to manipulate their financial statements.

TABLE 1

Descriptive Statistics of variables available to model the likelihood of earning manipulation

Variables	Min	Max	Range	Mean	Std. Dev.
Authorized Capital (Million BDT; as on 30/06/2017)	25.0	15,000.0	14,975.0	2,497.8	2,911.8
Paid-up Capital (Million BDT; as on 30/06/2017)	14.0	14,488.0	14,474.0	1,457.7	2,165.2
Net Profit (Million BDT; as on 30/06/2017)	-227.0	9,719.2	9,946.2	461.8	1,134.1
Years since incorporation (as on 30/06/2017)	5.0	104.0	99.0	25.1	15.0
Years since listing at DSE (as on 30/06/2017)	0.0	53.0	53.0	14.3	12.5
Total No of Directors in the Board (as on 30/06/2017)	2.0	19.0	17.0	6.1	2.5
No of Independent Directors in the Board (as on 30/06/2017)	0.0	5.0	5.0	1.8	0.8
Share holding % by Director/ Sponsor (as on 30/06/2017)	0.0	80.8	80.8	41.2	18.8
Share holding % by Govt. (as on 30/06/2017)	0.0	67.6	67.6	1.7	9.6
Share holding % by Institution (as on 30/06/2017)	0.0	51.8	51.8	16.7	9.9
Share holding % by Foreign Investor (as on 30/06/2017)	0.0	42.5	42.5	2.5	7.6
Share holding % by Public (as on 30/06/2017)	4.5	94.8	90.3	38.0	18.7
Short Term Loan (Million BDT; as on 30/06/2017)	0.0	19,676	19,676	1,079	2,268
Long Term Loan (Million BDT; as on 30/06/2017)	0.0	101,732	10,1732	1,612	9,991
Revaluation Reserve & Surplus w/o OCI (Million BDT; as on 30/06/2017)	-418.0	97,087	97,505	3,325	1,1369

DATA ANALYSIS

Data from more than 100 companies selected for the study were analyzed in two steps. First of all, the Beneish M-score model was applied to assess the quality of financial reporting and then using those empirical M-scores, the companies were profiled using econometric models, such as linear regression model as well as logistic regression model.

Application of Beneish M-score Model

The maximum M-score of the 105 companies were found to be 7.1 while the minimum was -9.0. The mean score was -2.1 and the standard deviation was 1.5. Figure 1 shows distribution of the Beneish M-scores across the sample of 104 companies selected for the study while Table 2 shows the average M-score across 86 companies from 6 major sectors. If a cut-off point of -1.78 is considered we could conclude that companies in food and allied sector are more likely to be earning manipulator compared to the rest in the study. However, if a cut-off point of M=-2.22 is considered, we could see that companies in engineering and IT sectors, too are more likely to fall in the category of earning manipulators.

TABLE 2

Summary of Beneish M-score and its components across major sectors

	Textile	Pharmaceuticals	Engineering	Food & Allied	Fuel & Power	IT
DSRI	1.18	1.35	1.23	1.42	1.07	0.95
GMI	0.98	0.83	0.69	1.06	0.94	1.26
AQI	1.00	0.99	0.98	1.01	1.05	1.00
SGI	1.04	1.06	1.13	1.09	1.24	1.38
DEPI	0.99	0.94	1.04	0.95	1.04	0.98
SGAI	1.10	1.14	1.01	0.97	3.00	0.83
TATA	-0.04	-0.04	0.05	0.07	-0.02	0.04
LVGI	1.09	1.01	1.05	1.12	1.01	1.15
No. of obs	28	11	21	8	10	8
Avg. M-score	-2.5	-2.4	-2.1	-1.71	-2.64	-1.91

