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Analysis of Market Diversification Trends and Network Characteristics Based on M&A Transactions in North America

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Despite the increasing investment opportunities in emerging technologies, strategic alliance and dynamic investment strategy suffer from a limited understanding of the market investment trends and industry convergence. Therefore, this study aims to develop a structured framework to examine the market diversification trend and the industry-to-industry influential degree. The proposed framework utilizes M&A transaction activities from the interests of buyer and target industries from 2009 to 2018 in North America. The M&A network is then examined for the difference in the structural characteristics between the buyer and target industries. This study identifies market irregularity and diversification trends and applies the initial findings as market-level evidence to elucidate industry convergence potentials. Degrees of a specific industry's influence on other industries are also presented and discussed from the perspectives of buyer and target industries. The findings of this study contribute to the development of industry convergence conceptual model and advances knowledge regarding market diversification, collaboration-driven industry convergence, and investment strategy.

Keywords: *Mergers and Acquisitions; Market Diversification; Convergence; Complex Network; Network Analysis.*

Introduction

Firms are increasingly facing a highly dynamic and rapidly changing environment (Preschitschek *et al.,* 2013). Companies are actively striving for sustainable growth in this business environment. They are pursuing cooperation or alliances with other companies in the same or different industries, including internal efforts to promote new business strategies or invest in technology development (J. Choi, Shin *et al.,* 2020). In addition, companies are actively pursuing mergers and acquisitions (M&As) as strategic alternatives to enhance growth and innovation (Bower, 2001; Cassiman *et al.,* 2005; Cefis, 2010; J. Choi, Chung, *et al.,* 2020; Hagedoorn & Duysters, 2002).

The M&As are recognized as a firm's strategic alliance and dynamic strategy in the current competitive business environment because they enable synergistic benefits, such as market expansion, performance improvement, and growth (Feldman & Hernandez, 2022; Hossain, 2021). The recently developed Synergy Lifecyle Model by Feldman and Hernandez's (2022) posits that the value created by M&A enables the knowledge advancement of synergistic value. Potential synergistic benefits of combining buyer and target firms' assets have been investigated in various disciplines (e.g., management, financial economics, and accounting) using multiple theoretical lenses such as resource-based view and behavioral theories (Feldman & Hernandez, 2022).

Analyzing the trends and characteristics of market diversification includes understanding the level of convergence at the individual–industry level and the overall growth trend of the industry. Industry convergence, defined as the innovation process of blurring boundaries between two or more industries, can effectively share common values such as technology, value chains, and markets (Broring, 2005; D. Choi & Valikangas, 2001; N. Kim *et al.,* 2015; Lekovic *et al.,* 2020; Preschitschek *et al.,* 2013). Industry convergence may occur at the technological or product-market level (Duysters & Hagedoorn, 1998) and is marked by converging value propositions, technologies, and markets (D. Choi & Valikangas, 2001) of formerly distinct industrial sectors (Preschitschek *et al.,* 2013).

Specifically, the industry convergence outcomes can create new consumer markets, value chains, and product and technology capabilities in other industries (Cozzens *et al.,* 2010; N. Kim *et al.,* 2015; Zhou *et al.,* 2019). Furthermore, the relative effects and trends can be identified by analyzing the convergence between each industry during market diversification.

Until recently, various studies have analyzed the correlation between industries and the influence of specific industries from a convergence perspective. These include media data analysis (N. Kim *et al.,* 2015; Sick *et al.,* 2019) and bibliometric analysis (Cui *et al.,* 2022; Curran *et al.,* 2010; Karvonen & Kassi, 2013; Preschitschek *et al.,* 2013).

In the case of media analysis, using media such as newspaper articles, reports, or press releases, inconsistency and quality issues of the data provided have been pointed out as limitations. Bibliometric analysis that uses patent citations or semantic keywords has several drawbacks, although it has been successfully applied to identify the convergence between industries (Karvonen & Kassi, 2013). This method does not reflect the entire industry because it mainly analyzes limited industries or technology areas (J. Choi & Chang, 2020). In addition, time lag exists for the case of bibliometrics analysis using patents or papers, there is a time lag (Chapman, 2014; Daim *et al.,* 2007) for useful application in the market because it generally takes one to three years from finishing documents to finally publishing a paper or applying for a patent (J. Choi, Chung *et al.,* 2020).

To resolve this problem, it is crucial to analyze the correlation between industries and the degree of effects by industry based on information on actual cooperation between companies in the market.

Therefore, this study presents a method to analyze market diversification based on M&A transaction information between companies. Using a trend analysis of the diversification status among industries based on actual M&A transactions between companies, correlation and effects between industries can be analyzed. Furthermore, it can provide insight into the characteristics of an M&A network, which is viewed as a complex system. Thus, an analysis of convergence based on market diversification at the corporate level is possible.

This study analyzes M&A transactions from 2009 to 2018 in North America. It uses Standard & Poor (S&P) Capital IQ platform, which provides financial data to public and private organizations. The M&A data provided by this platform are systematically classified based on the Global Industry Classification Standard (GICS).

The remainder of this paper is organized as follows. Section 2 presents the literature review concerning this research. Section 3 presents the data and methods used. The trends in M&A transactions and market diversification in North America over ten years are presented in Section 4. Section 5 analyzes the relative influences of industries from a market diversification perspective and identifies the specific correlations and influences between industries. Section 6 analyzes whether power laws exist in complex networks based on M&A transactions. Finally, Sections 7 and 8 discusses the study's findings and managerial implications, provides suggestions for further research, and draws a conclusion.

Literature Review

Mergers & Acquisitions, Technological Innovation, and its Synergistic Benefit

M&As refer to consolidating firms or assets through various financial transactions, including mergers, acquisitions, consolidations, tender offers, purchase of assets, and management acquisitions (Zollo & Meier, 2008). The M&As are perceived as activities that unify technology, products, businesses, or markets and provide synergistic benefits for the buyer firm (Aaldering *et al.,* 2019; Garskaite-Milvydiene & Burksaitiene, 2016; Garzella & Fiorentino, 2014). According to Feldman and Hernandez (2022), the value of M&A must be derived from a synergistic combination of buyer and target firms. For example, a synergetic benefit is realized only when the value of the buyer and target firms as a single entity exceeds that when the firms operate individually (Feldman & Hernandez, 2022).

From a technological change perspective, M&As are regarded as valuable resources for technological innovation and change. Based on the theoretical views of resource-based and industrial organizational economics, M&A studies mainly focused on market power and operational synergies (Rabier, 2017). These paradigms often assume firms' intention to own and/or control valuable assets (Feldman & Hernandez, 2022). However, the recent trend with the arrival of Industry 5.0 demonstrates that when firms share valuable assets through cooperation, additional sources of economic value are created. For example, when firms engage in collaborative exchanges, they can potentially create partners-specific value based on relational view theory (Dyer & Singh, 1998); moreover, the social network perspective shows that value exists in the structure of a firm's direct and indirect ties (Gulati, 1998). These views lead to understanding that M&A activities enable both internal and external cooperative environments by reformatting relationships with individual contractual partners (Feldman & Hernandez, 2022).

Thus, based on the conceptual synergistic benefits of M&As in the recent digital era context, this study primarily aims to extend the investigation of industry convergence through the lens of market investment trends. Given the growing evidence and importance of industry changes, researchers have attempted to understand industry convergence (Aaldering *et al.,* 2019; Curran *et al.,* 2010). Industry convergence leads to the emergence of a new industry while restricting additional market value creation in a traditional industry (Benner & Ranganathan, 2013; N. Kim *et al.,* 2015).

Market Diversification and the Role of M&A

M&A activities go concurrently with the increasing need for business diversification (Salter & Weinhold, 1978). Competition among the companies has intensified owing to business globalization. Market diversification significantly benefits firms interested in recreating or improving existing technological capabilities (H. Kim *et al.,* 2017). As a strategic means to achieve market diversification, many companies worldwide have merged together for enjoying the benefits of new markets and enhanced revenues (Bedi, 2018; Hossain, 2021). Furthermore, M&A can be leveraged as a strategic alliance for business, product, and geographic tactics for the international market (Hossain, 2021). Hossain (2021) emphasized that firms gain market competitiveness and risk diversification. Based on the resource-based view, existing technological capabilities lead to stronger diversification success, delivering a relatively low-risk yet profitable outcome (H. Kim *et al.*, 2017).

