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Exploring the differential impact of environmental sustainability, operational efficiency, and corporate reputation on market valuation in high-tech-oriented firms

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ABSTRACT

In this paper, we explore the strategic significance of three factors – operational efficiency, measured by data envelope analysis; environmental sustainability, represented by *Newsweek*'s Green Rankings; and corporate reputation, based on *Fortune*'s list of most admired companies in the world –and their relationship to the market valuation of high-tech-oriented companies. In particular, we estimate the impact of these factors on Tobin's Q, which represents the overall technological and market strength of a firm as a forward-looking market performance reflecting stakeholders' expectations of the value of a firm. Using complementary regression and a neural network approach, we find that operational efficiency has the largest impact on Tobin's Q, followed by corporate reputation and environmental sustainability. In addition to its findings on the relative importance of these strategic factors, the paper's findings also suggest that operational efficiency, which reflects efficiency-driven best practice and managerial proficiency, is a crucial determinant of the market-facing measure of Tobin's Q in high-tech industries. Using models to estimate the interaction between these variables, we find that environmental sustainability and its interaction with reputation has the largest synergistic effect on Tobin's Q, followed by the interaction of reputation and operational efficiency. Our results show that the interaction of unique performance metrics can provide insights that differ from those derived from models for which the interaction is not included. Furthermore, the discovery of varying impact patterns under distinguishable capabilities is another significant finding of the paper.

1. Introduction

With the ever-increasing pressure to become sustainable in today's rapidly changing and competitive economy, businesses are becoming more concerned about the prudent utilization of scarce resources. Accordingly, balancing the allocation of scarce resources is considered a precondition for firms to achieve a competitive advantage, and at the same time, promises greater strategic success for the firms, especially in the high-tech-oriented industries. Indeed, effective allocation of scarce resources, besides being a crucial aspect of managerial decision making for superior performance, can be a source of creating capabilities for sustained competitive advantages (Cohen and Maritan, 2011; Kawakami et al., 2015; Wade and Hulland, 2004). Capabilities, commonly conceived as the ability of the firm to transform itself, can be interpreted as repeatable patterns of good practices that enhance a firm's value through better utilization of committed resources during product offerings. Accordingly, more capable firms retain a higher level of efficiency in utilizing key resources, as compared to their less capable peers, and they accomplish their intended tasks with a certain degree of sufficiency (Dutta et al., 2005; Mu, 2017; Teece, 2014; Wade and Hulland, 2004). There are asymmetric returns on the equitable resources among firms with varying levels of capabilities.

In fact, high-tech-oriented firms operating in a rapidly changing competitive market are required to cope with unpredictable customer demands and time-sensitive product offerings through a two-pronged approach of refining standard operating procedures and imbuing technology innovation. Thus, capabilities that support '*doing things right*' are deemed insufficient; indeed, creating additional capabilities for '*doing right things*' is becoming a management mantra (Teece, 2014). However, given the complex decision-making processes in allocating limited firm resources, high-tech firms should be capable of testing the dynamic interplay of key resources and their potential effects on firm

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performance from a benchmarking perspective (Mohr et al., 2010; Sridhar et al., 2014). In this regard, discovering the distinctive characteristics of firms in terms of the relative influence of key resources and their corresponding impact on firm performance should be a crucial task for establishing the strategic competencies to enhance the capabilities of firms. The extant literature, however, contains few relevant empirical studies on this research agenda partly due to a lack of sound methodological foundations. Consequently, efforts to further scrutinize the relative contribution of strategic factors in firm performance under different levels of capabilities have not been reported thus far even though it is an intriguing research agenda for both academicians and managers alike. Indeed, it is still a challenging issue to identify which strategic factors are of relative importance in enhancing a firm's distinctive capability.

To address this important but under-covered gap in the research agenda, this paper explores the impact of key strategic factors on market-based firm performance, which includes environmental sustainability (hereafter referred to as a "green score"), represented by *Newsweek*'s Green Rankings; corporate reputation; operational efficiency; and other strategic factors, including research and development (R&D). The selected strategic factors cover crucial but still emerging business dimensions, including environmentally sound practices and technological innovation, as well as internal best practices and the external attractiveness of a firm. Indeed, the strategic potential of corporate sustainability via environmental greening, firm reputation via favorable social image and value, and R&D intensity for technological strengths, along with operational efficiency for best practice management, has become a great concern to most stakeholders in today's competitive market (Alon and Vidovic, 2015; Dangelico and Pontrandolfo, 2015; Yadav et al., 2017). Environmental sustainability is becoming an especially pivotal indication of the current performance and future potential of a firm, since integration of environmental sustainability with eco-friendly products and services will promote the firm's market valuation and competitiveness (Eccles et al., 2014; Lee, 2012; Nidumolu et al., 2012). Although it is generally perceived that corporate environmental sustainability contributes to enhanced competitiveness and better performance of a firm, there is still a lack of consensus on the impact of environmental sustainability with respect to firm valuation. Therefore, the controversial viewpoint on environmental sustainability can be abstracted into two focal questions: whether "*It Pays to Be Green*" or "*It Costs to Be Green,*" as termed by Trumpp and Guenther (2017). However, rather than affirming either a 'positive' or 'negative' linkage in the controversial debate by solely relying on a traditional linear model, this study explores the holistic effect of environmental greening in conjunction with other factors, while seeking new insights by using neural network as a nonlinear model.

In parallel with a strategic emphasis on environmental sustainability and firm reputation, operational efficiency in transforming committed resources to value creation is considered an important aspect of a firm's capabilities. Accordingly, operational efficiency represents a firm's overall ability to implement regular routines for better performance, reflecting efficiency-driven best practice operations and sound organizational processes (Krasnikov and Jayachandran, 2008; Yu et al., 2018). Indeed, for high-tech-oriented firms, operational excellence, in parallel with technological innovation, is a prerequisite to satisfying diverse demand patterns and to sustaining market leadership (Mohr et al., 2010; Slater et al., 2007). Hence, operational efficiency in conjunction with R&D commitment is considered a crucial strategic factor which impacts the market valuation of firms, especially in high-tech industries.

This study presents an innovative input-output framework for scrutinizing the impact patterns of these strategic factors with respect to Tobin's Q as a market-based performance measure. In so doing, this paper uniquely explores the interactions of key inputs and their progressive impacts on Tobin's Q, which is one of the most commonly used market-based forward-looking performance measures. Unlike accounting-based financial measures (e.g., ROA) which focus on current profitability, Tobin's Q fairly reflects the market valuation of a firm encompassing the firm's intangible assets and technological strengths. As a cohesive and dynamic performance indicator, Tobin's Q also mirrors the effectiveness of a firm's concerted efforts to allocate strategic resources for value creation. Accordingly, Tobin's Q is considered a meaningful performance measure for high-tech firms competing in a context of high environmental dynamism (Bardhan et al., 2013; Bharadwaj et al., 1999; Bharadwaj, 2000; Chen et al., 2013; Jacobs et al., 2016).

As an explorative study, this paper investigates the predictive impact of the aforementioned strategic factors on market-based firm valuation. More specifically, it intends to seek meaningful answers to the following questions: (1) What is the relative significance of selected strategic factors (e.g., green score, reputation, R&D, and operational efficiency) on the firm's market valuation? (2) What is the relative importance of selected strategic factors on the different capability levels (*high* vs. *low*)? (3) What is the interactive synergistic impact of selected strategic factors on the firm's market valuation? And, finally, (4) What is the comparative impact of selected strategic factors on the firm's market valuation, particularly with respect to its incremental resource commitment?

These challenging research questions necessitate an innovative analytic model with adaptive learning and nonlinear modeling capabilities. In particular, the model is required to provide a sound methodological basis to support a series of explanatory and predictive capabilities. Most importantly, the desired model should be capable of scoring the capabilities of firms and subsequently categorizing each firm into different levels of performance, as either above average (*high*) or below average (*low*). At its core, the desired empirical model should depart from conventional linear-averaging techniques. Satisfying these demands, the backpropagation neural network (BPNN) is deemed appropriate as a base model due to its inherent adaptive learning and generalization capabilities (Fausett, 1994; Kwon, 2017; Lam, 2004; Lee and Kwon, 2017). Specifically, this study explores both the predictive and explanatory potential of BPNN as a nonlinear curve-fitting model to provide a technical basis for a capabilities-based categorization of firms.

The research gap on this subject and the lack of a systematic approach prompted us to seek sound solutions to the proposed research questions, and to do so through sequential neural network modeling as a data-driven approach. Unlike earlier studies, this research intends to explore new insights into the strategic factors and their impact patterns, which conventional statistical techniques alone cannot properly provide. Unlike prior studies, with their primary focus on determining the statistical significance of individual factors, this paper presents an adaptive input-output framework with benchmarking potential to enhance managerial effectiveness in controlling strategic resources. In fact, both academicians and managers alike still face challenges in optimizing resource commitments and intra-industry benchmarking, which affects managerial competencies (Krasnikov and Jayachandran, 2008; Teece et al., 1997). In addition, the proposed analytic process enables *what-if* tests, which will increase managerial effectiveness in allocating strategic resources and properly setting desired performance goals. In a practical sense, it is of a high managerial concern to quantify the potential impact of each input and to estimate the optimal level of each strategic resource. Furthermore, the capability to balance the committed resources necessary to sustain above-average performance is another managerial imperative. This paper presents innovative and pragmatic approaches to these management challenges, thus providing a two-pronged strategic means for managers to control resources and set performance goals through a comprehensive impact analysis of strategic factors and market valuation.

