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Special Issue Reprint

Industrial Clusters, Agglomeration and Economic Development

Edited by
Kuchiki Akifumi

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Industrial Clusters, Agglomeration and Economic Development

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Guest Editor

Kuchiki Akifumi



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About the Editor

Akifumi Kuchiki

Akifumi Kuchiki is currently a visiting researcher at the Institute for International Trade and Investment. He received his Ph.D. in agricultural economics from Kyoto University in 1982. After joining the Institute of Developing Economies (IDE-JETRO) as a researcher in 1978, he gained prominent work and academic experience, including serving as a visiting research fellow in the Department of Economics at the University of Pennsylvania (1982–1984), working as a staff member at the Overseas Economic Cooperation Fund (JICA) (1989–1991), and serving as a senior economist in the Office of the Senior Vice President at the World Bank (2000–2002). He has taught at several universities, including Tokyo University as a specially-appointed professor and at Waseda, Keio, and Rikkyo universities as a part-time lecturer. He was also a visiting professor at Hiroshima University, Nagoya University, Ritsumeikan Asia Pacific University, and the Open University of Japan. From 2005 to 2008, he was the Executive Vice President of the Japan External Trade Organization. After gaining this solid experience, he taught at Nihon University as a professor from 2008 to 2020 and at the Open University of Japan as a visiting professor from 2016 to 2023.

His main research interests include clusters and agglomerations, spatial economics, and sequencing economics. He wrote many articles and co-edited several books on clusters and innovation, particularly in East Asia. He served as president of the board of directors of the International Academic Society for Asian Communities from 2011 to 2013. In 2019, he received an academic award from the Japanese Society of Regional and Agricultural Development.

Preface

Liberalization has been a major trend since World War II. Globalization has been promoted by the World Trade Organization (WTO). However, in recent years, economic liberalization has resulted in exposing uncertainty around the world. Currently, countries are facing the challenge of finding ways for companies to promote innovation under the progress of artificial intelligence in the Fourth Industrial Revolution. Countries need to shift to an “innovation” strategy that combines investment and innovation to escape from the uncertainty around the world.

One of the prerequisites for this is “clustering.” Michael Porter argued that the agglomeration of geographically proximate related industries promotes competitiveness and innovation. It is well known that corporate research and development activities generate spillovers through urban agglomeration and strengthen regional innovation. We consider clustering as a tool to promote a gear shift in innovation strategy.

This Special Issue analyzes clusters from various perspectives, including organizational management, spatial economics, and sequencing economics. First, spatial economics can be used as a tool to guide location decisions in economic decision making. Next, sequencing economics provides the construction theory of agglomeration, analyzes the dynamic process of efficiently constructing agglomeration segments, and discusses sequencing methods for the efficient construction of segments. Third, geographical management theory seeks to identify factors contributing to regional competitive advantages. Other approaches related to clusters and economic development are also adopted to understand their role in cluster development. This Special Issue aims to present original theoretical and empirical research and case studies on the various aspects of clusters.

The countries, regions, and topics covered in this reprint are as follows: Information Technology Clusters in Brazil and Spain; Industry 4.0 Adoption in Thai Manufacturing; Industrial Synergy Agglomeration, Urban Innovation Capacity, and Advanced Manufacturing Development in China; Reconstruction Challenges and Lessons Learned from the Great East Japan Earthquake; Sectoral Performance Trends and Differences in the Balkan and Eastern European Region. Analysis on Spatial Aspect of Global Value Chain in East Asia examines how ports and airports shape industrial clusters in East Asia. This reprint has identified the following facts: Brake Segment for Agglomeration Policy is engineers as human capital; Start Switch for Innovation in “Construction Sequencing” is research funding.

We hope that this reprint will be widely read and will contribute to the formation of clusters. Finally, we would like to express our gratitude to Dr. Gloria Yang for her significant contribution to the publication of this reprint.

Kuchiki Akifumi

Guest Editor

Article

Sectoral Performance Trends and Differences in the Balkan and Eastern European Region

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Abstract: This article provides an empirical analysis aimed at evaluating the financial trends and disparities at the sector level within the Balkan and Eastern European region. The dataset encompasses a period of nine years and comprises more than 20 million firm-year observations from 24 industries in 21 countries. It uses 19 financial ratios to assess sectoral performance. In the empirical investigation, trend analysis and the two-step cluster analysis methods were used. Following the global financial crisis, a significant proportion of financial ratios exhibited favorable trends, indicating robust business and economic circumstances. Nevertheless, this trajectory was temporarily disrupted in 2020 due to the onset of the COVID-19 pandemic. By 2021, the financial ratios had reverted back to their historical patterns. Country membership, margin, liquidity, trade turnover, profitability, and leverage ratios are the most effective variables for explaining differences in sectoral performance. Sector membership is a comparatively less influential factor. Although this study effectively identified significant disparities in financial ratio profiles, it does not suggest that companies in the most developed countries in the region attain the most favorable financial performance. Stakeholders who have a vested interest in this region should carefully contemplate the ramifications of the findings from this study.

Keywords: sectoral performance; financial ratios; financial performance; emerging markets finance; two-step cluster analysis

1. Introduction

Research on financial performance in emerging markets has attracted a lot of attention lately (Cumming et al. 2021; Bhaskar and Bansal 2022). Such markets, acting as research subjects, have attracted an idiosyncratic approach to combine research on investment and corporate finance with fields of international economics, development economics, law, demographics, and political science (Bekaert and Harvey 2002). Although their corporate leverage rates have increased since 2010 amid favorable global financial conditions, emerging market firms have experienced significant economic growth and have consequently emerged as significant players in global business (Demirkan et al. 2019; Alter and Elekdag 2020). Inter alia, one of the most fascinating emerging economic regions to research is the Balkan and Eastern European countries (Ipsmiller and Dikova 2021). Any region's development is significantly influenced by its industrial cluster formation policy (Kuchiki 2021).

Financial ratios have historically served as measures of a company's overall performance, which can then be combined to represent sectoral performance at the level of economic sectors (Kliestik et al. 2020). Financial ratios can also be grouped according to different approaches (Kovacova et al. 2019; Amoa-Gyarteng 2021). Recent empirical research in various settings has shown that sector and country membership influence a company's stock market performance, with country membership having a greater impact than the sector (Vidal-Llana et al. 2023).

This study aims to analyze financial trends and differences at the sector level in the Balkan and Eastern European region. As a result, this article fits into the academic

literature as a comparative empirical study at the regional level, covering the behavior of corporate financial ratios at the sector level in the field of emerging markets finance. Three research hypotheses have been formulated to substantiate our empirical research, which are elaborated upon in Section 2.

Empirical research in this study encompasses the collection of data for non-financial firms located in the Balkan and Eastern European region. Within the framework of this article, the Balkan and Eastern European region incorporates twenty-one countries as follows: Albania (AL), Belarus (BY), Bosnia and Herzegovina (BA), Bulgaria (BG), Croatia (HR), Czechia (CZ), Estonia (EE), Greece (GR), Hungary (HU), Kosovo (KV), Latvia (LV), Lithuania (LT), Moldova (MD), Montenegro (ME), North Macedonia (MK), Poland (PL), Romania (RO), Serbia (RS), Slovakia (SK), Slovenia (SI), and Ukraine (UA). Although these countries belong geographically to a well-defined region, national historical and cultural factors, courses of economic development, and differences in respective political environments lead them to substantially differ from each other. This aspect also applies to the financial performance of companies and sectors in given countries. Based on our current understanding, prior empirical investigations examining the financial performance of emerging markets have not taken into account this particular group of countries as a distinct research entity when analyzing sector-level corporate financial ratios.

This article makes use of a large corporate finance dataset that spans from 2013 to 2021 to examine trends and regional differences in sectoral performance. More than 20 million firm-year observations have been retrieved and processed using nineteen financial ratios in order to evaluate the financial performance of twenty-one countries and twenty-four sectors. Financial performance trends have been evaluated by fitting trend functions to the time series evolution of aggregated financial ratios. The next step involved applying multivariate cluster analysis to investigate sectoral performance disparities. Since country and sector membership are categorical variables and financial ratios are continuous, the two-step cluster analysis was used to handle mixed data types.

According to empirical findings, financial performance in the region can differ significantly by country because it is highly dependent on the specific countries. The significance of variations in margin, liquidity, trade turnover, profitability, and leverage ratios through the application of diverse methodologies and financial ratios was next examined. Comparing sector membership to country and financial ratios, the former has a greater impact on clustering. The empirical research indicates that the corporate financial profile at the sector level in the least developed countries in the region is the least favorable. However, it is important to note that this observation does not apply to the more developed countries. Although this study effectively identified significant disparities in financial ratio profiles, it does not suggest that the companies in the most developed countries in the region attain the most favorable financial performance.

This article contributes to the body of knowledge on emerging markets finance by essentially serving as a novel benchmark empirical study in the field of sectoral performance research applied to the Balkan and Eastern European region. The region's investors, creditors, corporate finance experts, risk managers, and economic policy analysts ought to be cognizant of the implications arising from the empirical findings. Since data on emerging markets are becoming more readily available, they can serve as a practical basis for future studies of a similar nature that may be carried out for other emerging economies. Because of this, it might be easier to compare and evaluate their sectoral performance and gain more insight into the development trends and turning points in financial performance.

The arrangement of the article is as follows. A comprehensive review of the literature on the field's research trends is provided in Section 2. The details of variable specification, data preparation, data collection, and the applied statistical methodological approach are described in Section 3. Section 4 analyzes the data and delves into the empirical results, while Section 5 presents conclusions and suggests avenues for future research.

2. Literature Review

To investigate current scholarly discussions in the research field, a systematic literature search for scientific publications released between 2018 and 2023 was conducted in Crossref. The first thousand items were taken into consideration, with the following applied keywords used: “economic sectors”, “industries”, “financial performance”, “financial ratios”, “sectoral performance”, and “competitiveness”. It was decided to focus solely on journal articles as a first filter step. Thus, additional publication outlets were eliminated; consequently, 644 items from the original dataset were left. Articles that contained specific references to businesses, the financial or public sectors, or those that were limited in their focus to a single industrial sector were also eliminated in the second filtering step. Additionally, articles that did not seem to be cross-sectoral studies were excluded based solely on their titles. After a thorough selection process, thirty-eight items made the shortlist for further analysis. After these articles were processed further, it was discovered that some of them used a variety of different approaches (such as categorization into sectors of micro and small enterprises or listed companies) rather than defining research sectors in relation to industrial groupings. The final range of reviewed articles was narrowed down to twenty-five as a result of this process, and these are now being evaluated.

2.1. COVID-19-Related Publications in the Research Field

It is not surprising that empirical research on COVID-19 has been very active in recent years, with numerous articles demonstrating varying experiences in developed and emerging nations. For example, Muthu and Wesson (2023) discovered that cash-flow-related variables significantly affected performance levels and that COVID-19 generally had a severe negative impact on industrial sectoral performance in South Africa. Significant differences were found between the sectors after Oppusunggu et al. (2023) looked at market indicators and Wijayanto and Seno (2021) used multivariate analysis of variance (MANOVA) methods to study trends of sectoral performance in Indonesian business sectors, with a focus on COVID-19.

The effect of the COVID-19 pandemic on sectoral performance in Türkiye was assessed by Ataman et al. (2022). Of the twenty-two sectors that were examined, ten showed a negative impact, and twelve showed a positive impact. Similar differences were discovered in important Indian sectors by Suman et al. (2022), who also identified the sectors that recovered more successfully than the others. Huynh et al. (2021) examined the divergent effects of COVID-19 on Australian businesses’ sectoral stock returns across a range of industries. The findings showed that sectors of the economy that received government funding were either insulated from the pandemic or had less of an impact.

Priya and Sharma (2023) looked into how economic disruption affected sectoral volatility in India using a variety of conditional volatility approaches.

2.2. Financial Performance-Related Publications in the Field

In certain empirical research, return on equity (ROE) and return on assets (ROA) ratios were used to measure and predict sectoral financial performance. The financial performance of industrial sectors in the Visegrad Four countries of Eastern Europe was researched by Kristóf and Virág (2022), who considered several financial ratios and machine learning techniques. It was determined that the ratios of leverage, turnover, and income margin were the best predictors. After analyzing the financial performance of Saudi Arabian companies in the manufacturing and insurance sectors, Rahman and Sharma (2020) came to the conclusion that size, leverage, operating cash flow, and industrial membership had a significant impact on financial performance. The best predictor ratios were cash turnover, asset turnover, and current ratio, according to Kurniawandi’s (2021) research on the drivers of market book value (MBV) and return on assets (ROA) in three Indonesian sectors. Similar research by Wira (2021) showed that net profit margins, accounts receivable turnover rates, and debt ratios all significantly impacted firm value.

The experience of empirical research in China demonstrated the significance of debt maturity and leverage in determining financial performance (Vijayakumaran and Vijayakumaran 2019). Furthermore, Manimannan and Lakshmi (2020) employed the k-means clustering method to identify sectoral performance differences according to fourteen financial ratios by forming five major sector groups from Indian industries.

Konar and Atmaca (2020) made an effort to rank and evaluate the financial performance of companies from three sectors that were listed on the Istanbul Stock Exchange by using different multi-criteria decision making (MCDM) techniques. The results showed that different rankings were obtained by applying the specified methods. Similar research was done for Egypt's manufacturing sectors, but the ranking methods showed no discernible differences (Abdel-Basset et al. 2020). In order to efficiently create a dynamic taxonomy in this context, Skoczylas and Batóg (2019) also presented a dynamic approach to measure and compare financial performance across sectors in Poland.

2.3. Novel Research Trends and Dissemination of Non-Financial Ratios

Studies pertaining to environmental, social, and governance (ESG) have been published much more frequently in recent years. Anqi and San (2022) conducted a study on heavy polluting industries in China and discovered that environmental performance had a positive impact on financial performance that went beyond the effects of revenue growth and company size. The relationship between environmental and financial performance was positively impacted by the proportion of female board members but negatively impacted by the total number of committees. After examining how audit committee characteristics affected ROA and Tobin's Q measures in Omani non-financial sectors, Shamsuddin and Alshahri (2022) came to the conclusion that corporate governance mechanisms needed to be improved in order to improve performance.

Vietnamese experience showed that auditors, supervisory size, and company size all significantly and negatively impacted performance (Dao and Ngo 2020). On the other hand, Pakistani empirical findings showed that social and financial performance were positively correlated (Shabbir et al. 2020). Moreover, research has shown that corporate social responsibility can help businesses become more resilient to adversity (Singh and Hong 2023).

In order to explain sectoral advancement in Nigeria, Tabash et al. (2022) and Omotola and Bank-Ola (2022) employed macroeconomic indicators as proxies of financial deepening. From this analysis, they derived recommendations for enhancing sectoral performance. Using S&P500 company data over a sizable historical period, VanderPal (2019) investigated the relationship between research and development (R&D) expenses and financial performance. Significant sectorial variance was found in this study with reference to this specific relationship.

2.4. Summary of the Literature Review and Hypothesis Formulation

Based on these results, it can be argued that since 2018, the majority of empirical studies have focused on the effects of COVID-19 on sectoral performance, optimizing statistical methods that had previously been used, identifying a range of relevant predictors, the emergence of ESG factors (mainly connected to corporate social responsibility), and the incorporation of macroeconomic and market indicators in applied research.

However, most studies were based on a limited number of observed sectors and companies; thus, typically a few thousand or a few hundred observations and multivariate clustering techniques were relatively underrepresented. Therefore, it is reasonable to conduct a novel empirical research exercise with a more extensive data background, indicating a research gap. Given that such data available to this extent are applied through traditional corporate financial ratios, our empirical research project utilizes these variables.

The following hypotheses have thus been formulated to support our empirical research:

H1: COVID-19 severely negatively influenced all financial ratios in the Balkan and Eastern European region in 2020.

H2: Country and sector classifications sufficiently explain differences in sector-level financial performance in the Balkan and Eastern European region.

H3: The variations in sectoral performance in the Balkan and Eastern European region can be adequately elucidated by leverage, profitability, liquidity, and margin indicators.

3. Materials and Methods

3.1. Data Collection and Analysis

Financial data for Balkan and Eastern European companies were available in Moody's Analytics Orbis database. The data collection period encompassed 2013 to 2021, with solely the financial records of active companies being taken into account. No restriction on company size was imposed.

Companies with registrations in Türkiye and the Russian Federation were excluded from this analysis. Although both countries are, to varying extents, geographically located in the Balkan peninsula and Eastern Europe, it would not have been possible to determine the exact geographical location of companies registered in either country, as they may, for instance, operate in Anatolia, Central Asia, or the Far East. Table 1 presents an analysis of the financial data collected by country. A grand total of 20,832,825 legitimate firm-year observations (corporate data records) were gathered.

Table 1. Country breakdown of corporate financial data.

Country	Available Corporate Financial Data									Total
	2013	2014	2015	2016	2017	2018	2019	2020	2021	
AL	90	257	251	218	196	1147	6866	7517	5504	22,046
BA	19,954	20,264	21,072	20,475	18,744	18,102	17,410	18,730	18,013	172,764
BG	225,422	241,147	257,229	270,427	285,723	298,340	304,499	308,263	313,644	2,504,694
BY	1523	1621	1646	1511	1552	1687	2568	1384	12,587	26,079
CZ	118,531	119,317	129,230	141,541	143,282	139,564	127,664	115,469	126,650	1,161,248
EE	75,504	83,748	97,735	108,780	118,461	129,165	137,215	145,158	141,839	1,037,605
GR	25,868	28,177	29,175	30,857	33,840	35,900	36,184	34,363	8258	262,622
HR	55,273	65,189	74,910	80,867	88,984	97,351	101,988	111,117	108,438	784,117
HU	219,342	234,312	251,101	264,049	276,913	289,914	289,871	318,273	329,863	2,473,638
KV	153	231	263	299	332	317	171	281	269	2316
LT	9052	9658	9514	10,861	12,519	19,202	63,977	69,629	71,463	275,875
LV	49,042	53,532	59,000	63,606	67,786	70,968	74,132	78,124	37,343	553,533
MD	438	392	338	270	4886	4957	4895	5287	5540	27,003
ME	1262	8977	10,525	10,633	10,148	10,273	10,651	10,760	10,253	83,482
MK	30,756	34,558	38,871	40,005	42,200	43,986	44,317	46,977	47,034	368,704
PL	81,129	90,544	101,433	97,168	184,337	204,845	213,586	222,910	221,814	1,417,766
RO	360,312	378,707	425,768	455,789	496,722	530,944	559,552	619,823	656,423	4,484,040
RS	59,285	51,248	51,866	68,705	87,843	91,913	162,493	173,950	167,288	914,591
SI	63,202	69,690	73,397	74,408	78,988	83,276	83,608	91,462	93,410	711,441
SK	119,801	135,486	147,006	158,714	169,692	178,089	182,432	196,483	203,881	1,491,584
UA	235,244	218,279	232,361	240,523	255,308	269,072	263,251	322,866	20,773	2,057,677
Total	1,753,196	1,847,348	2,014,706	2,141,722	2,380,473	2,521,030	2,689,349	2,900,846	2,602,308	20,832,825

The number of firm-year observations per country that were obtained from Moody's Analytics Orbis and used in this study is shown in Table 1.

The picture of financial data accessibility is not uniform. While corporate financial data from more developed nations are more thoroughly compiled and arranged in Moody's Analytics database, access to data is more challenging in other countries (like Albania, Belarus, Kosovo, and Moldova). Furthermore, it is evident that the quantity of data that was available grew annually, with the exception of 2021, when data availability in Ukraine

sharply declined. Reduced data accessibility may also result from the conflict between Russia and Ukraine, which broke out in February 2022.

The Bureau van Dijk (BVD) sector classification method was applied in order to provide sectoral analysis. When it was unclear which industry the downloaded records belonged to, they were discarded. This practice was also applied to companies in the “Banking, Insurance & Financial Services” and “Public Administration, Education, Health, Social Services” sectors because the different financial ratios applied to these sectors have different business meanings (which were already filtered out before the completion of Table 1).

There were only a few companies in each of the four information-technology (IT)-related sectors: “Communications”, “Computer Hardware”, “Computer Software”, and “Information Services”. These were later combined into an aggregated sector called “Information Technology and Communications”. The financial data analysis breakdown by aggregated sector is presented in Table 2.

Table 2. Sectoral breakdown of corporate financial data.

Sector	Available Corporate Financial Data							2020	2021	Total
	2013	2014	2015	2016	2017	2018	2019			
Agriculture, Horticulture & Livestock	91,339	95,882	102,326	106,116	115,249	119,302	117,827	125,402	87,882	961,325
Biotechnology and Life Sciences	5533	5686	6136	6462	7342	7726	7968	8723	7211	62,787
Business Services	342,224	365,080	398,559	429,240	483,108	514,154	553,554	612,371	557,676	4,255,966
Chemicals, Petroleum, Rubber & Plastic	18,678	19,295	20,584	21,357	23,480	24,384	25,160	26,900	22,327	202,165
Construction	163,661	172,015	190,127	205,395	233,639	252,895	271,890	298,650	282,747	2,071,019
Food & Tobacco Manufacturing	31,672	33,710	36,595	39,002	44,243	46,942	51,855	55,534	48,441	387,994
Industrial, Electric & Electronic Machinery	26,145	27,267	28,767	30,215	32,891	34,224	34,885	36,761	32,023	283,178
Information Technology and Communications	47,182	51,198	56,901	62,649	73,543	80,740	87,481	97,582	93,959	651,235
Leather, Stone, Clay & Glass products	10,539	10,882	11,558	11,910	13,062	13,603	14,389	15,373	12,377	113,693
Media & Broadcasting	13,886	14,895	16,459	17,902	21,039	22,842	24,387	26,254	24,186	181,850
Metals & Metal Products	33,693	35,515	37,841	40,163	44,168	46,765	48,758	51,934	47,661	386,498
Mining & Extraction	4690	4726	5076	5233	5760	5984	6076	6505	4884	48,934
Miscellaneous Manufacturing	4764	4973	5491	5931	6840	7382	8615	9259	8749	62,004
Printing & Publishing	18,556	19,199	20,218	20,849	22,675	23,335	23,981	25,095	20,889	194,797
Property Services	134,334	136,468	153,545	158,439	175,570	185,620	191,145	203,781	177,470	1,516,372
Retail	224,560	234,493	251,052	262,142	280,845	287,918	311,458	325,214	307,022	2,484,704
Textiles & Clothing Manufacturing	19,112	20,108	21,564	22,644	25,156	26,574	28,743	30,067	26,785	220,753
Transport Manufacturing	4442	4719	5153	5421	6052	6478	6705	7134	6270	52,374
Transport, Freight & Storage	96,688	104,458	114,924	125,216	140,654	150,899	163,496	178,428	167,056	1,241,819
Travel, Personal & Leisure	143,297	156,146	175,511	190,824	216,499	236,006	269,727	282,691	267,548	1,938,249
Utilities	14,712	15,408	16,942	17,446	20,281	21,454	22,893	26,627	22,840	178,603
Waste Management & Treatment	7350	7723	8427	8810	9985	10,439	10,613	11,341	9863	84,551
Wholesale	261,907	271,494	292,790	308,495	334,729	349,308	358,551	386,223	318,898	2,882,395
Wood, Furniture & Paper Manufacturing	32,219	33,994	36,145	37,845	41,646	44,038	47,173	50,977	45,523	369,560
Total	1,751,183	1,845,334	2,012,691	2,139,706	2,378,456	2,519,012	2,687,330	2,898,826	2,600,287	20,832,825

The sectoral breakdown of firm-year observations taken from Moody’s Analytics Orbis is examined in Table 2. The Business Services sector had the greatest number of available corporate records, followed by the Wholesale and Retail sectors.

3.2. Variable Specification

The study’s financial ratios are compliant with good practice in corporate finance. Nineteen financial ratios were considered in order to include indicators of profitability, margin, liquidity, capital structure, leverage, indebtedness, turnover, and efficiency. Table 3 compiles the definitions of the financial ratios.

Table 3. Definition of financial ratios.

Financial Ratio	Calculation Formula	References
ROA using Net income %	(Net income/Total assets) × 100	Kurniawandi (2021)
ROE using Net income %	(Net income/Shareholders' funds) × 100	Manimannan and Lakshmi (2020)
Profit margin %	(Profit (loss) before tax/Turnover) × 100	Wira (2021)
Gross margin %	(Gross profit/Turnover) × 100	Kristóf and Virág (2022)
EBIT margin %	(Operating profit/Turnover) × 100	Vijayakumaran and Vijayakumaran (2019)
EBITDA margin %	((Operating profit + Depreciation + Total amortization and impairment)/Turnover) × 100	Kristóf and Virág (2022)
Cash flow/Operating revenue %	((Net income + Depreciation + Total amortization and impairment)/Turnover) × 100	Muthu and Wesson (2023)
Net assets turnover	Turnover/Total assets less Current liabilities	Wira (2021)
Interest cover	Profit (loss) before interest/Interest paid	Kliestik et al. (2020)
Stock turnover	Turnover/Stock and work in progress	Kovacova et al. (2019)
Collection period days	(Trade debtors/Turnover) × 365	Wira (2021)
Credit period days	(Trade creditors/Turnover) × 365	Kristóf and Virág (2022)
Current ratio	Current assets/Current liabilities	Kurniawandi (2021)
Liquidity ratio	(Current assets – Stock and work in progress)/Current liabilities	Muthu and Wesson (2023)
Shareholders liquidity ratio	Shareholders' funds/Long-term liabilities	Kliestik et al. (2020)
Solvency ratio assets based %	(Shareholders' funds/Total assets) × 100	Manimannan and Lakshmi (2020)
Solvency ratio liability based %	(Shareholders' funds/Liabilities) × 100	Rahman and Sharma (2020)
Gearing %	((Short-term loans and overdrafts + Long-term liabilities)/Shareholders' funds) × 100	Kristóf and Virág (2022)
Cost of employees/Operating revenue %	(Remuneration/Turnover) × 100	Kristóf and Virág (2022)

The computation formulas for the financial ratios used in this study are shown in Table 3. These ratios, which express financial performance from various angles, are frequently used in corporate financial analysis.

3.3. Data Preparation and Aggregation

Financial ratio means were then determined for each year's sectors within each country. Twenty-one countries, twenty-four sectors, and a nine-year observation period were taken into account, yielding an aggregated unit of observation of 4536 records. Financial ratio means were computed without considering company-level missing values per year, country, sector, or financial ratio values.

Nevertheless, in some years, despite the enormous volume of data, there was absolutely no data available for specific sectors in particular countries for certain financial ratios. Imputation based on nearest neighbors was used to solve this problem. The country with the closest overall financial ratio mean for the year under review was the closest neighbor, as opposed to the nation with a missing value for a particular sector during the year under review.

3.4. Applied Multivariate Cluster Analysis Method

Because mixed feature types were prevalent, exploratory data analysis could not be conducted using traditional k-means cluster analysis. In order to handle both continuous and categorical variables, this study used two-step cluster analysis (TSCA) (Rundle-Thiele et al. 2015). TSCA is widely used to find patterns in a set of input variables by clustering records so that those in one group are more likely to be similar to one another than those in other groups (Popa et al. 2022). The two processes are pre-clustering and clustering, in that order.

During the pre-clustering phase, all records were examined, and their log-likelihood distances were measured to determine whether they could reasonably form pre-clusters based on the preset threshold criteria. The reduction in log-likelihood as two clusters merge to form a single cluster is correlated with the distance between them (Li and Sun 2011). The distance between the two clusters, j and i , assuming they exist, can be expressed as follows:

$$d(j, i) = \varepsilon_j + \varepsilon_i - \varepsilon_{<j,i>} \quad (1)$$

where

$$\varepsilon_j = -N_j \left[\sum_{k=1}^{K^A} \frac{\log(\sigma_k^2 + \sigma_{jk}^2)}{2} + \sum_{k=1}^{K^B} E_{jk} \right] \quad (2)$$

$$E_{jk} = - \sum_{l=1}^{L_k} \frac{N_{jkl}}{N_j} \log \frac{N_{jkl}}{N_j} \quad (3)$$

In which $d(j,i)$ denotes the distance between clusters j and i , $\langle j,i \rangle$ is the index representing the combination of clusters j and i . N_j is the number of records in cluster j , K^A is the number of considered continuous variables, K^B is the number of considered categorical variables, σ_k^2 is the variance of the k -th continuous variable in the original dataset, σ_{jk}^2 is the variance of the k -th continuous variable in cluster j , L_k is the number of categories for the k -th categorical variable, N_{jkl} is the number of records in cluster j , of which the k -th categorical variable takes the l -th level.

In the second phase, the formulated pre-clusters were integrated into the optimal number of clusters using a hierarchical algorithm to satisfy the minimum distance in (1). If a desired cluster number could not be predicted in advance, Schwarz's Bayesian information criterion (BIC) automatically determines the optimal number of clusters using the following formula (Harantová et al. 2023):

$$BIC(J) = -2 \sum_{j=1}^J \varepsilon_j + m_J \log(N) \quad (4)$$

where J is the number of clusters, K is the total number of continuous variable clusters, N is the total number of records, $m_J = 2KJ$.

4. Results and Discussion

4.1. Results of Sectoral Performance Trend Analysis

Trends in sectoral performance can be evaluated by examining the evolution of the financial ratio means for the region (Table 4). Beginning in 2013, financial ratios improved across the board, pointing to an important general trend: the effects of the previous global financial crisis had diminished, and substantial progress had been made. Furthermore, patterns in the data indicate that COVID-19 contributed to this trend's brief decline in 2020, especially in terms of profitability, margin, and solvency ratios. By 2021, financial ratio means, however, began to further strengthen the trend and advance. It should be noted that this study only included active companies. The COVID-19 pandemic may have claimed the lives of companies that were dissolved, liquidated, or declared bankrupt; however, there was insufficient data to include these companies in the study. Moreover, it is probable that these businesses faced more significant problems during the COVID-19 pandemic than trying to provide official data collection agencies with financial information.

The financial ratio trend analysis is shown in Appendix A. The logarithmic, polynomial, exponential, and linear trend functions can be used to effectively estimate the financial ratio time-series. The best fitting curve was selected for each ratio, and the trend fit was evaluated using the R-squared statistical measure.

It is important to keep in mind that the evolution of financial ratio means was examined using bottom-up average computations from particular corporate records. Consequently, countries that had access to more corporate data contributed more to the total numbers than those that had fewer observations. However, each country was given equal weight when clusters were created in the sectoral performance difference analysis that is subsequently presented because, in contrast, the sectoral average financial ratios for each country and year were formed by aggregating observations.

Table 4. Evolution of financial ratio means for the Balkan and Eastern European region.

Financial Ratio	2013	2014	2015	2016	2017	2018	2019	2020	2021
ROA using Net income %	3.967	4.618	6.264	7.715	7.972	8.555	9.416	7.778	9.822
ROE using Net income %	10.813	11.851	15.766	19.032	21.008	21.588	22.737	21.839	24.442
Profit margin %	6.886	8.445	8.875	9.980	10.081	10.725	11.794	10.727	12.999
Gross margin %	34.163	38.395	40.797	42.786	43.965	44.559	46.465	43.051	47.136
EBIT margin %	6.444	8.013	9.592	10.590	10.707	11.253	11.598	11.348	12.195
EBITDA margin %	11.647	12.554	13.935	14.613	14.389	14.966	15.389	15.129	16.790
Cash flow/Operating revenue %	8.258	9.193	10.640	11.456	11.564	12.313	12.663	12.239	13.824
Net assets turnover	9.364	9.497	8.909	8.834	8.888	8.819	9.148	8.862	9.299
Interest cover	36.635	33.131	36.807	41.070	41.050	41.977	43.122	44.135	47.828
Stock turnover	38.727	38.932	47.390	41.687	42.041	43.587	45.542	44.317	42.349
Collection period days	72.588	75.877	67.996	65.305	66.555	65.827	64.977	67.554	67.308
Credit period days	51.889	49.105	45.874	44.500	45.221	43.914	44.247	47.884	46.365
Current ratio	4.797	4.906	5.168	5.460	5.481	5.776	6.054	6.136	6.303
Liquidity ratio	3.782	3.898	4.135	4.276	4.375	4.565	4.838	5.029	5.276
Shareholders liquidity ratio	25.048	23.483	26.287	24.858	24.860	25.009	24.411	22.303	23.570
Solvency ratio assets based %	43.633	44.447	45.917	46.781	47.820	51.401	52.181	49.615	51.961
Solvency ratio liability based %	36.427	36.975	37.307	37.293	37.389	37.561	37.789	36.599	37.671
Gearing %	44.444	42.725	42.372	41.029	42.036	42.169	42.031	41.739	41.944
Cost of employees/Operating revenue %	22.176	22.224	22.213	22.889	23.439	23.778	24.395	25.605	24.704

Table 4 examines average financial ratio values at the regional level from 2013 to 2021. Table 3 displays the financial ratios' calculation formulas.

4.2. Results of Sectoral Performance Difference Analysis

The log-likelihood distance measure was employed in conjunction with the BIC method to select variables and establish clusters. Cluster solutions ranging from two to six were considered. Ultimately, it was discovered that a three-cluster solution struck the best balance between the cohesiveness of the model and the number of clusters.

Since the shareholder liquidity ratio did not meet the adaptive feature selection criteria, it demonstrated little to no potential to improve the model's overall goodness. As such, this variable was left out of any further analysis. The distribution of observations within the created clusters is shown in Table 5.

Table 5. The main features of the clusters.

Cluster	Number of Records	Share of Cluster (Percent)	Cluster Cohesion *
Cluster-1	1822	0.40	0.73
Cluster-2	1240	0.27	0.52
Cluster-3	1474	0.33	1.00

* 0.0 to 0.2 Poor | 0.2 to 0.6 Fair | 0.6 to 1.0 Good.

The 2542.0 chi-squared statistics with $p = 0.000$, which resulted from the chi-squared testing of the cluster formulation, demonstrated significant clustering. Each variable was assessed for its significance in relation to cluster formation using normalized across-cluster feature importance statistics. In Figure 1, the clustering variables of the study are ranked. The results indicate that country classification forms the strongest clustering variable, followed by four margin indicators (Cash flow/Operating revenue is also regarded as a margin variable), the two liquidity indicators, and the credit period. The feature importance of the other variables is less than 0.5. It is also noteworthy that the formation of clusters is largely unaffected by sector classification.

Based on the ranking of input variables according to the significance of within-cluster features, cluster profiles can be created. The traits of the three clusters are summed up as follows based on the strongest feature importance statistics.

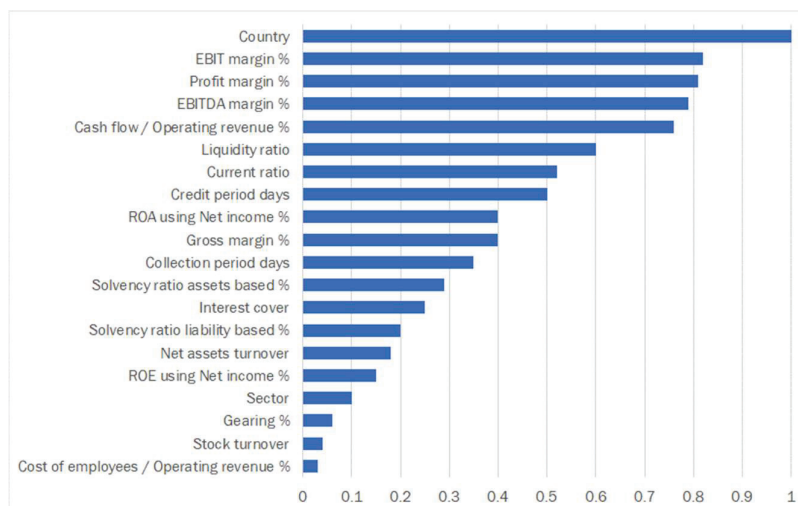


Figure 1. Across-cluster feature importance values. Figure 1 shows the rank of across-cluster feature importance when formulating clusters. This represents the importance of an input variable to the overall clustering solution. The calculation formulas of the financial ratios are located in Table 3.

Belarus, Montenegro, Kosovo, Bosnia and Herzegovina, Serbia, Albania, and Moldova have significantly overrepresented sectoral average financial ratios in Cluster-1. The highest within-cluster feature importance values are assigned to the credit period (0.63), profit margin (0.52), and EBIT margin (0.51), after the country classification (1.00). Sector membership is not important within this cluster. Thus, compared to the other clusters, Cluster-1 exhibits less favorable profitability and income margin indicators, lower liquidity, longer credit and collection periods, the highest leverage, and significantly lower interest cover. Nonetheless, compared to Cluster-2, gross margin and the ability to generate cash flow from operating revenue are more accurately represented. The lowest net asset and stock turnover period is observed in this cluster. The average sector-level financial ratios for each of the three clusters are shown in Table 6.

Table 6. Sector-level financial ratio means in the three clusters.

Financial Ratio	Cluster-1	Cluster-2	Cluster-3
ROA using Net income %	3.707	4.804	8.800
ROE using Net income %	12.939	16.978	21.664
Profit margin %	3.928	4.633	12.621
Gross margin %	39.090	34.343	55.858
EBIT margin %	4.087	4.808	13.085
EBITDA margin %	7.799	8.031	19.535
Cash flow / Operating revenue %	6.818	6.316	16.957
Net assets turnover	5.077	8.242	5.292
Interest cover	27.495	38.252	44.525
Stock turnover	39.438	50.398	57.633
Collection period days	119.145	60.740	71.583
Credit period days	99.315	54.886	49.894
Current ratio	2.987	4.286	6.358
Liquidity ratio	2.196	3.237	5.358
Solvency ratio assets based %	43.660	45.640	55.004
Solvency ratio liability based %	41.266	39.307	40.046
Gearing %	64.889	54.511	50.549
Cost of employees / Operating revenue %	26.718	22.777	25.849

The sector-level financial ratio means in each of the three clusters are assessed in Table 6. Interpreting the cluster profiles requires consideration of differences between financial ratio means in addition to the significance of within-cluster features. Table 3 contains the financial ratios' calculation formulas.

Sectoral average financial ratios from Latvia, Czechia, Ukraine, Poland, Slovakia, and Lithuania make up the majority of Cluster-2. Once again, the highest within-cluster feature importance in this instance is country classification (1.00), followed by cash flow/operating revenue (0.63), EBIT margin (0.60), EBITDA margin (0.57), profit margin (0.55), collection period (0.53), and credit period (0.52). Indicators of profitability, profit margin, liquidity, gearing, stock turnover, and interest cover are all higher in Cluster-2 than in Cluster-1, but they are lower than in Cluster-3. The best collection period and the most advantageous cost of employee efficiency indicators are found in this cluster. The net assets turnover period is by far the longest among the clusters, but gross margin, the ratio of shareholders' funds to liabilities, and the ability to generate cash flow from operating revenue all lag behind the other two.

Sectoral average financial ratios from Estonia, Romania, Slovenia, Hungary, Bulgaria, and North Macedonia are somewhat overrepresented in Cluster-3. The highest within-cluster feature importance in this instance is the EBIT margin (1.00), which is followed by the profit margin (0.99), the EBITDA margin (0.98), the cash flow/operating revenue (0.92), the country classification (0.58), and the liquidity ratio (0.55). Cluster-3 unequivocally shows the best profitability, margin, liquidity, and leverage profiles among the clusters. In contrast to Cluster-2, the indicators for asset turnover, collection time, shareholders' funds to liabilities, and employee cost efficiency are somewhat less favorable. In Cluster-3, the stock turnover period is the best among the clusters.

The financial ratios from Greece and Croatia are unclear in this research because it is difficult to categorize them into one of the three clusters. Although there are more Greek and Croatian observations in Cluster-1, which is the largest cluster *a priori*, it is impossible to determine which country group their sectoral financial performance is most similar to.

5. Conclusions

An identified research gap in the academic literature led to the decision to conduct this empirical study, since the majority of studies in the field of assessing sectoral performance in emerging markets concentrated on a relatively small number of observed sectors, companies, and countries. Moreover, in this field of study, multivariate clustering techniques have not been used as much in recent years. This served as the foundation for a thorough data collection effort that explored trends and variations in sectoral performance, as indicated by widely used financial ratios in corporate finance for twenty-one Balkan and Eastern European nations. Clusters were created using the TSCA method to handle mixed data types.

5.1. Results of Examining H1

H1 posited that the COVID-19 pandemic severely negatively influenced all financial ratios in the Balkan and Eastern European region in 2020. The study's conclusions lend credence to the idea that, as a whole, companies in the Balkan and Eastern European region saw an improvement in their financial performance between 2013 and 2021. Following the previous global financial crisis, the region enjoyed advantageous business and economic conditions, as evidenced by the majority of financial ratios that exhibit positive trends. The COVID-19 pandemic in 2020 appears to have caused a brief halt to the trends shown in Appendix A. This is especially notable in the case of profitability, margin, trade turnover, solvency, and leverage ratios, as also demonstrated by prior empirical studies *inter alia*, Muthu and Wesson (2023), Suman et al. (2022), and Wijayanto and Seno (2021).

However, the unfavorable impact of COVID-19 cannot be reported for stock turnover, interest cover, liquidity, and current ratios. The findings of this study indicate that the assumption made in H1, which posited that COVID-19 had a substantial adverse effect on all financial ratios in the region during 2020, was not supported. Consequently, H1 is rejected. Nevertheless, as results demonstrate, by 2021, financial ratios had returned to their historical trends.

5.2. Results of Examining H2

H2 investigated whether country and sector membership sufficiently explain differences in financial performance at the sector level in the Balkan and Eastern European region.

With a 100% normalized across-cluster feature importance, the country factor formed the strongest clustering variable according to sectoral performance difference analysis. It is interesting to note that, after country classification, four margin ratios were found to be the next most crucial variables for cluster creation.

Regarding sectoral performance, the three clusters exhibit notably disparate financial profiles across the region. Cluster-3 is generally considered to be the most favorable, followed by Cluster-2 and Cluster-1. Nineteen countries could be assigned to the clusters based on the relative overrepresentation of those countries in the clusters. However, because of the differences in the quality of their financial ratio profiles, Greece and Croatia could not be represented. Thus, it can be concluded that during the study period, both countries concurrently had more and less favorable sector-level financial ratios.

In relation to sector membership, the variable satisfied the criteria for adaptive feature selection based on the log-likelihood distance measure when choosing variables for cluster formation. However, the normalized across-cluster feature importance of the variable was found to be 10%, suggesting a relatively limited potential for enhancing the overall quality of the model.

The aforementioned findings indicate that country and sector membership are considered important factors that impact the financial performance at the sector level. As a result, H2 is accepted. The finding that country membership has a more significant influence than sector membership aligns with the previous research conducted by Vidal-Llana et al. (2023).

5.3. Results of Examining H3

H3 assumed that the variations in sectoral performance in the Balkan and Eastern European region can be adequately elucidated by leverage, profitability, liquidity, and margin indicators.

The findings indicate that the four margin ratios, as observed in the financial ratios, exhibited statistical significance and displayed the highest normalized across-cluster feature importance in the process of cluster formation. In a prior study, Kristóf and Virág (2022) obtained comparable findings within a narrower scope of analyzed time periods and nations. The ability and efficiency to achieve EBIT, profit, EBITDA, and cash flow from revenue are crucial factors in explaining the variance between sectoral financial ratio means and are the critical factors in performance differences. This characteristic is particularly prominent in Cluster-3, as depicted in Table 6.

The two traditional liquidity ratios follow the importance of margin ratios, emphasizing the necessity of possessing adequate current assets to meet short-term liabilities. The significance of these ratios has been acknowledged in several previous studies, including those conducted by Kurniawandi (2021) and Muthu and Wesson (2023).

The subsequent factors to consider are trade turnover, profitability, gross margin, and leverage ratios. The significance of their findings aligns with previous research conducted by Manimannan and Lakshmi (2020), Rahman and Sharma (2020), and Wira (2021), among others.

Based on the aforementioned narrative, the acceptance of H3 is justified due to the effective elucidation of variations in sectoral performance in the Balkan and Eastern European region through the utilization of leverage, profitability, liquidity, and margin indicators.

5.4. Implications

The findings indicate that, overall, a company's country membership is a more influential factor than its sector membership when evaluating financial performance. However, it is important to acknowledge and measure the significant variations at the company level in order to better predict important dependencies in specific countries or sectors.

The findings reveal significant disparities in the financial conduct of the businesses and economic sectors in the region. Margin, liquidity, profitability, and leverage account for a substantial amount of variation. However, the situation is not that clear when considering other variables that are considered less important.

The empirical research unequivocally demonstrates that the sector-level corporate financial profile of the least developed countries in the region (Belarus, Montenegro, Kosovo, Bosnia and Herzegovina, Serbia, Albania, and Moldova) is the least favorable, as indicated by the most significant variables (refer to Cluster-1). Nevertheless, this observation does not hold true for the countries that are more developed, as evidenced by Cluster-2 and Cluster-3. While this research successfully identified notable disparities in financial ratio profiles, it does not imply that companies in the most developed countries in the region achieve the most favorable financial performance.

Investors, creditors, corporate finance experts, risk managers, and economic policy analysts with an interest in the Balkan and Eastern European region should consider the implications of this study's findings. When it comes to sectoral performance and corporate financial effectiveness, this study can also be used as a benchmark study by policymakers in emerging markets. This makes the paper a noteworthy addition to the field of emerging markets finance research.

5.5. Limitations and Future Research Directions

A limitation of this study is that the financial ratios analyzed could not account for the actual impacts of the Russia–Ukraine war, the subsequent sanctions, or the subsequent energy and inflation crisis. A possible further limitation is the relatively limited accessibility of data from certain countries; ideally, this will improve in the future. One additional constraint of the study is the potential for bias in the results, which may arise from unobserved variables that could impact financial performance at the sector level. This limitation persists, despite the inclusion of a substantial number of observations and variables in the empirical research.

Potential avenues for future research in this particular field involve expanding the duration for data collection, exploring supplementary financial ratios, broadening the scope of countries under investigation, developing innovative research inquiries, and implementing diverse research methodologies.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

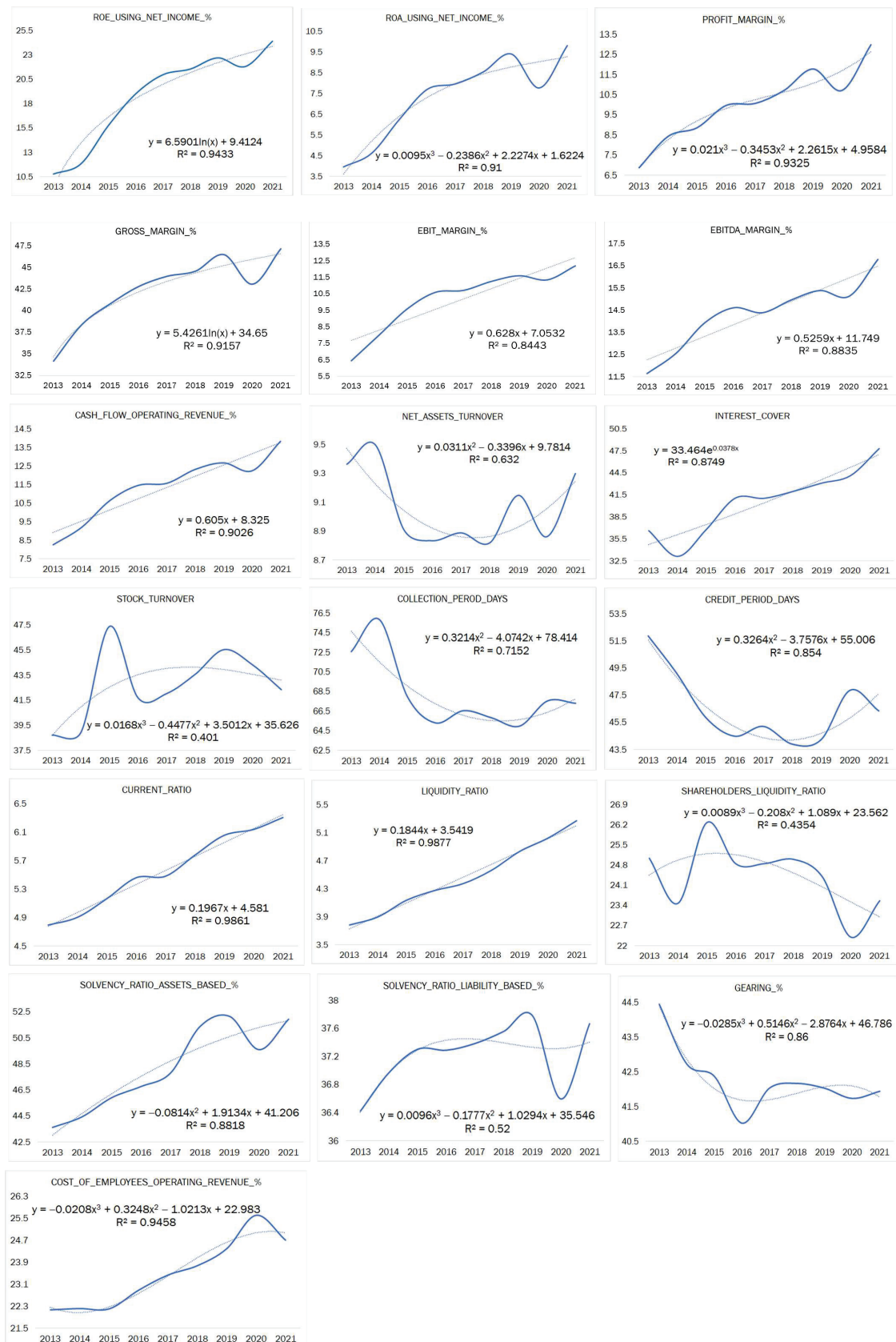


Figure A1. Trend analysis of financial ratio means in the Balkan and Eastern European region.

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Article

Industrial Synergy Agglomeration, Urban Innovation Capacity, and Advanced Manufacturing Development

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Abstract: This paper endeavors to construct an evaluative framework to assess the level of development in advanced manufacturing across the 31 provinces in China from 2003 to 2021. Additionally, it aims to investigate the impact of industrial synergy agglomeration on the development of advanced manufacturing by employing a moderated mediation model and the Spatial Durbin Model (SDM). The research results demonstrate that industrial synergy agglomeration facilitates the development of advanced manufacturing, with particularly pronounced effects in the eastern region of China and the 18 provinces that already possess national advanced manufacturing clusters. Urban innovation capacity plays an intermediary role, and both manufacturing intelligence and international capacity cooperation exhibit positive moderating effects in the direct and indirect pathways through which industrial synergy agglomeration influences the development of advanced manufacturing. Furthermore, industrial synergy agglomeration exhibits strong spillover effects on the development of advanced manufacturing. To boost the development of the advanced manufacturing industry, it is imperative to expedite the establishment of an industrial synergy spatial layout, foster a culture of enterprise innovation and intelligent transformation, emphasize inter-provincial communication and cooperation, and facilitate cross-border resource integration.

Keywords: industrial synergy agglomeration; advanced manufacturing; urban innovation capacity; manufacturing intelligence; international capacity cooperation

1. Introduction

In 2022, the added value of China's manufacturing industry accounted for 27.7% of GDP, and the scale of the manufacturing industry continued to maintain a world-leading position. Nevertheless, there still exists a gap between China's manufacturing industry and the world's advanced level in terms of independent innovation capability, resource-utilization efficiency, and the quality of benefits, among other aspects. Compared with traditional manufacturing, advanced manufacturing is located in the high-end part of the global production system, with high added value and technological content as its prominent features. Its strong innovation in technology and research and development keeps it highly competitive in the market (Peng et al. 2019, 2020; Zhao et al. 2020). Accelerating the development of advanced manufacturing is a key measure for China's manufacturing industry to achieve high-quality development.

How can the level of advanced manufacturing development across different provinces in China be evaluated? How can the further growth of China's advanced manufacturing industry be promoted? To answer these questions, it is crucial to first define the concept of "advanced manufacturing"; then, we must select appropriate indicators to scientifically measure the level of development in provincial regions. In academic research, "advanced manufacturing" is mainly defined in two forms. Some researchers have identified specific sub-sectors within manufacturing that exhibit a high application rate of advanced technologies, designating them as "advanced manufacturing", which is distinguished from "traditional manufacturing" sectors (Feng et al. 2022). This study, like the research

conducted by Hu and Zhang (2011), considers “advanced manufacturing” to be a holistic concept that reflects its advancement in terms of indicator selection. There are also two ways to measure advanced manufacturing. It can be measured through some single indicators such as the proportion of employees (Feng et al. 2020). Moreover, multiple indicators can be selected to comprehensively evaluate its level of development. When selecting multiple indicators, one can adopt a single-dimensional approach, such as using the 10Rs of advanced manufacturing capabilities to measure its development (Bag et al. 2021). Alternatively, one can follow the principles of scientific, systematic, and operational criteria to construct a multidimensional indicator system (Huang and Zhang 2021). Among these dimensions, technology, economy, and environmental considerations are fundamental aspects that can evaluate the research and utilization capabilities of advanced manufacturing technologies, the economic performance and profitability of manufacturing enterprises, and their sustainable development capabilities (Hu and Zhang 2011). The assessment of management level and social benefits are also reflected in relevant studies (Xu and Xie 2013). Compared to single indicators, a comprehensive indicator system allows for a multidimensional evaluation of advanced manufacturing development, yielding more scientifically grounded results. However, research on measuring the level of advanced manufacturing development using multidimensional indicator systems is still in the theoretical stage, with limited quantitative analysis conducted using provincial panel data. Additionally, there is a gap in empirical examinations that utilize comprehensive indicators to measure the level of advanced manufacturing.

In recent years, with the transition from an “industrial economy” to a “service-oriented economy” (Zhang et al. 2023), the global industrial layout has gradually shifted towards spatial diversification, and the coordinated development and efficient interactions between manufacturing and productive service industries have become a trend (Tu et al. 2019; Zheng et al. 2020). The productive service industry improves the production efficiency of manufacturing through industrial linkage effects, technology spillover effects, and other means, transforming the manufacturing industry into a “production + service” pattern (Ke et al. 2014). Regarding the issue of advanced manufacturing development, previous studies have acknowledged the role of industrial synergy agglomeration (Qiu and Gong 2021). Under the “collaborative agglomeration pattern”, the productive service industry runs through the entire process of advanced manufacturing, providing warehousing, logistics, design, financing, and other services. Compared with the previous “separation agglomeration pattern”, the production efficiency of manufacturing industry enterprises has significantly improved. At the same time, industrial collaborative agglomeration accelerates the decomposition, extension, and restructuring of the value chain, and endows the new value chain with a higher level of utility (Gao et al. 2020). How can industrial synergy agglomeration promote the development of advanced manufacturing? A few studies have delved into the influencing mechanisms from a singular perspective. When measuring the development of advanced manufacturing using green and environmentally friendly indicators, studies have found that industrial synergy agglomeration can reduce ecological pollution through the mediating effect of technological innovation (Zhuang et al. 2021; Yang et al. 2021). However, academic research on the question remains insufficient. To explore the pathways through which industrial synergy agglomeration influences the development of advanced manufacturing, it is necessary to build upon the scientific measurement of the development level of advanced manufacturing as a foundation. Subsequently, we will be equipped to explain the economic logic through which mechanism variables exert their influence on the development of advanced manufacturing. These variables should be incorporated into the same analytical framework for a comprehensive empirical examination.

Our study has two specific objectives: Firstly, we aim to construct an evaluative framework to gauge the level of development in advanced manufacturing. Secondly, we aim to determine whether industrial synergy agglomeration has a positive and significant impact on the development of advanced manufacturing, and to explore the mechanisms behind this influence. In order to address the existing research gaps in the measurements and

determinants of advanced manufacturing, this paper selects secondary indicators from five dimensions of advanced manufacturing technology: advanced manufacturing management, advanced manufacturing workforce, green advanced manufacturing, and advanced manufacturing efficiency. Then, calculating the development level of advanced manufacturing in 31 provinces¹ of China from 2003 to 2021, a comprehensive indicator is applied for empirical analysis. The findings reveal that industrial synergy agglomeration facilitates the development of advanced manufacturing. Urban innovation capacity plays a mediating role, while manufacturing intelligence and international capacity cooperation exhibit positive moderating effects in the direct and indirect pathways through which industrial synergy agglomeration influences the development of advanced manufacturing.

This paper makes two significant contributions. Firstly, we refine the evaluation index system for advanced manufacturing and quantitatively measure the development level of advanced manufacturing in different provinces of China using provincial panel data. Compared to previous research relying on single indicators, this research provides a more scientific measurement of advanced manufacturing development. Secondly, we employ a moderated mediation model that incorporates urban innovation, manufacturing intelligence, and international capacity cooperation into a unified analytical framework to investigate the mechanisms through which industrial synergy agglomeration influences advanced manufacturing.

The remainder of this paper is organized as follows: Section 2 conducts a comprehensive review of the relevant studies. Section 3 establishes a theoretical analytical framework and presents three research hypotheses. Section 4 provides an introduction to the model employed in the study, along with explanations regarding the selection of variables and measurement methods. Section 5 presents empirical findings, delving into the implications of the results and validating the hypotheses proposed in Section 3. Section 6 provides a summary of the research conclusions. Lastly, our conclusions are presented in Section 7.

2. Literature Review

Regarding the definition of advanced manufacturing, the academic community predominantly adopts two approaches. The first regards advanced manufacturing as a collection of several high-technology, high-value-added sub-industries. For instance, Zhu et al. (2020) compare manufacturing industries involved in the National Bureau of Statistics with the KLEMS industry standards and classify them into “high-tech manufacturing”, encompassing nine sectors such as “computer, communication, and other electronic equipment manufacturing”, “instrument and apparatus manufacturing”, and “pharmaceutical manufacturing”. The second perspective posits that advanced manufacturing is a comprehensive term encompassing industries that continuously absorb high-tech advancements in information, machinery, materials, and modern management. It represents the manufacturing sector’s pursuit of superior, efficient, low-consumption, clean, and flexible production. In other words, advanced manufacturing comprises manufacturing industries that showcase advancement in technology, management, environmental sustainability, and other aspects (Hu and Zhang 2011). Presently, articles studying the evaluation index system of advanced manufacturing often adopt the second definition, considering “advanced manufacturing” to be a holistic concept. They select indicators from different dimensions to reflect the advancement of the manufacturing industry (Xu and Xie 2013; Huang and Zhang 2021).

Regarding the driving forces behind the development of advanced manufacturing, Ocampo et al. (2017) construct a competitiveness evaluation index system for the manufacturing industry based on dimensions such as cost, quality, production flexibility, transportation time, and environmental protection. Their findings reveal that the utilization of advanced manufacturing tools enhances the competitiveness of the industry. Feng et al. (2020) discover that foreign direct investment promotes the development of advanced manufacturing, albeit with dual thresholds. Bag et al. (2021) point out that Industry 4.0 technologies provide digital solutions for manufacturing automation, significantly impacting the enhancement of advanced manufacturing capabilities in the resource “10R” cycle

process and sustainable development. Feng et al. (2022) found that the establishment of national manufacturing innovation centers can facilitate the development of advanced manufacturing, with an intermediate effect of innovation input expansion. Following the introduction of the “Carbon Peaking and Carbon Neutrality Goals”, the green transformation of the manufacturing industry has become a research hotspot. Scholars have empirically analyzed the efficiency of green growth in the manufacturing industry, highlighting the significant influence of industrial clustering (Lv and Lu 2022; Zhu et al. 2022).

The concept of industrial synergy agglomeration was initially proposed by Ellison and Glaeser (1997), referring to the phenomenon of manufacturing enterprises and upstream/downstream companies that produce accessory products agglomerating together in space. As research deepened, the spatial phenomenon of industrial synergy agglomeration was further confirmed, and the conceptual definition gradually improved. Andersson (2004) found that the location of productive service industries is a function of the location of the manufacturing industry, indicating the inevitability of their spatial agglomeration. Helsley and Strange (2014) point out that industrial synergy represents a transitional state from a single-industry pattern to a diverse and integrated economic structure, where multiple associated industries are heavily concentrated within a certain geographic area. With the improvement and upgrading of industrial structures, social division of labor tends towards specialization and refinement, and the dominance of the “industrial economy” is gradually being replaced by the emergence of the “service economy”. The trend of collaborative development between productive service industries and the manufacturing industry becomes increasingly evident (Ke et al. 2014).

In recent years, the academic community has linked industrial synergy agglomeration with the development of advanced manufacturing. However, due to the imperfect evaluation index system, existing studies mainly analyze certain prominent characteristics of advanced manufacturing. From the perspective of production efficiency and economic benefits, industrial synergy agglomeration enhances the overall factor efficiency of the manufacturing industry through green technological innovation (Yang et al. 2022). It also exerts a significant positive impact on China’s Green Economic Efficiency (GEE) through firm-level innovation and entrepreneurial innovation (Zhu et al. 2022). Expanding the perspective to the manufacturing industry’s value chain, research has found that industrial synergy agglomeration strengthens the resilience of the manufacturing industry’s value chain through technological innovation. This enhances the industry’s flexibility and adaptability in response to external environments, thereby creating a stable space for improving economic performance.

With the deepening of green and environmental concepts, several scholars have conducted research on the relationship between industrial synergy agglomeration and green sustainable development. Industrial synergy agglomeration can significantly improve energy efficiency (Liu et al. 2017), increase carbon productivity, and reduce carbon intensity. However, the effectiveness of carbon emissions reduction is constrained by the rational allocation of resources, which acts as a dual threshold (Li et al. 2019). Yang et al. (2021) utilize a Spatial Durbin Model and find that industrial synergy agglomeration effectively controls environmental pollution through technological innovation, particularly in reducing emissions of air pollutants such as SO₂, PM_{2.5}, and NO_x (Ye et al. 2022; L. Gao et al. 2023). Chang and Zheng (2023) discover that industrial synergy agglomeration significantly enhances green innovation efficiency within both the local region and in neighboring areas, but spatial spillover effects exhibit geographic decay.

