The Valuation of Small and Medium Enterprises: Based on the Resource Based View

ABSTRACT

This study derives key factors for the valuation of small and medium enterprises (SMEs), using the resource allocation strategy frame drawn from the resource-based view. As these factors vary according to the industry group characteristics, this study classifies industries into manufacturing and service industries. Subsequently, it selects the major factors through random forest-based dimension reduction and panel analysis; it performs K-means cluster analysis according to each major factor's characteristics. By analyzing the pattern of the highest productivity cluster, it reveals the characteristics of the cluster's major factors. This study contributes to suggest a RBV research frame for the valuation of SMEs in each industry, which breaks the traditional strategy studies focusing on the one dimension.

1. INTRODUCTION

Based on the resource-based view (RBV), the strategic management studies on firm valuations consider a single strategy, and thus provide a one-dimensional and incomplete evaluation of firm value. The strategic management studies focus on industry evolution (Helfat & Peteraf, 2003; Stieglitz & Heine, 2007) or competitive strategy (Alexy et al., 2016; Costa, Cool & Dierickx, 2013; Krakowski, Luger & Raisch, 2022; Ndofor, Sirmon and Xiaoming, 2011; Porter, 1980; Wibbens, 2021) from the financial (Wibbens, 2019) or nonfinancial perspective (Allen, Schepker & Chadwick, 2021; Barthélemy, 2017; Le Breton-Miller & Miller,2015), respectively. While it is important to examine good strategies, it is more important to identify strategies critical to firm survival. Accordingly, firms should modify the strategies that do not support their survival. As competition becomes severe, firms employ diverse complex strategies. For example, instead of diversifying resources, Kodak concentrated all its resources on the film market to achieve competitive advantage and superior performance. However, Kodak collapsed because of a failure to align its resource allocation strategy for the commercialization of digital cameras (Anthony, 2016). Conversely, Fujifilm's resource diversification and allocation strategy allowed the former to create value that is different from that of Kodak. Hence, an optimal resource allocation strategy can increase the valuation of enterprises, especially the resource-constrained small and medium enterprises (SMEs).

In Korea, SMEs account for 99.9 percent and 89.8 percent of all the businesses and employment, respectively; they are the key drivers of the domestic economy. However, SMEs suffer from a lack of working capital. The SMEs loan demand increased to almost US$ 107 billion in 2021. However, the continuing depression has also increased the probability of default. Given the scenario, it is critical for SMEs applying for a business loan to conduct a proper valuation. In other words, successful SME investment depends on proper firm valuation. However, it is difficult to determine the true value of SMEs, given the lack of information and high information asymmetry among the SMEs. In this regard, several studies on firm valuation employ indicators of cash flow or financial solvency, such as liquidity (Moretto & Tamborini, 2007), return on investment (ROI) (Adelaja et al., 1999; Beaver, McNichols, & Rhie, 2005; Kaplan & Dietrich, 1982), and Long-Term Debt ratio (Barton & Gordon, 1987; Limpaphayom & Polwitoon, 2004). These studies focus on the firm financial factors, and not the strategy perspective. In order to treat factors that cannot be ascertained by financial information, some studies complement financial information with non-financial characteristics such as industry characteristics (Miloud, Aspelund, & Cabrol, 2012) and innovation performance ((Kim et al., 2021; Köhn, 2018; Min & Smyth, 2016). Given the high number of limited or invisible factors of SMEs, the use of financial indicators has limitations for SMEs' valuation. Owing to the limited information, it is necessary find key SME valuation factors (classified by industry).

In order to conduct accurate SME valuation, this study considers heterogeneity among industries. Firms in the same industry are more likely to have similar technological opportunities, characteristics, knowledge and market structure. Hence, it is necessary to derive valuation factors by dividing industries into similar groups (De Jong & Marsili, 2006; Hawawini et al., 2003; Mauri & Michaels, 1998; Pavitt, 1984). In this study, we classify firms to manufacturing (including construction) and service industries, by referring to the taxonomy of Clark (1951) and Chenery (1960). Service industry produces intangible products. Relative to the manufacturing industry, service industry is characterized by a high dependence on human resources, low equipment cost, and low entry and conversion costs. In this regard, it must be noted that it is relatively easy to introduce new technologies in service SMEs with relatively limited resources.

This aspect is bringing about a rapid change in the service industry. However, manufacturing industry incurs a fixed cost for infrastructure or facilities. Hence, change is relatively slow and incremental in the manufacturing industry. Thus, this study conducts a cross-section analysis considering the heterogeneity caused by industry and potential financial factors.

In this context, this study reflects on complex firm strategies adopted to achieve firm value, using diversified observation and the resource allocation strategy frame. In response to the need for valuing firms using financial resource, this study suggests the use of the resource allocation strategy based on the complex strategy of firms. This study derives key factors that can predict the value of SMEs; it conducts the machine learning analysis, which simultaneously considers multiple factors. In order to derive the factors, we adopt the permutation importance utilizing the random forest regression, which is widely used in financial analysis and for deriving key factors for firm valuation (references). We use these factors to construct a cluster. To identify the significant factors, we perform regression analysis using all the factors as independent variables. By deriving the major factors using machine learning, we overcome the limitations of regression analysis attributed to the quantitative analysis of few factors. By comparing the productivity of clusters classified on the basis of factors, we suggest the main factors and patterns key to corporate management and investment strategies. Before proceeding further, this study discusses firm valuation in relation to the RBV.

2. Literature review

2.1 RBV-based firm valuation

The RBV is widely used to study the impact of the resource characteristics of a firm's value (Powell, 2001; Priem & Butler, 2001; Rouse & Daellenbach, 2002). Resource allocation plays a role in shaping a firm's a unique character and determining its direction (Penrose, 1959;

Wernerfelt, 1984). The RBV is a framework enabling firms to allocate resources in a manner that they gain sustainable competitive advantage (Barney, 1991). Beyond traditional material resources, including corporate assets, capabilities, and knowledge, the RBV comprises a bundle of resources. Firms use RBV for strategic management; hence, the framework is used in several related studies. Even though the firms' complex strategy is based on the financial and nonfinancial resources, the perspective is divided (Wibbens, 2019; Allen, Schepker & Chadwick, 2021; Barthélemy, 2017; Le Breton-Miller & Miller,2015).

There are three main streams of research on the RBV of strategic management. The first stream of research for competitive advantage focuses on valuable, rare, inimitable, and non-substitutable characteristics of resources. RBV assumes that this resource heterogeneity helps firms to sustain competitive advantage (Alexy et al., 2017; Costa, Coll & Dierickx, 2013; Mahoney & Pandian, 1992; Montgomery & Wernerfelt, 1988; Wernerfelt & Montgomery, 1988). The second stream shows that industry evolution changes the value, capabilities, and heterogeneity of resources sustaining the competitive advantage of companies (Hoopes et al., 2003). The third stream focuses on the resource allocation required to compete (Gruber et al., 2010). Several studies focus on identifying the most competitive strategy firms can implement to create value. It must be noted that no single strategy or resource can determine firm value. However, the cost and value of a resource can change firm strategy (Ghosh & John, 1999; Poppo & Zenger, 1998; Silverman, 1999). Since all the strategies are intertwined, it is necessary to consider a perspective encompassing competitive advantage and capabilities. This perspective is anchored in the resource allocation strategy. Corporate resource allocation enables firms to achieve the strategic goal of enhancing value. Given that a firm's resource is the principal source of strategy options, we believe that optimal resource allocation can positively influence the performance of each strategy (Terziovski, 2010).

2.2 RBV-based SME firm valuation

Previous studies treat performance and firm valuation as two different research areas. This can be attributed to the following two factors. First, most of the SMEs possess limited information. This makes it difficult to estimate the market value of firm through stock. Hence, some studies rely on alternative proxies to analyze SMEs' market value; these proxies include cumulative abnormal returns (Brav et al., 2000; Hendricks & Singhal, 1996; Wansley et al., 1983; Wruck, 1989), cash flow (Amoako-Adu & Eshun, 2018; Kaplan & Ruback, 1995; Visconti & Weis, 2020) or stock price (Abowd, 1989; Fama & French, 1998). Second, unlike large firms, SMEs possess different attributes such as less capital, resources, and information. Several studies focus on these liquid and unstable market and corporate values(Carter et al., 2003) with value-added (Das et al., 1998) as well as non-financial industrial and human factors influencing firm performance (Aspelund, Berg-Utby, & Skjevdal, 2005; Barniv et al., 1997; Franke, Gruber, Harhoff, & Henkel, 2008; Gimeno et al., 1997; Hall & Weiss, 1967; Miloud et al., 2012; Porter, 1980; Sapienza & Grimm, 1997; Siegel et al., 1993). However, these factors are insufficient to determine whether the firm's resource allocation strategy can improve profit.

Since financially constrained SMEs tend to depend on debt, the misallocation of resources can affect future financing through debt, and thereby impact projects for follow-on business units (Lopez-Gracia & Mestre-Barberá, 2015; Myers, 1977). In this scenario, a firm can deploy resources to internal revenue generating projects; in this case, firms can ensure optimal resource allocation by maximize each unit's returns. Overinvesting may increase the number of units without correspondingly boosting unit returns. However, underinvestment—underexploiting the growth opportunities—may reduce the firm's competitive advantage (Arrfelt, Wiseman, McNamara, & Hult, 2015).