From the technological change perspective, market diversification is expected to boost the potential convergence of scientific knowledge or technology. Interorganizational diversification enables firms to acquire competitive advantage with cost reduction or product differentiation by utilizing the interrelationships across different business units (N. Kim *et al.,* 2015). Moreover, to maintain competitive advantage, cooperation with external markets or firms have become critical. Specifically, the scope of diversification has expanded from an internal unit level to firm-to-firm within an industrial sector (N. Kim *et al.,* 2015). Kim et al. (2015) noted a strategic benefit of diversification as even unrelated diversification can be beneficial, because a firm can expand the market beyond its resources and capabilities.

Therefore, this study posits that M&A activities create irregularity of market investments trends and are often regarded as results of market diversification strategies. Moreover, based on prior studies on market diversification (Appendix. Table A1), the study suggests that market dynamics be investigated from both acquirer and target firms' perspectives to provide the basis for uncovering sources of synergy.

This study characterizes *market diversification* as an investment trend among industries, which can potentially initiate or lead to industry convergence depending on the level of collaboration.

Industry Convergence

Industry convergence is rooted in science and technology convergence, which creates a synergistic combination of two different firms or services in valuable and novel ways (Geum *et al.,* 2016; Zhou *et al.,* 2019). Technological convergence is regarded as an imperative path to the formation of emerging technology, leading to a potentially new industry. Based on the Curran and Leker's (Curran *et al.,* 2010) industry convergence model, industry convergence occurs only after technologies and markets have already emerged.

This study identifies several shortcomings in prior studies on industry convergence (Appendix. Table A2). Mainly, existing studies on technology or industry convergence rely on patent information to analyze patterns of industrial convergence from a technological perspective (Curran *et al.,* 2010; Preschitschek *et al.,* 2013). Although bibliometric analysis methods using patent information have proliferated, they have several limitations in demonstrating their effectiveness in providing a holistic picture of technology trends and convergence (J. Choi *et al.,* 2021).

For example, in the context of technology forecasting, bibliometrics are utilized as a quantitative and statistics-based technique for measuring the production and dissemination of information based on the literature or patent data (Daim *et al.,* 2007). These measures are then commonly applied for forecasting and decision making. However, in the case of bibliometric methods, time lag exists between inception and application in the market, as it takes one to three years for an article or patent to be published or applied (Daim et al., 2007). Furthermore, other critical drawbacks include quality, discipline variation, database variation, bias, and discrepancies. Thus, a new approach or methodological framework is required to improve the overall applicability in the actual business cases in the market (J. Choi, Chung *et al.,* 2020).

A new wave of strategic investment decision-making has been observed concerning Industry 5.0. Specifically, M&A now aims to resolve firms' struggles in facing new market structures and competencies for successful operations (Alkaraan, 2021). Aaldering et al. (2019) noted that M&A activities and interactions can deepen the understanding of the potential of industry convergence and its future development.

A comprehensive understanding of industry convergence is imperative from the perspective of both buyer and target firms because a lack of knowledge regarding trend characteristics also significantly contributes to an error in forecasting industry emergence technologies (Burmaoglu et *al.,* 2019; Grodal *et al.,* 2015). Acquisitions are an exceptionally important action shaping the course of convergence because they are highly visible to competitors and can trigger imitation and bandwagon effects as rivals compete for scarce targets, further accelerating convergence (Hsu & Prescott, 2017).

This study characterizes *industry convergence* as an emerging convergence that is observable in applying technologies across different industries. Industry convergence can provide critical information on industries undergoing restructuring regarding the emergence of new industries (Broring, 2005; D. Choi & Valikangas, 2001; N. Kim *et al.,* 2015; Lekovic *et al.,* 2020; Preschitschek *et al.*, 2013).

Complex Networks

Research on complex networks has been a tremendous scientific area over the past two decades, receiving inspiration from sociology and flourishing in statistical physics. Early on, studying complex networks was limited to graph theory in mathematics and social network analysis in sociology (Fujita et al., 2014; Shibata et al., 2008). Since then, researchers have witnessed substantial and dramatic advances in understanding large-scale structural properties of real-world complex networks (Albert & Barabasi, 2002; Newman, 2003; Sagarra *et al.,* 2013; Song & Havlin, 2005; Strogatz, 2001; Tsiotas, 2019). The availability of large-scale empirical data, advances in computing power, and theoretical understanding have led to diverse discoveries that have uncovered the topological properties in various real-world social, informational, biological, and technological networks (J. Choi, Yi, & Lee 2011). These studies have shown that most real networks are characterized by similar topological features: "small-world" properties, with high clusters and low path length (J. Choi *et al.,* 2011).

Another essential pattern found in complex real-world networks is the node degree distribution. Unlike the bell-shaped Poisson distribution of random graphs, the degree distribution of real-world networks show the power–law distribution (Amaral *et al.,* 2000; Barabasi & Albert, 1999; Mackay, 2005),

$$p(k) \sim k^{-r}$$

where *p(k)* denotes the probability that a node has *k* edges. Statistically, the power–law distribution implies that a few nodes in a complex network have many links. In other words, the distribution of node degrees has a long right tail of values far above the mean, contrasting the fast-decaying tail of a Poisson distribution (Amaral *et al.,* 2000; Barabasi & Albert, 1999; Braha & Bar-Yam, 2004). Unlike general normal distributions, a power–law distribution does not have a representative scale (Barabasi & Albert, 1999), indicating that one cannot select a representative or an average because of the considerable probability of finding much larger ones. Networks with power–law distributions are often referred to as scale-free networks (Barabási & Albert, 1999).

Data and Methods

This section introduces the data and analysis methods used in this study.

Data

To analyze firms' market diversification trends in the global market, where industry growth and technology exchanges are actively conducted, actual data that reflect the interaction between firms must be used. Therefore, this study proposed a method to identify trends in market diversification based on M&A activity information to measure the potential convergence trend of M&A transactions among industries.

Using S&P's Capital IQ platform, this study extracted M&A transactions based on the GICS, an industry taxonomy that classifies firms into sectors, industry groups, industries, and sub-industries based on core business activity for the global financial community (J. Choi & Chang, 2020).

A *sector* is the broadest economic segment with a large group of firms. An *industry groups* describes specific groups of firms with similar business activities. *Industries* then further classifies into more defined groups, allowing for a closer assemblage of related businesses.

The classification tree of S&P Capital IQ offers levels of analysis ranging from the most general sectors to the most specialized subindustry. For example, the IT sector has eight levels divided into 13 sub-industries at Level 4 and 85 sub-sub-industries at Level 5.

Furthermore, the platform provides information on the primary industry classifications to which each M&A participant belongs. In other words, in a primary industry, the buyer company (or companies) and the target company are affiliated separately. Additionally, each company participating in an M&A transaction may be affiliated with several primary industries depending on its size and characteristics.

Data were processed using the following method. M&A transaction data were downloaded from S&P's Capital IQ platform in multiple raw data files and saved in one Excel file, followed by basic preprocessing. Then, the programming language R was used to load the M&A data stored in an Excel file, an additional preprocessing was performed, and data analysis was conducted using a step-by-step process. First, 163,003 M&A transactions that occurred in North America from 2009 to 2018 were extracted, based on Level 1, which is the highest industry classification criterion, comprising 11 sectors. After excluding M&A transactions with missing values, 133,693 M&A transactions were obtained. Data were then processed to derive an 11 × 11 square matrix formed by the number of M&A transactions extracted. Based on the extracted M&A transaction information and derived M&A square matrix, the overall M&A transaction and market diversification trend was analyzed for the period of interest. An additional analysis of M&A transactions and market diversification trends by sector was performed from the buyer's and target's perspectives.