3. Research Hypothesis

The impact of industrial synergy agglomeration on the development of advanced manufacturing manifests in various aspects. Firstly, industrial synergy agglomeration swiftly elevates the level of advanced technology within manufacturing enterprises. During the initial phase of industrial synergy agglomeration, manufacturing plays a dominant role, while productive services act as auxiliary support (Yang et al. 2021). As the productive service system gradually matures, the deepening of regional industrial synergy and the in-

tegration of upstream and downstream cooperation mechanisms facilitate efficient division of labor and matching between the two industries. Through this enduring collaboration, information barriers between companies diminish, reducing search time, transaction costs, and simplifying transaction procedures. Consequently, this provides convenience for the extensive flow of manufacturing talents, information, and technology within the local region, leading to a rapid overall advancement in manufacturing technologies (Pandit et al. 2001).

Moreover, industrial synergy agglomeration contributes to green and sustainable development of the manufacturing industry. The spatial synergy and linkage between manufacturing and productive services optimize resource allocation between industries, generating economies of scale and centralized governance effects. This approach reduces raw material consumption and transport losses in intermediate product processing, lowers energy consumption per unit, enhances resource-utilization efficiency (Zeng and Zhao 2009; Wang et al. 2020), improves overall factor energy efficiency (Yang et al. 2020), and plays a positive role in achieving carbon reduction and pollution control (Zhuang et al. 2021; Wang et al. 2022).

Additionally, industrial synergy agglomeration enhances the management level of manufacturing enterprises. The synergy between manufacturing and productive services reduces the costs of information dissemination and learning. In high-synergy regions, advanced management techniques are rapidly shared, strengthening cost-control and risk-management capabilities, thereby demonstrating the positive external influence of synergy agglomeration (Fan and Scott 2003). Furthermore, industrial synergy agglomeration lowers the cost of information sharing among companies and drives technological innovation through knowledge spillover effects. To some extent, this fosters healthy market competition, improves production efficiency, and overall capacity levels of manufacturing enterprises, thereby promoting economic growth and capital expansion (Klein and Crafts 2020).

The promoting effect of industrial synergy agglomeration on the development of advanced manufacturing varies among different provinces. Taking the collaboration between the pharmaceutical manufacturing industry and medical services as an example, Hu et al. (2021) utilize a threshold regression model and find that the enhancement of coupling coordination between the two sectors can effectively promote further development, only when the pharmaceutical manufacturing industry reaches a relatively advanced level. We have listed the above literature in Table 1. Based on the discussion, we propose a research hypothesis, which is illustrated in Figure 1.

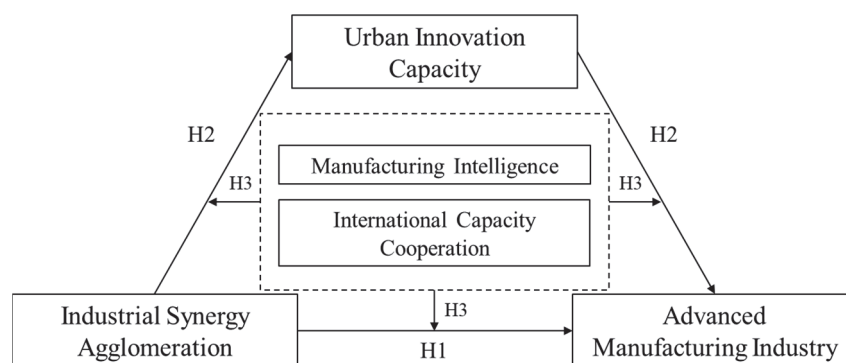


Figure 1. Mechanism of influence diagram.

H1. Industrial synergy agglomeration promotes the development of advanced manufacturing, and this promoting effect is more pronounced in provinces with a solid foundation for advanced manufacturing development.

Marshall advances four pivotal factors in the context of industrial synergy agglomeration, namely the relationships between intermediate inputs and final product suppliers, the sharing of labor markets, increased information exchange, and innovation opportunities, thereby linking the concepts of industrial synergy agglomeration with innovation

efficiency (Howard et al. 2016). As the spatial layout of industrial synergy takes shape, the integrated development of core industries with peripheral industries and the external economic effects stemming from specialized division of labor become evident, leading to enhanced innovation efficiency among regional manufacturing enterprises (Shen et al. 2019; Wang et al. 2019; Zhong et al. 2021; Peng et al. 2023). Notably, the impact of industrial synergy agglomeration on innovation performance is particularly prominent in high-tech manufacturing industries (Wu et al. 2021; Peng et al. 2022). For instance, the synergy between transportation and warehousing services and manufacturing industries reduces the time costs associated with information acquisition, while the financial sector provides services such as capital management and employee incentives to manufacturing enterprises. The synergy between these two sectors contributes to the improvement of regional innovation efficiency.

Table 1. Summary of studies on the impact of industrial synergy agglomeration on the development of advanced manufacturing.

Studies	Main Findings
(Pandit et al. 2001)	Industrial synergy agglomeration enhances the level of advanced manufacturing technologies.
(Hu et al. 2021)	The synergy between the pharmaceutical manufacturing industry and the healthcare services sector presents a threshold for facilitating the advancement of the pharmaceutical manufacturing industry.
(Zeng and Zhao 2009; Wang et al. 2020)	Industrial synergy agglomeration reduces the energy consumption of manufacturing units and enhances resource-utilization efficiency.
(Yang et al. 2020)	Industrial synergy agglomeration enhances the overall factor energy efficiency of the manufacturing industry.
(Zhuang et al. 2021; Wang et al. 2022)	Industrial synergy agglomeration plays a constructive role in achieving carbon reduction and pollution control in the manufacturing industry.
(Fan and Scott 2003)	Industrial synergy agglomeration facilitates the dissemination and sharing of advanced management technologies within the region, enhancing the capabilities of companies in cost control and risk management.
(Klein and Crafts 2020)	Industrial synergy agglomeration drives the growth of economic benefits and capital expansion for manufacturing enterprises.

Innovation serves as a crucial driving force for sustainable industrial development in a region, embodying the pulse and wellspring of urban economic progress (Wang and Deng 2022). The essence of the urban innovation chain lies in the openness of innovative elements, the synergistic operation of the entire system, and the value-added nature of innovation (Ambos et al. 2021). The concentration of innovation leads to a transformation in the hierarchical structure of urban innovation, rationalizing the allocation of innovative elements and consequently propelling the positive development of various industries within the region (Fan et al. 2021). Active innovation activities in a region yield abundant patent outputs, which, when implemented in the production processes of enterprises, translate into advanced technological achievements. Entrepreneurs often encourage socially responsible actions among enterprises, particularly those with strong innovation capabilities (Wei et al. 2021; Ahmad et al. 2022), addressing employment issues. Moreover, effective utilization of capital by enterprise management facilitates the establishment of a social network, leveraging internal and external employees, thereby enhancing productivity and generating economic benefits (Lafuente et al. 2020; Becerra-Vicario et al. 2023). The urban innovation chain can be divided into three stages: primordial, technological, and transformative. Zhang et al. (2022) construct a three-dimensional indicator system for urban innovation capabilities and measured innovation performance based on the development level of strategic emerging industries, revealing that urban innovation promotes the development of strategic emerging industries in the short term. Urban innovation

optimizes industrial structures, realizing efficient resource allocation, thereby accelerating the concentration of high-tech industries and enhancing economic efficiency. In recent years, academia has confirmed a symbiotic relationship between urban innovation and green development. In low-carbon pilot cities (LCPCs), green innovation has led to reduced energy consumption in industrial enterprises and improved resource-utilization efficiency (Tian et al. 2021).

The innovation in cities propels the upgrading of industrial technologies and facilitates advanced transformations, simultaneously expanding the scale of industrial personnel while enhancing production efficiency. Moreover, this influence encompasses sustainable development implications, extending its impact to advanced manufacturing. On the basis of Hypothesis 1, we further propose another hypothesis:

H2. *Industrial synergy agglomeration enhances urban innovation capabilities, thereby promoting the development of advanced manufacturing.*

Intelligent manufacturing stands as a crucial pathway for the ascent of China's manufacturing industry along the value chain. The development of intelligence, encompassing technological innovation, production efficiency, and economic benefits, exerts a profound influence on the level of advanced manufacturing. Industrial intelligence enhances corporate profits, expedites the transition towards sustainability, and ultimately elevates the overall production efficiency of the supply chain (Mahalakshmi et al. 2019). In manufacturing enterprises employing robots, human labor is supplanted, leading to substantial enhancements in production efficiency, as well as a noticeable increase in the value-added aspects of their products (Acemoglu et al. 2020). There exists a substitutive effect between industrial robots and the labor force, whereby the scarcity of labor supply compels manufacturing enterprises to engage in technological innovation, thus further enhancing labor productivity (Song and Zuo 2019). The proliferation of industrial robots also contributes to the reduction in industrial carbon emissions and promotes sustainable development (Wu 2023).

In recent years, with the development of the digital economy and the widespread adoption of artificial intelligence technologies, researchers have begun to focus on the specific pathways through which intelligent manufacturing influences the development of advanced manufacturing. Artificial intelligence enables enterprises to substitute low-end labor, thereby reducing costs, improving productivity, and enhancing their competitiveness—an endeavor that assists them in engaging more effectively in the division of labor within the global value chain. Intelligence significantly boosts the total-factor productivity of the manufacturing industry, with the objective of achieving carbon neutrality (Wang et al. 2023), thereby promoting the high-quality development of the manufacturing sector. In regions where the level of intelligent manufacturing is relatively high, there is greater efficiency in information exchange and resource allocation between industries, and the positive effects of industrial synergy on the development of advanced manufacturing become more pronounced, as is the capacity for urban innovation. Furthermore, technological innovation and the development of intelligent cities are mutually complementary (Cugurullo 2020), as the widespread adoption of artificial intelligence enhances urban innovation capabilities, thereby driving the construction of smart cities (Yigitcanlar et al. 2020). In regions with a solid foundation in intelligent development, the utilization of advanced technologies and the provision of well-equipped facilities are favorable, attracting a strong pool of talent, making the role of industrial synergy agglomeration in enhancing urban innovation capacity more apparent.

International capacity cooperation encompasses forms such as foreign trade, foreign direct investment, and overseas engineering contracts, with foreign direct investment occupying a predominant position. International capacity cooperation provides a platform foundation for enterprise technological upgrading, directly propelling the development of advanced manufacturing. From the perspective of foreign trade analysis, international trade contributes to the transformation and upgrading of the manufacturing industry,

and the improvement of total-factor productivity in manufacturing relies on technological progress. From the perspective of foreign direct investment analysis, multinational corporations can assist domestic enterprises in acquiring advanced technologies (Chen et al. 2012). From the perspective of overseas engineering contracts, on one hand, the contracting party can absorb advanced knowledge and technology from the contracting party and enhance their own production efficiency through the process of “learning by doing” (Lo 2014). On the other hand, in order to gain recognition during the project implementation process, the contracting party must actively improve their technological and service levels (Martinez-Noya et al. 2012), thereby creating a virtuous cycle. In regions with a high level of international capacity cooperation, there is frequent exchange and interaction between domestic and foreign entities, making it easier for Chinese manufacturing enterprises to access advanced foreign knowledge, technology, and management experience. With the strengthening of industrial synergy, the development of advanced manufacturing accelerates. Similarly, international capacity cooperation provides favorable support for enterprise innovation and research development—as the collaboration between manufacturing and productive service industries deepens, the improvement of urban innovation levels becomes more pronounced. Combined with the aforementioned two hypothesis, we come up with the last hypothesis:

H3. *Both manufacturing intelligence and international capacity cooperation exert positive regulatory effects in the direct and indirect pathways of industrial synergy on the development of advanced manufacturing.*

4. Methodology

4.1. Model

4.1.1. Two-Way Fixed-Effects Model

The primary focus of this study lies in ascertaining whether industrial synergy agglomeration has a positive and significant impact on the development of advanced manufacturing, while also delving into the underlying mechanisms of this influence. The baseline regression model is presented below:

$$ami_{p,t} = \mu_0 + \mu_1 coagglo_{p,t} + \sum_{i=2}^{T+1} \mu_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (1)$$

In Equation (1), p denotes provinces and t represents years. The dependent variable is the level of development in the advanced manufacturing industry denoted as $ami_{p,t}$. The core explanatory variable is the level of industrial synergy agglomeration, denoted as $coagglo_{p,t}$. $Z_{p,t}^i$ represents a set of control variables. u_p and v_t represent province fixed effects and time fixed effects, respectively. $\varepsilon_{p,t}$ denotes the error term. If μ_1 is significantly positive, then Hypothesis 1 is confirmed.

4.1.2. Mediation Effect Model

The mediation effect is examined using a stepwise regression approach. The constructed model is as follows:

$$ami_{p,t} = \alpha_0 + \alpha_1 uic_{p,t} + \sum_{i=2}^{T+1} \alpha_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (2)$$

$$uic_{p,t} = \beta_0 + \beta_1 coagglo_{p,t} + \sum_{i=2}^{T+1} \beta_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (3)$$

$$ami_{p,t} = \gamma_0 + \gamma_1 coagglo_{p,t} + \gamma_2 uic_{p,t} + \sum_{i=3}^{T+2} \gamma_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (4)$$

where the mediating variable is urban innovation capacity denoted as $uic_{p,t}$. Equation (2) tests the direct effect of urban innovation capacity on the development of advanced manu-

facturing. Equations (3) and (4) examine the mediating role of urban innovation capacity in the process of industrial synergy promoting the development of advanced manufacturing. If β_1 , γ_1 , and γ_2 are all significantly positive, then Hypothesis 2 is confirmed.

4.1.3. Moderated Mediation Effect Model

The effect of the moderating variable on both the direct and indirect effects is examined using hierarchical multiple regression (Baron and Kenny 1986; Sun et al. 2020). The constructed model is as follows:

$$ami_{p,t} = \eta_0 + \eta_1 coagglo_{p,t} + \eta_2 M_{p,t} + \eta_3 coagglo_{p,t} \times M_{p,t} + \sum_{i=4}^{T+3} \eta_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (5)$$

$$uic_{p,t} = \delta_0 + \delta_1 coagglo_{p,t} + \delta_2 M_{p,t} + \sum_{i=3}^{T+2} \delta_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (6)$$

$$uic_{p,t} = \lambda_0 + \lambda_1 coagglo_{p,t} + \lambda_2 M_{p,t} + \lambda_3 coagglo_{p,t} \times M_{p,t} + \sum_{i=4}^{T+3} \lambda_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (7)$$

$$ami_{p,t} = \theta_0 + \theta_1 uic_{p,t} + \theta_2 M_{p,t} + \sum_{i=3}^{T+2} \theta_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (8)$$

$$ami_{p,t} = \sigma_0 + \sigma_1 uic_{p,t} + \sigma_2 M_{p,t} + \sigma_3 uic_{p,t} \times M_{p,t} + \sum_{i=4}^{T+3} \sigma_i Z_{p,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (9)$$

where the moderating variables are manufacturing intelligence ($mi_{p,t}$) and international capacity cooperation ($icc_{p,t}$), represented as $M_{p,t}$ for simplicity. If η_3 , λ_3 , and σ_3 are all significantly positive, then Hypothesis 3 is confirmed.

4.1.4. Spatial Durbin Model (SDM)

In order to examine the spatial spillover effects of industrial synergy agglomeration on the development of advanced manufacturing at the provincial level, this study constructs an SDM model to further investigate their spatial relationship:

$$ami_{p,t} = \xi_0 + \xi_1 \sum_{j=1}^N \omega_{p,j} ami_{j,t} + \xi_2 X_{j,t} + \xi_3 \sum_{j=1}^N \omega_{p,j} X_{j,t} + \sum_{i=4}^{T+3} \xi_i \sum_{j=1}^N \omega_{p,j} Z_{j,t}^i + u_p + v_t + \varepsilon_{p,t} \quad (10)$$

In Equation (10) ξ_1 and ξ_3 represent the spatial lag coefficients for advanced manufacturing and industrial synergy agglomeration, respectively. $\omega_{p,j}$ denotes the spatial weight matrix. If ξ_1 is significantly positive, then the presence of spatial spillover effects in the development of advanced manufacturing itself is indicated. If both ξ_2 and ξ_3 are significantly positive, then it suggests that industrial synergy agglomeration has a positive spatial spillover effect on the development of advanced manufacturing at the provincial level.

4.2. Variable and Data

4.2.1. Explained Variable

The level of development in advanced manufacturing, which is the overall level of development in the manufacturing industry, is derived through a comprehensive calculation of multiple indicators that reflect advanced manufacturing capabilities. In this study, we construct an evaluation index system for advanced manufacturing from five perspectives: advanced manufacturing technology, advanced manufacturing management, advanced manufacturing workforce, green advanced manufacturing, and advanced manufacturing efficiency. A total of 21 secondary indicators are included, and the development level of advanced manufacturing in 31 provincial regions in China from 2003 to 2021 is calculated. Commonly used multivariate weighting methods include the entropy method and principal component analysis (PCA). In this study, we not only calculate the overall development level of advanced manufacturing but also separately calculate the development levels of

the five sub-dimensions for robustness testing. Due to the limited number of secondary indicators in the sub-dimensions (around four to five indicators each), PCA is deemed unsuitable. Therefore, the entropy method is chosen. The specific calculation process refers to the study conducted by Yu and Fan (2022). $M_{t,m}$ represents the original value of indicator m at time t , $\min(M_{t,m})$ represents the minimum value of the indicator, and $\max(M_{t,m})$ represents the maximum value of the indicator. $Y_{t,m}$ represents the standardized value. Equation (11) is used to handle positive indicators, while Equation (12) is used to handle negative indicators:

$$Y_{t,m} = (M_{t,m} - \min(M_{t,m})) / (\max(M_{t,m}) - \min(M_{t,m})) \quad (11)$$

$$Y_{t,m} = (\max(M_{t,m}) - M_{t,m}) / (\max(M_{t,m}) - \min(M_{t,m})) \quad (12)$$

Next, the weights $P_{t,m}$ and information entropy values $E_{t,m}$ for each indicator are determined using the following calculation method (where n represents the total number of years):

$$P_{t,m} = Y_{t,m} / \sum_{t=1}^n Y_{t,m} \quad (13)$$

$$E_{t,m} = -1/\ln n \times \sum (P_{t,m} \times \ln P_{t,m}) \quad (14)$$

Finally, the information utility value $Q_{t,m}$ for each indicator m and the weights $W_{t,m}$ for each indicator are calculated, as shown in Table 2. These values are then used to calculate the level of development in advanced manufacturing (AMI) for the 31 provinces in China, as well as the values for the five primary indicators. These values will be used in the baseline regression. The specific calculation process is as follows:

$$Q_{t,m} = 1 - E_{t,m} \quad (15)$$

$$W_{t,m} = Q_{t,m} / \sum_{t=1}^n Q_{t,m} \quad (16)$$

$$ami_{p,t} = \sum_{t=1}^n P_{t,m} \times W_{t,m} \times 1000 \quad (17)$$

Based on the calculations, the top-ten provinces in China for advanced manufacturing in 2021 are Jiangsu Province, Zhejiang Province, Shanghai Municipality, Guangdong Province, Anhui Province, Liaoning Province, Jiangxi Province, Tianjin Municipality, Hunan Province, and Beijing Municipality. The development trends of advanced manufacturing in these provinces from 2012 to 2021 are illustrated in Figure 2.

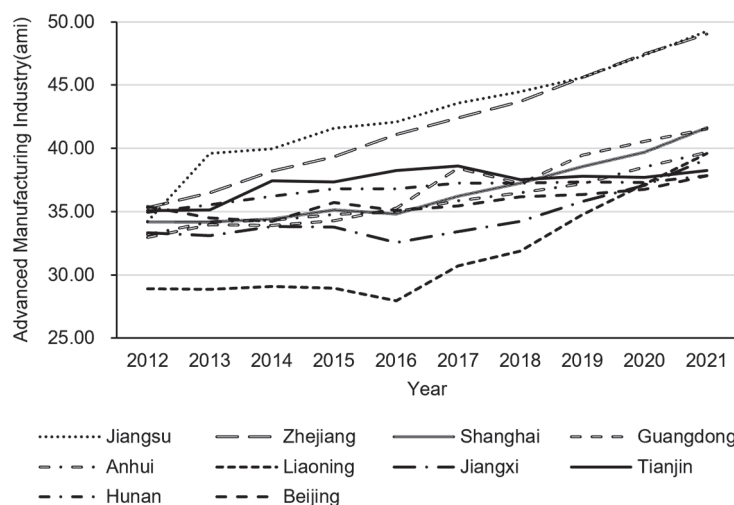


Figure 2. Development level of advanced manufacturing in provinces.

Table 2. Evaluation indicator system for advanced manufacturing.

Primary Indicators	Secondary Indicators	Attributes	Overall Weights	Individual Weights
Advanced Manufacturing Technology	Proportion of New Product Output to Industrial Output (%)	+	0.075	0.231
	Proportion of Research Institutions' Enterprises to Total Enterprises (%)	+	0.086	0.278
	Proportion of R&D Expenditure to Main Business Revenue (%)	+	0.105	0.359
	Proportion of Self-Funded Expenditure by Enterprises in Research Activities (%)	+	0.033	0.132
Advanced Manufacturing Management	Inventory Turnover Ratio (in times)	+	0.044	0.238
	Profitability Ratio (Cost-Expense-Profit Ratio) (%)	+	0.034	0.196
	Equity Ratio (%)	+	0.028	0.193
	Debt-to-Asset Ratio (%)	-	0.038	0.227
	Contribution Rate of Total Assets (%)	+	0.025	0.146
Advanced Manufacturing Workforce	Logarithm of Manufacturing Industry Employment (in number of individuals, Logarithm)	+	0.092	0.360
	Logarithm of Average Industry Employee Salary (in Chinese Yuan, Logarithm)	+	0.090	0.344
	Proportion of High-Educated Personnel in Research Activities (%)	+	0.033	0.125
	Proportion of R&D Personnel to Total Workforce (%)	+	0.046	0.171
Green Advanced Manufacturing	Compliance Rate of Industrial Wastewater Discharge Standards (%)	+	0.020	0.149
	Compliance Rate of Industrial SO ₂ Emissions Standards (%)	+	0.021	0.164
	Compliance Rate of Industrial Particulate Matter (PM) Emissions Standards (%)	+	0.031	0.303
	Comprehensive Utilization Rate of Industrial Solid Waste (%)	+	0.037	0.384
Advanced Manufacturing Efficiency	Rate of Capital Preservation and Appreciation (%)	+	0.031	0.206
	Industrial Value-Added Rate (%)	+	0.069	0.408
	Proportion of Operating Profit (%)	+	0.021	0.107
	Profit from Main Business Operations (in Chinese Yuan, Logarithm)	+	0.042	0.280

4.2.2. Explaining Variable

In the present study, an initial assessment is conducted to determine the level of industrial synergy agglomeration, referred to as “coagglo”. To define the productive service sector, existing research is taken into account, encompassing the amalgamation of five industries: “transportation, warehousing, and postal services”, “leasing and business services”, “information transmission, computer services, and software industry”, “financial

industry”, and “scientific research, technical services, and geophysical prospecting”. The specific methodology employed for computation is outlined as follows:

$$Magglo_{p,t} = (M_{p,t}/M_t) / (P_{p,t}/P_t) \quad (18)$$

$$PSagglo_{p,t} = (PS_{p,t}/PS_t) / (P_{p,t}/P_t) \quad (19)$$

$$coagglo_{p,t} = 1 - \left| Magglo_{p,t} - PSagglo_{p,t} \right| / \left(Magglo_{p,t} + PSagglo_{p,t} \right) + \left| Magglo_{p,t} + PSagglo_{p,t} \right| \quad (20)$$

In Equation (18), $M_{p,t}$ represents the number of manufacturing industry employees in province p during period t , $P_{p,t}$ denotes the total employment in province p during period t , M_t represents the national manufacturing industry employment during period t , and P_t represents the national employment during period t . By utilizing these variables, the level of manufacturing industry agglomeration $Magglo_{p,t}$ can be computed. Similarly, in Equation (19), the meanings of the respective indicators remain consistent, allowing for the computation of the level of agglomeration in the productive service sector $PSagglo_{p,t}$. Finally, Equation (20) yields the annual average level of industrial synergy agglomeration $coagglo_{p,t}$ for each province over the years.

4.2.3. Control Variables

The following reasons justify the selection of provincial economic development, foreign direct investment, human capital level, government support intensity, fixed investment level, industrial structure, and informatization level as control variables:

Economic Development (*pdgp*): A vibrant regional economy fosters a conducive social environment and injects impetus into industrial development, enhancing the innovation capacity of the manufacturing industry.

Foreign Direct Investment (*fdi*): Inflows of FDI lead to reduced domestic market share and intensified competition, creating a mechanism of natural selection that compels domestic firms to upgrade their technology to adapt to the new market environment. Additionally, foreign-funded enterprises possess advanced research and management capabilities, and the flow of personnel between domestic and foreign-funded enterprises can accelerate the formation of a comprehensive industry radiation effect in the region, promoting advanced manufacturing development in various aspects such as technology, management, and human capital.

Human Capital Level (*hcl*): The educational attainment of the regional population directly influences the quality of talent reserves. The longer the average years of education per person, the richer the reservoir of knowledge and skills, which are ultimately reflected in work capacity and efficiency.

Government Support Intensity (*gov*): Government actions have a significant impact on regional industrial development. On one hand, the government can promote industrial development through funding, tax incentives, and other means. On the other hand, improper government intervention can hinder regional industrial development and increase policy burdens on local enterprises.

Fixed Investment Level (*inv*): Economic growth hinges on fixed asset investment. However, excessive investment can increase enterprise investment costs, burden cash flow, and impede long-term development.

Industrial Structure (*str*): Industrial structure directly influences the level of innovation and research and development in enterprises. A rational industrial structure reduces the cost of cross-industry resource allocation and provides advanced production factors for enterprises to carry out research and innovation activities and achieve technological innovation.

Informatization Level (*inf*): With the evolution of economic structure towards informatization, factor markets provide ample knowledge information for the development of advanced manufacturing. Information resources are extensively shared, and new knowledge and technologies quickly disseminate across the industry, with advanced enterprises

playing a more prominent role. In this study, the level of informatization is measured using the volume of postal and telecommunications services in the region.

4.2.4. Mechanism Variables

Urban innovation capacity (*uic*) is gauged through the prism of patent indicators (Huang et al. 2022), taking into account the technological content and research and development costs. Thus, the quantity of granted patents for inventions serves as a quantifiable measure (Jin et al. 2019).

Manufacturing intelligence (*mi*) is assessed based on the import data of three categories of industrial robots, classified by their HS eight-digit codes: 84795010 (multi-functional industrial robots), 84795090 (industrial robots excluding multi-functional ones), and 84864031 (IC factory-specific automated handling robots) (Li et al. 2021).

International capacity cooperation (*icc*) encompasses various forms such as foreign trade, foreign direct investment, and contracted projects (Wang and Hui 2019). Thus, this study measures the level of international capacity cooperation by examining the proportion of total imports and exports, foreign direct investment, and contracted project amounts in the manufacturing industry to each province's GDP.

4.2.5. Data Sources

Advanced manufacturing indicators data are derived from publications such as *The China Statistical Yearbook*, *The China Industrial Statistical Yearbook*, *The China Science and Technology Statistical Yearbook*, and *The China Environmental Statistical Yearbook*. Industry synergy aggregation data are sourced from *The China Labor Statistical Yearbook*. Control variables, urban innovation capacity, and manufacturing intelligence data are obtained from the EPS database. International capacity cooperation data is sourced from *The China Foreign Economic Statistical Yearbook* (2003–2005) and *The China Trade and Economic Statistical Yearbook* (2006–2021).

To address missing values, linear interpolation is employed to construct panel data for the 31 provinces spanning from 2003 to 2021. The selection of substitute variables for each indicator and descriptive statistical results are presented in Table 3.

Figure 3 illustrates the scatter plot and fitted line depicting the relationship between industrial synergy agglomeration and the development of advanced manufacturing. The plot clearly demonstrates a positive correlation between the two variables, providing a solid foundation for the empirical research that follows.

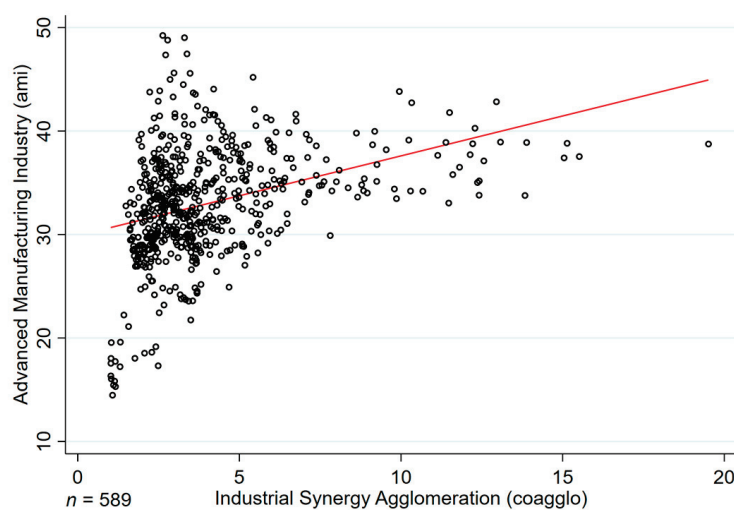


Figure 3. Correlation between industrial synergy agglomeration and the development of advanced manufacturing.

Table 3. The descriptive statistical analysis of the variables.

Variable Names	Variables	Obs	Mean	Sd	Min	Max
Advanced Manufacturing Industry	<i>ami</i>	589	32.96	5.37	14.48	49.24
Advanced Manufacturing Technology	<i>amt</i>	589	19.70	8.57	6.06	48.98
Advanced Manufacturing Management	<i>amm</i>	589	41.68	9.41	17.28	71.11
Advanced Manufacturing Workforce	<i>amw</i>	589	47.66	9.82	15.47	83.76
Green Advanced Manufacturing	<i>gam</i>	589	68.69	15.09	15.44	100.00
Advanced Manufacturing Efficiency	<i>ame</i>	589	18.84	5.66	10.70	90.95
Industrial Synergy Agglomeration	<i>coagglo</i>	589	3.99	2.49	1.02	19.51
Economic Development	<i>pdgp</i>	589	10.29	0.80	8.06	12.01
Foreign Direct Investment	<i>fdi</i>	589	21.17	3.81	0.00	24.89
Human Capital Level	<i>hcl</i>	589	10.77	1.54	0.00	12.61
Government Support Intensity	<i>gov</i>	589	21.88	7.32	0.00	26.58
Fixed Investment Level	<i>inv</i>	589	26.89	2.80	0.00	29.49
Industrial Structure	<i>str</i>	589	43.73	9.49	28.60	83.90
Informatization Level	<i>inf</i>	589	24.69	1.25	20.42	28.36
Urban Innovation Capacity	<i>uic</i>	589	0.48	0.95	0.00	7.07
Manufacturing Intelligence	<i>mi</i>	589	97.28	182.18	0.13	1091.58
International Capacity Cooperation	<i>icc</i>	589	0.13	0.76	0.00	10.63

5. Results

5.1. Baseline Regression

The *p*-value of the Hausman test is less than 0.05, indicating the adoption of a two-way fixed-effects (two-way FE) model. The regression results, presented in Table 4, column (1), reveal that the coefficient of industrial synergy agglomeration level is significantly positive, suggesting its promotion effect on the development of advanced manufacturing, and thus supporting H1. The levels of regional economic development, foreign direct investment, and informatization exhibit significant positive impacts on the development of advanced manufacturing. The government support intensity and fixed investment level demonstrate significant negative effects, aligning with the earlier description of control variables. The coefficient of human capital level is not significant, potentially due to the gradual accumulation of the positive impact of improved educational attainment among regional personnel on firm performance and industrial development, which may exhibit certain time-lag effects.

Table 4. Baseline regression and robustness testing.

Variables	Baseline Regression		IV	Replace X	Replace Y
	(1) <i>ami</i>	(2) <i>coagglo</i>	(3) <i>ami</i>	(4) <i>ami</i>	(5) <i>center</i>
<i>coagglo</i>	0.767 *** (0.130)		1.337 *** (0.515)		0.812 *** (0.187)
<i>EG</i>				1.934 *** (0.528)	
<i>L.coagglo</i>		0.623 *** (0.090)			
<i>pdgp</i>	2.109 ** (0.991)	−1.170 *** (0.414)	3.715 * (2.258)	1.810 ** (0.868)	0.440 (0.449)
<i>fdi</i>	0.087 ** (0.041)	0.004 (0.006)	0.072 (0.147)	0.072 * (0.041)	0.423 (0.541)
<i>hcl</i>	0.004 (0.133)	−0.106 (0.074)	0.097 (0.718)	−0.166 (0.134)	−0.252 (0.736)

Table 4. Cont.

Variables	Baseline Regression	IV		Replace X	Replace Y
	(1) <i>ami</i>	(2) <i>coagglo</i>	(3) <i>ami</i>	(4) <i>ami</i>	(5) <i>center</i>
<i>gov</i>	−0.088 *** (0.027)	−0.001 (0.005)	−0.099 ** (0.046)	−0.074 *** (0.028)	2.440 *** (0.713)
<i>inv</i>	−0.147 *** (0.041)	0.002 (0.003)	−0.156 *** (0.040)	−0.176 *** (0.042)	0.003 (0.009)
<i>str</i>	−0.002 (0.038)	0.015 * (0.008)	−0.023 (0.044)	0.046 (0.038)	0.014 (0.018)
<i>inf</i>	2.113 *** (0.773)	−0.179 (0.179)	2.575 * (1.421)	−5.668 *** (1.043)	−0.684 ** (0.280)
constant	−43.377 ** (18.509)			−18.560 (32.708)	−68.837 *** (24.114)
Provincial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes	Yes
First Stage F Statistics		47.580			
Kleibergen–Paap rk LM Statistics			7.402 [0.007]		
Kleibergen–Paap Wald rk F Statistics			47.580 [16.38]		
Anderon–Rubin Wald Statistics			3.753 [0.005]		
N	589	558	558	589	186
R ²	0.527		0.535	0.520	0.486

Notes: The values within parentheses represent clustered robust standard errors. The values within square brackets indicate the *p*-values for each test statistic. The values within curly braces represent the critical values of the Stock-Yogo test at the 10% level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.2. Robustness Testing

5.2.1. Addressing Endogeneity Issues

This empirical study may potentially face two sources of endogeneity issues. Firstly, there is the concern of bidirectional causality, whereby the development of advanced manufacturing stimulates the demand for the integration of manufacturing with upstream and downstream industries, thereby promoting the synergistic development of manufacturing and productive service sectors. Secondly, there is the issue of omitted variables, wherein certain variables that have an impact on the development of advanced manufacturing are not included in the model.

To tackle these concerns, we draw upon existing research and employ a two-stage least squares estimation (FE2SLS) with a lagged one-period industrial synergy agglomeration as the instrumental variable. The results of the first-stage regression, presented in Table 4, column (2), indicate that the coefficient of the instrumental variable is positive and statistically significant at the 1% level. Additionally, the first-stage F-statistic of 47.850 passes the weak instrument test. Moving to the second stage, the regression results in Table 4, column (3), reveal that the coefficient of industrial synergy agglomeration remains statistically significant and positive, providing support for H1. Furthermore, the instruments pass the tests for instrument validity and endogeneity.

5.2.2. Alternate Explaining ()Variable

Ellison and Glaeser (1997) develop the EG correction index based on the EG index, which is used to examine the level of industrial synergy agglomeration. Devereux et al. (2004) simplify this index, reducing data requirements, and it has been widely adopted

in current research. In this study, the EG index is recalculated to measure the level of industrial synergy agglomeration for robustness testing. The calculation process of this index is as follows:

$$EG = [H_{ij} - (H_i \times w_i^2 + H_j \times w_j^2)] / [1 - (w_i^2 + w_j^2)] \quad (21)$$

In Equation (21), variables w_i and w_j represent the proportions of employees in the manufacturing and productive service sectors, respectively, in relation to the total number of employees in both sectors. H_{ij} , H_i , and H_j , on the other hand, describe the overall geographic concentration of the two sectors as well as the individual concentration levels of the manufacturing and productive service sectors. The calculation methods for these variables are as follows:

$$H = \sum_{k=1}^n S_k^2 - 1/n \quad (22)$$

where S_k represents the proportion of employees in the manufacturing, productive service, or both sectors in a given province k relative to the total number of employees in the corresponding (sub-)sector nationwide. The value of EG index reflects the degree of industrial synergy agglomeration in the provincial region, with higher values indicating a higher level of agglomeration. As an alternative indicator for the level of industrial synergy agglomeration, we utilize the EG index as the core explanatory variable. The regression results, presented in Table 4, column (4), demonstrate that the coefficient of the EG index is statistically significant and positive. This finding suggests that industrial synergy agglomeration can indeed promote the development of advanced manufacturing, aligning with the conclusions drawn from the baseline regression.

5.2.3. Alternate Explained Variable

Starting from 2016, China began to establish regional manufacturing innovation platforms, with the first batch of national manufacturing innovation centers being established and expanded to 26 centers by the end of 2022. These centers are distributed across 17 provinces, including Guangdong, Beijing, and Shanghai. In recent years, a series of policies have been implemented to indicate the key directions for the development of advanced manufacturing. Measuring and considering relevant indicators can reflect the development status of advanced manufacturing in different provinces.

In this study, we select the number of national manufacturing innovation centers in the 31 provinces of China from 2016 to 2021, as an alternative indicator for the level of advanced manufacturing development, and conduct robustness testing. The results, presented in Table 4, column (5), demonstrate that industrial synergy agglomeration has a significant positive impact on the development of advanced manufacturing, which is consistent with the conclusions drawn from the baseline regression. Therefore, we can conclude that the findings regarding the positive influence of industrial synergy agglomeration on the development of advanced manufacturing remain robust, even when using the number of national manufacturing innovation centers as an alternative indicator for advanced manufacturing development.

5.2.4. Subdivision Evaluation Indicators

By building upon the regression analysis with the comprehensive index of advanced manufacturing development as the dependent variable, this study further examines the impact of industrial synergy agglomeration on five specific indicators: advanced manufacturing technology, advanced manufacturing management, advanced manufacturing workforce, green advanced manufacturing, and advanced manufacturing efficiency.

The results, presented in Table 5, columns (1) to (5), reveal that the coefficients of industrial synergy agglomeration are all statistically significant and positive. This signifies that the positive influence of synergy between the manufacturing and productive service sectors on advanced manufacturing development permeates across various aspects. Strengthening the collaborative development between these two sectors not only enhances

the independent research and innovation capabilities of manufacturing enterprises, leading to greater economic benefits, but also improves the overall quality of industry personnel, optimizes management models, and promotes sustainable development with a green and environmentally friendly approach.

Table 5. Subdivision advanced manufacturing evaluation indicators.

Variables	(1) <i>amt</i>	(2) <i>amm</i>	(3) <i>amw</i>	(4) <i>gam</i>	(5) <i>ame</i>
<i>coaggl</i>	1.304 *** (0.247)	0.343 * (0.192)	2.237 *** (0.209)	1.131 *** (0.306)	0.541 ** (0.248)
<i>pdgp</i>	−3.858 ** (1.886)	12.130 *** (1.468)	1.413 (1.600)	−20.236 *** (2.339)	−5.206 (4.116)
<i>fdi</i>	0.419 *** (0.078)	−0.143 ** (0.061)	0.309 *** (0.066)	0.934 *** (0.097)	0.033 (0.079)
<i>hcl</i>	0.019 (0.253)	0.286 (0.197)	0.585 *** (0.214)	1.126 *** (0.313)	0.140 (0.259)
<i>gov</i>	−0.178 *** (0.052)	−0.060 (0.041)	−0.074 * (0.044)	−0.166 ** (0.065)	−0.122 ** (0.054)
<i>inv</i>	−0.078 (0.078)	−0.174 *** (0.061)	0.299 *** (0.066)	0.465 *** (0.097)	−0.477 *** (0.080)
<i>str</i>	0.092 (0.071)	−0.460 *** (0.056)	−0.026 (0.061)	−0.196 ** (0.089)	0.102 (0.069)
<i>inf</i>	4.964 *** (1.472)	−3.434 *** (1.146)	7.459 *** (1.249)	1.243 (1.825)	0.084 (0.103)
constant	−80.718 ** (35.242)	23.325 (27.426)	−189.949 *** (29.903)	−50.921 (43.697)	104.302 (69.468)
Provincial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	589	589	589	589	589
R ²	0.656	0.733	0.657	0.687	0.163

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.3. Heterogeneity Analysis

5.3.1. Based on Regional Divisions

By stratifying the geographical regions into four sub-samples, namely the Eastern, Central, Western, and Northeastern regions², a regression analysis is conducted, and the results are presented in columns (1) to (4) of Table 6. It is discerned that industrial synergy agglomeration significantly stimulates the development of advanced manufacturing in the eastern provinces and exerts a positive influence on the northeastern region. However, in the central and western regions, this impact is not statistically significant. An analysis of these disparities reveals that industrial synergy agglomeration has a positive impact on the development of advanced manufacturing, with industry development foundations serving as a threshold. The eastern region, boasting a generally favorable state of advanced manufacturing development, effectively showcases the promotional role of industrial synergy agglomeration. As a longstanding industrial powerhouse, the northeastern region possesses a solid industrial development foundation, thereby enabling industrial synergy agglomeration to facilitate manufacturing transformation and propel the advancement of advanced manufacturing. In contrast, the central region exhibits significant disparities in the level of advanced manufacturing development, rendering the overall impact of industrial synergy agglomeration on advanced manufacturing development inconclusive. The western region lags behind in advanced manufacturing development, where, relative

to factors such as absolute input magnitude, the impact of industrial synergy agglomeration is relatively modest. Hence, the region urgently requires an uplift in the level of advanced manufacturing, supporting H1.

Table 6. Heterogeneity analysis.

Variables	East	Central	West	Northeast	Clusters	No Clusters
	(1) <i>ami</i>	(2) <i>ami</i>	(3) <i>ami</i>	(4) <i>ami</i>	(5) <i>ami</i>	(6) <i>ami</i>
<i>coagglo</i>	0.354 *** (0.136)	−0.004 (0.440)	0.830 (0.823)	0.739 * (0.206)	0.538 *** (0.125)	0.378 (0.541)
<i>pdgp</i>	8.210 (4.703)	−5.591 (3.912)	5.518 *** (1.672)	24.130 ** (4.989)	4.717 *** (1.363)	4.868 ** (2.103)
<i>fdi</i>	−0.176 (1.078)	−1.198 ** (0.541)	0.055 (0.052)	1.332 (1.820)	−2.066 *** (0.278)	0.085 * (0.048)
<i>hcl</i>	0.925 (0.776)	0.135 (0.184)	−0.017 (0.190)	−2.499 (2.309)	0.464 *** (0.149)	−0.185 (0.231)
<i>gov</i>	−0.050 (0.045)	−0.034 (0.043)	−0.077 (0.054)	0.056 (0.028)	0.051 (0.032)	−0.133 *** (0.047)
<i>inv</i>	−4.250 (2.467)	−0.099 ** (0.050)	−0.171 ** (0.070)	−6.694 *** (0.641)	−2.564 *** (0.605)	−0.194 *** (0.047)
<i>str</i>	−0.172 (0.175)	−0.167 * (0.092)	0.029 (0.058)	0.374 ** (0.074)	−0.049 (0.051)	0.023 (0.054)
<i>inf</i>	5.575 (3.597)	−2.475 (3.267)	4.005 *** (1.467)	−7.004 (3.615)	3.456 *** (0.944)	2.150 (1.502)
constant	−67.748 (102.839)	173.990 ** (67.846)	−117.919 *** (39.871)	119.937 * (32.052)	9.678 (23.938)	−61.715 * (34.141)
Provincial Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	190	114	228	57	342	247
R ²	0.608	0.784	0.578	0.909	0.671	0.530

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.3.2. Based on the Presence of National Advanced Manufacturing Clusters

In November 2022, the Ministry of Industry and Information Technology released a list of 45 national advanced manufacturing clusters, with 18 provinces having national advanced manufacturing clusters³. Among them, Jiangsu Province topped the list with 11 clusters, followed by Guangdong Province with 7 clusters. Hunan Province and Zhejiang Province both had four clusters, ranking third nationwide. The remaining 13 provinces currently do not have national advanced manufacturing clusters. Based on this criterion, two sub-samples are formed, one with provinces that have national advanced manufacturing clusters and the other without. Separate regressions are conducted for each sub-sample, and the results are presented in Table 6, columns (4) and (5). It is observed that, in provinces with advanced manufacturing clusters, industrial synergy agglomeration significantly promotes the development of advanced manufacturing. However, in provinces without advanced manufacturing clusters, this positive influence is not significant. This result is similar to the findings of the regional heterogeneity analysis. The underlying reason is that the promotion of advanced manufacturing through the synergy between the manufacturing and productive service sectors requires a solid industrial development foundation in the region.

5.4. Intermediate Effect Test

The mediational analysis results can be found in Table 7, encompassing columns (1) through (4). The initial regression findings unveil a remarkable positive impact of industrial synergy agglomeration on the development of advanced manufacturing. Subsequently, in the second regression, the coefficient of the core explanatory variable exhibits a significant positive value, implying that industrial synergy agglomeration enhances urban innovative capabilities. Furthermore, upon integrating industrial synergy agglomeration and urban innovative capabilities into the equation in the third step, their combined influence on the development of advanced manufacturing remains significantly positive. Hence, it can be inferred that industrial synergy agglomeration enhances urban innovative capabilities, thereby fostering the advancement of advanced manufacturing, thereby lending support to H2. Moreover, it is worth noting that, in column (2), the coefficient for urban innovative capabilities exhibits a significant positive value, thus confirming H2.

Table 7. Intermediate effect test.

Variables	(1) <i>ami</i>	(2) <i>ami</i>	(3) <i>uic</i>	(4) <i>ami</i>
<i>coagglo</i>	0.767 *** (0.130)		0.266 *** (0.031)	0.400 *** (0.131)
<i>Uic</i>		1.563 *** (0.162)		1.379 *** (0.172)
<i>Pgdp</i>	2.109 ** (0.991)	0.925 (0.877)	0.093 (0.237)	1.982 ** (0.936)
<i>Fdi</i>	0.087 ** (0.041)	0.055 (0.039)	0.022 ** (0.010)	0.057 (0.039)
<i>Hcl</i>	0.004 (0.133)	0.048 (0.126)	−0.051 (0.032)	0.075 (0.126)
<i>Gov</i>	−0.088 *** (0.027)	−0.058 ** (0.026)	−0.019 *** (0.007)	−0.063 ** (0.026)
<i>Inv</i>	−0.147 *** (0.041)	−0.183 *** (0.039)	0.023 ** (0.010)	−0.179 *** (0.039)
<i>Str</i>	−0.002 (0.038)	0.006 (0.036)	0.001 (0.009)	−0.003 (0.035)
<i>Inf</i>	2.113 *** (0.773)	1.358 * (0.726)	0.264 (0.185)	1.749 ** (0.732)
constant	−43.377 ** (18.509)	−3.152 (15.807)	−11.434 *** (4.419)	−27.609 (17.603)
Provincial Fixed Effects	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes
N	589	589	589	589
R ²	0.527	0.571	0.493	0.578

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The implementation of the bootstrap method, renowned for its scientific rigor and accuracy, is employed in this study to examine the robustness of the mediating effects. As per the findings in Table 8, within a 95% error-corrected confidence interval, it is observed that the indirect effect of industrial synergy agglomeration on the development of advanced manufacturing, mediated through the enhancement of urban innovative capabilities, amounts to 0.367 (CI = [0.202, 0.591]). The confidence interval, devoid of the inclusion of zero, attests to the presence of a mediating effect. Furthermore, the direct effect of industrial synergy agglomeration on the development of advanced manufacturing is

estimated at 0.400 (CI = [0.161, 0.602]) within the same confidence interval, signifying a positive and significant impact even when controlling for the mediating variable of urban innovative capabilities. Thus, urban innovative capabilities play a partial mediating role in the process of industrial synergy agglomeration fostering the advancement of advanced manufacturing. The results of the bootstrap test likewise provide support for H2.

Table 8. The results of the bootstrap mediation analysis.

Explained Variable	Mediating Variable	Effect Class	Effect Size	The 95% Error-Corrected Confidence Interval		
				Standard Error	Lower Limit of Interval	Upper Limit of Interval
<i>ami</i>	<i>uic</i>	Indirect Effect	0.367	0.093	0.202	0.591
		Direct Effect	0.400	0.109	0.161	0.602

5.5. Moderated Mediating Effect Test

5.5.1. The Regulating Effect of Manufacturing Intelligence

Columns (1) to (5) in Table 9 present the moderating effect of manufacturing intelligence on the relationship between industrial synergy agglomeration and advanced manufacturing development. Column (1) indicates that the coefficient of the interaction term between industrial synergy agglomeration and manufacturing intelligence is significantly positive, suggesting that manufacturing intelligence plays a positive moderating role in the direct path through which industrial synergy agglomeration promotes advanced manufacturing development. Furthermore, in columns (3) and (5), the coefficients of the interaction term between industrial synergy agglomeration and manufacturing intelligence, as well as the coefficients of urban innovative capabilities and the interaction term between manufacturing intelligence, are all significantly positive. This indicates that manufacturing intelligence exerts a positive moderating effect in both of the two-step indirect paths through which industrial synergy agglomeration fosters advanced manufacturing development, thereby supporting H3.

Table 9. The regulating effect of manufacturing intelligence.

Variables	(1) <i>ami</i>	(2) <i>uic</i>	(3) <i>uic</i>	(4) <i>ami</i>	(5) <i>ami</i>
<i>coagglo</i>	0.621 *** (0.131)	0.232 *** (0.032)	0.229 *** (0.030)		
<i>Uic</i>				1.448 *** (0.166)	1.210 *** (0.217)
<i>Mi</i>	2.817 *** (0.394)	0.127 *** (0.039)	0.965 *** (0.089)	0.437 *** (0.151)	−0.507 (0.578)
<i>coagglo*mi</i>	0.769 *** (0.120)		0.279 *** (0.027)		
<i>uci*mi</i>					0.529 * (0.312)
<i>Pgdp</i>	1.382 (0.953)	0.050 (0.235)	−0.152 (0.216)	1.051 (0.872)	0.722 (0.892)
<i>Fdi</i>	0.082 ** (0.039)	0.022 ** (0.010)	0.020 ** (0.009)	0.056 (0.039)	0.066 * (0.039)
<i>Hcl</i>	0.029 (0.127)	−0.049 (0.031)	−0.043 (0.029)	0.059 (0.126)	0.046 (0.126)
<i>Gov</i>	−0.079 *** (0.026)	−0.017 *** (0.007)	−0.016 *** (0.006)	−0.056 ** (0.026)	−0.057 ** (0.026)
<i>Inv</i>	−0.170 *** (0.039)	0.021 ** (0.010)	0.015 * (0.009)	−0.185 *** (0.039)	−0.183 *** (0.039)

Table 9. Cont.

Variables	(1) <i>ami</i>	(2) <i>uic</i>	(3) <i>uic</i>	(4) <i>ami</i>	(5) <i>ami</i>
<i>Str</i>	0.005 (0.036)	0.001 (0.009)	0.004 (0.008)	0.003 (0.035)	0.009 (0.036)
<i>Inf</i>	2.801 *** (0.746)	0.318 * (0.184)	0.489 *** (0.169)	1.663 ** (0.729)	1.781 ** (0.731)
constant	−50.613 *** (17.735)	−11.767 *** (4.381)	−13.907 *** (4.011)	−11.287 (15.947)	−11.477 (15.920)
Provincial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	589	589	589	589	589
R ²	0.569	0.503	0.586	0.577	0.580

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.5.2. The Regulating Effect of International Capacity Cooperation

The results of the moderation analysis, examining the moderating effect of international capacity cooperation on the relationship between industrial synergy agglomeration and advanced manufacturing development, are presented in Table 10, spanning columns (1) to (5). Column (1) reveals that the moderating factor exhibits a positive moderating effect in the relationship between industrial synergy agglomeration and advanced manufacturing development. Further investigation of the moderated mediation effects within the indirect paths reveals that international capacity cooperation plays a positive moderating role in both the relationship between industrial synergy agglomeration and urban innovative capabilities, as well as the relationship between urban innovative capabilities and advanced manufacturing development. These findings support H3, indicating that international capacity cooperation positively moderates the indirect effects within the mediation process.

Table 10. The regulating effect of international capacity cooperation.

Variables	(1) <i>ami</i>	(2) <i>uic</i>	(3) <i>uic</i>	(4) <i>ami</i>	(5) <i>ami</i>
<i>coagglo</i>	0.486 *** (0.128)	0.146 *** (0.024)	0.110 *** (0.021)		
<i>uic</i>				1.386 *** (0.224)	0.745 ** (0.301)
<i>icc</i>	0.009 *** (0.002)	0.006 *** (0.000)	0.006 *** (0.000)	0.002 (0.002)	0.000 (0.002)
<i>coagglo*icc</i>	0.002 *** (0.000)		0.001 *** (0.000)		
<i>uic*icc</i>					0.001 *** (0.000)
<i>pgdp</i>	1.647 * (0.971)	0.528 *** (0.177)	0.059 (0.161)	1.115 (0.893)	1.088 (0.885)
<i>fdi</i>	0.067 * (0.039)	0.011 (0.007)	0.010 (0.006)	0.055 (0.039)	0.072 * (0.039)
<i>hcl</i>	−0.016 (0.127)	−0.019 (0.024)	−0.048 ** (0.021)	0.052 (0.126)	−0.002 (0.126)
<i>gov</i>	−0.069 ** (0.027)	0.006 (0.005)	−0.002 (0.004)	−0.051 * (0.027)	−0.060 ** (0.027)
<i>inv</i>	−0.176 *** (0.039)	0.012 (0.007)	0.007 (0.006)	−0.183 *** (0.039)	−0.179 *** (0.039)

Table 10. Cont.

Variables	(1) <i>ami</i>	(2) <i>uic</i>	(3) <i>uic</i>	(4) <i>ami</i>	(5) <i>ami</i>
<i>str</i>	−0.002 (0.036)	−0.013 ** (0.007)	−0.004 (0.006)	0.001 (0.036)	0.016 (0.036)
<i>inf</i>	1.794 ** (0.739)	−0.088 (0.139)	0.010 (0.122)	1.265 * (0.731)	1.420 * (0.726)
constant	−26.694 (17.638)	−4.812 (3.308)	−2.337 (2.922)	−2.576 (15.811)	−6.516 (15.727)
Provincial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Temporal Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	589	589	589	589	589
R ²	0.578	0.719	0.782	0.572	0.580

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.6. Spatial Spillover Effect Test

Based on the GDP and the latitude–longitude of each province, an economic, geographic, nested matrix is constructed. The global Moran’s I index is computed for the levels of industrial synergy agglomeration and advanced manufacturing development from 2003 to 2021, accompanied by the creation of a scatter plot. The core variable Moran’s I indices all exhibit significant positive values, indicating the presence of spatial positive autocorrelation.

Initially, an LM test is conducted, encompassing the LM (lag) test (183.745 ***), the R-LM (lag) test (9.030 ***), the LM (error) test (198.843 ***), and the R-LM (error) test (24.128 ***). The results of all these tests are significant, suggesting the adoption of the Spatial Durbin Model (SDM). Subsequently, Wald and LR tests are performed. The Wald (SAR) test (32.42 ***) and Wald (SEM) test (32.45 ***) reject the null hypothesis that the SDM model can be degraded to either SAR or SEM models, thus passing the test. Similarly, the LR (SAR) test (31.56 ***) and LR (SEM) test (31.64 ***) also support the aforementioned conclusion. Finally, the Hausman test yielded a *p*-value below 0.05, leading to the adoption of the fixed-effects SDM model.

The regression results are presented in Table 11. From column (1), it can be observed that the main effect is significantly positive, indicating a positive influence of industrial synergy agglomeration on the development of advanced manufacturing within the province, aligning with the baseline regression results. In column (2), the coefficient of the core explanatory variable is significantly positive, suggesting a preliminary promotion effect of increased levels of industrial synergy agglomeration within the province on the development of advanced manufacturing in other provinces. However, the presence of spatial spillover effects still needs to be examined through the coefficients of the indirect effects. Columns (3) to (5) reflect the spatial spillover effects of various variables on the development of provincial advanced manufacturing. It can be observed that both the direct and indirect effects of industrial synergy agglomeration are significantly positive, indicating the existence of positive spatial spillover effects. Even when the economic geographic nested matrix is replaced by an economic distance matrix, the aforementioned conclusions remain valid.

Table 11. Spatial spillover effect test.

Variables	(1)	(2)	(3)	(4)	(5)
	Main	Wx	Direct	Indirect	Total
<i>coagglom</i>	0.468 *** (2.69)	1.769 ** (2.50)	0.465 *** (2.62)	1.691 ** (2.38)	2.156 *** (3.54)

Table 11. Cont.

Variables	(1)	(2)	(3)	(4)	(5)
	Main	Wx	Direct	Indirect	Total
<i>pgdp</i>	1.493 (1.55)	5.012 (1.03)	1.391 * (1.64)	5.036 (0.95)	6.427 (1.22)
<i>fdi</i>	0.047 (1.19)	−0.211 (−0.61)	0.051 (1.18)	−0.205 (−0.59)	−0.155 (−0.44)
<i>hcl</i>	−0.047 (−0.37)	−1.024 * (−1.66)	−0.036 (−0.26)	−1.027 (−1.53)	−1.063 (−1.55)
<i>gov</i>	−0.091 *** (−3.54)	−0.134 (−1.13)	−0.096 *** (−3.19)	−0.135 (−1.27)	−0.231 ** (−2.04)
<i>inv</i>	−0.090 ** (−2.05)	1.317 *** (4.04)	−0.091 ** (−2.17)	1.310 *** (4.22)	1.219 *** (3.70)
<i>str</i>	0.001 (0.04)	−0.229 (−1.27)	0.001 (0.04)	−0.220 (−1.15)	−0.219 (−1.10)
<i>inf</i>	3.137 *** (3.84)	−0.871 (−0.23)	3.047 *** (3.98)	−0.529 (−0.17)	2.518 (0.79)
rho Statistics	−0.048 (−0.35)				
sigma2_e Statistics	4.419 *** (17.16)				
N	589	589	589	589	589

Notes: The values within parentheses represent clustered robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6. Discussion

The synergistic agglomeration of manufacturing and productive service industries infuses the development of advanced manufacturing with a wellspring of vitality (Qiu and Gong 2021; Song et al. 2023). In this study, we construct an indicator system to assess the level of development of advanced manufacturing in Chinese provinces. Subsequently, empirical analysis is conducted to examine the direction and mechanisms through which industrial synergy agglomeration influences the development of advanced manufacturing. Furthermore, we examine the spatial spillover effects of industrial synergy agglomeration.

In line with previous research (Gao et al. 2020), our findings confirm that industrial synergy agglomeration promotes the development of advanced manufacturing. As manufacturing and service industries deepen their collaboration within regions, the costs of factor mobility and information sharing decrease, facilitating the dissemination of advanced manufacturing technology (Pandit et al. 2001), significantly improving the management capabilities of manufacturing enterprises. Consequently, this leads to increased economic benefits (Klein and Crafts 2020). The optimization of spatial layout in these two industries engenders the effects of concentrated governance and economies of scale, curbing carbon emissions and environmental pollution (Wang et al. 2022), thereby enhancing the green growth efficiency of the manufacturing sector (Lv and Lu 2022; Zhu et al. 2022). In comparison to the above-mentioned existing studies that focus on the effects of industrial synergy agglomeration on advanced manufacturing development from singular perspectives such as technology, management, or environmental sustainability, this study employs a comprehensive index to measure the level of advanced manufacturing development, ensuring a more scientific and comprehensive approach. Furthermore, our research reveals that the promoting effect of industrial synergy agglomeration on advanced manufacturing development is more pronounced in the eastern regions of China and in 18 provinces with national advanced manufacturing clusters. This finding indicates that the process through which industrial synergy agglomeration exerts its influence is influenced by the heterogeneity

of the regional foundation for advanced manufacturing development, aligning with the research results that focused on the pharmaceutical manufacturing industry (Hu et al. 2021). However, some earlier studies have raised objections to the results of our research. Wang and Wang (2023) find that the impact of industrial synergy agglomeration on regional economic growth exhibits scale effects and congestion effects, with a “U-shaped” relationship curve present in both the local region and neighboring areas.

This study enriches the research on the drivers of advanced manufacturing by incorporating innovation as a mediating factor into the regression equation (Zhuang et al. 2021; Yang et al. 2021). It reveals that industrial synergy agglomeration enhances urban innovation capabilities, thereby promoting the development of advanced manufacturing. As the spatial layout of industrial synergy agglomeration takes shape, the external economic effects generated by specialized division of labor become evident, leading to improved innovation efficiency among regional manufacturing firms (Shen et al. 2019; Wang et al. 2019; Peng et al. 2023). The enhancement of innovation capabilities, coupled with rationalized factor allocation, drives the positive development of various industries within the region (Fan et al. 2021). The output of innovation activities, when integrated into the production process of enterprises, transforms into advanced technological achievements, with positive and long-term effects on economic benefits (Lafuente et al. 2020; Becerra-Vicario et al. 2023). However, Zhang et al. (2022) argue in their research that the impact of urban innovation on the development level of emerging industries follows an inverted “U-shaped” curve, contradicting the findings of this study.