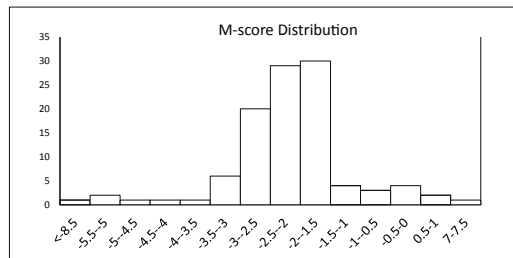


Figure 1. Distribution of Beneish M-score

Further, according to the ‘gross margin index’ (GMI), both IT and food & allied industries’ average scores are indicative of earning manipulation. According to ‘asset quality index’ (AQI), any value larger than 1 may represent the tendency of avoiding expenses by capitalizing and deferring costs to preserve profitability. Food & allied sector as well as fuel & power sector should get more scrutiny in this regard. Almost all the companies in the major sectors analyzed showed that ‘sales growth index’ (SGI) were more than 1 and arguably, it showed good health of the industry involved. However, such a positive growth could also put pressure on managers in

maintaining a company's positions, achieving earnings targets that may lead to earning manipulation in near future. Engineering and fuel & power sector involve capital machineries worth millions of taka and 'depreciation index' (DEPI) there shows alarming signs. Any DEPI value greater than 1 represents a declining depreciation rate that can increase earnings. Hence, analysts should be cautious while analyzing the financial reports in the concerned companies. A 'sales, general, and administrative expenses index' (SGAI) value more than 1 represents a disproportionate increase in sales compared to SGA and it may reveal companies' intention to manage the perception of continuing growth by manipulating sales and earnings. As the table reveals, high values of SGAI in fuel & power, textile, and pharmaceutical companies could be an indicator of earnings manipulation. Finally, companies in textile, engineering, food & allied, and IT sectors showed a 'leverage index' (LVGI) of more than 1 and this may indicate to motivation for manipulation of earnings.

Tables 3 & 4 show a relatively more general summary of the companies' M-scores as well as the eight components of the model. The companies are grouped following a cut-off point of -2.22 grouped into two categories – an M-score >-2.22 considered to be likely earning manipulator while an M-score <-2.22 considered to be less likely to fall into the group of earning manipulators.

TABLE 3

Average Beneish M-score of companies less likely to manipulate earning

<i>Sector</i>	<i>Count</i>	<i>Average M-Score</i>
Cement	3	-2.67
Ceramics	1	-2.68
Engineering	6	-3.05
Food & Allied	3	-2.55
Fuel & Power	5	-3.90
IT	3	-2.54
Miscellaneous	2	-2.59
Paper & Printing	1	-2.55
Pharmaceuticals	6	-2.96
Textile	18	-2.99

The two Tables 3 and 4 also reveal that distribution of companies that are less likely to be earning manipulators are negatively skewed having lower peak and less dispersion around the mean unlike the other group. Further the components values are relatively lower in the companies that are less likely to be earning manipulators.

TABLE 4

Average Beneish M-score of companies likely to manipulate earning

Sector	Count	Average M-Score
Cement	3	-2.00
Ceramics	2	-1.55
Engineering	15	-1.72
Food & Allied	5	-1.20
Fuel & Power	5	-1.39
IT	5	-1.53
Jute	1	-0.44
Miscellaneous	6	-0.26
Pharmaceuticals	5	-1.74
Textile	10	-1.63

Development of Econometric Model

Once M-scores were calculated those were regressed against variables corresponding to company’s sector, size (in terms of authorized capital, paid up capital, net profit), age (in terms of age since incorporation and since listing), shareholding structure, board composition, outstanding loan – both long term and short term, and revaluation reserve etc. A multiple linear regression was developed first with probability of earning manipulation to be the dependent variable. Earning likelihood was measured using the M-score and normal probability table. Later a logistic regression model was developed to further facilitate profiling a likely earning manipulator.