As an illustrative example, a further analysis of a specific sector, Information Technology (IT), was performed to advance the understanding of convergence trends in that sector. Therefore, 6,136 M&A transaction data points were collected within the IT sector at the sub-subindustry level (Level 5) for additional analysis. These M&A transactions were divided into 85 sub-sub-industry criteria. Thus, an 85 × 85 square matrix was created to analyze the market diversification trends based on these transactions.

Methods

The analysis methods to be presented are as follows:

First, as suggested earlier, the overall M&A transactions and market diversification trends was analyzed over ten years. Moreover, M&A transactions and market diversification trends by sector was analyzed from the buyer's and target's perspectives. Through these trend analyses, the overall market diversification trend could be understood and the degree of market diversification by sector could be compared.

Second, to understand the convergence between industries, more specifically, analyzing the relative influence of specific sectors and interdependence between industries in the diversification process based on M&A activity is necessary. Through this analysis, the influence of industries that play an essential role as buyers or targets in the market diversification process can be objectively identified using quantified data. This study presents a revised analysis method that supplements the decision-making trial and evaluation laboratory (DEMATEL) method to analyze industries' interdependence through M&A activities.

The DEMATEL is considered an effective and a widely used method to identify the causal relationships in complex systems (Falatoonitoosi et al., 2014; Jassbi et al., 2011, 2011; Si et al., 2018). DEMATEL has its roots in decision science and is based on matrix computation methods to study complex and intertwined problems, which require considering complex factors such as multiple evaluation criteria (Aaldering et al., 2019; H. H. Wu & Tsai, 2011; W. W. Wu, 2008), 2008). The DEMATEL approach can quantify the causality and strength of the dependencies among interacting factors (Aaldering et al., 2019). The direct relation matrix (DRM) is an n × n matrix obtained from the pair-wise comparisons of the relationship between decision criteria. The DRM is calculated by averaging the individual experts' judgments of criteria. In other words, subjectivity exists in the evaluation process. Therefore, we analyzed the interdependence between the buyer and target industry using the actual number of M&A transactions without expert intervention to prevent subjectivity.

Finally, this study analyzed whether the power law, a representative characteristic of complex networks, existed in M&A networks created from M&A activities. Each M&A transaction has a target company and one or more buyers. Thus, network analysis among industries is possible by identifying the industry to which each company belongs. The overall framework is illustrated in **Appendix. Figure A1**.

Trend Analysis for Market Diversification

This section presents the trends in market diversification through M&A activities in North America from 2009 to 2018. Specifically, the overall trend of M&A transactions and market diversification was analyzed for the entire and each sector. The analysis includes the number of M&A transactions and market diversification ratios. The diversification ratio represents the number of M&A transactions between firms belonging to a specific economic segment, such as a sector, and companies belonging to other economic segments, to the total number of M&A transactions between economic segments conducted by year. This is expressed as follows:

Diversification Ratio

= (Number of M&A transactions between companies in different economic segments) / (Total number of M&A transactions across all economic segments).

This helps identify the volatility of the M&A market over time through a trend analysis of M&A transaction volumes by measuring the diversification ratio of M&A transactions. In addition, the analysis results for each sector are presented by dividing the market diversification trend into buyer and target perspectives. Thus, comparing and analyzing market diversification trends by sector becomes possible.

Overall Trend Analysis

Level 1 is the highest level of industry classification and comprises 11 sectors. Fig. 1 shows the trend analysis results for approximately 140,000 M&A transactions in North America from 2009 to 2018. In addition, the results of the analysis for each sector are presented by dividing the market diversification trend into buyer and target perspectives. Thus, market diversification trends by sector can be compared and analyzed.

As Figure 1 shows, M&A transactions in North America have generally exhibit an upward trend over the past decade. Additionally, as the M&A transaction volume within the entire sector increases, the overall diversification ratio also increases. During some periods when the M&A transaction volume decreases, the diversification ratio also shows a similar declining pattern, suggesting a very high correlation between the two indicators. Approximately 30–40% of all M&A transactions were made through market diversification and convergence with other sectors, and the remaining 60–70 % were within the same sector.

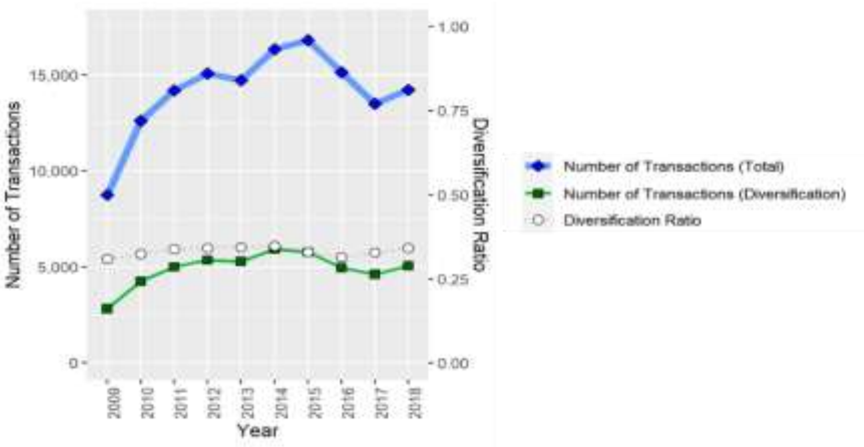


Figure 1. The Overall Trend of M&A Transactions and Market Diversification

Trend Analysis by Sectors

The analysis discussed above concerns the overall M&A transaction trend, which can be analyzed separately by sector. It can also be analyzed from the perspective of both the buyer and the target of M&A transactions.

Considering that the buyer is the subject of market diversification, this study first presented the M&A transaction volume and market diversification ratio from the buyer's perspective, as shown in Figure 2.