Allocating resources for innovation can increase firm's market dominance, reduce costs (Cohen & Klepper, 1996), avoid competition in a new market position (Porter, 1980), and improving resource coordination and integration (Eisenhardt & Martin, 2000; Teece, Pisano, & Shuen, 1997). However, a sole emphasis on innovation may not profit the SMEs, given their lack of resources. This indicates that an SME's R&D expenditure may disrupt its growth (Müller & Zimmermann, 2009; Yasuda, 2005) and survival rate (Buddelmeyer et al., 2010; Cefis & Marsili, 2011).

Since all the strategies have their positive and negative aspects, it is impossible to assess the value of a company only from the aspect of innovation or any other single aspect. Therefore, it is necessary to look at a complex resource allocation strategy to improve firm value—its performance. A firm's strategic decision significantly impacts its performance and value. In this context, the strategic perspective based on the RBV has been used in a limited manner in firm valuation studies.

Based on the RBV and various financial variables, we study corporate value derivation in relation to the resource allocation strategy. Although various factors have been used in financial studies on corporate value research, they are limited in that they focus on limited factors, and hence fail to extract the resource allocation strategies. Several studies refer to the return on asset (ROA) and return on equity (ROE), which indicates the relationship between a firm's productivity and its invested asset or equity. Several studies also discuss factors indicating a firm's efficiency, status, and characteristics (Adelaja et al., 1999; Beaver et al., 2005; Kaplan & Dietrich, 1982). Similarly, debt-related factors capture a firm's financial soundness. Studies focus on the debt-to-equity and long-term debt ratios showing a firm's financial structure and project status (Barton & Gordon, 1987; Limpaphayom & Polwitoon, 2004). In similar contexts, studies also consider the liquidity ratio, indicating a firm's ability to repay short-term debt (Moretto & Tamborini, 2007). Since each element represents a fragmentary aspect of a firm, it is impossible to grasp the accurate firm value by observing only one firm strategy or a specific part of a resource. Moreover, studies on firm valuation mainly estimate the present value of a company in the accounting field and observe it in terms of the cumulative outcome of past earning. The methodology performed in the accounting field is suitable only for the firm's managers; it presents a limited insight to external investors considering the future value of the firm (Miralles-Quiros et al., 2017). Under limited information, firm valuation might lead to biased value estimation (Hall et al., 2009; Hoffman et al., 1998). Therefore, to estimate firm value by including a complex strategy from the RBV, it is crucial to consider the resource allocation frame of the firm.

2.3 Manufacturing and service industries

Firms in the same industry are likely to have similar technological opportunities, knowledge, and market structure. However, these features differ for firms in different industries. By classifying heterogeneity at the industry-level, this study reduces the complexity of research results (De Jong & Marsili, 2006; Hawawini et al., 2003; Mauri & Michaels, 1998; Pavitt, 1984). We classify the industries into manufacturing and service industries.

According to the RBV, manufacturing and service industries incur different initial costs, which makes them adopt different resource allocation strategies. Since manufacturing involves the production of tangible products, manufacturing employs physical equipment and process knowledge to produce products. These resources are used to conduct the production process and shape the firm's core competency (Schroeder, Bates, & Junttila, 2002; St John & Harrison, 1999). The firm's performance is affected by its human resources so that investment in human resource learning (e.g., employee training) is positively related to firm performance (Adler & Clark, 1991; Pisano, 1994). It can be a source of sustainable competitive advantage and new knowledge (Schroeder et al., 2002).

Concerning service industry, service providers create intangible and temporary services using tangible and intangible inputs. Since the service industry does not use physical equipment, its importance is relatively low. In this industry, it is crucial for human resources to possess the requisite expertise and business know-how (Chatterjee, 2017). The knowledge is different from the process-oriented knowledge of human resources in the manufacturing industry. These differences require the industries to adopt different strategies and resource allocation plans. Owing to the heterogeneity between the two groups, studies handling cross-sectional data of the two industries focus on the non-financial factors rather than the financial factors. In this regard, it must be noted that manufacturing and service industries require different human resource management systems and dependencies (Shen & Chen, 2007). The type of innovation also differs in the two industries (Forsman, 2011; Forsman & Rantanen, 2011), and some service industries are more dependent on external R&D (Tether & Tajar, 2008). The service industry places a higher importance on customer management than the manufacturing industry (Edvardsson et al., 2000; Song et al., 1999). The overall financial resource allocation strategy could reflect the non-financial aspects (Gruber et al., 2010). For example, if customer management is given importance, the financial resource allocation for customer management would be more in regarded part.

In light of the studies on the RBV-based resource allocation strategy, it must be understood that the proper allocation of a firm's internal resources would imply financial soundness and the adoption of an appropriate strategy. This approach can connect resource allocation to firm value. In the given context, this study suggests financial factors representing a firm's true value, by considering the characteristics of manufacturing and service industries.

3. RESEARCH MODEL

3.1. Data

In this study, we set sales information as a dependent variable. We extract 114 factors from financial information—including the number of patents firm published and credit rating. Furthermore, we analyze the historical change in financial information from 2012 to 2019. Among them, Table 1 summarize the descriptive statistics of four fundamental financial variables used to analyze productivity. Based on the value obtained by multiplying the inter quartile range of the distribution by variable by 1.5, we classify the records outside of this value as outliers and winsorized. Through preprocessing, we reduce the number of observations from 2,146,000 to 828,902. We could not have achieved this reduction through general computer specifications, given the large number of observations and feature dimensions processed by the machine learning. In the machine learning analysis, including the preprocessing phases, we simultaneously run two 64-core advanced micro devices' central processing units and use over 100GB of random access memory to handle over two gigabytes of text files. We convert all the won unit values into dollars based on the international exchange rate as of May 27, 2022. We also treat the standard industrial classification categorical data.

INSERT TABLE 1 HERE

3.1.1. Standard industrial classification

Major countries, including Korea, designate classification codes by referring to the industrial classifications defined by the scholars (Clark, 1940). Statistics Korea defines the service industry as a business producing intangible economic goods that change the state of the economic activities of other economic entities. The service industry has also been defined, as shown in Table 2, based on the Korea standard industry code. This definition considers the scalability and consistency of domestic statistical indicators, and major value-added industrial activities (Notification of Statistics Korea No. 2018-390, 2018). Table 2 presents the definition considering the distinction between the public interest industry (including social overhead capital) and the primary and secondary industries. The Korean National Statistical Office classifies the service industry as "D." By adding "electricity, gas, steam, and air conditioning supply businesses," 17 codes (out of 21 classification codes) were classified as service industries, and 4 codes were classified as manufacturing industries, corresponding to the primary and secondary industries.

INSERT TABLE 2 HERE

3.2. Ranking the importance of variables

3.2.1. Variance inflation factor

Random effects regression is suitable for longitudinal studies or panel data (Benfratello, 2014). The multicollinearity problem emerges with an increase in the number of independent variables used in the dependent variable regression model (Frisch, 1934). To address this, regression studies calculate the variance inflation factor (VIF), determine whether variables with high VIF values exhibit multicollinearity, and remove values with multicollinearity, respectively (Craney & Surles, 2002; Stine, 1995).

$$VIF_i = \frac{1}{1-R_i^2} \quad ,(1 \leq i \leq n) \qquad (1)$$

To obtain VIF_i in Equation (1), we first perform the regression analysis by designating the ith variable as the dependent variable and the remaining $n-1$ variables as independent variables. We remove the existing dependent variables from this regression analysis because multicollinearity measures the correlation between the input variables. If the coefficient of determination R_i^2 in the regression analysis comes out significant, the value of VIF_i can be obtained.

3.2.2 Permutation importance

Researchers utilize intelligent methods to predict various financial indicators of the firms. For example, several researchers use statistical and machine learning models such as the multiple linear regression analysis, multiple logistic regression, and support vector machine (Kim & Ahn, 2012; Shin & Han, 2001). Studies also propose different classification models for problems such as overfitting, which requires excessive adjustment of parameters in learning each data, as the range of independent variables increase. This range has been increasing in recent studies.

The recent years have also seen the emergence of the random forest (RF) regression. The RF algorithm is a bagging ensemble model based on B decision trees (Liaw & Wiener, 2002), as shown in Figure 1. For prediction, we use the RF regression model obtained by learning the existing combination of independent variables. We also find the importance $PI(F^j)$ of each independent variable and select the top nine variables in the order of importance as independent variables of the final multiple regression model.