We further examine the mechanisms through which industrial synergy agglomeration impacts advanced manufacturing development and reveal that manufacturing intelligence and international capacity cooperation, as moderating factors, play a positive role in both the direct and indirect pathways of industrial synergy agglomeration’s impact. In regions with higher levels of manufacturing intelligence, there is a better utilization of advanced technologies, improved facility conditions (Yigitcanlar et al. 2020), stronger talent attraction, and higher efficiency in information exchange and resource allocation among industries (Song and Zuo 2019). International capacity cooperation provides favorable support for enterprise innovation and research and development by facilitating the flow of mobile factors (Chen et al. 2012). In regions with higher levels of international capacity cooperation, there is frequent exchange of learning and communication between domestic and foreign entities, enabling Chinese manufacturing enterprises to access advanced knowledge, technology, and management experience from abroad more easily (Martinez-Noya et al. 2012). As the synergistic effect of industry agglomeration strengthens, the improvement in urban innovation levels becomes more evident, leading to the more rapid development of advanced manufacturing.

Lastly, research from the perspective of green development in the manufacturing industry indicates that the synergistic collaboration between manufacturing and productive service industries has a spatial spillover effect in suppressing atmospheric pollution (Zhuang et al. 2021). This study further deepens the spatial-level research and utilizes the Spatial Durbin Model (SDM) to verify the positive spatial spillover effects of industrial synergy agglomeration on the comprehensive development of advanced manufacturing at the provincial level. As the development of productive service industries becomes more refined, the supporting services provided to advanced manufacturing enterprises become increasingly specialized (Ke et al. 2014). When the demands of advanced manufacturing enterprises in a province are met, upstream and downstream service enterprises, in search of new business opportunities, actively engage in cross-provincial cooperation, thereby providing support for the development of advanced manufacturing in neighboring provinces.

7. Conclusions

This study formulates a comprehensive indicator system for evaluating the advancement of the manufacturing industry and proceeds to quantitatively assess the development level of advanced manufacturing across 31 provinces in China. Expanding upon this,

the study delves into the pathways through which industrial synergy agglomeration promotes the development of advanced manufacturing at the provincial level. Notably, it unveils the partial mediating role played by urban innovation capabilities, while highlighting the positive moderating effects of manufacturing intelligence and international capacity cooperation.

At the academic level, this paper makes two significant contributions. Firstly, it enhances the evaluation indicator system for advanced manufacturing and employs panel data at the provincial level to quantitatively assess the development level of advanced manufacturing across various provinces in China. In comparison to previous studies that relied on single indicators, this paper's measurement of advanced manufacturing development is more scientifically rigorous, filling the gap in comprehensive indicators for assessing advanced manufacturing. Secondly, this paper employs a moderated mediation model (Baron and Kenny 1986; Sun et al. 2020) that incorporates urban innovation, manufacturing intelligence, and international capacity cooperation into a unified analytical framework. By delving into the mechanisms through which industrial synergy agglomeration influences advanced manufacturing, this study goes beyond existing research that solely focuses on mediating effects. It also takes into account the role of moderating variables, thereby deepening the understanding of the drivers behind advanced manufacturing development.

Furthermore, this study holds valuable implications for the formulation of China's manufacturing development policies. Specifically, provincial regions should focus on the synergistic development of manufacturing and productive service industries and seek optimal solutions for industrial synergy agglomeration based on their own industrial development foundations. Additionally, provinces should strengthen the cultivation of enterprise innovation capabilities, optimize the layout of innovation chains, and establish city-based manufacturing innovation centers. Moreover, in the current complex and ever-changing international landscape, provinces should focus on localized research and development of intelligent manufacturing technologies, fostering a comprehensive industry layout for manufacturing intelligence. Lastly, provinces should actively promote international capacity cooperation to catalyze the development of advanced manufacturing.

This study may have certain limitations in examining the spatial spillover effects. Currently, the study has examined the direct impact of industrial synergy agglomeration on the development of advanced manufacturing, but has not examined the indirect pathway of urban innovation. It would be beneficial to investigate whether the positive regulatory effects of manufacturing intelligence and international capacity cooperation exhibit significant spatial spillover characteristics among provinces.

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Notes

¹ Our sample does not include data from Hong Kong, Macau, and Taiwan.

² The Eastern region comprises ten provinces and municipalities, namely Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central region encompasses six provinces, namely Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western region includes twelve provinces, regions, and municipalities, namely Inner Mongolia,

Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Lastly, the Northeastern region consists of three provinces, namely Liaoning, Jilin, and Heilongjiang.

- ³ Apologies for the previous incorrect information. The 18 provinces with national advanced manufacturing clusters are as follows: Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Hubei, Hunan, Guangdong, Chongqing, Sichuan, and Shaanxi.

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Article

Spatial Aspect of Global Value Chain in East Asia: How Ports and Airports Shape Industrial Clusters in East Asia

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Abstract: This paper examines how geography matters for the location of industries in East Asia, employing regression analyses on a novel and comprehensive regional GDP dataset. This study examines how geography affects industrial location patterns, particularly the role of infrastructure, such as ports and airports. This paper analyzes the current economic geography of East Asia using the novel dataset. The regression analyses utilize location quotients as the dependent variable and incorporate explanatory variables, such as domestic/foreign market access, per capita income, population density, and distance-based dummies for ports and airports. The findings reveal that the determinants of industrial location differ significantly across industries. The relative importance of domestic versus foreign market access and proximity to ports and airports varies across sectors. The results imply that countries/regions cannot easily host industries of their choice, as different industries require distinct locational characteristics.

Keywords: economic geography; global value chains; East Asia; industrial location; infrastructure

JEL Classification: F14; F63; R12

1. Introduction

There are two seemingly contradictory perceptions of geography in the globalized world. One is represented by the phrases “the death of distance” (Cairncross (2001)) and “the world is flat” (Friedman (2006)). Information and communication technology and ever-lowering trade costs make economic activities scattered worldwide, yet connected by Global Value Chains (GVCs). On the other hand, the other perception of geography is represented by the phrase “geography matters”. Even in our highly globalized world, physical proximity is still vital for economic activities, making industrial agglomerations possible.

Indeed, economic interactions are still greatly affected by distance. Crafts and Venables (2003) showed that the trade flows between countries 8000 km apart from each other are reduced to only 7% for countries located at a distance of 1000 km. Foreign direct investment (FDI) keeps 42% of the volume of trade within an 8000 km distance. At the same time, technology flows, which intuitively would seem indifferent to distance, are mostly affected by distance and reduced to only 5% if two places are located at a distance of 8000 km.

The world seems to be in the middle of being flat. Krugman and Venables (1995) show a “history of the world” in which economic activities are distributed unevenly when the level of trade costs is in the middle. Suppose the world is composed of two regions, North and South, and the economy comprises an agricultural sector with a constant return to scale (CRS), and a manufacturing sector with an increasing return to scale (IRS). When the trade costs are very high, both regions have manufacturing sectors to serve their domestic markets and have the same real wages. However, once the trade costs are lowered below a certain threshold, the North begins to host more manufacturing sectors to serve both regions because of the work of the IRS. In this phase, the industrialized North earns higher wages than the agricultural-based South. Then, the trade costs are further lowered, and it

becomes profitable for a firm to locate in the South, which provides cheaper labor and has less severe market competition, causing the relocation of the manufacturing sector. The income gap between North and South starts to narrow as trade costs decline, and finally, the real wages of both regions converge at a trade cost of zero. Today, they seem to be in the “core-periphery” phase toward convergence.

In this paper, we examine how geography matters for the location of industries in East Asia by a novel geo-economic dataset. Specifically, we focus on the distance from infrastructure, such as airports and ports, and conduct a regression analysis to examine the determinants of industrial location. While it is plausible that proximity to airports and seaports gives locational advantages to industrial agglomerations, two key aspects remain unclear: (1) the specific industries that benefit more from such proximity to transport infrastructure, and (2) the distance thresholds within which the advantages of being near airports or seaports can be effectively exploited. An empirical investigation is necessary to clarify these hypotheses and quantify the relationships between industrial clusters and their access to major transportation hubs.

This paper makes two contributions to the previous literature. First, we focus on the role of infrastructure, such as ports and airports, in addition to traditional location determinants, such as market access and labor costs, proxied by per capita income. Second, we investigate industrial locations in East Asia. The previous literature has investigated mainly the US and Europe, or industrial locations within a specific country, such as China (Cheng and Kwan 2000) and India (Saikia 2011), while not even investigating East Asia. These contributions are made possible by our novel dataset of GDP by industry, covering 16 East Asian countries/regions at the sub-national level and port and airport location data, with the realistic route selection mechanism implemented in the CGE model, as discussed below. Hitherto, the lack of a reliable and comprehensive dataset of industry-specific GDP at a sub-national level for the East Asia region has impeded such research. Moreover, while many studies have used Euclidean distance as the distance measure, in reality, the transportation modes utilized differ by industry, rendering Euclidean distance a poor approximation of actual market access.

This paper is structured as follows: First, we briefly examine what economic theories say about the location of industries. Second, we present the current economic geography of East Asia through a novel and comprehensive regional GDP dataset. Third, we examine how geography affects the location of industries by regression analyses. Fourth, building upon the results from the previous section, we discuss and contrast our findings with those of the existing literature. The last part concludes this paper with some policy implications.

2. Economic Theories on the Location of Industries

A large amount of the literature has investigated the determinants of the location of industries, since Marshall (1890) identified three main sources of industrial agglomeration, namely, labor market pooling, input sharing, and knowledge spillovers. However, until spatial economics developed in the 1990s, mainstream economics had analyzed the location of industries as a part of international economics. The core concept of industrial location in global economics is a well-known comparative advantage. The theory of comparative advantage argues that a country/region hosts the industry that is comparatively advantageous to that country/region. The source of the comparative advantage may be an abundance of a specific production factor, like labor or capital (Heckscher–Ohlin theorem), or a higher production efficiency (Ricardian theorem).

Traditional international economics is based on CRS and cannot treat trade costs well. Spatial economics, or new economic geography, is a new theory that explains complex production and trade patterns in a globalized, but not flat, world. Spatial economics explains the location of industries and trade patterns as the interactions between concentration and dispersion forces (Fujita et al. (1999)). One typical example of an agglomeration force is the IRS in production. The IRS makes producing goods in one big plant more economical than multiple smaller plants. On the other hand, a typical example of a dispersion force is the

high cost of transport, including various border costs (Anderson and Van Wincoop (2004)). If it is costly to export goods from one country to another, firms may choose to locate their factories in each country and serve the market where they produce the goods to save on transport costs.

Market demand is another crucial factor in spatial economics. When firms choose where to locate, they prefer to locate in larger markets to minimize transport costs. But it is precisely this movement, “located in the larger market”, which makes larger markets even larger. This mechanism is the primary circular causation that makes industrial agglomerations.

Krugman (1993) showed the relationship between the IRS, transport costs, and the number of agglomerations that appeared in a hypothetical world, the so-called racetrack economy, in which every city is located on a circle at an equal distance. Krugman showed that higher economies of scale and lower trade costs result in fewer agglomerations. Industries with a larger-scale economy tend to be located in fewer places. In comparison, industries with a smaller-scale economy tend to be located in more places. The number of agglomerations declines as trade costs are lowered.

Among empirical works, Midelfart et al. (2004) investigated the location of industries in Europe, and found that the industrial structure of European countries converged during the 1970s, but has diverged since then. They concluded that factor costs and geographical factors, such as the existence of an educated labor force, access to intermediate goods, and the degree of scale economy, can largely explain the cross-country differences in industrial structure. Brülhart and Traeger (2005) found that during the period 1975–2000 in Europe, the manufacturing sector exhibited a statistically significant increase in its concentration relative to the spatial distribution of overall employment, while simultaneously experiencing a statistically significant decrease in its concentration relative to geographic space. Cheng and Kwan (2000), by estimating the effects of determinants on foreign direct investment (FDI) in 29 Chinese regions from 1985 to 1995, found that large regional markets, good infrastructure, preferential policies, and FDI’s self-reinforcing effect had positive impacts, while wage costs had a negative impact and education’s effect was insignificant. Head and Mayer (2004) found that market potential explains some part of the location choice of Japanese foreign direct investment in Europe. Arauzo-Carod et al. (2010) surveyed the various literature on industrial location and concluded that the factors considered in location choice, such as tax policies, wages, and agglomeration forces, have not altered since the 1980s, but newer datasets and theoretical models have confirmed that these factors work as predicted by theoretical models.

3. Economic Geography of East Asia

East Asia has a considerable production base of manufacturing goods with GVCs among its member countries/regions. East Asia seems to be an example of a “flat world”, in which one product is been sent from one country to another to be a final product, through various production stages. However, this across-country value chain is economically viable because of considerable differences in nominal wages and factor endowments among the regions. Each production stage seems to be located in a suitable place to conduct that specific production stage utilizing these differences. For instance, the production stage, which is very labor intensive, was typically in China, a formerly labor-abundant country, and is now shifting to Vietnam, Cambodia, and Myanmar.

In this section, we depict the basic economic geography of East Asia using a comprehensive geographical dataset, the Geo-Economic Dataset for Asia (GEDA) 2005, compiled by IDE-JETRO. The GEDA dataset provides sub-national Gross Domestic Product (GDP) data for 25 sectors across the following industries: agriculture, fishing and forestry, mining, manufacturing (16 sectors), and services (7 sectors). The GDP figures are nominal and have been converted to US dollars using the average exchange rate between the local currency and US dollars in 2005, based on data from the International Financial Statistics (IFS) by the International Monetary Fund (IMF). The GEDA dataset encompasses regional demographic statistics including population and land area, coupled with the GDP by industrial sector.

The regional divisions in the GEDA follow the administrative boundaries within each country. Except for Hong Kong, Macao, Singapore, and Brunei, GEDA adopts a primary-level administrative division, although secondary-level administrative divisions are adopted for China, India, Indonesia, Bangladesh, and Myanmar. For more details on the data sources and methods used in compiling the GEDA, please refer to the “Data source and notes” section of the GEDA website (<https://www.ide.go.jp/English/Data/Geda.html> (accessed on 15 May 2024)). Table 1 shows the number of administrative divisions by country/regions in the GEDA.

Table 1. Number of administrative divisions by country/regions.

Bangladesh	64	Laos	17
Brunei	1	Macao	1
Cambodia	24	Malaysia	15
China	342	Myanmar	64
Hong Kong	1	Philippines	17
India	579	Singapore	1
Indonesia	435	Taiwan	25
Japan	47	Thailand	76
Korea	16	Vietnam	61
Total			1786

Source: author.

3.1. Basic Information

Figure 1 shows the population density by region in 2005. The regions with a high population density of over 500 people/square km are observed in the Ganges Basin, the coastal areas of China, and Java Island, in addition to most of the capital regions of each country. The distribution of population is very much uneven in East Asia.

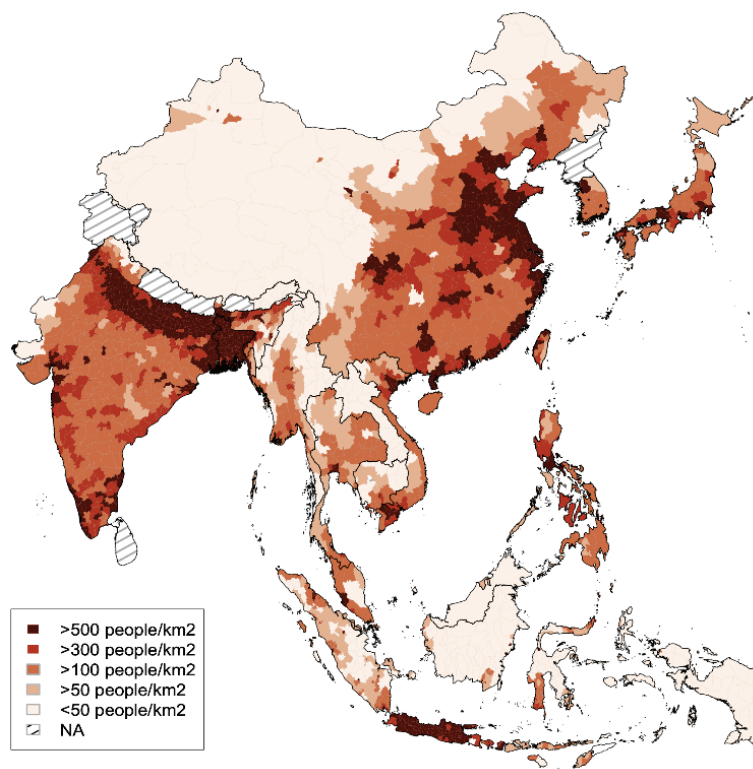


Figure 1. Population density (2005). Source: author, based on GEDA 2005.

Figure 2 shows the GDP per capita by region in 2005. The income distribution among East Asian regions is highly uneven, both internationally and intranationally. The regions with isolated high incomes are capital or mineral-resource-rich regions.

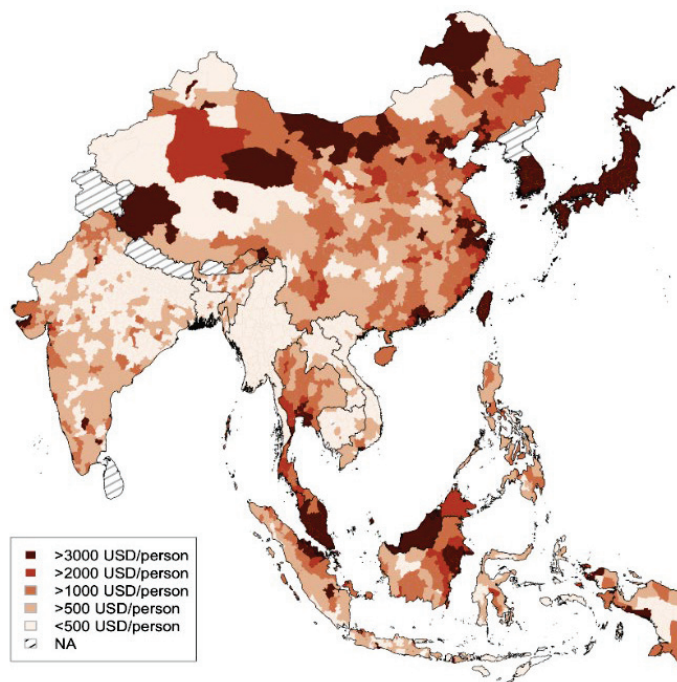


Figure 2. GDP per capita (2005). Source: author, based on GEDA 2005.

Figure 3 shows the GDP per square km, or “GDP Density”. This index seems to be a good measure of the agglomeration of economic activities (Panayotou 1997; Apergis and Ozturk 2015), because it is a product of the population density and GDP per capita, as follows:

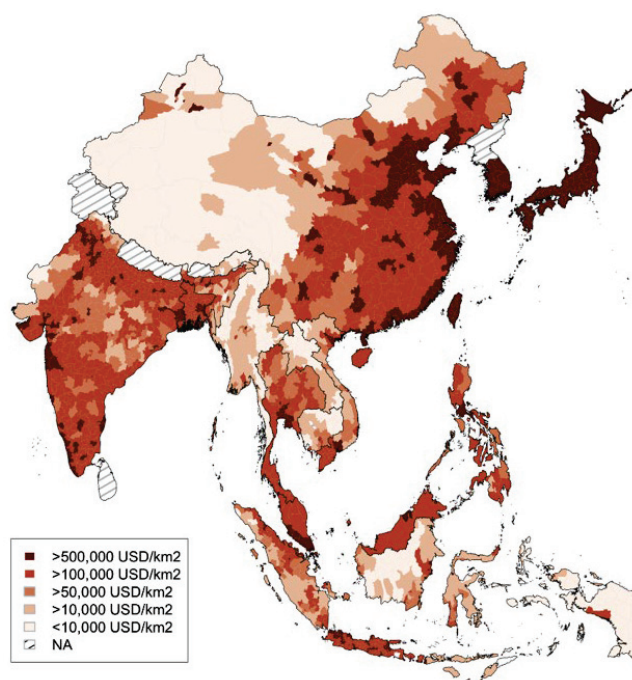


Figure 3. GDP per square km (2005). Source: author, based on GEDA 2005.

East Asia's economic geography is very much uneven (Table 2). For per capita income, the lowest to highest ratio is almost 1:1000; it is 1:100,000 for population density; and it is 1:1,000,000 for GDP density.

Table 2. Summary of statistics of geo-economic data for East Asia, 2005.

	Obs.	Min	Median	Mean	Std. Dev.	Max	Min/Max
GDP per capita	1786	69.8	713.2	2365.5	6119.9	69,730	998
Population density	1786	0.26	261.5	704.3	2554.2	25,630	97,452
GDP per sq. km ('000USD)	1786	0.4	190.0	3077.7	20,851.9	408,800	1,064,583

Source: author.

3.2. Industrial Agglomeration

One of the indices used to measure the degree of industrial agglomeration is the location quotient (LQ). The LQ for industry i in region r is defined as follows:

$$LQ_{ir} = \frac{q_{ir}/q_r}{Q_i/Q} = \frac{q_{ir}/Q_i}{q_r/Q} \quad (1)$$

where q_{ir} is industry i 's employment in region r , q_r is the total employment in region r , Q_i is industry i 's employment in the reference area, and Q is the total employment in the reference area. The LQ is a theoretically substantiated agglomeration index that exhibits a relatively unbiased nature, rendering it a suitable index for evaluating economic activity concentration or spatial clustering within a specific geographic region relative to a broader reference area (Billings and Johnson 2012).

Here, we set 16 countries/regions in East Asia as the reference areas. For example, if the automotive industry accounts for 3% of the total employment in a sub-national region, while it accounts for 2% of the total employment in 16 East Asian countries/regions, then the LQ for the automotive industry for the region is $3\%/2\% = 1.5$. So, an $LQ > 1$ means an industry concentrates in a region more than the average for the reference area.

Unfortunately, the GEDA 2005 has no information on the numbers employed by region and industry. Alternatively, we can calculate the proxy of employment by industry and region as follows:

$$q_{ir} = GDP_{ir}/GDP_r \cdot Pop_r \quad (2)$$

In this case, the LQ is calculated as follows:

$$LQ_{ir} = \frac{q_{ir}/Pop_r}{\sum_r q_{ir}/\sum_r Pop_r} \quad (3)$$

Figures 4 and 5 show the LQ of each region's automotive and food processing industries in 2005. The automotive industry agglomerates in relatively small areas, while the food processing industry is located in broader regions.

Next, we compare the degree of agglomeration between industries. The Theil index is used for this purpose and is calculated as follows:

$$T_i = \sum_r q_{ir}/Q_i \cdot \ln(LQ_{ir}) \quad (4)$$

The index takes 0 if the distribution of a specific industry perfectly follows the distribution of a reference value, in this case, total employment. A bigger index value means more concentration compared with the reference value. One of the merits of the Theil index is that inequality/dissimilarity can be decomposed into multiple layers, such as between-country and within-country inequality (Conceição and Ferreira (2000)).

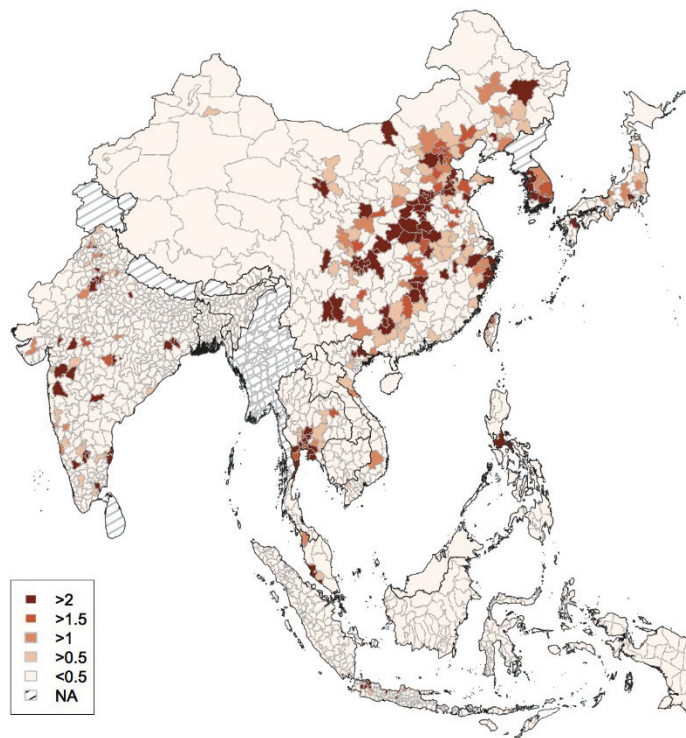


Figure 4. LQ for automotive industry (2005). Source: author, based on GEDA 2005.

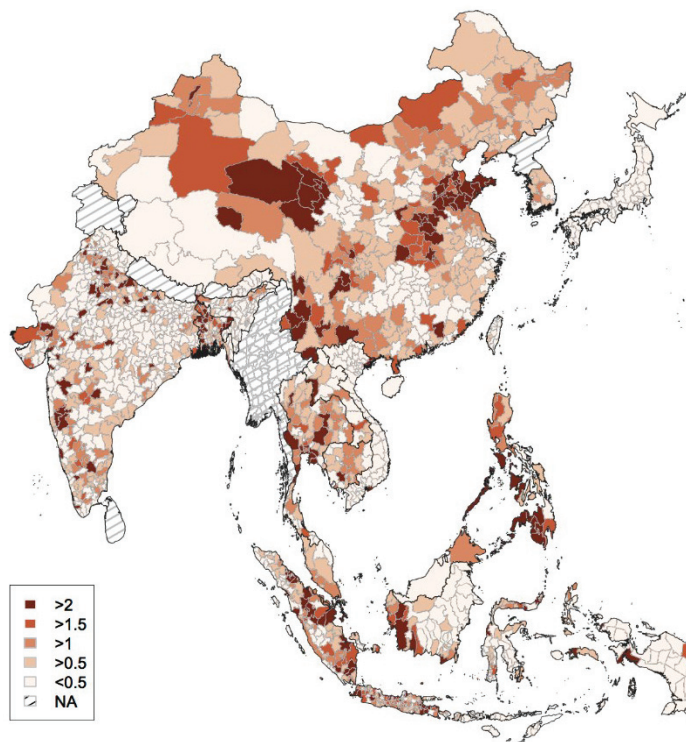


Figure 5. LQ for food processing industry (2005). Source: author, based on GEDA 2005.

Figure 6 shows the Theil index for ten industries. The Theil indices for the agricultural and services sectors are very low, showing that these industries exist in every region and country. The automotive sector has the highest index value among the manufacturing industries, and the electric and electronic (E&E) sector follows. These industries tend to agglomerate in a smaller number of regions. The food industry has the lowest Theil index, showing that the industry tends to be located in many regions. If you look at the

between-country Theil index, the textile and garment industry has the highest value, and the wood industry follows, meaning that these industries tend to agglomerate in selected countries/regions. On the other hand, the petroleum and chemical, food processing, and iron and steel industries have the lowest values, meaning that these industries tend to be located in every country.

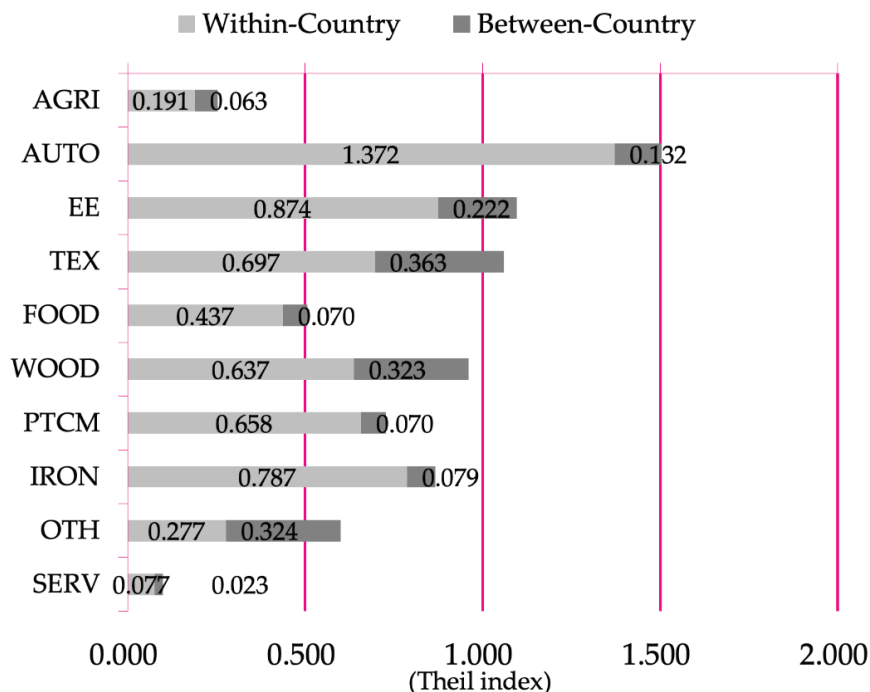


Figure 6. Theil index of 10 industries for East Asia (2005). Source: author's calculations based on GEDA 2005.

A theoretical interpretation is as follows. As discussed in Section 1, spatial economics predicts that an industry with a higher scale economy and lower trade costs is located in fewer places. The automotive industry has a higher IRS, while the E&E industry has lower transport costs than their goods' value. So, the higher concentration of both industries is understandable. The food industry has a lower IRS, higher transport costs, and less concentration.

For the between-country Theil index, the textile and wood and paper industries have relatively higher values, i.e., higher international concentration. This seems to be explained not by spatial economics but by the comparative advantage of traditional international economics. The textile industry is highly labor intensive, and the wood and paper industry is resource-based. Both industries seem to be internationally concentrated in countries/regions with abundant labor and wood resources. As for the automotive industry, the between-country Theil index is low, meaning there is less international concentration. It can be interpreted that the automotive industry's trade costs are very high because of various protectionist policies in each country. So, they tend to be located in each country while showing a high intranational concentration.

4. What Are the Determinants of the Spatial Distribution of Economic Activities?

In this section, we conduct an econometric analysis to identify the determinants of the spatial distribution of economic activities. Specifically, we conduct a regression analysis to identify the locational factors for industries in 2005 for each of the 1786 sub-national regions across the 16 countries/regions covered in the GEDA dataset. The dependent variables used are the location quotients (LQs) for each industry, while various explanatory variables are included in the regression model.

Spatial economics predicts that economic agglomerations tend to be located near large markets. One of the measures for the goodness of a location is market access. Market access is a concept that measures the proximity to markets, classically defined as the distant weighted sum of GDP for each market as follows:

$$MA_r = \sum_s GDP_s / T_{rs} \quad (5)$$

where GDP_s denotes the Gross Domestic Product for region s , and T_{rs} represents the trade costs incurred between region r and region s .

Redding and Venables (2004) showed that market access in a country is highly correlated with its per capita income. They used the theory-backed market access variable, but here, we calculate it using Equation (5) for simplicity. The GDP data used in this analysis include not only the 1786 sub-national regions across the 16 countries/regions covered in the GEDA dataset, but also the GDP data for 68 additional countries, represented by their respective capitals. This allows us to consider market access to regions outside of East Asia as well.

For the trade cost measures, we utilize the road network data used in a CGE model called IDE-GSM (see Kumagai et al. 2013). Instead of using Euclidean distances, we constructed trade cost data that consider actual road, rail, sea, and air transportation routes, rather than just direct distances. We use the functionality implemented in IDE-GSM to select the optimal multimodal transportation network for each industry–origin–destination combination. We also consider the waiting time and costs at border crossing points to construct the trade cost data when calculating the trade costs for foreign markets.

Market access can be divided into domestic market access (DMA) and foreign market access (FMA). DMA shows whether a region has good access to the market within the same country, while FMA shows whether an area has good access to foreign markets. The importance of market access may differ by industry, and the relative importance of FMA and DMA may vary, too.

Here, we use the LQ as the dependent variable. For the independent variables, we include DMA and FMA. So, we may estimate using the following equation:

$$LQ_{ir} = \alpha_i + \beta_{1i} \log(DMA_r) + \beta_{2i} \log(FMA_r) + \phi_i X_r + \varepsilon_{ij} \quad (6)$$

where X_r is the vector of other control variables, such as the GDP per capita and the population density of a region, and ε_{ij} is the error term.

In addition to the above equation, we try to capture the impacts of transport infrastructure, such as ports and airports, on the location of industries. Limao and Venables (2001) showed that infrastructure is an essential determinant of trade costs, and an improvement in the quality of infrastructure from the median to the 25th percentile makes trade costs 17% points lower, equivalent to 2358 km closer to all trade partners.

To see the effects of transport infrastructure on the location of industries, we add the port/airport dummy into the estimation of Equation (6). If the nearest port/airport for a region is within specific distance brackets from the capital city of that region, the corresponding dummy variable takes 1. In constructing these dummy variables, we considered 191 ports and 65 airports in 16 countries/regions covered by the GEDA. The distance from the ports and airports to each region is based on the Euclidean distance between the ports/airports and the capital cities of the respective regions. By estimating the coefficients of each dummy variable, we can detect if access to the port/airport matters for the industrial agglomeration. The rationale for employing Euclidean distance here is rooted in its simplicity, which facilitates the creation of distance-based dummy variables and enhances the interpretability of the results. The trade costs, accounting for multimodal route choice behavior when constructing the market access variable, encompass various elements, rendering it difficult to reduce the discussion to a mere distance measure. Furthermore, since the distances from each capital city to the nearest port or airport are predominantly domestic and relatively proximate, these can be well approximated with Euclidean distances.

Now, the equation used to estimate is as follows:

$$LQ_{ir} = \alpha_i + \beta_{1i}\log(DMA_r) + \beta_{2i}\log(FMA_r) + \delta_i^d PD_r^d + \gamma_i^d AD_r^d + \phi_i X_r + \varepsilon_{ij} \quad (7)$$

where PD_r^d denotes a port dummy variable that takes a value of 1 if the distance from region r to the nearest port falls within the distance bracket d , and 0 otherwise. The distance brackets considered are less than 50 km, 51–100 km, 101–150 km, 151–200 km, 201–300 km, and 301–500 km. Similarly, let AD_r^d be an airport dummy variable defined analogously, taking a value of 1 if the distance from region r to the nearest airport lies within the distance bracket d , and 0 otherwise. The distance brackets for airports are specified identically to those for ports.

While there are endogeneity concerns regarding the relationship between the locations of ports and airports and the locations of industries, the major ports and airports in many East Asian countries/regions were established much earlier, often during the colonial period, long before industrialization began. Consequently, endogeneity concerns are considered to be low, and it is difficult to find the proper instrumental variables. So, we use the common OLS for the estimation measure. Given these constraints, this study's estimated relationship between ports/airports and industrial agglomerations should be interpreted as a correlation rather than as a causal effect. However, we posit that regardless of whether ports/airports induce industrial agglomerations or industrial agglomerations drive the construction of ports/airports, the underlying fact remains that the existence of such industrial agglomerations necessitates the presence of ports or airports.

4.1. Automotive Industry

Table 3 shows the estimation results. The coefficients of each explanatory variable on the LQ differ significantly by industry. DMA has positive and statistically significant effects on the automotive industry, while the coefficient of FMA is negative and statistically insignificant. This means that size and domestic market access are essential for the automotive industry. Considering that the coefficients of the port dummies are generally negative and statistically insignificant, the general locations of the automotive industry in East Asia in 2005 seem to not be export-oriented. The positive and statistically significant impact of airports within 100 km are interpreted as indicating that the ease of international travel is vital for the automotive business, because the automotive industry in developing Asia was dominated by MNCs in 2005.

Table 3. Results of regression.

	AUTO		E&E		TEXT		FOOD		WOOD		PTCM		IRON	
Intercept	−4.439 (7.627)		−59.434 (6.721)	***	−32.463 (6.309)	***	9.182 (4.640)	**	2.493 (8.450)		−14.809 (5.800)	**	−24.359 (6.463)	***
DMA	0.305 (0.077)	***	−0.048 (0.068)		0.206 (0.064)	***	0.043 (0.047)		−0.139 (0.086)		0.006 (0.059)		0.280 (0.065)	***
FMA	−0.127 (0.348)		2.534 (0.307)	***	1.343 (0.288)	***	−0.449 (0.212)	**	−0.006 (0.386)		0.563 (0.265)	**	0.831 (0.295)	***
Port50	−0.381 (0.186)	**	0.414 (0.164)	**	0.435 (0.154)	***	0.278 (0.113)	**	1.140 (0.206)	***	0.761 (0.141)	***	−0.192 (0.157)	
Port100	−0.143 (0.185)		0.845 (0.163)	***	0.460 (0.153)	***	0.033 (0.113)		0.682 (0.205)	***	0.173 (0.141)		−0.154 (0.157)	
Port150	−0.158 (0.188)		0.514 (0.166)	***	0.794 (0.156)	***	0.138 (0.114)		0.708 (0.208)	***	0.221 (0.143)		0.115 (0.159)	
Port200	−0.320 (0.206)		0.417 (0.182)	**	1.317 (0.171)	***	0.147 (0.126)		0.587 (0.229)	**	0.271 (0.157)	*	0.047 (0.175)	
Port300	0.077 (0.185)		0.287 (0.163)	*	0.484 (0.153)	***	0.250 (0.113)	**	0.546 (0.205)	***	0.072 (0.141)		0.011 (0.157)	
Port500	−0.090 (0.170)		0.050 (0.150)		0.103 (0.141)		−0.163 (0.104)		0.314 (0.189)	*	−0.014 (0.129)		−0.010 (0.144)	

Table 3. Cont.

	AUTO		E&E		TEXT		FOOD		WOOD		PTCM		IRON
Airport50	0.849	***	1.165	***	1.016	***	−0.350	**	−0.648	**	−0.066		−0.162
	(0.235)		(0.207)		(0.195)		(0.143)		(0.261)		(0.179)		(0.199)
Airport100	0.501	**	0.380	*	0.731	***	−0.139		−0.882	***	−0.091		0.047
	(0.223)		(0.197)		(0.185)		(0.136)		(0.247)		(0.170)		(0.189)
Airport150	0.088		0.137		0.346	**	0.120		−1.062	***	−0.261		−0.160
	(0.212)		(0.187)		(0.176)		(0.129)		(0.235)		(0.162)		(0.180)
Airport200	−0.244		0.084		0.142		0.096		−0.861	***	−0.163		−0.250
	(0.219)		(0.193)		(0.182)		(0.134)		(0.243)		(0.167)		(0.186)
Airport300	−0.132		0.077		0.047		−0.183	*	−0.847	***	−0.152		0.060
	(0.163)		(0.144)		(0.135)		(0.099)		(0.181)		(0.124)		(0.138)
Airport500	−0.080		−0.013		−0.103		−0.013		−0.700	***	−0.087		−0.076
	(0.146)		(0.129)		(0.121)		(0.089)		(0.162)		(0.111)		(0.124)
GDPPC	0.193	**	0.423	***	−0.324	***	0.047		0.158	*	0.266	***	0.110
	(0.084)		(0.074)		(0.069)		(0.051)		(0.093)		(0.064)		(0.071)
POPD	0.018		0.096	**	0.016		0.078	***	0.091	*	0.113	***	−0.044
	(0.045)		(0.040)		(0.037)		(0.027)		(0.050)		(0.034)		(0.038)
obs=	1722		1722		1722		1722		1722		1722		1722
Adj. R ²	0.09		0.19		0.09		0.03		0.05		0.10		0.07

Note: standard errors in parentheses. ‘***’, ‘**’, and ‘*’ shows significance at 1%, 5%, and 10% level, respectively.
Source: author.

4.2. E&E Industry

For the E&E industry, FMA has positive and statistically significant impacts, while DMA does not. This means that access to foreign markets is very important for the industry, while the size and access to local markets do not matter much. Considering that both the port dummies within 300 km and the airport dummies within 100 km have positive and statistically significant effects, the E&E industry in East Asia in 2005 seems to have been highly export-oriented and integrated into GVCs.

4.3. Textile and Garment Industry

DMA and FMA positively and statistically significantly impact the textile and garment industry. Exports are crucial for this industry, since both the port dummies within 300 km and the airport dummies within 150 km have positive and statistically significant effects. Still, the domestic market is also essential, indicated by the coefficient of DMA. One notable result is that the coefficient of the GDP per capita is negative and statistically significant. This means that the textile and garment industry tends to avoid locations in regions with higher incomes. This result is consistent with the intuition that the industry needs abundant, low-cost labor.

4.4. Food Processing Industry

For the food processing industry, the coefficient of DMA is positive but statistically insignificant, and the FMA is negative and statistically significant. The results are hard to interpret. The coefficients of the port/airport dummies are also hard to explain. Considering the positive and highly significant coefficient of population density, and the lowest adjusted R² value of 0.03 among all industries, the food processing industry is located in highly populated regions to serve their needs, and other factors are hard to detect in this analysis.

4.5. Wood and Paper Industry

For the wood and paper industry, both the coefficients of DMA and FMA are negative, but statistically insignificant. The coefficients of the port dummies within 500 km are positive and statistically significant, while those for the airport dummies within 500 km are negative and statistically significant. The port dummies are easy to interpret if you consider that wood products need ports for export, but interpreting the airport dummies is difficult. The wood and paper industry is resource-based and less affected by market access, but ports seem essential.

4.6. Petroleum and Chemical Industry

DMA is not statistically significant for the petroleum and chemical industry, while FMA is positive and significant. The port dummy within 50 km is positive and highly significant, while the airport dummies are all statistically insignificant. The petroleum and chemical industry seems export-oriented, and ports are essential.

4.7. Iron and Steel Industry

DMA and FMA are positive and statistically significant for the iron and steel industry. The other explanatory variables are all statistically insignificant. From this analysis, the industry seems to locate nearer to larger markets within a country and internationally.

Figure 7a–c graphically show the port/airport dummies coefficients listed in Table 2 for selected industries. It indicates that the economic impacts of ports/airports differ significantly by industry, and how far their impacts last also differ by industry. For the E&E industry (Figure 7a), the impacts of airports are highest within 50 km, but then fade out fairly quickly. On the other hand, the impacts of ports last as far as 200–300 km from the ports. Airports have no statistically significant impacts on the petroleum and chemical industry (Figure 7b), while ports have substantial and strong impacts only within 50 km. For the textile and garment industry (Figure 7c), the economic impacts are most considerable in the 151–200 km bracket. In contrast, the economic impacts of airports are most substantial within 50 km, and statistically significant up to within 150 km.

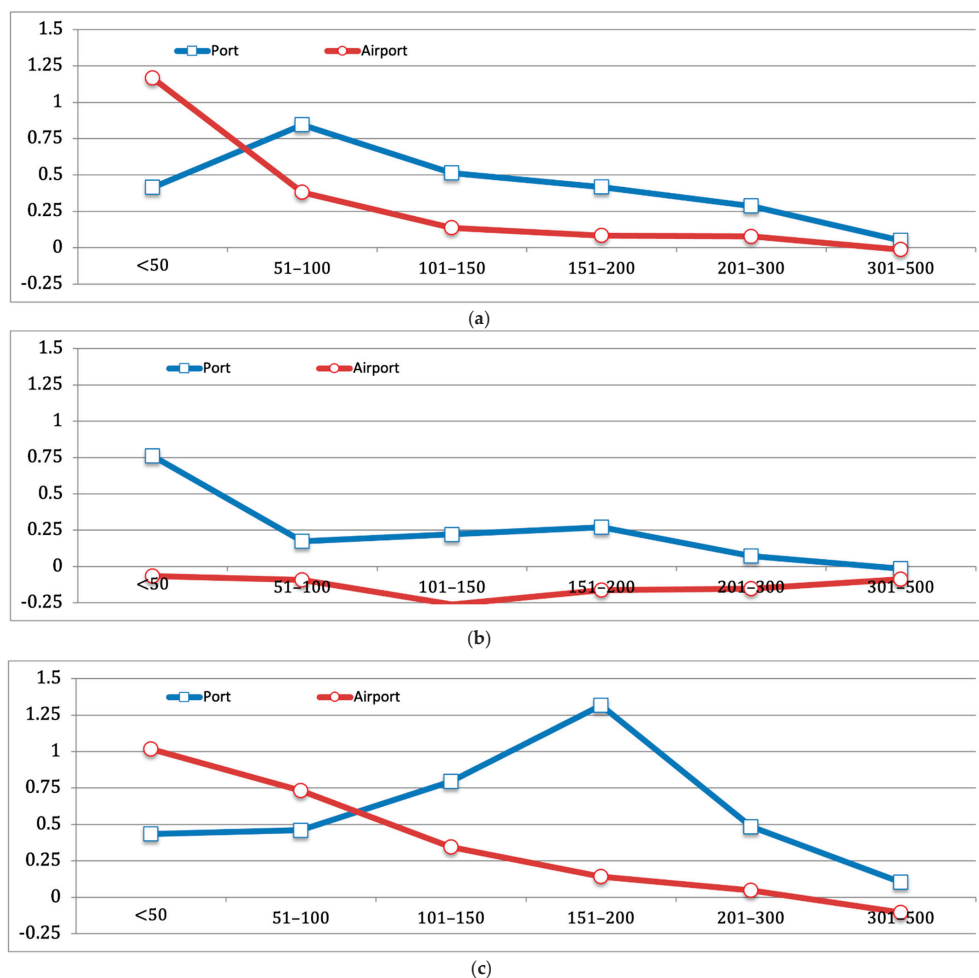


Figure 7. (a) Economic impacts of ports/airports on E&E industry. Source: plotted from the coefficients in Table 3. (b) Economic impacts of ports/airports on petroleum and chemical industry. Source: same as Figure 7a. (c) Economic impacts of ports/airports on textile and garment industry. Source: same as Figure 7a.

5. Discussion

The regression analysis conducted in the previous section reveals several interesting facts. First, the factors influencing industrial agglomeration differ significantly across industries. For some industries, like the automotive industry, domestic market access is crucially important, while for the E&E industry, access to foreign markets is extremely important. This can be understood by considering the history of the automotive industry in East Asia, which developed as an import-substitution industry in most countries (Busser 2013; Natsuda et al. 2013; Okamoto and Sjöholm 1999), except in Japan and South Korea. Conversely, the E&E industry in East Asia has been an export-oriented industry (Hobday 2001; Rasiah 2008) from its inception, making access to foreign markets important, and is consistent with the results. On the other hand, access to domestic and foreign markets is found to be unimportant for resource-based industries like the wood and paper industry. This is unsurprising, considering that the location of industries utilizing natural resources depends on their geographic endowment.

Second, the importance of ports and airports also varies significantly across industries. For the E&E and textile and garment industries, proximity to both airports and ports is important, while for the wood and paper and petrochemical industries, only proximity to ports matters. These results indicate that the research by Song and Geenhuizen (2014), which claimed that ports promote regional output in general, is inadequate, as it fails to consider industry differences. In contrast, Huang (2011) estimated the impact of ports on industrial agglomeration by industry, showing a positive effect for industries like tobacco, sericulture, and oil refining, but not conducive for the textile industry or clerical machinery manufacturing. While their results are broadly consistent with our study, the finding that ports do not positively influence textile agglomeration differs, possibly due to differences in industrial classification or because Shunquan's study focused solely on China, whereas our analysis encompasses a broader geographic scope.

Third, the distance to ports and airports is found to have varying impacts on industrial agglomeration across industries. To our knowledge, such findings are novel. For instance, while being within 50 km of an airport is important for the electronics industry, the textile and garment industry benefits most when a port is located 151–200 km away, and the petrochemical industry benefits from being within 50 km of a port. Considering the time sensitivity of the electronics industry, proximity to airports is crucial. The observation that petrochemical plants worldwide are often located adjacent to ports aligns with our finding that being within 50 km of a port is advantageous for this industry. Proximity to ports facilitates the cost-effective transportation of bulk raw materials, such as crude oil and natural gas, as well as the shipment of finished petrochemical products. For the textile and garment industry, as road transportation is feasible, proximity to ports is important but does not necessarily require extreme closeness, making the result persuasive.

The one thing we can determine from the above results is that time costs are the key to understanding the impacts of ports/airports. Air cargo is mainly used to save time costs; thus, it must be very near to firms. In the case of the E&E industry, it should be located within 50 km to take advantage of the airport, while it is acceptable for the textile and garment industry to be within 100 km. Maritime transport is not very time conscious, and the impacts last as far away as 300 km for some industries.

6. Summary and Policy Implications

The distribution of industry is naturally uneven. However, the degree of unevenness differs by industry. From the viewpoint of spatial economics, industries with a higher IRS and lower transport costs tend to agglomerate in a small number of regions.

What affects the location of an industry may differ significantly by industry. The relative importance of DMA and FMA differs. A DMA-sensitive industry is more challenging to host in countries/regions with smaller markets. Developing infrastructure and reducing tariffs and non-tariff barriers can increase FMA.

The importance of specific transport infrastructure also differs by industry. For the E&E industry, the proximity to airports is essential, while the proximity to ports is essential for the petroleum and chemical industries. The impacts of ports on industrial locations generally last within 300 km, while the impacts of airports last within 50–100 km. This paper implies that a country/region cannot host a specific industry of choice as one likes. Different industries are located in places with different characteristics. This paper makes a significant contribution to the formulation of regional industrial promotion policies, especially by demonstrating that the distance from crucial infrastructure, such as airports and seaports, is an extremely important determinant of industrial location.

This detailed analysis of the relationship between industrial location and infrastructure within East Asia was made possible by combining a new geo-economic dataset, called the GEDA, and the realistic route selection mechanism implemented in the CGE model, called IDE-GSM. This represents a significant advantage of our paper over the existing literature.

While the data used in this study are from 2005, the GEDA dataset is the only comprehensive source covering industry-specific GDP at the sub-national level across multiple East Asian countries; moreover, industrial agglomerations form gradually over time and tend to persist once established, so the insights gleaned from the 2005 data remain relevant for understanding the determinants of industrial location patterns in the region today, despite the desirability of more recent data.

Here, we analyzed the economic geography at an industry level. Still, it might not be fine-enough criteria to analyze the spatial aspect of GVCs, because the further fragmentation of the production process makes a specific production process separately located from other processes in the same industry (Kimura (2006); Baldwin (2013)). For instance, in the automotive industry, the production of engines has a more significant scale economy. It tends to be located in a limited number of places, while wire harness assembly can possibly be located in a larger number of places. Considering these points, future research should employ more disaggregated industry classifications and newer data. Moreover, it is desirable to utilize panel data sources, which would necessitate the construction of detailed regional- and industry-level GDP datasets for East Asia.

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Article

Brake Segment for Agglomeration Policy: Engineers as Human Capital

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Abstract: A “segment” is a component of the organization of an agglomeration. The organization of agglomeration is formed by the construction of segments. Manufacturing agglomeration segments can be divided into four main categories: human resources including engineers, physical infrastructure, institutions, and living environment. Each segment then has a specific function in the process of building industrial agglomeration. We focus on the process of building segments in agglomeration formation. We define a “brake segment” as a segment that has a “function” to decelerate the speed of the process. The purpose of this paper is to identify the existence of this brake segment in the process of constructing the segments of the manufacturing agglomeration. We obtained the following three results. First, a modified version of the spatial economic model yields that the number of agglomerated firms is inversely related to the wages of skilled workers. Second, a factor analysis of the data on investment environment costs indicates that in the case of the manufacturing industry, the number of agglomerated firms are inversely related to the wages of engineers. Third, the factor analysis of the six countries in the JBIC survey reveals that the segment that poses the investment issue in foreign direct investment in India is engineers as human capital. We conclude that engineers as human capital are a brake segment. The implication is that the sustained development of “engineers” as human capital is essential for the success of manufacturing industry agglomeration.

Keywords: brake segment; function; engineers; human capital; spatial economics

1. Introduction

Special economic zones (SEZs) are strongly positive in attracting foreign direct investment (FDI) in China, according to UNCTAD (2019). The notion of industrial hubs by Oqubay and Lin (2020) is a generic term for agglomerations of economic activity that have developed since the Industrial Revolution. Special economic zones (SEZs), industrial parks, and export processing zones (EPZs) have been widely used to catch up and transform the economies of newly industrializing economies in East Asia. However, Zheng and Aggarwal (2020) found that India could not match the scale and success of China’s SEZs.

The literature on industrial hubs has focused on different types of industrial hubs: industrial districts, EPZs and SEZs, and small industrial clusters, according to Oqubay (2020) as follows. First, FIAS World Bank’s occasional paper by FIAS (2008) views SEZs as ‘a tool to enhance industry competitiveness’ and defines ‘a geographically delimited area, offering certain incentives to businesses which physically locate in the zones’ (Farole and Akinci (2011); Zeng (2010)). Second, New Structural Economics by Lin (2012), focuses on a developing country strategy oriented to a latent comparative advantage.

The construction of an agglomeration is not instantly completed, but a sequential process of building the segments. It took more than ten years to construct the manufacturing agglomerations. Third, Kanai and Ishida (2000) called research on the dynamic process of agglomeration building as ‘process analysis’. Kuchiki and Tsuji (2011) and Fujita and Kuchiki (2006) use a flowchart approach to industrial agglomeration. The flowchart

approach analyzes the process of constructing agglomeration segments. The flowchart approach was applied to many cases all over the world, as follows: the Malaysian electronics industry by Meyanathan (2011), the Wuhan Optical Valley industry in China by Hu and Liu (2011), the automobile industry in China by He (2011), the Rio de Janeiro Software industry by Botelho et al. (2010), the Austin Technopolis in the US (2008), the Industrial Cluster Plan promoted by the Ministry of Economy, Trade and Industry Japan. Macasaquit (2008) applied it to industrial agglomeration in the Philippines, and Mitra and Mehta (2011) applied this approach to industrial agglomeration in India. They analyze the process of constructing agglomeration segments.

In economic theory, Krugman (1991) built the prototype model to examine where economic activity occurs and why. Fujita et al. (1999) extended the prototype model to establish spatial economics. Using a Hotelling-type framework in central place theory, Henkel et al. (2000) obtained the breaking conditions of agglomeration equilibria on spatial allocation decisions in which consumers are active in a marketplace. Helpman and Krugman (1985) provided a new trade theory in spatial economics, in which the equilibrium number of firms is derived based on a general equilibrium model.

By analyzing data on industrial hubs based on a model of spatial economics, the following three conclusions were drawn. First, Kuchiki (2021) used the model of Henkel et al. (2000) to derive the segment that is the master switch in the construction of tourism industrial agglomeration. It is the introduction of both infrastructure that reduces transport costs and heterogeneous goods with low elasticity of substitution.

Second, Kuchiki and Sakai (2023) used the hybrid model of Krugman (1991) and Alonso (1964) to derive the segment that is the master switch of urban agglomeration. It is the introduction of both infrastructure that reduces commuter costs and heterogeneous goods with low elasticity of substitution. Third, Kuchiki (2023) used Helpman and Krugman's (1985) model to derive the segment that is the "accelerator" in the construction of manufacturing agglomerations. It is the "leased" industrial park.

The "segments" constitute the organization of industrial agglomeration. The organization of agglomerations is formed by building segments. The segments comprise four major categories: human resources, physical infrastructure, institutions, and living conditions, according to Kuchiki (2023). Table 1 illustrates some of the investment survey items for the manufacturing industry. The major category of human resources consists of segments: general workers, general office staff, engineers, and section chief staff, or managers.

Each segment has a "function". Its function includes the role of a master switch or accelerator. Ports and roads have the function of master switches for industrial agglomeration policy. Industrial parks have the function of accelerators. We focus on the process of building segments in agglomeration formation.

This paper understands the transition process as a process of constructing segments of an agglomeration and clarifies the importance of the "process of policy implementation". The "sequencing economics" of the construction of segments is then addressed. This paper discusses segments that function to decelerate the process of building segments toward industrial agglomeration. This paper defines the segment as the "brake segment". India has not succeeded in establishing export-oriented SEZs through the introduction of foreign direct investment. Therefore, it is conjectured that some segments function to bake the process of establishing industrial agglomeration. No study has taken up a case study to examine whether brake segments exist and what they are from the viewpoint of theoretical and quantitative analysis when constructing segments of manufacturing agglomerations.

The purpose of this paper is to identify the existence of this brake segment. We will compare India with countries in East Asia, including Vietnam and Thailand, for the purpose of examining in this hypothesis. India did not succeed in introducing export-oriented foreign capital and switched to foreign capital for the domestic market, while Vietnam and Thailand succeeded in introducing foreign capital.

Table 1. Segments and investment-related costs.

Category Segment	Segments	Function	
Human resource	worker (general laborer)	Brake	W1
	engineer		W2
	middle management (section chief)		W3
	staff (general office work)		W4
	manager (section chief)		W5
Physical infrastructure	Industrial zone	Accel	Z1
	Industrial zone	Accel	Z2
	Offices		Z3
	Electricity		P1
	Water		P2
	Gas		P3
	Ports	Master switch	C1
		Master switch	C2
	Road	Master switch	
	Airport	Master switch	
Institutions	Deregulation	Master switch	
	Preferential treatments	Master switch	
	One-stop services	Master switch	
	Laws and regulations		
Living conditions	Housing		
	International schools		
	Hospitals		
	Entertainment & shopping		

Source: Author's based on Japan External Trade Organization (JETRO 2022).

The results of this paper were derived in the following three steps. First, a modified version of the spatial economic model yields that the number of agglomerated firms is inversely related to the wages of skilled workers. Second, a factor analysis of the data on investment environment costs indicates that in the case of the manufacturing industry, skilled workers are engineers. In other words, the number of agglomerated firms are inversely related to the wages of engineers. Third, the factor analysis of the six countries in the JBIC survey reveals that the segment that poses the investment issue in foreign direct investment in India is engineers as human capital. A regression analysis of the factor score data confirms this fact.

This paper concludes that engineers as human capital is a brake segment. The implication is that sustained development of “engineers” as human capital is essential for the success of manufacturing industrial agglomeration. To avoid pedaling the brakes in the transition process to an agglomeration equilibrium, it is necessary to sustainably develop engineers as human capital.

Sequencing economics in architecture theory related to agglomeration is applied to sequencing the segments of an agglomeration in terms of ‘economies of sequence’. The concept of ‘economies of sequence’ is defined as the selection and sequencing of any two segments from among the entire group of segments of an industrial agglomeration toward the efficient building of the agglomeration, according to Kuchiki (2021).

This paper is to link the theory of spatial economics with the practice of sequencing economics. Industrial agglomeration consists of organizations, and organizations consist of segments. Sequencing economics is used to embody the theoretical model of spatial economics into agglomeration policy. The “function” of the segments, which are the building blocks of agglomeration, is clarified. The “design” of agglomeration policy is essential for policy makers to design its construction process.

The flowchart approach has so far arrayed segments in the process of building industrial agglomeration. In this approach, the concept of “economies of sequence” was introduced to introduce the perspective of “efficiency” of segment construction. In order to consider efficiency, the “function” of the segment was identified.

Previously, master switches and accelerators were identified as examples of “functions”. In addition to these, this paper identifies the engineers as human capital segment

as a segment of the “brake” function. In sequencing economics, identifying the function of a segment leads to efficient implementation of the agglomeration policy. Therefore, sequencing economics is useful for policy makers to implement agglomeration policies.

Section 2 presents preceding studies on the function of segments such as master switch. Section 3 provides an overview of industrial zones in Vietnam and Thailand and special economic zones in India. In Section 4, we explain the materials and methods. In Section 5, we obtain the brake segment using factor analysis and regression analysis. Section 6 concludes this paper.

2. Literature Review on Sequencing Economics

On one hand, Fujita et al. (1999) established in spatial economics ‘the study of where and why economic activity takes place’. The results can be used in sequencing economics as location conditions in economic decision-making. On the other hand, Kuchiki (2023) proposed sequencing economics as an architectural theory of agglomeration. Kuchiki (2023) analyzed special economic zones (SEZs) as agglomerations from the perspective of both spatial economics and sequence economics.

The process of constructing an agglomeration identified by Kuchiki (2023) is as follows. The first step in building agglomerations is to determine where to locate them. Spatial economics determines the conditions for this location. Next, the segments of areas determined are constructed to satisfy those conditions.

The analysis of the construction process addressed by Kuchiki (2023) is in the following way. The organization of industrial agglomeration consists of segments. Each of these segments has a function. Kuchiki and Sakai (2023) identified (1) master switches and (2) accelerators as examples of sequencing economics, respectively. Kuchiki and Sakai (2023) found that the segment that reduces transport costs is the master switch and that the segment that reduces fixed costs is the accelerator. This paper finds out which are (3) the “brake” segments that decelerate the construction process of the agglomeration segment.

Figure 1 illustrates the relationship that the master switch, to efficiently construct the segments that make up the agglomeration in sequencing, is the segment that satisfies the symmetry breaking condition.