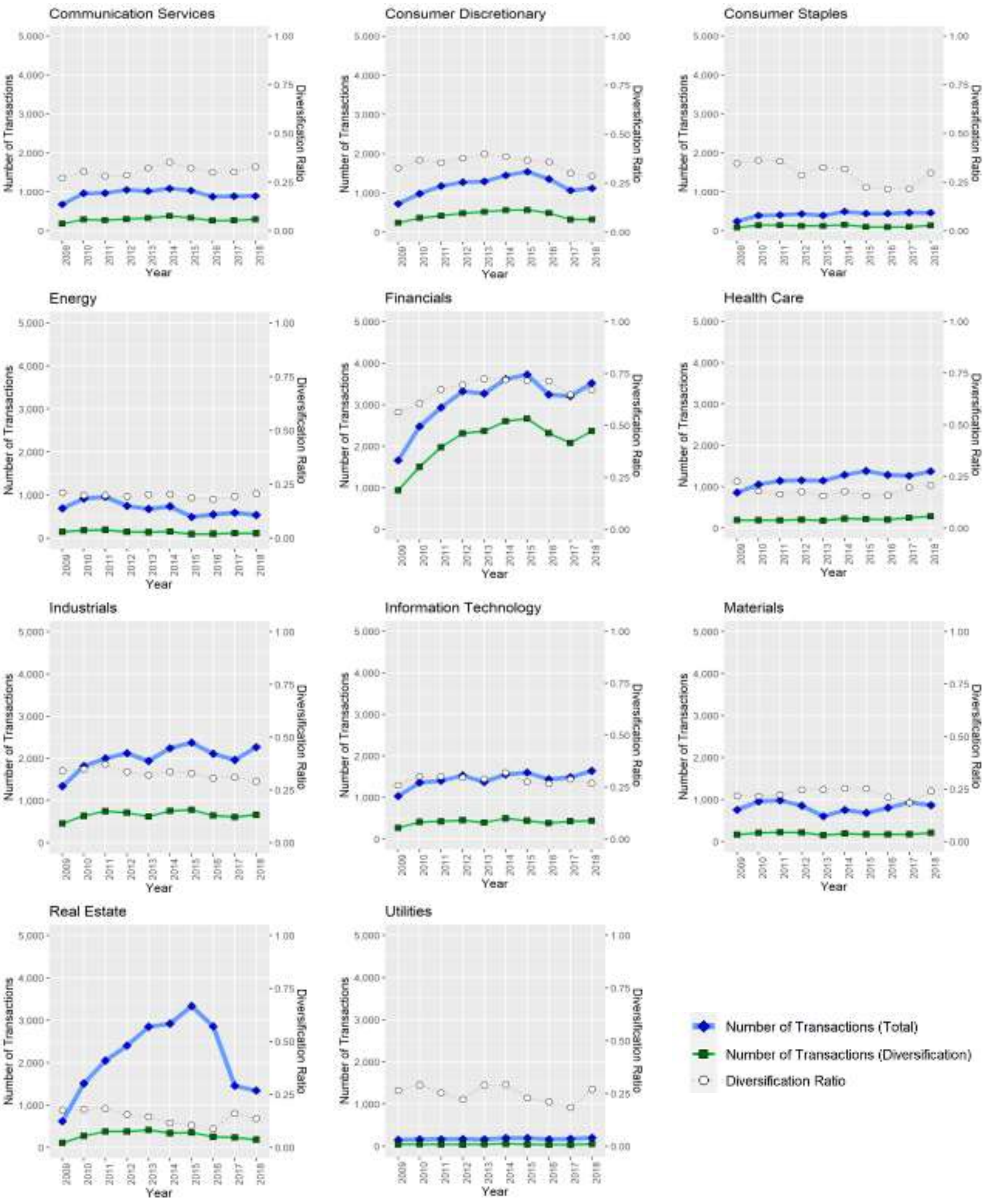


Figure 2. Overall Trend by Sector (Buyer's perspective)

From a buyer's perspective, there are significant differences in M&A transaction volumes by sector. The notable analysis results regarding transaction volumes are as follows:

First, the financial, industrial, and real estate sectors account for a large proportion of M&A transactions, and the consumer staples and utilities sectors have a relatively low proportion of M&A transaction volumes. Second, the consumer discretionary, financial, health care, industrial, and IT sectors show overall increasing patterns, with fluctuations in some periods; however, the energy sector shows a decreasing pattern over the entire period. Specifically, the real estate sector shows sharp increasing and decreasing patterns for the entire period.

The M&A diversification ratio trend showed interesting results for the M&A transaction volume trends. First, the M&A diversification ratio in most sectors is approximately 20–40 %, but the financial sector showed a higher diversification ratio of 55–70 %. Second, the diversification ratio of the communication service, financial, and health care sectors showed an overall increasing pattern over the entire period. In contrast, the consumer staples, industrial, and real estate sectors showed decreasing diversification trends. In particular, the utilities sector showed repetitive fluctuating patterns. Other sectors showed no significant change in the diversification ratio over the entire period.

The overall trend in the number of M&A transactions and the market diversification ratio from the target's perspective is shown in Figure 3.

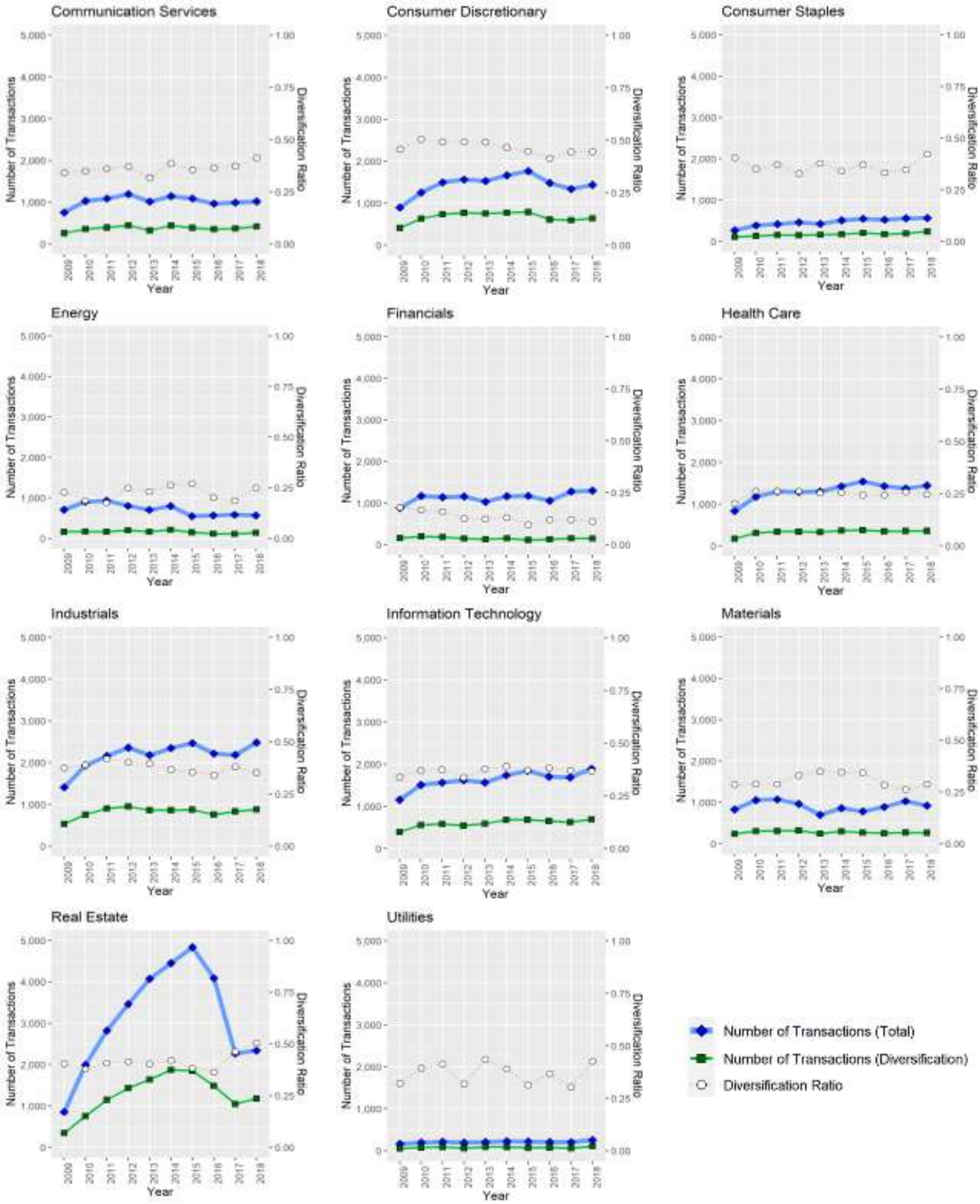


Figure 3. The Overall Trend by Sector (Target's perspective)

From the target's perspective, the analysis results of the overall trend in M&A transaction volume and market diversification by sector are as follows:

First, the industrial, IT, and real estate sectors had relatively high proportions of M&A transactions. Second, the consumer discretionary, health care, industrial, and IT sectors showed a volatile pattern in the number of M&A transactions in some periods but were overall on an upward trend over the entire period. However, the energy sector exhibited a decreasing trend. Finally, the real estate sector showed sharp fluctuations.

The key results related to the M&A diversification ratio from the target's perspective are as follows:

First, the M&A diversification ratio in most sectors was approximately 20–40%, but the consumer discretionary sector showed a very high diversification trend of 40–50% compared with other sectors. In addition, unlike the high ratio seen from the buyer's perspective, the financial sector had a meager market diversification ratio of approximately 10–20 % from the target's perspective. Second, the diversification ratios of some sectors, such as communication service and health care, generally increased over the entire period. Contrastingly, the financial sector showed an overall decreasing diversification pattern. Finally, the consumer staples, energy, industrial, IT, and utilities sectors showed a repeated pattern of increase and decrease, albeit with a difference in intensity.

Industry Convergence based on Market Diversification

This section analyzes in-depth the market diversification trends through M&A transactions. First, each sector's relative influence on industry convergence through diversification is analyzed from the perspectives of the buyer and target. Second, the influence of each industry (sector or sub-sub-industry) or other industries (sectors or sub-sub-industries) on market diversification is analyzed from the buyer's and target's perspectives. The results were visualized so that the overall status could be understood intuitively.

As in the analysis presented in Section 3, M&A transactions within the same industry (sector or sub-sub-industry) were excluded from the analysis of market diversification in other industries.