2. Theoretical foundations for selected strategic factors

Corporate sustainability via sound environmental practices is an area that is now an integral part of everyone's thought processes, and companies are using it to directly influence strategic and operational decision making. Hence, it is important for executives to examine whether sustainability practices will have a significant effect on their company's bottom line in both the short and long run. According to Fisher (2010), corporate sustainability is important to organizations for two reasons: (1) firms have a social responsibility to the environment and to future generations; and (2) becoming more efficient often reduces costs, ultimately leading to higher profits and a better image for the organization. In fact, corporate sustainability may present an opportunity for firms to develop a core competency that will give them an advantage over their competitors (Eccles et al., 2014; Hopkins, 2009).

Early research focused on firms that made efforts to positively change a broad range of sustainability indicators such as innovation and social responsibility. The firms were significantly aided by a positive long-term value for their stakeholders (Funk, 2003). For example, Enticott and Walker (2008) discovered that sustainable management is positively associated with organizational performance, and asserted that the success of organizational performance was directly and indirectly influenced by sustainability management and stakeholders' involvement. Ameer and Othman (2012) also showed that sustainable companies have higher mean sales growth, return on assets (ROA), profit before taxation, and cash flows from operations in most sectors. As such, it is generally understood that firms with a higher emphasis on sound environmental practices are likely to achieve greater financial performance in the long run (Ameer and Othman, 2012; Argon-Correa and Rubio-Lopez, 2007; De Lange et al., 2012; Gobble, 2012; Klron et al., 2013). However, contrary to this positive notion of the impact of environmental sustainability on firm performance, there is still a question as to whether or not environmental greening conclusively contributes to the improvement of firm performance at the expense of stockholders, particularly because of the growing investment cost of committing to environmentally sound practices and greening efforts (Dixon-Fowler et al., 2013; King and Lenox, 2002; Nicolăescu et al., 2015). In this sense, the lack of consensus on this matter still remains debatable, calling for a more detailed and comprehensive analysis with respect to the impact of environmental sustainability on firm performance. Indeed, we may need to pay more attention to inconsistencies in its effect. As pointed out in recent studies (Orlitzky, 2013; Trumpp and Guenther, 2017), the complexity of greening's impact may go beyond the linear relationship (positive or negative), and cannot be oversimplified into two bipolar effects (costs vs. benefits). In this sense, in agreement with Trumpp and Guenther (2017), the impact of environmental greening still deserves more explorative analysis.

Research and development for technological capability. Research and development (R&D) is composed of investigative activities conducted by a company with the goal of making a new discovery that may lead to the development of new products or procedures, or improvements to existing products and procedures. The question still remains whether increased spending on R&D positively affects firm performance. Traditionally, it is generally believed that successful innovation through effective R&D activity can have a positive impact on firm performance and market growth (Ghaffar and Kahn, 2014; Lee, 2012; Lee and Habte-Giorgis, 2004; Morbey and Reithner, 1990). Proactive R&D activity may result in new products and technologies that help the firm develop and sustain its competitive advantage, acquire additional competitive market share, or penetrate new markets.

It has been noted that new product performance through competitive R&D activity has a significant impact on overall firm performance as new products that meet a unique set of customers' wants or needs have an inherent product advantage (Haroon et al., 2010). Haroon et al. (2010) also made the point that as new customer needs are discovered and met, those companies who are on the cutting edge of innovation maintain a competitive advantage, at least in the short term. Companies today are looking to take advantage of future opportunities, particularly firms in high-tech-oriented industries. The strategic proactive drive for R&D activity can accelerate new product development that is more socially, environmentally, and economically sustainable (Chapas et al., 2010). In fact, most firms are striving to be creative and to seek ways to drive the continued utilization of existing resources, since they can gain a competitive advantage through efficient R&D investment. Across all industries, there is an overwhelming need for investment in R&D functions to gain a sustainable competitive advantage (Krishnan et al., 2009). Therefore, it is crucial for companies to find an appropriate, balanced, and competitive level of investment in R&D to keep customers and stakeholders happy. Although high levels of R&D expenditure do not eliminate the possibility of declining sales during a recessionary period, it has been shown that firms with a higher R&D intensity perform significantly better than firms with a modest level of R&D intensity (Tubbs, 2007, 2008). As such, R&D is a competitive strategic resource, since it is at the heart of a firm's strategy for technological improvements in products and operational processes. Several studies have empirically investigated the relationship between R&D investment and performance and have found a positive impact on a firm's financial profits in the form of market growth, irrespective of industry context and firm size (Franko, 1989; Hoskisson and Hitt, 1988; Lee, 2012; Lee and Kwon, 2017).

Corporate reputation for social value and image. As one of the most competitive intangible factors in a corporation's social value and image, corporate reputation is a critical factor in maintaining a competitive advantage in today's global market. It is generally perceived that corporate reputation is a strategic indicator of increases in a firm's value (Flammer, 2012; Love and Kraatz, 2017; McGuire et al., 1988). Indeed, a good reputation is identified as an intangible resource which may provide the organization with a basis for sustaining a competitive advantage, given its valuable and hard-to-imitate characteristics (Barney, 1991; Hall, 1993; Krueger and Wrolstad, 2016; Roberts and Dowling, 2002). Furthermore, firms with good reputations are better suited to introduce innovative products and reach customers, especially in high-technology markets. As such, reputation is a competitive strategic determinant of a firm's performance, with interactive functions across R&D and marketing (Dutta et al., 1999). While the majority of studies assert that corporate reputation has a positive effect on firm performance, a stream of papers also present a reversed or reciprocal effect, where reputation is treated as a result of sound financial and market performance (Rose and Thomsen, 2004; Sabate and Puente, 2003). Rose and Thomsen (2004) reported that financial performance was driver in building reputation, challenging the conventional wisdom, and Sabate and Puente (2003) found that reputation and performance had a bidirectional relationship. Despite the diversity of views on the role of reputation, it is generally perceived that there is a positive relationship between corporate reputation and firm performance in terms of both financial profit and market-value performance. Indeed, a strategic driver of corporate reputation can provide firms with a sustainable competitive advantage if managed properly (Eberl and Schwaiger, 2005; Gatzert, 2016; Hall and Lee, 2014; Roberts and Dowling, 2002).

Operational efficiency for best management practices. Operational efficiency represents a firm's managerial competence, or how well it harmonizes inputs to achieve outputs in the production process. Accordingly, operational efficiency is a surrogate indicator of a firm's operational excellence to transform various resources into value-added outputs (Amess & Girma, 2009). By pairing strategic factors and performance, the relative efficiency of a firm measured by DEA reflects a firm's overall technical efficiency in generating outputs (e.g., sales revenue) for allotted resources. Hence, a high level of operational efficiency is an indicator of best management practices of a firm in a competitive environment. DEA, introduced by Charnes et al. (1978), determines the relative efficiency of decision-making units (DMUs) as a nonparametric optimization tool, and the efficiency score has been commonly used as an aggregate performance measure. Indeed, by encompassing multiple input-output vectors and abstracting them into a scalar representation, DEA efficiency is larger in its scope and more comprehensive in analysis than simple ratio metrics (Jacobs et al., 2016). In this study, DEA efficiency is based on three inputs, which include the cost of goods sold (COGS), sales, general and administrative costs (SG&A), and invested capital (ICAP), and a single output (sales revenue). Accordingly, by utilizing overall costs and capital investment as DEA inputs, which is in line with prior studies, we define operational efficiency as the proficiency of firms in maximizing sales revenue through controlling the committed resources of a firm and best practice management on collective efforts across overall functional areas (Jacobs et al., 2016; Demerjian et al., 2012). In this study, operational efficiency, thus obtained, is considered a potential determinant of market valuation alongside other strategic factors in the subsequent analytic processes.

Among DEA studies, a majority of which focus on measuring efficiency, only a small number have explored the impact of efficiency on firm performance (Amess & Girma, 2009; Kohers et al., 2000; Shamsuddin and Xiang, 2012). This includes Shamsuddin and Xiang (2012) and Kohers et al. (2000), who reported a positive relationship between production efficiency to stock return and market value in their studies of banks. Ray et al. (2006), in their research on manufacturing firms, found a significant relationship between efficiency and market valuation. They also found that this relationship was an indication of a positive market reaction by a firm's productive resources. In addition, Amess and Girma (2009) pointed out efficiency as a barometer of a firm's best practices, especially with respect to managing resource utilizations, which eventually leads to favorable market value. While these are meaningful contributions, these studies have all examined the effect of efficiency in a partial and narrowly-scoped manner using statistical models. The literature shows a lack of empirical evidence of utilizing efficiency in conjunction with key strategic factors to scrutinize their relative impact on forward-looking market performance, that is, Tobin's Q, especially in high-tech firms. Therefore, we uniquely adopted DEA efficiency alongside other strategic factors in this neural network modeling.

Forward-looking market valuation for firm performance. The need to create a competitive advantage through sustainable firm performance is perceived as having been a central concern to firms facing strong market competition. Although the firm's return-based accounting performances (e.g., ROA, ROE, and ROI), which are historical in nature, have been used in most empirical studies, they are often recognized as the narrowest indicators of firm performance (Rappaport, 2000; Toit and Wet, 2007). In contrast, as a market valuation approach, Tobin's Q (Chen et al., 2013, Lang and Stulz, 1994; Miller, 2004) can be used to reflect investors' expectations of a firm's future market performance, and also to assess the fair value of market performance, particularly with respect to the strategic nexus between the firm's equity-based market value (a firm's equity value of the market) and assets-based value (the collective value of a firm's net assets). Therefore, Tobin's Q is one of the most robust measures of a firm's market valuation and growth opportunity to increase a firm's expected market performance (Bracker and Ramaya, 2011; Ioannou and Serafeim, 2017; Ragothaman and Carr, 2008). As such, it is conventionally supported that Tobin's Q is one of the more meaningful forward-looking market performance measures of operational business resources, along with environmental sustainability. Notwithstanding the noticeable advantages of using a market-valuation approach in deriving intuitive managerial implications regarding market performance, there is still a lack of empirical studies to assess the relative impact of strategic factors, especially in large high-tech firms.