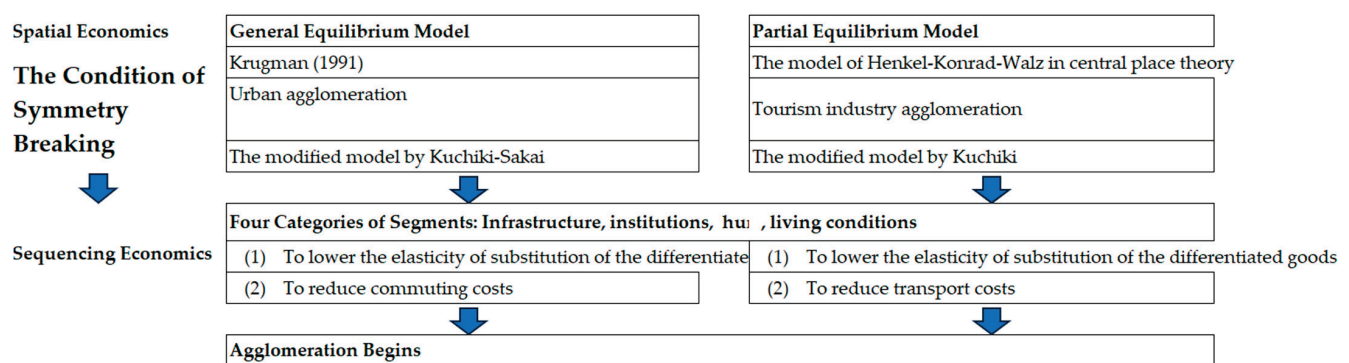


Figure 1. “Master Switch” for agglomeration policy. Source: Author’s Illustration.

2.1. The Segments of Master Switch

Kuchiki (2021) used a symmetry breaking condition derived from the Henkel et al. (2000) model in central place theory. This model is a “partial equilibrium” analysis of tourism industrial agglomeration in spatial economics.

Kuchiki (2021) found that in sequencing the tourism agglomeration segments, the master switch was to give first priority to the opening of Universal Studios Japan, which reduces the elasticity of substitution among differentiated goods, and second priority to the construction of Kansai International Airport, which reduces transportation costs. The opening of Universal Studios Japan increased the number of foreign passengers at Kansai International Airport with a two-year lag. Subsequently, the increase in the number of

foreign passengers was lagged by some years, leading to an increase in the number of arrivals and departures at Kansai International Airport, as well as an increase in the number of foreign tourists in Osaka Prefecture.

The economy is a symmetric equilibrium in which manufacturing is equally divided between the two regions as Fujita et al. (1999) defined in Section 5. It found the conditions of the symmetry breaking. Kuchiki and Sakai (2023) used symmetry breaking conditions derived from a “general equilibrium” model in a monocentric city setting as a master switch. Krugman (1991) was used to derive the condition of master switch.

As shown in Figure 2, when a stable symmetric equilibrium is broken, then the construction of segments of an agglomeration equilibrium begins. Kuchiki and Sakai (2023) present the conditions for the master switch to be turned on and identify what segments satisfy those conditions. The condition is that there is a critical value (threshold) for transport costs, and it is necessary to construct segments that reduce transport costs below the critical value. The segments are illustrated as roads, ports, simplification of investment procedures, etc.

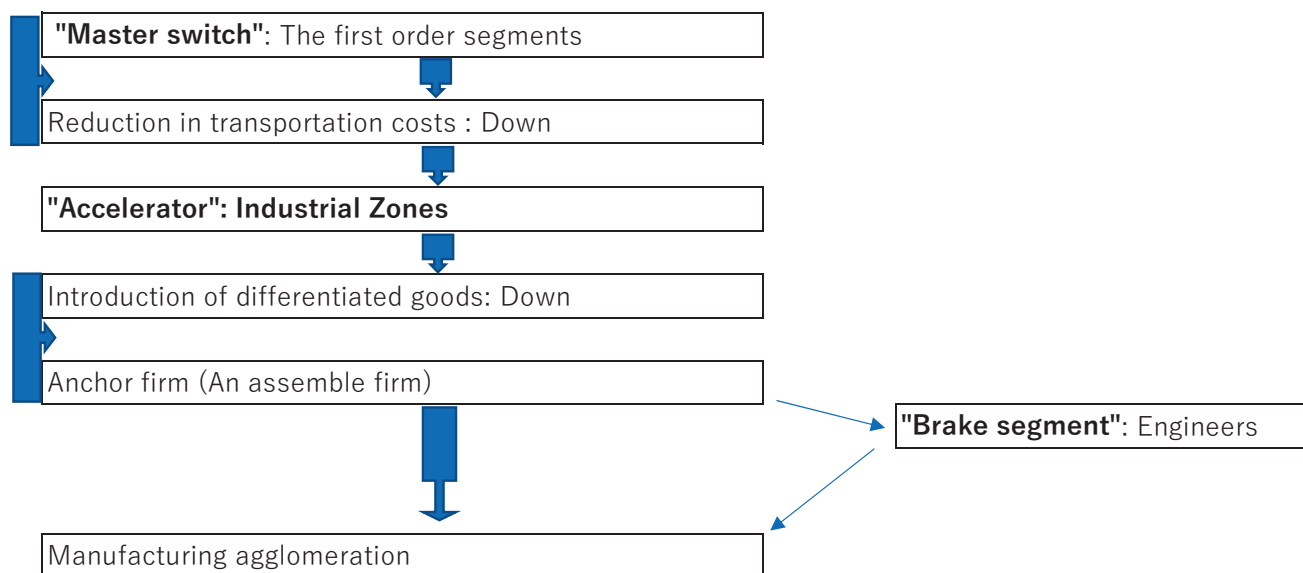


Figure 2. Manufacturing agglomeration policy. Source: Author’s illustration.

2.2. The Segments of Accelerator

Figure 2 shows the flow from the master switch through the accelerator to the anchor firm. The conditions for the accelerator segment were derived from Helpman and Krugman’s (1985) model of spatial economics. According to the new trade theory of spatial economics, the number of firms in an agglomeration is inversely related to its fixed costs. The main accelerator segment of agglomeration after the master switch is turned on is the formation of segments that reduce firms’ fixed costs.

Kuchiki (2023) identifies the accelerator required for the process of agglomeration formation. In the case of manufacturing agglomeration formation, the accelerator segment is specifically industrial parks. The function of this segment is to speed up the process of building the segments of the manufacturing industry agglomeration.

2.3. Brake Segment

Segments that function to decelerate the process of building segments for industrial agglomeration are defined as “brake segments”. In the following, we identify the segments that serve as brakes in the segment building process. We then empirically confirm that engineers as human capital is a brake segment.

3. Industrial Agglomerations in Vietnam, Thailand, and India

India has not succeeded in manufacturing agglomeration and is implementing agglomeration policies through the Make in India policy. Many east-Asian countries, including China, have succeeded in establishing manufacturing agglomerations.

In 1981, China and India had approximately the same GDP per capita: USD 275 for India and USD 288 for China; in 2023, India's GDP per capita is USD 2612 and China's is USD 12,541¹. One can presumably attribute this difference in part to the success of the Special Economic Zone (SEZ) policy that was launched in China in 1979, based on a chronological and statistical analysis by Kuchiki (2023).

Zheng and Aggarwal (2020) conclude that India has failed to match the size and success of China's SEZs in attracting FDI. Ahluwalia et al. (2018) found that India lost its comparative advantage in labor-intensive production in the early stages of development despite its relative abundance of unskilled labor. With regard to the use of SEZs to establish industrial agglomeration, there are differences in the effectiveness of SEZs in India and China.

Two Asian countries that have typically succeeded in using the sequencing economics of agglomeration are Vietnam and Thailand. These countries have been successful in manufacturing agglomeration through the use of ODA as well as the introduction of foreign capital. Sequencing has been optimal in the construction of master switches and acceleration segments.

In the case of these countries, the sequence of ODA implementation along with FDI was optimal. NESDB (2016) of the Thai government identified the results of the Eastern Seaboard Development Program agglomeration with Japanese ODA. Lecler (2002) described the automobile industrial agglomeration in the Eastern Seaboard Development Program, while Shimomura (2000) presented the Japanese contribution to the program and a third-party evaluation. Watanabe (2004) concluded that the combination of FDI and ODA was effective in promoting automobile accumulation in Thailand. The automobile agglomeration is called "Detroit in East Asia".

Similarly, Tran et al. (2003) positively evaluated the impact of Japanese ODA and FDI on industrial agglomeration in northern Vietnam. FDI was in the industrial agglomeration in the north of the country. Mitsui (2004) evaluated that the construction of National Highway 5 with ODA was effective for the agglomeration of FDI. ODA provided the master switch and accelerator through optimal sequencing.

This section presents the segment sequencing. The section highlights successful cases of the introduction of export-oriented foreign direct investment in Vietnam and Thailand, in contrast to unsuccessful cases in India. The process of building master switches and accelerator segments in the process of building industrial agglomeration in Vietnam and Thailand will be illustrated. In this context, the process of developing engineers as human capital with a control function in the Vietnamese process will be highlighted. For the SEZs in India, we will focus on the process of shifting from export-oriented to domestic market-oriented foreign investment without much success in introducing foreign capital.

The cases of Vietnam and Thailand in Kuchiki (2007) are reviewed in these subsections (1) and (2), as shown in Figures 3 and 4. The segments of industrial agglomeration have a master switch and an accelerator pedal as functions. These cases are reinterpreted with respect to the function of the segments.

In this section, on the one hand, Vietnam and Thailand implemented the policy of fostering engineers as human capital. On the other hand, India has implemented agglomeration policies using Special Economic Zones, but has not sufficiently trained engineers as human capital as a segment that constitutes the investment environment in its agglomeration policies.

In the next section, we will theoretically demonstrate that agglomeration does not progress when there is a lack of engineers as human capital based on a model of spatial economics. Thus, we theoretically confirm that the failure of India's manufacturing agglomeration was due to the lack of engineers as human capital.

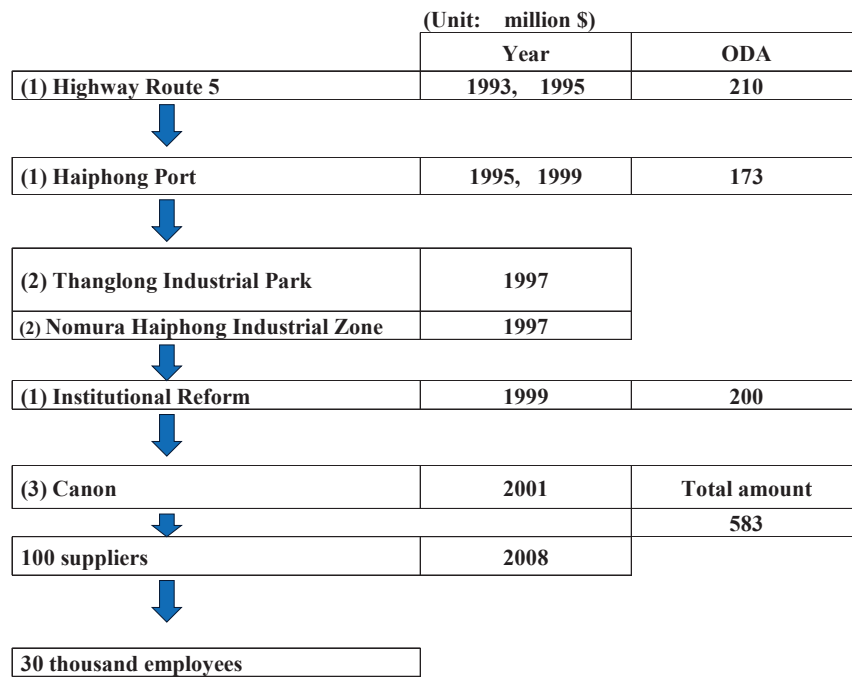


Figure 3. The electronics industry agglomeration in northern Vietnam. Source: Tran et al. (2003) based on JBIC-IDCJ (2003). Note: ODA is official development assistance.

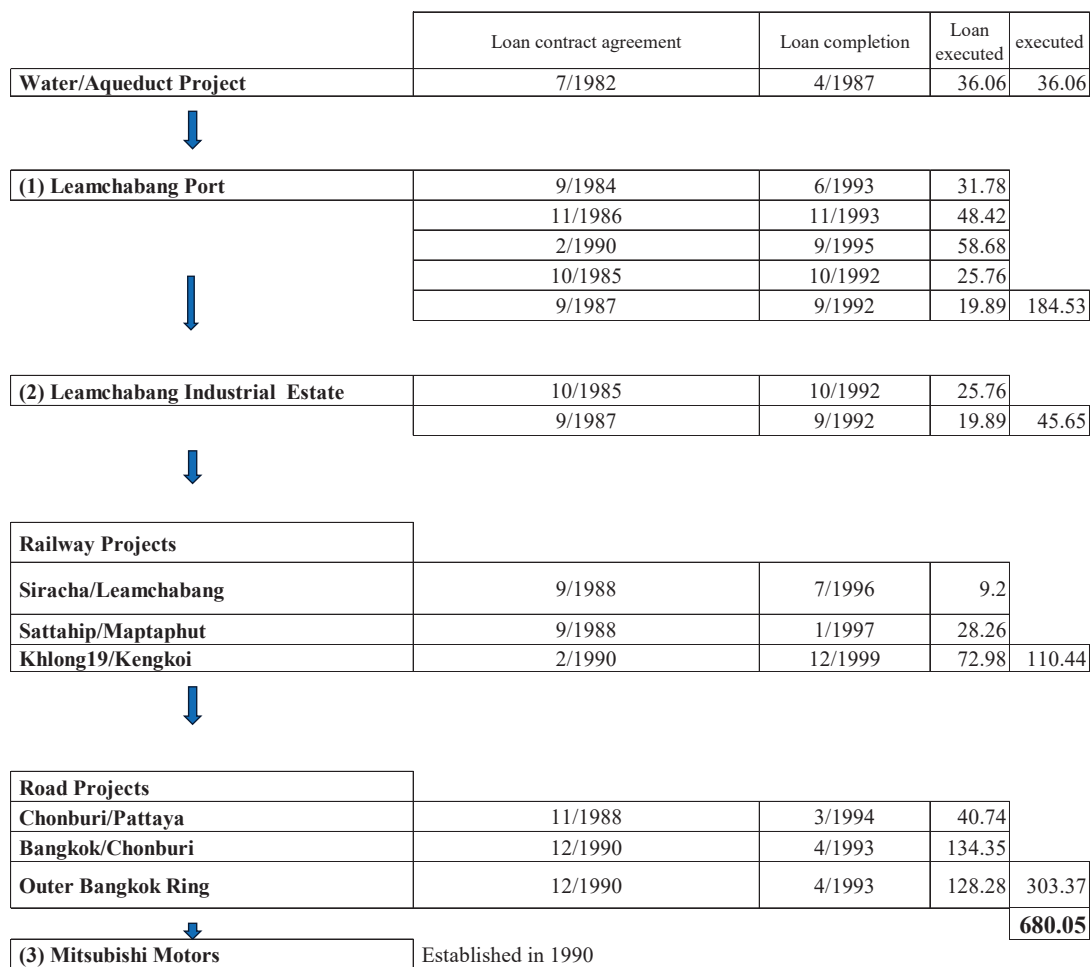


Figure 4. Eastern Seaboard. Source: Kuchiki and Tsuji (2011) based on Shimomura (2000).

3.1. Agglomerations in Northern Vietnam

This subsection identifies the role of the “master switch” and accelerator in the establishment of industrial agglomeration through Japanese official development assistance in the case of industrial agglomeration in northern Vietnam².

3.1.1. Roads and Ports: Reduction of Transport Costs as Master Switch

The construction and renovation of National Highway No. 5 and Haiphong Port were effective as master switches for the building of industrial agglomeration. Figure 3 shows that JPY (Japanese Yen) 21 billion was provided for the construction of National Highway 5 and JPY 17.3 billion for the renovation of Haiphong port in 1993 and 1995.

3.1.2. Institutions: Reduction of Transport Costs as Master Switch

In April 1999, Japanese Minister of Finance Miyazawa pledged JPY 20 billion to support a private sector development program. The loan was agreed upon and implemented in September 1999.

According to the JBIC-IDCJ survey (2003), as shown in Table 2 and Figure 5, private companies evaluate the effect of institutional change on transportation cost reduction from four main perspectives³. First, the approval system for new business was abolished and changed to a registration system. Second, sub-licences are abolished. Changes in company formation streamlined administrative procedures. Third, the collateral and access to banks are improved. Lastly, trade was liberalized. The number of restricted or prohibited industries decreased from 400 to 250.

Table 2. Benefit of Well-developed Infrastructure.

Type	Production	Market-Local	Market-Export	Import	Hai Phong Port	Highway No. 5	Example
1	Hanoi		Haiphong	Haiphong	B	B	Canon
2	Hanoi	Local	Haiphong	Haiphong	B	B	TOTO
3	Hanoi	Local		Haiphong	B	C	Vietnam Float Glass
4	Hanoi		Via internet	CAD technology			Yabashi
5	Hanoi		Noi Bai	Haiphong	C	C	Sumitomo Bakelite
6	Haiphong		Haiphong	Haiphong	B		As'ty
7	Haiphong	Local		Haiphong	B	C	San Miguel Yamamura
8	Haiphong	Local	Haiphong	Haiphong	A (inc.local distribution by ship)	B	Han-Viet Heavy Industry & Construction
9	Haiphong		Noibai	Noibai		B	ESTELL
10	Vinh Phuc	Local		Haiphong	C	C	Honda

Note: A, B and C show frequency of use. A: extremely frequent, B: very frequent, C: frequent. Source: Kuchiki (2007) based on JBIC-IDCJ (2003).

3.1.3. Thang Long Industrial Park and Nomura Haiphong Industrial Zone as Accelerator

Both Thang Long Industrial Park (TLIP) and Nomura Haiphong Industrial Zone (NHIZ) served as accelerators to help investors reduce their initial fixed costs. The development area is 121 hectares for TLIP and 180 hectares for NHIZ.

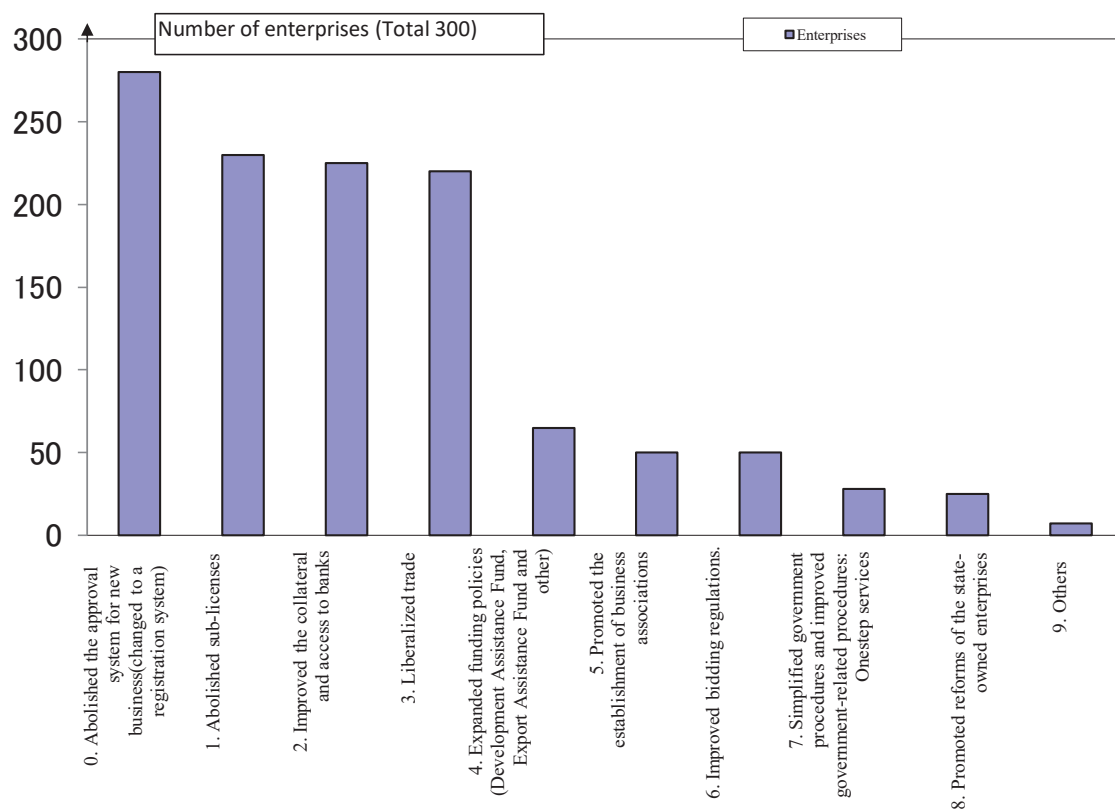


Figure 5. Institutional reforms Note: Data collected from private companies only. Source: Kuchiki (2007) based on JBIC-IDCJ (2003).

3.1.4. Engineers as Human Capital

Many projects developed engineers as human capital to keep the manufacturing agglomeration process from decelerating. One project at Hanoi Institute of Technology taught skills in machining, metalworking, and electrical control. The Haiphong High-Tech Skill Training School was established in December 2001. Major subjects included information and graphics, electrical and electronic engineering, polymers, welding, and milling. Students from both schools first graduated in 2003.

3.1.5. Industrial Agglomerations in Northern Vietnam

Based on the data on foreign direct investment growth from 2000, before the completion of the electronics industry agglomeration, to 2004, after its completion, the macroeconomic effects of National Highway No. 5 on the economy of northern Vietnam are shown in Table 3.

Table 3. Change in direct investment (registered amount) and number of investments by region. (lower: number of investments; higher: US\$ millions).

	2000	2001	2002	2003	2004	2004/2000
North	62.3	272.9	375.4	604.5	1195.9	19.2
Central	58.7 (18)	128 (35)	145.1 (39)	218.4 (59)	405.2 (39)	6.9 2.2
South	707.1 (284)	2102.2 (378)	992.1 (536)	1061.1 (484)	2609.6 (486)	3.7 1.7

Source: Kuchiki (2007).

The data are shown in Table 3 for Hanoi and Haiphong in northern Vietnam, Danang in central Vietnam, and Ho Chi Minh City in southern Vietnam. In 2004, the growth rate in

the north was higher at 19.2%, while the growth rates in the central and southern regions were lower at 6.9% and 3.7%, respectively.

3.2. *The Case of Eastern Seaboard Region in Thailand*

This subsection identifies the role of the “master switch” and accelerator in the establishment of industrial agglomeration through Japanese Official Development Assistance in the case of the Eastern Seaboard Region in Thailand.

The objective of the Eastern Seaboard Development Program was to establish industrial agglomeration in Laem Chabang as a location for export-oriented industries and general industrial estates⁴. The Laem Chabang program included the construction of port facilities and the Laem Chabang Industrial Estate, with associated infrastructure improvements related to water supply, communications, railroads, roads, and urban development⁵.

The Japan Bank for International Cooperation (JBIC, formerly the Overseas Economic Cooperation Fund) provided 27 loans for 16 projects under the Eastern Seaboard Development Program; over an 11-year period from 1982 to 1993, at a total cost of approximately USD 680 million, the process of automobile industrial agglomeration shown in Figure 5 was completed⁶.

The “Laem Chabang Regional Development Plan” consisted primarily of the development of Laem Chabang Port and the construction of Laem Chabang Industrial Park. Loan agreements for the water supply project and the “Laem Chabang Port” project were agreed in 1982 and 1984, respectively. The loan agreement for the Laem Chabang water pipeline project was agreed in 1984. The loan agreement for the Laem Chabang Industrial Park was signed in 1985. The loan agreement for the railroad and road project was agreed upon in 1988.

3.2.1. Master Switch

Laem Chabang Port was designed as a new deep-water port to replace Bangkok Port. The port plays an important role in Laem Chabang Industrial Estate’s function as an export processing zone.

3.2.2. Accelerator Segment

As of 1999, Laem Chabang Industrial Park covers an area of 420 ha. Total loans amounted to JPY 2.576 billion since 1985 and JPY 1.989 billion since 1987. Mitsubishi Motors began operations at Laem Chabang Industrial Park in 1992 as an assembly anchor company. The industrial park functioned as an accelerator segment of the automotive industrial agglomeration by reducing the fixed costs of moving in component suppliers.

3.2.3. Engineers as Human Capital

The Council of Engineers Thailand (COET) is a statutory body under the Engineer Act, B.E. 2542 (1999). The professional engineering services in Thailand are regulated and controlled under the Act which is the central regulatory body for engineering services in Thailand. Policies promoting STEM (Science, Technology, Engineering, and Mathematics) education were introduced in 2014 (ASEAN NOW 2014).

3.2.4. Agglomeration

The peak period for the establishment of industrial parks in the Eastern Seaboard provinces of Chonburi, Prachinburi, Chachoengsao, and Rayong was from 1985 to 1995. These provinces established industrial parks for Toyota in the Gateway City Industrial Park, GM in the Eastern Seaboard Industrial Park, and BMW in the Amata City Industrial Park (see JETRO (2009))⁷. Along Route 331 in the Eastern Seaboard region, the Thailand automobile industry agglomeration was developed.

3.3. The Indian SEZ Policy

3.3.1. EPZ (Export Processing Zone) (1965)

The Indian Government used Export Processing Zones (EPZs) to promote exports. The first EPZ in Asia was established in Kandla, Gujarat as well as Kaohsiung, Taiwan in 1965. The success of Kaohsiung is well known⁸.

3.3.2. SEZ Policy 2000

Though the EPZs had a similar structure to SEZs, the Government initiated the establishment of SEZs, which differ from the EPZs, under the Foreign Trade Policy in 2000. The SEZ Policy 2000 set up under the EPZ regime aimed to address issues arising from numerous regulatory controls, inadequate infrastructure, and unreliable fiscal regimes, and to attract higher foreign direct investment into India from international and multinational companies. This was modeled after China's Special Economic Zones, according to Aggarwal (2006).

However, Zheng and Aggarwal (2020) found that the SEZ Policy 2000 under the EPZ regime made a limited contribution to the Indian economy and that in 2003–2004, all seven EPZs created a mere 8.94 kilo square meter and 88,700 workers at 1 per cent of formal manufacturing employment. The share of FDI in total EPZ investment was as low as 25 per cent in 2003.

3.3.3. SEZ Act 2005 and SEZ Rules 2006

In 2005, the EPZs were converted into the Special Economic Zones Act 2005 (SEZ) to address the infrastructure and bureaucratic issues they faced. The Act was amended to make the SEZ policy with the goal of making India a global manufacturing powerhouse.

The SEZ Rules 2006 set out a complete procedure for the development of SEZs or the establishment of establishments in SEZs. As a result, the SEZ category includes various multiple types of zones, such as free trade zones, EPZs, industrial estates (IEs), free ports, free trade warehousing zones, and urban enterprise zones. A number of EPZs were converted into SEZs, including Noida (Uttar Pradesh), Chennai (Tamil Nadu), Santacruz (Maharashtra), and Kandla (Gujarat). The SEZ Act amended India's SEZ policy.

However, the SEZ Act 2005, which aimed to transform the country into a global manufacturing powerhouse, had a very limited effect. India adopted a cautious approach to SEZ policy and the SEZ Act 2005 gave way to pessimism and foreign investors largely stayed away. The 262 SEZs established during the period from 2005 to 2022 had only 5576 units in operation and accounted for less than 20% of exports⁹.

3.3.4. Development Enterprises and Services Hub (DESH) Bill 2022

The Special Economic Zone Policy 2005 was replaced by a new law in the 2022 budget. The Development Enterprises and Services Hub (DESH) Bill aims to establish development hubs. Its objectives are to maintain the competitiveness of "manufacturing" and exports, promote economic activity, create jobs, integrate with global supply and value chains, develop infrastructure facilities, and promote investment, including research and development.

The bill is expected to shift the focus from exports to domestic investment and lead to a paradigm shift by integrating several SEZ models, including Special Economic Zones, Coastal SEZs, and Food and Textile Parks¹⁰. The purpose of the bill is to go beyond an export-oriented approach and establish "manufacturing clusters through foreign direct investment for domestic production in India".

As of 2024, some incentives for setting up procurement and manufacturing platforms within India's SEZs include duty-free import and domestic procurement of goods, 100% income tax exemption on export income from SEZ units for the first five years, 50% for five years thereafter, and 50% of export profits ploughed in for the next five years¹¹.

As of September 2022, the Indian state of Tamil Nadu had the highest number of operational Special Economic Zones (SEZs), followed by Maharashtra and Telangana. As of

2023, India has 272 SEZs, employing a combined 2.8 million people¹². These SEZs generate approximately USD 133 billion in exports, with services exports, rather than manufacturing exports, accounting for about 60% of these exports.

3.3.5. Issues in the Segment of the Investment Environment

The Government of India has initiated several steps to improve the investment attractiveness of SEZs and has constituted the Baba Kalyani Committee to recommend changes in India's SEZ policy based on inputs from various stakeholders¹³. Investment attractiveness, or the investment environment, depends on which segments of the agglomeration are well-developed.

This paper examines the shortfalls of segments in India in terms of foreign direct investment compared to China and other Asian countries and identifies the factors that contribute to this shortfall. The conclusion is that the shortage of engineers is the cause of the brake on the building of manufacturing industrial agglomeration.

4. Methods and Materials

4.1. The Model of Helpman and Krugman on Human Capital

The analysis is discussed in the following three steps. In this section, we obtained the hypothesis that the number of manufacturing agglomerations is inversely proportional to the present value of the lifetime wages of the "skilled labor force as human capital", which constitutes fixed capital, through a modified model of spatial economics. In other words, the number of manufacturing agglomerations is inversely related to the shortage of "skilled labor as human capital".

We follow the original model of Helpman and Krugman (1985) in their new trade theory in spatial economics: "They derived the equilibrium number of firms based on a general equilibrium model; Their model consists of two countries, 1 and 2, where the two sectors are manufacturing and agriculture, the population L_k of country k ($=1, 2$) is constant; The model assumes that firms produce a variety of differentiated goods in both countries 1 and 2".

We describe the behavior of the consumer. The consumer's expenditure minimization problem is solved. There are two types of consumption goods: agricultural consumption, which is homogeneous goods, and differentiated goods consumption. Agricultural consumption for unskilled workers in country k is denoted as A_k . Differentiated goods consumption is denoted by M_k and is a CES type of substitution function defined over a continuous variety of consumption goods.

In the first step, minimizing a representative consumer's expenditure subject to differentiated goods consumption M_k yields the first-order conditions. Notations are as follows: the number of differentiated products, or firms, in country k is given as n_k ; $p_{sk}(i)$ is the price of the goods i produced in country s and consumed in country k ; m_{sk} is the consumption of goods produced in country s and consumed in country k ; and the parameter σ is the elasticity of substitution between any two of the varieties of goods. Minimizing (2) subject to (1) yields the first-order conditions, where M_k is given as

$$M_k = \left[\sum_{s=1}^2 \int_0^{n_s} m_{sk}(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \text{ for } k = 1, 2, \text{ and} \quad (1)$$

a representative consumer's expenditure is

$$\sum_{s=1}^2 \int_0^{n_s} p_{sk}(i) m_{sk}(i) di. \quad (2)$$

In the second step, the utility maximization problem is solved subject to budget constraints. The utility function of a representative skilled worker in country k is given as

$$U_k = M_k^\mu A_k^{1-\mu}, \text{ for } k = 1, 2. \quad (3)$$

The budget constraints for representative skilled workers in country 1 and country 2, respectively, are given as

$$y_k = \sum_{s=1}^2 \int_0^{n_s} p_{sk} m_{sk}(i) di + A_k, k = 1, 2. \quad (4)$$

The utility function of a representative skilled worker in country k is a Cobb–Douglas type. Then, Helpman and Krugman (1985) obtained

$$m_{sk}(i) = (p_{sk}(i)^{-\sigma} / P_k^{1-\sigma}) y_k \mu, \text{ for } k = 1, 2, s = 1, 2, \quad (5)$$

where $P_k = [\sum_{s=1}^2 \int_0^{n_s} p_{sk}(i)^{1-\sigma} di]^{1/(1-\sigma)}$, for $k = 1, 2$.

Next, firms maximize profit. Each firm produces and also trades one good and incurs a variable cost c and a fixed cost F_k . The profit $\pi_k(i)$ of a firm producing variety i in country k and selling in countries k and s is given as

$$\pi_k(i) = \pi_{kk}(i) + \pi_{ks}(i) - F_k = (p_{kk}(i) - c) m_{kk}(i) L_k + (p_{ks}(i) - \tau c) m_{ks}(i) L_s - F_k, \quad (6)$$

for $k = 1, 2, s = 1, 2, s \neq k$,

where L_k is the population number, τ is the “iceberg” transport costs.

The first-order conditions determine the equilibrium prices,

$$p_{kk}(i) = p = \sigma c / (\sigma - 1), p_{ks}(i) = \tau p, \text{ for } k = 1, 2, s = 1, 2, s \neq k, \text{ and} \quad (7)$$

$$P_k = p (n_k + n_s \varphi)^{1/(1-\sigma)}, \text{ for } k = 1, 2, s = 1, 2, s \neq k, \quad (8)$$

where $\varphi \equiv \tau^{1-\sigma}$.

Substituting (5), (7), and (8) in (6) obtains the firm’s profits producing variety i in country k :

$$\pi_k(i) = (\mu/\sigma) [(y_k L_k)/(n_k + \varphi n_s) + (\varphi y_s L_s)/(\varphi n_k + n_s)] - F_k.$$

for $k = 1, 2, s = 1, 2, s \neq k$.

Here, different from Helpman and Krugman’s (1985) fixed costs, this paper assumes that fixed capital consists of human capital (H) and physical capital (F). According to Pflüger (2003), manufacturing engineers, or skilled labor, belong to human capital. Their lifetime wage is assumed to be W_{kE} . In the “manufacturing” sector, engineers and so-called skilled workers are included in the category of skilled labor. Hence, engineers and skilled workers can be assumed to be human capital as a fixed factor of production rather than a variable factor of production.

$$F_k = W_{kE} H_{kE} + F_{kP}$$

where W_{kE} are the lifetime wages of skilled labor in country k , H_{kE} are the number of engineers in country k , and F_{kP} are the fixed costs of physical capital in country k .

Thus, the zero-profit conditions obtain

$$n_k = (\mu/\sigma) [y_k L_k / (F_k - \varphi F_s) + \varphi y_s L_s / (\varphi F_k - F_s)], k = 1, 2, s = 1, 2, s \neq k.$$

We derive the following equation:

$$\partial n_k / \partial W_{kE} = -(\mu/\sigma) H_{kE} [y_k L_k / (F_k - \varphi F_s)^2 + \varphi^2 y_s L_s / (\varphi F_k - F_s)^2] < 0, \text{ and}$$

Thus, the above equation reveals that the number of firm agglomerations is inversely related to the fixed cost F_k . The higher W_{kE} is, the closer the number of firms approaches zero. In other words, $N \rightarrow 0$ when the number of skilled labor as human capital is insufficient and

$W_{kE} > W_{kE}^{UL}$. We obtain the following result:

Result 1. *The number of manufacturing agglomerations is inversely related to the shortage of “skilled labor as human capital”.*

4.2. Materials

Factor analysis extracts the common factors (f) latent behind the observed variables. The observed data are the explained variable (x_i). The common factor is the “communality”, or the explanatory variable (f), and the part that cannot be explained by the common factor is the “uniqueness” (u_i), which is the unique factor of (x_i), then $x_i = b_{ij} f + u_i$. The coefficient (b_{ij}) of the explanatory variable that is the common factor are the factor “loadings”. Using the variance–covariance matrix of x_i , they are obtained by multiplying the square root of the eigenvalues of the factor loading matrix by the eigenvector u .¹⁴

Factor “scores” are explained in the following. The factor loadings in factor analysis represent the correlations between observed variables (x_i) and the underlying latent factors (f). Each factor loading (b_{ij}) indicates the strength and direction of the relationship between a particular variable and a particular factor. Higher factor loadings indicate a stronger association between the variable (x_i) and the factor (f), suggesting that the variable (x_i) contributes more to the definition of the factor (f).

Factor scores in factor analysis refer to the estimated scores or values of the latent factors (f) for each individual or observation in the data set. These scores are calculated based on the observed variables and the factor loadings obtained from the factor analysis model. The factor score essentially reflects the degree to which each individual exhibits the characteristics associated with the latent factors (f) identified by the factor analysis.

JETRO (2022) examines a segment of investment-related costs, as shown in Table 4 as an example. The costs correspond to the segments of Japanese companies operating in 100 cities and regions in about 60 countries. The original data used are shown in “Table A2. Data for Factor Analysis” in Kuchiki (2023). Table 9 in Kuchiki (2023) is the list of the survey cities used in this paper. The result of the factor analysis is shown in Appendix Table A3 in Kuchiki (2023).

Table 4. Segments and investment-related costs.

The Environmnet of Investment in the Manufacturing Industry		US\$
W1	worker (general labor)(per month)(manufacturing)	469
W2	engineer (intermediate technician) (per month)(same as above)	768
W3	middle management (section chief) (per month)(same)	1677
W4	staff (general office work) (per month)(non-manufacturing)	722
W5	manager (section chief) (per month)(same as above)	1584
Z1	industrial zone (land) (purchase price) (per square meter)	27.8
Z2	industrial zone rent (per square meter, per month)	4.76
Z3	office rent (per squre meter, per month	30.1
P1	commercial electricity rates (pre 1 kWh)	0.54
P2	commercial water rates (per cubic meter)	0.77
P3	commercial gas rates (per 1 kg)	0.64
C1	container transport to Japan (40 ft)	1420
C2	container transport to the third country (40 ft)	12,450

Note: The environment is the case of Mumbai, India. Source: Author’s based on Japan External Trade Organization (JETRO 2022).

Table 4 is the list of the investment-related costs consisting of the wages of workers (general labor) (W1), engineers (intermediate technician) (W2), middle management (section chief) (W3), staff (general office work) (W4), and managers (section chief) (W5) in the case of Mumbai, India. Other costs are leased prices of industrial zones (Z2), purchased rents for industrial zones (Z1), commercial electricity rates (P1), and container transportation to Japan (C1). Here, W1, W2, W3, W4, and W5 refer to the monthly wages of the various types of labor.

JBIC (2007–2022) Survey Report on Overseas Business Operations by Japanese Manufacturing Companies from 2007 to 2022 aimed to research and analyze the current status and future prospects for overseas business development of Japanese manufacturing companies. The companies targeted in this survey are Japanese manufacturing companies which have three or more overseas affiliates. This paper uses the data of the details of both issues and promising reasons, and, in particular, focuses on the details of issues. Factor analysis is applied to the top ten countries from 2007 to 2022. The six countries are India, Vietnam, Indonesia, Thailand, the US, and China. For example, regarding (Japan Bank for International Cooperation) (JBIC 2007–2022), the number of surveyed companies is 946, and the number of respondents is 531. This paper provides a factor analysis regarding the reasons for the high potential and the reasons for the issues in investing in the promising investment countries.

China was the first promising country in 2018. Appendix A illustrates the statistics of promising and issue items in Tables A1 and A2, respectively. Among the issue items in Table A2, which are China's challenges, the issue item with the highest number of firms is (o) Intense competition with other companies with 132 firms, and the item with the second-highest number of firms is (m) Rise in labor costs with 129 firms. However, it is noteworthy that the issue items with consistently high loading scores in the factor analysis are institutional reasons such as (h) Insufficient protection of intellectual property rights and (i) Foreign exchange and remittance restrictions.

We use high potential, or promising reasons, which are conditions that promote industrial agglomeration in each country. Appendix B shows the factor loadings as follows: The first factor, ML1, represents 'FDI-led agglomeration': (o) Local logistics services (1.1); (n) Local physical infrastructure (1); (r) Stable political and social conditions (1); (l) Profitability of local market (0.9); and (m) A base for product development (0.7).

The second factor, ML2, represents 'Human resources of low-wage labor': (b) Low-wage labor (0.7); (a) Excellent human resources (0.5); and (f) Risk diversification receptacle for other countries (0.6).

The third factor, ML3, represents 'Export processing zone': (p) Preferential tax incentives for investment (0.9); (q) Stable policies to attract foreign investment (0.9); (h) An export base to Japan (0.8); (g) An export base to third countries (0.6); and (d) A supply base to assemble makers (0.4).

The fourth factor, ML4: 'Raw material procurement': (i) Advantage in procurement of raw materials (0.6); and (c) Cheap parts and raw materials (0.5). Here, the values of parentheses are factor loadings (Kuchiki (2023), pp. 10–11).

This paper focuses on the issues that hinder industrial agglomeration. Regarding the factor loadings of the issues of investment, ML1 of Institutional Issues consists of (h) Insufficient protection of intellectual property rights (1), (i) Foreign exchange and remittance restriction (1), (b) Unclear operation of legal system (0.9), and (p) Difficulty in collecting payments (0.9).

In terms of the operation of the legal system, they are (f) Strengthening of taxation (0.9), (j) Import regulations and customs procedures (0.8), (e) Strengthening taxation (0.8), (g) Investment licensing procedures are complicated and unclear (0.8), (m) Rise in labor costs (0.8), (d) Operation of the tax system is unclear (0.7), (q) Difficulty in raising funds (0.5), and (n) Labour issues' (0.5).

ML 2 of Industrial Agglomeration consist of (r) Underdevelopment of local supporting industries (1.1), (a) Underdeveloped legislation (1), (t) Underdeveloped infrastructure (0.9), (o) Intense competition with other companies (−0.9), (v) Lack of information on investing countries (0.9), and (s) Lack of currency and price stability (0.7).

ML 3 of Human Capital of Engineers and Managers consists of (k) Difficulty in securing local engineers (0.8) and (l) Difficulty in securing management-level personnel (0.8).

ML 4 of Insecurity and Social Instability consists of (u) Insecurity and social instability (0.8) and (c) Complexity of the tax collection system (0.5).

The factors that this paper will pay particular attention to in the next section are ML 3, Engineers and Managers. In particular, engineers as capital stock as a fixed factor of production in the manufacturing industry.

5. Empirical Analysis of Brake Segments

In this section, a factor analysis using JETRO data divided the investment environment segments into three factors: The first factor is workers (general labor) and staff (general office work). The second factor is middle management (section chief) and managers (section chief). The third factor is engineers (intermediate technician) for W2.

Furthermore, a factor analysis was conducted on the investment issues of FDI in the six most promising investment destinations for Japanese firms using JBIC data: the six countries are India, Vietnam, Thailand, Indonesia, China, and the United States. As discussed in Sections 3.3.3 and 3.3.4, among these countries, India has been braking because it is not as agglomerated as other countries in terms of exports. The results of the factor analysis and regression analysis proved the hypothesis that the issue in India's investment environment from 2007 to 2021, or a brake segment, is the "engineers" segment. Hence, we can conclude that the brake segment is engineers as human capital.

A summary of the results obtained by factor analysis reveals that only India has a factor score of more than 1 for having issues with engineers from 2007 to 2021 (not including 2022). For the other countries, the factor score exceeds 1 for Vietnam only for 2007 and 2008, and for Thailand only for 2020. In other words, we can conclude that engineers are the factor that poses a challenge to the establishment of industrial agglomeration in India.

5.1. Factor Analysis of Workers, Engineers, and Managers

Industrial agglomeration is basically formed at the city level. In most countries, the leading cities drive the economic growth of the country at the national level. Kuchiki (2020) in the Oxford Handbook of Industrial Hubs and Economic Kuchiki (2023) showed this fact for China and ASEAN, respectively. Therefore, we will conduct a factor analysis on a city-by-city basis.

As shown in Appendix C, the conclusion obtained in this section is that investment-related costs can be categorized into three factors. The first factor of ML 1 is workers (general labor) in W1 and staff (general office work) in W4. The second factor of ML 2 is middle management (section chief) for W3 managers and managers (section chief) for W5. The third factor of ML 3 is engineers (intermediate technician) for (W2). The definition of engineers (intermediate technician) (W2) does not include so-called skilled workers.

Therefore, the paper supposes that ML 3 of "engineers" belongs to skilled labor as the human capital of fixed costs in the manufacturing industry. Integrating this result with Result 1 yields the following result:

Result 2. *The number of manufacturing agglomerations is inversely related to the shortage of engineers as "human capital".*

5.2. Promising Factors of Investment

As shown in Table 5a, we conclude the characteristics of the factor scores for each country in the following. Vietnam has high scores for Factor 2, ranging from 1.13 to 3.09 between 2007 and 2022, and is promising with respect to inexpensive labor. Thailand has high scores for Factor 3, ranging from 0.5 to 2.44 between 2007 and 2022, and is promising in terms of foreign investment in EPZs, etc. The US has high scores for Factor 1, ranging from 0.97 to 3.18 between 2007 and 2022, and is promising in terms of industrial agglomeration. China has high scores for Factor 4, ranging from 0.77 to 2.15 between 2007 and 2015, and is promising for investment in cheap raw materials and cheap parts.

Table 5. (a) Factor scores of investment promising reasons by year by country by factor analysis. (b) Factor scores of investment issues by year by country by factor analysis.

(a)																								
India				Vietnam				Thailand				Indonesia				China				U.S.				
Agglo	FDI	Worker	Materi	Agglo	FDI	Worker	Materi	Agglo	FDI	Worker	Materi	Agglo	FDI	Worker	Materi	Agglo	FDI	Worker	Materi	Agglo	FDI	Worker	Materi	
2007	-0.77	-0.52	0.96	0.37	-0.32	1.28	3.09	-1.85	0.17	2.08	0.43	0.37	-0.90	-0.57	0.57	2.67	-0.88	0.59	-0.07	2.16	2.76	-1.06	-0.17	-0.61
2008	-0.74	-0.70	0.60	-0.12	-0.58	1.00	2.24	-1.53	0.11	1.63	0.08	-0.13	-0.93	0.66	0.43	1.76	-0.71	0.16	-0.20	2.10	2.05	-1.48	-0.24	-0.99
2009	-0.85	-0.83	0.43	0.27	-0.68	0.67	1.72	-0.69	0.21	2.26	-0.07	0.39	-0.84	0.21	0.22	1.09	-0.75	0.26	-0.25	2.00	1.42	-1.54	-0.44	-1.21
2010	-0.85	-0.68	0.56	0.76	-0.60	0.51	1.89	-0.23	0.02	2.06	-0.34	1.46	-0.82	-0.24	0.70	1.26	-0.43	0.10	-0.68	2.03	1.75	-1.33	-0.47	-0.91
2011	-0.79	-0.60	0.35	0.48	-0.84	0.29	1.64	0.64	0.17	2.45	-0.49	1.09	-0.71	-0.08	0.52	0.78	-0.55	0.19	-0.84	1.66	1.95	-0.86	-0.63	-0.65
2012	-0.89	-0.71	0.13	0.67	-0.88	0.35	1.52	0.03	0.36	2.42	-0.37	0.15	-0.79	-0.35	0.39	0.23	-0.53	-0.13	-1.01	1.28	2.04	-1.15	-0.43	-0.83
2013	-0.80	-0.59	-0.02	0.25	-0.62	-0.03	1.92	-0.55	0.70	2.30	-0.30	-0.24	-0.62	-0.26	0.26	0.20	-0.38	-0.26	-1.48	0.93	2.40	-1.09	-0.25	-0.52
2014	-0.80	-0.80	0.00	0.34	-0.62	0.08	1.49	-0.36	0.36	2.34	-1.21	0.70	-0.64	-0.52	-0.14	-0.27	-0.21	-0.37	-1.23	0.77	3.19	-1.16	0.15	-0.68
2015	-0.79	-0.45	-0.17	0.32	-0.12	-0.16	1.85	-1.07	-0.13	1.52	-0.96	1.02	-0.60	-0.60	0.15	0.29	-0.17	-0.58	-1.58	1.03	2.23	-0.97	-0.48	-0.68
2016	-0.74	-0.63	-0.29	0.14	-0.34	-0.40	1.27	-0.96	-0.17	1.48	-0.95	-0.10	-0.74	-0.46	-0.21	-0.02	-0.25	-0.58	-1.38	0.36	2.41	-1.06	-0.37	-0.58
2017	-0.73	-0.62	-0.05	0.04	-0.28	0.00	1.72	-0.87	0.19	1.57	-0.70	-0.79	-0.65	-0.40	-0.12	0.33	-0.20	-0.45	-1.40	0.63	1.63	-1.11	-0.87	-0.29
2018	-0.68	-0.59	-0.29	0.08	-0.33	0.24	1.60	-0.59	0.33	1.16	-0.42	-0.92	-0.61	-0.51	-0.42	-0.26	0.02	-0.44	-1.33	0.49	1.60	-0.80	-0.77	-0.84
2019	-0.70	-0.55	-0.17	0.21	-0.12	0.12	1.36	-1.18	0.42	0.99	-0.79	-0.70	-0.60	-0.37	-0.14	-0.84	0.10	-0.41	-1.54	0.08	0.97	-0.87	-1.07	-0.79
2020	-0.85	-0.53	0.00	0.31	-0.38	-0.01	1.14	-0.93	0.24	0.51	-0.42	-0.92	-0.77	-0.31	-0.16	-0.27	-0.03	-0.50	-1.66	0.61	1.80	-0.80	-0.79	-0.67
2021	-0.87	-0.55	-0.15	0.24	-0.27	0.48	1.60	-1.79	0.32	1.90	-0.57	-1.51	-0.75	0.11	0.03	-0.18	0.23	-0.31	-1.50	0.00	1.50	-1.00	-0.66	-1.05
2022	-0.73	-0.46	0.01	-0.43	0.09	0.76	2.24	-1.50	0.47	1.95	0.07	-1.02	-0.49	-0.13	0.15	-0.28	0.24	-0.33	-1.46	0.04	1.91	-0.80	-0.66	-0.73

(b)																								
India				Vietnam				Thailand				Indonesia				China				U.S.				
Engi	Agglo	Insti	Secu	Engi	Agglo	Insti	Secu	Engi	Agglo	Insti	Secu	Engi	Agglo	Insti	Secu	Engi	Agglo	Insti	Secu	Engi	Agglo	Insti	Secu	
2007	1.20	-0.77	-0.44	-0.09	0.73	0.36	0.15	-0.08	0.65	0.11	0.31	0.53	-0.81	0.90	0.41	1.59	0.12	-1.11	1.27	-0.08	0.89	-1.26	-1.16	-1.01
2008	0.80	-0.70	-0.43	0.27	1.75	2.23	-0.41	-1.65	0.03	0.50	-0.49	0.78	-1.01	1.67	-0.17	1.10	-0.44	0.37	2.43	0.21	-0.52	-1.43	-1.13	-1.15
2009	0.86	-0.68	-0.84	-0.31	1.01	1.40	-0.49	-0.59	0.34	0.83	-0.15	0.30	-1.24	1.40	-0.33	0.96	-0.40	0.18	2.21	0.36	-1.22	-1.31	-1.48	-1.57
2010	1.20	-0.78	-0.70	-0.16	0.94	1.16	-0.21	-0.70	0.67	0.67	-0.36	0.87	-1.47	1.28	-0.05	1.08	-0.91	-0.35	1.97	-0.17	-0.76	-1.36	-1.35	-1.57
2011	0.98	-0.59	-0.96	0.25	0.59	0.86	-0.55	-0.84	0.27	0.03	-0.66	-0.29	-1.52	1.23	1.08	1.37	-0.33	-0.38	2.11	-0.10	-1.26	-1.26	-1.37	-1.48
2012	1.23	-0.72	-0.78	0.12	-0.38	1.47	0.05	-0.41	-0.18	0.62	-0.24	0.16	-1.52	1.23	1.08	1.37	-0.91	-0.31	2.29	0.45	-1.56	-1.40	-1.25	-1.62
2013	0.82	-0.75	-0.84	-0.32	0.26	1.48	-0.45	-0.94	0.06	0.62	-0.32	0.09	-1.58	1.39	0.07	1.01	-0.53	-0.41	2.21	0.18	-1.06	-1.21	-1.23	-1.35
2014	1.40	-0.87	-0.82	-0.46	0.45	1.12	-0.36	-0.67	0.47	0.56	-0.22	0.40	-1.78	1.29	1.01	1.89	-0.46	-0.60	1.94	0.32	-1.51	-1.43	-1.20	-1.42
2015	1.02	-0.69	-0.70	0.14	0.94	1.36	-0.02	-0.47	0.47	0.73	0.27	0.48	-1.67	1.37	0.28	1.67	-0.24	-0.75	2.10	0.60	-1.20	-1.33	-1.07	-1.35
2016	1.46	-0.68	-0.66	-0.33	0.68	0.62	-0.13	-0.90	0.24	0.65	0.58	0.94	-1.71	1.30	0.55	2.12	-0.18	-0.78	1.84	0.00	-1.48	-1.28	-1.48	-1.57
2017	1.54	-0.70	-0.68	0.18	0.53	0.76	-0.16	-0.37	-0.05	0.38	0.42	0.53	-1.83	1.25	0.35	2.01	-0.19	-0.85	1.62	0.03	-0.64	-1.29	-1.30	-1.29
2018	1.73	-0.77	-0.52	-0.03	0.84	0.70	-0.05	-0.51	0.86	0.31	0.51	1.06	-1.33	1.31	0.81	2.32	-0.46	-0.73	1.96	0.47	-0.29	-1.28	-1.09	-1.10
2019	1.41	-0.86	-0.73	-0.17	0.94	0.74	-0.05	-0.84	0.03	0.26	0.19	0.41	-1.27	1.04	0.41	1.05	-0.07	-0.85	1.42	-0.26	-0.14	-1.31	-1.08658875	-1.02
2020	0.96	-0.96	-0.75	-0.48	0.69	0.47	-0.23	-1.27	0.54	0.34	-0.13	0.12	-1.07	1.11	0.29	1.17	0.32	-0.99	1.29	0.03	0.06	-1.24	-1.01	-0.90
2021	1.24	-0.84	-0.67	-0.66	0.50	0.26	-0.24	-0.92	1.11	0.50	0.05	0.20	-1.10	0.70	0.08	1.39	-0.26	-1.03	1.40	-0.07	0.30	-1.23	-1.17	-1.03
2022	0.91	-1.02	-0.64	-0.19	0.17	0.46	0.39	-0.41	0.39	0.60	0.57	0.89	-1.27	1.14	0.45	1.95	-0.13	-1.06	1.53	0.31	0.78	-1.17	-1.18	-0.69

Note: Agglo = Agglomeration, FDI = Foreign Direct Investment-led, Worker = Workers, Materi = Materials. Note: fa(p33,nfactors = X, fm = "ml", rotate = "promax") Scores by Program R. X = Number of eigen values greater than 1. Engi = Engineers, Insti = Institutions, Secu = Security. fa(p33,nfactors = X, fm = "ml", rotate = "promax") by Program R. X = Number of eigen values greater than 1. Source: Author's calculation.

When a factor score is 0.7, the variable has a strong relationship with the factor. When a factor score is 1.0, the variable is completely related to the factor.

Finally, India, however, is promising for investment in terms of engineers as human capital only in 2007 and 2008, but not in other areas.

5.3. Issues of Investment as “Brake Segment”

In this subsection, we reach the main conclusion of this paper that “engineers” are a brake segment as human capital for industrial agglomeration policies in the manufacturing industry. Factor scores of India are high at the factor consisting of both the items of difficult to secure technical/engineering staff and difficult to secure management-level staff.

5.3.1. Factor 1: Institutions

As shown in Figure 6, institutional issues were identified as the number one factor for investment issues in promising countries. These include ‘Insufficient protection of intellectual property rights’ (1), ‘Foreign exchange and remittance restriction’ (1), ‘Unclear operation of legal system’ (0.9), and ‘Difficulty in collecting payments’ (0.9). In terms of the operation of the legal system, ‘Investment licensing procedures are complicated and unclear’ (0.8) and ‘Operation of the tax system is unclear’ (0.7) were cited. ‘Difficulty in raising funds’ and ‘Labour issues’ (0.5) were also cited.

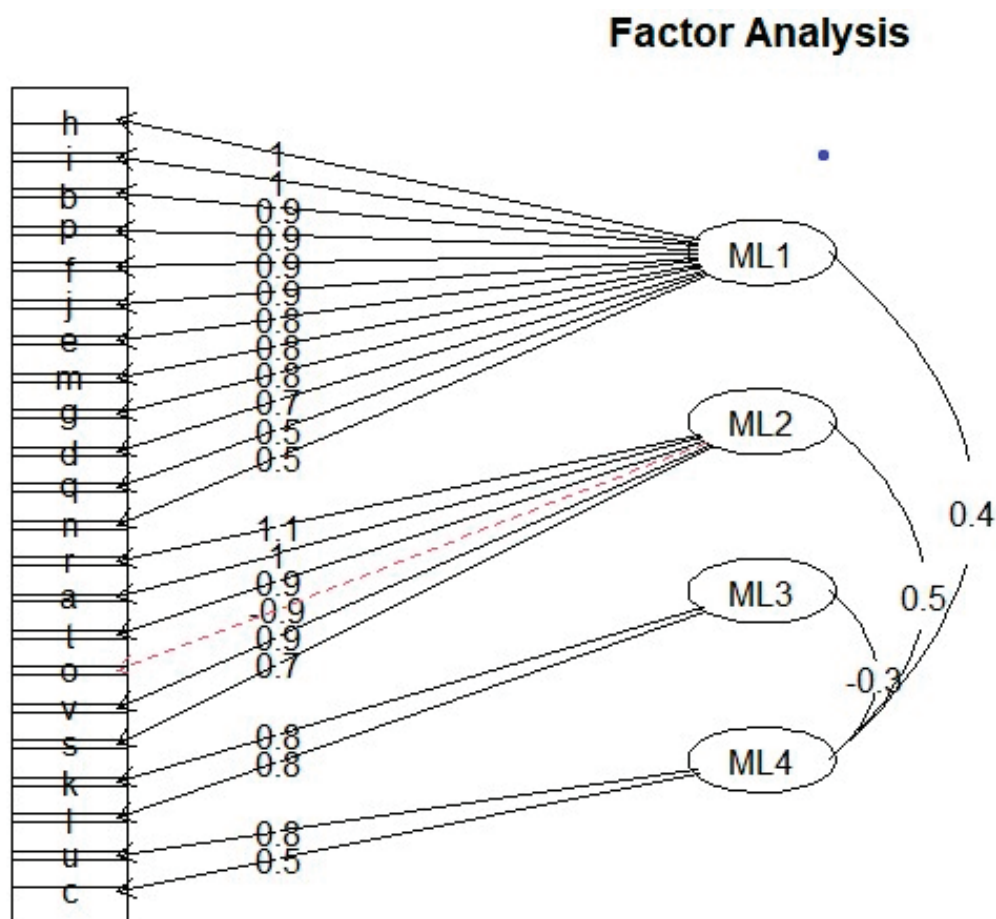


Figure 6. Factor loadings of investment issues. Note: The numbers above the arrows are factor loadings. Source: Author’s calculation.

5.3.2. Factor 2: Industrial Agglomeration

The following industrial agglomeration factors were identified: ‘Underdevelopment of local supporting industries’ (1.1); ‘Underdeveloped legislation’ (1); ‘Underdeveloped infrastructure’ (0.9); ‘Lack of information on investing countries’ (0.9) and ‘Lack of currency and price stability’ (0.7).

5.3.3. Factor 3: Human Capital of Engineers

‘Difficulty in securing local engineers’ (0.8), and ‘Difficulty in securing management-level personnel’ (0.8).

5.3.4. Factor 4: Insecurity and Social Instability

The issue of ‘insecurity and social instability’ (0.8) is significant. Note that ‘complexity of the tax collection system’ (0.5) is included in Factor 4.

Next, this section examines the characteristics of each country’s factor score regarding issues in investment. As shown in Table 5b, India alone has high scores for Factor 3, ranging from 0.80 to 1.73 between 1.2 in 2007 and 0.91 in 2022, indicating issues for engineers and managers. Vietnam has high scores for Factor 2, ranging from 0.86 to 2.23 between 2.23 in 2007 and 1.36 in 2018, indicating that industrial agglomeration was the issue. Thailand has no high scores for all factors.

Indonesia has high scores for both Factor 1 and Factor 4. Factor 1 ranged from 0.96 to 2.32 between 1.1 in 2007 and 1.59 in 2022, and Indonesia faced issues related to institutions and instability, such as social unrest and the tax collection system. Factor 4 ranged from 0.7 to 1.67 between 1.67 in 2007 and 0.9 in 2022, and Indonesia faced the problem of security. China has high scores for Factor 1, ranging from 1.27 to 2.43, indicating issues with the legal system. The US has no high scores for all factors between 2007 and 2018.

Table 6 is summary by combining the results of a and Table 5a,b India shows no promising item for investment and has issues with engineers and managers. Vietnam has issues with engineers only in 2007 and 2008 but has an abundance of low-wage labor and has been a good recipient of China’s relocation. Thailand has no investment issues and is promising for the introduction of foreign direct investment. China has no promising points and has issues with its legal system. Indonesia has the issues of both institutions and security. The US has no investment issues and is promising for industrial agglomeration.

Thus, the issues related to investment in India are engineers and managers. The issues of engineers are the factors that hinder the industrial agglomeration of SEZs in India and are the “brake segment” for building industrial agglomeration.

The summary of issues and promising reasons by factor analysis in Table 6 gives policy recommendations as of 2022 to promote manufacturing agglomeration to the five target countries other than India. China has an issue on institutions but does not have an issue on engineers as human capital. Therefore, institutional reform is needed. Indonesia has both issues of institutions and security, so institutional reform and improvement of security are needed.

The US and Thailand will have no issues in 2022. In the US, the agglomeration item is promoting, and in Thailand, the FDI-led item is promoting. Both countries should continue developing engineers as human capital in order to promote the agglomeration of manufacturing industries. In Vietnam, the workers item is promoting, and the issue of engineers as human capital was resolved in 2022. Therefore, it is necessary to continue the current development of engineers as human capital. As a whole, the results in Table 6 indicate that the condition for the continuation of the process of industrial agglomeration in any country is the development of engineers as human capital.