We obtain the out-of-bag (OOB) error for each independent variable for constructing the RF regression model. OOB refers to data that do not belong to the learning data when randomly extracted through the bootstrap. $OOBError$ in Equation (1) is the sum of the squares of the difference between the predicted value y_p and the actual value y_r, obtained through the decision tree by learning the data not included in the bootstrap.

$$OOBError = \frac{1}{n}\sum_{i=1}^{n}(y_{r,i} - y_{p,i})^2 \quad (1)$$

In order to obtain the permutation importance $PI_i(F^j)$ of ith tree, we randomly rearrange F^j used in $OOBError_i$. Subsequently, we find $OOBError_i'$ while fixing the remaining independent variables and subtract it in Equation (2) below:

$$PI_i(F^j) = OOBError_i' - OOBError_i \quad (2)$$

We calculate the final permutation importance $PI,$ for the value of each independent variable F^j, by averaging the permutation importance PI_i of ith tree as shown in Equation (3):

$$PI(F^j) = \frac{1}{c}\sum_{i=1}^{c} PI_i(F^j) \quad (3)$$

INSERT FIGURE 1 HERE

3.2.3. Random effect panel regression

We perform the panel analysis by grouping data into one entity to analyze the 8-year imbalance panel data for each company from 2012 to 2019. We analyze the panel with a random effect, in the multiple regression analysis model. We randomize the level of factors from a number of independent variables, as shown in Equation (4). We set Y and sales as dependent variables using the multiple regression analysis model. We utilize 124 independent variables, and exploit the final 9 independent variables in the service and manufacturing industries in the multiple regression analysis model, respectively, through the permutation importance analysis. X_i indicates each independent variable. β_i is the slope coefficient of each independent variable, and β_0 and ϵ are the intercept and error terms, respectively.

$$Y = \beta_0 + X_1\beta_1 + X_2\beta_2 + \cdots + X_{124}\beta_{124} + \epsilon \quad (4)$$

3.2.4. K-means clustering analysis

To present a strategy based on firm value evaluation, we apply the K-means cluster analysis to identify the efficiency patterns of each cluster, based on the characteristics of the main factors. The K-means cluster analysis proposed by MacQueen (1967) is one of the mutually exclusive cluster methods, and the number of k clusters is predetermined to identify the cluster to which each entity corresponds. We use the following procedures to perform the K-means cluster analysis:

(i) Initialize the whole dataset into k clusters

(ii) Extract the center point of each cluster

(iii) Determine the Euclidean distance between the center points: We calculate t of the extracted cluster and other objects to assign the object so that the nearest center point corresponds to the corresponding cluster.

(iv) Repeat processes (ii) to (iv) until there no event in which each entity is assigned to another cluster.

Setting the number of clusters (k) for the K-means cluster analysis substantially affects the result of the analysis. Therefore, we repeatedly perform the number of clusters (k) from 1 to 20, as shown in Figure 2. Subsequently, we analyze the sum of the distances between the centroid and the entity in each group according to each trial as inertia. Through this process, we select three clusters and respond to each cluster by dividing them into 376,497 and 432,838 entities. We remove outliers from the service and the manufacturing industries divided based on the SIC code, by year.

INSERT FIGURE 2 HERE

3.3. Stochastic frontier analysis

After dividing the clusters, we conduct the stochastic frontier analysis (SFA) and the meta-frontier analysis (MFA) to measure the efficiency of each cluster. We compare the factors of the most efficient and non-efficient clusters to identify factors for firm investment (Kim, Lee, & Hwang, 2018; Yang, Lee, Hwang, & Shin, 2013).

SFA estimates technical efficiency using the frontier production function. It represents the relationship between the input and output elements as a production function and represents the maximum output relative to the input. At this time, a company's technical efficiency (TE) refers to the relative position of a company's technology level compared to the efficiency technology level in the form of a frontier production function. The farther the technology level of the company is from the frontier production function, the lower is the efficiency of the company.

Based on Bathesse & Coelli (1992), we measure efficiency using the SFA model in Equation (5) below to reflect the change in efficiency over time.

$$Y_{it} = f(x_{it}, \beta) e^{V_{it} - U_{it}}, \mathrm{i} = 1,2, \ldots, \mathrm{N}, \mathrm{t} = 1, 2, \ldots, \mathrm{T} \qquad (5)$$

At this time, Y_{it} is the output of company i at time t, *xit* is the input vector of firm i at time t, $f()$ is the production function, β is the parameter of the production function. It is and Vit is independent from Uit and is a random error following a distribution of $\mathrm{N}(0, \sigma_v^2)$, and Uit is a non-negative random variable indicating the TE of firm i at time t. If V_{it} is a general random error in the regression equation, U_{it} represents the company's inefficiency. To show that it is always inefficient, the unit itself is not considered negative. We assume that U_{it} follows a half-normal distribution.

From Equation (5), the technical efficiency TE_{it} at time t of Company i is given as Equation (6) below:

$$TE_{it} = e^{-U_{it}} = \frac{Y_{it}}{f(X_{it}, \beta) e^{V_{it}}}, i = 1,2, \ldots, N, t = 1,2, \ldots, T \qquad (6)$$

The Cobb–Douglas and translog functions are the most widely used production functions of

SFA. However, the Cobb–Douglas function tends to oversimplify the output variables because they are viewed as linear combinations of input variables only. Therefore, we implement the translog function in this research. Particularly, we use the random effects time-varying production model and assuming a production function in the form of a translog. Equation (6) can be expressed as Equation (7) below:

$$lnY_{it} = \beta_0 + \sum_{m=1}^{3} \beta_m lnx_{mit} + \sum_{m=1}^{3}\sum_{k\geq m}^{3} \beta_{mk}\, lnx_{mit}\, lnx_{kit} + V_{it} - U_{it} \tag{7}$$

In the meantime, m represents the mth input of the ith company at time t. Y_{it} indicates the net sales of the ith company at time t. x_i is an input element of i = 1, 2, and 3, which represent net assets (K), number of employees (L), and cost of sales (M), respectively. The parameter estimates of each variable may be derived by applying the input (M, L, K) and output (Y).

3.4. Meta-frontier analysis

Comparisons of technological efficiency between clusters cannot be accepted using traditional SFAs because the technological efficiency of certain firms is difficult to compare with those operating with other technologies. Therefore, to compare the efficiency levels of different clusters operating under different technical conditions, we apply the meta-frontier production function. It encompasses the production functions of all clusters (Battese & Rao, 2002). By following Battese, Rao, and O'Donnell (2004), we define the meta-frontier production function model as follows:

$$Y_{it}^{*} = f(x_{it}, \beta^{*}) = e^{x_{it}\beta^{*}}, \mathrm{i} = 1,2,\dots,\mathrm{N}, \mathrm{N} = \sum_{i=1}^{R} N_j, \mathrm{t} = 1,2,\dots,\mathrm{T}, \tag{8}$$
$$\mathrm{s.t.}\, x_{it}\beta^{*} \geq x_{it}\beta_{(j)}\ for\ all\ j = 1,2,\dots,T$$

In this case, j means each cluster, and β^{*} is an unknown variable vector of a meta-frontier function . Based on Equation (8), the graph of the meta-frontier production function is located above the graph of the production frontier function of each cluster, for all periods. In other words, the meta-frontier production function becomes an envelope of the frontier function of each cluster based on the same technology. For simplicity, assuming that the function $f = e^{x_{it}\beta_{(j)}}$ of Equation (5), we transform Equation (9) as follows:

$$Y_{it} = e^{-U_{it(j)}} \times \frac{e^{x_{it}\beta_{(j)}}}{e^{x_{it}\beta^*}} \times e^{x_{it}\beta^* + V_{it(j)}} \tag{9}$$

Dividing both sides of Equation (5) by $e^{x_{it}\beta^* + V_{it(j)}}$, we get Equation (10) as follows:

$$\frac{Y_{it}}{e^{x_{it}\beta^* + V_{it(j)}}} = e^{-U_{it(j)}} \times \frac{e^{x_{it}\beta_{(j)}}}{e^{x_{it}\beta^*}} \tag{10}$$

In the above Equation (10), the first part on the right, $e^{-U_{it(j)}}$ is the technical efficiency of cluster *j (TE).* The second part is denoted as the ratio of the group *j* to the meta-frontier function, which is called the technical gap ratio (TGR) or the meta-technology ratio. TE* representing the technical efficiency of the meta-frontier function can be expressed as follows.

$$TE_{it}^* = \frac{Y_{it}}{e^{x_{it}\beta^* + V_{it(j)}}} = TE_{it} \times TGR_{it} \tag{11}$$

Among the measurement methods representing the parameters of the meta-frontier function, the linear programming (LP) minimizes the sum of the absolute values of deviations. According to Battese et al. (2004), *LP* can be defined as follows:

$$\mathrm{LP:}\ \min_{\beta^*} L^* = \sum_{t=1}^{T}\sum_{i=1}^{N} |x_{it}\beta^* - x_{it}\hat{\beta}_{(j)}|,\ x_{it}\beta^* \geq x_{it}\hat{\beta}_{(j)} \tag{12}$$

4. RESULTS

4.1. Dimension reduction

Firstly, the factors with multicollinearity are eliminating. Appendix table 1 and 2 show the RF regression after eliminating values with multicollinearity. Secondly, using random forest regression, the results of permutation importance of factors is shown in Figure 3. Tables 3 and 4 (these could not be included because of the length limit) show the names and permutation importance figures corresponding to the numbers of each independent variable. Appendix table 1 and 2 (these could not be included because of the length limit) show the RF regression after eliminating values with multicollinearity.