3. Methodological foundation

3.1. Backpropagation neural network (BPNN): brief overview

BPNN, as an intelligent analytic tool, has been popular in dealing with nonlinear input-output relationships and has been proven effective for a wide range of applications. By replicating a biological neural system, BPNN is characterized by its adaptive learning and generalization capability, even under conditions such as limited or noisy information (Baesens et al., 2003; Das and Datta, 2007; Fausett, 1994; Kourentzes, 2013; Lam, 2004). BPNN is commonly compared to a conventional regression model (e.g., ordinary least squares multiple regression, or OLSMR); however, previous research has reported several advantages of BPNN over OLSMR. For example, as a nonparametric model, BPNN does not require *a priori* knowledge of input distributions. That is, BPNN is an assumption-free model, as opposed to OLSMR, which requires strict statistical conditions. Accordingly, BPNN is not bounded by normality and linearity assumptions. In addition, BPNN has its strength in approximating nonlinear relationships and forecasting outcomes of uncertain events (Kim et al., 2005; Lee and Kwon, 2017; Mazhar et al., 2007; Wong and Chan, 2015; Zhang et al., 2004).

A typical BPNN structure consists of three layers of neurons, as shown in Fig. 1. As a connectionist model, the massively parallel connections (weights) between adjacent neurons retain functional relationships between input and output of the presented data. As illustrated in the figure, learning occurs in four sequential steps: (1) input presentation; (2) information feedforward; (3) error calculation; and (4) error backpropagation, followed by weight update for interconnecting neurons (Fausett, 1994; Kwon and Lee, 2015).

Let f_h and f_o represent sigmoid transfer functions applied to net outputs of neurons in the output and hidden layers, $\mathbf{W}_h$ and $\mathbf{W}_o$ denote weight vectors interconnecting input-hidden and hidden-output neurons, $\mathbf{Y}$ represent prediction output, (.) symbolize the inner product of vectors, and E indicate the error between target (T_k) and predicted (Y_k) output for a neuron k. Then the BPNN learning process can be expressed by the following formula:

$$f_{o\,h}(x) = \frac{1}{1 + \exp^{-x}} \tag{1}$$

$$\mathrm{Y} = f_o(\mathrm{W_o} \cdot f_h(\mathrm{W_h} \cdot \mathrm{X})) \tag{2}$$

$$E = \frac{1}{2}\sum_k \|T_k - Y_k\|^2 \tag{3}$$

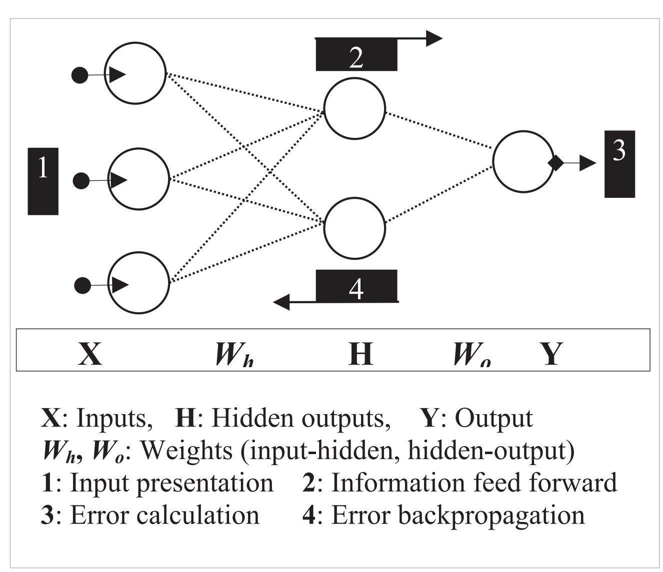


Fig. 1. BPNN prediction model.

$$W_{o,h}(t+1) = W_{o,h}(t) - \eta(t)\frac{\partial E}{\partial W_{o,j}(t)} \tag{4}$$

where η(t) represents the decreasing fractional number of learning coefficient at time t. The iterative supervised learning process continues until the termination conditions are met or no further improvement can be made. In implementing BPNN models, the number of hidden neurons is a core model parameter, which is influenced by the complexity of the data and also demands a certain level of heuristics. The trial-and-error efforts in search of an optimal network structure and a lack of explanatory power due to its hidden nature of learning are commonly pointed out as drawbacks of BPNN. These shortfalls, however, do not erode the strength of BPNN in dealing with complex and nonlinear input-output patterns. Moreover, the adaptive learning capability makes BPNN a suitable choice for modeling unknown relationships subsequently lacking a theoretical basis, which is not the case with statistical approaches such as OLSMR.

3.2. Empirical design and analytic process

The analytic process introduced in this study consists of four distinctive modeling sequences built on both parametric and nonparametric methods, as illustrated in Fig. 2, which includes DEA preprocessing, explanatory analysis using OLSMR, and two subsequent prediction experiments for extended impact analysis. In the first-stage experiment, as a preliminary step, the DEA model determines the efficiency of each firm as an aggregate measure on a multiple input-output setting. By using three inputs (COGS, SG&A, and ICAP) and a single output (sales revenue), the DEA efficiency score indicates a firm's relative level of operational excellence in transforming committed resources to the generation of sales revenue reflecting sound management practices and organizational processes.

Following the front-end DEA-preprocessing, the second-stage analysis is centered on an explanatory analysis using OLSMR to determine the individual effect of each strategic factor on Tobin's Q as a performance outcome. In addition to operational efficiency, the regression model evaluates the effect of six other factors, which include firm size, capital intensity, inventory turnover, R&D intensity, environmental sustainability (hereafter green score), and reputation, on Tobin's Q by utilizing data from 148 high-tech-oriented firms. The regression analysis in the second stage provides a meaningful empirical basis for the follow-on neural network models, which use the same data set for further exploration of the impact of these strategic factors. Then, departing from a conventional parametric approach, the third stage analysis aims to predict the relative impact of each factor using BPNN and is further devoted to investigating the synergistic effect of joint variables on the increase of Tobin's Q. Unlike OLSMR, the BPNN model does not determine the statistical significance of each factor. However, the strength of BPNN in its prediction ability gives rise to its explanatory potential in observing the degree of impact of a variable on the output by means of sensitivity analysis (Xu et al., 2013). By detecting a system response to the changing input, the sensitivity analysis captures cause and effect relationships of input-output variables and exposes the relative importance of each variable in terms of its impact on output. From a procedural perspective, the neural network model computes a new output for the change of the first input while keeping other inputs constant. This process repeats for all inputs and a comparison of each prediction gap exposes the relative importance of each input, which eventually enhances the explanatory power of BPNN. In this sense, the BPNN model is expected to supplement OLSMR, implying greater benefits of complementary use of both models (Chen et al., 2013; Lee and Kwon, 2017; Xu et al., 2013). Indeed, the detection of the relative impact of each factor using BPNN inspires a synergistic effect analysis to gain additional insights that traditional parametric models (e.g., OLSMR) alone cannot provide. For this extended analysis, the BPNN model estimates the variation of output upon a simultaneous increase of two joint factors while holding other factors constant. Then, the discrepancy between predicted output and the sum of the individual impact indicates the level of the synergistic effect. In so doing, the BPNN model in the third stage analysis presents a salient analytic procedure for in-depth impact analysis of the strategic factors. In addition, the BPNN model (BPNN *A*), built on the entire data set, captures average performance patterns and the resulting decision surface provides valuable criteria for segmenting firms into *high* and *low* performers in the next stage.

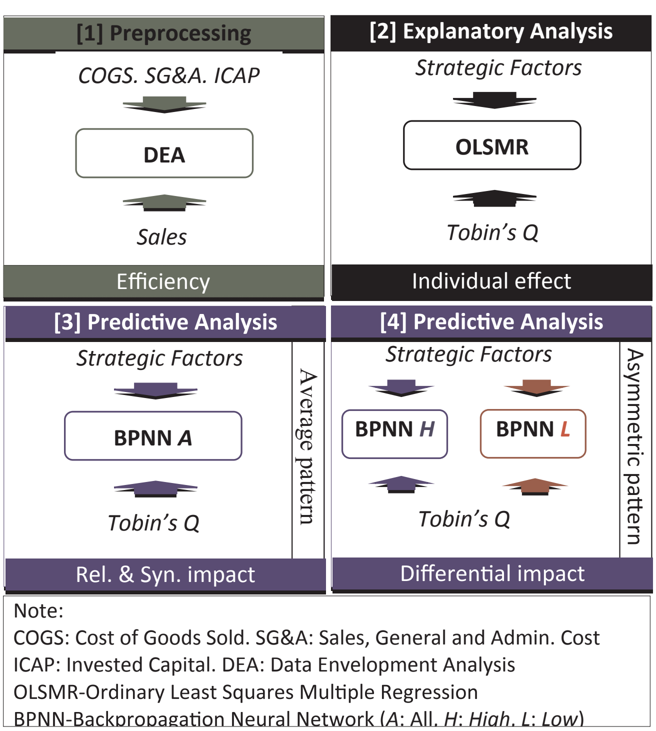


Fig. 2. Schematic diagram of the multi-stage analytic process.