TABLE 5

Multiple Linear Regression Estimation of ‘the likelihood of earning manipulation’

Variable Description	Estimated Parameter	t-stat	p-value
Intercept	8.97	-1.82	0.07
% shares held by Govt (% shareholding by government)	0.59	4.02	<0.01
No of years since listing at DSE	-0.32	-1.88	0.06
Textile (1, if the sector is textile; 0 otherwise)	-5.99	-1.71	0.09
Engineering (1, if the sector is Engineering; 0 otherwise)	-5.96	-1.57	0.12
Revaluation reserve & surplus w/o OCI, in million BDT	-0.0002	-1.53	0.13
No of Independent directors in the board	-2.18	-1.29	0.20
Yr since incorporation (no of years since incorporation)	0.32	2.31	0.02
Number of Observations= 104			
Adjusted R Square = 18.2%			

Dependent variable: Probability of earning manipulation (as obtained from M-score)

Table 5 shows the estimation of multiple linear regression model with probability of earning manipulation that was calculated from Beneish M-score. The model has a poor goodness-of-fit and at $\alpha=0.10$, the variables such as ‘engineering’, ‘revaluation reserve’, and ‘no of independent directors in the board’ were found to be statistically insignificant. The model also reveals a positive relationship between probability of earning manipulation and variables such as ‘% shares held by govt.’ and no of years since incorporation. In the context of an emerging economy like Bangladesh, the lack of good governance could explain the positive relationship between extent of government ownership and likelihood of earning manipulation. On the other hand, ‘yr since listing’ and ‘textile’ variables are found to be negatively related to probability of earning manipulation. A company’s age since incorporation may increase the chance of earning manipulation, but once it gets listed, increased pressure of corporate governance should make it less likely to manipulate financial statement. This may explain the signs of variables – age since incorporation and age since listing.

TABLE 6

Binary Logistic Regression Estimation of ‘the likelihood of earning manipulation’

Variable Description	Estimated Parameter	Wald-stat	p-value
Intercept	-0.93	1.45	0.23
No of years since listing	-0.078	6.29	0.012
%shareholding by general public	0.02	2.39	0.12
Amount of short term loan outstanding in million BDT	0.00026	2.75	0.097
No of years since incorporation	0.051	3.31	0.069
Amount of long term loan outstanding in million BDT	-0.00032	0.234	0.63
Net profit in million BDT	-0.00014	0.197	0.657

Number of Observations = 104			
Cox & Snell R Square = 0.141			
Nagelkerke R Square = 0.188			
Dependent variable: 1, if earning manipulator; 0 otherwise			

Table 6 shows the estimation of binary logistic regression model with dependent variable that takes value of 1 if the company is a potential earning manipulator or, 0 otherwise. The cut-off value was taken to be -2.22. A total of 57 companies were found to fall into the category of likely earning manipulator. The resulting model reveals that variables such as % shareholding by general public, amount of long term loan and net profit in million BDT are statistically insignificant at $\alpha=0.10$. The model's goodness-of-fit can be described by Cox & Snell R Square (14.1%) and Nagelkerke R Square (18.8%). Among the statistically significant variables the relationship between likelihood of earning manipulation and age since incorporation as well as age since listing seem to follow the same pattern found in multiple regression model earlier. Additionally, the positive sign of the coefficient of 'Short Term Loan' indicates that higher level of short term loan increases the chance of a company's being earning manipulator.

CONCLUSION

Beneish M-score is one of many quantitative tools to supplement the qualitative techniques to assess the quality of financial reporting. The eight component-model sought to identify companies that are likely to manipulate earning and have long been used by both corporate analysts and academic researchers worldwide. A cross sectional analysis among more than 100 companies listed in Dhaka Stock Exchange (DSE) revealed that around half of those are likely manipulators using an M-score cut-off point of -2.22. Further analysis was carried out to facilitate profiling those with respect to characteristics not readily included in Beneish M-model. The multiple linear regression model with likelihood of earning manipulation as the dependent variable pointed to a number of statistically significant variable involving age, extent of government ownership, and sector of the company. Also, the binary logistic regression model revealed few statistically significant variables such as age, short term loan, and percentage of shares owned by general public. Interestingly, both models indicated to a similar pattern of relationship between age and likelihood of earning manipulation. The relationship between likelihood of earning manipulation and age since incorporation was found to be positive, while the relationship between age since listing at DSE and likelihood of earning manipulation was found to be negative. This pattern might have suggested that once a company getting mature it tends to manipulate its earning but, once it gets listed the likelihood decreases possibly, due to increased disclosure.