Table 6. Summary of issues and promising reasons by factor analysis.

		Issues				Promising Items			
	Year	Engineers	Agglomeration	Institutions	Security	Agglomeration	FDI-led	Workers	Raw Materials
India	2007	1.2							
	2021	1.24							
	2022	0.91							
Vietnam	2007	1.74	2.23					3.09	
	2008	1.01	1.4					2.24	
	2011		1.47					1.63	
	2014		1.36					↓	
	2022							2.24	
Thailand	2007						2.07		
						↓			
	2018					1.15			
	2020	1.11				0.99			
	2021					1.9			
2022		1.94							
Indonesia	2007			1.67	1.09				2.7
	2010			1.23	1.07				1.26
	2022			↓ 0.9	↓ 1.59				
China	2007			2.42					2.15
	2015			↓					1.02
	2016			↓					
	2022			1.26					
U.S.	2007					2.75			
	2022					↓ 1.9			

Source: Author's.

Next, the relationship between the “industrial agglomeration” factor of the promising reasons in Table 5a and the “four factors” of the issues in Table 5b will be regressed. The industrial agglomeration factor of the promising reasons for the investment environment in Table 5a is the objective variable, and the factor scores of the issues of “engineers”, “agglomeration”, “safety”, and “institutions” in Table 5b are the independent variables. The results are as follows:

$$\text{Agglomeration} = 0.01007 - 0.49339 \text{ Engineers} - 0.34550 \text{ Agglomeration issue}$$

$$(0.158) (-6.744) *** (-4.479) ***$$

$$-0.28121 \text{ Institutions} - 0.41943 \text{ Security}$$

$$(-3.781) *** (-4.404) ***$$

(Adjusted R-squared is 0.6059, F-statistic is 37.52 on 4 and 91 DF, and p-value is 2.2×10^{16} and *** is significant at the 0 percent level. The numbers in parentheses are t-values).

The factor scores for the investment environment issues of engineers, agglomeration, safety, and institutions are negatively related to the factor scores for the promising reasons for industrial agglomeration. The coefficients for all independent variables are negative, indicating that these issues have a negative impact on agglomeration building. The coefficient for engineers was 0.493, the highest of the four factors. In other words, the issue of engineers was confirmed to have a negative impact on the promising reasons for industrial agglomeration.

In summary, first, this paper applied a spatial economic model to obtain Result 1. In the “manufacturing” sector, engineers and so-called skilled workers are included in the category of skilled labor. Engineers can be assumed to be human capital as a fixed factor of production rather than a variable factor of production. Therefore, the shortage of engineers in the manufacturing sector can be a brake on agglomeration.

Second, factor analysis using JETRO data found that investment-related costs can be categorized into three factors. The first factor of ML 1 is workers (general labor) in W1 and staff (general office work) in W4. The second factor of ML 2 is middle management (section chief) for W3 managers and managers (section chief) for W5. The third factor of ML 3 is engineers (intermediate technician) for (W2). The definition of engineers (intermediate technician) (W2) does not include so-called skilled workers. The paper supposes that ML 3 of “engineers” belongs to skilled labor as the human capital of fixed costs in the manufacturing industry. Integrating this result with Result 1 yields the following Result 2: the number of manufacturing agglomerations is inversely related to the shortage of engineers as “human capital”.

Third, the factor analysis based on the manufacturing survey reveals that the factors that make up ML 3, where the factor scores for investment challenges in India are higher, are (k) Difficulty in securing local engineers (0.8) and (l) Difficulty in securing management-level personnel (0.8). In other words, India’s investment challenge is the shortage of managers and engineers.

Taking the above three points together, we can judge that engineers as human capital belong to a brake segment. It is noted that we do not rule out the possibility that other segments, including managers, belong to a brake segment. In conclusion, the segment of “engineers” as human capital is one of the “brake segments”.

6. Conclusions and Summary

India has not matched the size and success of East Asian industrial hubs, including China. Therefore, it is necessary to identify the missing segments of the investment environment for the introduction of foreign direct investment. The “segments” constitute the organization of agglomerations. Each segment then has a specific function in the process of building industrial agglomeration. We focus on the process of building segments in agglomeration formation. We define a “brake segment” as a segment that has the “function” of decelerating the speed of the process of building segments.

This paper identifies brake segments in the process of constructing segments of industrial agglomeration. A variant model of spatial economics and factor analysis of investment environment cost data yielded the result that the number of agglomerated firms is inversely related to the wages of engineers. Factor analysis and regression analysis of the six most promising investment destinations for Japanese firms using JBIC data were conducted on the investment challenges of foreign direct investment. The six countries are India, Vietnam, Thailand, Indonesia, China, and the US. Only India has a braking segment, due to the fact that it is the only one of these countries that has not increased its agglomeration as much as the others. As a result of the analyses, India’s issue for the investment environment from 2007 to 2021 was the “engineer” segment. Hence, the conclusion of this paper is that the “brake segment” is “engineers as human capital”.

As a policy recommendation, this paper provides steps that can be used for industrial agglomeration policies, as shown in Figure 2. First, the construction of agglomeration begins with an onset of the master switch. The master switch for manufacturing agglomer-

ation is to develop transportation infrastructure that reduces transport costs and attracts firms that produce heterogeneous goods with low elasticity of substitution. Second, the accelerator segment of agglomeration is the construction of industrial parks.

Third, identifying the braking segment is an essential proposition for policy makers in regions where the process of segment building is not yet in progress. Since the segment that acts as a brake in the agglomeration building process is engineers as human capital, the implication of this paper is to implement human resource development for engineers from “the initial stage”. The process of building industrial agglomeration requires “the continuous development” of engineers as human capital. If the development of human capital becomes a bottleneck, the process of building industrial agglomeration will likely come to a standstill.

This approach can be used to determine the sequencing of official development assistance (ODA) in developing countries. First, ODA can be effective in building segments that will be turned on by a master switch to initiate an agglomeration policy. Second, human resource development of engineers needs to be implemented and continued from the beginning. Policy makers need to keep these two points in mind to initiate and continue the process of building the manufacturing agglomeration.

Table 7 summarizes the contributions of this paper. We linked spatial and sequence economics for tourism, urban agglomeration, and manufacturing. We focused on the segments that constitute the organization of agglomerations. We then identified the functions of the segments and specified master switch and accelerator segments. This paper identified the brake function.

Table 7. Linking spatial economics and sequencing economics.

Agglomeration	Location	Function	Segment	Spatial Economics	Sequencing Economics
Tourism industry	Osaka, Japan	(1) Master switch	commuter costs	Henkel et al. (2000)	Kuchiki (2021)
Urban agglomeration	Sapporo, Japan	(1) Master switch	commuter costs	Krugman (1991), Alonso (1964)	Kuchiki and Sakai (2023)
Manufacturing	Industrial hubs, China	(2) Accel	industrial zones	Helpman and Krugman (1985)	Kuchiki (2023)
Manufacturing	Industrial hubs, India	“(3) Brake”	“engineers”	Helpman and Krugman (1985)	“This paper”

Source: Author’s.

The contribution of identifying segment functions can be explained below. Descriptive case studies on industrial agglomeration are numerous. The Oxford Handbook of Industrial Hubs and Economic Development by Oqubay (2020) provides a comprehensive analysis of the factors behind the success and failure of industrial agglomeration in Asia, Latin America, and Africa. The Oxford Handbook of Industrial Hubs and Economic Development by Lin and Oqubay provides a comprehensive analysis of the factors behind the success and failure of industrial agglomeration in Asia, Latin America, and Africa. Oqubay (2020) pointed out that Taiwan successfully pioneered an export processing zone at Kaohsiung Harbour, which aimed to attract investment and develop the manufacturing sector, especially for exports. Pietrobelli (2020) found that most examples in Latin America managed to create the conditions at the local level for private–private, public–private, and public–public collaboration. Oqubay and Kefale (2020) conclude that in Africa, effective mechanisms to develop production linkages remain weak in Ethiopia. Ahluwalia et al. (2018) argue that India lost its comparative advantage in labor-intensive production in the early stages of development due to very restrictive labor regulations in the formal sector and strong trade unions. Descriptive case studies on industrial agglomeration are numerous in this way.

However, this paper identified the factors that pose issues to industrial agglomeration from the following different perspectives. This paper contributes to the analysis of the

process of industrial agglomeration formation posed by Kanai and Ishida (2000). The process of agglomeration formation proceeds through the construction of the segments that structure the agglomeration. This paper identifies the role, or function, of these segments, and, in particular, identified segments that function to decelerate the speed of the process.

In particular, the paper contributes to providing a means by which the theory of “spatial economics” can be used in industrial agglomeration policy. The location theory of spatial economics presents the breaking conditions from symmetric equilibrium to agglomeration equilibrium. However, the process of transition to an agglomeration equilibrium does not initiate unless those conditions are satisfied. This allows policy makers in industrial agglomeration to specifically determine the sequence of policy implementation. This paper presented successful examples of segment sequencing in the case of official development assistance (ODA) in Vietnam and Thailand.

There are four issues to be addressed in the future of this paper. First, the most important task is to identify the segment with the function of innovation activity. This paper focuses on the process of agglomeration. Fujita and Kuchiki (2006) defined industrial clusters as consisting of two components: agglomeration and innovation activation. The study of the function of segments for innovation activation is essential under the fourth industrial revolution.

Second, the number of case studies needs to be increased and inductive conclusions strengthened. There are similar research issues for other industry agglomerations. Knowledge industry, tourism industry, and urban agglomeration are some possible examples. We need to increase the number of case studies in order to attain conclusions, especially with regard to the empirical study.

Third, although factor analysis was used as the statistical method, it would be worth exploring other statistical methods to identify the functions of segments.

Fourth, the validity of the spatial economic model on which the conclusions of this paper are based also needs to be reexamined. With regard to the theoretical model, we need to consider cases in which the assumed assumptions change.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Promising items of investment.

		China 2018	
	Survey Item	# of Companies	Unit: %
a	Excellent human resources	25	11.3
b	Cheap labor	29	13.1
c	Inexpensive parts and raw materials	16	7.2
d	A supply base for assembly manufacturers	53	24.0
e	Industrial agglomeration	49	22.2
f	Hubs of risk diversification in other countries	5	2.3

Table A1. *Cont.*

		China 2018	
	Survey Item	# of Companies	Unit: %
g	An export base to Japan	10	4.5
h	An export base to third countries	23	10.4
i	Advantages of raw material procurement	9	4.1
j	Current size of local market	141	63.8
k	Future growth potential of local markets	161	72.9
l	Profitability of local market	18	8.1
m	Product development hubs	16	7.2
n	Well developed local infrastructure	30	13.6
o	Well developed local logistics services	18	8.1
p	Preferential tax treatment for investment	9	4.1
q	Stable policies to attract foreign investment	1	0.5
r	Stable political and social conditions	6	2.7
Total		221	100.0

Note: 1. # of companies = number of companies. 2. China is the first promising country in 2018 to invest. 3. For the factor analysis in this paper, 16 data sets from 2007 to 2022 were used for each of the tables of promising investment items and investment issues for China. For India, 16 data sets from 2007 to 2022 were also used. Similarly, 16 datasets were used for each of the other countries in Thailand, Vietnam, Indonesia, and the United States. Thus, the total number of data observed in each table used in the factor analysis is 96. Source: JBIC (2018).

Table A2. Issues of investment.

		China 2018	
	Survey Item	# of Companies	Unit: %
a	Underdeveloped legislation	18	8.1
b	Unclear operation of legal system	99	44.8
c	Insecurity and social instability	18	8.1
d	Operation of the tax system is unclear	39	17.6
e	Strengthening taxation	53	24.0
f	Control of foreign currency	45	20.4
g	Complicated and unclear investment licensing procedures	33	14.9
h	Insufficient protection of intellectual property rights	79	35.7
i	Foreign exchange and remittance restriction	62	28.1
j	Import regulations and customs procedures	53	24.0
k	Difficulty in securing local engineers	39	17.6
l	Difficulty in securing management-level personnel	43	19.5
m	Rise in labor costs	129	58.4
n	Labour issues	41	18.6
o	Intense competition with other companies	132	59.7
p	Difficulty in collecting payments	52	23.5
q	Difficulty in raising funds	11	5.0
r	Underdevelopment of local supporting industries	9	4.1
s	Lack of currency and price stability	14	6.3
t	Underdeveloped infrastructure	11	5.0
u	Complexity of the tax collection system	33	14.9
v	Lack of information on investing countries	6	2.7
Total		221	100.0

Note: 1. # of companies = number of companies. 2. China is the first promising country in 2018 to invest. 3. For the factor analysis in this paper, 16 data sets from 2007 to 2022 were used for each of the tables of promising investment items and investment issues for China. For India, 16 data sets from 2007 to 2022 were also used. Similarly, 16 datasets were used for each of the other countries in Thailand, Vietnam, Indonesia, and the United States. Thus, the total number of data observed in each table used in the factor analysis is 96. Source: JBIC (2018).

Appendix B

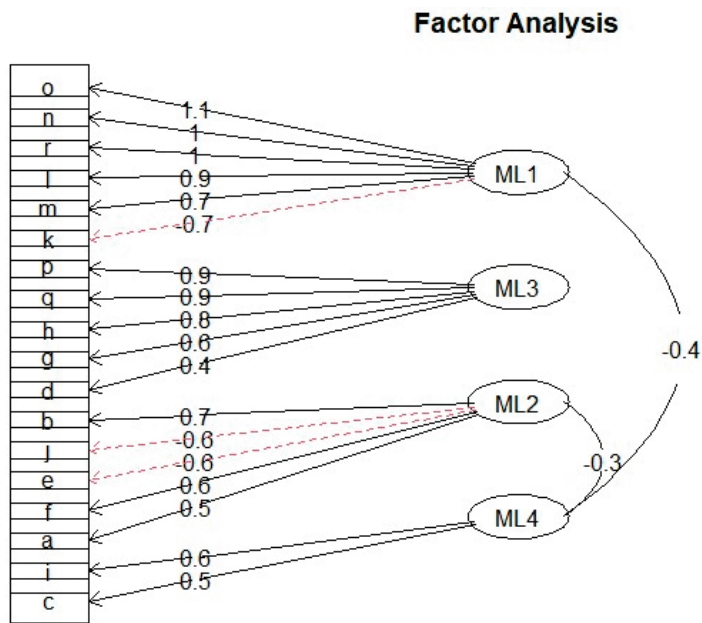


Figure A1. Source: Kuchiki (2023). Note: The numbers above the arrows are factor loadings.

Appendix C

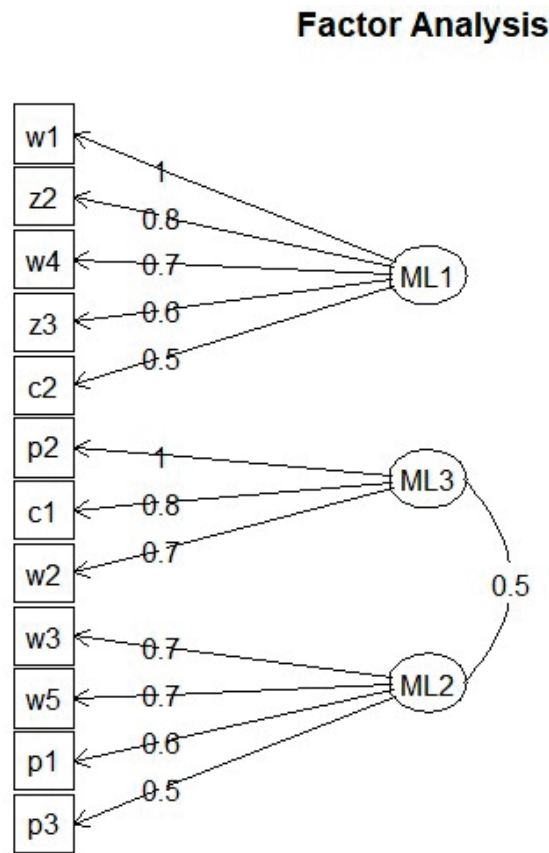


Figure A2. Source: Kuchiki (2023). Note: The numbers above the arrows are factor loadings.

Notes

- ¹ Data on GDP per capita are obtained from International Monetary Fund (2024).
- ² The facts of this section are based on Tran et al. (2003).
- ³ Mitsui (2004) also introduced the facts.
- ⁴ NESDB (2016) (Office of The National Economic and Social Development Board of Thailand and Office of The Eastern Seaboard Development Committee) outlined the Eastern Seaboard Development Program for industrial development in Thailand.
- ⁵ Lecler (2002) explains the Eastern Seaboard Region Program.
- ⁶ Shimomura (2000) and Ariga and Ejima (2000) provide the details.
- ⁷ Watanabe (2004) examined how Official Development Assistance worked for agglomeration.
- ⁸ Oqubay (2020) explains the Asian success in industrial hubs.
- ⁹ Next IAS (2022) estimates the value of exports.
- ¹⁰ The bill is subject to World Trade Organization standards.
- ¹¹ Other incentives include income tax exemption on income for up to 10 years, exemption from customs and excise duties, tax exemptions and surcharges. In September 2019, the Minimum Alternate Tax was reduced from 18.5% to 15%. See Dezan Shira & Associates (2023).
- ¹² Rathore (2023) studies the history of Indian special economic zones.
- ¹³ See note 10 above.
- ¹⁴ Factor analysis is performed by “Program R”. The number of factors is the same as that of eigen values greater than 1. Rotation method is “romax method”. Kuchiki (2023) explained it at p. 10.

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Article

Resident Evaluation of Reconstruction Challenges and Lessons Learned from the Great East Japan Earthquake: Recommendations for Reconstruction and Industrial Policies 12 Years after the Disaster

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Abstract: The year 2023 marks the 12th anniversary of the Great East Japan Earthquake (GEJE). Immediately after the disaster, the number of evacuees reached approximately 470,000, but by November 2022, the number had decreased to approximately 31,000. The reconstruction of housing, disposal of debris, public infrastructure development, and overall restoration and reconstruction has progressed steadily. However, a re-examination of the status of industrial restoration and reconstruction reveals that restoration and reconstruction have not progressed in some areas. This research statistically analyzes how the Japanese public perceives the issues around the recovery process and what memories and records they would like to learn from regarding the GEJE. The purpose of this study is to ask about reconstruction issues and lessons learned from the GEJE by conducting a web-based survey with 2000 respondents in Japan. The method of estimation is the use of ordinal logistic regression analysis to statistically estimate whether there are differences in recovery issues and lessons learned depending on individual attributes. The results suggest that those who are interested in, remember, and express anxiety about the recovery issues and lessons learned tend to be men, do not have children, are highly educated, and have a higher income. In sum, many of Japan's citizens are highly interested in the reconstruction of agriculture, forestry, fisheries, housing, urban development, living environment, industry, and livelihood in the affected areas. In the future, they will play a central role in modernizing, scaling up, and integrating the agriculture, forestry, and fisheries industries, as well as in rebuilding towns and livelihoods. In the affected areas, it will be necessary to draw on the lessons learned from the GEJE and create reconstruction plans for the future, and then, policymakers will need to formulate reconstruction policies that reflect the concerns of the Japanese people.

Keywords: TEPCO Fukushima Daiichi nuclear power plant accident; Great East Japan Earthquake; reconstruction policy; citizen survey; logistic regression analysis

1. Introduction

In 2023, Japan marked the 12th anniversary of the Great East Japan Earthquake (GEJE). Immediately after the disaster (14 March 2011), the number of evacuees had reached approximately 470,000, but by November 2022, it had decreased to about 31,000 (Reconstruction Agency of Japan 2023a). Furthermore, progress has been made in rebuilding homes, leading to a decrease in the number of occupants in emergency temporary housing (Reconstruction Agency of Japan 2023a). The number of residents in prefabricated temporary housing in Fukushima Prefecture decreased from 10,893 in April 2018 to 4 in January 2023, and construction-type temporary housing supply in Miyagi and Iwate Prefectures ended in fiscal year 2020 (Reconstruction Agency of Japan 2023a). Additionally, in the

three disaster-affected prefectures of Iwate, Miyagi, and Fukushima, disaster waste had reached 19.64 million tons (Iwate: 4.39 million tons; Miyagi: 12.23 million tons; Fukushima: 3.02 million tons) and tsunami deposits reached 10.48 million tons (Iwate: 1.84 million tons; Miyagi: 7.28 million tons; Fukushima: 1.36 million tons) (Reconstruction Agency of Japan 2023a). However, by the target date of the end of March 2014, debris processing in Iwate and Miyagi was completed, and debris processing in Fukushima, excluding the countermeasure areas, was completed by the end of August 2017 (Reconstruction Agency of Japan 2023a). As of the end of September 2022, except for coastal measures (96%), coastal disaster prevention forests (95%), transportation networks in prefectures and municipalities (99%), school facilities, medical facilities, agricultural land, and fixed fishing grounds (99%), all public infrastructure had been completed (Reconstruction Agency of Japan 2023a). The construction of disaster public housing and the development of residential areas on high ground were completed by the end of 2020 (Reconstruction Agency of Japan 2023a). The GEJE caused various landslide disasters in northeastern Japan (Miyagi et al. 2011). Landslides are dynamic soil catastrophes that pose a serious threat to the lives and economic property of the surrounding population (Liu et al. 2023). However, the full extent of the landslide generated by this earthquake is still unknown (Miyagi et al. 2011). The actual tsunami height generated by this earthquake was also not estimated (Suppasri et al. 2013). Under these circumstances, reconstruction and recovery efforts, such as housing construction, debris processing, and public infrastructure development, have steadily progressed, leading to the recovery and reconstruction of disaster-affected areas.

However, upon the re-evaluation of the recovery and reconstruction of industries, areas where recovery and reconstruction have not progressed become apparent. The shipment value of manufactured goods in the three disaster-affected prefectures has generally recovered to pre-disaster levels, with the construction industry (66.4%) and transportation industry (50.5%) surpassing pre-disaster sales levels. On the other hand, sales in the lodging and hotel industry (20.1%) and the fisheries and food processing industry (27.5%) have declined compared to pre-disaster levels, especially with the tourism industry experiencing significant declines in sales due to the spread of COVID-19 since 2020. In agriculture in the six Tohoku prefectures, of the targeted farmland for recovery, excluding land converted from tsunami-damaged areas (19,660 hectares), farming has resumed on 18,640 hectares. In the three disaster-affected prefectures, efforts to consolidate farmland through extensive aggregation and land use rationalization using reconstruction subsidies are progressing. However, among seafood processing businesses, only 17% have recovered sales to pre-disaster levels, with 49% recovering more than 80%. In other words, while infrastructure, manufacturing, construction, and transportation have recovered after the disaster, recovery in industries such as tourism and seafood processing has stagnated, resulting in significant disparities in industrial recovery. Summarizing research on Fukushima's reconstruction and regeneration over time, the following leading studies are mentioned:

Kawasaki (2013) conducted a survey of residents regarding decontamination in the Fukushima City Oonami district one year after the disaster, highlighting the need for the reconsideration of decontamination and the establishment of systems to support living arrangements. Maehara (2014), 2 years and 8 months after the nuclear accident, pointed out that 150,000 people (96,000 in the prefecture and 54,000 outside the prefecture) were living in evacuation zones, with uncertainties in the restoration and reconstruction of not only the evacuation zones including the 30 km radius but also surrounding community areas. Lee et al. (2019), 8 years after the nuclear accident, emphasized that Fukushima's recovery primarily focused on infrastructure development, with a lack of soft infrastructure development addressing challenges from local communities and residents. Nakano et al. (2020), 9 years after the nuclear accident, pointed out a tendency in previous Fukushima recovery studies to prioritize scientific investigations and socioeconomic analyses, with discussions often predetermined. With the approach of the 10th anniversary of the disaster in 2021, research on Fukushima's recovery and regeneration has also been conducted. Kawasaki (2021) examined policies for long-term recovery in Fukushima from 2011 to 2020,

revealing ongoing challenges despite some progress, including the difficulty of returning to areas designated as difficult to return to, as well as addressing issues such as accident containment and radioactive contamination. Yamakawa and Seto (2018) discuss various aspects of Fukushima's recovery and reconstruction efforts after the earthquake, focusing on fundamental issues of support, the verification of the lives and situations of the affected people, the impact on industries, international trends, and disaster prevention education. Additionally, they present findings from research addressing Fukushima's recovery support, post-evacuation community building, and the process of reconstruction ten years after the nuclear accident (Yamakawa and Hatsuzawa 2021). This research highlights significant challenges in the recovery and reconstruction process, such as ongoing nuclear concerns, reputational issues affecting agricultural products, disparities in compensation between forced and voluntary evacuees, housing shortages for victims, and health issues among evacuees.

However, despite 11 years passing since the disaster, previous studies evaluating Fukushima's economic recovery and decontamination policies are often critical of national and prefectural policies. For instance, Schreurs (2021) notes that while the Tohoku region aims to become a global leader in tsunami disaster management, recovery, nuclear disaster recovery, and renewable energy development, many evacuees have not returned home due to the complex challenges associated with post-nuclear accident cleanup. Fujimoto (2016) highlights the complexities and political challenges in determining the scope and scale of radiation contamination in post-disaster Japan. Nagamatsu et al. (2020) discusses the possibility of recovery promotion expenses outweighing benefits if residents remain unresponsive to decontamination efforts in areas designated as restricted access zones. Liu et al. (2016) mention areas with high radiation levels where nuclear accident damages can only be confirmed through satellite imagery. These studies suggest that Japan's recovery from the nuclear disaster has yet to address complex issues adequately, with implications for the effectiveness of recovery budgets.

The year 2021 marked 10 years since the GEJE. More than ten years have passed since the disaster, and many studies have been conducted on the reconstruction and revitalization of Fukushima. Zhang et al. (2019) stress the need for local adaptation and innovation in Fukushima's economic recovery, emphasizing the importance of creative and sustainable economic recovery strategies that capitalize on existing resources to turn disaster-related challenges into opportunities. Nakamura et al. (2023) conducted statistical analyses on recovery and regeneration efforts in Fukushima Prefecture, revealing low satisfaction among elderly and affected individuals with government recovery policies. Yokemoto (2023) notes that despite the lifting of evacuation orders in certain areas since April 2014, community rebuilding remains a new challenge in such regions.

The national and prefectural governments have implemented various policies to support Fukushima's recovery. Hoshi (2021) notes that macroeconomic indicators such as prefectural gross domestic product and mining industry production indices have returned to pre-disaster levels, with some signs of progress in areas such as the advancement of secondary industry and clustering of automobile-related industries. However, despite businesses reopening in the disaster-affected areas, there are still concerns about low sales leading to financial difficulties or bankruptcies among some businesses.

Numerous studies have addressed industrial clustering in Japan. For instance, Shimizu and Matsubara (2014) discuss the ongoing challenges in industrial recovery in heavily affected areas despite progress in relocating factories to distant locations. Furthermore, they emphasize the need for the regional reconstruction of manufacturing industries in the Tohoku region, considering both the heavily impacted coastal areas and the inland areas where new industrial locations are advancing. Regarding agricultural clustering, Monma (2013) mention the importance of new support organizations for agricultural recovery based on the evaluation of decontamination effects and monitoring of radioactive substances. Owada and Kitamura (2019) note the trend in agricultural land aggregation and dispersion in areas with significant population decline in the disaster-affected areas.

Regarding seafood processing industry clustering, Yamaguchi (2013) highlights the necessity of creating industry recovery visions, town planning considering industrial clustering reconstruction, and support for individual business strategy formulation, using the seafood processing industry in Kesennuma City, Miyagi Prefecture, as an example. Additionally, regarding commercial clustering, Nagasaka (2018) compares the restoration and reconstruction support for commercial clustering between the GEJE and the Hanshin-Awaji Earthquake, revealing the formation of commercial clusters with reduced economic burden for businesses in the disaster-affected areas. On the other hand, regarding tourism clustering, Kuchiki (2020) mentions the promotion of tourism through transportation infrastructure development, leading to the construction of segments promoting tourism after the completion of transportation infrastructure, resulting in the efficient clustering of tourism industries. However, Fukui (2020) notes that while tourism policies are effective in metropolitan areas, they may not be effective in all regions, potentially exacerbating regional disparities between metropolitan and rural areas. Furthermore, Igarashi and Kawasaki (2017) mention delays in the restoration of tourism resources in coastal areas of the disaster-affected regions, with most municipalities facing challenges in tourism recovery efforts and only half of them implementing inbound tourism policies. The importance of industrial clustering, including commercial, agricultural, and tourism clustering, is highlighted in the disaster-affected areas. Tsuji (2016) reveals an increase in public participation in reconstruction town meetings with age and education level. Additionally, Yamakawa (2016) position commercial base formation as essential for supporting the daily lives of victims and evacuees, emphasizing the need for community reconstruction and receiving overwhelming support from the national government for reconstruction efforts. Yamakawa (2018) compares the GEJE with the Kumamoto Earthquake, suggesting that lessons to be learned from the GEJE for Kumamoto's recovery include ensuring the regeneration of "hometown values" in reconstruction policies; otherwise, the reconstruction of disaster-stricken areas in a declining population and aging society may become cost-ineffective.

Since the Great East Japan Earthquake, there has been progress in the industrial concentration of agriculture, fisheries, and tourism. However, as Star Hoshi (2021) points out, the effects expected from the establishment of industrial concentration and research and development bases, such as increased productivity, industrial sophistication, and the creation of new industries, are still limited. Reconstruction from the GEJE has achieved significant success in most areas, including housing, industry, and agriculture. However, tourism and fisheries have not yet recovered to pre-disaster levels. How do the Japanese people evaluate policies related to housing, community development, living environment, industry, and livelihoods? Currently, there are few studies evaluating the reconstruction of industries and livelihoods twelve years after the earthquake.

According to the Reconstruction Agency of Japan (2021), "memory" (*kioku*) is defined as "remembering things without forgetting them and keeping them in mind". While records are written to be preserved, memories are stored in people's hearts, and memories are lost when people forget them. "Record" (*kiroku*) is defined as "writing down facts for later transmission, or the document itself". The "memory" of the disaster needs to be "recorded" in documents and other forms. However, if the "record" is not transmitted to people, it loses its meaning. "Lesson" (*kyoukun*) is defined as "teaching or instructing, or the words used for that purpose". People who do not know about the disaster learn "lessons" from the "records". "Tradition" (*denshou*) is defined as "hearing or learning something from others". People of future generations who have learned the "lessons" of the disaster need to "transmit" them to the next generation. The "transmission" of the GEJE will be evaluated by future generations, so it is necessary to reconsider what lessons the people of modern Japan want to derive from it.

Taking the above as the basis, this research statistically analyzes how the Japanese people, twelve years after the GEJE, perceive the challenges of reconstruction and what memories or records they want to derive lessons from. This research statistically analyzes

the personal attributes of the survey respondents who tended to remember the earthquake, take lessons from the written records from their memories, and have the will to pass them on. This study aims to conduct a web survey of 2000 individuals nationwide, asking about the challenges of reconstruction and lessons learned from the GEJE.

The structure of this paper is as follows:

Section 2 explains the survey design, target areas, methods of aggregation, and comparison methods.

Section 3 examines whether citizens feel that victims of the GEJE are being supported and evaluates how citizens assess aspects such as “housing and community development”, “living environment”, “industry and livelihoods”, “reconstruction projects”, and “memories or records of the disaster”. It also discusses how citizens prioritize the importance of post-disaster reconstruction and lessons. Furthermore, it grasps how individuals evaluate lessons such as “lessons learned in rebuilding agriculture, forestry, and fisheries in disaster-affected areas” and “lessons in inheriting memories or records of the disaster”, as well as “lessons in rebuilding industries, commercial facilities, and shopping districts in disaster-affected areas”.

Section 4 statistically estimates whether there are differences in individual attributes regarding reconstruction challenges and lessons from the GEJE using ordered logistic regression analysis.

Section 5 summarizes the residents’ attitudes toward reconstruction challenges and lessons from the GEJE.

2. Research Methodology

2.1. Hypotheses of This Paper

This research statistically examines the differences in the decision-making and thinking of local residents based on individual attributes such as gender, presence of children, age, education level, income level, etc.

Table 1 presents the hypotheses of this paper. From the table, consider whether hypotheses H_1 to H_3 are rejected.

Table 1. List of hypotheses.

No.	Hypothesis
H_1	There is no difference in lessons learned in the reconstruction of agriculture, forestry, and fisheries industries based on individual attributes.
H_2	There is no difference in lessons learned in passing on memories and records of the disaster by individual attributes.
H_3	There is no difference in the lessons learned from the reconstruction of industries, commercial facilities, and shopping streets in the disaster area by individual attributes.

The questions used to estimate the hypotheses employ a 5-point scale based on the Likert scale, i.e., a five-item scale. When estimating data using a five-item scale, ordered logistic regression analysis is applied. Ordered logistic regression analysis is used for regression analysis when the dependent variable is an ordinal variable with three or more categories in multivariate data. Although the logistic regression analysis model predicts values between 0 and 1, it is a nonlinear model, making the interpretation of the estimated parameters difficult. Therefore, in Chapter 4, we apply ordinal logistic regression analysis.

2.2. Survey Target Area

The survey was conducted throughout Japan, with questionnaires collected from each of the 47 prefectures. The survey instrument was distributed under the title “Resident Assessment of Reconstruction Lessons and Know-How in the Great East Japan Earthquake”. The Reconstruction Agency of Japan (2023b) has formulated the “Basic Policy for Reconstruction from the GEJE” into the following phases: I. Intensive Reconstruction

Period (March 2011–March 2016); II. First Reconstruction and Revitalization Period (April 2016–March 2021); III. (April 2021–March 2026) continues the philosophy of Phase II. In Phase III, the government aims to (1) meticulously address the remaining issues in the earthquake- and tsunami-damaged areas and (2) continue to take the lead in addressing the remaining issues in the nuclear disaster-damaged areas in the medium- to long-term, with the national government taking the initiative. Finally, (3) the government aims to pass on memories and lessons to future generations by establishing state-run memorial and prayer facilities and by compiling effective reconstruction methods and initiatives, as well as private-sector know-how.

As described above, the current period is now under Phase III. The current period is the second phase of reconstruction and revitalization, and is a time to test the extent to which reconstruction measures are evaluated by the public. Therefore, in this paper, the survey is conducted in all regions of Japan, and the question is asked as to how the people evaluate the reconstruction measures.

2.3. Aggregation Methods

The survey targeted the entire country of Japan, collecting survey forms from all 47 prefectures.

The survey was conducted as a web survey using the Pollfish service. The survey received complete responses from 2000 individuals. Sample size was calculated using the following formula: $1.96\sqrt{0.5(1-0.5)/n} = 0.05$ (Kurihara and Tokeigaku 2021). Since the sample proportions are unknown because the survey was conducted before the survey, 0.5, which has the largest sample error, is included in this formula for the worst-case scenario (Kurihara and Tokeigaku 2021). This formula yields $\sqrt{n} = 19.6$, which means that if a sample of 384 ($n = 384$) is collected, a 95% confidence interval of the population ratio can be estimated with an error within $\pm 5\%$ (Kurihara and Tokeigaku 2021). In other words, in statistics, if the number of samples is about 400, the sample error can be estimated within $\pm 5\%$. There are a plethora of online sample size calculators that result in a minimum sample size of 385 given a confidence level of 95% and a tolerance rate of 5% (SurveyMonkey 2024).

The response rate was 94.6%. The survey period was from February 22 (Wednesday) to February 23 (Thursday) in 2023, according to Japan Standard Time. The sample was collected using the Pollfish consumer research online survey service. Pollfish (2024) identifies inevitable data quality problems for consumer monitoring at an early stage, such as respondent “panel fatigue” and “unconsciously biased” responses. AI fraud detection is then applied to remove responses that do not meet quality criteria, and responses are randomly selected. Here, the authors also checked the sample but did not do any work to remove the sample because it was randomly selected.

It was possible to set quotas for various factors (sex, age, region) prior to publishing the survey. However, this was not carried out due to financial constraints, so it is inevitable that certain groups or regions will be over-represented. As participants were volunteers, there is the inevitable issue of self-selection bias. Participants were more likely to be interested in the topic than average citizens, and there is a high probability that many of them were motivated by opposition to government policy, resulting in a non-representative outcome. This is an unavoidable limitation of web surveys and should be taken into consideration.

2.4. Estimation Method

The following summarizes the estimation methodology used.

Tables 2–4 list the objective variables (OVs) used for estimation. OV101 to OV112 in Table 2 correspond to H_1 , OV201 to OV206 in Table 3 correspond to H_2 , and OV301 to OV312 in Table 4 correspond to H_3 . Ordinal logistic regression analysis estimates the objective variables ordered into five levels (disagree = 1, not so much disagree = 2, undecided = 3, somewhat agree = 4, agree = 5). The questions listed in Tables 2–4 were created by referring to the Reconstruction Agency’s “Lessons and Know-How Collection

for Reconstruction from the Great East Japan Earthquake” (2021) and extracting relevant questions.

Table 5 lists the explanatory variables (EVs). Gender (EV1) is a dummy (male = 1, female = 0) explanatory variable. Age (EV2), number of children (EV3), and distance from Fukushima nuclear power plant (EV6) are continuous variables. Educational attainment (EV4) and income bracket (EV5) are discrete variables.

Long (1997) stated that in multiple regression analysis, the model is stable even with a relatively small number of samples, but in logistic regression analysis, at least 200 samples are necessary because the maximum likelihood method is used, and 20 samples should be added for each explanatory variable. The estimation in this paper has a maximum of six explanatory variables, resulting in $200 + (6 \text{ explanatory variables} \times 20) = 320$ samples, which satisfies the minimum sample size.

In general, when estimating ordinal logit models, the heterogeneity of residuals is tested, and robust standard errors are measured if the model is estimated to be heterogeneous. In the model of this paper, since heteroscedasticity is not assumed, normal standard errors are used.

Below, the “cut” in tables of Section 4 represents the threshold, where $\Pr(y = 1) = \Pr(\beta x < \text{cut1})$, and $\Pr(y = 2) = \Pr(\text{cut1} < \beta x < \text{cut2})$ correspond accordingly (y is the category of the dependent variable, x is the explanatory variable, and β is the parameter).

Table 2. List of objective variables for H_1 .

No.	Objective Variable	Question
OV101	Large parcels of farmland	Farmland and agricultural facilities should be restored as soon as possible in the affected areas, and large plots should be created to improve productivity.
OV102	Early resumption of farming	Farmers who have been operating in the affected areas should be provided with alternative land to resume farming as soon as possible.
OV103	Effective use of farmland	New farmers should be secured in the affected areas, and farmland should be distributed to them in order to make effective use of farmland.
OV104	Expansion of agricultural business	Farmers in the affected areas should resume farming in cooperation with companies outside the prefecture and work to expand their businesses.
OV105	Development of new sales channels for agriculture	In order to develop sales channels for the fisheries industry, new sales channels should be developed through the development of unique, high value-added products.
OV106	Introduction of advanced technology in agriculture	Agriculture in the affected areas should improve productivity by introducing advanced technologies such as ICT.
OV107	Creation of agricultural business models	Agriculture in the affected areas should collaborate with companies from other industries to create new business models.
OV108	Diversification of agriculture business	Agriculture in the affected areas should develop diversified businesses in cooperation with companies from different industries.
OV109	Creation of business opportunities in the fisheries industry	To develop sales channels for the fisheries industry, exhibitions and business meetings should be held and exhibited to create business opportunities with new businesses.
OV110	Development of new sales channels in the fisheries industry	Fisheries in the affected areas should develop new products using local resources, promote branding, and develop new sales channels.
OV111	Creation of business models for the fisheries industry	In order to upgrade and advance the fisheries industry, new technologies should be introduced to develop high value-added products and create new business models.
OV112	Development of management innovation in the fisheries industry	In order to advance and develop the fisheries industry, management innovation should be developed based on flexible ideas in response to changes in the market.

Table 3. List of objective variables for H₂.

No.	Objective Variable	Question
OV201	Disaster Prevention through Public-Private Partnership	The national government, local governments, universities, and private companies should work together to collect and preserve a wide range of disaster-related materials and promote their utilization for disaster prevention and mitigation.
OV202	Dissemination of know-how on lessons learned from the earthquake	Disseminate information on the recovery status and lessons learned and know-how from the earthquake both domestically and internationally to contribute to strengthening disaster prevention and recovery measures around the world, as well as to provide continuous support for the recovery of disaster-stricken areas.
OV203	Preservation of earthquake remains	The preservation of earthquake remains should be studied over a sufficient period of time and with the collection of diverse opinions.
OV204	Establishment of facilities for handing down lessons from the disaster	The public and private sectors should cooperate and collaborate to establish and maintain “facilities for handing down the legacy of the disaster.
OV205	Development of programs to pass on lessons	To prevent the tragic damage from the earthquake from happening again, we should establish a program for effective learning about the disaster.
OV206	Support for disaster education	Create opportunities for people to be involved in earthquake disaster education and handing down the lessons of the disaster, and provide support for the continuation of such activities.

Table 4. List of objective variables for H₃.

No.	Objective Variable	Question
OV301	Corporate financing support	Disaster-stricken companies should be provided with prompt and smooth cash management support.
OV302	Long-term business restructuring support	A system should be established to solve the problem of double debts of the affected companies, and the rehabilitation support councils, in cooperation with financial institutions, should provide long-term support for business rehabilitation.
OV303	Promotion of full-scale industrial recovery	Promote full-scale industrial recovery by strategically clustering next-generation growth industries.
OV304	Support for regional industrial clusters	Strengthen local industrial clusters and support their development.
OV305	New product development and sales channel development	New businesses should be established based on the experience of the disaster, new products should be developed, and new sales channels should be opened.
OV306	Product development through industry-academia collaboration	Promote joint industry-academia research and corporate collaboration to develop new products.
OV307	Cultivation of start-up companies	Local government-led initiatives should be utilized to create start-up companies and promote their development.
OV308	Secure employment for disaster victims	Unemployed disaster victims should be provided with jobs for recovery work to secure their employment.
OV309	Secure employment for young people and women	Provide a comfortable work environment, improve the image of the industry, and secure employment for young people and women.
OV310	Management reform and change of mindset	Increase opportunities for exchanges with advanced business people and promote awareness-raising that will change the conventional way of management.
OV311	Commercial concentration and planned development	Promote commercial concentration in the city center and systematically develop shopping streets.
OV312	Area management implementation	Area management should be implemented by city development companies, etc.

Table 5. List of explanatory variables.

No.	Personal Attributes
EV1	Male
EV2	Age
EV3	Number of children under 12 years old
EV4	Education level
EV5	Income level
EV6	Distance from Fukushima Daiichi NPP

3. Survey Overview

3.1. Sample Attributes

The sample attributes are given in Appendix A. Men comprised 52.5% and women 47.6% of the sample. The average age was 35.9 and the number of children was 1.586. The most common annual income level was JPY 8.36 million to JPY 11.15 million (20.2%), followed by JPY 2.8 million to JPY 5.58 million (18.9%) and JPY 5.58 to JPY 8.36 million (18.5%). Regarding educational level (educational background), the most common was high school or below (54.6%), followed by junior college/vocational school (21.6%) and university (21.1%). Regarding marital status, the majority of respondents were married (44.5%), followed by single (33.3%).

3.2. Support for Victims of the Great East Japan Earthquake

Nakamura et al. (2023) examined whether the residents of Fukushima Prefecture were satisfied with the support for disaster victims 10 years after the earthquake. The results showed that only 16.7% of Fukushima Prefecture residents were satisfied with the support provided to disaster victims. Although not directly comparable given the different sample areas, a comparison between these results and the results of the current research is possible.

Appendix B gives the results of the survey questions on victim support. The largest percentage of respondents (30.6%) believe that “the livelihood of evacuees is being supported”. Following this, a significant portion of respondents (29.3%) believe that “the connection between evacuees and the affected areas is being maintained”, while others (28.2%) think that “the revitalization of the affected areas is being promoted”. Approximately 30% of citizens still feel that victims have been supported in various ways, even 12 years after the earthquake. The percentage of respondents who believe that “none of the support for victims is satisfactory” has decreased to 6.8%.

More respondents feel that the disaster victims are being supported in the current survey than in the 2023 survey. However, between 69.4% and 75.0% of the Japanese respondents feel that the victims of the GEJE are still not being supported.

3.3. Development of Housing, Community Building, and Living Environment in the Affected Areas of the Great East Japan Earthquake

The 2023 survey found that 35.4% of Fukushima residents were satisfied with the reconstruction of their homes and towns, while 21.9% were not.

The current research asked a similar question (Appendix C), and the largest percentage of respondents (28.3%) believe that “the reconstruction or relocation projects of the affected towns are progressing”. This is followed by those (27.7%) who believe that “the direction of community building in the affected areas is being indicated”, and others (26.0%) who think that “coordination and support for the aggregation and resolution of emergency temporary housing are progressing”. Additionally, some respondents (26.0%) believe that “disaster public housing considering the elderly and local communities is being constructed”. Overall, there is a consensus that “housing, community building, and living environment have all been developed to some extent”, with only a small percentage (7.1%) believing that “none of these aspects have been developed”.

Compared to the 2023 survey, more respondents feel that housing, community development, and the living environment have been improved in the affected areas. However,

77.9% to 75.0% of the Japanese respondents feel that housing, community development, and the living environment have not been improved in the affected areas.

3.4. Support for Industries and Livelihoods in the Affected Areas of the GEJE

In the 2023 survey, 35.4% of Fukushima Prefecture residents were satisfied with the recovery of industry and livelihoods, compared to 24.7% of those who were satisfied with the recovery of industry and livelihoods.

In the current survey, participants were asked to rate the “industries and livelihoods being supported in the areas affected by the Great East Japan Earthquake” (Appendix D). The largest proportion of participants believe that “the attraction of businesses to the affected areas is progressing” (27.5%), followed by those who think that “information to attract tourists to the affected areas is being disseminated” (26.5%), “financial support for the reconstruction of affected businesses is being provided” (26.2%), and “farmland and agricultural facilities in the affected areas have been restored” (25.9%). Overall, a small percentage (6.1%) of citizens believe that “none of the industries and livelihoods are being supported”.

The number of respondents who feel that industries and livelihoods are being supported is slightly higher in the current survey. However, 72.5% to 77.1% of the Japanese respondents feel that the industries and livelihoods in the affected areas are not being supported.

3.5. Collaboration in Reconstruction Projects and Preservation of Memories and Records by NPOs, Private Companies, and Government Agencies

Respondents were asked to rate the public’s evaluation of the reconstruction projects and inherited memories and records that are being carried on by NPOs, private companies, and government agencies working together in cooperation (Appendix E). According to the results, the largest proportion of respondents (29.1%) believe that “lessons and know-how from the GEJE are incorporated into local disaster prevention plans”. This is followed by those who think that “lessons and know-how for reconstruction are disseminated through the Reconstruction Agency’s website, preserving memories and records” (27.4%) and those who believe that “the national and local governments collaborate with NPOs to provide reconstruction support” (26.5%). Additionally, some respondents (26.1%) think that “support for the monitoring of elderly and children’s lives has been realized”. Nearly 30% of citizens feel that lessons and know-how are being utilized. Overall, a small percentage (5.5%) of citizens believe that “collaboration is lacking, and memories and records are not being preserved”.

In summary, approximately 30% of citizens feel that victims have been supported, and over a quarter believe that community development, industries, and livelihoods have recovered in the affected areas, with lessons and know-how from the earthquake being preserved.

3.6. Importance of Post-Disaster Reconstruction and Lessons Learned

Figure 1 presents the ranking of the “importance of post-disaster reconstruction and lessons learned”. According to the results, “support for victims” (2.468) ranked the highest. Next, “reconstruction of housing and communities” (2.481) had the second-highest average rank, with 26.2% of respondents selecting it as their top priority. Following closely, “revival of industries and livelihoods” (2.505) had the third-highest average rank, with 26.2% of respondents selecting it as their second priority. “Collaboration and succession” (2.547) ranked fourth.

In summary, after the earthquake, the most important thing for the Japanese people was to support the victims, followed by the reconstruction of their homes and towns. Most people wanted to see the revival of industries and livelihoods as their lives became more viable, and people began to cooperate in the recovery efforts and eventually take over the process.

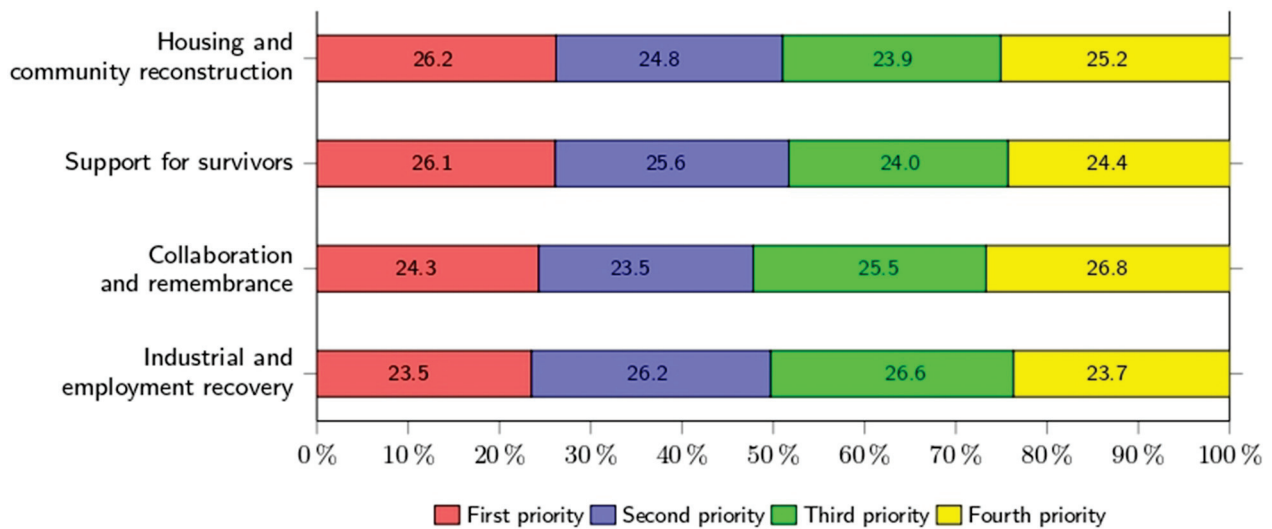


Figure 1. Post-disaster recovery and importance of lessons learned.

3.7. Lessons Learned for Rebuilding Agriculture, Forestry, and Fisheries in the Affected Areas

Figure 2 gives the results of responses regarding the evaluation of “lessons learned for rebuilding agriculture, forestry, and fisheries in the affected areas (H1)”. The highest-rated item was “creation of agricultural business models (OV107)” (46.3%). Following this were “consolidation of farmland (OV101)” (46.0%), “effective utilization of farmland (OV103)” (46.0%), and “creation of agricultural business models (OV107)” (45.5%). Around 40% of respondents indicated a desire to learn lessons for rebuilding agriculture, forestry, and fisheries in the affected areas, expressing expectations for the development of new agricultural and industrial clusters.



Figure 2. Lessons learned in rebuilding agriculture, forestry, and fisheries in the affected areas. Note: See Table 2 for the evaluation items for OV101 to OV112 in the figure.

3.8. Lessons Learned for Inheriting Memories and Records of the Earthquake

Figure 3 illustrates the evaluation of “lessons learned for inheriting memories and records of the earthquake (H2)”. The highest-rated items were “disaster prevention through public–private collaboration (OV201)” and “dissemination of earthquake lessons and know-how (OV202)” (both 46.4%). About 40% of respondents expressed a desire to learn lessons for inheriting memories and records of the earthquake.

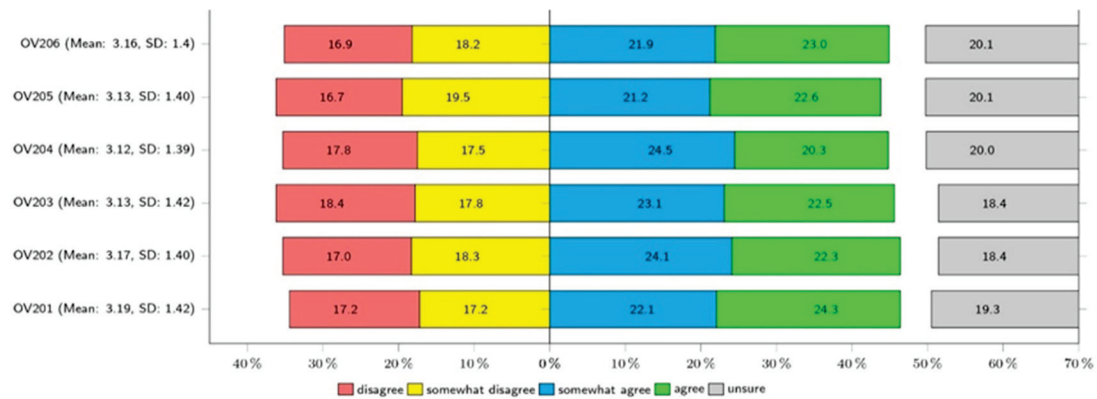


Figure 3. Lessons learned in passing on memories and records of the disaster. Note: See Table 3 for the evaluation items for OV201 to OV206 in the figure.

3.9. Lessons Learned for Rebuilding Industries, Commercial Facilities, and Shopping Districts in the Affected Areas

Figure 4 depicts the evaluation of “lessons learned for rebuilding industries, commercial facilities, and shopping districts in the affected areas (H3)”. The highest-rated items were “long-term business revival support (OV302)” (46.8%), “promotion of full-scale industrial recovery (OV303)” (45.0%), and “product development through industry-academia collaboration (OV306)” (44.6%). Approximately 40% of respondents indicated a desire to learn lessons for rebuilding industries, commercial facilities, and shopping districts in the affected areas.



Figure 4. Lessons learned in the reconstruction of industries, commercial facilities, and shopping areas in the affected areas. Note: See Table 4 for the evaluation items for OV301 to OV312 in the figure.

4. Estimation Results

4.1. Estimation Results for Lessons Learned in Rebuilding Agriculture, Forestry, and Fisheries in the Affected Areas

In the previous section, it was shown that the level of satisfaction with the support for disaster victims, urban development in the affected areas, and industry and livelihood was higher 12 years after the earthquake than 10 years after the earthquake, but many citizens were not satisfied with the support for disaster victims and reconstruction policies. Also, over 40% of respondents expressed a desire to adopt lessons for rebuilding agriculture, forestry, and fisheries; inheriting memories and records of the earthquake; and rebuilding industries, commercial facilities, and shopping districts in the affected areas. This section summarizes the ordinal logistic regression analysis that was applied to the data to determine the role individual attributes play in shaping satisfaction with the relief efforts and policies, and in how the lessons learnt should be implemented.

Table 6 presents the estimation results for lessons learned in rebuilding agriculture, forestry, and fisheries in the affected areas (H_1). Due to space constraints, only coefficients that were significant at the 1% to 5% significance level will be statistically interpreted.

For OV101, OV103, and OV107, the coefficients for EV4 (0.143, 0.167, and 0.076, respectively) and EV5 (0.090, 0.050, 0.076 respectively) are positive. This indicates that individuals with higher education levels and higher incomes believe that the large-scale consolidation of farmland, the effective utilization of farmland, and collaboration with other industries to create new business models should be pursued in the affected agricultural areas.

Regarding OV102, the coefficients for EV2 (0.001) and EV4 (0.091) are positive. This suggests that elderly individuals and those with higher education levels believe that the early resumption of farming activities by affected farmers should be realized.

For OV104, the coefficient of EV4 (0.114) is positive, indicating that high-income earners believe that agriculture in disaster-affected areas should collaborate with companies from other prefectures to resume farming and expand operations.

For OV105, OV106, and OV110, the coefficients of EV3 (each -0.134 , -0.070 , and -0.128) are negative, while those of EV4 (each 0.167, 0.092, and 0.071) and EV5 (each 0.050, 0.070, and 0.049) are positive. This suggests that individuals without children, those with higher education levels, and high-income earners believe that in the disaster-affected agriculture sector, (1) efforts should be made to develop new products and brands using local resources to explore new markets, (2) productivity should be improved by adopting advanced technologies like ICT, and (3) new sales channels should be developed through the creation of high-value-added products with distinctive features in the fisheries industry.

For OV108 and OV109, the coefficients of EV3 (each -0.137 and -0.097) are negative, while those of EV2 (each 0.013 and 0.007), EV4 (each 0.157 and 0.127), and EV5 (each 0.067 and 0.047) are positive. This indicates that individuals without children, the elderly, those with higher education levels, and high-income earners believe that (1) the agriculture sector in disaster-affected areas should engage in diverse businesses through collaboration with other industries and (2) to expand the sales channels in the fisheries industry, trade opportunities with new businesses should be created through hosting trade fairs and exhibitions.

For OV111, the coefficients of EV1 (0.183) and EV5 (0.106) are positive, while that of EV3 (-0.074) is negative. This suggests that males, individuals without children, and high-income earners believe that to advance and modernize the fisheries industry, new business models should be created.

For OV112, the coefficient of EV4 (0.119) is positive, indicating that individuals with higher education levels believe that for the advancement of the fisheries industry, management innovation should be pursued.

Table 6. Estimation results on lessons learned in restoring agriculture, forestry, and fisheries in the affected areas (ordinal logistic regression analysis estimation results).

OV/EV	EV ₁	EV ₂	EV ₃	EV ₄	EV ₅	EV ₆	cut1	cut2	cut3	cut4	LR	AIC	χ ²	pseudoR ²
OV101	Coef.	0.135	−0.053	0.002	0.143 ***	0.090 ***	0.757	−0.235	−0.970	−2.107	5619.5 ***	5639.5	46.5	0.008
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.178)	(0.175)	(0.176)	(0.182)				
OV102	Coef.	0.150 *	−0.045 ***	0.001 ***	0.091	0.063	0.901	−0.053	−0.780	−1.958	5641.5 ***	5661.5	23.7	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.186)	(0.184)	(0.184)	(0.190)				
OV103	Coef.	−0.133	−0.052	0.001	0.167 ***	0.050 **	0.969	0.000	−0.765	−1.854	5634.8 ***	5654.8	36.2	0.006
	SE	(0.085)	(0.034)	(0.003)	(0.034)	(0.024)	(0.164)	(0.160)	(0.161)	(0.167)				
OV104	Coef.	0.153 *	−0.042	0.000	0.114 ***	0.041 *	0.971	−0.030	−0.841	−1.921	5656.5 ***	5676.5	24.1	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.023)	(0.177)	(0.174)	(0.176)	(0.181)				
OV105	Coef.	−0.001	−0.134 ***	0.005 *	0.161 ***	0.053 **	0.703	−0.169	−1.060	−2.157	5619.3 ***	5639.3	49.4	0.009
	SE	(0.085)	(0.033)	(0.003)	(0.033)	(0.023)	(0.153)	(0.149)	(0.150)	(0.157)				
OV106	Coef.	0.053	−0.059 **	0.002	0.076 ***	0.076 ***	1.197	0.101	−0.769	−1.808	5647.6 ***	5667.6	23.0	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.184)	(0.180)	(0.181)	(0.185)				
OV107	Coef.	0.053	−0.059 *	0.002	0.076 **	0.076 ***	1.197	0.101	−0.769	−1.808	5647.6 ***	5667.6	23.0	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.184)	(0.180)	(0.181)	(0.185)				
OV108	Coef.	0.077	−0.137 ***	0.013 ***	0.157 ***	0.067 ***	0.597	−0.383	−1.197	−2.292	5617.6 ***	5637.6	60.9	0.011
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.023)	(0.162)	(0.159)	(0.161)	(0.168)				
OV109	Coef.	−0.066	−0.097 ***	0.007 **	0.127 ***	0.047 **	0.908	−0.062	−0.845	−1.936	5647.3 ***	5667.3	30.0	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.033)	(0.023)	(0.164)	(0.160)	(0.162)	(0.168)				
OV110	Coef.	−0.066	−0.097 ***	0.007	0.127 **	0.047 **	0.908	−0.062	−0.845	−1.936	5647.3 ***	5667.3	30.0	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.033)	(0.023)	(0.164)	(0.160)	(0.162)	(0.168)				
OV111	Coef.	0.183 **	−0.074 **	0.004	0.055 ***	0.106	0.912	0.029	−0.815	−1.935	5630.6 ***	5650.6	38.5	0.007
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.204)	(0.202)	(0.203)	(0.207)				

Table 6. Cont.

OV/EV	EV ₁	EV ₂	EV ₃	EV ₄	EV ₅	EV ₆	cut1	cut2	cut3	cut4	LR	AIC	χ ²	pseudoR ²
Coef.	0.102	0.014 ***	0.001	0.119	0.039	0.000	0.846	−0.128	−0.957	−1.982	5662.6 ***	5682.6	20.7	0.004
SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.181)	(0.178)	(0.179)	(0.184)				

Note: (1) ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels. (2) cut refers to threshold values, where cut1 represents the threshold between “disagree” and “not so much agree,” cut2 represents the threshold between “not so much agree” and “neither agree nor disagree,” cut3 represents the threshold between “neither agree nor disagree” and “somewhat agree,” and cut4 represents the threshold between “somewhat agree” and “agree” (Tables 7 and 8 are also similar). (3) See Table 5 for EV1 to EV6 (Tables 7 and 8 are also similar). (4) For OV101 to OV112, see Table 2.

4.2. Estimation Results for Lessons Learned in Inheriting Memories and Records of the Disaster

Table 7 presents the estimation results for lessons learned in inheriting memories and records of the disaster (H_2).