The empirical process so far is based on the average performance of firms under consideration. The consecutive prediction experiment in the fourth stage, however, expands the neural network analysis into the detection of distinct characteristics of firms (i.e., *high* and *low* performers) in terms of asymmetric returns on the equitable resources, also referred to as capabilities. It is a common notion that capable firms are more efficient in terms of resource utilization for the creation of value in meeting customer demands. From strategic management perspectives, capability drives firms to pursue above-average performance (Mu, 2017). In this sense, the BPNN decision surface segmenting firms into two different levels of capability, *high* and *low*, provides new insights into understanding the differential impact of strategic factors. Indeed, the difference between actual (y_a) and prediction (y_{nn}) outcomes (BPNN *A*) provides valuable insights into the distinctive capability of a firm linking strategic factors to the performance measure, which is Tobin's Q in this study. As illustrated in Fig. 3, the positive gap reflects above-average production of a firm for given resources, thus indicating a *high* capability. On the contrary, the negative gap represents below-average performance of a firm as compared to its peer and indicates a *low* capability of a firm (Kwon et al., 2018; Lee and Kwon, 2017).

The fourth stage of the analysis is conducted by two consecutive BPNN models with its empirical basis on the salient categorization of firms in the previous stage. By utilizing two separate subgroups of data (i.e. *high* vs. *low*), two additional BPNN models (i.e. BPNN *H* and BPNN *L*) capture the contrasting impact patterns of strategic variables in accordance with varying capabilities. In effect, the trained BPNN models not only capture the differential impact of factors but also allow for a pragmatic mechanism to estimate the desired outcomes for the given or hypothetical level of resources, which will support managerial decision-

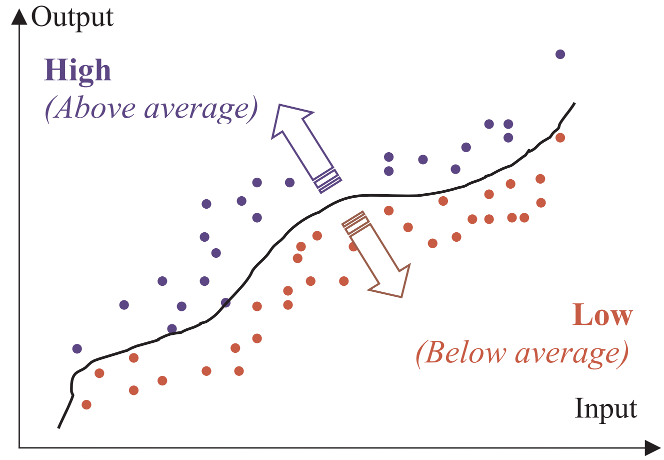


Fig. 3. Capability segmentation by BPNN (Adapted from Kwon et al., 2018).

making processes. Accordingly, the proposed analytic process provides a new methodological paradigm for strategic resource management and control. Throughout the sequential empirical processes, this paper explores the explanatory potential of BPNN intensively as a complementary feature of its commonly recognized prediction capability.

3.3. Sample data and collection

In order to investigate the strategic impact of competitive determinants, the initial sample for the present study consisted of high-tech-oriented U.S. firms with information available on sustainability and reputation over a five-year period (2009–2013). The green score for corporate sustainability and corporate reputation for social image and social responsibility were selected from *Newsweek's* Green Rankings[1] and *Fortune's* World's Most Admired Companies,[2] respectively. All other key strategic variables, including control variables, were selected from *S&P Research Insights-North America*.

Due to the sample selection criteria and limited availability of data, the final sample for the present study was comprised of a total of 148 high-tech-oriented firms, as presented in Table 1. The selected data are arithmetic averages for the five-year period, 2009–2013.

3.4. Description and measurement of strategic determinants and market value performance

Tobin's Q. As a ratio of the market value of a firm (i.e. the present value of future cash flows) to the replacement cost of its tangible assets, Tobin's Q represents the growth prospects of a firm and the returns from long-term or tangible assets. For example, Tobin's Q values below 1 indicate that the firm earns less than the required rate of return; a marginal dollar invested in the firm's assets results in future cash flows whose present value is less than $1. Tobin's Q is measured in the following manner:

Tobin's Q = (Market value of shareholder's equity + Liquidating value of the firm's outstanding preferred stock + Book value of total debts)/(Book value of total assets) (Chung and Pruitt, 1994).

Key strategic determinants. We use four key strategic variables –green score for corporate sustainability, R&D intensity for technology strengths, corporate reputation for social value and image, and operational efficiency for best management practices – that relate to the main theme of this study. (1) ***Green score.*** As one of the key strategic determinants of sustainable market performance, green score is a comprehensive, quantitative, and standardized measurement of the overall environmental impact of a company's global operations. (2) ***R&D intensity***. R&D intensity of a firm's technological capability is one of the crucial strategic determinants of the firm's market valuation. The barometer to gauge a firm's technological strengths and capabilities is the extent to which the firm concentrates on research and development. R&D intensity is computed as the ratio of book values of R&D expenditure to the total sales (= R&D Expenditure/Sales Revenue). (3) ***Corporate reputation***. As a proxy variable for corporate social responsibility and image, corporate reputation was measured using *Fortune's* World's Most Admired Companies. *Fortune*, using a total of nine criteria, solicits the opinions of experts, executives, members of boards of directors, and corporate analysts in assessing corporate reputation (see World's Most Admired Companies by *Fortune* for details). *Fortune's* listing of most-admired companies has been previously validated as a measure of corporate reputation and social responsibility (Chakravarthy, 1986; Lee, 2012; Lee and Hall, 2008; McGuire et al., 1990). (4) ***Operational efficiency.*** As the technical efficiency of a firm measured by DEA, operational efficiency is a surrogate performance indicator in terms of utilizing a firm's base resources for the creation of intended outputs in the most cost-effective manner possible. In fact, operational efficiency is likely to represent continuous improvement in utilizing available operational resources for a firm's performance. As a relative measure, operational efficiency represents the overall managerial competence of a firm in its transformation process for value creation. For this study, we use the CCR model of DEA using DEA Solver-Pro12f software (Saitech, 2013).

In the DEA analysis, the smaller deviation of DMUs from the frontier indicates higher efficiency, and, accordingly, the efficiency scores are fractional numbers with a maximum of one. Assuming n-DMUs with r-input and s-output vectors, the efficiency of DMU_k using the Cooper-Charnes-Rhodes (CCR) model (Charnes et al., 1978) can be expressed as follows:

$$h_k = \max \sum_{j=1}^{s} u_j y_{jk} / \sum_{i=1}^{r} v_i x_{ik} \tag{5}$$

$$\text{s.t} \sum_{j=1}^{s} u_j y_{jp} / \sum_{i=1}^{r} v_i x_{ip} \le 1,\ p = 1,\ \dots, n \tag{6}$$

$u_j,\ v_i \ge \eta > 0,$

η: a positive infinitesimal value,

where y_{jp} (x_{ip}) is output (input) of DMU_p and u_j (v_i) is a nonnegative

[1] *Newsweek*'s Green Rankings (NGR), as one of the world's foremost and comprehensive corporate environmental performance indicators, gives the largest publicly traded corporations a benchmark to compare overall environmental performance, with respect to carbon, energy, water, waste, and a broad range of governance for sustainability. Even though there are still some controversial issues with how it judges overall environmental performance, it has been suggested that there is a compelling link between the *Newsweek* rankings and observed financial returns and shareholder value, and that this could serve as a roadmap for future research in this field (Lyon and Shimshack, 2012). In addition, the NGR provides an exclusive and comparable evaluation of the firms' actual environmental performances, with respect to environmental practices and efforts regarding sustainability, in a simple and easily interpretable format (Yadav et al., 2017).

[2] *Fortune*'s listing of most admired companies has been validated as a measure of corporate reputation and social responsibility (Gwebu et al., 2018; Huang and Kang, 2018; Love et al., 2017; McGuire et al., 1990; Neville et al., 2005), and it is also known as one of the most widely used measures of corporate reputation, with respect to the dynamics of financial performance for sustainability (Fombrun and Shanley, 1990; Fryxell and Wang, 1994; Love and Kraatz, 2017; Roberts and Dowling, 2002). Additionally, it has been conventionally argued that *Fortune*'s listing of the most admired companies has been known as one of the most predominant and validated measures of corporate reputation and corporate social responsibility in the fields of business and management (Brown and Perry, 1994; Chakravarthy, 1986; Haleblian et al., 2017; McGuire et al., 1990). In fact, the list of *Fortune*'s Most Admired Companies is a distinctive report on corporate reputation since most ranked companies are selected according to a diversity of attributes related to their competencies, from investment value and quality of management and products to social responsibility to attract and maintain talented employees.

Table 1
High-tech industry specification by SIC-codes.

Industry classification	SIC-code	No. of firms
Chemicals and allied products	2800–2899	34
Petroleum and refining	2900–2999	7
Machinery and computer equipment	3500–3599	30
Electrical products	3600–3699	21
Transportation equipment	3700–3799	14
Scientific instruments	3800–3899	18
Tech related business services	7370–7399	20
Engineering and management services	8700–8799	4
Total		148

weight. Detailed discussions on technical and managerial aspects of DEA are found in the literature (Charnes et al., 1978; Emrouznejad et al., 2008; Liu et al., 2013a, 2013b).