FIGURE 3 HERE

The main factors of the value of each service and manufacturing industry obtained through dimension reduction are described in the following sub-sections.

4.1.1. Cost of sales, Selling costs to sales ratio, and wage

Indicators related to cost of sales and wage are the costs incurred for producing goods and services. Since we measure corporate productivity in terms of sales, it can be stated that indicators related to the cost of sales and wage are directly related to total sales. Among them, sales cost and salary represent the costs incurred to manufacture products; they are the major indicators of the size of productivity. However, the selling costs to sales ratio represent the efficiency by showing the performance in relation to the input cost incurred for production.

4.1.2. Fringe benefit

Fringe benefits are expenses incurred to improve the working environment and willingness to work. These two factors are considered human resource investments, in the academic field. There is a perception that capital and material-related indicators are more important than human resources in the manufacturing industry. However, the results of this study show that indicators related to human resources such as wage and fringe benefit significantly influence the productivity of SMEs.

4.1.3. Interest expense and interest expense to sales ratio

This indicator plays a more important role in reducing the feature dimension of the service industry than that of the manufacturing industry. Interest expenses are in the form of fixed expenses incurred as a result of using the company's debt. In financial indicators, more than a certain amount of debt can mean that an entity is willing to carry out a project through leverage.

4.1.4. Accounts payable

If a firm produces goods, it may incur accounts payable in relation to the costs of goods manufactured. Large-scale accounts payable can represent the size of production, market position of the companies, and trust. The larger the value, the more aggressive are the company's production activities and the higher is its reliability in the market.

4.1.5. Return on asset

The ROI is an indicator of the corporate management efficiency. Representatively, ROA and ROE are used. The return on total assets represents the return on invested assets and is an indicator of the efficiency of corporate operations as a ratio to profits.

4.1.6. Allowance for doubtful account (account receivable)

It refers to the irreparable losses that occur when conducting transactions with other firms. Assuming that the allowance for bad debts occurs at a certain rate of sales, it can be interpreted that the cost increases with an increase in the sales volume. According to the results of the dimension reduction, the cost related to the allowance for doubtful accounts is high only in the manufacturing industry. Unlike the service industry, where raw materials are tangible, but the products sold are intangible, it can be assumed that the sales price may be received later, such as the accounts payable when selling products. This can be attributed to the tangible nature of both the raw materials and products.

4.1.7. Entertainment expenses

Entertainment expenses have a low priority in reducing the efficiency level of the manufacturing industry. However, they assume a high priority in the service sector. This can be attributed to the importance attached to the interaction between companies and their human resources in the service industry or to the characteristics of the specific service industry incurring high entertainment expenses. The high entertainment cost means investing in relationships with other companies. The positive correlation between entertainment expenses and performance is realized through the interaction between companies.

4.2. Multiple linear regression analysis

In the service industry, as shown in Table 3, all variables are statistically significant at the 10 percent significance level. Excluding entertainment expenses, all the variables are statistically significant at the 1 percent significance level. The explanatory power of the model is 0.686 to 0.713. Compared to Appendix Table 1 (it is not included because of the length limit), there is similarity between the explanatory power of the model when using 56 independent variables and the explanatory power of the model using the top nine independent variables with the highest PI. While the cost of sales has a positive correlation, the selling costs to sales ratio has a negative correlation. The interest expense to sales ratio also has a negative correlation.

INSERT TABLE 3 HERE

In the manufacturing industry, as shown in Table 6, all the variables are statistically significant at the 10 percent significance level. Excluding the accounts payable, all the variables are statistically significant at the 1 percent significance level. The explanatory power of the model is 0.943 to 0.972. Compared to Appendix Table 2(it is not included because of the length limit), there is similarity between the explanatory power of the model when using 56 independent variables and the explanatory power of the model using the top nine independent variables with the highest PI. While the cost of sales has a positive correlation, the selling costs to sales ratio and the accounts payable have a negative correlation.

INSERT TABLE 4 HERE

4.3. K-means cluster analysis

4.3.1. Service industry

In the case of the service industry Cluster 1, in Figure 4, the cost of sales is low and the deviation is very small compared to Clusters 2 and 3. Furthermore, in the case of the selling costs to sales ratio, it can be seen that companies with large sales, relative to the cost of sales, are classified as Cluster 1. When comparing the cost of sales and the selling costs to sales ratio, Cluster 1 incurs a lower selling costs to sales ratio when the cost of sales is low. In the service industry, companies register high sales even at a low sales cost. In addition, in the case of Cluster 1, sales are higher than the interest expenses, based on the other independent variables. Particularly, based on the cost of sales, several individuals incur interest expense to sales ratio even at a low cost of sales. In addition, when looking at the selling costs to sales ratio of independent variables in Cluster 1, several individuals, in companies with low cost of sales, show good indicators related to employee welfare such as the wage (selling, general, and administrative expenses (SG&A)) and fringe benefits (SG&A). The independent variables such as the interest expense, wage (SG&A), accounts payable, fringe benefits (SG&A), and ROA have similar values, on an average. However, Cluster 1 shows very small deviations overall. Cluster 3 shows the highest cost of sales, and Cluster 2 exhibits an intermediate distribution between Clusters 1 and 3.

INSERT FIGURE 4 HERE

4.3.2. Manufacturing industry

In the case of the manufacturing industry cluster, in Figure 5, based on the cost of sales, Custer 3 shows the lowest and smallest deviation, and Cluster 2 shows the highest and largest deviation. Except for this, all the clusters exhibit similar levels of average for the other independent variables—the selling costs to sales ratio, wage (SG&A), accounts payable, fringe benefits (SG&A), ROA, fringe benefits (costs of goods manufactured), interest expenses, and allowance for doubtful accounts (accounts receivable)—with the smallest cluster and the largest deviation. Overall, it can be seen that the part with many independent variables showing a similar level of average between clusters shows a relatively constant distribution based on the level of cost of sales in the manufacturing rather than service industry. For example, in the manufacturing industry cluster, the cost of sales is listed at a constant figure, relative to selling costs to sales ratio in the service industry. Companies with low cost of sales do not have a lower or higher selling costs to sales ratio than companies with high cost of sales. Cluster 2 shows the best degree of welfare in terms of selling costs to sales ratio, when considering the fringe benefits (SG&A) and fringe benefits (costs of goods manufactured). In light of the above circumstances, it can be seen that, in the manufacturing industry cluster, companies with a high cost of sales record high sales at a certain rate. The other financial indicators such as fringe benefits also register good numbers.

INSERT FIGURE 5 HERE

4.4. Productivity analysis

4.4.1. Service industry

Table 5 shows that the production function of each cluster. We the production function through the SFA and MFA, using MATLAB. Based on Table 5, we calculate the productivity of each cluster in Table 6. Cluster productivity is the lowest in Cluster 2. However, when comparing productivity between clusters, we find that Cluster 3 exhibits the lowest productivity. Concerning the TE* value, the TE* value is smaller even though the productivity is better than that of Cluster 3. This can be attributed to the low productivity of Cluster 2. Concerning individual clusters, Cluster 3's shows the highest productivity. However, when comparing the three clusters, we find that Cluster 1 exhibits the highest productivity.

INSERT TABLES 5 and 6 HERE

4.4.2 Manufacturing industry

Table 7 shows that the production function of each cluster. We obtained this function through h SFA and MFA, using MATLAB. Based on Table 7, we calculate the productivity of each cluster in Table 8. Cluster 2 shows the lowest productivity (TE), among all the clusters. However, since SFA assumes different production functions, it is not possible to compare between clusters. Hence, using MFA, we obtain TGR and TE* and conduct comparison between clusters. When comparing productivity between clusters, it can be seen that Cluster 2 has the highest productivity.

INSERT TABLES 7 and 8 HERE

4.5 Results summary

The results reveal that firms should employ different strategies according to the characteristics of each industry. These characteristics can be determined by deriving the important indicators in each industry. Concerning these characteristics, the cost of sales, cost of sales ratio and wage (SG&A), and ROA show similar patterns in both service and manufacturing industries. However, fringe benefits, account payables, and allowance for doubtful accounts are more important in the manufacturing than service industry. The service industry attaches a high priority to interest expenses and entertainment expenses. Finally, we analyze the characteristics of the group with the highest productivity in both the industries in order to suggest productivity improvement strategies.

The key factors are cost of sales and cost of sales ratio. Although crucial, the two factors exhibit different patterns in the two industries. In the case of infrastructure industries, the larger the scale, the higher is the technology productivity, based on indicators such as cost of sales, fringe benefit, and wage. In the service industry, when the cost of sales is low, the cost of sales ratio tends to be low or the interest expense to sales ratio tends to be large. Combining this result with the productivity results, relative to performance, the lower the production cost, the better is the firm performance; the higher the productivity, the higher is the amount of loans received.

In conclusion, in the manufacturing industry, firms with a high cost of sales and fringe benefit have a higher value, as they have good overall indicators. However, in the service industry, the lower the cost of sales, that is, the less expensive the production costs (e.g., in professional occupations), the better is the welfare in the service industry. In other words, the professional services firms have a high value in the service industry.