For OV201 and OV205, the coefficients of EV4 (0.154 for both) and EV5 (0.109 and 0.076, respectively) are positive. This indicates that individuals with higher education levels and higher incomes believe that collaboration between the government and the private sector should be promoted to utilize disaster prevention and mitigation efforts effectively, and effective programs for learning from disasters should be established.

For OV202, the coefficient of EV3 (−0.083) is negative, while those of EV2 (0.010) and EV4 (0.123) and EV5 (0.065) are positive. This suggests that individuals without children, the elderly, those with higher education levels, and high-income earners believe that disseminating information about the recovery status and lessons learned from the disaster domestically and internationally can contribute to continued support for the recovery of affected areas.

For OV203, the coefficient of EV3 (−0.068) is negative, while those of EV4 (0.133) and EV5 (0.094) are positive. This implies that individuals without children, those with higher education levels, and high-income earners believe that preserving the remains of the disaster should involve collecting diverse opinions over a sufficient period for consideration.

For OV204, the coefficient of EV5 (0.056) is positive, while that of EV6 (−0.00035) is negative. This indicates that high-income earners and those living closer to the Fukushima Daiichi Nuclear power plant believe that collaboration between the government and the private sector is necessary to establish and maintain “disaster heritage facilities”.

For OV206, the coefficients of EV1 (0.198) and EV4 (0.112) are positive. This suggests that males and individuals with higher education levels believe that opportunities related to disaster heritage and disaster prevention education should be created, and support should be provided for continued activities.

Table 7. Estimation results on lessons learned in passing on memories and records of the disaster (ordinal logistic regression analysis estimation results).

OV/EV		EV ₁	EV ₂	EV ₃	EV ₄	EV ₅	EV ₆	cut1	cut2	cut3	cut4	LR	AIC	χ^2	pseudoR ²
OV201	Coef.	−0.044	−0.012	0.006 *	0.154 ***	0.109 ***	0.000	0.535	−0.423	−1.240	−2.251	5613.1 ***	5633.1	52.51	0.009
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.176)	(0.174)	(0.175)	(0.181)				
OV202	Coef.	−0.001	−0.083 **	0.010 ***	0.123 ***	0.065 ***	0.000	0.688	−0.296	−1.066	−2.167	5628.4 ***	5648.4	35.44	0.006
	SE	(0.084)	(0.034)	(0.003)	(0.034)	(0.024)	(0.000)	(0.168)	(0.164)	(0.166)	(0.173)				
OV203	Coef.	−0.002	−0.068 **	0.005	0.133 ***	0.094 ***	0.000	0.634	−0.303	−1.078	−2.152	5629.5 ***	5649.5	42.13	0.007
	SE	(0.084)	(0.033)	(0.003)	(0.034)	(0.023)	(0.000)	(0.166)	(0.163)	(0.164)	(0.170)				
OV204	Coef.	0.134	0.004	−0.004	0.059 *	0.056 **	0.000 **	1.379	0.450	−0.405	−1.552	5646.6 ***	5666.6	21.73	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.036)	(0.024)	(0.000)	(0.211)	(0.209)	(0.208)	(0.211)				
OV205	Coef.	−0.109	−0.060 *	0.001	0.115 ***	0.076 ***	0.000	1.182	0.122	−0.730	−1.722	5644.7 ***	5664.7	31.28	0.006
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.168)	(0.163)	(0.164)	(0.168)				
OV206	Coef.	0.198 **	−0.032	0.000	0.112 ***	0.052	0.000	1.021	0.023	−0.809	−1.810	5647.7 ***	5667.7	27.85	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.000)	(0.188)	(0.185)	(0.186)	(0.190)				

Note: (1) ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels. (2) See Table 3 for OV201 to OV206.

Table 8. Estimation Results on Lessons Learned in Reconstructing Agriculture, Forestry, and Fisheries in the Affected Areas (Ordinal Logistic Regression Analysis Estimation Results).

OV/EV		EV ₁	EV ₂	EV ₃	EV ₄	EV ₅	EV ₆	cut1	cut2	cut3	cut4	LR	AIC	χ^2	pseudoR ²
OV301	Coef.	−0.085	−0.073 **	0.006 *	0.113 ***	0.117 ***	0.000 *	0.630	−0.347	−1.216	−2.270	5631.0 ***	5651.0	49.1	0.009
	SE	(0.085)	(0.033)	(0.003)	(0.033)	(0.024)	(0.000)	(0.162)	(0.158)	(0.160)	(0.167)				
OV302	Coef.	0.018	−0.021	−0.004	0.152 ***	0.034	0.000	1.006	0.150	−0.618	−1.799	5624.0 ***	5644.0	27.3	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.023)	(0.000)	(0.170)	(0.166)	(0.167)	(0.173)				
OV303	Coef.	0.045	−0.033	0.007 **	0.173 ***	0.093 ***	0.000	0.373	−0.603	−1.394	−2.374	5624.5 ***	5644.5	53.4	0.009
	SE	(0.085)	(0.034)	(0.003)	(0.034)	(0.024)	(0.000)	(0.168)	(0.166)	(0.168)	(0.174)				
OV304	Coef.	0.072	−0.006	−0.004	0.068 **	0.063 ***	0.000	1.394	0.314	−0.546	−1.628	5637.3 ***	5657.3	16.5	0.003
	SE	(0.085)	(0.034)	(0.003)	(0.034)	(0.024)	(0.000)	(0.189)	(0.184)	(0.185)	(0.189)				
OV305	Coef.	−0.035	−0.040	0.009 ***	0.125 ***	0.032	0.000	0.597	−0.297	−1.189	−2.230	5657.1 ***	5677.1	26.1	0.005
	SE	(0.084)	(0.033)	(0.003)	(0.034)	(0.023)	(0.000)	(0.162)	(0.160)	(0.162)	(0.168)				
OV306	Coef.	0.130	−0.046	0.005	0.060	0.060 *	0.000 **	1.021	0.060	−0.797	−1.871	5658.4 ***	5678.4	18.5	0.003
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.000)	(0.193)	(0.191)	(0.193)	(0.197)				
OV307	Coef.	0.020	0.022	−0.006 *	0.148 ***	0.036	0.000	1.009	−0.025	−0.854	−1.911	5656.1 ***	5676.1	27.5	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.166)	(0.162)	(0.164)	(0.169)				
OV308	Coef.	0.053	−0.071 **	0.004	0.086 **	0.035	0.000	1.028	0.068	−0.750	−1.768	5665.9 ***	5685.9	16.0	0.003
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.023)	(0.000)	(0.173)	(0.170)	(0.171)	(0.176)				
OV309	Coef.	0.025	−0.075 **	0.005	0.166 ***	0.074 ***	0.000	0.673	−0.316	−1.104	−2.208	5637.1 ***	5657.1	46.2	0.008
	SE	0.084	0.033	0.003	0.034 ***	0.024 **	0.000	0.166	0.162	0.164	0.170				
OV310	Coef.	0.098	0.008	0.004	0.118	0.055	0.000	0.706	−0.228	−1.076	−2.202	5652.0 ***	5672.0	25.9	0.005
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.184)	(0.182)	(0.183)	(0.189)				
OV311	Coef.	0.081	−0.032	−0.002	0.037	0.085 ***	0.000	1.156	0.179	−0.656	−1.736	5664.9 ***	5684.9	20.7	0.004
	SE	(0.085)	(0.033)	(0.003)	(0.035)	(0.024)	(0.000)	(0.200)	(0.198)	(0.199)	(0.203)				
OV312	Coef.	0.077	−0.020	0.004	0.105 ***	0.039	0.000	1.000	−0.023	−0.852	−1.945	5662.1 ***	5682.1	18.5	0.003
	SE	(0.085)	(0.033)	(0.003)	(0.034)	(0.024)	(0.000)	(0.183)	(0.181)	(0.182)	(0.186)				

Note: (1) ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels. (2) See Table 4 for OV301 to OV312.

4.3. Estimation Results for Lessons Learned in Rebuilding Industries, Commercial Facilities, and Shopping Streets in Disaster-Affected Areas

Table 8 presents the estimation results for lessons learned in rebuilding industries, commercial facilities, and shopping streets in disaster-affected areas (H₃).

For OV301 and OV309, the coefficients of EV₃ (−0.073 and −0.075, respectively) are negative, while those of EV₄ (0.113 and 0.117, respectively) and EV₅ (0.166 and 0.074, respectively) are positive. This indicates that individuals without children, those with higher education levels, and high-income earners believe that (1) quick and smooth support should be provided to financially support affected companies and (2) providing a comfortable working environment and improving the image of industries are essential for securing employment for young people and women.

For OV302, the coefficient of EV₄ (0.152) is positive, indicating that individuals with higher education levels believe that creating systems to solve the double indebtedness issue of affected companies and providing long-term support for business recovery are necessary.

For OV303, the coefficients of EV₂ (0.007), EV₄ (0.173), and EV₅ (0.093) are positive. This suggests that the elderly, individuals with higher education levels, and high-income

earners believe that strategically concentrating next-generation growth industries can promote comprehensive industrial revival.

For OV304 and OV310, the coefficients of EV4 (0.068 and 0.118, respectively) and EV5 (0.063 and 0.055, respectively) are positive. This indicates that individuals with higher education levels and high-income earners believe that (1) strengthening industrial clustering in the region can support development and (2) increasing opportunities for interaction with innovative businesspeople can lead to a transformation in traditional management practices.

For OV305, the coefficients of EV2 (0.009) and EV4 (0.125) are positive. This suggests that the elderly and individuals with higher education levels believe that launching new businesses based on disaster experiences, developing new products, and exploring new sales channels are necessary.

For OV306 and OV311, the coefficients of EV5 (0.060 and 0.085, respectively) are positive. This indicates that high-income earners believe that (1) promoting joint research between academia and industry and developing new products are necessary and (2) planning and developing shopping streets in downtown areas should be carried out systematically.

For OV307 and OV312, the coefficients of EV4 (0.148 and 0.105, respectively) are positive. This suggests that individuals with higher education levels believe that (1) creating and nurturing startup companies through initiatives led by local governments is important and (2) urban management should be implemented by companies specializing in community development.

For OV308, the coefficient of EV3 (-0.071) is negative, while that of EV4 (0.086) is positive. Those who do not have children and those who are highly educated believe that unemployed disaster victims should be provided with jobs in restoration work to ensure their employment.

4.4. Hypothesis Verification

Before discussing the results, let us verify the three hypotheses (H_1 to H_3) based on the estimation results of the ordinal logistic regression analysis. The results of the verification showed that explanatory variables related to individual attributes such as gender, parenthood status, education level, and income were significant, leading to the rejection of the null hypothesis. This indicates that statistically significant differences exist among individuals in Japan regarding their interest, memory, and concerns related to reconstruction issues and lessons learned from disasters. As previously mentioned, Tsuji (2016) has shown that participation in community meetings on post-disaster reconstruction increases with age and education level. This study observed a similar trend.

5. Discussion

This study conducted a survey of residents' attitudes toward reconstruction issues and lessons learned from the GEJE, analyzed them statistically, and provided insights. The following points were revealed:

Firstly, around 30% of respondents felt that support was being provided to victims of the GEJE, and few respondents felt that none of the support measures were effective. Furthermore, over 20% of respondents felt that housing, community development, living environments, and industries and livelihoods in the affected areas were being supported. Similarly, over 20% of respondents felt that lessons and know-how were being utilized in collaborative reconstruction projects involving NGOs, private companies, and government agencies.

Secondly, when asked to prioritize the importance of post-disaster reconstruction and lessons learned, "support for victims" ranked first, followed by "reconstruction of housing and communities", "revival of industries and livelihoods", and "collaboration and inheritance". Over 40% of respondents in disaster-prone Japan expressed a desire to incorporate these lessons into future endeavors, including lessons learned from rebuilding

agricultural, forestry, and fisheries industries in disaster-affected areas; inheriting memories and records of the disaster; and lessons learned from rebuilding industries, commercial facilities, and shopping streets in disaster-affected areas.

The results of the ordinal logistic regression analysis revealed that males, individuals without children, the elderly, those with higher education levels, and high-income earners had a strong intention, statistically speaking, to incorporate lessons from rebuilding agricultural, forestry, and fisheries industries in disaster-affected areas. Similarly, males, the elderly, those with higher education levels, and high-income earners showed a strong intention to inherit memories and records of the disaster, while those living closer to the Fukushima Daiichi Nuclear power plant expressed a desire for the establishment of disaster heritage facilities. Furthermore, males, individuals without children, the elderly, those with higher education levels, and high-income earners showed a strong intention to incorporate lessons from rebuilding industries, commercial facilities, and shopping streets in disaster-affected areas.

Going forward, Japan's disaster-affected areas must continue to pursue reconstruction policies that focus on the revitalization of agriculture, forestry, fisheries, and industry and livelihoods. The Japanese government also needs to reconsider its disaster prevention plan based on the lessons learned from the GEJE and pass on the lessons of the disaster to the people of Japan.

6. Conclusions

In summary, the differences in individual attributes were clearly reflected in attitudes toward post-disaster reconstruction issues and lessons learned from the GEJE. Those who intend to recover from the disaster, remember it, and inherit its records tend to be males, the elderly, those with higher education levels, and high-income earners. These leading members of Japanese society have a strong interest in rebuilding agricultural, forestry, and fisheries industries, as well as housing and community development, living environments, industries, and livelihoods. The results of this research show that the strong willingness of residents to pass on memories and records of the earthquake to the nucleus of the community, and to pass on lessons learned in the reconstruction process, can be expressed as statistically significant results. They are likely to take the lead in promoting the modernization, large-scale development, and clustering of agricultural, forestry, and fisheries industries, as well as in rebuilding communities and livelihoods. However, as Yamakawa (2018) points out, despite the promotion of compact community development in disaster-affected areas, the reality is that urban development centered around large stores is progressing, resulting in commercial clustering different from traditional shopping streets. In Fukushima Prefecture, for example, the population is predicted to halve by 2060 compared to 2010 (Fukushima Prefecture Reconstruction and Comprehensive Planning Division 2019). Therefore, reconstruction policies focusing on downsizing for a shrinking population should be recommended in disaster-affected areas. Moreover, reconstruction policies and industrial policies under the shock doctrine (radical market-oriented reforms implemented in the wake of major disasters) should not be implemented in disaster-affected areas. Instead, policymakers should develop reconstruction policies tailored to the differences among Japanese citizens, taking into account the lessons learned from the GEJE and planning for the future.

7. Future Challenges

Finally, although this study statistically analyzed post-disaster reconstruction issues and lessons learned from the GEJE, it is important to address future challenges. The survey in this paper was conducted among residents who are highly interested in various issues related to the nuclear power plant accident in Fukushima. In a survey dealing with the nuclear accident, if only those who agree with the reconstruction policy are surveyed, the number of respondents who agree with the policy will increase. On the other hand, if only those who oppose the reconstruction policy are surveyed, the number of respondents

who oppose the policy will increase. Therefore, this paper takes a neutral position without advocating for or against the reconstruction policy. The estimation results of this study showed that approximately 25% of people feel that support for disaster-affected areas, housing and community development, living environments, and lessons and know-how are being effectively utilized. However, looking at these results in reverse, approximately 75% of people may feel that reconstruction support and lessons are not being effectively utilized. As mentioned above in Section 2.3 (tabulation method), self-selection bias may have been caused by the inclusion of the intention to oppose the reconstruction policy of the Japanese government. Yamakawa (2018) mentioned that post-disaster reconstruction policies implemented after the GEJE were heavily skewed toward infrastructure development in disaster areas, resulting in insufficient guarantees for the livelihoods of disaster victims. It cannot be determined from the estimation results of this study alone whether Japanese citizens feel that their country's reconstruction support measures and lessons learned are not being utilized or if they are simply indifferent. Future research would include a web survey of Fukushima and Miyagi Prefectures to statistically analyze how GEJE survivors evaluate Japan's reconstruction support measures and lessons learned. Additional research would examine memorializing and recording the GEJE. When continuing the study, we would like to develop a questionnaire to further reduce self-selection bias.

Finally, in recent years, the perspective of enhancing the quality of society, such as comfort, natural environment, safety, and security, has also become important, and project evaluation methods need to respond accordingly. Until now, no measurement method has been established for the benefits related to ensuring the safety and security of society against disasters. In this paper, we have not yet developed a method to evaluate the benefits related to the uncertainty of disasters. We would like to study this issue at another time in the future.

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Appendix A

Table A1. Sample attributes (n = 2000).

Personal Attributes		Freq.	%
Sex	male	1049	52.5%
	female	951	47.6%
Income	lower_i (under 2.8 million yen)	327	16.4%
	lower_ii (2.8–5.58 million yen)	377	18.9%
	middle_i (5.58–8.36 million yen)	369	18.5%
	middle_ii (8.36–11.15 million yen)	404	20.2%
	high_i (11.15–13.94 million yen)	114	5.7%
	high_ii (11.15–16.73 million yen)	124	6.2%
	high_iii (16.73 million yen or more)	181	9.1%
	prefer_not_to_say	104	5.2%

Table A1. *Cont.*

Personal Attributes		Freq.	%
Education	high_school	1091	54.6%
	vocational_technical_college	431	21.6%
	university	422	21.1%
	postgraduate	56	2.8%
Marital Status	single	666	33.3%
	married	889	44.5%
	living_with_partner	130	6.5%
	divorced/separated	81	4.1%
	widowed	34	1.7%
	prefer_not_to_say	200	10.0%
Personal Attributes		Average	SD
Age (years)		35.9	15.0
Number of children		1.586	1.509
Distance from Fukushima Daiichi NPP(km)		438.4	288.0
Source: prepared from survey results by Pollfish.			

Appendix B. Evaluation of Support for Victims of the Great East Japan Earthquake (Multiple Responses)

Assessment Item	Freq.	%
Livelihoods of evacuees are being supported.	612	30.6%
Links between evacuees and the affected area are being maintained.	586	29.3%
Revitalization of the affected area is being promoted	564	28.2%
Livelihoods of the affected people are being rebuilt	562	28.1%
Support for those who rebuild their lives by themselves is being provided.	560	28.0%
Education on reconstruction and disaster prevention is being promoted at schools after the disaster	550	27.5%
Mental and physical care is being provided to those who are engaged in disaster relief work	547	27.4%
Culture in the affected area is being restored.	526	26.3%
Communities are being formed in the areas where the disaster victims have moved or relocated.	499	25.0%
None of the support for disaster victims can be evaluated	136	6.8%
Other	446	22.3%

Appendix C. Housing, Community Development, and Living Environment in the Areas Affected by the Great East Japan Earthquake (Multiple Responses)

Evaluation Items	Freq.	%
Rebuilding and relocation projects in the affected communities are in progress	565	28.3%
Direction of community development in the affected areas is being provided.	553	27.7%

Evaluation Items	Freq.	%
Progress is being made in coordinating and supporting the consolidation and elimination of emergency temporary housing.	519	26.0%
Disaster public housing is being constructed with consideration for the elderly and the local community.	519	26.0%
The central city area, which was destroyed by the earthquake, is being restored and rebuilt.	513	25.7%
Temporary housing buildings are being maintained and managed.	513	25.7%
Railroads, ports, and airports have been restored and reconstructed	504	25.2%
An adequate number of public disaster housing units have been established	499	25.0%
Road networks have been restored/reconstructed	465	23.3%
Coastal levees, etc. are restored/reconstructed	459	23.0%
Relocation sites purchased by municipalities are efficiently utilized	456	22.8%
Disaster public housing is efficiently maintained and managed	442	22.1%
None of the housing, community development, or living environment has been improved.	141	7.1%
Other	411	20.6%

Appendix D. Industries and Livelihoods Supported in Areas Affected by the Great East Japan Earthquake (Multiple Responses)

Evaluation Items	Freq.	%
Progress is being made in attracting businesses to the affected areas	550	27.5%
Information is being disseminated to attract tourists to the affected areas	529	26.5%
Financing is being provided to support the recovery of businesses affected by the disaster	523	26.2%
Farmland and agricultural facilities in the affected areas are being restored	518	25.9%
New industries are being created in the affected areas	514	25.7%
Progress is being made in securing industrial human resources in the affected areas	512	25.6%
Advancement of the agriculture and forestry industries in the affected areas	510	25.5%
Progress in developing sales channels for the fisheries industry in the disaster area	510	25.5%
	508	25.4%
Progress is being made in developing sales channels for the agriculture and forestry industries in the disaster area	493	24.7%
Progress is being made in the sophistication and development of the fishery industry in the disaster area.	485	24.3%
New tourism demand, such as foreign tourists, is being created in the disaster area.	457	22.9%
None of the industries and livelihoods are being supported	122	6.1%
Other	402	20.1%

Appendix E. Reconstruction Projects in Which NPOs, Private Companies, and Government Agencies Cooperate with Each Other, and Memories and Records That Have Been Handed Down (Multiple Responses)

Evaluation Items	Freq.	%
Lessons learned and know-how from the Great East Japan Earthquake are utilized in local disaster prevention plans.	581	29.1%
Recovery lessons and know-how are published on the website of the Reconstruction Agency, and memories and records are being passed on.	548	27.4%
Reconstruction assistance is provided in cooperation and collaboration with the national government, local governments, and NPOs.	530	26.5%
Support for the elderly and children is being realized.	522	26.1%
Support is being provided for the revitalization of local communities where people have strong ties with each other.	509	25.5%
Intermediary support organizations at the prefectural level are coordinating and supporting the activities of NPOs, etc.	505	25.3%
Records of the disaster are being preserved, and lessons learned from the disaster and the recovery process are being disseminated.	502	25.1%
Affected local governments are able to secure support staff on a long-term and continuous basis.	497	24.9%
Preservation of earthquake remains and establishment of a base for handing down the lessons of the disaster	495	24.8%
The affected local governments are prepared to receive support staff.	492	24.6%
Memories, records, and experiences of the disaster are being passed on.	482	24.1%
Public-private partnerships have been established	476	23.8%
None of the above are collaborated, and the memories and records are not inherited.	109	5.5%
Other	445	22.3%

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Article

Enhancing Competitiveness: Driving and Facilitating Factors for Industry 4.0 Adoption in Thai Manufacturing

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Abstract: Adopting Industry 4.0 (I4.0) is inevitable for Thailand's manufacturing sector to remain competitive because global markets increasingly demand higher quality, faster delivery, and greater customization. While firms need to enhance productivity and optimize resource utilization, they also need to reduce operation costs, which require advanced technologies and data-driven operations. However, successful adoption requires skilled human resources, which is challenging for small and medium-sized enterprises (SMEs). This research explores factors driving and facilitating the implementation of Industry 4.0 (I4.0) in Thai manufacturing firms among SMEs and large firms. We employed qualitative analysis using semi-structured interviews with SMEs and large manufacturing firms in Thailand. Five key factors emerged as crucial for I4.0 adoption: awareness of I4.0, strong and proactive support from top management, self-funding capabilities, and effective human resource development strategies. While large multinational enterprises (MNEs) possess more significant resources and capabilities to adopt I4.0 technologies, SMEs face considerable challenges. They require a strategic approach tailored to their unique needs and resources to develop a feasible I4.0 roadmap. Additionally, governments and industry associations can play a significant role by providing training, funding, and other resources to empower SMEs to embrace I4.0.

Keywords: digital transformation; human resource development strategy; top management support; Industry 4.0; capability building

1. Introduction

The shift to Industry 4.0 (I4.0) has been a catalyst for significant transformation in the manufacturing sector, driven by technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics. This change is crucial for maintaining global competitiveness, especially for countries like Thailand. Traditional production methods, which rely heavily on manual processes and basic automation, have not met the increasing demand for efficiency, customization, and quality. Therefore, researching the factors that drive and support I4.0 adoption in Thai manufacturing firms is essential to help them make this transition effective.

Thai manufacturing firms are actively pursuing I4.0 adoption to maintain their global competitiveness. However, the successful adoption of I4.0 entails a complex endeavor with several factors, especially for small and medium-sized enterprises (SMEs). The extent and manner of I4.0 adoption in developing countries, such as Thailand, remain underexplored. While previous studies have investigated the concept of I4.0 and its potential benefits, a gap exists in the literature between the conceptual approach to I4.0 and the reality of its adoption regarding the specific local context of the Thai manufacturing sector, which is robust to the unique challenges faced by Thai firms (Jeenanunta et al. 2017; Jermstittiparsert et al. 2020). The specific research goal is to identify key factors driving and facilitating I4.0

adoption in Thai manufacturing firms through an in-depth qualitative case study approach, providing actionable insights for industry stakeholders and policymakers.

Recent studies have explored various aspects of I4.0 adoption in different regions. For example, research on Malaysian SMEs found that leadership and organizational flexibility are critical to I4.0 adoption, but many firms lack strategic flexibility (Hossain et al. 2023). In Italian Micro, Small, and Medium Enterprises (MSMEs), adopting I4.0 technologies increased labor productivity by 7%, yet there were challenges related to cost efficiency and knowledge creation (Bettiol et al. 2023). In Bangladesh, the main barrier was a lack of technical knowledge about I4.0, which slowed its adoption (Hossain et al. 2023). Miah et al. (2024) proposed the Skills and Employability Framework for I4.0, focusing on the South Asian region. They mentioned that training and development, financial constraints, and regulatory issues are significant challenges to I4.0 technology adoption.

While our analysis references global trends in I4.0, to establish a comparative framework, it is crucial to understand how these global patterns can be adapted to the Thai context. Studies from other countries offer valuable insights into the challenges and best practices of implementing I4.0, which is crucial for tailoring strategies specific to Thailand. Recent studies have highlighted significant strides in adopting Industry 4.0, within Thailand. Jeenanunta et al. (2017) also highlighted the challenges in human resource development for technological upgrades in Thailand, pointing out the significant gaps in skills and innovation capabilities. Sureeyatanapas et al. (2023) found that despite the potential benefits, Thai sugar producers are still at a low readiness level to adopt I4.0 technologies due to high investment costs. Small businesses struggle to find qualified employees, collaborate with reliable technological partners, and adapt to new working methods. Rauch et al. (2021) emphasized that Thailand needs to build a robust foundation for I4.0 implementation.

Previous studies on drivers and obstacles of I4.0 adoption have been conducted in developed countries, especially Western countries (Castelo-Branco et al. 2019). Such studies in Asian developing countries, especially, are still limited (Bellantuono et al. 2021). Furthermore, many studies have shown contradictory and different conclusions about the driving factors and challenges of I4.0 adoption (Bellantuono et al. 2021; Delera et al. 2022; Himang et al. 2020; Khin and Kee 2022). Miah et al. (2024) also identify six challenges, such as training and development, financial constraints, and regulatory issues, that must be addressed to grab maximum potential. Stentoft et al. (2021) conducted a mixed-method analysis to examine the drivers and barriers to I4.0 readiness and practice among Danish small and medium-sized manufacturers. Based on the qualitative results of four firms, the most perceived drivers were cost reduction, legal requirement (only for low technology intensity firms), customer requirements, and conscious strategy on I4.0 (for medium-high and high technology intensity firms). The most acknowledged obstacles were a lack of management's understanding of the strategic importance of I4.0 (only for low and medium-low technology intensity firms), lack of employee knowledge about I4.0 (except for a high-intensity firm), and lack of employee readiness (only for a high-intensity firm). However, the quantitative findings (190 firms) contradicted the results of other studies (Vuksanović Herceg et al. 2020) stating that barriers (e.g., lack of knowledge, lack of employee readiness) did not significantly influence the I4.0 technology adoption.

Despite these insights, there is still a significant gap in the understanding of the specific challenges and support needed for Thai manufacturers. While there are distinct differences between SMEs and large firms in their approach to I4.0, there are also notable similarities. Large firms typically possess more robust financial resources, established technological infrastructure, and access to skilled labor, which facilitate the adoption of advanced technologies. In contrast, SMEs often struggle with financial constraints and a lack of technological expertise. However, SMEs and large firms share common objectives, such as cost reduction, improving operational efficiency, increasing competitiveness, and adapting to market changes. Both face challenges related to integrating new technologies with existing systems and the necessity for ongoing employee training. Understanding

these similarities and differences is crucial for developing tailored strategies to support the implementation of I4.0 across different types of firms. This study aims to fill this gap by focusing on the unique socioeconomic conditions of Thai manufacturing firms, especially SMEs, which face different challenges compared to larger enterprises. Our study seeks to bridge this gap by analyzing the factors driving and supporting I4.0 adoption in Thai manufacturing firms. Unlike other studies that offer broad regional analyses, our research focuses on the Thai context. We conducted semi-structured interviews with crucial SMEs and large-firm stakeholders to gather detailed insights. By identifying critical factors such as top management support, financial challenges, and human resource capabilities, our research offers practical recommendations for policymakers and industry leaders to better support the I4.0 transition.

This research adds valuable insights to both the academic literature and practical applications. Academically, it enriches our understanding of I4.0 adoption by providing evidence from the small-, medium-, and large-sized Thai manufacturing sector, offering a localized perspective. The findings highlight the different and similar driving and facilitating factors for I4.0 adoption across different firm sizes and types. Our findings provide an initial exploration into the driving and facilitating factors for I4.0 adoption in Thailand, which can serve as a foundation for broader, more comprehensive studies. We aim to contribute to the ongoing discussion and provide preliminary insights rather than definitive conclusions regarding the Thai manufacturing sector. Additionally, this study contributes empirical data on Thai firms' specific challenges and opportunities, enriching the literature on industrial modernization in developing economies.

Practically, our findings can serve as a guide for policymakers, industry associations, and manufacturing firms. The insights can help develop strategies and policies that address the specific needs of Thai manufacturing firms, particularly SMEs, improving their readiness and capability to adopt I4.0 technologies. It recommends targeted policy interventions, such as increasing financial support for SMEs, developing comprehensive skill enhancement programs, and improving technological infrastructure. These recommendations are based on empirical findings and aim to address the unique challenges identified in the study.

To understand the Thailand approach to I4.0, Section 3 conducts a systematic literature review to identify the driving and facilitating factors of I4.0 implementation in varied contexts. Section 4 describes the methodology used to understand the driving and facilitating factors in the Thai manufacturing context. Section 5 presents the results. Section 6 concludes this study.

2. The Adoption of I4.0 in Thailand in the Context of Neighboring Countries

In this section, we explore the adoption of Industry 4.0 in Thailand, contextualized within the experiences of neighboring Asian countries. This comparative analysis highlights Thai manufacturers' unique challenges and opportunities and the broader regional trends influencing Industry 4.0 adoption. By examining the strategies and outcomes in Malaysia, Vietnam, and Indonesia, we aim to comprehensively understand the regional dynamics and how they impact Thailand's I4.0 adoption efforts.

The Thai government has launched many projects in cooperation with the Japanese government, such as the Automotive Human Resource Development Project (AHRDP) in 2006–2011, to support and cultivate knowledge and the technological development of manufacturing firms, especially among SMEs, to improve their productive activities. The Thai government has also accelerated industrial upgrading and structural change by promoting digital transformation of existing manufacturing and automation-related businesses since it announced new policies such as Thailand 4.0 in 2016 (Wongwuttivat and Lawanna 2018) and the development of new S-curve industries in the Eastern Economic Corridor (EEC) in 2016 (Kohpaiboon 2020). The Lean Automation System Integrator (LASI) training program launched in 2018 is one of the international cooperation programs for capacity building among the Thai and Japanese governments and private and educational

sectors to promote the understanding and adoption of I4.0. However, many firms struggle to develop sustained digital transformation and I4.0 implementation. In 2015, the Office of Industrial Economics reported that about 25% of the firms' production process is entirely manual, 35% is a combination of computer numerically controlled (CNC) and manual, 25% is a combination of CNC and automated handling system, 10% is CNC and robot, and only 5% of the firms were fully automated (OIE 2015). The Federation of Thai Industries (FTI) developed the self-assessment 4.0 model to assess a manufacturing firm's readiness for I4.0. Of 1335 firms, only 2% reached I4.0, 28% are in I3.0, 61% are in I2.0, and 9% are in I1.0 (FTI 2021). Comparatively, other Southeast Asian countries have progressed in adopting I4.0 technologies at varying paces (Miah et al. 2024). The adoption of key Industry 4.0 technologies is still in its early stages in Vietnam. About 6.9% of firms use cloud computing for business tasks, 1.5% use Big Data or AI for marketing purposes, only 6.1% of firms use advanced methods for manufacturing, 5.9% use robots, and 1.8% of manufacturing firms use additive manufacturing technologies (Cirera et al. 2021). There are still hesitant applications for these new technologies, as represented by their low readiness levels (Le et al. 2023). The Vietnamese government's support and the increasing presence of multinational companies have been crucial drivers of this adoption. In Malaysia, production efficiency and cost reduction were the strongest drivers for I4.0 adoption in the electrical and electronics industry. However, the most significant obstacles were the talent shortage and skilled workforce, limited financial support, and a lack of substantial business evidence to support such investment (Wong and Kee 2022; Yeap et al. 2024). De Marchi et al. (2022) discussed the network architecture of Education and Training for Automation 4.0 (ETAT) centers, which aims to develop a skilled workforce equipped for Automation 4.0. These studies underscore the importance of tailored educational frameworks for fostering industry readiness and competitiveness. The diversified situation of I4.0 adoption among Thai firms and the gap among countries suggests unexplored untapped country, sector, and firm-specific driving and hindering factors of I4.0 adoption. Therefore, more studies should be conducted to determine the antecedent factors of I4.0 implementation in different contexts and industry characteristics (Khin and Kee 2022; Stentoft et al. 2021).

3. Literature Review

A literature review was conducted using a comprehensive search of peer-reviewed scholarly articles written in English from several databases. The databases used were Web of Science, Emerald, IEEE, Taylor & Francis, Science Direct, and the Thai Journal Citation Index (TCI). The leading search phrases were digital transformation, I4.0, I4.0 implementation, I4.0 technology, factors affecting I4.0 implementation, human resource development toward I4.0, organizational strategy for I4.0, case study, and qualitative. Articles were selected based on their relevance to the study's objectives. The process for identifying driving and facilitating factors involved analyzing the findings and discussions of the selected articles. Key themes and factors were extracted and categorized to ensure comprehensive coverage of the literature and reliability of the results. As a result, we identified three driving factors and six facilitating factors as shown in Table 1.

Table 1. Driving and facilitating factors for Industry 4.0.

Themes	Sub-Themes	Source(s)
Driving factors	I4.0 Awareness	Awodele et al. (2024); Ersoz et al. (2018); Sari et al. (2020)
	Expected benefits and opportunities	Horváth and Szabó (2019); Khin and Kee (2022); Kiel et al. (2017); Müller et al. (2018); Stentoft et al. (2021)
	Customer pressure	Khin and Kee (2022); Vuksanović Herceg et al. (2020)

Table 1. Cont.

Themes	Sub-Themes	Source(s)
Facilitating factors	Top management support	Khin and Kee (2022); Vuksanović Herceg et al. (2020)
	Financial support	Awodele et al. (2024); Khin and Kee (2022); Vuksanović Herceg et al. (2020)
	I4.0 communication channel	EDB (2020)
	Inter-company collaboration	Khin and Kee (2022); Vuksanović Herceg et al. (2020)
	Stakeholders support	
	Digital skill development	Khin and Kee (2022); Moktadir et al. (2018); Vuksanović Herceg et al. (2020)

3.1. Driving Factors

The three driving factors include I4.0 awareness (Awodele et al. 2024; Ersoz et al. 2018; Sarı et al. 2020), expected benefits and opportunities (Khin and Kee 2022), and customer pressure (Khin and Kee 2022; Vuksanović Herceg et al. 2020).

3.1.1. I4.0 Awareness

Understanding I4.0 is the first step before firms implement or adopt it (Awodele et al. 2024). Awareness of the potential advantages of I4.0 opens opportunities for firms to embrace and invest in I4.0 technologies (Sarı et al. 2020). Understanding the benefits motivates companies to explore I4.0 solutions and consider their potential impact on their operations. In the Czech Republic and Kazakhstan, many firms had not implemented I4.0 because they had a low awareness (Basl 2017; Dikhanbayeva et al. 2021; Horváth and Szabó 2019; Stentoft et al. 2021). Many firms have only adopted and used technologies with a clear and demonstrably high-value proposition for their specific needs and existing processes (Awodele et al. 2024; Sarı et al. 2020). In South India, firms with less information on the I4.0 concept and its components had inadequate future actions and expectations (Safar et al. 2020). In contrast, firms with a high awareness of the benefits of I4.0 technologies and competitive advantages had already moved toward I4.0 with concrete strategic plans and actions (Ersoz et al. 2018; Sarı et al. 2020). However, some studies argued that even though the firms were aware of the potential advantages of I4.0, only a few used these concepts in particular activities, such as monitoring industrial processes (Mittal et al. 2018; Moeuf et al. 2018).

3.1.2. Expected Benefits and Opportunities

I4.0 involves significant investments in technology, infrastructure, and workforce training (Horváth and Szabó 2019; Khin and Kee 2022). Moreover, it also changes how businesses operate. If firms clearly understand and perceive the potential benefits opportunities, such as increased productivity, cost reduction, or improved product quality, they might consider moving toward I4.0 (Horváth and Szabó 2019; Khin and Kee 2022; Müller et al. 2018; Vuksanović Herceg et al. 2020). Khin and Kee (2022) proposed a list of benefits firms expect from I4.0 implementation, such as production and cost efficiency, traceability, flexibility, productivity, and better quality. They also showed a list of opportunities, such as customers' confidence in quality, more export markets, more high-end customers, and more significant market share.

3.1.3. Customer Pressure

Customer pressure forces firms to continuously improve their efficiency and performance. I4.0 technologies allow firms to adapt to changes faster and be more responsive to customers' demands quickly. Customers expect a wider variety of products, faster customization, and shorter delivery times. Firms that embrace I4.0 can gain a competitive edge by offering more innovative and efficient products and services. Vuksanović Herceg et al. (2020) found that customers' requirements dominated the decision to adopt I4.0 compared with employees' requirements. Firms prioritize customer satisfaction over the company's

profitability (Vuksanović Herceg et al. 2020). Furthermore, firms with I4.0 technologies can be perceived as leaders in adopting I4.0 and perceived as an image of innovation and forward-thinking, which can attract more customers.

3.2. Facilitating Factors

The six facilitating factors consist of top management support (Khin and Kee 2022; Vuksanović Herceg et al. 2020), financial support (Awodele et al. 2024), expected benefits and opportunities (Awodele et al. 2024; Khin and Kee 2022; Vuksanović Herceg et al. 2020), I4.0 communication channel, inter-company collaboration, stakeholder support (Khin and Kee 2022; Vuksanović Herceg et al. 2020), and digital skill development (Khin and Kee 2022; Moktadir et al. 2018; Vuksanović Herceg et al. 2020).

3.2.1. Top Management Support

Several studies have highlighted the importance of top management support in driving I4.0 implementation (Miah et al. 2024; Srivastava et al. 2022). The top management's perception of opportunities and challenges obtained from I4.0 drives I4.0 implementation (Müller et al. 2018). Realizing that I4.0 can maintain and expand its opportunities to be more competitive in the market, increasing operational efficiencies, and improving quality are crucial motivators for its adoption. Management's understanding and assessment of these benefits are essential for overcoming the inherent challenges and uncertainties associated with I4.0. Moreover, studies indicate that acknowledging challenges like organizational and production fit, competitiveness, and future viability are pivotal in shaping the decision-making process for I4.0 implementation (Fettermann et al. 2018; Moktadir et al. 2018; Müller et al. 2018; Veile et al. 2020). Therefore, top management's dual recognition of opportunities and challenges drives the strategic direction and ensures a balanced and informed approach to I4.0 adoption. Market uncertainty of business significantly drove I4.0 adoption in the short, medium, and long term (Prause 2019). Top management support is required to achieve a long-term strategy for I4.0 implementation, especially (Prause 2019).

Top management also plays a crucial role in handling the resistance from employee and middle management levels, which significantly hinders the adoption of I4.0 technology (Bellantuono et al. 2021). Dynamic leadership is also required to convince resistant individuals of the benefits of embracing a change toward I4.0 and build an innovative mindset among employees and an organizational culture (Parhi et al. 2022).

Such influences of top management leadership should be strengthened by concrete gains from digital transformation to make I4.0 strategies successful. Top management can support and facilitate a team to develop a successful pilot I4.0 project, showing employees the benefits of utilizing digital technologies and demonstrating how technologies will help them improve their work performance, not replace them. If the benefits of adopting I4.0 are not clear, it will create more barriers to I4.0 initiation (Horváth and Szabó 2019).

3.2.2. Financial Support

Financial support is also essential for developing and improving I4.0 systems. Financial resources are indispensable to secure I4.0 technologies, hardware, software, and other resources. However, firms can start an I4.0 pilot project using the existing resources available within the firms and avoid new investments as much as possible. Firms must constantly update and improve technologies to catch up with fast-paced technological changes and stay competitive. Even so, the lack of financial support limits organizations' ability to acquire or develop I4.0 technologies and makes hiring a skilled workforce to manage and maintain the new technologies difficult. SMEs with limited financial capability needed financial support to facilitate I4.0 adoption (Veile et al. 2020). However, financial constraints are not always a major hindrance. Khin and Kee (2022) showed contradicting findings suggesting that some SMEs proactively initiated the I4.0 project without any support from the government because I4.0 was worth starting.

3.2.3. I4.0 Communication Channels

To facilitate the transition to I4.0, management should communicate regularly with employees. This includes showing a clear vision and mission of I4.0 adoption, explaining the benefits of I4.0, and the “why” behind the changes. Regular discussions help employees understand how their roles contribute to this vision and to the company’s success. To our knowledge, previous studies have not included this factor in their analyses. However, this factor is used as an assessment criterion for the Smart Industry Readiness Index developed by Singapore (EDB 2020). This criterion includes the organization’s building block, structure, management pillar, and inter- and intra-company collaboration dimensions. It focuses on internal and external collaborations with partners to achieve a shared vision and purpose. Current studies have mainly focused on the infrastructure of communication systems, such as sharing data through the IoT or advanced technologies (Mourtzis et al. 2016; Mourtzis et al. 2018; Zhao et al. 2020). Therefore, investigating the influence of establishing formal communication channels for information sharing on I4.0 adoption can reveal new practices that SMEs can easily adopt.

3.2.4. Inter-Company Collaboration

Inter-company collaboration is critical in enhancing I4.0 readiness and adoption (Bettiol et al. 2023; Li et al. 2022; Veile et al. 2024). Effective collaboration between companies can lead to shared resources, knowledge transfer, design new product features and functionality, and enhanced innovation capabilities (Ganotakis et al. 2013; Müller et al. 2020; ul zia et al. 2023). Collaborative networks facilitate the exchange of knowledge, expertise, and best practices about I4.0 technologies and business cases, allowing SMEs to leverage larger firms’ expertise and capabilities (Camarinha-Matos et al. 2017). This collective knowledge pool can accelerate learning curves and shorten the time it takes for each firm to achieve its I4.0 goals. Firms can also collaborate to develop a new I4.0 solution for existing or potential problems. Firms engaged in collaborative efforts with partners are better positioned to exploit I4.0 technologies and successfully implement I4.0 (Bettiol et al. 2023; Müller et al. 2018).

3.2.5. Stakeholder Support

According to Vuksanović Herceg et al. (2020), manufacturing firms in Serbia need different support from each stakeholder. Suppliers and users of I4.0 technologies play the most critical role in resolving technical issues. Financial support from the government is essential. On the other hand, support from universities and research institutions is needed to educate human resources about I4.0 and provide knowledge regarding technical issues (Vuksanović Herceg et al. 2020).

3.2.6. Digital Skills Development

Digital technologies are constantly evolving, and employees need to be able to adapt and learn new skills quickly to stay current. This can be a significant challenge for organizations, particularly in industries where technology is rapidly changing and skills that were once in demand can quickly become obsolete (Li 2022; Nambisan et al. 2017). The quality of human capital positively affects the I4.0 technologies adoption, and most of them are highly educated and highly skilled workers (Corò and Volpe 2020). Employees need to develop domain-related competencies, develop analytical ability, and learn new digital knowledge and skill sets related to automation and the Internet of Things (IoT) to efficiently utilize and configure advanced I4.0 technologies (Alam and Dhamija 2022; Cooke et al. 2022; da Silva et al. 2022; Ghobakhloo 2020). Parhi et al. (2022) also showed that workforce empowerment and technical capabilities played a significant role in the success of I4.0 implementation in India. The findings from Veile et al. (2020) also emphasized that financial resources, employees’ skills, education, and training support were also crucial factors for I4.0 adoption. Nevertheless, the lack of a skilled workforce is a significant challenge and obstacle to I4.0 implementation, especially in developing countries (Kiel

et al. 2017; Müller et al. 2018; Vuksanović Herceg et al. 2020). Kapoor and Kabra (2014) found that budget and other resource allocation were major challenges organizations face in building the workforce's digital skills. The lack of internal capabilities to design, implement, and monitor the effectiveness of a capability-building program is another challenge for organizations in human resource development (HRD).

4. Methodology

We employed qualitative analysis, specifically a multiple-case study approach (Gustafsson 2017; Stake 2013), using semi-structured interviews with manufacturing firms in Thailand to capture insights, explore, and analyze the driving and facilitating factors and barriers that affect their decision to adopt I4.0. Qualitative analysis allows us to develop unique insights and in-depth understanding that are difficult to obtain from a closed-ended survey questionnaire. Moreover, broader perspectives can be explored during the interviews through interviewees' perceptions (Horváth and Szabó 2019; Miles and Huberman 1984).

We focus on the manufacturing sector because it is significantly affected by I4.0 (Arnold et al. 2016; Butt 2020; Felsberger et al. 2022; Johnson et al. 2008; Sarı et al. 2020). The sample was carefully selected using a non-random approach with purposive sampling techniques to guarantee comprehension of the studied phenomenon and gain deep insight from top-level management regarding the important driving and facilitating forces and barriers behind I4.0 adoption of the companies (Onwuegbuzie and Collins 2007; Strauss and Corbin 1994; Vuksanović Herceg et al. 2020). We used the directory of the Federation of Thai Industries (FTI), the National Electronics and Computer Technology Center (NECTEC), and the Department of Industrial Works, Ministry of Industry to contact and invite manufacturing firms in many manufacturing subsectors to participate in the research.

Seven interviewee firms included one small-sized firm (employed less than 51 employees) from the automotive parts industry, two medium-sized firms (those with 51–200 employees) from the automotive parts and electronics industry, and three large-sized firms (those with more than 200 employees) from the automotive, textile, and footwear industries (Saunders et al. 2018). The selection of these companies carefully considered various factors, including Thailand's representative industries, diversity in firm size and production engineering, their known engagement with I4.0 technologies, and their willingness to participate in detailed interviews. Their diversity allows for capturing broader perspectives and experiences in I4.0 adoption. The interviews were conducted from different viewpoints, including factory owners, CEOs, and managers at various levels, to avoid bias from a high degree of differing opinions from various job positions. We ensured the interviewees had at least a senior management level (Phillips 1981; Seidler 1974). Interviews were conducted both face-to-face and via the online channel from August 2022 to February 2023. The interview duration was between 60 and 90 min per interview. Each firm has one participant from at least the senior management level. A list of questions was provided to the interviewees before the interview date. All interviews were recorded, coded, and transcribed. We treated the interviewees' information as confidential and anonymous.

The interview questions were adapted from the literature (Awodele et al. 2024; Ersoz et al. 2018; Horváth and Szabó 2019; Khin and Kee 2022; Kiel et al. 2017; Moktadir et al. 2018; Müller et al. 2018; Stentoft et al. 2021; Vuksanović Herceg et al. 2020). The interview consisted of three main parts. The first part collected general information about the firm, such as establishment information, main customers and suppliers, and the firm's activities and movement toward I4.0. The second part discussed their current status of I4.0, technology adoption, and readiness to adopt I4.0. The third part focused on the driving and facilitating factors, barriers, and challenges in adopting I4.0. Table 2 exemplifies the questions.

Table 2. Example of questions for the proposed themes and sub-themes.

Themes	Sub-Themes	Key Interview Questions
Driving factors	I4.0 Awareness	- Why would you decide to adopt I4.0? - What are the driving factors for adopting it?
	Expected benefits and opportunities	- What are the benefits you expect from I4.0 adoption? - What opportunities do you foresee by adopting I4.0?
	Customer pressure	- Does your customer request that you adopt I4.0?
Facilitating factors	Top management support	- What kind of support do you receive from top management? - Have you implemented I4.0 strategy?
	Financial support	- Do you receive financial support from a firm or government?
	I4.0 communication channel	- Do you have a formal channel to communicate about I4.0?
	Inter-company collaboration	- Do you collaborate with customers/suppliers?
	Stakeholders support	- Do you collaborate with other partners?
	Digital skill development	- Do you have a training program to upskill and/or reskill regarding I4.0 technologies? - How do you invest in employee training and development programs for I4.0 technologies and skills?

The data were analyzed using thematic analysis, which involves identifying patterns, themes, and categories within the interview transcripts to systematically explore the interviewees' responses (Nowell et al. 2017). The transcripts were read and re-read to gain an understanding of the data. The data were coded, labeled, and categorized based on their content to capture key concepts and ideas. In the theme development process, codes were organized into themes and sub-themes representing patterns or commonalities across the data, guided by existing literature or research questions. Then, themes were reviewed, refined, and validated through discussions among authors and participant feedback to ensure that they accurately represented the data. The last step was summarizing the results to show the key themes and findings (Braun and Clarke 2006; Nowell et al. 2017).

5. Results

This research aims to explore the driving factors, facilitating factors, and obstacles to I4.0 adoption in the manufacturing sector in Thailand to gain insight into I4.0. This section summarizes the findings of the interviews by driving and facilitating factors.

5.1. General Information of Firms

Table 3 shows the manufacturing firms' profiles and their readiness toward I4.0. There is one small-sized firm (Firm G), two medium-sized (Firms E and F), and four large-sized firms (Firms A, B, C, and D) from various manufacturing sectors, such as the automotive industry (Firms B, F, and G), textile (Firms B, C, and D), and electronics and electrical sectors (Firms A and E). The average firm age is 27 years. Four (Firms A, B, C, and G) are Tier-1 suppliers directly providing complete components, sub-assemblies, or modules to the original equipment manufacturer (OEM) that assembles the final product. Firms D, E, and F are Tier-2 suppliers that supply raw materials, parts, or sub-components directly to Tier-1 suppliers. Firms A and B are the Original Brand Manufacturers (OBM), while Firms D to G are the Original Equipment Manufacturers (OEM). Firm C is both an OEM and an OBM. For the capital structure, Firms A and B are Multinational Enterprise (MNE) from Switzerland and Germany, respectively. Firms C, D, and G are 100% Thai-owned companies. Firm F is a joint venture (JV) with Japan. For the transactional relationship with suppliers, Firms A, B, E, and F have significant local and international suppliers, while Firms C, D, and G have only local suppliers. For market orientation, Firms A, B, and E

have the main customers in many countries. Firm C exports only to Asian countries. Firm D's primary customers are in Europe and Asia. Firm F's primary customers are Thailand and Japan. Firm G's main customers are in Thailand and Europe.

Table 3. Profile of the firms.

	Firm A	Firm B	Firm C	Firm D	Firm E	Firm F	Firm G
Product	Sewing machine	Automobiles	Leather and shoes	Yarn dyeing, fabric dyeing, and finishing	Plastic injection molding, parts	Automotive parts	Automotive parts
Age (years)	33	25	29	32	24	27	21
Tier	1	1	1	2	2	2	1
Size	Large	Large	Large	Large	Medium	Medium	Small
No. of employees	700+	1000+	1054	300+	190	152	25
OEM/OBM	OBM	OBM	OBM/OEM	OEM	OEM	OEM	OEM
Capital structure	MNE (Switzerland)	MNE (Germany)	100% Thai owned	100% Thai owned	100% Thai owned	JV with Japan	100% Thai owned
Major suppliers	Local and International	Local and International	Local	Local	Local and International	Local and International	Local
Major customers	Multinational	Multinational	Asia	Europe, Asia	Multinational	Local and Japan	Local and Europe
Main market	Export	Export	Export	Export	Domestic	Domestic	Domestic
Technology adoption	80% adopted automation and technology replaced with I4.0	Fully adopted automation	CNC and automation	Manual	Initiate cloud-based software, data storage, and analysis	CNC and semi-automation	CNC and manual
Readiness of I4.0	Very high	Very high	High	Very low	Medium	Medium	Very low
Adopt I4.0	Yes	Yes	Yes	No	Yes	No	No

In 2023, Firm A adopted automation and I4.0 technologies for about 80% (self-estimation) of the factory, such as autonomous robots, big data applications, cloud computing, simulation, IoT, and system integration. Firm B's production was fully automated. Firm C also integrated an automation system with high-performance CNC machines, while Firm F had a semi-automation system. Firm E was in the phase of implementing I4.0 technologies, such as the installation of sensors and robots, to increase productivity as a pilot project. The production of Firm G was mainly manual, and CNC was used for specific processes. Firm D also operated manually and had used the machines since the factory started. Firms A to C were highly ready to adopt I4.0. Firms E and F had medium readiness to adopt. In contrast, Firms D and G had not initiated any I4.0 activities and were not ready to adopt. In summary, Firms A, B, C, and E have implemented I4.0, while Firms D, F, and G have not implemented.

5.2. Driving Factors

Table 4 shows a comparison of the driving factors for each firm.

Table 4. Thematic analysis of driving factors.

Themes	Sub-Themes	Firm A	Firm B	Firm C	Firm D	Firm E	Firm F	Firm G
Driving factors	I4.0 awareness		Fully aware		Aware		Somewhat aware	
	Expected benefits	Production efficiency Transparency Supply chain integration Traceability Flexibility Better quality		Production efficiency	Productivity Cost efficiency		Better quality Production efficiency	
		Customers' confidence in quality More supply to meet higher demand			Customers' confidence in quality			
		Bigger market share More high-end customers			More export market		Better-imaged products	
	Expected opportunities			More high-end customers New market with better margin				
Customer pressure		No		Yes		No		

5.2.1. I4.0 Awareness

This study measures I4.0 awareness into four levels: fully aware, aware, somewhat aware, and low. Fully aware means firms deeply understand I4.0 concepts, technologies, and potential benefits. They are likely actively exploring or implementing I4.0 solutions in manufacturing processes by having dedicated teams or resources focused on I4.0 adoption. Aware means firms have a general understanding of I4.0 and its potential impact. They are interested in adopting I4.0 technologies but may lack a clear understanding of how to implement them or the specific benefits of their operations. They are actively seeking information and exploring options for I4.0 adoption. Somewhat aware refers to firms with limited knowledge of I4.0 and no idea about its implications. Low refers to firms that have heard about the term but are still confused about the definitions and complexity of the concept. It is difficult for them to identify the real scope and objectives of I4.0 (Awodele et al. 2024; Dikhanbayeva et al. 2021; Ersoz et al. 2018; Sarı et al. 2020). Table 4 presents the awareness level of each interviewed firm.

Firm A and Firm B are large-sized MNEs. Their top management and employees fully know the I4.0 concept and how it can increase its competitive advantage and business performance. Their overseas headquarters force every factory to adopt I4.0 technologies. Firm B introduced I4.0 to the Thai factory in 2018, using the concept of “Operational Excellence and Digitalization” as set up by the CEO. The strategies and roadmap are well-organized and align with the business mission. More than 80% of all employees clearly understand and embrace I4.0. Firm A’s Thai factory has transformed toward I4.0 since 2012 by implementing Kaizen and lean manufacturing and using the latest technologies to solve their problems in the supply chain. Top management set up a policy for digital transformation and focused on setting the same high standards for all factories. Most of the employees are aware of the I4.0 concept and benefits. Firm C is also fully aware of and understands I4.0 technologies and implementation. Top management recognizes the potential for increased productivity and enhanced quality through implementing Industry 4.0 technologies by visiting many exhibitions and show cases in Thailand and overseas. Top management launched a clear roadmap and policies to support the company’s digital transformation.

In contrast, Firms D and F suggest that firm size and capital structure are insufficient conditions to reach the highest awareness level. These two firms have not implemented I4.0 because their top management has not understood the I4.0 concept. The top management of Firm D somewhat understood the basic concept of I4.0. They informally talked about it in a few meetings with employees but did not seriously consider adopting it soon. This firm considered implementing IoT in production lines, such as sensors and RFID. However, the investment costs were very high, and its organizational structure, strategies, and human resources were not ready for digital transformation. Therefore, the top management decided not to invest in the new technologies, and the I4.0 project was not initiated. The top- and middle-level management did not clearly understand what I4.0 meant for Firm F. It attended many I4.0 seminars organized by the public sector. However, many factories are still confused and question what I4.0 is, which degree of technology adoption needs to be called I4.0, and how many robots or machines they must use to be called I4.0. Firm F is studying I4.0, conducting a cost/benefit evaluation, and considering the potential to use robots to replace the workforce in the production line. Firm G is considering adopting I4.0 because the automotive market shift focuses on electronic vehicles within 5–10 years.

5.2.2. Expected Benefits and Opportunities

(1) Benefits. Firms A and B (large MNEs) fully aware of I4.0 are expected to gain productivity, cost efficiency, production efficiency, transparency, supply chain integration, traceability, flexibility, and high quality. Firms C and F are expected to increase their productivity, costs, and production efficiency. Firm G only aimed for productivity and cost efficiency, while Firm E expected to increase productivity, cost efficiency, and better quality. Firm D only expected productivity and cost efficiency. In other words, all firms expect

quality and cost control improvements, whereas Firms A and B expect additional benefits that improve their entire supply chain operation and governance.

(2) Opportunities. Firm A and Firm B (large MNEs), who are fully aware of I4.0, believed that I4.0 adoption might lead to opportunities to gain customers' confidence in quality, improved people and culture, more significant market share, more supply to meet higher demand, and having more high-end customers. Large Thai-owned firms (Firm C) that exported to the Asian market expected customers' confidence in quality, more supply to meet higher demand, and more export market. Firm D was highly confident about its product quality. Therefore, the expected opportunities from I4.0 are more export markets, more high-end customers, and new markets with better margins. Firm E expected that I4.0 could increase customers' confidence in quality, increase export markets, increase high-end customers, and create new markets with better margins. In contrast, Firm F expected customers' confidence in the quality and more export market. Firm G needed customers' confidence in the quality and better-imaged products because it was a small-sized OEM with a limited understanding of I4.0.

The two large MNEs with full awareness of I4.0 expected benefits and opportunities other than improvements in daily operational performance. However, the findings from the rest of the firms suggest that these expectations will depend on various factors, such as strategic orientations and operational priorities.

5.2.3. Customer Pressure

Contrary to the results of the literature review, only Firm E has received pressure from its main customers to adopt I4.0. Firm E must satisfy the increasing demand for high-quality and precise products from its customers. Firm E's business field of plastic injection and molding is machine-intensive. Therefore, the firm needs to invest in sensors and robots to increase productivity and improve quality. The rest of the firms did not receive any pressure to adopt I4.0.

However, only large firms with the highest awareness levels proactively implemented I4.0, as discussed in Section 5.1. Firm D and Firm F, who are not proactive and do not have any support from top management, still use existing technologies to operate because their productivity is adequate. These findings imply that top management awareness and customer-supplier relationships will affect the role of customer pressure in I4.0 implementation.

5.3. Facilitating Factors

Table 5 shows a comparison of the facilitating factors for each firm.

5.3.1. Top Management Support

After the concept of I4.0 was recognized and introduced in the organization, top management played a crucial role in facilitating the planning and implementation of I4.0 projects and activities. The top management of Firm A set up an organizational strategy that facilitates the adoption of I4.0. Moreover, to sustain I4.0 implementation, the top management has to regularly monitor and evaluate the project's progress. Top management of Firm B set digitalization strategy and mission for every department, starting from routine tasks. Managers must present monthly progress on digitalization and I4.0, projects, and success cases and share the best practices of their departments. A key performance indicator (KPI) was set to evaluate the performance. The CEO also offers appreciation rewards such as the project of the Week/Month, an IMotion activity that promotes innovative ideas from employees, and monetary rewards. Firm C proactively invested in I4.0 technology and collaborated with its partner, specializing in IoT and smart factory technologies. The top management supported the I4.0 projects and worked with consultants to launch pilot projects to reduce waste in the production system. Sensors and IoT devices were installed on the shop floor to monitor production. The top management monitored the project closely through a monthly report. Firm E is developing the policy and strategies of I4.0, with full support from the top management.

Table 5. Thematic analysis of facilitating factors.

Themes	Sub-themes	Firm A	Firm B	Firm C	Firm D	Firm E	Firm F	Firm G
Facilitating factors	Top management support	Proactive, fully supportive, involved, and committed to I4.0 projects. Initiated and driven by top management with clear goals, directions, roadmap, action plan, and strategies.						
	Financial support			Self-investment	No	Reactive and involve	No	No
							Need funding and support from the government	Self-investment
	I4.0 communication channel	Formal communication channels are established with the official record						
	Inter-company collaboration	Informal communication						
	Stakeholder support	Whole supply chain		Main customers and suppliers	No		Main customers and suppliers	
		Customer Supplier		Customers Suppliers Universities Research institutions	No		Customer Supplier	No
	Digital skill training program	Innovative and adaptive training program for future skill	Structured training programs	Basic program for specific job function	Structured training programs	Basic program for specific job function	Informal mentorship and apprenticeship	

5.3.2. Financial Support

Firms A, B, C, and E allocated their budget to invest, especially in I4.0 projects and activities, because they knew that investing in I4.0 needed a high upfront budget. All large firms mentioned that I4.0 provides new opportunities for the firm to digitalize the production system and fulfill customer-specific requirements more effectively and efficiently.