Control variables. The strategic impact of green score, R&D intensity, corporate reputation, and operational efficiency for a firm's market performance is also affected by other factors that may distinguish the firm's potential confounding factors from those of other competitors across different industry sectors. Therefore, this study also employed three other key control variables, namely, firm size, capital intensity, and inventory turnover. (1) ***Firm size.*** As one of the main possible barriers to entry (Acs and Audretsch, 1987; Hall and Weiss, 1967; Lee and Hall, 2008), firm size is measured by the natural logarithm of total sales revenues. Firm size, represented by total assets, may increase attainable profitability, and it may raise the capital requirement as a barrier to entry in the market. (2) ***Capital intensity.*** A variable which represents capital intensiveness is measured by the ratio of the net amount of the plant and equipment to the total assets. This may be interpreted as a measure of the efficiency of the firm in using capital. (3) ***Inventory turnover.*** As one of most important proxy measures of lean management for market performance, many studies have centered on the optimal level of inventory (Demeter and Matyusz, 2011; Eroglu and Hofer, 2011; Koumanakos, 2008). Thus, one of the commonly used benchmarks to measure inventory management is the inventory turnover ratio, because management can generate more free cash flow and also enhance market value when it speeds up inventory turnover. Inventory turnover is measured by the ratio of the cost of goods sold to the average inventory.

4. Empirical analysis and discussion

4.1. Descriptive statistics and correlations

Descriptive statistics with means, standard deviations, and intercorrelations for all basic variables employed in this study are presented in Table 2. First, operational efficiency, which indicates the efficient utilization of a firm's internal resources, is highly and positively correlated with firm size, inventory turnover, and a firm's market performance at the 0.01 level, but it is negatively correlated with capital intensity ($p < 0.01$). Thus, optimizing a firm's distinctive operational resources is most likely to be linked to firm performance and quick inventory turnover. Furthermore, most key strategic factors (i.e., green score, R&D intensity, reputation, and operational efficiency) are significantly and positively correlated with a firm's market performance, at least at the 0.05 level. Regardless of the debate over the impact of strategic determinants such as corporate sustainability, R&D intensity, and corporate reputation, they are likely to strengthen a firm's competitive position and to promote a firm's market performance (Lee, 2012; Sabate and Puente, 2003; Servaes and Tamayo, 2013). Such strong and significant interrelations among key variables employed in this study appear to be enough to justify our initial motives for using the progressive and predictive model.

4.2. Relative impact analysis: OLSMR vs. BPNN

The first stage of the empirical analysis is centered on determining the statistical significance of strategic variables and figuring out the general impact pattern of the variables through complementary usage of OLSMR and BPNN. The OLSMR analysis not only provides intuitive information with respect to the significance of variables, but it also lays a comparative basis for further scrutiny of strategic variables with regard to their relative impacts, especially using BPNN. Both methods are different in their theoretical foundations and usage but provide valuable insights into the strategic determinants of a firm's market performance. Therefore, the first-stage experiment is centered on the comparative analysis of these two methods, primarily focusing on explanatory analysis.

As presented in Table 3, the conventional linear regression model with respect to performance appears to be fairly robust and highly significant at the 0.001 level ($R^2 = 0.529$; Adj. $R^2 = 0.505$; $F = 22.4$, $p < 0.001$), indicating that it is useful for investigating the significant effect of the strategic determinants of a firm's market performance, particularly in terms of Tobin's Q (Cohen, 1988; Renaud and Victoria-Feser, 2010). Most of the strategic factors, except inventory turnover, are statistically significant (at least at a 5% level of significance) and positively associated with Tobin's Q. In addition, there are no signs of multicollinearity problems since the variance inflation factors (V.I.F.s) for all explanatory variables are far less than 10, the cutoff for nonexistence of multicollinearity. The results also provide a meaningful cursory look into the strategic determinants. The two most impactful variables are operational efficiency and reputation, which account for internal operations practices and external customer response, respectively. Furthermore, the green score for corporate responsibility and the R&D intensity for technological strength are also considered significantly impactful strategic factors for a better market performance in high-tech-oriented industries (Bardhan et al., 2013; Chen et al., 2013). Contrary to our expectation, however, inventory turnover for efficient inventory management, as well as supply chain performance, is not significantly associated with a firm's market performance.

For neural network analysis, we used NeuralWare Predict software (NeuralWare, 2013). The software package provides built-in functions in search of a model structure. For this study, we selected one hidden

Table 2
Means, standard deviations, and correlations [a].

Variables	Mean	SD	1	2	3	4	5	6	7
1. Firm size	9.314	1.056							
2. Capital intensity	1.406	0.628	-.217**						
3. Inventory turnover	10.156	11.338	.340**	-.074					
4. R&D intensity	7.300	7.603	-.196*	.483**	.017				
5. Green score	65.256	8.498	.255**	.188*	.326**	.329**			
6. Reputation	6.271	0.671	.255**	.005	.193*	.041	.192*		
7. Operational efficiency	0.773	0.083	.364**	-.587**	.235**	-.069	-.071	.125	
8. Tobin's Q	1.470	0.758	-.215**	.123	.090	.411**	.194*	.353**	.283**

Note: [a] n = 148; *P < 0.05; **P < 0.01; ***P < 0.001.

Table 3
Results of OLS multiple regression (OLSMR) analysis.

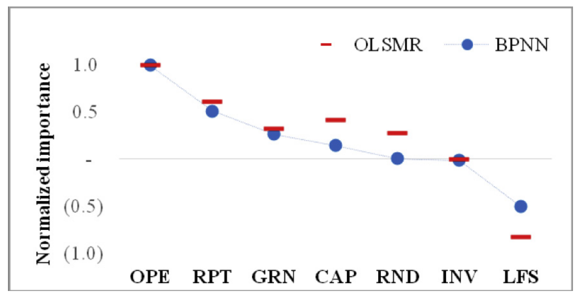
Variables	Unstandardized		Stand. β	t-value	Sig. Level	V.I.F.
	β	(Std. ε)				
(Constant)	−3.607	(.812)		−4.442		
Firm size (LFS)	−0.347	(.051)	−0.483	−6.776	***	1.509
Capital intensity (CAP)	0.296	(.105)	0.245	2.833	**	2.230
Inventory turnover (INV)	0.000	(.004)	0.001	0.012		1.270
R&D intensity (RND)	0.016	(.008)	0.160	2.084	*	1.749
Green score (GRN)	0.017	(.006)	0.191	2.728	**	1.458
Operational efficiency (OPE)	5.333	(.762)	0.583	7.002	***	2.058
Reputation (RPT)	0.405	(.069)	0.358	5.872	***	1.106
R^2 = 0.529; Adj. R^2 = 0.505; F-ratio = 22.424***						

Note: V.I.F. indicates Variance Inflationary Factor to detect the multicollinearity problem.
*$P < 0.05$: **$P < 0.01$; ***$P < 0.001$.

layer structure with incremental learning options, which allows an optimal number of hidden neurons. To prevent over-training of the model, the data set was partitioned into three subsets (training-test-validation) before training. During the model-building process using the training subset (104), the test subset (22) was used to monitor network learning and potential overfitting to the training data. Upon completion of the network training, the holdout subset (22) which is unseen to the network, validates the trained model. Therefore, comparable performance (e.g., Pearson R) for both training and validation subsets are a good indication of a reliable model with no hints of overfitting. The training result shows a Pearson R of 0.758, correlations between actual and prediction outputs, with comparable levels for each subset (training: 0.779, test: 0.746, validation: 0.770). The results are aggregated into Table 7 with follow-up BPNN outcomes in consecutive analysis. After the training of BPNN, a sensitivity analysis was performed to measure the relative influence of each input. By observing the network response to the variation of each input, the causal and relative effects of input variables on the output can be determined. That is, while holding other variables constant, only one variable is changed at a smaller scale, and a change of the relevant output is recorded (Barros and Wanke, 2014; Delen, 2009; Lee and Kwon, 2017). This process continues for each input variable and detects the relative impact of each input. Table 4 summarizes the impact analysis showing the prediction result, marginal impact as an actual effect, and normalized impact. In so doing, this approach adds explanatory power to BPNN on top of its well-known predictive capacity.

Fig. 4 visualizes the relative impact of those variables captured by BPNN and compares the outcome with the result obtained by OLSMR (i.e., standardized coefficient after normalization).

Both results show similar patterns of the relative importance of selected strategic factors, and like OLSMR, BPNN determines operational efficiency (OPE) and reputation (RPT) as two of the most positively influential factors and detects a negative impact of the firm size (LFS) on firm performance. Overall, the selected variables, except for inventory turnover (INV) and firm size (LFS), are considered meaningful strategic determinants for high-tech-oriented firms. Two



Note: OPE: operational efficiency; RPT: corporate reputation; GRN: green score; CAP: capital intensity; RND: R&D intensity; INV: inventory turnover; LFS: firm size (natural log value of sales revenue)

Fig. 4. Comparative impact of major determinants of Tobin's Q. Note: OPE: operational efficiency; RPT: corporate reputation; GRN: green score; CAP: capital intensity; RND: R&D intensity; INV: inventory turnover; LFS: firm size (natural log value of sales revenue).

variables (i.e., INV and LFS) are not considered in follow-up experiments because of their insignificant and inefficient impacts on market performance. As such, it is confirmed that the relative impact of the selected strategic factors, except inventory turnover and firm size, can be used as major strategic determinants of firm performance with respect to Tobin's Q in high-tech-oriented firms. Furthermore, the sensitivity analysis hints at a promising use of BPNN for explanatory analysis, as discussed earlier. However, it is worth mentioning that the sensitivity analysis capitalizes on the prominent prediction scheme of BPNN. Indeed, as compared to OLSMR in Table 5, the BPNN model demonstrates a better prediction performance, as represented by a higher Pearson R (0.719 vs. 0.758) and lower MAPE (34.8% vs. 23.4%). Unlike OLSMR, however, the BPNN model is built on a partial data set (i.e., training data) rather than relying on the entire data set. To make fair evaluations between the two methods, the performance of both models was compared for the same subsets of data partitioned for BPNN (i.e., training, test, and validation), which affirms the superior performance of BPNN to OLSMR across all subsets of data. The favorable prediction performance of BPNN is in alignment with the majority of prior studies and adds to the rationale of selecting BPNN as a primary

Table 4
Results of relative impact analysis using BPNN.