5. DISCUSSIN AND CONCLUSION

The corporate strategy research usually considers a single strategy frame such as innovation. However, one strategy may not reflect true firm value. This study proposes a resource allocation strategy frame from the RBV perspective, by considering the financial information drawn from a firm's complex strategy. Resource allocation represents a company's complex strategy. It is difficult to understand only with the specific financial factors that have been studied. Therefore, it is necessary to consider factors related to firm performance, besides the key financial factors influencing the efficiency of a company.

Previous research focuses on strategies for gaining comparative advantage (Barney, 1991; Mahoney & Pandian, 1992; Montgomery & Wernerfelt, 1988; Wernerfelt & Montgomery, 1988), which is important to be competitive but it should not be neglected to determine whether the company is using its resources properly by conducting firm valuation through resource allocation. Although this has been studied from the financial side, it lacks a strategic perspective. Although these studies conduct valuation, they employ a one-dimensional perspective, and hence fail to consider a firm's complex strategy. While studies conduct firm valuation based on the complex resource allocation strategy, they do not analyze the process of extracting factors related to the firm's value—performance.

The studies on corporate productivity for value evaluation mostly model regression functions based on limited indicators and past productivity of a specific period. However, the development of new models and computing improvements have facilitated the inclusion of several other variables (Gruber et al., 2010; Kim & Ahn, 2012; Liaw & Wiener, 2002; MacQueen, 1967). Even though this has increased the possibility of improved valuation, the limited financial information of SMEs calls for simultaneously considering a large number of independent variables when processing data for SMEs' valuation. Therefore, we derive the valuation factors influencing the productivity and corporate value of a company measured by sales by using dimensionality reduction, cluster analysis, SFA, and MFA, and the RF regression. In addition, since the elements of firm valuation differ according to the characteristics of each industry, we derive the factors in the manufacturing and service industries, in the process of dimension reduction. Subsequently, we perform cluster analysis and we classify them according to characteristics analyzed using SFA and MFA.

This study academically and managerially contributes to expand the study on SME valuation by considering the factors for valuation from the RBV perspective, and it takes corporate strategy. In order to increase the firm value, we suggest firms to set the direction of business operation and investment, using the proposed resource allocation strategy frame. We focus on financial indicators from the perspective of a company's resource allocation strategy, and thereby expand the factors considered for SME valuation in different industries, respectively. Previous studies focus on financial or non-financial factors to make industry comparisons. Other than innovation, they consider only company characteristics or performance factors. However, this study shows the necessity of investment, based on the patterns of the proposed factors. Specifically, we derive the major factors based on the priority of indicators related to sales. The results show the importance of factors such as accounts payable, fringe benefits, and entertainment and bad debt expenses. These factors reflect the heterogeneity in the characteristics of the base and service industries. By presenting such a frame, this study prepares a framework for RBV-based SME valuation research.

Combining the results of clustering and productivity comparison, we show that the larger the scale, the better the technological productivity of the manufacturing industry. These results are reverse in the case of service industry. The manufacturing industry firms must first secure the market to increase firm value. However, professional services firms in the service industry are more efficient; these firms do not incur a high production cost. It can be explained that the clusters with high productivity in the two industries have the opposite trend. Therefore, SMEs or investors in the manufacturing industry can improve productivity by making investments to increase scale. Conversely, when investing in the service industry, investors should consider the most productive cluster based on technological productivity. They should invest in businesses related to professional services or those with low production costs.

Although this study suggests the importance of resource allocation factors not previously considered through an advanced methodology, the future research must consider the following non-financial and technical factors. First, future research should consider non-financial indicators affecting the value and performance of SMEs. We did not consider these factors because of our emphasis on the resource allocation strategy frame. This future research can present detailed corporate strategies based on this study's resource allocation frame. The performance and value of SMEs are affected by various non-financial factors. For example, there can be a follow-up study considering the small size and short business history of SMEs. This study can consider the characteristics of founders and their influence on corporate performance and can investigate whether the founder is the most important human resource of the company. Second, future research based on information related to the company's technology would be interesting. This study uses the R&D investment ratio and the number of patents in relation to the company's technology. Although the number of patents is related to a company's innovation activities, it provides only quantitative information. Therefore, future studies can consider the qualitative aspect of patents by using indicators related to patent citation (Katila, 2004; Trajtenberg, 1990). This qualitative aspect can relate to a specific strategy such as the collaboration strategy, based on the resource allocation strategy frame suggested in this study. The future research can also clarify the impact of a company's technology, by analyzing the company's technological development process (Belderbos, Faems, Leten, & Looy, 2010; Wu & Shanley, 2009). Future studies can use a company's technical information and the complex resource allocation strategy frame to reveal the effect of SMEs' technology on productivity, through each strategy.

REFERENCES

Abowd, J. M. (1989). The effect of wage bargains on the stock market value of the firm. *The American economic review*, 774-800.

Adler, P. S., & Clark, K. B. (1991). Behind the learning curve: A sketch of the learning process. *Management science*, *37*(3), 267–281. https://doi.org/10.1287/mnsc.37.3.267

Allen, W. D., Schepker, D. J., & Chadwick, C. (2021). Firms' responses to changes in frictions in related human capital factor markets. *Strategic Management Journal*.

Amoako-Adu, B., & Eshun, J. P. (2018). SME financing in Africa: Collateral lending vs cash flow lending. *International Journal of Economics and Finance, 10*(6), 151–159. https://doi.org/10.5539/ijef.v10n6p151

Anthony, S. (2016). Kodak's downfall wasn't about technology. *Harvard Business Review*, *15*, 1-5.

Arrfelt, M., Wiseman, R. M., McNamara, G., & Hult, G.T.M. (2015). Examining a key corporate role: The influence of capital allocation competency on business unit performance. *Strategic Management Journal*, *36*(7), 1017–1034. https://doi.org/10.1002/smj.2264

Aspelund, A., Berg-Utby, T., & Skjevdal, R. (2005). Initial resources' influence on new venture survival: A longitudinal study of new technology-based firms. *Technovation, 25*(11), 1337–1347. https://doi.org/10.1016/j.technovation.2004.06.004

Alexy, O., West, J., Klapper, H., & Reitzig, M. (2018). Surrendering control to gain advantage: Reconciling openness and the resource-based view of the firm. *Strategic Management Journal*, *39*(6), 1704-1727.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barniv, R., Agarwal, A., & Leach, R. (1997). Predicting the outcome following bankruptcy filing: A three-state classification using neural networks. *Intelligent Systems in Accounting, Finance & Management, 6*(3), 177–194. https://doi.org/10.1002/(SICI)1099-1174(199709)6:3<177::AID-ISAF134>3.0.CO;2-D

Barton, S. L., & Gordon, P. I. (1987). Corporate strategy: useful perspective for the study of capital structure? *Academy of Management Review*, *12*(1), 67-75.

Barthélemy, J. (2017). The impact of technical consultants on the quality of their clients' products: Evidence from the B ordeaux wine industry. *Strategic Management Journal*, *38*(5), 1174-1190.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. In: *International applications of productivity and efficiency analysis* (pp. 149–165). Netherlands: Springer. https://doi.org/10.1007/978-94-017-1923-0_10

Battesse, G. E., & Rao, D. S. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business Economics, 1*(2), 87–93.

Battesse, G. E., Rao, D. S. P., O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis, 21*(1), 91–103. https://doi.org/10.1023/B:PROD.0000012454.06094.29

Beaver, W. H., McNichols, M. F., & Rhie, J. W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies, 10*(1), 93–122. https://doi.org/10.1007/s11142-004-6341-9

Belderbos, R., Faems, D., Leten, B., & Looy, B. V. (2010). Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms. *Journal of Product Innovation Management, 27*(6), 869–882. https://doi.org/10.1111/j.1540-5885.2010.00757.x

Benfratello L. (2014) Random effects regression for panel data. In: A. C. Michalos (Ed.), Encyclopedia of quality of life and well-being research (pp. 5387–5389). Dordrecht: Springer. https://doi.org/10.1007/978-94-007-0753-5_2402

Brav, A., Geczy, C., & Gompers, P. A. (2000). Is the abnormal return following equity issuances anomalous? *Journal of financial economics*, *56*(2), 209-249.

Buddelmeyer, H., Jensen, P. H., & Webster, E. (2010). Innovation and the determinants of company survival. *Oxford Economic Papers*, *62*(2), 261-285.**오류! 하이퍼링크 참조가 잘못되었습니다.**Carter, D. A., Simkins, B. J., & Simpson, W. G. (2003). Corporate governance, board diversity, and firm value. *Financial review*, *38*(1), 33-53.

Cefis, E., & Marsili, O. (2011). Born to flip. Exit decisions of entrepreneurial firms in high-tech and low-tech industries. *Journal of Evolutionary Economics, 21*(3), 473–498. https://doi.org/10.1007/s00191-010-0210-4

Chatterjee, J. (2017). Strategy, human capital investments, business-domain capabilities, and performance: a study in the global software services industry. *Strategic Management Journal*, *38*(3), 588–608. https://doi.org/10.1002/smj.2505

Chenery, H. B. (1960). Patterns of industrial growth. *The American Economic Review, 50*(4), 624–654.