Findings from such study should help the regulators remain vigilant regarding possible manipulation of financial statements of certain companies. With limited resources, the regulators such as Securities and Exchange Commission (SEC) strive to detect earning manipulation of listed companies to safeguard investors' interest. Studies similar to the current one could help regulators formulate guidelines, i.e., for internal use, to sample certain companies for in-depth analysis and focus their limited resources more prudently and with more effects. Besides, such studies could also help general investors profile suitable companies to invest and to avoid investing in companies prone to earning manipulation.

The study has been a relatively unique effort to detect possible earning manipulations using empirical method and then profiling those companies by econometric models such as linear regression and logistic regression models. The study could extend its scope by including data corresponding to multiple years. Moreover, the Beneish model needs to be calibrated using data from Bangladesh or, like nations before applying to categorize on the basis of vulnerability to earning manipulation. In order to further improve the current study, the problem of reporting bias as well selectivity bias should have been taken care of in future. Due to poor state of corporate

governance, the financial data of only prominent and well established firms are available. Once the sample size increases to include the poor performing companies more lights could be shed on quality of financial reporting. In addition, inclusion of non-listed companies could enrich the sample and facilitate more in-depth analysis.

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APPENDIX

TABLE A1

Beneish M-score along with components for 105 companies listed in DSE (2016-17)