Relative Influence by Sector on Market Diversification

First, an M&A complex network is built, and the causal relationship between industries is analyzed using the DEMATEL approach. As the first step, this study obtained the DRM from pairwise comparisons of the relationship between economic segments, namely sectors. Subsequently, as mentioned in Section 3, the DRM matrix—the interdependence between the buyer and target sectors—was analyzed using the actual number of M&A transactions.

M: M&A transactions Matrix
B_n: N^{th} Buyer
T_n: N^{th} Target
M_{nn}: Number of M&A transactions between N_{th} buyer and N_{th} target

$$\mathbf{M} = \begin{array}{c c} & \begin{array}{cccc} T_1 & T_2 & \cdots & T_n \end{array} \\ \begin{array}{c} B_1 \\ B_2 \\ \vdots \\ Bn \end{array} & \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \cdots & m_{nn} \end{bmatrix} \end{array}$$

The total relation matrix (TRM), an infinite series of direct and indirect effects of each criterion, was then calculated to derive the total effects of each row and column in the matrix (Aaldering et al., 2019).

N (Normalized DRM) = $S \cdot$ M

$$S = min\left[\frac{1}{\max_i \sum_{j=1}^{n} m_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} m_{ij}}\right]$$

The TRM was obtained using the following equation, where I is the identity matrix:

$$\mathrm{T} = \mathrm{N} \cdot (\mathrm{I} - \mathrm{N})^{-1}$$

The total effect value of each row (R_i), indicating its influence as a buyer, and that of each column (C_j), denoting its influence as a target, were then analyzed for 11 sectors by year. To analyze the relative influence between the 11 sectors, normalized values were derived by dividing the influence values for each sector by the maximum influence values (Max R_i, Max C_j) of all sectors from the perspectives of buyers and targets.

The normalized values for each sector, the X and Y coordinates, are displayed on the chart. Since the normalized values of R_i and C_j in each sector are between 0 and 1 for each X-and Y axis, a relative comparison between the sectors is possible. All data processing and analysis procedures presented above were conducted using the R programming language.

The analysis results for each year are shown in Fig. 4. Based on the relative position of each sector, this study visually identifies the influence of each sector as a buyer or target in the M&A market that occurs in the year.

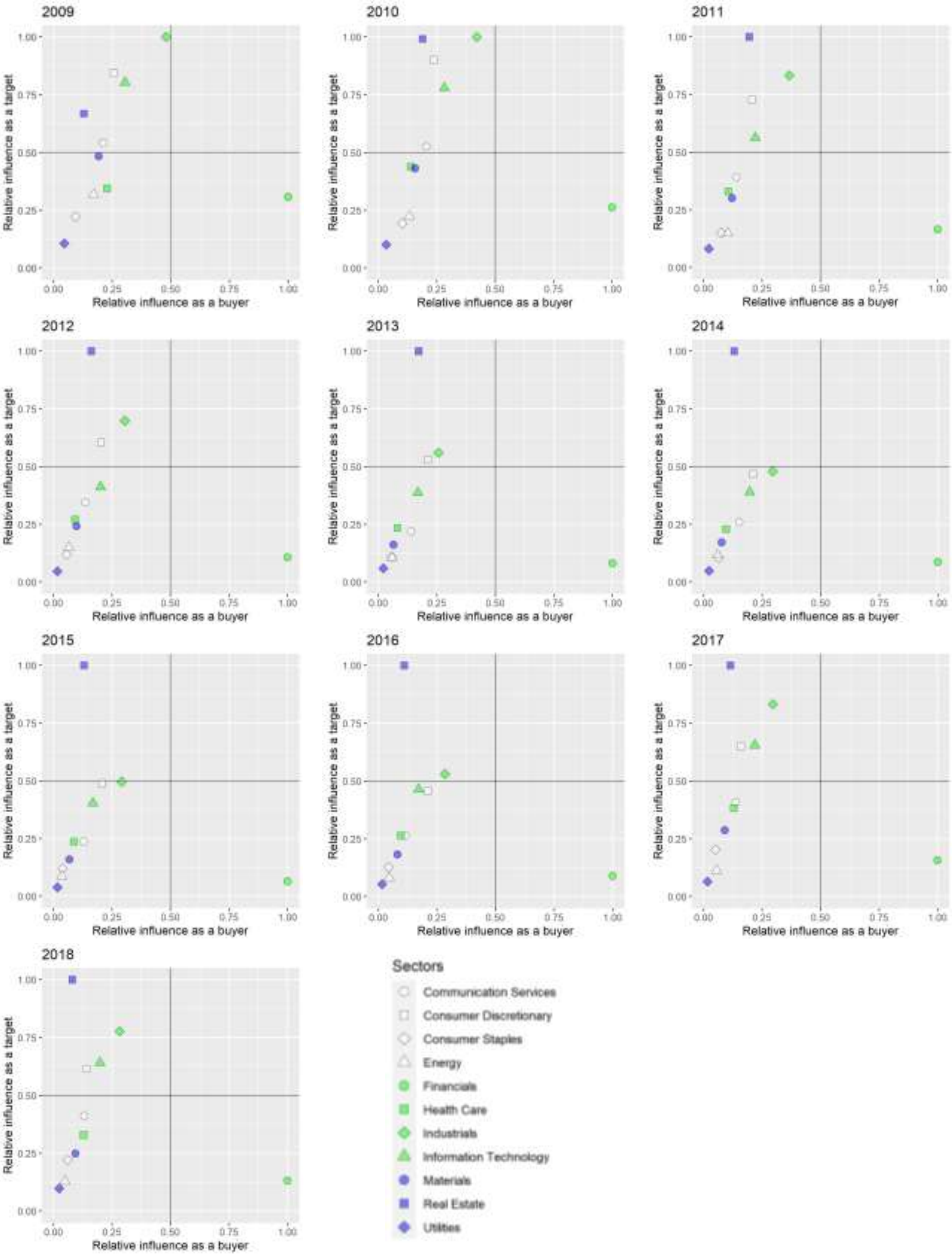


Figure 4. Relative Influence by Sector on Market Diversification

The analysis results from the buyer's perspective are as follows. The financial sector dominantly appeared to influence convergence over the entire period.

The influence of the industrial and IT sectors was relatively lower than that of the financial sector; nonetheless, these sectors had a strong influence as buyers. The relative influence of these two sectors as buyers declined gradually from 2009 to 2013; however, it increased again from 2016 to 2018.

The health care sector showed a relatively significant influence as a buyer only in 2009, which was not observed since then. In addition, the relative influence of the communication services, consumer discretionary, and consumer staples sectors on buyers was generally constant over the entire period.

The above analysis presents the results by sector, which has the highest industry classification level on a one-year basis. However, if the analysis target period is subdivided into a shorter period, expanded into a more extended period, or conducted on a lower industry classification criterion than a sector, more specific and detailed results can be derived.

The analysis results from the target's perspective are as follows: First, the real estate sector had an unrivaled influence throughout the entire period, except in 2009. In contrast, the financial sector, which exerted the most substantial influence from the buyer's perspective, showed very low influence for most of the period except 2009~2010. It was identified that the industrial sector, which had the most significant influence in 2009, showed a gradually decreased relative influence as a target from 2009 to 2015 and rose again from 2017 to 2018.

Similarly, the IT sector had a gradually decreased attractiveness as a target from 2009 to 2012, maintaining a similar level without a significant change for several years and then receiving high interest again in 2017–2018.

The consumer discretionary and health care sectors showed a significant influence from the target's perspective compared with other periods between 2009 and 2010. Subsequently, their influence remained low; however, these sectors almost recovered their initial influence from 2017 to 2018. The consumer staples, energy, and utilities sectors were relatively less influential as buyers throughout the period and remained at this level almost continuously. Similarly, more precise and certain outcomes can be achieved when the target period is expanded or shortened, or when the analysis is carried out using less stringent industry classification criteria.

Cause–Effect Analysis of Market Diversification

Through the trend and relative effects analyses presented above, this study measured the volatility of market diversification based on information on M&A transactions and the influence of each sector. However, it is limited in that it does not provide a clear causal relationship, as it does not provide quantitative figures on the influence of sectors through M&A transactions. To overcome this problem, the study used the DEMATEL methodology (Aaldering et al., 2019) to analyze the causal relationships between sectors in M&A transactions. This makes it possible to compare the market influence of each sector from an objective viewpoint of the buyer and target. In addition, it is possible to understand the cross-impact between different industries over the entire period and the year-over-year comparative and trend analyses for overall industry convergence.