Cheng, J. L., & Kesner, I. F. (1997). Organizational slack and response to environmental shifts: The impact of resource allocation patterns. *Journal of management*, *23*(1), 1-18.

Choudhury, P., Allen, R. T., & Endres, M. G. (2021). Machine learning for pattern discovery in management research. *Strategic Management Journal*, *42*(1), 30-57.

Clark, C. (1951). *The conditions of economic progress*. Cohen, W. M., & Klepper, S. (1996). Firm size and the nature of innovation within industries: The case of process and product R&D. *The Review of Economics and Statistics, 78*, 232–243. https://doi.org/10.2307/2109925

Costa, L. A., Cool, K., & Dierickx, I. (2013). The competitive implications of the deployment of unique resources. *Strategic management journal*, *34*(4), 445-463.

Craney, T. A., & Surles, J. G. (2002). Model-dependent variance inflation factor cutoff values. *Quality*

Engineering, 14(3), 391–403. https://doi.org/10.1081/QEN-120001878

Das, S., Sen, P. K., & Sengupta, S. (1998). Impact of strategic alliances on firm valuation. *Academy of Management Journal*, *41*(1), 27-41.

De Jong, J. P., & Marsili, O. (2006). The fruit flies of innovations: A taxonomy of innovative small firms. *Research Policy*, *35*(2), 213-229.

Dietrich, J. R., & Kaplan, R. S. (1982). Empirical analysis of the commercial loan classification decision. *Accounting Review*, 18-38.

Edvardsson, B., Johnson, M. D., Gustafsson, A., & Strandvik, T. (2000). The effects of satisfaction and loyalty on profits and growth: Products versus services. *Total Quality Management, 11*(7), 917–927. https://doi.org/10.1080/09544120050135461

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10–11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E

Fama, E. F., & French, K. R. (1998). Taxes, financing decisions, and firm value. *The Journal of Finance*, *53*(3), 819-843.

Frisch, R. (1934). *Statistical confluence analysis by means of complete regression systems* (Vol. 5). Oslo: Universitetets Økonomiske Instituut.

Forsman, H. (2011). Innovation capacity and innovation development in small enterprises. A comparison between the manufacturing and service sectors. *Research policy, 40*(5), 739–750. https://doi.org/10.1016/j.respol.2011.02.003

Forsman, H., & Rantanen, H. (2011). Small manufacturing and service enterprises as innovators: a comparison by size. *European Journal of Innovation Management, 14*, 27–50. https://doi.org/10.1108/14601061111104689

Ghosh, M., & John, G. (1999). Governance value analysis and marketing strategy. *Journal of marketing*, *63*(4_suppl1), 131-145.

Gimeno, J., Folta, T. B., Cooper, A. C., & Woo, C. Y. (1997). Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly*, 750-783.

Gruber, M., Heinemann, F., Brettel, M., & Hungeling, S. (2010). Configurations of resources and capabilities and their performance implications: an exploratory study on technology ventures. *Strategic Management Journal*, *31*(12), 1337-1356

Hall, M., & Weiss, L. (1967). Firm size and profitability. *The Review of Economics and Statistics, 49*, 319–331. https://doi.org/10.2307/1926642

Hawawini, G., Subramanian, V., & Verdin, P. (2003). Is performance driven by industry-or firm-specific factors? A new look at the evidence. *Strategic Management Journal*, *24*(1), 1-16.

Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal*, *24*(10), 997-1010.

Hendricks, K. B., & Singhal, V. R. (1996). Quality awards and the market value of the firm: An empirical investigation. *Management science*, *42*(3), 415-436.

Hoffman, K., Parejo, M., Bessant, J., & Perren, L. (1998). Small firms, R&D, technology and innovation in the UK: a literature review. *Technovation*, *18*(1), 39-55.

Hoopes, D. G., Madsen, T. L., & Walker, G. (2003). Guest editors' introduction to the special issue: why is there a resource-based view? Toward a theory of competitive heterogeneity. *Strategic Management Journal*, *24*(10), 889-902.

Kaplan, S. N., & Ruback, R. S. (1995). The valuation of cash flow forecasts: An empirical analysis. *The Journal of Finance*, *50*(4), 1059-1093.

Katila, R. (2004). Using patent data to measure innovation performance. *International Journal of Business Performance Management, 2*(1/2/3), 180–193. https://doi.org/10.1504/IJBPM.2000.000072

Kim, H., Lee, D., & Hwang, J. (2018). The effect of online platform maturity on the efficiency of offline industry. *Telematics and Informatics, 35*(1), 114–121. https://doi.org/10.1016/j.tele.2017.10.003

Kim, J., & Makadok, R. (2021). Unpacking the "O" in VRIO: The role of workflow interdependence in the loss and replacement of strategic human capital. *Strategic Management Journal*.

Kim, J., Yang, I., Yang, T., & Koveos, P. (2021). The impact of R&D intensity, financial constraints, and dividend payout policy on firm value. *Finance Research Letters*, *40*, 101802.

Kim, K. J., & Ahn, H. (2012). A corporate credit rating model using multi-class support vector machines with an ordinal pairwise partitioning approach. *Computers & Operations Research, 39*(8), 1800–1811. https://doi.org/10.1016/j.cor.2011.06.023

Köhn, A. (2018). The determinants of startup valuation in the venture capital context: a systematic review and avenues for future research. *Management Review Quarterly, 68*(1), 3–36. https://doi.org/10.1007/s11301-017-0131-5

Krakowski, S., Luger, J., & Raisch, S. (2022). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*.

Liaw, A., & Wiener, M. (2002). Classification and regression by RandomForest. *R news, 2*(3), 18–22.

Limpaphayom, P., & Polwitoon, S. (2004). Bank relationship and firm performance: Evidence from Thailand before the Asian financial crisis. *Journal of Business Finance & Accounting, 31*(9–10), 1577–1600. https://doi.org/10.1111/j.0306-686X.2004.00585.x

Lopez-Gracia, J., & Mestre-Barberá, R. (2015). On the relevance of agency conflicts in SME debt maturity structure. *Journal of Small Business Management*, *53*(3), 714–734. https://doi.org/10.1111/jsbm.12083.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1*(14), 281–297.

Mahoney, J. T., & Pandian, J. R. (1992). The resource-based view within the conversation of strategic management. *Strategic Management Journal*, *13*(5), 363-380.

Mauri, A. J., & Michaels, M. P. (1998). Firm and industry effects within strategic management: An empirical examination. *Strategic Management Journal*, *19*(3), 211-219.

Miloud, T., Aspelund, A., & Cabrol, M. (2012). Startup valuation by venture capitalists: An empirical study. *Venture Capital, 14*(2–3), 151–174. https://doi.org/10.1080/13691066.2012.667907

오류! 하이퍼링크 참조가 잘못되었습니다. Miralles-Quiros, M. d. M., Miralles-Quiros, J. L., & Arraiano, I. G. (2017). Sustainable development, sustainability leadership and firm valuation: Differences across Europe. *Business strategy and the environment*, *26*(7), 1014-1028.

Montgomery, C. A., & Wernerfelt, B. (1988). Diversification, Ricardian rents, and Tobin's q. *The RAND Journal of Economics*, 623-632.

Moretto, M., & Tamborini, R. (2007). Firm value, illiquidity risk and liquidity insurance. *Journal of Banking & Finance*, *31*(1), 103-120.

Müller, E., & Zimmermann, V. (2009). The importance of equity finance for R&D activity. *Small Business Economics*, *33*(3), 303-318.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/10.1016/0304-405X(77)90015-0

Ndofor, H. A., Sirmon, D. G., & He, X. (2011). Firm resources, competitive actions and performance: investigating a mediated model with evidence from the in-vitro diagnostics industry. *Strategic Management Journal*, *32*(6), 640-657.

Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research Policy*, *13*(6), 343-373.

Penrose, E. (1959). *The Theory of the Growth of the Firm*. London: Basil Blackwell.

Pisano, G. P. (1994). Knowledge, integration, and the locus of learning: An empirical analysis of process development. *Strategic Management Journal*, *15*(S1), 85–100. https://doi.org/10.1002/smj.4250150907

Poppo, L., & Zenger, T. (1998). Testing alternative theories of the firm: transaction cost, knowledge-based, and measurement explanations for make-or-buy decisions in information services. *Strategic*

Management Journal, *19*(9), 853-877.

Porter, M. E. (1980). Industry structure and competitive strategy: Keys to profitability. *Financial Analysts Journal, 36*(4), 30–41. https://doi.org/10.2469/faj.v36.n4.30

Powell, T. C. (2001). Competitive advantage: logical and philosophical considerations. *Strategic Management Journal*, *22*(9), 875-888.

Priem, R. L., & Butler, J. E. (2001). Tautology in the resource-based view and the implications of externally determined resource value: Further comments. *Academy of Management Review*, *26*(1), 57-66.

Rouse, M. J., & Daellenbach, U. S. (2002). More thinking on research methods for the resource-based perspective. *Strategic Management Journal*, *23*(10), 963-967.