Variables	LFS	CAP	INV	RND	GRN	OPE	RPT
Prediction ([a]Tobin's Q)	1.175	1.440	1.376	1.384	1.489	1.790	1.591
Marginal impact	(0.206)	0.059	(0.005)	0.002	0.108	0.409	0.210
Normalized impact	(0.503)	0.145	(0.011)	0.006	0.264	1.000	0.513

Note.
[a] Default prediction: 1.381. LFS: firm size (natural log value of sales revenue); CAP: capital intensity; INV: inventory turnover; RND: R&D intensity; GRN: green score; OPE: operational efficiency; RPT: corporate reputation.

Table 5
Prediction performance: OLSMR vs. BPNN.

Data	Pearson R		MAPE	
	OLSMR	BPNN	OLSMR	BPNN
All	*0.719*	*0.758*	*34.8%*	*23.4%*
Training	0.727	0.779	36.8%	21.9%
Test	0.723	0.746	33.3%	30.7%
Validation	0.736	0.770	26.8%	23.1%

Table 6
Joint impact analysis using BPNN.

Tobin's Q: 1.381	Prediction of Tobin's Q (Impact on Tobin's Q)				
	OPE	RPT	CAP	GRN	R&D
OPE	[a]*1.790* ([b]*0.409)*				
RPT	[c]2.030 ([d]0.649)	*1.591 (0.210)*			
CAP	1.862 (0.481)	1.657 (0.276)	*1.440 (0.059)*		
GRN	1.917 (0.536)	1.719 (0.338)	1.554 (0.173)	*1.489 (0.108)*	
RND	1.792 (0.411)	1.593 (0.212)	1.443 (0.062)	1.492 (0.111)	*1.384 (0.002)*

Note: OPE: operational efficiency; RPT: reputation; GRN: green score; CAP: capital intensity.
RND: R&D intensity; INV: inventory turnover; LFS: firm size.
[a] Impact (prediction) of a single input (i.e. OPE) on output-on diagonal line.
[b] Marginal effect on actual output from a single variable (i.e. OPE) on diagonal line.
[c] Impact (prediction) of combined variables (i.e. OPE + RPT) on output-off diagonal line.
[d] Joint effect on actual output from combined variables (i.e. OPE + RPT)-off diagonal line.

analytic tool in the follow-up predictive analysis (Chen et al., 2013; Xu et al., 2013).

4.3. Synergistic effects of key strategic determinants

The explanatory analysis introduced in the previous stage provides insights into the significance of each strategic determinant. The next stage is further devoted to the exploration of the synergistic effect of combined sets of strategic factors. Although it is an intriguing research agenda, the theoretical basis for the interaction effect of strategic factors is still shallow and lacks empirical evidence. Hence, the synergistic effect of joint variables is further investigated as an *a posteriori investigation*. BPNN, as an assumption-free adaptive model, is considered appropriate for the task. For the experiment, the trained BPNN model is used for a series of experiments. We compared the outputs in response to a variation of each input (i.e., 10% of means) and to the simultaneous changes of input pairs to determine the synergistic effects of interacting variables.

Table 6 summarizes the experiment's results in a two-dimensional matrix form. The values on the diagonal represent the BPNN prediction output upon increase of each variable and the relative increase from the actual value of Tobin's Q (i.e., 1.381) in parentheses. For example, BPNN predicts a Tobin's Q of 1.790 for the variation of operational efficiency, which is an increase of 0.409 from the actual average of 1.381. As such, the impact of a single variable on Tobin's Q and the relative scale change can be seen in the table. In contrast, the values off the diagonal indicate prediction outputs upon simultaneously increasing a pair of inputs, with the resulting impact scales in parentheses. For example, BPNN predicts a Tobin's Q of 2.030 for the increase of combined variables OPE and RPT, which represents an increase of 0.649 from the initial output of 1.381. Of note is that the joint impact of combined variables (i.e., OPE + RPT: 0.649) is bigger than the sum (0.619) of individual impacts (i.e., OPE: 0.409, RPT: 0.210), which exposes a synergistic effect expected from two combined variables. In effect, Table 6 quantifies the potential benefit of using BPNN in exploring a synergistic effect from the interactions of strategic factors.

To generalize the detection of this synergistic effect, let x_1 and x_2 be two arbitrary inputs for simplicity. Then, the impacts of x_1 and x_2 become $\{f(x_1^+, x_2) - f(x_1, x_2)\}$ and $\{f(x_1, x_2^+) - f(x_1, x_2)\}$, respectively, and the joint impact can be expressed as $f(x_1^+, x_2^+) - \{(f(x_1^+, x_2) + (f(x_1, x_2^+)\}$. Accordingly, the synergistic effect of two joint variables can be defined as: $[f(x_1^+, x_2^+) - \{(f(x_1^+, x_2) + (f(x_1, x_2^+)\}] \cdot \{(f(x_1, x_2^+) + (f(x_1^+, x_2)\}^{-1}$. Fig. 5 graphically summarizes the synergistic effects of joint variables by percentage across all combinations.

The result, as illustrated in Fig. 5, provides a managerial insight that the strategic variables, besides being significant strategic determinants, can also create a synergistic effect when jointly employed. As presented

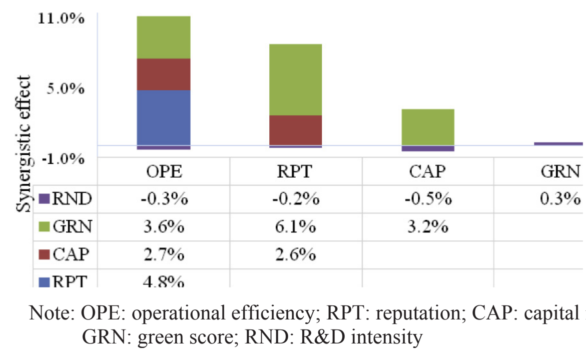


Fig. 5. Interactive synergistic effects of combined strategic variables. Note: OPE: operational efficiency; RPT: reputation; CAP: capital intensity; GRN: green score; RND: R&D intensity.

in the figure, noticeable synergistic effects are observed from interactions of three key factors (i.e., GRN-RPT-OPE), representing 6.1% (GRN-RPT), 4.8% (RPT-OPE), and 3.6% (OPE-GRN), followed by less impactful (i.e., CAP) and minimal (i.e., R&D) interactions. The result asserts that the three major strategic determinants of green score (GRN), corporate reputation (RPT), and operational efficiency (OPE) are likely to generate impactful synergistic effects for a firm's market value, in addition to being crucial individual factors, as illustrated in Fig. 3. Accordingly, the result implies that focused efforts on these strategic factors may contribute to an enhanced market valuation and strengthen the strategic positioning of a firm in a high-tech-oriented industry. Distinguished from other variables, the synergistic effect of R &D, in combination with GRN, is very low (0.3%), with minimal negative values and other factors indicating no evidence of an interaction effect.

In fact, it is traditionally known that proactive R&D investment can contribute to a firm's long-term growth, particularly through new products and services that may enable the firm to distinguish itself from its competitors (Chan et al., 2001; Capasso et al., 2015; Lee, 2012). However, it is commonly understood that R&D by itself does not have a positive effect on the corporate reputation for firm performance if R&D activities do not lead to valuable innovations that have social benefits (McWilliams and Siegel, 2000; Padgett and Galan, 2009; Padgett and Moura-Leite, 2014).

Interestingly, our study also does not show any meaningful synergistic effects of R&D on market valuation, in contrast to the fair number of synergistic effects from joint factors of OPE, GRN, and RPT. However, it is still worth noting that the relative impact of R&D on Tobin's Q as a standalone factor is dismal as compared to other factors (R&D-GRN-OPE-RPT: 0.002-0.108-0.409-0.210), as specified in Table 4 and Fig. 4. From this perspective, the lack of synergistic effect of R&D in association with other factors is mainly due to the minimal effect of R&

D in this study. From a procedural perspective, the prediction model for both relative importance and the synergistic outcomes shows consistent outcomes, which implies that BPNN models are reliable. However, the low effect of R&D remains a puzzle that invites follow-up studies. The result still raises a conventional question as to whether technological innovation through R&D investment can lead to better firm performance (Ahuja et al., 2008).