Ticker	Sector	M-Score	DSRI	GMI	M-Score Co-efficient					
					AQI	SGI	DEPI	SGAI	TATA	LVGI
SQURPHARMA	Pharmaceuticals	-4.37	1.49	0.99	1.00	1.10	1.11	1.04	-0.54	0.74
RENATA	Pharmaceuticals	-2.32	0.88	1.01	0.98	1.13	0.93	1.00	0.02	0.79
BXPHERMA	Pharmaceuticals	-2.31	1.08	1.00	1.00	1.20	1.07	0.99	-0.02	1.03
ACMELAB	Pharmaceuticals	-1.92	1.41	0.95	1.00	1.07	1.08	1.00	0.03	0.98
PHARMAID	Pharmaceuticals	-1.64	0.96	0.95	1.00	1.18	0.97	0.98	0.15	0.87
ACI	Pharmaceuticals	-1.84	1.23	0.97	1.00	1.22	1.05	1.07	0.07	1.24
ACTIVEFINE	Pharmaceuticals	-2.60	0.96	0.94	1.00	1.12	0.93	1.17	-0.02	1.11
AMBEEPHA	Pharmaceuticals	-2.97	0.96	0.99	1.00	1.03	0.34	0.98	-0.08	1.01
SALVOCHEM	Pharmaceuticals	-1.71	2.18	0.88	0.89	0.98	1.06	1.41	-0.01	1.26
IBNSINA	Pharmaceuticals	-1.59	1.57	1.00	0.99	1.15	0.86	0.99	0.05	1.00
SQURETEXT	Textile	-5.38	1.25	1.40	1.05	0.94	1.23	1.09	-0.68	1.36
ARGONDNIM	Textile	-2.42	1.04	1.02	1.00	1.01	1.00	1.00	-0.01	0.88
ENVOYTEX	Textile	-2.08	0.90	1.06	1.14	1.28	0.83	1.01	0.04	1.07
APEXSPIN	Textile	-2.82	0.93	1.01	1.00	0.95	1.13	0.99	-0.06	0.95
DELTASPIN	Textile	-2.42	1.15	0.98	0.92	1.00	1.03	0.88	-0.01	1.00
DSSL	Textile	-2.10	0.98	0.99	1.03	1.22	0.47	1.07	0.05	0.92
FAMILYTEX	Textile	-2.13	1.90	1.58	0.99	0.60	1.14	2.88	-0.01	1.25
AL_HAJTEX	Textile	-2.22	1.42	0.78	1.00	0.79	0.87	1.22	0.05	0.98
ANLIMAYARN	Textile	-2.55	0.97	1.15	1.00	0.83	1.13	1.23	0.01	0.98
ETL	Textile	-2.74	0.90	0.98	0.94	1.07	1.03	0.99	-0.04	1.02
FEKDIL	Textile	-2.07	0.99	1.22	0.99	1.04	0.91	0.91	0.05	0.86
GENNEXT	Textile	-2.61	0.93	0.77	1.08	1.09	1.06	1.30	-0.02	0.78
HFL	Textile	-2.68	0.88	0.97	1.00	0.96	0.69	1.02	0.00	1.03
HRTEX	Textile	-3.25	0.63	1.04	1.00	1.12	0.91	0.98	-0.12	0.98
HWAWELLTEX	Textile	-2.82	0.92	1.00	1.00	0.95	0.79	0.89	-0.07	0.73
RAHIMTEXT	Textile	-0.96	2.88	1.04	1.00	1.14	0.91	1.16	-0.05	1.18
MATINSPINN	Textile	-0.46	2.35	1.25	1.22	1.50	0.64	0.88	0.05	1.27
NURANI	Textile	-2.48	0.88	1.00	0.98	1.06	0.72	1.37	0.01	0.69
PTL	Textile	-4.50	0.62	1.51	0.93	1.66	1.04	0.62	-0.54	1.10
REGENTTEX	Textile	-1.61	2.08	1.14	0.95	0.53	1.62	1.27	0.07	1.41
RNSPIN	Textile	-3.95	0.62	-0.73	1.00	1.52	1.13	0.68	-0.11	1.64
SAIHAMCOT	Textile	-1.66	1.35	1.04	1.00	1.25	1.00	0.85	0.05	1.06
SAIHAMTEX	Textile	-2.54	1.10	0.79	1.00	0.93	1.01	1.16	0.01	1.08
SHASHADNIM	Textile	-2.35	0.92	1.01	0.99	1.11	1.06	1.15	0.03	1.08
SHEPHERD	Textile	-1.27	1.25	0.95	1.00	0.98	0.99	1.03	0.22	1.02
TOSRIFA	Textile	-3.45	0.72	0.88	0.71	0.85	0.99	1.20	-0.01	2.02
ZAHINSPINN	Textile	-1.92	1.38	0.83	1.09	1.09	1.24	0.76	0.03	1.08
ZAHINTEX	Textile	-2.57	1.21	0.86	1.00	0.75	1.14	1.27	0.02	1.10
CONFIDCEM	Cement	-2.56	1.12	1.25	0.87	1.00	0.97	1.41	-0.03	1.12
HEIDELBCEM	Cement	-2.24	1.08	1.30	1.00	0.92	0.94	1.14	0.03	1.01
LHBL	Cement	-2.20	1.11	1.61	1.00	1.01	0.97	1.58	0.01	1.22
MEGHNACEM	Cement	-3.21	1.61	1.02	0.97	0.94	0.93	5.72	-0.09	1.00
MICEMENT	Cement	-1.83	1.51	1.08	0.87	1.05	1.13	1.16	0.05	1.18
PREMIERCEM	Cement	-1.96	1.15	1.29	0.99	1.10	1.03	0.82	0.03	1.06
AMCL(Pran)	Food & Allied	-2.52	1.04	1.02	1.00	1.14	1.05	1.06	-0.05	0.97
APEXFFODS	Food & Allied	-1.79	1.64	0.79	1.00	0.81	1.01	1.01	0.09	1.05
FINEFOODS	Food & Allied	-1.74	0.93	1.54	1.02	1.37	1.06	0.76	0.06	1.44
GEMINISEA	Food & Allied	0.55	2.79	1.01	1.00	1.22	0.75	0.93	0.26	1.02
GHAIL	Food & Allied	-1.10	2.36	1.00	1.01	1.07	0.58	0.90	0.04	1.32
NTC	Food & Allied	-2.48	0.68	1.18	1.00	1.03	1.14	1.05	0.03	0.97