Sapienza, H. J., & Grimm, C. M. (1997). Founder characteristics, start-up process, and strategy/structure variables as predictors of shortline railroad performance. *Entrepreneurship Theory and Practice, 22*(1), 5–24. https://doi.org/10.1177/104225879702200101

Schroeder, R. G., Bates, K. A., & Junttila, M. A. (2002). A resource-based view of manufacturing strategy and the relationship to manufacturing performance. *Strategic Management Journal*, *23*(2), 105–117. https://doi.org/10.1002/smj.213

Shin, K. S., & Han, I. (2001). A case-based approach using inductive indexing for corporate bond rating. *Decision Support Systems, 32*(1), 41–52. https://doi.org/10.1016/S0167-9236(01)00099-9

Siegel, R., Siegel, E., & Macmillan, I. C. (1993). Characteristics distinguishing high-growth ventures. *Journal of business venturing*, *8*(2), 169-180.

Silverman, B. S. (1999). Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics. *Management science*, *45*(8), 1109-1124.

Song, X. M., Benedetto, C. A. D., & Zhao, Y. L. (1999). Pioneering advantages in manufacturing and service industries: Empirical evidence from nine countries. *Strategic Management Journal*, *20*(9), 811-835.

St. John, C. H., & Harrison, J. S. (1999). Manufacturing-based relatedness, synergy, and coordination. *Strategic Management Journal*, *20*(2), 129–145. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<129::AID-SMJ16>3.0.CO;2-F

Stieglitz, N., & Heine, K. (2007). Innovations and the role of complementarities in a strategic theory of the firm. *Strategic Management Journal*, *28*(1), 1-15.

Stine, R. A. (1995). Graphical interpretation of variance inflation factors. *The American Statistician*, *49*(1), 53-56.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Terziovski, M. (2010). Innovation practice and its performance implications in small and medium enterprises (SMEs) in the manufacturing sector: a resource-based view. *Strategic Management Journal*, *31*(8), 892-902.

Tether, B. S., & A. Tajar. (2008). The organizational-cooperation mode of innovation and its prominence amongst European service firms. *Research Policy, 37*, 720–739. https://doi.org/10.1016/j.respol.2008.01.005

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The Rand Journal of Economics, 21*, 172–187. https://doi.org/10.2307/2555502

Visconti, M. R. (2020). *The valuation of digital intangibles*. Springer International Publishing. https://doi.org/10.1007/978-3-030-36918-7

Wansley, J. W., Lane, W. R., & Yang, H. C. (1983). Abnormal returns to acquired firms by type of acquisition and method of payment. *Financial management*, 16-22.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171-180.

Wernerfelt, B., & Montgomery, C. A. (1988). Tobin's q and the importance of focus in firm performance.

The American economic review, 246-250.

Wibbens, P. D. (2019). Performance persistence in the presence of higher-order resources. *Strategic Management Journal*, *40*(2), 181-202.

Wibbens, P. D. (2021). The role of competitive amplification in explaining sustained performance heterogeneity. *Strategic Management Journal*, *42*(10), 1769-1792.

Wruck, K. H. (1989). Equity ownership concentration and firm value: Evidence from private equity financings. *Journal of financial economics*, *23*(1), 3-28.

Wu, J., & Shanley, M. T. (2009). Knowledge stock, exploration, and innovation: Research on the United States electromedical device industry. *Journal of business research, 62*(4), 474–483.

Yang, A., Lee, D., Hwang, J., & Shin, J. (2013). The influence of regulations on the efficiency of telecommunications operators: A meta-frontier analysis. *Telecommunication Policy, 37*(11), 1071–1082. https://doi.org/10.1016/j.telpol.2013.02.004

Yasuda, T. (2005). Firm growth, size, age and behavior in Japanese manufacturing. *Small Business Economics*, *24*(1), 1-15.

TABLE 1 Descriptive statistics of productivity indicators [Unit: dollar]

	Mean	Median	Minimum	Maximum	Standard Deviation
Net Sales	820999.57	609509.58	0.0	3692558.29	700272.41
Employee	2.94	3.0	0	15.15	2.53
Net Capital	97542.37	2.39	-202560.65	443889.92	113444.22
Net Cost	573495.06	397853.09	-5138.85	2265735.99	560454.39

TABLE 2. The industry classification

Code	Definition	Classified by Statistics Korea	Refer to Industry Classification by Chenery H. B. (Chenery, 1960)	Observations
A	Agriculture, forestry, and fishing	-	Manufacturing	1,581
B	Mining and quarrying	-	Manufacturing	922
C	Manufacturing	-	Manufacturing	380,995
D	Electricity, gas, steam, and air conditioning supply	-	Service	1,593
E	Water supply; sewage, waste management,	Service	Service	5,575

	and materials recovery			
F	Construction	-	Manufacturing	56,782
G	Wholesale and retail trade	Service	Service	211,278
H	Transportation and storage	Service	Service	17,739
I	Accommodation and food service activities	Service	Service	14,475
J	Information and communication	Service	Service	33,876
K	Financial and insurance activities	Service	Service	507
L	Real estate activities	Service	Service	33,911
M	Professional, scientific, and technical activities	Service	Service	28,778
N	Business facilities management and business support services; rental and leasing activities	Service	Service	14,032
O	Public administration and defense; compulsory social security	Service	Service	225
P	Education	Service	Service	4,509
Q	Human health and social work activities	Service	Service	10,144
R	Arts, sports, and recreation related services	Service	Service	3,547
S	Membership organizations, repair, and other personal services	Service	Service	8,420
T	Activities of households as employers; undifferentiated goods- and services producing activities of households for own use	Service	Service	13
U	Activities of extraterritorial organizations and bodies	Service	Service	0

TABLE 3 Results of multiple linear regression analysis for the top nine factors of permutation importance in the service industry

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Constant	2.74E+05	1510.2	181.28	0	2.71E+05	2.77E+05
Cost of Sales	1.0511	0.0013	818.21	0	1.0486	1.0536
Selling Costs to Sales Ratio	-222.22	51.345	-4.3279	0	-322.85	-121.58
Interest Expense to Sales Ratio	-489	113.72	-4.2999	0	-711.89	-266.1
Interest Expense	4.2984	0.0443	97.085	0	4.2117	4.3852
Wage (SG&A)	0.15	0.0013	118.99	0	0.1475	0.1524
Accounts Payable	0.2605	0.0057	45.594	0	0.2493	0.2717
Fringe Benefit (SG&A)	0.6973	0.0092	76.141	0	0.6793	0.7152
ROA	0.0023	0.0002	9.3974	0	0.0018	0.0027
Entertainment Expenses	12.789	7.413	1.7252	0.0845	-1.7404	27.318

TABLE 4 Results of multiple linear regression analysis for the top nine factors of permutation importance in the manufacturing industry

	Coefficient	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Constant	3.15E+04	546.97	57.514	0	3.04E+04	3.25E+04
Cost of Sales	1.1111	0.0005	2348.2	0	1.1102	1.1121
Selling Costs to Sales Ratio	-974.32	52.985	-18.389	0	-1078.2	-870.47
Wage (SG&A)	1.1964	0.0038	317.77	0	1.189	1.2038
Accounts Payable	-0.0037	0.0021	-1.71	0.0873	-0.0079	0.0005
Fringe Benefit (SG&A)	3.3348	0.0261	127.78	0	3.2836	3.3859
ROA	18.284	6.6764	2.7386	0.0062	5.1986	31.37
Fringe Benefit (Costs of Goods Manufactured)	0.0034	0.001	3.2617	0.0011	0.0013	0.0054
Interest Expense	0.7838	0.0137	57.289	0	0.757	0.8106
Allowance for Doubtful Accounts (Account Receivable)	0.092	0.0096	9.6159	0	0.0733	0.1108

TABLE 5 Results of SFA and MFA analyses

	Cluster 1		Cluster 2		Cluster 3		MFA
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	LP
Constant	1642016.500***	1.017	1866.803***	1.000	-15175.303***	1.954	0.001
$\ln x_1$	-364847.480***	1.539	-875.712***	0.998	-431.949***	0.671	1962081.674
$\ln x_2$	511616.730***	1.562	932.958***	0.997	-2142.968***	0.910	80527.493
$\ln x_3$	-200858.550***	1.550	-3771.919***	0.999	-3018.465***	0.682	-1862553.528
$(\ln x_1)^2$	18608.592***	0.235	57.541***	0.504	129.578***	0.094	-155578.093
$(\ln x_2)^2$	0.095	0.037	-0.048***	0.014	0.015***	0.102	0.518
$(\ln x_3)^2$	2.443***	0.159	-0.255	0.320	-0.021	0.066	-0.264
$\ln x_1 * \ln x_2$	-40567.514***	0.177	-74.052***	0.145	169.975***	0.121	-6386.169
$\ln x_2 * \ln x_3$	15921.466***	0.381	299.565***	0.797	239.532***	0.152	147687.077
$\ln x_3 * \ln x_1$	0.044	0.099	0.143*	0.097	-0.073***	0.098	-0.029