4.4. Differential performance segmentation for a new paradigm of strategic competencies

The empirical experiment so far has centered on analyzing the relative impact of each strategic determinant and its synergistic effect within the realm of average performance. However, an average-performance model may oversimplify potentially complex relationships between variables and neglect asymmetric returns to the equivalent resources. Hence, the averaging approach with generalization is not capable of differentiating firms of asymmetric performance and capturing contrasting impact patterns of strategic factors in each performance segment. Noting that the previous literature rarely shows a pragmatic resolution for this crucial issue, the next stage of the experiment aims at exploring the contrasting impact patterns of strategic determinants among two categories of performers, *high* and *low*. The two categories of performers are characterized by asymmetric returns, indicating distinguishable capabilities in utilizing scarce resources in increasing market valuations. Therefore, the *high* performers produce greater output for the same level of input due to established capabilities (Mu, 2017). According to Mu (2017), capabilities drive firms to achieve above-average performance throughout a reconfiguration of resources and competencies. In this analytic approach, the nonlinear segmentation scheme of BPNN (i.e., above- and below-average) has provided an effective methodological basis for differentiating capabilities. Furthermore, besides the value of its empirical soundness, the nonlinear segmentation contributes to reliable neural network modeling, owing to the improved monotonicity of a segmented subset of data (Kwon et al., 2018; Lee and Kwon, 2017; Pendharkar and Rodger, 2003). In essence, the BPNN approach enables innovative analytics as a robust model. Table 7 summarizes the training results of BPNN (BPNN_H and BPNN_L) for the segmented subsets (*high* and *low*), determined by the initial model (BPNN_A) built on the entire data set. The initial model segments all 148 firms into 75 *high* and 73 *low* firms, and the subsequent models built on subsets of data show improved performance, as indicated by a higher correlation (Pearson R) and mean absolute percentage error (MAPE). In addition, comparable levels of correlations for each subset (training-test-validation) for all the models indicate no evidence of overfitting problems in these models. Fig. 6 further illustrates an improved monotonicity, as reflected by smaller error scales of subsequent BPNN models.

Table 7
BPNN Training results.

Model	BPNN_[a]A	BPNN_[b]H	BPNN_[c]L
Data sample	Total: 148	Total: 75	Total: 73
	Train: 104	*Train: 53*	*Train: 51*
	Test: 22	*Test: 12*	*Test: 12*
	Valid.: 22	*Valid.: 10*	*Valid.: 10*
Network structure	16-7-1	15-4-1	15-4-1
	Input: 16	*Input: 15*	*Input: 15*
	Hidden: 7	*Hidden: 4*	*Hidden: 4*
	Output: 1	*Output: 1*	*Output: 1*
Pearson R	All: 0.758	All: 0.855	All: 0.884
	Train: 0.779	*Train: 0.853*	*Train: 0.878*
	Test: 0.746	*Test: 0.814*	*Test: 0.928*
	Valid.: 0.770	*Valid.: 0.897*	*Valid.: 0.845*
MAPE	23.4%	15.1%	13.3%

Note.
[a] A: All data.
[b] H: High (capabilities).
[c] L: Low (capabilities).

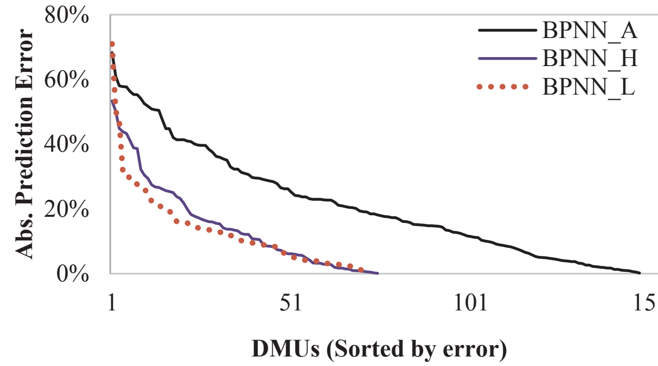


Fig. 6. Diminishing error from monotonic subsets.

Firms in the *high* category are considered more capable than their peers in the *low* category, due to their superior ability to create higher outputs for given resources. In other words, they are more efficient in terms of utilization of scarce resources and, accordingly, are more capable. To detect differential impact patterns in the two contrasting groups, each BPNN model was tested by steadily increasing each variable from 1% up to 15% (−15%–15% for CAP) while keeping all other factors constant. The sensitivity analysis provides an effective way of observing the marginal effect of a specific input as a system response, especially when the internal mechanisms of the analytic model are not visible as a Blackbox. Indeed, the distinctive complementary capability of BPNN in terms of explanatory and predictive analysis has prompted this innovative differential impact analysis. Table 8 summarizes the incremental impact of strategic determinants between the two contrasting categories, *high* vs. *low*, which is further visualized in Fig. 7 for pairwise comparisons. As presented in the table, firms in the *high* category generate higher outputs, and the increase of input also results in more lucrative returns across most of the strategic variables, but with noteworthy exceptions for certain strategic variables like GRN and CAP.

Fig. 7 shows the performance trajectory of each category as a response to the incremental value of strategic factors, which reveals contrasting impact patterns of each factor on firm performance (Tobin's Q) between *high* and *low* groups. Amongst the five strategic factors, the effect of green score (GRN) exposes noteworthy impact patterns, namely, an inverse U-shaped pattern for the *low* group, and a sinusoidal pattern for the *high* group. In addition to nonlinear impact patterns, the figure shows that BPNN can further detect the desirable and discernible level of GRN to yield an optimal output (Tobin's Q) for each group. The *low* group shows a curvilinear pattern with an optimal output value at an approximately 8% increase of GRN, thereafter producing diminishing returns. In contrast, for the *high* group, the optimal performance is observed at a 3% increase of GRN, with a sinusoidal effect afterwards. The result implies that the impact of GRN is comparatively in effect for the *high* group, thus demanding a smaller amount of additional commitment. On the contrary, the *low* group can expect a greater impact of GRN, which may prompt further investment in GRN initiatives.

In the case of R&D investment, both *low* and *high* groups can expect a steady improvement of output, but with somewhat higher rates in the *low* group. As for corporate reputation (RPT), both *low* and *high* groups can enhance market value with an improving reputation, with greater improvement potential for the *high* group. However, the *low* group retains a greater rate of impact up to a 4% level of increase. Operational efficiency (OPE), as discussed earlier, is one of the most impactful variables on performance and exposes far greater potential for market valuation for both performance groups, but with much higher expectations of improvement for the *high* group. Unlike increasing impact patterns (i.e., R&D, RPT, and OPE), capital intensity (CAP) shows a

Table 8
Differential impact of variables on output.

Input change	GRN (I)		RND (I)		OPE (I)		CAP (I)			RPT (I)	
	[a]high (O)	[b]low (O)	high (O)	low (O)	high (O)	low (O)	high (O)	[c]high-	low (O)	high (O)	low (O)
1%	1.721	1.106	1.712	1.104	1.751	1.124	1.708	1.712	1.108	1.714	1.105
2%	1.725	1.108	1.714	1.105	1.791	1.145	1.705	1.714	1.113	1.714	1.108
3%	1.724	1.111	1.715	1.106	1.843	1.167	1.702	1.715	1.117	1.717	1.111
4%	1.721	1.113	1.716	1.107	1.909	1.188	1.699	1.716	1.122	1.725	1.115
5%	1.718	1.115	1.718	1.108	1.968	1.209	1.696	1.717	1.127	1.740	1.120
6%	1.717	1.116	1.719	1.109	2.012	1.230	1.692	1.717	1.131	1.764	1.124
7%	1.714	1.117	1.720	1.110	2.051	1.249	1.689	1.716	1.135	1.789	1.129
8%	1.707	1.117	1.721	1.111	2.091	1.267	1.685	1.715	1.140	1.818	1.134
9%	1.700	1.117	1.722	1.112	2.135	1.284	1.681	1.713	1.144	1.838	1.140
10%	1.696	1.117	1.724	1.113	2.178	1.299	1.677	1.711	1.148	1.857	1.147
11%	1.693	1.117	1.724	1.114	2.219	1.313	1.673	1.709	1.152	1.873	1.155
12%	1.691	1.116	1.726	1.115	2.256	1.325	1.669	1.706	1.156	1.890	1.162
13%	1.690	1.115	1.727	1.116	2.288	1.336	1.664	1.703	1.159	1.907	1.170
14%	1.690	1.114	1.728	1.117	2.318	1.345	1.660	1.699	1.163	1.923	1.179
15%	1.692	1.113	1.729	1.118	2.351	1.353	1.656	1.696	1.167	1.937	1.188

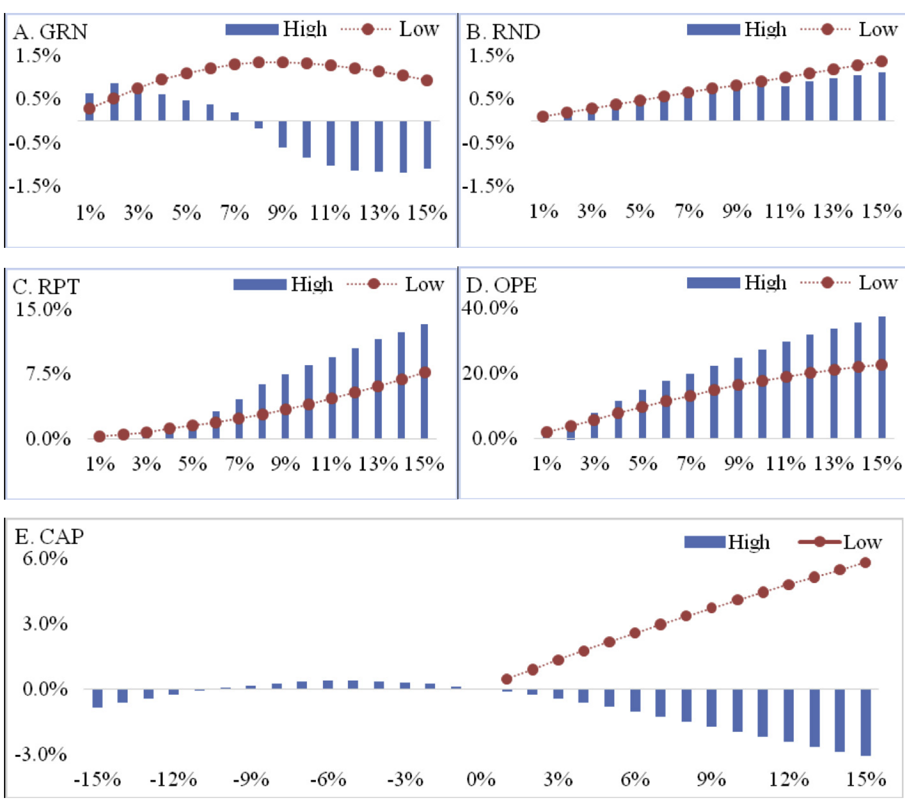
Note.
[a] Output (*high* category) measured by BPNN_H.
[b] Output (*low* category) measured by BPNN_L.
[c] Output (*high* category) upon decrease of input.

remarkable contrast between the two performance groups. Steady improvement of capital intensity positively affects market valuation in the case of the *low* group, whereas the *high* group shows an adverse impact. For the *high* group, even though weak, BPNN detects a curvilinear impact pattern with an optimal effect estimated at a 5% decrease of input.