Ticker	Sector	M-Score	DSRI	GMI	M-Score Co-efficient					
					AQI	SGI	DEPI	SGAI	TATA	LVGI
OLYMPIC	Food & Allied	-1.91	0.93	1.01	0.99	1.03	1.06	1.00	0.13	1.00
RDFOOD	Food & Allied	-2.67	0.98	0.92	1.03	1.08	0.97	1.05	-0.03	1.20
FUWANGCER	Ceramics	-1.35	2.52	0.74	0.90	0.56	1.06	1.04	0.11	1.66
RAKCERAMIC	Ceramics	-2.68	0.76	1.07	1.01	1.25	0.90	0.96	-0.05	0.99
SPCERAMIC	Ceramics	-1.75	1.66	0.97	1.00	1.05	0.98	0.99	0.02	0.98
ATLASBANG	Engineering	-0.31	4.45	-0.02	1.00	0.59	1.21	1.79	0.00	1.02
AFTABAUTO	Engineering	-1.93	0.76	1.12	1.09	1.56	1.05	0.77	0.04	1.17
APOLOISPAT	Engineering	-1.93	1.12	1.16	1.01	1.08	1.01	0.98	0.07	1.10
AZIZPIPES	Engineering	-3.29	0.90	0.69	1.00	1.07	1.16	1.10	-0.13	0.99
BBS	Engineering	-1.64	1.13	1.02	1.01	1.05	1.33	0.75	0.12	0.98
BBSCABLES	Engineering	-1.89	0.85	1.01	1.00	1.36	1.06	0.88	0.07	0.93
BDAUTOCA	Engineering	-2.42	1.16	0.81	1.00	1.14	0.77	0.83	-0.03	0.92
BDLAMPS	Engineering	-2.24	1.01	0.99	1.00	0.99	0.86	1.00	0.05	0.86
DESHBONDHU	Engineering	-0.73	1.21	1.30	1.00	1.30	0.98	1.03	0.27	1.46
GOLDENSON	Engineering	-5.21	1.38	-4.30	0.99	0.76	0.96	1.28	0.01	1.20
GPHISPAT	Engineering	-2.16	1.17	0.95	0.81	1.36	1.09	0.99	-0.01	1.14
IFADAUTO	Engineering	-1.69	0.80	0.98	1.00	1.48	0.57	0.67	0.12	1.07
KDSALTD	Engineering	-2.21	1.20	1.06	1.05	0.99	1.11	0.96	0.01	1.11
NAHEEACP	Engineering	-1.93	0.87	0.97	1.00	1.31	0.97	1.04	0.08	0.88
NAVANACNG	Engineering	-2.34	1.13	1.02	0.75	1.00	1.63	1.11	0.04	1.39
NPOLYMAR	Engineering	-2.78	1.26	1.01	0.93	1.06	1.01	0.98	-0.11	1.13
OIMEX	Engineering	-2.15	1.19	1.00	1.02	1.07	0.73	1.01	0.02	0.95
OLYMPIC	Engineering	-1.91	0.93	1.01	0.98	1.03	1.14	1.00	0.13	1.00
RANFOUNDRY	Engineering	-1.80	1.29	1.01	0.98	1.12	1.00	1.08	0.06	0.87
RSRMSTEEL	Engineering	-1.45	1.00	0.72	1.00	1.39	1.07	0.89	0.17	0.97
WSMSHIPYARD	Engineering	-2.09	0.92	0.96	0.94	1.06	1.10	0.96	0.09	0.94