Moreover, I4.0 can trace and track the processes throughout supply chains in real-time to achieve higher flexibility and quality of production processes (Khin and Kee 2022) and higher supply chain efficiency. Therefore, most large firms, which are influential in operating their entire supply chains, anticipate a significant benefit from I4.0, and are well-prepared for investment in new technologies. SMEs recognized the benefits of I4.0, but perceived that investment cost was higher than the expected return on investment after exploring the feasibility of I4.0 investment. It is a considerable risk for SMEs to invest without any support or funding from the government. Therefore, Firms D, F, and G need funding and support from the government to initiate I4.0 projects.

5.3.3. I4.0 Communication Channel

Firms A, B, and C established formal communication channels within the firms and officially recorded the I4.0 activities and technologies that they adopted. They also addressed concerns about employees' fear of losing their jobs or being replaced by automation. This transparency fosters understanding, reduces resistance, and encourages employee buy-in for a successful transition. Firms D to G had no formal communication channels. They relied on informal channels such as discussing I4.0 in some meetings, personal chat, or hallway discussions. Communication through these channels could lead to misunderstanding or misinformation about I4.0. Moreover, information across different informal channels could create confusion and make it difficult for employees to grasp the company's overall I4.0 vision and strategy.

5.3.4. Inter-Company Collaboration

Firms A and B collaborated with their partners across the supply chain by integrating I4.0 technologies and cloud computing with enterprise resource planning (ERP) systems and supply chain management (SCM) systems. This transparent collaboration facilitated improved communication, data sharing, better coordination, real-time visibility of production processes, and faster response times to disruptions among different partners in the supply chain. Firms C, E, F, and G only collaborated with their primary customers and suppliers in specific activities, such as product development, problem-solving, and sharing production status. Firm D had no inter-company collaboration.

5.3.5. Digital Skill Training Program

Firms A and B have proactively developed training programs to identify and incorporate innovative learning and development practices and training for future skill sets. The program is robust and adaptive to keep up with the pace of technology changes. The training programs are regularly reviewed, refreshed, and customized based on the insights provided by key stakeholders through feedback loops. These firms also organized in-house training through internal and external experts from universities and the private sector. The internal experts can organize training in I4.0 technologies for their employees. They also have internal training facilities and knowledge management systems that allow employees to access e-learning platforms anywhere and anytime. Firms D and F only provided basic training programs for specific job functions. Firms C and E had structured training programs designed to run continuously and expand employees' digital skill sets. They developed a continuous training program aligned with the organization's needs and HR functions. Firm G only had informal mentorship and apprenticeship. Since Firms D and G did not see the urge to implement I4.0 technology, they focused mainly on training specific technical skills in necessary job functions.

5.4. Discussions on Conditions of I4.0 Adoption

What are the critical factors that determine the level of readiness for I4.0 (hereafter, I4.0 adoption)? To identify key elements from the interviews, we focus on the firms at a very high level of readiness of I4.0 (i.e., Firms A and B) and those at a deficient level (i.e., Firms D and G).

Firms A and B share common characteristics. These two firms have the same driving and facilitating factors. However, they only have different technological adoption attributes (i.e., Firm A is 80% automated and replaced with I4.0, and Firm B has fully adopted automation). Among the firm attributes, only these two firms have the capital structure of MNE, suggesting MNE as a sufficient condition of the very high level of I4.0 in this case study, which aligns with Horváth and Szabó (2019), who mentioned that MNEs were more flexible in allocating financial resources to invest in new technologies for new developments. Although we do not conclude that this finding is robust, it does, in combination with comparisons with other firms, provide rich insights into the condition of I4.0. For example, Firm C has characteristics similar to those of Firms A and B, such as large size, full awareness, proactive support from top management, and formal communication channels. However, unlike Firms A and B, Firm C is 100% owned by Thai and expects a narrower scope of benefits to its own productivity, production, and cost efficiency. This evidence suggests that some Thai firms are still focusing on the limited interests of their stakeholders and their supply chains, which makes the adoption of I4.0 at a lower level satisfactory.

In the same way as the analysis, Firms D and G, with a deficient level of I4.0 and high dependence on manual processes, do not receive any stakeholder support, which is a uniqueness of these two firms. This finding implies that the lack of stakeholder support can be a sufficient condition for the deficient level of I4.0 adoption. Although these two firms are different in size (i.e., Firm D is large and Firm G is small), their top management does not support I4.0 projects, which may discourage Firms D and G from accessing stakeholder support. This finding also suggests the importance of competitive environments, leadership style, and other determinants of firm strategies for I4.0, in understanding I4.0 adoption. These findings support the hypothesis that management issues are a crucial obstacle to I4.0 adoption if top management can neither identify opportunities from I4.0 adoption nor recognize the importance of I4.0 technology (Horváth and Szabó 2019; Khin and Kee 2022; Vuksanović Herceg et al. 2020).

Productivity and cost efficiency are expected benefits from I4.0 for all interviewed firms, irrespective of their size and capital structure. In addition, all the interviewed local firms are OEMs. The findings in this subsection indicate that firm- and factory-level efficiencies are fundamental motives for attempting I4.0, especially for local firms in Thailand and probably for other developing countries focusing on manufacturing activities in supply chains.

The barriers and challenges of the studied firms can be summarized as two main issues. First, management issues, lack of initiative, and support from top management (Firms D, F, and G) hinder I4.0 adoption. Top management fails to recognize the importance or potential opportunities of I4.0 technologies in the long term. Firms with proactive leadership that provides a supportive working environment are more likely to achieve I4.0 adoption. Second, there is a lack of stakeholder support for firms with low levels of I4.0 adoption, such as Firms D and G. This suggests that stakeholder support is crucial for successful I4.0 implementation. The absence of stakeholder support can be a significant barrier, especially for firms that are heavily reliant on manual processes.

6. Conclusions

The qualitative analysis of this study investigated the driving and facilitating factors of Thai manufacturing firms toward I4.0. The findings of this study contribute to the literature on I4.0 adoption among Thai manufacturing firms, offering valuable insights into the driving factors and facilitating conditions. The different levels of awareness and understanding of I4.0 concepts among firms, with larger MNEs exhibiting a more

profound comprehension and proactive approach than smaller, local firms, are consistent with Horváth and Szabó (2019); Sari et al. (2020). This variance also reflects the critical role of top management in fostering awareness and creating a favorable environment for I4.0 adoption. Top management in MNEs has clear strategies, well-organized roadmaps, and a strong leadership commitment to digital transformation initiatives. However, smaller firms often face challenges in grasping the implications and benefits of I4.0, particularly when top management lacks a comprehensive understanding or fails to prioritize its adoption. Additionally, SMEs may lack the organizational capacity and infrastructure to drive I4.0 initiatives effectively, leading to slower progress and limited innovation compared to their larger counterparts.

Financial resources emerge as a crucial facilitator of I4.0 adoption, particularly for smaller firms with limited budgets. Larger firms are better positioned to access the financial and non-financial resources crucial for I4.0 implementation, giving them an advantage over SMEs (Sari et al. 2020). While larger MNEs are willing to invest in I4.0 technologies, recognizing their long-term benefits and competitive advantages, smaller firms struggle to justify the high upfront costs without external support or funding. This finding shows the importance of tailored strategies to communicate the potential benefits and opportunities of I4.0 in different types of firms, considering their size, sector, and market position. Moreover, the study highlights the significance of top management support in driving I4.0 initiatives within organizations, with proactive leadership playing a pivotal role in setting clear strategies, providing resources, and supporting technological change.

Moreover, collaboration and communication within supply chains present contrasting scenarios for large MNEs and SMEs. MNEs leverage their global networks and resources to foster collaboration between suppliers and customers, facilitating enhanced transparency, data sharing, and coordination. In contrast, due to limited resources and organizational capabilities, SMEs may face challenges in establishing formal communication channels and inter-company collaboration. Horváth and Szabó (2019) also confirmed that a lack of network-level collaboration and technology integration at the supply chain level is a key hindrance to I4.0 implementation.

Another crucial aspect is the importance of training and skill development programs to prepare employees for the challenges and opportunities presented by I4.0. Large MNEs invest significantly in comprehensive training programs to upskill and reskill their workforce and ensure they can effectively utilize I4.0 technologies. These findings are consistent with Di Sabato and Savov (2023), who show that large firms provide more support to employee training programs than SMEs, especially for MNEs. However, SMEs face challenges in providing adequate training and skill development opportunities, limiting their ability to harness the full potential of I4.0.

Furthermore, most manufacturing SMEs operate as OEMs, catering to the specific requirements of their customers. When their current skills, knowledge, and experiences suffice to meet customer demands, these firms may struggle to recognize the critical importance of reskilling or upskilling in the context of I4.0 technologies. The obvious example is Firm G, which hesitated to initiate I4.0 adoption due to uncertainty regarding the potential shift in automotive production from combustion engines to electric vehicles within the next 5–10 years. If such a transition occurs, Firm G would need to adapt its production processes, technologies, and human resource capability to manufacture parts for electric vehicles. However, if this transition does not occur as expected, investing in new technologies could result in unnecessary costs for the company. Firms need to consider the uncertainties from government policies, charging infrastructure development, and consumer preferences for electric vehicles, which might affect the transition in the future.

To assist Thai manufacturing firms, especially SMEs, experts from the public sector, such as government agencies, the private sector, and the academic sector, should educate them to understand the I4.0 implementation steps and benefits clearly. Ensure that they have a clear direction and confidence to move toward I4.0. The absence of a cohesive digitalization strategy is an obstacle to I4.0 adoption for SMEs. Firms should know how

to acquire and disseminate up-to-date technological knowledge and reflect on the shared goals and collaborative efforts of all stakeholders within the firm and between partners in supply chains.

This study demonstrates that all firms share common goals, such as cost efficiency and productivity. Moreover, they encounter challenges related to integrating new technologies with existing systems and the need for ongoing employee training. The factors influencing I4.0 adoption among Thai manufacturing firms range from awareness and understanding to financial resources, top management support, and skill development. Thai SMEs encounter distinct challenges due to several factors, including limited financial resources, a lack of economies of scale, lower technological advancement, and insufficient skilled labor compared to large firms. These constraints can hinder their ability to invest in new technologies and the training required for I4.0. SMEs often have less access to government support than large firms do, while SMEs and large firms strive to implement I4.0. As a result, their approaches to common challenges can vary significantly. Larger firms can adopt advanced technologies rapidly, with more robust financial resources, established technological infrastructure, and access to skilled labor.

Addressing these challenges and creating an enabling environment for I4.0 adoption requires concerted efforts from policymakers, industry associations, and organizational leaders to tailor strategies, provide support mechanisms, and foster collaboration within supply chains. By doing so, Thailand's manufacturing sector can harness the transformative potential of I4.0 to enhance competitiveness, drive innovation, and secure sustainable growth in the digital age.

The limitation of this paper is that the results are based on human perception, which can introduce subjective biases. Specifically, the findings reflect the views of individuals at different managerial levels within the studied firms. Top management support, for instance, was assessed by individuals in top managerial positions, which might have introduced self-assessment bias. Therefore, the results might differ in different industries, firm sizes, and countries. Despite these insights, the sample size is relatively small and may not capture the full diversity of the Thai manufacturing sector. We acknowledge that a sample size of seven companies cannot fully represent the entire industry. This could potentially limit the generalizability of the findings to a broader population of Thai manufacturing firms.

Additionally, the sample may not fully represent the diversity of manufacturing sub-sectors or company sizes within the country. As the study relies on qualitative analysis of semi-structured interviews, there may be inherent subjectivity and bias in the interpretation of the data. The perspectives and experiences of participants may vary, and the findings may not capture the full spectrum of views on I4.0 adoption among Thai manufacturing firms. The study's cross-sectional design provides a snapshot of the current state of I4.0 adoption among Thai manufacturing firms. However, it does not capture longitudinal changes or trends over time.

Future research should consider more extensive and varied samples to validate these findings. Additionally, longitudinal studies can provide a deeper understanding of the adoption process over time. Moreover, comparative designs could provide deeper insights into the dynamics of I4.0 adoption and its impact on firm performance. To address subjective biases, we included additional respondents from middle management and operational levels to provide a broader perspective and reduce potential bias. However, we acknowledge that this approach does not eliminate bias, as perceptions can vary widely within a firm. Future studies could benefit from including a more significant number of respondents from each company to further enhance the reliability and validity of the findings. These findings can be used as a basis for benchmark analyses in countries that share similarities with Thailand. A quantitative cross-country empirical study is recommended for future research.

Moreover, other external factors, such as economic conditions, government policies, and technological advancements, could impact the adoption and implementation of I4.0 technologies in ways that are not fully captured or accounted for in the study. Investi-

gating the impact of specific I4.0 technologies, such as IoT, AI, and robotics, on different industry sectors can provide more detailed insights. Furthermore, comparative studies of Thailand and other countries with similar economic profiles can offer valuable lessons and best practices.

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Article

The Structure and Nature of Social Capital in the Relationship between Spin-Offs and Parent Companies in Information Technology Clusters in Brazil and Spain

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Abstract: The objective of this research is to determine how proximity between organizations promotes the intensity of relationships and facilitates the exchange of information and knowledge in the relationship between the parent firm and the spin-off and its influence on organizational performance. Therefore, four constructs related to business competitiveness are integrated: networks, social capital, spin-offs, and innovation. The loci of the research were two clusters of Information and Communication Technology, with a sample of 166 companies in Brazil and 66 in Spain. Structural Equation Modeling was applied. The results indicate that geographical proximity between organizations promotes the intensity of relationships and facilitates the exchange of knowledge between the parent firm and the spin-off, but it cannot be said that geographical proximity impacts innovation for the parent firm. Furthermore, because the parent firm relates to its spin-off, the parent firm did not perform better than the nonparent companies with other companies. This study improves the understanding of companies that are in a business cluster, and its results have both institutional and business implications for the Information and Communication Technology (ICT) sector.

Keywords: spin-off; business cluster; structural equation modeling; Information and Communication Technology

1. Introduction

The present study addresses the environments in which Information and Communication Technology (ICT) impact interorganizational and work relationships. This is particularly important due to the growing demand for innovations and the incentive for the formation of new companies (Wallin 2012). In these environments, according to the literature on entrepreneurship, many new businesses arise from other companies (Parhankangas and Arenius 2003), and this phenomenon is called spin-off in the literature (Wallin 2012; Bagley 2019b; Furlan and Cainelli 2020). The justification for the choice of subject was that there are few studies on the relationship between the parent firm and the spin-off, especially regarding what happened between the two after the separation, which is important for studies of spin-offs, due to its relevance to the regional economy and national level (Wallin 2012) and also for studies of inter-organizational relations of cooperation and trust, as well as social capital (Oudeniotis and Tsobanoglou 2022).

This relationship can occur in several types of contexts in the ICT sector. One of them is that of clusters, defined as an environment where economic and social relations are mixed (Molina et al. 2008; Torres et al. 2021). It is not uncommon for social capital to emerge in

industrial clusters (Molina-Morales et al. 2013). Social capital is an important construct for explaining the probability of survival and success of new ventures, as well as individual access to external knowledge through social networks to develop the ability to recognize and explore new ventures, business opportunities (Audretsch et al. 2011).

This research aims to determine whether geographic proximity¹ between organizations promotes the intensity of relationships and facilitates the exchange of information and knowledge in the relationship between the parent firm and spin-off and its influence on organizational performance. For this purpose, an adaptation was made to the theoretical model developed by (Molina et al. 2008), as this study aimed to fill the following gap: conducting research in another economic sector, different from the ceramic sector, and choosing ICT. Additionally, the study contributes by discussing the subject of social capital in the interorganizational relationship between parent companies and spin-offs and by making a comparison between two countries, Brazil and Spain. In methodological terms, the use of structural equation modeling favors a more integrated and comprehensive understanding of different constructs (Hair et al. 2005), going beyond the original proposal by Molina et al. (2008).

2. Social Capital, Innovation, and Spin-Off in Clusters: Theoretical Proposal and Hypotheses

Territorial clusters (or clusters) have been studied in various economic sectors, including in the area of technology (Kerr and Robert-Nicoud 2020; Eiriz and Barbosa 2022). Clusters of ICT companies correspond to the largest number of related investigations (Stam and Elfring 2008; Wallin 2012; Bagley 2019a, 2019b). ICT clusters are characterized by the formation of Small and Medium-sized Enterprises (SMEs), such as Silicon Valley and Route 128 in the USA (Saxenian 1996) and 22@Barcelona in Spain (Viladecans-Marsal and Arauzo-Carod 2012).

ICT companies generally have the potential for innovation development and knowledge accumulation, which is rooted in their human capital, that is, employees or owners (Agarwal et al. 2004). When individuals working in clusters leave their parent companies to form a new company (spin-off), they take their knowledge and contacts, becoming part of the initial resource base of the new company (Agarwal et al. 2004). By preserving the link with the parent firm, the spin-off can use some of the assets of the parent firm, safeguarding some advantages in a network relationship. In addition, compared with other new companies, spin-offs are born with a competitive advantage, as they may have gained from previous experiences and the relationships built (McKendrick et al. 2009; Bagley 2019a; Furlan and Cainelli 2020; Juhász 2021).

In the theoretical body of research on organizational networks, several approaches (Zaheer et al. 2010) have identified three levels of relationships: the dyad (between two actors), the interorganizational set (double, one organization with others), and interorganizational networks (all organizations united by relationship bonds). In this study, relationships at the dyad level are adopted because they are relationships between two organizations: one is the parent firm, and the other is its respective spin-off (Fryges et al. 2014).

The ties can be strong or weak (Granovetter 1983). Strong ties tend to unite similar people in long-term relationships. In contrast, weaklings are superficial or casual and are characterized by little emotional investment. The strength of ties is defined as the intensity and diversity of relationships based on a combination of four criteria: the frequency of contact, the intensity of the emotional relationship, the degree of intimacy, and the reciprocal commitments between the actors (Granovetter 1983). that each of them is independent of the other but intracorrelated. Although studies have demonstrated the advantages and importance of weak ties (Granovetter 1983), other authors consider that both weak and strong ties play important roles in relationships (Hite 2003). Thus, the bond is a relevant variable in networks, and for this reason, the following hypothesis is proposed:

H1. *The interrelationship between the parent firm and its spin-off in the clusters determines a dense structure and strong ties.*

Research suggests that frequent and repeated links between two organizations increase trust between them and engender future ties (Oudeniotis and Tsobanoglou 2022; Soda and Zaheer 2012). Greater trust in interorganizational relationships reduces transaction costs and allows greater benefits from these relationships (Zaheer et al. 2010), improving firm performance (Soda and Zaheer 2012). In particular, the interorganizational relationships between parent companies and their spin-off companies generate exchanges of resources (McKendrick et al. 2009), such as specialized knowledge (Fryges et al. 2014).

Information and knowledge are terms that can have several definitions depending on the perspective researched and the authors who studied them, yet they are interconnected (Stenmark 2002). However, the aforementioned author defines information as something objective, independent, with a reality on the basis of content, and that needs knowledge to be interpreted. Knowledge, on the other hand, requires confidence, beliefs, values, experiences, skills, and insights, among other attributes, which can be tacit or explicit.

Technological know-how is usually incorporated into human capital, where skills and techniques are easily transferred as they are embedded in specialized work (McKendrick et al. 2009). When separating, the founders of new ventures often take advantage of their knowledge and skills or routines, which usually form the core of their activities (McKendrick et al. 2009; Juhász 2021). These bonds can support the transmission of knowledge between companies, which often occurs through employee mobility. Hence, the second research hypothesis is as follows:

H2. *The interrelationship between the parent firm and its spin-off in the clusters promotes the exchange of quality information and knowledge through strong ties.*

Social relationships influence economic action, which can result from the decision-making process of an individual, taking into account both personal and social factors (Granovetter 1983). Based on these relationships, social networks are created. Social networks can have various definitions in the organizational sphere and, in a broader sense, are a set of actors (individuals or organizations) connected by a certain type of relationship built through the identification of ties (formal or informal) where exchanges take place between tangible and intangible resources (Anand et al. 2002). Some authors argue that social networks can become the means by which the managers of organizations acquire knowledge from outside the firm (Anand et al. 2002; Nahapiet and Ghoshal 1998).

Social capital comprises norms, values, and social relationships embedded in the structures of groups in society that allow people to coordinate actions to achieve desired goals. People in companies are part of the different social groups that determine attitudes, beliefs, and values, as well as access to resources, opportunities, and power (Molina-Morales et al. 2013). In addition, social capital can be considered the set of available resources incorporated in the environment and derived from a network of relationships that an individual or an organism has (Molina-Morales et al. 2013). The central proposal of these definitions is that relationship networks are a valuable resource, both for the individual and for the organization (Padilla-Melendez et al. 2012).

A parent firm that develops spin-offs while maintaining ties with them takes more advantage of the new knowledge created and the exploration of new ideas due to the possibility of complementarity in their activities (Bagley 2019b; Agarwal et al. 2004). These network structures, managed by the parent firm, can reduce the high volatility of rents arising from the exploitation of new ideas. Thus, spin-offs allow the parent firm to preserve its property rights and, at the same time, maintain social networks (López-Iturriaga and Martín-Cruz 2008). Therefore, the following hypothesis is proposed:

H3. *The relationships between the parent firm and its spin-off in business clusters produce norms and values that regulate the exchange of knowledge between them.*

The essence of social capital lies in the structure and content of the social actions of each actor, and its impact derives from the amount of information, influence, and cooperation

that is made available to each actor (Oudeniotis and Tsobanoglou 2022; Anand et al. 2002). According to the aforementioned authors, social capital acts as a driver in the formation of cooperative organizational alliances due to interactions among its members.

These social interactions are important for the creation and diffusion of innovation, so that individuals linked to others will improve their ability to share knowledge and thus create new knowledge and innovate (Padilla-Melendez et al. 2012). In their study in Silicon Valley, (Audretsch et al. 2011) reported that the production of knowledge and innovations offers opportunities for the development of social capital, which is necessary for the creation of new companies.

However, (Molina et al. 2008) believe that excessive interaction between the same actors within a cluster can reduce the efficiency of their economic relations from a certain point onward. This argument is supported by (Nooteboom 2006), who considers clusters to hinder perceptions of external changes due to the strong relationships between actors internally. (Glasmeier 1991) exemplifies what happened to the Swiss watch industry, which went into decline in the 1970s due to the low flow of new external information.

(Molina et al. 2008) proved that the positive effect of social interactions is not necessarily linear. According to the latter authors, initially, the new contacts that are formed generate positive effects, but then a reduction in these benefits or even antagonistic effects is expected. This can be found in the literature as evidence that the relationship between the benefits of strong ties and returns may even be negative as the relationship grows in a cluster (Nooteboom 2006). Thus, the fourth research hypothesis is presented:

H4. *The strong ties in the social relationships between a geographically grouped parent firm and its spin-off produce a decrease in results after a certain point or level of intensity.*

From a sociological point of view, social and professional ties and networks, trust, relationship length, and values and rules are factors identified as important for business clusters (Hite 2003; Nadvi 1999). The economic relationships between firms occur within a web of social relationships in which institutionalized social norms and values internalized by economic actors tend to influence the emergence of interfirm relationships (Granovetter 1983; Nadvi 1999).

The organizations seek to emphasize cooperation and coordination among themselves rather than domination, power, and control. However, the environment imposes pressure on organizations to justify their activities and results, which motivates them to increase their legitimacy so that agreements with norms, rules, beliefs, or expectations of external constituents appear (Oliver 1990). The legitimacy of actors' actions is associated with the fulfillment of these agreements, reducing uncertainties, as interactions share meanings that are altered or reproduced among participants in a process of constant interpretation of reality (Nadvi 1999).

Furthermore, (Molina et al. 2008) argue that even in cases where the benefits obtained from dense networks are important, the obligations—in terms of trust, reciprocity, solidarity, etc., as well as the difficulties of companies in trying to minimize these obligations—reduce their capacity to obtain new business opportunities. For the aforementioned authors, the effort and time spent by companies to maintain these relationships negatively influence their results. Based on these arguments, the fifth research hypothesis is proposed:

H5. *Common norms and values generate obligations between the parent firm and its spin-off and produce decreasing returns after a certain point or level.*

Performance usually refers to the economic and financial aspects of a company, such as an increase in the company's market value (Chesbrough 2003), investments in R&D (Fryges et al. 2014), or revenue growth (Sapienza et al. 2004). Some studies also use the number of spin-offs that the parent firm has as a performance measure (Klepper 2011), and others use the company survival time as a performance indicator (Agarwal et al. 2004).

Innovation plays an important role in the relationship between parent companies and spin-offs, especially in the information technology sector (Agarwal et al. 2004). Innovation is measured in several ways, including by the number of patents, the intensity of investment in R&D (Andersson et al. 2012), or the development of new products (Fryges et al. 2014).

For this study, the performance construct was constructed with measures related to innovation, using a combination of indicators adapted from (Molina et al. 2008): the number of patents or legal protection rights, the number of R&D contracts, the number of new products/services, the number of distinct technologies introduced by the company, the number of quality marks, awards or some type of certification that the firm won, the introduction of new production/service control systems, the company's level of innovation compared with its competitors, the level of investment in R&D, the speed of developing new products/services compared with competitors, and the customers' evaluation of the innovations that the firm develops.

According to the study by (Dahlstrand 1997), technology-based spin-off companies perform better than nonspin-off companies do in clusters. According to this author, these better results are attributed to their relationship with the parent companies. Some authors, such as (McKendrick et al. 2009), have studied what happens to a parent firm after it has a spin-off. They found that there is a positive relationship with the technological performance of the parent firm, with its market realignment, and with having a spin-off. Thus, the sixth research hypothesis is presented:

H6. *The interrelationship between the parent firm and its spin-off produces greater levels of innovation for the parent firm than for nonparent companies with other companies.*

Several authors point to evidence that local institutions impact the results of companies in territorial clusters (Hoffmann et al. 2014). A study by (Saxenian 1996) comparing Silicon Valley and Route 128 highlights the importance of local institutions as potential drivers of the formation of business clusters. According to (Molina et al. 2008), the notion of a community of people who predominate in clusters can be seen as a homogeneous system of values and social norms because they have the same expectations, forms of conduct, language, etc., which are spread throughout the cluster.

Within the clusters, there are local, public, and private institutions, such as universities, public officials, and business and professional associations, that provide their services to territorially agglomerated companies (Molina et al. 2008). According to (Hoffmann et al. 2014), these local institutions play a key role in clustering because, in addition to benefiting from the agglomeration of companies in a particular sector, they are responsible for the flow of knowledge and the attraction of qualified personnel to the geographical area (Molina-Morales et al. 2013).

Notably, the relationships of companies with local institutions can also affect innovation (Molina et al. 2008). According to (Hoffmann et al. 2014), public institutions and local government support are essential for the establishment of public policies that encourage technological innovation by companies. Based on these empirical contributions, the following hypothesis is proposed:

H7. *Local institutions act as intermediaries, providing clusters with a variety of knowledge resources that lead to higher levels of innovation in the parent firm.*

Originating in the area of strategy, entrepreneurial orientation (EO) is understood as entrepreneurship at the organizational level, portraying processes, methods, and management styles used to create new ventures (Miller 1983; Lumpkin and Dess 1996; Lee et al. 2001; Parga-Montoya and Cuevas-Vargas 2023). Several researchers have devoted efforts to studying the relationship between EO and organizational performance. Their results indicate that entrepreneurial orientation can positively influence performance, highlighting the fact that organizations with higher EO tend to be more successful than organizations with lower EO (Wiklund and Shepherd 2005) and are more involved with innovation.

Conceptually, (Lee et al. 2001) distinguish three dimensions of EO: innovation capacity, propensity to take risks, and proactivity. In the study by (Venkatraman 1989), the three dimensions were investigated using primary data, asking company managers about their perceptions of them.

The first dimension is innovation capacity, which reflects a firm's propensity to engage in a new generation of ideas, experiences, and R&D activities, resulting in new products, services, and processes (Lumpkin and Dess 1996). In the second dimension, companies exhibit a propensity for risk-taking behaviors, in which they seek to invest resources in high-risk activities and in businesses with high returns. This dimension assesses the ability to perceive new businesses or their propensity to take risks in uncertain ventures (Lee et al. 2001). The last dimension of EO is proactivity, which refers to a company's willingness to explore market opportunities and to pioneer the introduction of new products/services (Lumpkin and Dess 1996; Venkatraman 1989).

Entrepreneurship is responsible for the creation of new companies (Andersson et al. 2012), and the phenomenon of giving rise to another firm can also be the formation of a spin-off. If the company that gave rise to another (parent firm) has an entrepreneurial orientation, this will reflect on the relationship with its spin-off through the exchange of resources and knowledge, which may reflect the performance of the parent firm. The eighth hypothesis of this study is as follows:

H8. *Compared with those of nonparent companies, the entrepreneurial orientation of parent companies in business clusters results in greater levels of innovation.*

According to (Molina et al. 2008), the results point in the direction of initial expectations that companies in clusters have high density in their relationships; consequently, they have shared norms and values and benefit from access to quality information, which can contribute to access to new knowledge. These findings support the idea of relating the structure and nature of interorganizational links to the innovation capacity of companies. To address the gaps noted in the conclusions of the studies by (Molina et al. 2008), this study proposes adapting the model of the aforementioned authors, as shown in Figure 1.

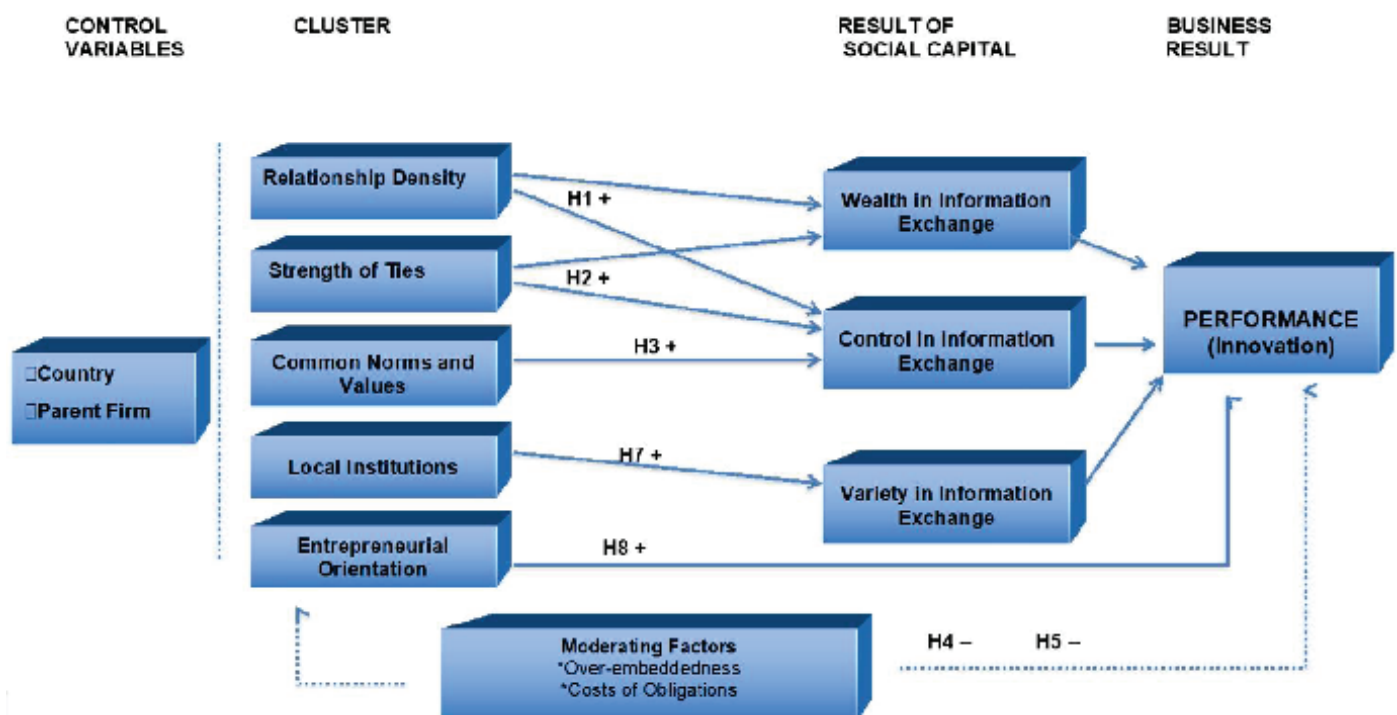


Figure 1. Theoretical Research Investigation Model. Source: Authors' study based on the original study by Molina et al. (2008).

3. Materials and Methods

To better understand the phenomenon to be investigated, a descriptive study with a quantitative approach was adopted. As in the study by Molina et al. (2008), a survey was administered. The sample collected in this study was nonprobabilistic, voluntary, and convenient.

Data collection was performed in two clusters. The choice of the cluster of the State of Santa Catarina in Brazil is because the ICT sector of Santa Catarina has stood out both in the Brazilian and global scenarios. In Spain, the ICT cluster of the Province of Barcelona was chosen because of its importance for Spain and Europe, as it stands out as a knowledge and innovation economy (Barcelona City Council 2012). The Brazilian government, through the Ministry of Development, Industry and Foreign Trade—MDIC/Brazilian Observatory of Local Productive Arrangements, defines the Santa Catarina ICT cluster as integrated by several cities such as São José, Joinville, Blumenau, Lages, Brusque, Palhoça, Jaraguá do Sul, Penha, Chapecó, and Criciúma, among others, with Florianópolis as the hub city (http://icts.unb.br/jspui/bitstream/10482/42226/1/2021_RoseNofal.pdf, accessed on 22 August 2015). In this way, the study in Santa Catarina involved the cities of Florianópolis (capital and hub), Joinville, Blumenau, and Brusque. The justification is given by the presence of the main associations of companies in the ICT cluster of Santa Catarina, which are ACATE (Florianópolis), BLUSOFT (Blumenau), and SOFTVILLE (Joinville). For the Brazilian Government and the State of Santa Catarina, these regions are considered a single geographic territory for the ICT cluster. In Spain, due to the lack of official data, an aggregate number of companies from all the studied clusters was not found. Thus, based on the number of companies that each business center reports on their websites or in their yearbooks, 2000 companies were estimated in the ICT cluster of the Province of Barcelona in the following business centers: 22@Barcelona, Parc Tecnològic del Vallès, Esadecreapolis, BarcelonaTech, Fundació b_Tec, Orbital 40, Parc Científic de Barcelona, Parc de Recerca UAB, TecnoCampus Technological Park, and Technova Barcelona. In the same way as in Brazil, these business centers are understood as a single ICT cluster.

To reach the companies surveyed, records were obtained from AMETIC (Multi-sector Association of Electronics, Information and Communication Technologies, Telecommunications and Digital Content Companies) and 22@Barcelona in Spain and from ACATE (Santa Catarina Technology Association) and Oficina da Net in Brazil. Thus, the sample collected in this research was characterized by being non-probabilistic, and for convenience, that is, despite work being carried out to raise awareness of the importance of the study, the individual responded to the questionnaire optionally. A pretest was applied to five companies in each ICT cluster (Brazil and Spain), and the final questionnaire was sent through Google Docs to the 540 companies registered in Barcelona and 560 in Brazil. After 30 days, telephone interviews were conducted via Google Docs with companies that did not respond. The final sample consisted of 160 companies in Barcelona (29.63% return) and 66 companies in Brazil (11.79% response rate), for a total of 226 questionnaires answered, for a return rate of 20.55%.

The variables used were adapted from the study by Molina et al. (2008), according to Table 1.

The scale underwent a new validation due to the inclusion of the variable “entrepreneurial orientation,” and tests of internal consistency and reliability of the measurement scales were performed using Cronbach’s alpha with multi-item scales (Molina et al. 2008). All the constructs had indices greater than 0.7, which is considered appropriate (Lattin et al. 2011). In addition to the variables in Table 1, control variables were used, with dummy variables indicating whether the respondent was a parent firm or not or another country of origin. Regarding the outliers, the few cases that emerged were maintained for theoretical reasons related to the innovation construct (Hair et al. 2005).

Structural Equation Modeling (SEM) was used as the data analysis technique. The maximum likelihood (ML) method was chosen as the estimation technique because it is the most widely used method and is appropriate for samples from more than 100 observa-

tions (Hair et al. 2005; Marôco 2014; Gu et al. 2023); additionally, all the methodological assumptions were met for this study.

Table 1. Research variables.

Variables	Indicators
Density of the relationship (Density)	Degree of knowledge and information overlap; degree of interconnection and dependence that the firm has on this network to obtain these resources.
Strength of ties (Strength)	Intimacy (proximity of contact); frequency (number of times of contact); to the extent that managers and workers have already worked in other companies in the same area of the cluster.
Rich exchange of information and knowledge (Rich)	Quality information and tacit knowledge; organizational learning; information more relevant and detailed than that of the market.
Common norms and values (norms)	Trust, reputation, reciprocity, and conflict resolution without legal proceedings and no contractual regulation between companies.
Local institutions (institutions)	Number of positions or important positions in the associations; importance for obtaining information and knowledge; and for innovation.
Entrepreneurial orientation * (Orientation)	Innovative capacity, proactivity, and risk-taking.
Innovation (Performance)	Number of patents and other property rights; contracts; number of new products; technologies used; number of product or firm certifications and introduction of improved processes; evaluation of innovation in relation to its competitors.

* Source: (Lumpkin and Dess 1996; Perlines 2014).

4. Results and Discussion

Table 2 presents the descriptive statistics (mean, median, standard deviation, kurtosis, and asymmetry) and the standardized variables. Missing data were filled in by the mean of each of the observable variables, and the number of respondents for all questions was equal to 226.

In Table 2, for the confidence interval of this research, the value 4 was taken as a reference, which is the center of the scale from 1 to 7. Thus, situations in which the number 4 is between the lower limit and the upper limit indicate neutrality. Upper limits below this level indicate non-agreement with the statement (Kline 2011).

For univariate analysis, measures of central tendency, mean, and median were used. In the constructs “Density of the Relationship,” “Rich Exchange of Information and Knowledge,” “Common Norms and Values,” all observable variables have a mean and median greater than 4, that is, approaching the maximum value of the scale. In the “Strength of Ties” construct, only the variable P3_4 presents a mean lower than 4, but the mean of the construct as a whole is 4.51. The same occurs with the constructs “Performance/Innovation” and “Entrepreneurial Orientation,” which have some variables below 4 (global means of 4.12 and 4.64, respectively). Only the “Local Institutions” construct presents a global mean of 3.36, but, despite being lower than 4, it is close to it. In the work of Molina et al. (2008); (Molina et al. 2008), only the “Innovation” construct presented a mean lower than the central value of the scale.

Table 2. Descriptive statistics of the observable variables of the constructs.

Construct	Observ. Variable	Min. *	Max. *	Inf. Lim. **	Mean	Upper Limit **	Mn	Stand. Dev.	Kurt.	Asym.
Density of the Relationship	P2_1	−1.86	1.58	4.02	4.25	4.48	4	1.74	−0.273	−0.939
	P2_2	−1.99	1.30	4.39	4.63	4.87	5	1.82	−0.460	−0.958
	P2_3	−1.99	1.49	4.21	4.44	4.66	5	1.72	−0.280	−0.908
	P2_4	−2.09	1.54	4.24	4.46	4.67	5	1.65	−0.346	−0.818
Strength of Ties	P3_1	−2.73	1.11	5.07	5.27	5.47	6	1.56	−1.086	0.581
	P3_2	−2.22	1.26	4.60	4.82	5.05	5	1.72	−0.568	−0.719
	P3_3	−2.22	1.39	4.47	4.69	4.91	5	1.67	−0.634	−0.314
	P3_4	−1.07	1.75	2.99	3.27	3.55	3	2.13	0.426	−1.223
Rich ex-change of Information and Knowledge	P4_1	−2.06	1.50	4.25	4.47	4.69	5	1.69	−0.374	−0.896
	P4_2	−1.94	1.53	4.12	4.35	4.58	5	1.73	−0.315	−1.002
	P4_3	−2.07	1.49	4.27	4.49	4.71	5	1.68	−0.350	−0.793
	P4_4	−1.84	1.41	4.16	4.40	4.64	5	1.84	−0.290	−1.191
Common norms and values	P5_1	−3.33	1.03	5.40	5.58	5.76	6	1.38	−1.371	1.883
	P5_2	−2.49	1.16	4.88	5.09	5.31	6	1.65	−0.852	−0.165
	P5_3	−4.00	1.04	5.60	5.76	5.91	6	1.19	−1.704	3.871
	P5_4	−4.42	0.99	5.55	5.72	5.89	6	1.29	−1.889	4.515
Performance	P6_1	−0.63	2.06	2.12	2.41	2.70	1	2.23	1.234	−0.124
	P6_2	−0.70	1.90	2.31	2.61	2.91	1	2.31	1.025	−0.596
	P6_3	−1.32	1.91	3.21	3.45	3.70	3	1.86	1.044	−0.454
	P6_4	−1.27	1.57	3.41	3.69	3.97	3	2.12	0.550	−1.165
	P6_5	−1.63	1.39	3.99	4.25	4.51	4	1.99	−0.025	−1.151
	P6_6	−0.93	1.99	2.65	2.92	3.18	3	2.05	0.698	−0.645
	P6_7	−1.80	1.81	3.24	3.50	3.75	4	1.94	0.131	−1.108
	P6_8	−3.20	1.35	5.05	5.22	5.40	5	1.32	−0.642	0.049
	P6_9	−3.25	0.99	5.42	5.60	5.79	6	1.42	−1.333	1.382
	P6_10	−2.10	1.74	4.08	4.28	4.49	4	1.56	−0.254	−0.496
	P6_11	−2.95	1.52	4.78	4.96	5.13	5	1.34	−0.551	0.028
	P6_12	−2.81	1.60	4.65	4.83	5.00	5	1.36	−0.577	0.066
	P6_13	−4.39	1.10	5.65	5.80	5.94	6	1.09	−1.524	3.544
Local institutions	P7_1	−1.31	1.93	3.19	3.43	3.67	3	1.85	0.346	−0.496
	P7_2	−0.67	2.53	2.01	2.26	2.50	1	1.88	1.204	0.169
	P7_3	−2.16	1.50	3.88	4.13	4.38	4	1.91	−0.243	−1.081
	P7_4	−1.98	1.94	3.31	3.54	3.77	4	1.79	0.171	−1.017
	P7_5	−1.96	2.10	3.16	3.38	3.61	3	1.72	0.138	−0.991
	P7_6	−1.98	2.05	3.21	3.44	3.67	3	1.74	0.239	−0.844
Entrepreneurial orientation	P8_1	−2.77	1.15	5.03	5.23	5.44	6	1.53	−0.935	0.117
	P8_2	−2.31	1.43	4.50	4.71	4.92	5	1.61	−0.486	−0.676
	P8_3	−2.64	1.30	4.82	5.02	5.22	5	1.52	−0.785	−0.067
	P8_4	−3.27	1.15	5.26	5.44	5.62	6	1.36	−0.963	0.329
	P8_5	−3.54	1.17	5.34	5.51	5.68	6	1.28	−1.077	0.835
	P8_6	−2.66	1.25	4.88	5.08	5.29	5	1.54	−0.735	−0.161
	P8_7	−1.86	1.85	3.80	4.01	4.22	4	1.61	0.030	−0.895
	P8_8	−2.02	1.68	4.06	4.27	4.49	4	1.62	−0.239	−0.739
	P8_9	−1.48	2.11	3.26	3.48	3.70	3	1.67	0.312	−0.736
	P8_10	−1.97	2.04	3.75	3.95	4.15	4	1.50	0.102	−0.635
	P8_11	−2.06	1.46	4.29	4.51	4.74	5	1.71	−0.259	−1.040
	P8_12	−2.58	1.50	4.60	4.79	4.98	5	1.47	−0.427	−0.568
	P8_13	−1.55	1.61	3.70	3.95	4.19	4	1.90	−0.025	−1.264
	P8_14	−2.87	1.39	4.86	5.04	5.23	5	1.41	−0.693	0.162

Note. Source: Own preparation. * Standardized score. ** 95% confidence interval. Mn: Median.

These values indicate that the surveyed companies agreed that these characteristics are associated with social capital and are present in the clusters of Brazil and Spain (Cardoso et al. 2019). In other words, the indicators of the constructs obtained a mean of responses

that suggest, in this first descriptive evaluation, that these latent variables influence the interorganizational relationships studied. An interorganizational relationship is a relationship of interdependence that involves the exchange of resources, and this is at the heart of the relationships between economic subjects (Håkansson and Snehota 2006). These interactions lead to partnerships that seek solutions to common problems and produce mutual guidance and commitment (Håkansson and Snehota 1995; Andrighi et al. 2011). Interorganizational relationships and the flow of resources between organizations also occur in clusters (Hoffmann et al. 2014). Since the studies of Granovetter (MS Granovetter 1973; Mark Granovetter 1985; Nahapiet and Ghoshal 1998) and Maurer and Ebers (2006), the role of the density of relationships and common norms and values has been highlighted as facilitators of the exchange of information and knowledge between actors. This result is in line with that reported in the study by Molina et al. (Molina et al. 2008).

The standard deviation values of the observable variables shown in Table 1 suggest that there are no major discrepancies in the responses of the survey participants. This result presents the first evidence that the country effect did not influence the sample investigated (Cardoso et al. 2019). Some studies in more than one country, such as those by Parhankangas and Landström (Parhankangas and Landström 2006) and (de Figueiredo et al. 2013), did not reveal differences between samples from different countries. However, the literature indicates that there are differences between countries that can affect the results between the countries surveyed (Hofstede 1983; d'Iribarne 2009).

The normality of the data was verified in Table 1 by analyzing the values of the skewness and kurtosis measures, which were calculated for the observable variables of the evaluated structural model. According to Marôco (2014), it can be assumed that if a set of variables presents univariate normality, then the conditional distribution of the variables is multivariate normal. According to the aforementioned author, some normality tests are more sensitive to small deviations, such as Kolmogorov–Smirnov and Shapiro–Wilk tests, and are not available in Structural Equation Modeling (SEM) software. This is because they are likely to commit a type I error (concluding that the variable does not have a normal distribution when the distribution is normal) in the case of large samples.

Thus, Marôco (2014) suggests that it is common to use measures of distribution shape, asymmetry (Sk), and flatness or kurtosis (Ku) to assess the normality of variables. Kline (2011) suggests that only values of $|Sk| > 3$ and $|Ku| > 10$ indicate conditions of extreme violation of normality, in which the quality of the adjustment indices and parameter estimates are questionable. Thus, it can be observed in Table 1 that only the variables P5_3, P5_4, and P6_13 presented values for (Sk) above the limits suggested by Kline (2011), but in a non-significant way, that is, slightly above 3. In the case of (Ku), no value was exceeded for the variables used in the original and final models tested in this study.

The original model was adapted from (Molina et al. 2008), and an acceptable level of relationship between the items and the respective constructs was observed, expressed as factor loadings above 0.4, eliminating the variables that presented lower factor loadings. The global measurement model was confirmed after the second adjustment. This model has nine latent variables and 35 observable variables. The quality of the model was assessed by evaluating the model fit (Marôco 2014), as indicated in Table 3.

In Table 3, all the models estimated in this study presented values considered good for χ^2/gL and RMSEA, and only the original model (0.082) could be classified as a mediocre fit. Regarding the CFI, the 2nd adjustment (0.854), 2nd Country Adjustment (0.810), and 2nd Classification Adjustment (0.735) models presented indices considered good, although they did not reach values greater than 0.90, according to Byrne (2010) and Marôco (2014). For the TLI, all the estimated models presented values within the acceptable range. Thus, based on the results presented, the 2nd adjustment in the model (Figure 2), as well as the 2nd adjustment country and classification, exhibited better quality than did the original model (Arbuckle 2013; Byrne 2010).

The studies conducted by (Stam and Elfring 2008) in technology companies found results considered optimal for the fit of their model, following the recommendations of (Byrne 2010; Marôco 2014; Arbuckle 2013), and are close to those results of this study. study after the 2nd adjustment (Figure 2).

Table 3. Fit indices of the estimated models.

Models	Index						
	χ	GL	χ^2/GL	CFI	RMSEA	RMSEA90 *	TLI
Original	2843.309	1124	2.530	0.693	0.082	0.078–0.086	0.679
2nd Adjustment	1184.449	557	2.126	0.854	0.071	0.065–0.076	0.844
Original Country	4672.108	2248	2.078	0.629	0.069	0.069–0.072	0.612
2nd Grant Country	2025.786	1114	1.818	0.810	0.060	0.056–0.065	0.797
2nd Class Assistance	2341.999	1114	2.102	0.735	0.070	0.066–0.074	0.717
Reference Values	-	-	1 a 5	Closer to 1. the better.	≤ 0.08	-	Closer to 1. the better.

Note. Source: Prepared by the authors based on Marôco (2014), Arbuckle (2013), and Byrne (2010). (*) 90% confidence interval for RMSEA index.

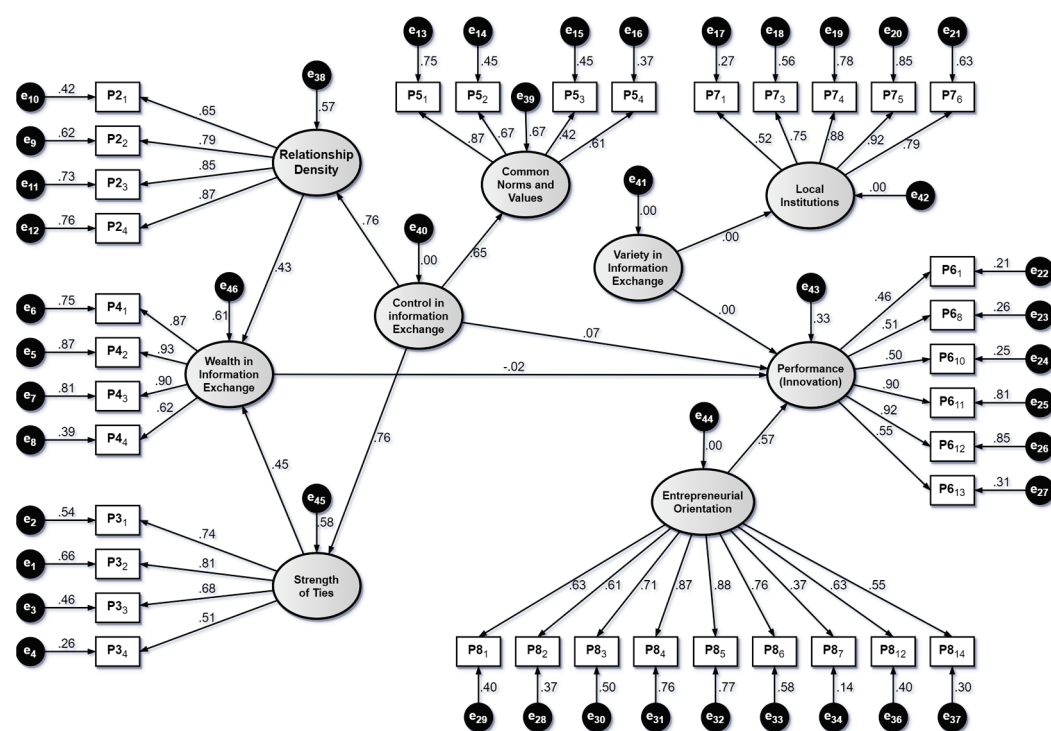


Figure 2. Final model with the 2nd fit. Source: Prepared by the author based on the survey data.

The evaluation of the measurement model was performed through the verification of internal consistency, convergent validity, and discriminant validity. One of the most widely used measures for assessing internal consistency is Cronbach's alpha (Marôco 2014). All the constructs presented coefficients above 0.7, the minimum recommended value (Hair et al. 2005; Lattin et al. 2011). Convergent validity was tested via factor loadings above 0.30 (Laros 2005) and the fit measures of the model. In both tests, evidence of the convergent validity of the observable variables was obtained. Discriminant validity was assessed using confirmatory factor analysis (CFA) performed for pairs of constructs. The results obtained presented values less than 0.90, indicating that there is evidence of discriminant validity (Hair et al. 2005; Byrne 2010).

Table 4 shows that of the ten relationships tested, six are significant. The density construct is associated with the exchange of resources and the strength of ties between the actors involved, as noted by (Zaheer et al. 2010). According to (Nadvi 1999), the relationships in clusters are governed by norms, rules, and values that organize production so that knowledge is disseminated, allowing control of the exchange of information between their actors (Xavier Molina-Morales et al. 2013; Cardoso et al. 2019).

Table 4. Estimates of the 2nd model fit.

			Estimation	Standard Errors. IF	CR	p Value	Standardized Regression Estimation
Density	<--	Control	1.157	0.124	9.341	***	0.757
Strength	<--	Control	1.17	0.119	9.858	***	0.76
Wealth	<--	Density	0.447	0.088	5.099	***	0.428
Wealth	<--	Bond	0.468	0.091	5.143	***	0.451
Norms	<--	Control	0.853	0.1	8.509	***	0.649
Performance	<--	Orientation	0.695	0.094	7.435	***	0.57
Performance	<--	Variety	0	0.258	0	1	0
Institutions	<--	Variety	0	0.486	0	1	0
Performance	<--	Control	0.093	0.131	0.711	0.477	0.076
Performance	<--	Wealth	−0.018	0.074	−0.237	0.813	−0.023

Note. Source: Prepared by the authors based on data from the research sample. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.001$.

The constructs “Relationship Density”, “Control in Information Exchange”, “Strength of Ties”, “Wealth in Information Exchange”, and “Common Norms and Values” are specified by several authors as part of the social capital construct, such as Nahapiet and Ghoshal (1998); Molina et al. (2008) and Hoffmann et al. (2023). Similarly, the relationship between entrepreneurial orientation and performance was studied by (Wiklund and Shepherd 2005), which corroborates the findings of previous studies.

The results presented do not confirm H1; however, they do not reject H2. The relationship between the variables “Wealth in Information Exchange” and “Relationship Density” was not significant, whereas for “Wealth in Information Exchange” and “Strength of Ties,” it was significant. This result is not consistent with (Molina et al. 2008) and with the study by (Chen et al. 2020), who reported that a higher degree of interconnection contributes to a dense network and to obtaining spillovers of resources.

This result is consistent with the findings of Parhankangas and Arenius (2003); Sapienza et al. (2004); Stam and Elfring (2008) or Bagley (2019b) on companies in the ICT sector, in which the relationships between companies and mothers and spin-offs involve sharing resources. Thus, there is evidence that the association between spin-offs and parent companies results in better allocation of resources and faster learning than does the association between spin-offs and independent ventures.

The results do not support H3, as they were statistically significant for the relationships between the variables “Norms and Common Values” and “Control in Information Exchange,” indicating that there is a link between these constructs. In the literature, the production of common norms and values facilitates trust and cooperation in knowledge exchanges and favors the development of innovations (Nahapiet and Ghoshal 1998). However, for (Molina et al. 2008; Xavier Molina-Morales et al. 2013), obligations derived from trust, reciprocity, etc. reduce the ability to search for new opportunities, which indicates ambiguity. Regarding the relationship between parent companies and spin-offs in the ICT sector, norms, values, and social relationships are very important for the creation and diffusion of innovation (Padilla-Melendez et al. 2012).

Hypotheses 4 and 5 are linked to moderating factors and were not confirmed. In Table 5, the variables “Strength of Ties” and “Norms and Common Values” were tested as quadratic functions to verify whether the data fit an inverted “U.” To test H4, we investigated the existence of overembeddedness in the relationship between the parent firm and its spin-off firm in an ICT cluster. This result agrees with the studies by (Stam and Elfring 2008)

on young companies in the ICT sector. Differences in sectoral and economic characteristics may explain the disparate results in the literature and with (Molina et al. 2008).

Table 5. Result model 2nd fit.

Variables			Parent Company		Nonparent Company		Comparison
			Estimate	p-Value	Estimate	p-Value	z Test
Density	<---	Control	0.407	0.133	1.114	***	2.332 **
Bond	<---	Control	0.42	0.153	1.104	***	2.126 **
Wealth	<---	Density	0.312	0.199	0.513	***	0.768
Wealth	<---	Bond	0.813	0.001 **	0.356	***	−1.681 *
Norms	<---	Control	0.24	0.321	0.853	***	2.3 **
Performance	<---	Orietation	0.768	0.004 **	0.671	***	−0.34
Performance	<---	Variety	−0.17	0.623	0.114	0.643	0.67
Institutions	<---	Variety	0.416	0.457	0.18	0.627	−0.351
Performance	<---	Control	0.283	0.441	0.068	0.611	−0.549
Performance	<---	Wealth	−0.257	0.21	0.012	0.875	1.225

Note. Source: Prepared by the authors based on data from the research sample. * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.001$.

In H5, the quadratic relationship was not significant. In the studied sample, there was no evidence that, from a certain point on, the common norms and values in the parent firm and spin-off relationship negatively influence the development of innovations in the companies. According to (Zaheer et al. 2010), periodic communication or frequent contact between actors are opportunities for learning technologies and contribute to the reduction of transaction costs.

A comparative evaluation was performed for the second fit of the model. The estimates related to the classification (parent firm vs. nonparent firm) were not statistically significant, i.e., the fact that the parent firm relates to its spin-off did not present evidence of better performance than the relationships of the nonparent companies with other companies did. Thus, the results of the estimated models do not confirm H6. A possible explanation for this result lies in the characteristics of the sector itself, in which a relationship with strong ties could be almost as good as one with weak ties (Molina et al. 2008).

The comparative results found with the sample of this study differ from those found in the literature on spin-offs (McKendrick et al. 2009), as they examined the effects of spin-offs on the innovation capacity of the parent companies of ICT companies and found evidence that spin-offs benefit them. The study by (Sapienza et al. 2004) suggested that the parent firm and spin-off relationship, as long as there is an exchange of knowledge, can benefit both parties in the form of performance.

The results do not confirm H7 of this study. The results of the 2nd model fit were not significant for the associations between the variables “Local Institutions” and “Variety in Information Exchange.” This result is not consistent with the study by (Molina et al. 2008) (Hoffmann et al. 2023), who found that companies linked to local institutions are associated with higher levels of innovation production (performance).

The literature points out that associations create bonds in the relationships between their members and contribute to the exchange of knowledge and information that can lead to the production of innovations. The local institutions are in contact with other external circles and are also part of the cluster’s internal networks. This effect was also observed in the studies of (Hoffmann et al. 2014) in the furniture industry, (Hoffmann and Campos 2013) in the tourism sector, and (Chen et al. 2020) in the automotive industry.

Regarding H8, which states that the entrepreneurial orientation of the parent firm, compared with that of nonparent companies in business clusters, produces greater levels of innovation, this hypothesis is not confirmed because there is no significant difference between the variables for the two types of companies. The literature on entrepreneurial orientation indicates that this construct positively influences the performance of companies because those with an entrepreneurial attitude have the ability to prospect new

opportunities and continuously promote the innovation of their products and services (Parga-Montoya and Cuevas-Vargas 2023; Wiklund and Shepherd 2005; Lazzarotti et al. 2015). This result behaved similarly when the country variable was evaluated. In both countries, the relationships between the parent firm and its spin-off and between the nonparent firm and another firm were statistically significant when the entrepreneurial orientation and performance (innovation) constructs were compared. This shows that in the two dyadic relationships described above, entrepreneurial orientation contributes to the development of innovations in ICT clusters. In their study, (Stam and Elfring 2008) found that the links between established companies and new companies contribute to the association between entrepreneurial orientation and performance. The justification for this result may be associated with the nonprobability sample, which included mostly SMEs whose profile is typical of the ICT sector.

For the comparative analysis between the clusters of the two countries, the control variable country (Spain and Brazil) was used. Of the ten relationships tested, only three were significant in both models: relationship density and control in information exchange, strength of ties and control in information exchange, and entrepreneurial orientation and performance (innovation).

Several results are noteworthy regarding the 2nd country adjustment model because they are related to the dependent variable Performance (Innovation). The estimates related to this variable, Innovation, associated with the variables that were derived from the model by (Molina et al. 2008), such as Wealth in Information Exchange and Performance (Innovation), Variety in Information Exchange and Performance (Innovation), and Control in Information Exchange and Performance (Innovation), were not significant, and there were no significant differences between countries. A summary of the hypothesis test is shown in Table 6.

Table 6. Summary of the hypothesis tests.

H1	The interrelationship between the parent firm and its spin-off in the clusters determines a dense structure and strong ties.	Not confirmed
H2	The interrelationship between the parent firm and its spin-off in the clusters promotes the exchange of quality information and tacit knowledge through strong ties.	Confirmed
H3	The relationships between the parent firm and its spin-off in business clusters produce norms and values that regulate the exchange of knowledge between them.	Confirmed
H4	The strength of ties in the social relations between the geographically grouped parent firm and its spin-off produces a decrease in results after a certain point or level of intensity.	Not confirmed
H5	Common norms and values generate obligations between the parent firm and its spin-off and produce decreasing returns after a certain point or level.	Not confirmed
H6	The interrelationship of the parent firm and its spin-off produces higher levels of innovation for the parent firm than nonparent companies with other companies.	Not confirmed
H7	Local institutions act as intermediaries, providing the clusters with a variety of knowledge resources that lead to higher levels of innovation in the parent firm.	Not confirmed
H8	The entrepreneurial orientation of the parent firm compared with nonparent companies in business clusters produces higher levels of innovation.	Not confirmed

Source: Prepared by the authors.

As shown in Table 6, most of the hypotheses were not confirmed. This was a study involving ICT companies from two countries and specific regions within them, which were

characterized as ICT clusters. However, this does not imply that the theory is wrong, but that for these specific cases, it was not confirmed. Hypotheses, by definition, are possible and provisional answers to the research problem.