Level 1

This study performed a TRM analysis based on the DEMATEL methodology for 11 sectors using M&A data over the past ten years (2009–2018). The analysis results for 2018, the most recent analysis period, are shown in Fig. 5. In the 11 × 11 matrix composed of 11 sectors, the results are presented in the form of a heat map to facilitate understanding and comparative analysis of the overall situation, rather than suggesting the degree of intersectoral influence as a simple numerical analysis result. In their next study, the authors plan to build an interactive web-based decision-making system to identify and compare figures easily.

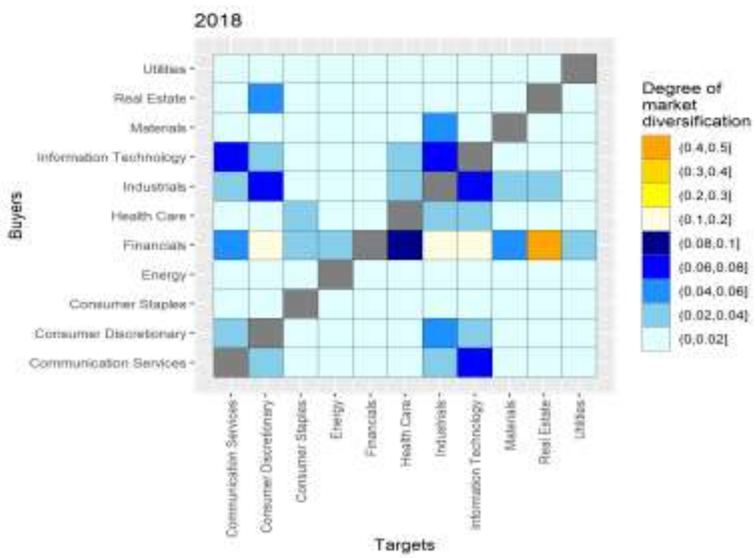


Figure 5. Illustration of Industry Convergence Based on the Cause–Effect Analysis of Market Diversification (Level 1)

As shown in Figure 5, from the buyer's perspective, the financial sector plays the most significant role, followed by the IT and industrial sectors. The financial sector exerted remarkable influence on the real estate sector as an M&A target and played a significant role as a buyer in the consumer discretionary, industrial, and IT sectors. Additionally, the financial sector significantly influenced the health care, communication services, and materials sectors.

In contrast, from the target's perspective, the real estate, IT, industrial, and consumer discretionary sectors received significant attention. However, a substantial difference was observed between them. The real estate sector received absolute attention only from the financial sector, while the other three sectors were M&A targets from several sectors. For example, the IT sector has received considerable attention as an M&A target from the financial, industrial, and communication services.

The above analysis provides a holistic understanding of the cross-sector impacts based on M&A deals. Although the above analysis is for a specific year, a comparative analysis between specific years and an integrated analysis combining multiple years is also possible. In addition, trend analysis results based on annual changes can be identified. Furthermore, more precise and thorough results can be obtained by further segmenting the period, examining it at a lower level, or comprehending the patterns and distinctions across other periods.

Level 5

To further confirm the method's effectiveness, this study presents the analysis results of the relative influence between the sub-sub-industries belonging to the IT sector in Figure. 6. The IT sector consists of 75 subindustries.

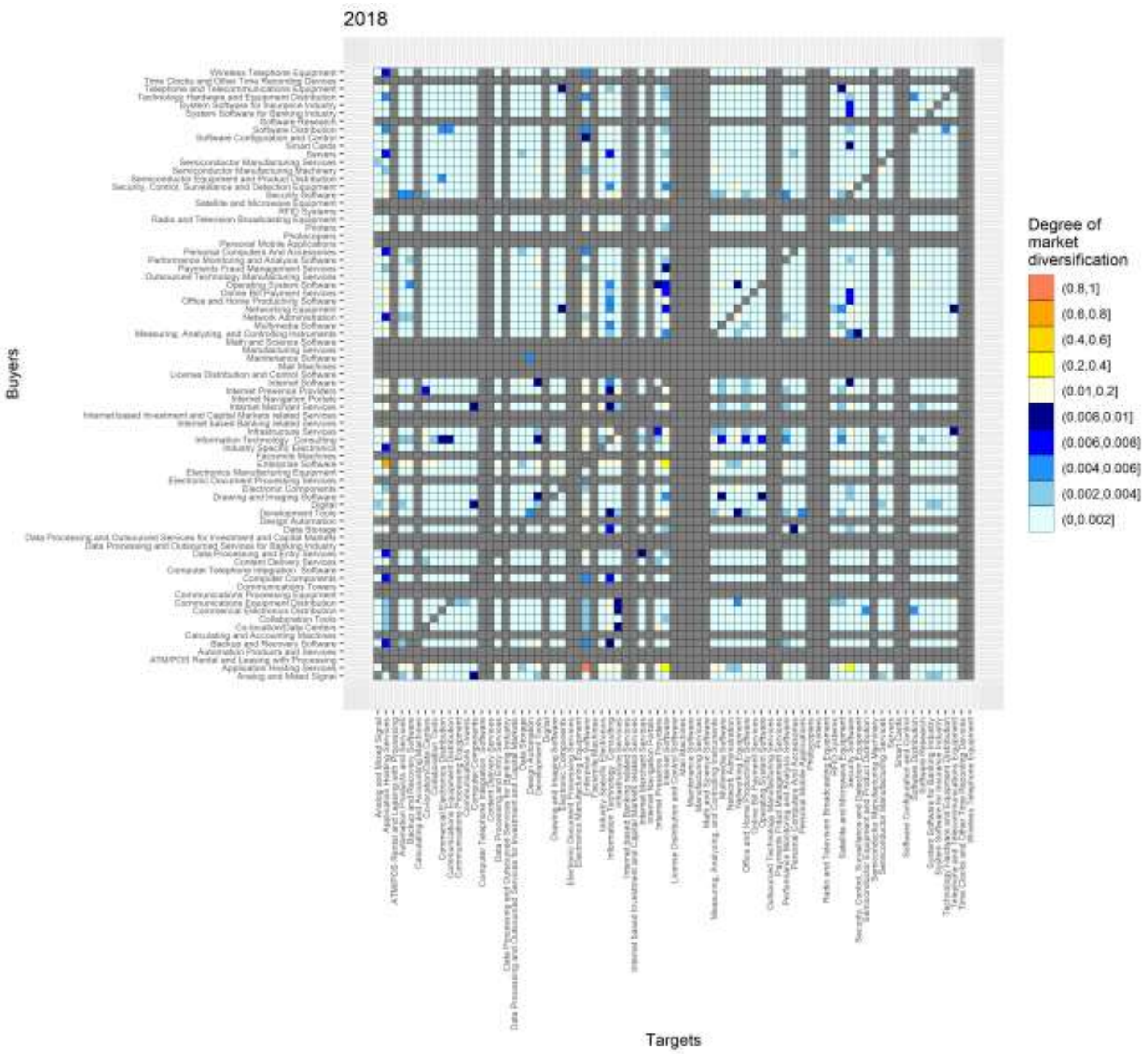


Figure 6. Illustration of Industry Convergence Based on the Cause–Effect Analysis of Market Diversification (Level 5)

From the buyer's perspective, application hosting services and enterprise software sub-sub-industries played the most significant role, especially in the enterprise, internet, and security software sub-sub-industries, followed by the enterprise software sub-sub-industry. The enterprise software sub-sub-industry substantially influenced application hosting services and internet software sub-sub-industries. Security software, operating system software, internet presence providers, infrastructure services, and development tools were also highly influential in various sub-sub-industries as buyers. Meanwhile, several sub-sub-industries, including time recording devices, software research, satellite and microware equipment, and RFID Systems, showed no influence as buyers in 2018.