BARAKAPOWER	Fuel & Power	-1.78	1.21	1.18	1.00	1.18	1.11	0.80	0.04	0.99
BDWELDING	Fuel & Power	-2.04	2.07	1.16	1.00	0.46	0.47	1.36	0.01	1.22
CVOPRL	Fuel & Power	-8.98	0.00	-0.24	1.00	0.04	1.02	21.63	-0.10	1.23
DESCO	Fuel & Power	-2.67	1.07	0.82	0.97	1.07	1.10	1.05	-0.04	1.02
DOREENPWR	Fuel & Power	0.82	0.84	1.21	1.42	4.33	1.44	0.31	0.01	1.02
GBBPOWER	Fuel & Power	-2.12	1.43	1.15	1.00	1.02	0.94	1.09	-0.02	1.07
KPCL	Fuel & Power	-1.81	1.31	1.19	1.00	0.90	0.98	0.40	0.05	0.88
LINDEBD	Fuel & Power	-2.36	1.08	0.99	1.00	1.16	1.15	1.09	-0.03	0.79
POWERGRID	Fuel & Power	-2.47	0.96	0.98	1.11	1.13	1.20	1.01	-0.03	0.99
SPCL	Fuel & Power	-3.01	0.77	0.93	0.95	1.08	0.95	1.23	-0.07	0.82
AAMRANET	IT	-0.27	0.46	2.56	0.86	2.86	0.87	0.42	0.07	1.46
AAMRATECH	IT	-2.41	1.07	1.06	1.00	1.05	0.88	0.92	0.00	1.17
AGNISYSL	IT	-1.96	1.28	1.10	1.00	0.97	1.11	0.80	0.03	0.92
BDCOM	IT	-1.65	1.32	1.45	0.99	1.17	0.88	0.87	0.04	1.12
DAFODILCOM	IT	-1.94	1.31	0.81	1.01	1.05	1.06	1.05	0.08	1.14
INTECH	IT	-1.83	0.52	1.08	1.16	1.67	0.87	0.63	0.10	1.46
ISNLTD	IT	-2.45	0.81	1.05	1.00	1.10	1.11	0.90	0.01	0.95
ITC	IT	-2.76	0.81	0.99	0.98	1.16	1.02	1.07	-0.05	1.01
NFML	Miscellaneous	-1.82	1.25	0.99	1.00	1.02	0.77	0.93	0.09	1.02
MIRACLEIND	Miscellaneous	-1.70	1.73	0.94	1.00	1.02	0.49	0.87	0.04	1.07
SAVAREFR	Miscellaneous	-2.67	0.92	1.03	1.00	1.17	1.08	1.01	-0.06	1.04
USMANIAGL	Miscellaneous	7.06	11.23	1.16	0.99	0.96	1.04	1.10	0.03	1.12
SINOBANGLA	Miscellaneous	-2.52	0.95	0.98	1.00	1.11	0.98	0.96	-0.02	0.96
AMANFEED	Miscellaneous	-2.21	0.94	1.04	1.00	1.11	1.36	1.13	0.04	1.07
HAKKANIPUL	Miscellaneous	-0.88	2.26	0.88	0.94	1.25	1.02	0.74	0.07	1.20
BEXIMCO	Miscellaneous	-2.00	1.11	1.19	1.00	1.05	0.87	0.96	0.05	1.01
NORTHERN	Jute	-0.44	1.22	0.93	1.17	1.57	0.67	0.74	0.28	1.11
KBPPWBIL	Paper & Printing	-2.55	1.30	0.93	1.00	0.68	1.02	1.20	-0.01	0.87
BXSYNTH	Pharmaceuticals	-3.19	2.12	-0.52	1.00	0.44	0.96	1.90	-0.05	1.14