5. Major findings, implications, and limitations

5.1. Major findings

This study is an attempt to explore an innovative research framework for a better understanding of strategic determinants of market valuation in high-tech industries, especially with varying capability levels. The sequential empirical process introduced in this research



Note: GRN: green score; RND: R&D intensity; RPT: reputation; OPE: operational efficiency; CAP: capital intensity

Fig. 7. Comparative impact patterns of strategic factors for performance. Note: GRN: green score; RND: R&D intensity; RPT: reputation; OPE: operational efficiency; CAP: capital intensity.

enables a multifaceted analysis and provides meaningful managerial insights within the realm of strategic management. At its core, the progressive neural network model explores the impact of crucial strategic factors and their synergistic effects, and detects contrasting impact patterns following the performance segmentation. Previous studies relied on conventional statistical approaches (e.g., OLSMR) grounded in *a priori* assumptions and constraints, thus lacking adaptive learning and nonlinear modeling capabilities. Moreover, the extant literature rarely shows the integration of crucial factors (e.g. GRN, R&D, RPT, and OPE), especially for the progressive pairwise and segmented impact analysis. Most of them have a short-term orientation with a major focus on a return-based financial performance (e.g., sales revenue, profit, and ROA), rather than a market-based performance. Accordingly, this research is innovative from an empirical perspective, and it is also comprehensive in that it explores key strategic variables and their dynamic effects on long-term market valuation.

This paper presents several insightful findings. First, besides determining the significance of each strategic factor, this research identifies operational efficiency (OPE) and corporate reputation (RPT) as two of the most impactful factors in market valuation. The result empirically affirms the conventional wisdom of harmonizing internal best practices and external attractiveness as a precondition for enhancing the market valuation of a firm. Second, as a salient analytic process, this study captures the integrative synergistic effects of combined factors using neural networks. The BPNN model was used to further explore whether any two strategic factors would be more impactful than the individual factors when they were integrated together. Aside from the relative importance of each factor, the combination of GRN and RPT appears to generate a greater synergistic effect on the firm's market performance than any other pairs. When GRN and RPT are taken together, their joint effects are nearly 6.1% higher than the sum of their individual effects on firm performance. Overall, three variables (i.e. GRN, RPT, OPE) were determined to be the most impactful strategic factors in terms of synergistic effects, as well as individual influence. Interestingly, R&D is not likely to generate any significant synergistic effect on a firm's market performance. Third, the discovery of varying impact patterns under distinguishable capabilities is another meaningful finding of this paper. In this effort, two performance levels segmented by asymmetric returns to the equitable commitment of strategic factors is considered a surrogate capability indicator. Accordingly, capturing different impact patterns for *high* and *low* performers in terms of capability is a significant contribution of this study. In particular, the detection of curvilinear and sinusoidal patterns of GRN and its optimal levels provides valuable managerial insights into managing and committing scarce resources. Altogether, these findings show the potential advantages of using neural networks as an adaptive analytic tool.

5.2. Strategic and managerial implications

Despite the fact that there are still some inconclusive conversion issues from a managerial perspective, this study demonstrates that the key strategic factors (i.e., green score for environmental sustainability, R&D investment for technological strength and power, corporate reputation for social value and image, and operational efficiency for best management practices) can be used as major competitive determinants for a firm's market value performance. Although prudent management of scarce strategic resources is a precondition for a competitive advantage, an emphasis on limited strategic factors alone may not be sufficient for a company to achieve superior performance. Instead, adaptive control and a flexible decision mechanism to harmonize the commitment level of scarce resources are, in practical terms, a demanding managerial imperative. In accordance with the findings of this research, a firm can expect greater returns when it increases its sustainability efforts while simultaneously pursuing operational excellence as a best practice. More importantly, by being aware of its capability to generate market value for given strategic resources, a firm can refine its strategic directions and decide on an appropriate level of resources. For example, as discussed earlier, a firm that belongs to a *high* capability group may improve its commitment level to corporate sustainability (e.g., 2%) in conjunction with making continual efforts to improve its operational practices. In contrast, a firm in a *low* capability group needs to make far greater efforts to improve its corporate sustainability (e.g., 9%) while steadily improving internal operations practices.

In fact, by being able to identify an optimal level of environmental commitment as represented by the green score, the proposed approach makes a significant contribution to the literature from both academic and managerial perspectives with respect to environmental sustainability. Indeed, from an academic perspective, this study proposes a new research paradigm for exploring the effect of environmental sustainability. The bisected view of the impact of sustainability, namely, whether it has a positive or negative effect on performance, results from using a conventional linear model. This study, by departing from this view, presents new insights with additional explanations. Unlike traditional linear models, the innovative neural network approach detects the nonlinear impact patterns of environmental sustainability. Not only does this study deepen recent insights into the curvilinear effect based on the average pattern (Trumpp and Guenther, 2017), it also makes a unique contribution in that it finds asymmetric patterns. Specifically, these patterns are a sinusoidal pattern and an inverse U-shape pattern, depending on whether the capability level is high (above-average) or low (below-average). From a managerial perspective, it is generally understood that many companies are looking for ways to continue to improve their operations, particularly through their commitment to environmental management as one of the most critical strategic competencies (Eccles et al., 2014; Hong et al., 2016). In this sense, managerial competency in determining the optimal level of scarce resources and in predicting their desired impact on the crucial performance dimension can equip managers with a pragmatic two-pronged strategic management tool, especially in managing corporate sustainability. In essence, the main approach presented in this study is expected to enhance managerial competency in dealing with the ‘cost vs. benefit’ dilemma, and to alleviate the concern over doing ‘too much vs. too little.

Altogether, from a managerial perspective, it is imperative that companies make a long-term commitment to vital value-chain activities for corporate sustainability, corporate reputation, and R&D investment in order to maintain their lead in their respective industries (Fisher, 2010; Krishnan et al., 2009; Lee, 2012). Furthermore, it is crucial that high-tech-oriented firms continue to maintain their competitive advantage by pursuing best operations practices through continuous improvement efforts alongside the aforementioned strategic initiatives. In addition to managerial insights, this study presents a salient modeling approach based on an artificial neural network. The integrative sequential model using BPNN provides a sound methodological basis for a nonparametric analysis, and is a promising tool in overcoming the shortfalls of conventional OLSMR analysis. Specifically, the BPNN-based nonlinear segmentation approach in this study provided a valuable means of categorizing firms by different capabilities and then performing a subsequent differential analysis.

5.3. Contributions and caveats

Most of the previous studies which examined the significance of key determinants of market valuation (e.g., corporate sustainability, R&D intensity, and corporate reputation) relied on parametric models such as regression analysis to test the preset hypothesis. Departing from linear-averaging statistical methods, this paper presents a nonparametric neural network approach. With its inherent strength in nonlinear mapping and functional approximation, the progressive BPNN model explores the relative impact of each strategic determinant, scrutinizes their synergistic effects, and detects the contrasting impact patterns in two categories of firms differentiated by capabilities. The proposed neural network approach combines both explanatory and predictive analyses, which has rarely been attempted until now. In fact, very few studies have addressed the puzzling issues of strategic determinants of firm performance. Major findings of this study will potentially provide solutions for the challenges inherent in strategic resource management, particularly in high-tech-oriented firms. Accordingly, the neural network-based approach will give new insights into analysis of a firm's strategic resources and their efficient utilization. In addition, the findings of this study will provide researchers, as well as practitioners, with a new paradigm of strategic competencies based on differential performance segmentation, especially in technology-oriented industries.

Nonetheless, there are still controversial issues with respect to the strategic effect of corporate sustainability, R&D investment, and corporate reputation on firm performance across different industry sectors. It is generally perceived that the impact of corporate sustainability and corporate reputation on firm performance may vary, depending on which aspects are being operationalized, because of their multifaceted dimensions, particularly with respect to managerial perspectives and social, economic, and environmental practices (Rezaee, 2017). Thus, a more consolidated framework, with comprehensive and rigorous measures of sustainability, needs to be further considered to explore the strategic relationship between sustainability and performance with greater accuracy (Mahon and Wartick, 2012; Maron, 2006; Trumpp and Guenther, 2017). Similarly, a more in-depth study would have to be conducted to see if this were true with any other types of sustainability and reputation indicators. In addition, the study was limited in the number of strategic control variables that could be included. The authors acknowledge that the final results may have been unduly influenced by the selection of control variables and that adjusting for industry effects may have strengthened the development of this body of research. It may also be beneficial for future research to analyze different industrial sectors in order to identify whether the impact of sustainability and reputation varies per grouping, as well as to compare industries against their counterparts in the competitive global market.

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