However, from the target's perspective, application hosting services and enterprise software received considerable attention from diverse sub-sub-industries. Similarly, the IT consulting, networking equipment, and security software sub-sub-industries received high interest from diverse sub-sub-industries.

As in the case of the buyer viewpoint, many sub-sub-industries, including computer telephone integration software and content delivery services, did not receive any attention as M&A targets. In particular, the math and science software, manufacturing services, maintenance software, mail machines, license distribution, and control software sub-sub-industries located in the middle area of the diagram in Fig. 6 did not influence each other as buyers and targets.

The above analysis provides a holistic understanding of the cross impacts between sub-sub-industries based on M&A deals. However, owing to the extensive number of sub-sub-industries, it is difficult to identify them accurately. To this end, the authors of this study plan to provide flexible and accurate analysis for a specific sub-sub-industry by establishing a web-based interactive system as the following research topic. Using a web-based decision-support system, sub-sub-industries that offer market diversification above a certain level may be identified. In addition, the authors expect to perform period-by-period and trend comparisons and a more granular period analysis for a specific sub-sub-industry convergence.

Power–law Analysis

Network analysis has been widely adopted in studies investigating various characteristics of complex networks (Aaldering *et al.,* 2019; Wellman, 1983; Zhu & Guan, 2013). Notably, a most interesting and essential feature of complex real-world networks is their node degree distribution (J. Choi & Hwang, 2014).

Many studies have demonstrated that the degree distribution of real-world networks has a power–law distribution (Amaral *et al.,* 2000; Barabási & Albert, 1999; Mackay, 2005). For example, if the complex network of M&A transactions follows a power law, influential industries in the M&A network can be identified. The direction or characteristics of an M&A network can be identified based on those of a complex network.

Therefore, this study analyzed whether a power law exists in an M&A network structure. However, Level 1 in the S&P industry hierarchy comprises 11 sectors with a small number of network nodes; therefore, it is not appropriate to investigate the power–law phenomenon. When analyzed based on the highest level (Level 1), an appropriate network structure was not formed because there were only 11 target nodes (sectors). Thus, this study selected a specific sector (IT) and then formed a convergence network between 75 sub-sub-industries (Level 5) where actual M&A transactions have occurred in the last ten years. Subsequently, it was verified whether a power law existed in this complex network.

In particular, the M&A transaction network consists of a weighted network. An adjacency matrix can mathematically represent a weighted network with entries that are not zero or one but equal to the weights of the edges (Newman, 2004).

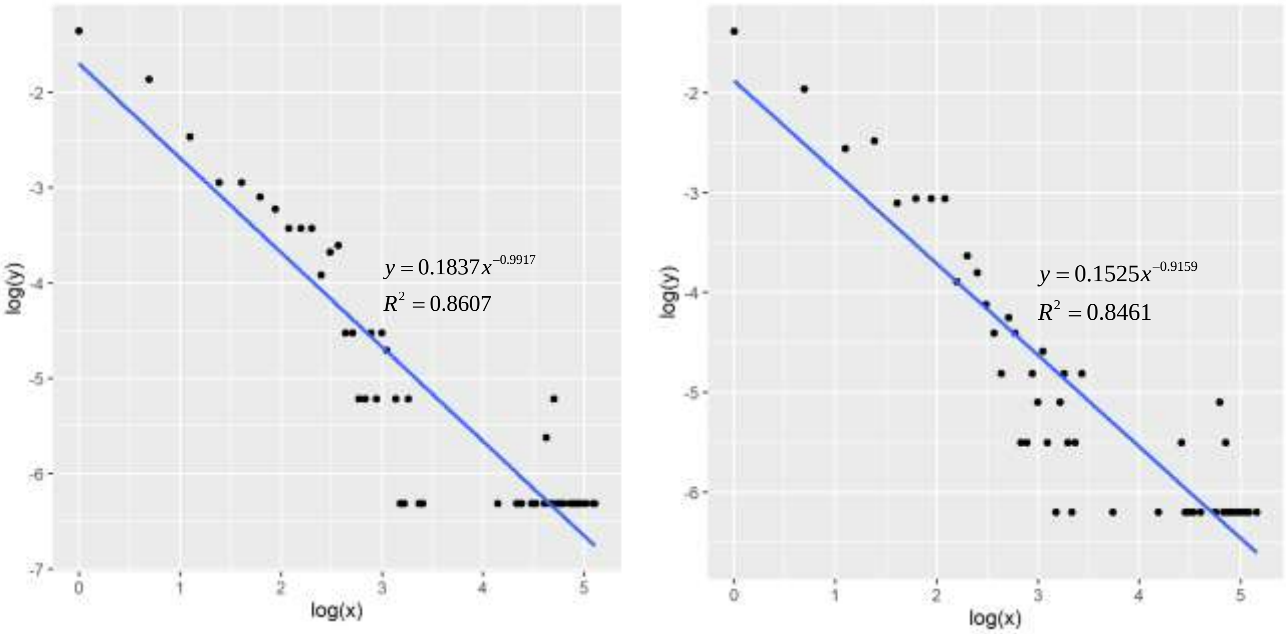
The M&A deals are conducted between one or more buyers and the target company. From the industry perspective of the companies participating in M&A transactions, many-to-many (M to N) relationships are established between the buyer's and the target's primary industries. Therefore, an M&A transaction generally consists of a total of M (industries) x N (industries) convergence links. Therefore, the weight of each link connecting the industries within a specific M&A transaction is as follows:

$$\omega(weight) = 1/(\mathrm{M} \times \mathrm{N})$$

If a specific M&A transaction consists of multiple links, the weight of each link can be obtained using this method. For example, in an M&A transaction, if there are two buyers, each included in a different primary industry, and the target company is included in two different primary industries, there will be four (2 × 2) interindustry convergence networks. Therefore, the weight of each link connecting industry and industry is 1/4.

After constructing a weighted network between industries based on each M&A transaction information that occurred in a specific sector, it was identified whether the power–law phenomenon existed in the M&A complex network structure. Specifically, a weighted network was constructed among 75 sub-sub-industries (level 5) based on M&A transaction data from the IT sector over ten years.

The detailed analysis results are shown in Figure 7.



(a) Buyer's perspective (b) Target's perspective

Figure 7. Nodal Degree Distribution of M&A Complex Network

As shown in Figure 7, the log-log plot of the node degree distribution of the M&A complex network follows a power–law distribution from both the buyer's and target's perspectives. In particular, the buyer's perspective trend is stronger than that of the target. The power–law distribution explains that some nodes play a hub's role in the M&A transaction network structure. This network structure indicates that the hub nodes (sub-sub-industries) have links to other sub-sub industries. Therefore, the power–law distribution in the M&A transaction network signifies that some sub-sub-industries act as core elements and are frequently used to connect with relevant sub-sub-industries for market diversification.

Discussion

This study highlights theoretical and managerial implications to methodically analyze market trends and mutual influences between industries based on M&A transactions from a convergence perspective.

First, the M&A transaction information as market evidence is considered when identifying convergence trends. Burmaoglu et al. (2019) emphasized the importance of trend classification based on two trends: (i) radical or dominant emergence, which occurs without a background, thus creating an unexpected trend; and (ii) incremental emergence, which can be traced and forecasted.

The patent analysis of previous studies provides essential information about how industries converge at the technological level; however, it does not provide any market-level evidence of industry convergence nor consider market irregularity and diversification trends (J. Choi *et al.,* 2021; N. Kim *et al.,* 2015). This study, based on information on M&A activities, attempts to understand the overall flow of industry and economy through a time-series analysis of the market diversification ratio of each industry within a specific region.

In addition, this could be applied to other studies by presenting the results of analyzing the degree of influence of a specific industry on other industries through the improved DEMATEL method. Second, information on M&A activity represents high-growth technology value, market potential, and global expansion (J. Choi *et al.,* 2021). Thus, business analysts and executives can use analyses of the status and trend of convergence among industries based on companies' M&A activities as strategic decision-making information for new market expansion and business cooperation.