TABLE A2

Summary Beneish M-score components for companies less likely to be earning manipulator

	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
Count	48	48	48	48	48	48	48	48	48
Mean	-2.98	1.01	0.80	0.98	1.02	1.00	1.60	-0.06	1.04
Standard Error	0.16	0.04	0.12	0.01	0.03	0.03	0.44	0.02	0.03
Median	-2.60	0.97	0.99	1.00	1.06	1.01	1.05	-0.03	1.01
Standard Deviation	1.14	0.31	0.85	0.06	0.24	0.18	3.03	0.15	0.23
Variance	1.29	0.09	0.72	0.00	0.06	0.03	9.21	0.02	0.05
Kurtosis	16.61	4.60	28.46	9.34	6.57	5.88	42.81	10.56	7.44
Skewness	-3.68	0.44	-4.99	-2.58	-1.28	-0.31	6.44	-3.24	2.10
Range	6.76	2.12	5.81	0.39	1.62	1.30	21.02	0.73	1.33
Minimum	-8.98	0.00	-4.30	0.71	0.04	0.34	0.62	-0.68	0.69
Maximum	-2.22	2.12	1.51	1.11	1.66	1.63	21.63	0.05	2.02

TABLE A3

Summary of Beneish M-score components for companies likely to be earning manipulator

	M-Score	DSRI	GMI	AQI	SGI	DEPI	SGAI	TATA	LVGI
Count	57	57	57	57	57	57	57	57	57
Mean	-1.45	1.59	1.07	1.01	1.19	0.98	0.99	0.07	1.10
Standard Error	0.17	0.19	0.04	0.01	0.07	0.03	0.05	0.01	0.02
Median	-1.81	1.23	1.01	1.00	1.08	1.01	0.98	0.05	1.07
Standard Deviation	1.32	1.46	0.31	0.09	0.54	0.22	0.35	0.07	0.17
Sample Variance	1.74	2.14	0.09	0.01	0.29	0.05	0.12	0.00	0.03
Kurtosis	31.45	34.59	11.55	8.95	21.24	1.13	14.44	2.79	1.11
Skewness	5.11	5.41	1.46	2.02	3.99	-0.18	2.82	1.53	1.09
Range	9.27	10.77	2.58	0.61	3.87	1.15	2.57	0.34	0.80
Minimum	-2.21	0.46	-0.02	0.81	0.46	0.47	0.31	-0.05	0.86
Maximum	7.06	11.23	2.56	1.42	4.33	1.62	2.88	0.28	1.66

AUTHOR'S BIOGRAPHY

Shirin Sharmin is the VP (Investments) and Head of Research at LR Global Bangladesh Asset Management Company Ltd. She is pursuing PhD at Bangladesh University of Professionals (BUP). She holds an MBA (Finance) from Institute of Business Administration (IBA) and an MBA (Marketing) from Faculty of Business Studies, University of Dhaka. A graduate civil engineer from BUET, she also holds a Masters in Economics from Dhaka School of Economics. Her research interests include financial reporting and capital market analysis.

Ashraful Arefin is a Lecturer (adjunct) of Accounting at Independent University, Bangladesh. He also teaches accounting courses at North South University, Bangladesh. He earned both his Bachelor and Masters Degree in Accounting from University of Technology Sydney (UTS), Australia. He worked in both academia and corporate sector in Australia. Research interests include financial reporting and corporate governance.

Mohammad Arman is an Assistant Professor at Department of Accounting and Finance, North South University, Bangladesh. He received his PhD and Masters Degree from Purdue University, IN. He is a certified FRM and holds an MBA (Finance) from Institute of Business Administration (IBA), University of Dhaka. His research interests include infrastructure finance, capital market analysis, banking, and risk management.