TABLE 6 Results of productivity analysis by cluster

Cluster	Mean	St. dev.	Maximum	Minimum
TE				
Cluster 1	0.978	0.000	0.979	0.978
Cluster 2	0.752	0.102	0.993	0.354
Cluster 3	0.998	0.000	0.998	0.998
TGR				
Cluster 1	0.476	0.253	1.000	0.000
Cluster 2	0.206	0.261	1.000	0.000
Cluster 3	0.169	0.274	1.000	0.000
TE*				
Cluster 1	0.465	0.000	0.979	0.000
Cluster 2	0.155	0.027	0.993	0.000
Cluster 3	0.168	0.000	0.998	0.000

TABLE 7 Results of SFA and MFA analyses

	Cluster 1		Cluster 2		Cluster 3		MFA
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	LP
Constant	-427.000***	1.000	-15400.000***	1.000	583.000***	1.010	0.000
ln x_1	49.600***	1.000	1240.000***	0.999	-268.000***	1.340	-13209.819
ln x_2	-773.000***	1.000	-2440.000***	0.999	395.000***	1.380	-5020.597
ln x_3	-1080.000***	1.000	2150.000***	0.999	-3460.000***	1.260	14880.426
$(\ln x_1)^2$	-1.210	1.000	-1.420*	0.912	17.600***	0.107	1047.460
$(\ln x_2)^2$	-0.007	1.000	-0.036	0.593	0.017***	0.003	0.232
$(\ln x_3)^2$	0.069	1.000	-0.024	0.733	0.089***	0.009	0.141
ln x_1 * ln x_2	61.400***	1.000	193.000***	0.898	-31.300***	0.110	397.984
ln x_2 * ln x_3	85.800***	1.000	-170.000***	0.850	274.000***	0.103	-1179.768
ln x_3 * ln x_1	-0.041	1.000	-0.050	0.884	-0.049***	0.008	-0.341

Table 8 Productivity Analysis Results by Cluster

Cluster	Mean	St. dev.	Maximum	Minimum
TE				
Cluster 1	0.972	0.002	0.986	0.931
Cluster 2	0.771	0.047	0.907	0.457
Cluster 3	0.999	0.000	0.999	0.999
TGR				

Cluster 1	0.878	0.061	1.000	0.157
Cluster 2	0.942	0.084	1.000	0.194
Cluster 3	0.896	0.071	1.000	0.168
TE*				
Cluster 1	0.854	0.000	0.986	0.146
Cluster 2	0.726	0.004	0.907	0.089
Cluster 3	0.895	0.000	0.999	0.168

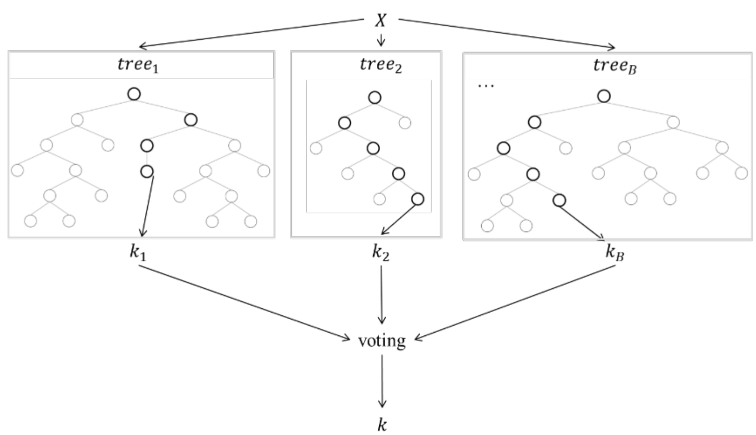

FIGURE 1 Algorithmic diagram of a random forest model

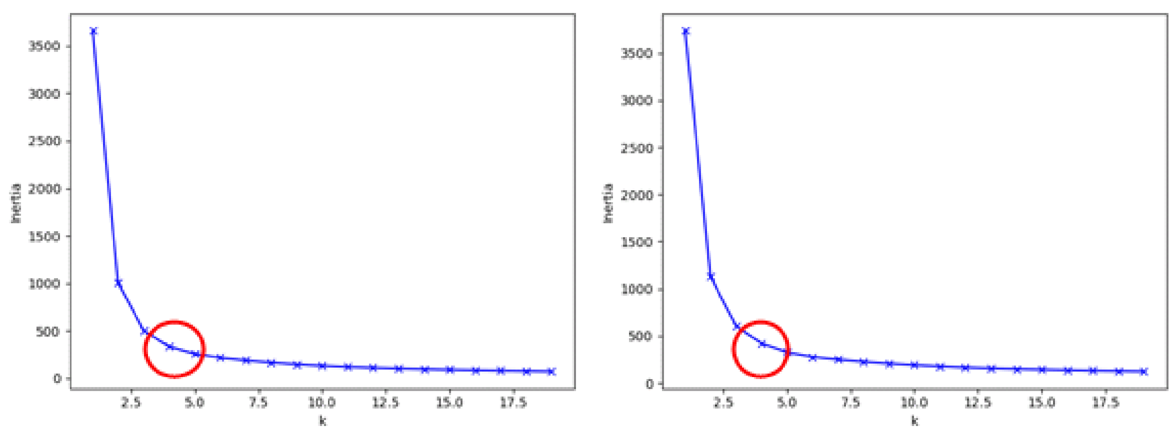

FIGURE 2. Elbow method for analyzing inertia based on k value

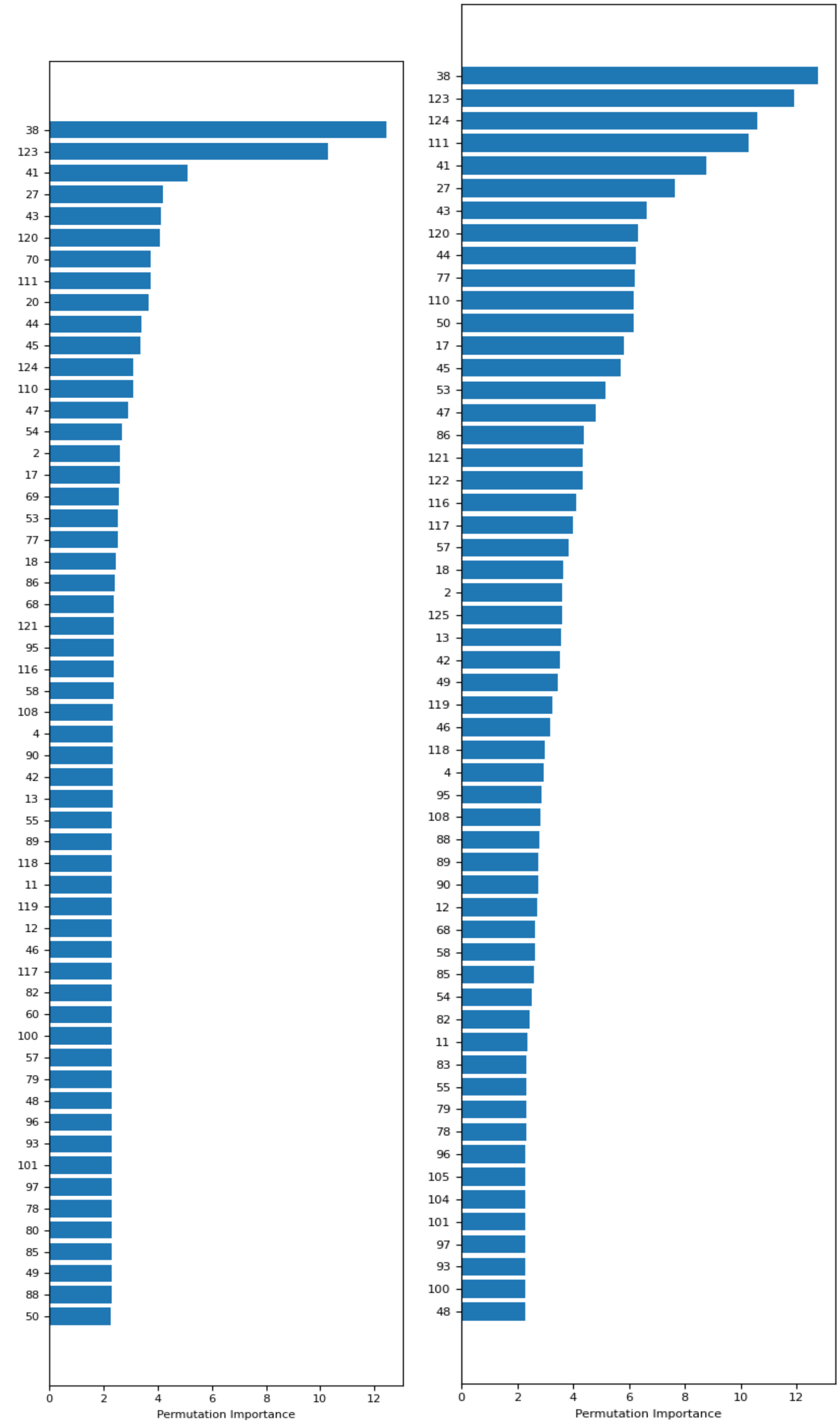

FIGURE 3. The permutation importance of factors results in Manufacturing industry (left) and Service industry (right)

FIGURE 4. Pairplot of nine factors in service industry clusters

FIGURE 5. Pairplot of nine factors in manufacturing industry clusters