Finally, buyers wanting to participate in M&A transactions can identify companies in the same industry or technology area that have invested in other promising areas. Based on the identified information, the areas with relatively high investment values in the market can be selected and predicted. Similarly, target companies that want to participate in M&A can identify other industry/technology areas that have invested in companies in the corresponding industry or technology area. Such information can also enable R&D policymakers and strategic investors to select appropriate promising industries and technology areas to cultivate and invest in positive financial outcomes (J. Choi, Shin, *et al.,* 2020). The method used in this study can be used as a reliable method to analyze promising industries by objectively presenting dynamic correlations between industries through quantitative analysis.

This study presented the primary analysis results to demonstrate a new methodology and validity. The results can be utilized as a basis for a multidimensional convergence analysis in the upcoming study which will facilitate a web-based information analysis system for effective decision-making.

Conclusion

The underlying processes of the market competition structure and boundaries from the convergence perspective remains mostly unexplored (Aaldering et al., 2019). Considering the lack of research on the relationship between M&A transactions and convergence, this study offers insights into the comprehensive review of market diversification through M&A activities between various industries, namely sectors, and sub-sub-industries, exploring the market influence of each industry and analyzing the characteristics of complex M&A networks.

To analyze the convergence between industries and their degree of influence based on M&A activities in the market, this study presents a method to analyze market diversification based on M&A transactions in North America over ten years.

First, overall M&A transactions and market diversification trends were analyzed over the entire study period. The analysis results for each sector were then shown by dividing the market diversification trend into buyer and target perspectives. Second, the relative influence of each sector from the perspectives of buyers and targets was identified to understand the volatility of market diversification based on M&A transactions and the influence of each sector. Furthermore, the causal relationship between industries, namely, sectors and sub-sub-industries, was analyzed based on M&A transactions to compare the mutual influence between various industries for the entire study period. Third, based on the assumption that the M&A network is a complex network existing in the real world, it was determined whether a power law exists in the M&A complex network structure.

However, the study has potential limitations that can be regarded as issues for future research. First, only the number of M&A transactions was considered as the subject of analysis related to M&A transactions. Promising industries can be identified by analyzing the growth momentum properties of M&A activities composed of two quantitative indicators: the number and value of M&A transactions (J. Choi *et al.,* 2021). Consequential results can be derived if an analytical method that combines the two types of M&A information is presented. Second, only provisional and fragmentary analysis results were presented for a specific period. In a future study, the authors expect to establish an effective decision support system that facilitates investment-related decisions by providing an interactive interface and analysis function. Finally.

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Appendix

Table A1

Extant Studies Focusing on Diversification Strategy Using Market Data

References	Key issues explored	Diversification setting
(Feng *et al.*, 2022)	- To examine whether and how business diversification affects financialization in nonfinancial corporations	Chinese stock markets (2007–2018)
(Arte & Larimo, 2022)	- To examine the impact of international diversification on firm performance; to further examine firms with low/high and related/unrelated product diversity and firm performance	263 effect sizes from 187 primary studies (1974–2021)
(S.C. Lin & Kim, 2020)	- To examine the relationship between geographic location, brand, segment diversification, and failure rates	A case of Texas Comptroller of Public Accounts (2000–2018)
(Hossain, 2021)	- To explore the M&A to assess motives, methods, financing sources, announcement effects, cross-border competitions, success-failure, valuation issues, business strategies.	155 recent and relevant papers (2015–2020)
(Perruchas *et al.,* 2020)	- To elaborate an empirical analysis of the temporal and geographical distribution of green technology, and on how specific country characteristics enable or thwart environmental inventive activities	Patent data on 63 countries (1971 – 2012)
(Huynh *et al.,* 2020)	- To investigate the role of AI, robotics stocks, and green bonds in portfolio diversification.	Daily data of NASDAQ Artificial Intelligence and Robotics Index (2017–2020)
(Elsayed, 2020)	- To explore the time patterns of volatility spillovers between energy market and stock prices of seven major global financial markets.	Oil prices stock prices of seven major global financial markets (2000–2018)
(Schommer *et al.,* 2019)	- To study the relationship between diversification and firm performance in the context of the decline in levels of diversification over time.	150,000 firm-level observations from over 60 years of research on the diversification–firm performance relationship

Table A2

Summary of Concepts Related to Industry and Technology Convergence

Article	**Definition of convergence related to industry or technology**	**Key issues explored**
(Sick *et al.,* 2019)	- Industry convergence: a sequential process with four steps including science, technology, market, and industry convergence resulting in structural changes in the respective industries	- Develops a framework based on novel indicators that enable identification and monitoring of industry convergence trends in a high technology environment.
(J. Kim *et al.,* 2019)	- Technological convergence: a breakthrough that combines at least two or more existing technologies into hybrid technologies	- Proposes a systematic approach to anticipating technological convergence that can be used to guide organizations towards reacting in a timely manner to challenges posed by increasingly permeable technology boundaries
(Zhou *et al.,* 2019)	- Converged emerging technology: technologies in an early phase of development, which may have a significant impact on the socio-economic structure	- Integrates the machine-learning topology clustering and visualization methods and analyzes paper citation networks.
(Kose & Sakata, 2019)	- Technological convergence: blurring of boundaries between at least two hitherto disjoint areas of science, technology, markets, or industries, including fusion	- Identifies the technology convergence more precisely than before by using a new methodology named “module-based mining methodology;” second, to extract the patterns of technology convergence; and finally to examine the processes of technology convergence in the field of robotics research
(Geum *et al.,* 2016)	- Industrial convergence: the point at which applicational convergence transitions into shifts in industry boundaries, and is recognized as a driving force of economic development through the impetus of technological convergence	- Identifies the pattern of industry convergence through a clustering analysis to classify the characteristics of each cluster
(Preschitschek *et al.,* 2013)	- Industry convergence: a phenomenon which on implies new opportunities for the involved firms regarding the opening up of new markets and the attraction of new customers	- Develops a concept to anticipate convergence even in small samples, simultaneously providing more detailed information on its origin and direction

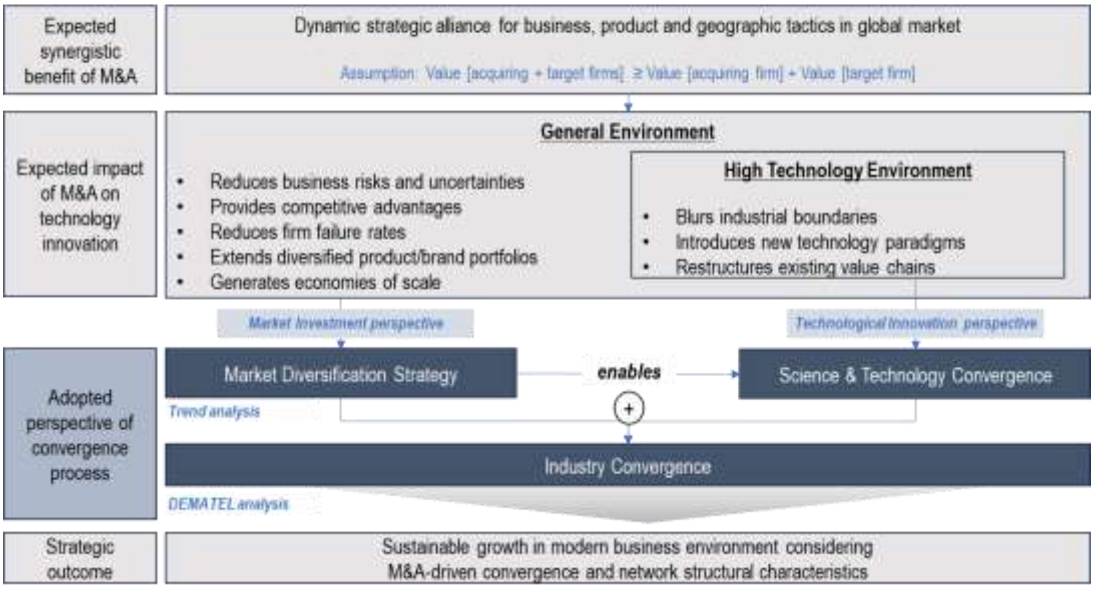

Figure A1. Proposed Framework to Examine the Market Diversification Trend and the Industry-To-Industry Influential Degree

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