5. Conclusions

The objective of this study was to determine how proximity between business organizations promotes the intensity of relationships, facilitates the exchange of information and knowledge in the interorganizational relationship between parent companies and spin-offs, and influences business results.

The theoretical model was adapted from (Molina et al. 2008). Based on the gaps identified by the aforementioned researchers, the aforementioned study was continued to assess the replicability of the findings. In this context, the model has explanatory power for the variables related to social capital. However, it does not have the same characteristic in regard to supporting institutions or performance when it is subjected to a reality different from the original one.

According to the original model by (Molina et al. 2008), the relationships studied were also in a cluster, but they were interorganizational and not dyadic. Thus, from a theoretical point of view, it is possible to affirm that social capital serves to explain different types of relationships, particularly in regard to business clusters, since in this study, it was used to explain dyadic relationships in cluster contexts, where relationships are usually interorganizational.

Regarding the role of institutions, it is clear that in the ICT sector, they may not properly motivate innovation, as this ends up occurring within the network of companies. In this case, local institutions can serve more as labor enablers than as knowledge generators; however, this individual-company-local institution contact also contributes to knowledge spillover. According to (Del-Corte-Lora et al. 2017), there are many ways in which knowledge and information can spillover, such as through courses, workshops, meetings, and seminars with class associations, local universities, and technical and research institutes, among others. This role is important in a cluster (Hoffmann et al. 2014) but is less common among companies. It follows that the importance of institutions will depend on the type of exchange that is performed between them and the companies or on the type of participation they have in the networks created to innovate.

A novel finding was the inclusion of the variable entrepreneurial orientation in the model by (Molina et al. 2008). This variable was shown to be significantly associated with the production of innovation when tested in the 2nd fit of the model. The fact that EO is linked to innovative performance, regardless of the type of company from a theoretical point of view, is noteworthy because a superior result would be expected for the parent companies. However, innovation in clusters is a process of collective action, as noted by (Halbert 2012; Wahyuni and Sara 2020), regardless of the type of interorganizational relationship. Thus, when the scope is innovative, the relationships between the parent firm and its spin-offs are no longer beneficial than the relationships between companies without this type of link. Thus, the parent firm–spin-off relationship is a type of relationship among the possible types within a cluster whose advantage in establishing itself would also be focused on innovation and is no different from that of other types of IIRs.

It is also concluded that entrepreneurial orientation does not have a discriminating force when evaluating a cluster of SMEs in the ICT sector. Thus, the size of the company ends up weighing in when evaluating this construct. Notably, one of the components of entrepreneurial orientation is the propensity to risk (Wahyuni and Sara 2020). Kim et al. (2010) established that in the ICT sector, companies are committed to meeting the constant needs of consumers for innovations. Thus, innovation must be constant in the sector, and it depends on an R&D process, which in turn involves varying doses of risk. It is concluded that when evaluating a sector with intense innovation, an entrepreneurial orientation will be present.

Although most of the hypotheses were not confirmed, this does not imply that the research with the theories studied is wrong or flawed. However, due to the local characteristics of the countries covered in the study and the type of interorganizational (dyadic) relationships, they may have influenced the non-confirmation of some of them. This could open up new perspectives and variables that could moderate the relationships studied.

Compared with those of Brazil and Spain, the data from these countries showed some differences. As the data from Brazil points to a propensity for being an entrepreneur three times greater than in Spain, it is concluded that there may be a relationship between the propensity for entrepreneurship and the generation of spin-offs in clusters of the ICT sector.

It is also concluded that in ICT clusters, the components of social capital have different configurations. Because the clusters surveyed differ in terms of age, it is possible that the age of the cluster itself and that of its companies and institutions may lead to different configurations of relationships. Thus, in a cluster where there are networks of different types created for the development of innovation, there will be social capital, but this capital will not have the same configuration. These two contributions of this study are related to the suggestions of (Molina et al. 2008). One of them was to conduct future research in a sector other than the ceramics sector; therefore, this study was conducted in the ICT sector. The other suggestion was to conduct a study in a different location in Castellón, Spain. The present study was conducted in a comparative manner at two locations and in two other countries (Barcelona, Spain; Santa Catarina, Brazil).

This study has several methodological and theoretical limitations, as mentioned above. The first of these was the non-use of a qualitative approach in the study. Another limitation is related to the generalizability of the results, as the study was conducted in one cluster of each country. Another limitation was the instrument for collecting primary data through questionnaires, which involves what is called common source bias in the literature. This occurs when the same respondent answers the questions regarding the independent and dependent variables, which may cause distortions in the results (Podsakoff et al. 2003). Finally, the cultural differences between Brazil and Spain were not evaluated in the model.

It is suggested that variables related to culture be included to verify whether there are differences between two countries. Another aspect that could serve as a future study would be the use of in-depth interviews to understand details that quantitative data cannot capture. A final suggestion is to replicate the theoretical model of this study in other ICT clusters or even test the same model in other economic sectors.

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Institutional Review Board Statement: At the time of conducting the research, in our National Legislation, it was not mandatory to obtain an authorization from the Ethics Committee.

Informed Consent Statement: Permission was received from all participants to guarantee the anonymity of their answers (Blank informed Consent).

Data Availability Statement: The data for this research were collected through questionnaires applied to entrepreneurs in the sector and also on government websites in both Brazil and Spain. The data

sources are available at the link <http://repositorio2.unb.br/jspui/handle/10482/22904> (accessed date 1 July 2024).

Conflicts of Interest: The authors declare no conflict of interest.

Notes

- ¹ Geographic proximity refers to the physical space in which a business agglomeration or cluster is defined (Balland et al. 2022).

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Article

Start Switch for Innovation in “Construction Sequencing”: Research Funding

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Abstract: Clusters of knowledge-intensive industries and manufacturing industries form industrial agglomeration in Step I and activate innovation in Step II. Industry clusters are formed by building segments. “Construction sequencing” in the construction industry refers to the process of determining the sequence of segments to optimize a project’s resources, budget, and scheduled timeline. The process usually begins by dividing a project into segments. Urban segments consist of public spaces, airports, factories, health, housing, etc. A “segment” is a component of a cluster; the organization of a cluster consists of constructing segments. These segments can be divided into four main categories: human resources, physical infrastructure, institutions, and the living environment. Each segment has a specific function in the process of building a cluster. This study focused on innovation in Step II and extended the Fujita–Thisse model of spatial economics to hypothesize that research expenditure per researcher leads to value being added. The Granger causality was tested for the knowledge and manufacturing industries in nine major countries including China and the U.S. The results showed that the hypothesis was significant in identifying the starting segment of innovation in Step II. Accordingly, it can be concluded that research funding is the start switch that triggers innovation. The policy implication is that activating innovation in cluster policies begins with the establishment of a research fund for researchers in its assigned clusters.

Keywords: construction sequencing; innovation policy; start switch; research funding; sequencing economics; spatial economics

1. Introduction

According to UNCTAD (2022), the world is at the beginning of a new technological revolution based on Industry 4.0 technologies such as artificial intelligence, robotics, and the Internet of Things. In addition, the impact of and response to the coronavirus outbreak (COVID-19) has accelerated the spread of this digital economy and activated innovation.

Agglomeration can be defined as the spatial concentration of economic activity. Oqubay and Lin (2020) noted that industrialization, supported by the “agglomeration” of industrial hubs, is widely associated with structural transformation and catch-up in developing, emerging, and developed countries. Mayer and Banga (2020) examined whether industrial hubs are effective at activating innovation in developing countries when the digital economy and industrial hubs are complementary. It is necessary to examine how agglomeration relates to innovation activation.

According to Fujita (2003), a cluster is the formation of an agglomeration and the activation of innovation within it. Cluster formation involves an industrial agglomeration step and an innovation activation step. Kanai and Ishida (2000) noted that studying the process of cluster formation is essential for the success of cluster policies. As shown in Figure 1, Kuchiki and Tsuji (2010) divided this process into two steps: Step I is agglomeration, and Step II is innovation.

With respect to Step I (agglomeration), there are three theories: (i) spatial economics, (ii) construction sequencing, and (iii) sequencing economics, as shown in Table 1.

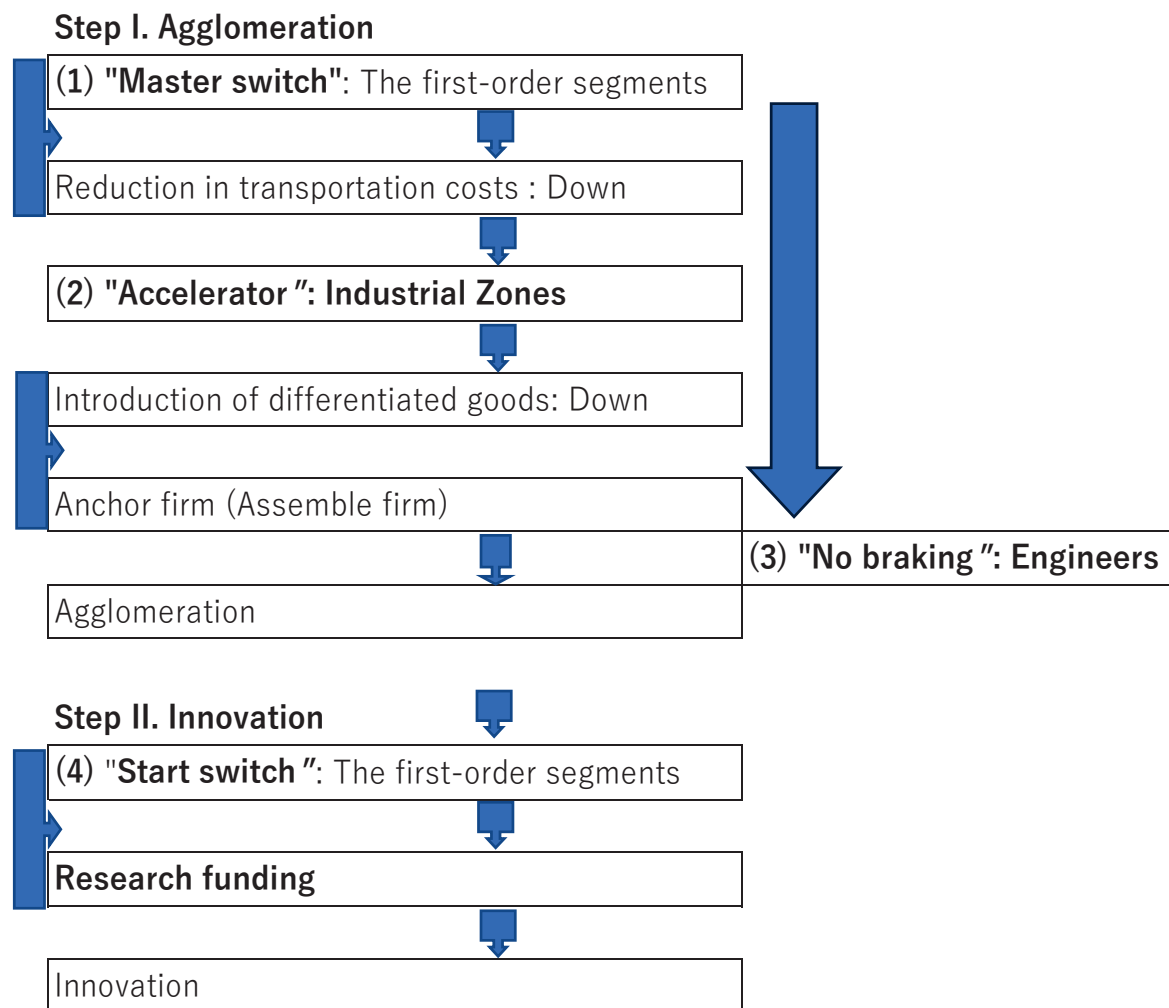


Figure 1. Cluster policy. Source: Author's illustration.

Table 1. Construction sequencing and start segment.

Economics	(i) Spatial Economics	(ii) Construction Sequencing	(iii) Sequencing Economics
	(i) Fujita and Thisse (2003)	Architecture-engineering-construction industry	Kuchiki and Sakai (2023) and this paper
Theory	(i) Theory of location: Agglomeration	(ii) Sequencing: PERT (program evaluation review technique), CPM (critical path method), BIM (building information modeling) etc.	(iii) Theory of sequencing
Charateristics	(i) Breaking conditions from symmetry equilibrium to agglomeration equilibrium	(ii) construction sequencing	(iii) Economies of sequence & Function of segments
Key factors	Transport costs, the elasticity of substitution between differentiated goods	Segments: public spaces, airports, factories, health, residential, IT OS and data center business, and international opportunities	Function of segments: (iii) Start switch, Master switch, Accelerator, No brake

Source: Author's based on A. Kuchiki and H. Sakai.

(i) Spatial economics is a location theory by Fujita et al. (1999). The main factors are the transport costs and the elasticity of substitution between differentiated goods. The theory defines the conditions of breaking away from symmetric equilibrium to agglomeration equilibrium.

(ii) The construction industry is the foundation of our economy and is essential to our daily life. Construction is the biggest industry in the world. As stated in UNHABITAT (2007), urban strategic planning is essentially a dynamic process. Outbuild (2024) noted that in an industry where 72% of firms state that projects are taking longer than expected and 78% of engineering and construction firms believe that project-related risk is increasing, the importance of starting with a first-class construction sequence is evident.

“Construction sequencing” is a method of construction planning, as described by McKinsey & Company (2020). “Construction sequencing” in the construction industry refers to the process of determining the sequence of segments in order to optimize the project’s resources, budget, and scheduled timeline (see Brown and Hamilton 2024). The timeline for efficient construction sequencing is as follows: pre-construction planning, creating a breakdown of the work’s structure, sequencing based on dependencies, and estimating the durations and lead times (see Outbuild 2024). Ignoring the dependencies may be one of the most common actions and the most damaging to a project (Outbuild 2024).

The process usually begins by dividing a project into “segments”. Urban segments consist of public spaces, airports, factories, health, housing, IT OS and data center businesses, and international opportunities (Larsen and Toubro Limited 2024).

Sequencing is a huge factor in many common planning methods including the critical path method (CPM) (see Levy et al. 1963), the program evaluation and review technique (PEPT) (see Danao 2024), and building information modeling (BIM) (see Azhar et al. 2012).

(iii) Sequencing economics is a theory of agglomeration construction that, according to Kuchiki and Sakai (2023), focuses on the process of constructing segments. Sequencing economics in agglomeration-related architectural theory is applied to sequencing agglomeration segments in terms of the “economies of the sequence” and the “function” of the segments. The “economies of the sequence” are defined as the selection and sequencing of any two segments from among the entire group of segments of an industrial agglomeration toward the efficient building of the agglomeration, according to Kuchiki (2021). In statistical analysis, the economy of the sequence from variable X to variable Y is defined as the relationship where X Granger-causes Y.

Agglomerations are organized by building segments. According to Kuchiki (2023), the segments comprise four major categories, namely human resources, physical infrastructure, institutions, and living conditions. Appendices A.1 and A.2 show the segments of the tourism industry and the manufacturing industry.

Kuchiki (2023) found that the formation of industrial agglomeration proceeds through the construction of segments and identified the conditions for a master switch in the case of a manufacturing agglomeration. A segment has the “function” of forming an agglomeration, and one of the master switch segments reduces transportation costs such as highway transportation costs, as shown in Table 2. The functions of segments.

As summarized in Table 1, this study attempts to integrate (ii) “construction sequencing” in the construction industry and (iii) sequencing economics by using (i) the method of Fujita and Thisse (2003).

With respect to Step II, according to Simmie (2008), the concept of innovation can be defined as the introduction of a new or changed product, process, service, or form of organization into the market. According to Kim and Mauborgne (1997, 1999), the definition of innovation used in this study is something that makes “the competition irrelevant by offering fundamentally new and superior buyer value in existing markets and by enabling a quantum leap in buyer value to create new markets”. In other words, innovation is the commercialization of new ideas or “value added”.

Table 2. Function of segments.

	Function	Segment	Spatial Economics	Sequencing Economics	Location
Step I. Agglomeration					
	<i>“Construction sequencing”</i>				
Urban agglomeration	(1) Master switch	Transport costs	Krugman (1991), Alonso (1964)	Kuchiki and Sakai (2023)	Sapporo, Japan
Manufacturing	(2) Accelerator	Industrial zones	Helpman and Krugman (1985)	Kuchiki (2023)	Industrial hubs, China,
Manufacturing	(3) No braking	Engineers	Helpman and Krugman (1985)	Kuchiki (2024)	Industrial hubs, India
	<i>“Function”</i>	Segment	Spatial economics	Sequencing economics	Location
Step II. Innovation					
Knowledge and manufacturing industry	(4) <i>“Start switch”</i>	<i>“Research funding”</i>	Fujita and Thisse (2003)	<i>This paper</i>	Nations

Source: Author's.

In prior studies, Hernández (2020) analyzed innovation in relation to how it is adopted in clusters and how it can contribute to cluster-level, regional, and “national” development and competitiveness. They discussed important factors that were not considered in Diamond model of Porter (1998) such as the importance of the “multinational activity effect” and the role of the government in regulating regional and international interactions.

University–industry linkages (UILs) and the national innovation system (NIS) play a key role in explaining innovation, according to Hershberg et al. (2007). Brimble and Doner (2007) found few UILs and weak NISs in the case of Thailand, where the Thai industry showed little interest in innovation at that time. Conversely, high-tech zones in China were built in close proximity to universities and public research institutes with the goal of promoting UILs, as shown by Chen and Kenney (2007) and Kuchiki (2021). Wu (2007) analyzed UILs in the context of NISs and found that UILs were exceptionally active in Beijing. However, it was not concluded whether a UIL, an NIS, or any other segment was the starting segment for Step II.

Kanai and Ishida (2000) emphasized the importance of the cumulative process, as it takes time to build any segment of an agglomeration. The Mind Tools Content Team (2024) followed Weiss and Legrand (2011) and described a four-stage innovation process.

The above-mentioned studies can be summarized regarding the purpose of this study as follows. First, these studies explored what determinants were involved in activating innovation in cluster formation and also explored the process of innovation activation. Integrating these ideas, this study focused on the process of segment building for innovation in Step II of the cluster policy, as shown in Figure 2. The process of innovation proceeds through the construction of segments, therefore, an attempt was made to identify a start switch for innovation.

The purpose of this study was to examine whether research expenditure per researcher leads to value being added. For Step II, the innovation process, we conducted an econometric analysis of the knowledge services and knowledge manufacturing industries and the five manufacturing industries in nine countries using data from the WIPO (2002–2019), NSF (2002–2019), and UNESCO (2002–2019). Granger causality tests were conducted between research expenditure per researcher and each of the value added, patents, and papers with lags of one to five years.

Construction sequencing:**Step I :**

Agglomeration

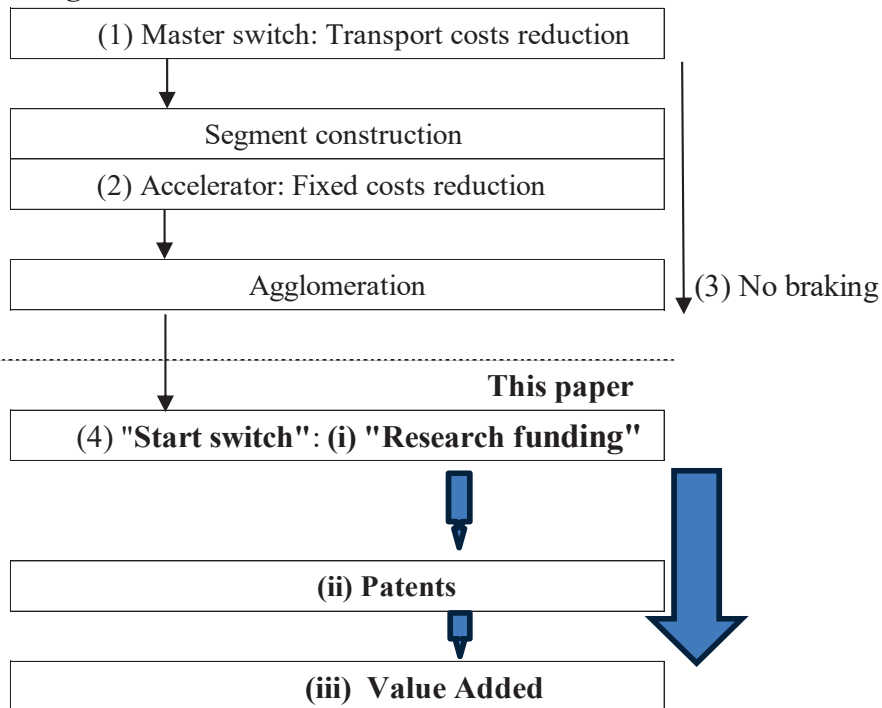


Figure 2. Start switch in construction sequencing. Source: Author's illustration.

Table 3 shows the value added, patents, papers, research expenditure per researcher, and research expenditure per capita data used in this study. This study analyzed the relationship between research expenditure per researcher and the amount of value added created. No relationship was found between research expenditure per head of population and the creation of value added.

The relationship between research expenses per researcher and knowledge/technology services was the same for the first-ranked USA and the ninth-ranked Russia. For research expenses per researcher, those of China, South Korea, Japan, Italy, the UK, and France were around 50% of the first-ranked USA. The countries with knowledge/technology services around 10% of the USA, which was in first place, were Japan, Germany, France, the UK, and South Korea. However, Germany tied with the USA in first place. The country with the largest population (China, 1.4 billion) had 28% of the value added of the USA.

The results of the Granger causality tests indicate that the hypothesis that research expenditure per researcher Granger-causes value added was significant. We also identified the starting segment of innovation activation. Kuchiki and Sakai (2023) and Kuchiki (2023, 2024) linked spatial economics to sequencing economics in Step I (agglomeration), as shown in Table 1. This study concluded that the starting segment of Step II (innovation) is research funding.

The rest of this paper is organized as follows. In Section 2, we derive our hypothesis by introducing the model of Fujita and Thisse (2003). Section 3 explains the data on innovation in nine countries. In Section 4, we perform Granger causality tests and regression analysis to find the starting segment in Step II (innovation). A summary and the conclusions are given in Section 5.

Table 3. Data for analysis.

3.1. Knowledge-intensive industries: Value added (2019)		Unit: Row 1. world ranking; Row 2. US\$; Row 3. % of world ranking 1.							
Knowledge/technology manufacturing	China	US	Japan	Germany	Korea	Italy	UK	France	Russia
	1	2	3	4	5	7	8	11	18
	1,981,928	1,301,712	582,386	448,517	248,095	113,710	112,978	98,758	45,893
	100	66	29	23	13	6	6	5	2
computer	China	US	Korea	Japan	Germany	UK	France	Italy	Russia
electronics, optical instrument	1	2	3	5	6	11	13	15	19
	373,195	310,124	111,575	76,800	39,349	17,968	13,455	8592	5204
	100	83	30	21	11	5	4	2	1
Knowledge/technology services	US	China	Japan	Germany	France	UK	Korea	Italy	Russia
	1	2	3	4	5	6	8	9	12
	1,034,456	285,503	147,906	145,206	131,487	127,777	93,077	60,483	32,672
	100	28	14	14	13	12	9	6	3
IT/information services	US	China	Japan	Germany	UK	France	Italy	Korea	Russia
	1	2	3	4	5	6	8	10	16
	655,779	149,643	124,853	104,293	94,448	74,167	37,780	29,830	1514
	100	23	19	16	14	11	6	5	0
3.2. Knowledge industry: Number of patents (2022)		Unit: Row 1. world ranking; Row 2. number; Row 3. % of world ranking 1.							
semi- conductor/manufacturing	China	Japan	US	Korea	Germany	France	UK	Italy	Russia
	1	2	3	4	5	6	9	14	25
	3045	2641	1541	773	325	122	59	22	5
	100	87	51	25	11	4	2	1	0
computer technology	China	US	Japan	Korea	Germany	UK	France	Italy	Russia
	1	2	3	4	5	6	7	17	19
	10,657	7631	3342	2306	812	482	427	85	78
	100	72	31	22	8	5	4	1	1
digital communication technology	China	US	Japan	Korea	Germany	France	UK	Italy	Russia
	1	2	3	4	7	9	10	17	21
	10,596	6143	2736	2327	358	196	164	40	13
	100	58	26	22	3	2	2	0	0
telecommunication technology	China	US	Japan	Korea	Germany	France	UK	Italy	Russia
	1	2	3	4	6	8	9	13	20
	2109	1344	1050	876	112	89	79	28	10
	100	64	50	42	5	4	4	1	0

Table 3. Cont.

3.3. Knowledge industry: Number of papers (2022)		Unit: world ranking, number, % of world rank 1.							
sciences (total)	China	US	Germany	UK	Japan	Italy	Russia	Korea	France
	1	2	4	5	6	7	8	9	13
	898,949	457,335	113,976	105,584	103,723	90,586	84,252	76,936	65,888
	100	51	13	12	12	10	9	9	7
computer sciences	China	US	Germany	Japan	UK	Italy	Korea	France	Russia
	1	3	4	5	6	7	8	9	10
	102,524	33,405	11,826	9127	8433	7766	7669	6419	6396
	100	33	12	9	8	8	7	6	6
3.4. All industries: Research expenses per researcher and research expenses per capita (2021)		Unit: US\$.							
per researcher	US	Germany	China	Korea	Japan	Italy	UK	France	Russia
	3	11	18	19	20	21	24	28	60
	484,471	327,722	276,195	256,033	253,151	248,674	239,846	227,542	120,554
	100	68	57	53	52	51	50	47	25
per capita	US	Korea	Germany	UK	Japan	France	Italy	China	Russia
	4	5	11	16	17	20	29	36	41
	2359	2325	1814	1449	1427	1178	666	466	328
	100	99	77	61	60	50	28	20	14
3.5. Manufacturing: Value added (2019)		Unit: Row 1. world ranking; Row 2. US\$; Row 3. % of world ranking 1.							
automobile/manufacturing	China	US	Japan	Germany	Korea	UK	Italy	France	Russia
	1	2	3	4	6	9	11	14	17
	299,268	149,391	148,741	137,307	29,812	19,392	14,766	12,971	5500
	100	50	50	46	10	6	5	4	2
machinery	China	US	Japan	Germany	Italy	Korea	UK	France	Russia
	1	2	3	4	5	6	7	10	16
	401,285	166,982	158,186	120,827	42,936	37,447	19,243	13,176	6498
	100	42	39	30	11	9	5	3	2
chemical	China	US	Japan	Germany	Korea	France	UK	Italy	Russia
	1	2	3	4	5	9	12	13	20
	326,874	208,576	76,153	50,973	30,636	20,046	15,754	12,950	7662
	100	64	23	16	9	6	5	4	2
electronics	China	Japan	US	Germany	Korea	Italy	France	Russia	UK
	1	2	3	4	5	6	10	11	13
	318,792	71,213	65,004	42,432	26,509	11,800	6668	5894	5552
	100	22	20	13	8	4	2	2	2
medicine	US	China	Japan	Germany	UK	France	Italy	Korea	Russia
	1	2	3	4	7	8	9	12	19
	182,383	158,924	27,004	24,796	19,137	14,363	10,333	7390	1742
	100	87	15	14	10	8	6	4	1

Table 3. Cont.

3.6. Manufacturing: Number of patents (2022)		Unit: Row 1. world ranking; Row 2. number; Row 3. % of world ranking 1.							
automobile	Japan	China	US	Germany	France	Korea	UK	Italy	Russia
	1	2	3	4	5	7	8	9	21
	800	727	530	425	286	184	133	98	29
	100	91	66	53	36	23	17	12	4
machinery	Japan	China	US	Germany	Korea	Italy	France	UK	Russia
	1	2	3	4	5	6	9	10	22
	1073	763	522	501	201	101	67	61	12
	100	71	49	47	19	9	6	6	1
chemical	US	China	Japan	Germany	Korea	France	UK	Italy	Russia
	1	2	3	4	5	6	7	9	23
	1089	963	721	499	375	229	192	102	23
	100	88	66	46	34	21	18	9	2
electronics	China	US	Japan	Korea	Germany	France	UK	Italy	Russia
	1	2	3	4	5	6	7	10	25
	5997	5539	2355	2095	2000	569	295	174	34
	100	92	39	35	33	9	5	3	1
medicine	US	China	Korea	Japan	Germany	UK	France	Italy	Russia
	1	2	3	4	5	6	7	8	22
	4759	2446	858	718	405	341	336	295	48
	100	51	18	15	9	7	7	6	1
3.7. Manufacturing: Number of papers (2022)		Unit: Row 1. world ranking; Row 2. number; Row 3. % of world ranking 1.							
engineering	China	US	Germany	Korea	Japan	Russia	Italy	UK	France
	1	2	4	5	6	7	8	9	12
	228,189	49,437	16,542	15,472	13,324	12,911	12,833	11,860	8669
	100	22	7	7	6	6	6	5	4
chemical	China	US	Japan	Germany	Russia	Korea	Italy	UK	France
	1	3	4	5	6	7	9	10	11
	72,033	13,693	6927	6453	6040	5611	3813	3613	3504
	100	19	10	9	8	8	5	5	5
physics	China	Japan	Korea	US	Germany	France	UK	Italy	Russia
	1	2	4	5	6	7	8	10	25
	5997	5539	2355	2095	2000	569	295	174	34
	100	92	39	35	33	9	5	3	1
biology	US	China	Korea	Japan	Germany	UK	France	Italy	Russia
	1	2	3	4	5	7	8	13	22
	4759	2446	858	718	405	336	295	163	48
	100	51	18	15	9	7	6	3	1

Source: Author's based on NSF in Appendix B.

2. The Fujita and Thisse Model

2.1. Agglomeration and Innovation (Figure 2)

This study focused on the process of segment construction in cluster formation. We address sequencing economics, which determines the sequence of segment construction. An important concept in sequence economics is the economy of the sequence.

Figure 2 illustrates the process of cluster formation. In this study, the process of cluster formation involves Step I (agglomeration) and Step II (innovation). This study focused on the “process” of segment building to activate innovation (Step II). This concept is defined as the sequencing of segments in the efficient construction of segments that form an agglomeration. In the process of activating Step II (innovation), if the starting segment works, innovation will proceed, and added value will be generated.

Step I, the agglomeration building process, as pointed out by Kuchiki (2023), is as follows. The first step in agglomeration construction is to determine where the agglomerations will be located. Spatial economics determines this location. Table 2 shows an example of spatial economics coupled with sequencing economics, and an example of the sequencing economics of an agglomeration is shown. The organization of an industrial agglomeration consists of segments. Each of these segments has a “function”.

As shown in Figure 1 and Table 2, the functions of the segments are (i) the “master switch”, (ii) “accelerator”, and (iii) “brake”. Kuchiki and Sakai (2023) identified the master switch on the basis of the results of Krugman (1991) and Alonso (1964). Kuchiki (2023) and Kuchiki (2024) identified the accelerator and the brake, respectively, by drawing on the work of Helpman and Krugman (1985).

The master switch segment of Step I (agglomeration) in manufacturing is the transport infrastructure, which specifically reduces the “transport costs”. For example, ports and roads serve as master switches. The accelerator segment reduces the fixed costs for the tenant firms (i.e., “leased industrial parks”). The brake segment is “the lack of engineers”. The agglomeration process is initiated when firms producing differentiated goods with no brakes and a low elasticity of substitution move to an agglomeration region.

In this section, first, the model of spatial economics of Fujita and Thisse (2003) was applied to obtain the master switch that initiates the construction of an industrial agglomeration segment in the knowledge industry. This switch is the construction of segments where the transport costs are below a certain threshold. The knowledge-intensive industries in Table 3 consist of knowledge-intensive manufacturing industries and knowledge-intensive service industries.

Next, we extended the model of Fujita and Thisse (2003) to prove the hypothesis that research expenditure per researcher Granger-causes value added. In this study, we defined a “start switch” as the segment acting as the starting point for the process of innovation, as shown in Figure 2.

In the following sections, an econometric analysis identifies the starting segments that trigger innovation in Step II of the knowledge and manufacturing industries.

2.2. The Model

This section presents the part of the model of Fujita and Thisse (2003) related to the master switch in the first step of agglomeration. The economy consists of two regions, s and t , and three production sectors: the traditional sector (T), the modern sector (M), and the innovation sector (R). In M, the production of any variety requires the use of a “patent” specific to this variety, which has been developed in R.

The number of modern varieties of goods in Region s and Region t is denoted as M_s and M_t , respectively, and is positive at any given time. Consider the case in which a firm producing a variety of goods can freely decide its location at each time, irrespective of the region in which the goods were innovated.

The Cobb–Douglas utility function for all workers is given by

$$u = Q^\mu T^{1-\mu} / \mu^\mu (1 - \mu)^{1-\mu}, \quad (1)$$

where T is the consumption of homogeneous traditional goods, μ is the share of expenditure of modern varieties, and Q stands for the index of the CES consumption of the modern varieties, which is given by

$$Q = \left[\int_0^M q(i)^{(\sigma-1)/\sigma} di \right]^{\sigma/(\sigma-1)}, \quad (2)$$

where M is the total mass of modern varieties available in the global economy at Time t , σ is the elasticity of substitution between any two varieties, and $q(i)$ is the consumption of Variety i .

Let λ_r be the share of skilled workers in Region r , so that $\lambda_s \equiv \lambda$ and $\lambda_t \equiv 1 - \lambda$. For the chosen value of the share of skilled workers in a region, λ , $V_r(0; \lambda)$ stands for the lifetime indirect utility of a skilled worker in Region r ($=s$ and t), and $v_r(t; \lambda)$ is the corresponding instantaneous indirect utility at Time t . This means that

$$V_r(0; \lambda) = \int_0^\infty e^{-\gamma t} \ln[v_r(t; \lambda)] dt \quad (3)$$

where $\gamma > 0$ is the subjective discount rate common to all consumers.

Let E_r be the total expenditure in Region r at the time in question and let P_r be the price index of the modern goods in this region. The total demand for Variety i produced in Region r is equal to

$$q_r(i) = \mu E_r p_r(i) P_r + \mu E_s [p_r(i) \Gamma] P_s \Gamma, \quad (4)$$

where $r, s = A, B$, and $r \neq s$, $p_r(i)$ is the price of Variety i in Region r , and Γ accounts for the “iceberg” melting during its transportation. The corresponding profit is

$$\pi_r(i) = [p_r(i) - 1] q_r(i). \quad (5)$$

The firms’ profits must be identical across regions; thus, $q_s^* = q_t^*$, where q_r^* denotes the equilibrium output of any variety of goods produced in Region r . The equilibrium output of any variety produced in Region r and the equilibrium profit are given by

$$q_r^* = \mu \rho [E_r/(M_r + \varphi M_s) + E_s/(M_s + \varphi M_r)], \quad \pi_r^* = q_r^*/(\sigma - 1), \quad (6)$$

where $\varphi \equiv \Gamma^{-(\sigma-1)}$ and M_r represent the number of modern varieties produced in Region r at the time in question. The modern goods are agglomerated in Region s , which has a greater share of the innovation sector.

Turning to the innovation sector, when the knowledge capital in Region r is K_r , and the share of skilled workers in Region r is λ_r , the number of patents developed per unit of time in Region r is

$$n_r = K_r \lambda_r.$$

The equation of motion for the number of patents/varieties per unit of time in the economy is

$$DM = n_s + n_t = M\{\lambda [\lambda + \eta(1 - \lambda)]^{1/\beta} + (1 - \lambda)(1 - \lambda + \eta \lambda)^{1/\beta}\},$$

where $DM = dM(t)/dt$, t is time, and

$$g(\lambda) = \lambda [\lambda + \eta(1 - \lambda)]^{1/\beta} + (1 - \lambda)(1 - \lambda + \eta \lambda)^{1/\beta},$$

where η ($0 \leq \eta \leq 1$) expresses the intensity of knowledge spillovers between the two regions. The growth rate of the number of patents/varieties (DM/M) in the global economy is given by

$$DM/M = g(\lambda),$$

where the distribution of skilled workers is λ . Here, $g(\lambda)$ is symmetric about $1/2$, so that

$$g(0) = g(1) = 1.$$

The condition of breaking from symmetric equilibrium at $\lambda = 1/2$ to agglomeration equilibrium for an agglomeration policy is given by

$$d[V_1(0; \lambda) - V_2(0; \lambda)]/d\lambda > 0.$$

When the transport costs of the modern goods, Γ , are low, the equation is

$$\Gamma \leq C \equiv [(\sigma + \mu)/(\sigma - \mu)]^{-(\sigma-1)}. \quad (7)$$

Then, in the core–periphery structure, the whole innovation sector begins to agglomerate in the core region. “Breaking conditions” are the conditions that trigger the transition from symmetric equilibrium to agglomeration equilibrium in knowledge-based industries. The master switch of industrial agglomeration is the construction of segments that satisfy the breaking conditions. The segments in this model are those that reduce the transport costs in a broad sense.

In this study, we introduced the following two assumptions. First, Fujita and Thisse (2003) assumed that human capital $h(j)$ is the number of papers read by an individual and that the knowledge capital K_r available in Region r depends on human capital. In this study, we assumed that the number of papers depends on the research expenditure.

Assumption 1. $h(j) = f(\text{research expenditure per researcher})$.

Second, Fujita and Thisse (2003) assumed that the number of patents M equals the number of varieties. Patents lead to new varieties of products, and varieties generate added value. This is the process of innovation. In this study, we assumed that the value added depends on the number of patents.

Assumption 2. $\text{Value added} = g(M)$.

By integrating these two assumptions, we obtained the following causal sequence: *research expenditure per researcher*, *papers*, *patents*, *varieties*, and *value added*. Therefore, the following hypothesis holds.

Hypothesis 1. *Research expenditure per researcher causes value added.*

Section 3 describes the data used in the econometric analysis of this study. Section 4 tests the Granger causality of the hypothesis presented here.

2.3. The Case of the Taiwan Semiconductor Manufacturing Company (TSMC)

In this subsection, Equation (8) is obtained via Equation (7). This equation is used to define the master switch in building an agglomeration. In this subsection, we study the case of a semiconductor agglomeration formed by Taiwan’s TSMC, which built a factory in Kumamoto Prefecture.

In Step I of the industrial agglomeration shown in Figure 1, the master switch was to use subsidies to attract TSMC to Kumamoto Prefecture. As a result of the master switch being pushed, the semiconductor agglomeration in Kumamoto Prefecture started to form clusters. This is explained below.

Note that the hypothesis presented in the previous subsection of this article is the hypothesis regarding the starting switch of Step II following Step I (agglomeration). The following subsections test this hypothesis.

In this subsection, Equation (8) is also proposed for the master switch of agglomeration as a valid suggestion for the cluster policy. In other words, it has implications regarding what the policy should be for the threshold of transport costs in a broad sense, which

should be lowered. The following equation was obtained by the partial differentiation of C in Equation (7) via σ .

$$\frac{\partial C}{\partial \sigma} = 2(\sigma - 1)\mu(\sigma - \mu)^{-2}[(\sigma + \mu)/(\sigma - \mu)]^{-\sigma} > 0, \quad (8)$$

since $\sigma > 1$ and $0 < \mu < 1$.

This equation shows that the smaller the σ , the smaller the C . In other words, as a breaking condition for the start of a knowledge industry-related agglomeration, agglomeration does not begin unless the reduction in its transport costs is greater than the threshold C in the case of heterogeneous goods and services in knowledge-intensive industries with a lower elasticity of substitution.

TSMC created a dedicated IC semiconductor foundry business model when it was founded in 1987. In 2023, TSMC served 528 customers and manufactured 11,895 products for various applications covering a variety of end markets including high-performance computing, smartphones, the Internet of Things (IoT), automotive, and digital consumer electronics (TSMC 2024).

TSMC is capable of producing two nano-semiconductors. These products have a very low elasticity of substitution σ . Theoretically, the breaking condition from symmetric equilibrium to agglomeration equilibrium cannot be established unless the transport costs in a broad sense are very low.

TSMC decided to expand its plant to Kumamoto Prefecture in Japan on 14 October 2021 (Nikkei 2024). At that time, Japan's Ministry of Economy, Trade, and Industry decided to provide JPY 476 billion (USD 3 billion; USD 1 = JPY 155) in subsidies for the first plant to manufacture 12 nano-semiconductors (Ohta 2021).

Subsequently, TSMC decided to expand to a second plant, and METI announced more subsidies. The subsidy for the second plant, which produces semiconductors of 6 nanometers with high product differentiation (i.e., a smaller σ should be increased to up to JPY 732 billion (USD 4.72 billion), thereby lowering the threshold of transport costs). It can be interpreted that the "subsidy" broadly contributed to the reduction in transport costs.

Fifty-six companies announced their intention to establish or expand operations in Kumamoto by February 2024 (Ministry of Economy, Trade, and Industry 2023). The effect of TSMC has led to a semiconductor-related industrial agglomeration around Kumamoto Prefecture. The agglomeration includes major Japanese semiconductor companies such as the Ebara Corporation, Renesas Electronics, Tokyo Electron Kyushu, Mitsubishi Electric, and Fujifilm. New buildings, expansions, and new factories were constructed not only in Kumamoto Prefecture, but also throughout Kyushu Island including Rohm Semiconductor in Fukuoka Prefecture and Japan Semiconductor in Ohita Prefecture (Kumamoto Prefecture 2024).

3. Materials

In this section, we aim to understand the results for the nine countries for which data were analyzed. These data cover knowledge-intensive industries and five types of manufacturing. The situation in the nine countries was outlined in terms of value added, patents, the number of publications, research expenditure per researcher, and research expenditure per capita. The nine countries were chosen because, with the exception of Russia, their policies have had a significant impact on research expenditure and value added per researcher as well as their high world rankings. In particular, we tried to identify the underlying preconditions that indicate that research expenditure per capita Granger-causes value added.

Table 3 shows that for both the added value of knowledge and technology services and for knowledge and technology manufacturing in knowledge-intensive industries, there were only eight countries with a value added of more than 5% of that of the country that ranked first, taking the value added of the country that ranked first as 100%. One country whose value added was below 3% of that of the country in first place was Russia. Table 3 shows that in the four manufacturing sectors, with the exception of electronics, the top

seven countries had a value added of more than 5% of that of the top-ranked country, taking the value added of the country that ranked first as 100%. In addition, Russia was the only country where the value added was below 2% of that of the country in first place. In other words, the top eight countries in the knowledge-intensive and manufacturing industries occupied the top positions in the global value-added ranking.

This study therefore analyzed nine countries including the top eight countries for knowledge-intensive industries, and Russia, as a country below the threshold of the global value-added rankings.

The relationship between research expenditure per researcher and the value added of knowledge/technology services was the same for the USA, which was in first place, with Russia in ninth place. In terms of research expenditure per researcher, China, South Korea, Japan, Italy, the UK, and France had around 50% of that of the USA. Countries with knowledge/technology services around 10% of that of the USA were Japan, Germany, France, the UK, and South Korea. Germany tied with the USA in first place. In China, which has a population of 1.4 billion, the value added was 28% of that of the USA.

The statistics of value added in the knowledge-intensive industries and the manufacturing industries were obtained from the NSF (U.S. National Science Foundation). Knowledge-intensive industries were divided into (i) knowledge/technology-intensive manufacturing and (ii) knowledge/technology-intensive services. According to the definition of the OECD, knowledge/technology-intensive manufacturing includes computer electronics and optical equipment, aerospace, pharmaceuticals, weapons and arms, automotive, medical equipment, mechanical equipment, chemical, electrical equipment, and rail and transportation equipment, whereas knowledge/technology-intensive services include the IT and information-related service industry, scientific research and development services, and the software publishing industry.

Statistics on patents were obtained from the WIPO (2002–2019), statistics on papers were from the NSF (2002–2019), and statistics on the total research expenditure for each country were from UNESCO (2002–2019) (UNESCO Institute of Statistics). The total research expenditure for each country was divided by the number of full-time equivalent researchers; the number of researchers was obtained from ISCO (International Standard Classification of Occupations) 88 Major Category 2, namely “professionals” who are actually engaged in research and development.

This section presents the rankings for value added, patents, publications, and research expenditure per researcher. These rankings are not related to the results of the hypothesis tested in the next section. However, in the UK and Russia, the results for the manufacturing industries are likely to be related to the low rankings of value added, patents, and research expenditure per researcher.

Hernández (2020) explains clusters as follows. Porter’s diamond model stands out for its approach to the competitiveness of a nation, given that it limits the capacity to innovate the national or territorial scope. According to the diamond model, clusters play a very noteworthy role in national or territorial competitiveness. Accordingly, this study used country-level data that were available.

3.1. Ranking of Knowledge-Intensive Industries in Terms of Value Added

This section examines the world’s major countries in terms of their knowledge-intensive industries in terms of value added.

In the knowledge/technology-intensive manufacturing industry, China ranked first and the USA ranked second. In knowledge/technology-intensive manufacturing, the USA accounted for two-thirds of China’s value added. In third place was Japan, followed by Germany, and Korea. In sixth place and below were Italy, the UK, and France, with about 5%; Russia followed with 2%.

Similarly, for computer technology and optical instruments, China was in first place, with the USA in second place, accounting for 83% of China’s value added. In computer technology, in third place and below, Korea, Japan, and Germany had around 25% of

China's total value added; in sixth place and below, the UK and France had around 5% of China's total value added.

In knowledge/technology-intensive services, the first and second positions of the USA and China were reversed. The USA was in first place, with a higher ratio than the other countries, while China was in second place. China's value added was 28% of the USA's value added, followed by Japan, Germany, France, and the UK, which accounted for around 13% of the USA's value added. South Korea and Italy followed with 9% and 6%, respectively, and Russia had 3%.

The same ranking applied to the IT information service sector up to fourth place. The USA ranked first, with a higher share than the other countries, followed by China in second place. The ratio of China's value added to that of the USA was 23%, followed by Japan in third place and Germany in fourth place with 19% and 16%, respectively. Italy and South Korea (seventh and eighth) followed with 6% and 5%, respectively. As for Russia, the above-mentioned industries accounted for 1–3% of the value added of the top-ranking country.

3.2. Ranking of the Number of Patents Acquired

Next, we examined the ranking for the number of patents acquired by the knowledge-intensive industry. "Semiconductor manufacturing" was selected as representative of the knowledge/technology-intensive manufacturing sector. In addition, "computer technology" was taken to represent computer technology and optical instruments. "Digital communication technology" represents the knowledge and technology service industries, and "telecommunication" represents the IT information service industry.

(i) Semiconductor manufacturing

China ranked first in the number of patents for semiconductor manufacturing, with Japan in second place. The ratio of the number of patents in Japan to those in China was 87%, and the proportions for the USA (third), Korea (fourth), and Germany (fifth) to the number of patents in China were 50%, 25%, and 11%, respectively. Other countries included France in ninth place with 4%, and Italy in fourteenth place with 1%.

(ii) Computer technology

For the number of patents related to computer technology, China ranked first, followed by the USA. The ratio of the number of patents in the USA to those in China was 72%, while the ratios for Japan and South Korea compared with China were 31% and 22%, respectively. Germany ranked fifth, the UK ranked sixth, and France ranked seventh, with 8%, 5%, and 4% compared with the number of patents in China, respectively. Italy and Russia were last at 1%.

(iii) Digital communication technology

China ranked first in the number of patents in digital communication technology, followed by the USA. The ratio of the number of U.S. patents to the number of Chinese patents was 58%; the ratios of Japan and Korea compared with the number of Chinese patents were 26% and 22%, respectively; those for Germany, France, and the UK were 3%, 2%, and 2%, respectively, and the ratios of Germany and the UK relative to China were 3% and 2%, respectively.

(iv) Telecommunication

For the number of telecommunication patents, China ranked first, followed by the USA. The ratio of U.S. patents to Chinese patents was 64%, the ratios of Japan and Korea compared with China were 50% and 42%, respectively, and the ratios of Germany, France, and the UK were 5%, 2%, and 2%, respectively.

In summary, China ranked first in all industries, with the USA, Japan, and South Korea occupying the second, third, and fourth places, respectively. In Germany, France, and the UK, the number of patents acquired by the knowledge industry was less than 10% of the

number acquired by China across the four industries, with the exception of semiconductors in Germany. Italy and Russia had less than 1% of the number of patents acquired by China.

3.3. *Number of Papers (2022) and Research Expenditure per Researcher and per Capita (2021)*

Data on the number of papers on computer science were analyzed.

(i) Number of computer science papers

China ranked first in the number of computer science papers, while the USA ranked second. The ratio of U.S. papers to Chinese papers was 33%, while the ratios of Germany (third) and Japan (fourth) were 12% and 9%, respectively. The ratios of the other countries (the UK, Italy, Korea, France, and Russia) were 6–8%.

(ii) Research expenditure per researcher and research expenditure per capita

In terms of research expenditure per capita, the USA ranked first and Korea second; these countries had the same level of research expenditure per capita. Germany ranked third, the UK fourth, Japan fifth, and France sixth, with ratios of 77%, 61%, 60%, and 50%, respectively, compared with the USA's per capita research expenditure. Italy, China, and Russia's percentages of the USA's per capita research expenditure were much lower at 28%, 20%, and 14%, respectively.

In terms of research expenditure per researcher, the USA was number one, with Germany in second place at two-thirds of the USA's research expenditure per researcher. Among the other countries, China had 57% of the USA's research expenditure, and France had 47%. Other countries (South Korea, Japan, Italy, and the UK) had about half of the USA's research expenditure, while Russia had a quarter of the USA's research expenditure.

The following section presents the results of an analysis of the research expenditure per researcher.

3.4. *Ranking of Manufacturing Industries in Terms of Value Added*

The following is an overview of the situation in the world's major countries in terms of value added. Five manufacturing industries were addressed: automotive, machinery, chemical, electronics, and pharmaceuticals.

In the automotive, machinery, chemical, and electrical machinery industries, China, the USA, Japan, Germany, and South Korea ranked first through to fifth, with the exception of the machinery industry, where Italy ranked fifth. China ranked first in value added for all industries, except for pharmaceuticals. Except for Japan, which ranked second in value added in the electronics industry, the USA, Japan, and Germany ranked second, third, and fourth, respectively, for the other three industries. The value added of the manufacturing industries in the UK, Italy, and France was approximately 5% or less of the value added of China, which ranked first for all industries. Russia's value added was about 1–2% of that of China.

In the pharmaceutical industry, the USA ranked first and China second, while the value added for Japan, Germany, the UK, and France was about 10% of that of the USA. The value added of Italy and South Korea was about 5% of that of USA, and that of Russia was 1% of that of the USA.

3.5. *Ranking of Manufacturing Industries in Terms of Patents*

In the five manufacturing industries, Japan, China, the USA, Germany, and Korea ranked first through to fifth, except for the automotive industry, where France ranked fifth. Japan ranked first in terms of the number of patents in the automotive and machinery industries, while China ranked first in the electrical industry. China also ranked second in four other industries. The USA ranked first in the number of patents in the chemical and pharmaceutical industries, second in the electrical industry, and third in the automotive and machinery industries. Germany ranked fourth in the number of patents, except for those in the electrical industry and the pharmaceutical industry. Korea ranked sixth in the number of patents in the automotive industry, fifth for those in the mechanical

and chemical industries, fourth for those in the electrical industry, and second in the pharmaceutical industry. France, Italy, and the UK had around 10% of the number of patents in the manufacturing industry compared with the country ranking first for each industry. Russia had about 1–4% of the number of patents compared with the country ranked first for all industries.

3.6. Ranking of Manufacturing Industries in Terms of Papers

Regarding the number of papers, data on the number of papers in the fields of engineering, chemistry, and physics were available. For engineering, chemistry, and physics, China ranked first. The USA ranked second in engineering and chemistry, with 22% and 19% of China's share, respectively. In engineering and chemistry, Germany, Korea, Japan, Russia, Italy, the UK, and France had less than 10% compared with China's papers. Regarding the number of papers on physics, China remained in first place, but Japan was in second place, with 92% compared with China's papers. The number of papers in Korea, the USA, and Germany was about one-third of that of China, while France, the UK, Italy, and Russia had less than 10%.

4. Econometric Analysis: Research Funding

This section examines whether the starting segment of Step II is research funding. The nine countries included in the following analysis were China, Italy, the UK, the USA, Japan, Russia, France, Germany, and Korea. Granger causality tests were conducted between research expenditure per researcher and each of the value added, patents, and papers with lags of one to five years. The process of innovation is described as research expenses, papers, patents, and value added. The hypothesis is that innovation proceeds in the order of research expenses, papers, patents, and value added. The alternative variable for innovation is value added. This research assumed that innovation equaled value added in the econometric analysis.

The industries analyzed were (K1) knowledge/technology-intensive manufacturing; (K2) computers, electronics, and optical instruments; (K3) knowledge/technology-intensive services; and (K4) IT and information services, according to the NSF's value-added classification. In addition, according to the WIPO's classification of the number of international patent applications, the industries corresponding to each of the four were (K1) semiconductor technology, (K2) computer technology, (K3) digital communication technology, and (K4) telecommunications technology.

In the NSF classification of the number of scientific papers, the computer science sector corresponded to the computer, electronic, and optical instruments industry in the value-added classification; for per capita research expenditure, the average of all industries was used for further analysis.

The conversions among value added, patents, and papers used in this study were as follows. In terms of value added, the knowledge-intensive industries were classified into the following categories: (K1) knowledge/technology-intensive manufacturing, (K2) computers and electronics, (K3) knowledge/technology-intensive services, and (K4) IT information. These were converted to patents related to (K1) semiconductors, (K2) computers, (K3) digital communication technology, and (K4) telecommunication technology.

Next, in terms of value added, manufacturing industries were classified into the following categories: (M1) automobiles, (M2) machinery, (M3) chemicals, (M4) electronics, and (M5) medicine. These were converted into automobiles, machinery, chemicals, electronics, and medicine, respectively, in terms of patents, and into engineering (M1 and M2), chemistry (M3), physics (M4), and biology (M5) in terms of papers. The data are presented in Appendices B.1 and B.2.

In this section, Tables 4–7 show the results of regression analyses and Granger causality tests from all countries from 2002 to 2019, with the exception of the UK, which was analyzed from 2002 to 2017.

4.1. Linear Regression: Knowledge-Intensive Industries

Table 4 shows the results of three linear regressions of the knowledge industry. First, linear regression analysis was conducted with research expenditure as the independent variable and value added as the dependent variable. Second, regression analysis was conducted with research expenditure as the independent variable and papers as the dependent variable. Third, a regression analysis was conducted with research expenses as the independent variable and patents as the dependent variable.

Table 4. Regression analysis on knowledge-intensive industries.

		China	US	Russia	Germany	France	Korea	Japan	UK	Italy
		<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value
research	knowledge manufac-turing	1.7×10^{10} ***	8.56×10^{12} ***	0.0119 *	0.000000312 ***	0.000128 ***	1.50×10^{11} ***	RE ->Pt->VA	-	-
expenses [RE]	knowledge services	0.00000000115 ***	1.08×10^9 ***	0.000128 ***	1.60×10^{12} ***	0.0119 *	1.92×10^{10} ***	RE ->Pt->VA	0.000055 ***	-
→ Value added [VA]	computer	0.00000000274 ***	1.34×10^{11} ***	-	0.00705 **	-	5.91×10^{13} ***	0.00173 **	-	-
	ITS	0.00000000265 ***	2.07×10^9 ***	0.000353 ***	6.18×10^{13} ***	0.00000946 ***	3.55×10^{10} ***	-	0.0162 *	-
Research expense → paper	computer	0.000103 ***	0.00015 ***	0.00004868 ***	0.00000061810 ***	0.00004868 ***	0.00521 **	0.0000161 ***	0.0464 *	-
research	knowledge manufac-turing	0.000016921 ***	0.000506 ***	-	0.0219 *	-	1.80×10^7 ***	1.18×10^6 ***	-	-
	knowledge services	0.0000000798 ***	-	-	0.000000381 ***	-	0.00763 **	0.0031 **	-	-
→ patent	computer	0.00006495 ***	0.00003581 ***	0.00529 **	-	0.00529 **	1.69×10^8 ***	2.34×10^{11} ***	0.0381 *	-
	ITS	5.81×10^{10} ***	0.000019855 ***	-	-	-	4.98×10^{10} ***	7.63×10^{10} ***	0.0382 *	0.0136 *
patent [Pt]	knowledge manufac-turing	0.000000017 ***	0.00481 **	0.000274 ***	0.00895 **	0.01009 *	0.000000086 ***	0.00878 **	-	0.0275 *
→ VA	knowledge services	1.04×10^{11} ***	-	0.01009 *	8.00×10^8 ***	0.000274 ***	0.00364 **	0.0331 *	0.000497 ***	-
	computer	0.0000000185 ***	0.00021 ***	-	-	-	0.000000225 ***	0.000951 ***	-	0.025 *
	ITS	1.82×10^{13} ***	0.000000616 ***	-	-	-	0.0000000145 ***	-	-	-

Note 1: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Note 2: RE = Research expenses, Pt = Patents, VA = Value added. Source: Author's calculation.

As shown in Table 4, an additional regression analysis was conducted with patents as the independent variable, and value added as the dependent variable.

In particular, in the first regression analysis with research expenditure as the independent variable and value added as the dependent variable, the countries for which research expenditure was not significant for the knowledge/technology-intensive manufacturing and service industries were the UK and Italy. For all of the other seven countries, the regression of research expenditure on value added was significant. Notably, for Japan's knowledge/technology-intensive services and knowledge/technology-intensive manufacturing industries, the third and fourth regression analyses showed that the research expenditure regressed significantly with regard to patents, and patents regressed significantly with regard to value added. In other words, the research expenditure indirectly significantly regressed with regard to the value added. Therefore, the UK and Italy remain countries where research expenditure did not significantly regress on the value added.

4.2. Granger Causality Test: Knowledge-Intensive Industries

The Granger causality test allowed us to examine whether the findings regarding the “economies of sequences” were significant or not. Consider the two variables x and y . Model 1 is an autoregressive model of y , and Model 2 is an autoregressive model of x and y . Granger causality holds if the value of the prediction error of Model 2 is smaller than that of Model 1. Suppose that the lags of x and y are n ($n = 1, 2, 3, 4$, or 5 , in our models) and e_i ($i = 1, 2$) is an error term.

$$\text{Model 1: } y(t) = b_{11}y(t-1) + \dots + b_{1n}y(t-n) + e_1,$$

$$\text{Model 2: } y(t) = b_{21}y(t-1) + \dots + b_{2n}y(t-n) + c_{21}x(t-1) + \dots + c_{2n}x(t-n) + e_2.$$

In the case where all values of c_{2i} are 0, x does not Granger-cause y . We applied the F-test to find the causal relationships between research expenses per researcher and value added.

Time-series analyses assume stationary stochastic processes, while drift is an intercept component in a time series. On the other hand, ordinary least square estimations with a drift term (constant term) are non-stationary stochastic processes. It is generally accepted that equations without a drift term should be used for stationary stochastic processes. Thus, Model 1 and Model 2 were adopted without a drift term once it was confirmed that equations with a drift term provided results for non-stationary stochastic processes (see Kuchiki 2021 for details).

As shown in Table 5, we tested three types of Granger causality for each of the nine countries in the regression analysis in Table 4. In each case, we tested the Granger causality for all lags from one to five years. First, we tested whether the research expenditure per researcher Granger-caused value added. Second, we tested whether research expenditure per researcher Granger-caused papers. Third, we examined whether research expenditure per researcher Granger-caused patents. Regarding the first Granger causality tests for the knowledge/technology-intensive manufacturing and services industries, the countries in which research expenditure per researcher Granger-caused value added were, in order, China, the USA, Russia, Italy, and the UK. Thus, Italy and the UK showed significant Granger causality between research expenditure and value added with a time lag, although research expenditure did not significantly regress on value added, as seen in Table 4.

Table 5. Granger causality on knowledge-intensive industries.

		1. China		2. US		3. Russia		4. Italy		5. UK		France		Germany		Korea		Japan	
		Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value	Time Lag	p- Value
research	knowledge manufacturing	3	0.0003	5	0.0091	5	0.0426	5	0.0014	4	0.0635			4	0.0030				
expenses	knowledge services	3	0.0028	1	0.0254	2	0.0538	1	0.0076	2	0.0016	1	0.0295						
→ VA	computer	3	0.0046			5	0.0112	1	0.0513	5	0.0139								
	ITS	3	0.0046					1	0.0243	5	0.0205								
research																			
expense → paper	computer	3	0.0046	3	0.0213			2	0.0003			1	0.0015	1	0.0143	1	0.0012	1	0.0152
research	knowledge manufacturing			4	0.0254	1	0.0460	1	0.0360	4	0.0058							5	0.0007
expenses	knowledge services					1	0.0177	1	0.0133	3	0.0329			1	0.0489			1	0.0429
→ patent	computer	3	0.0003	2	0.0177			3	0.0024	1	0.0107	3	0.0105						
	ITS	1	0.0127					5	0.0003	1	0.0367			4	0.0229	5	0.0223	4	0.0229

Source: Author’s calculation.

4.3. Regression Analysis and Granger Causality Tests: Manufacturing Industries

Table 6 presents the regression analysis results for research expenditure per researcher, the number of papers, the number of patents, and value added for the five manufacturing

industries in the nine countries. The countries where research expenditure per researcher significantly regressed on value added in at least four of the five industries were China, Germany, the USA, and Korea. The countries where research expenditure per researcher did not significantly regress on the number of patents were France, Japan, Italy, Russia, and the UK.

Next, Table 7 presents the results of the Granger causality tests for the five manufacturing industries. The results show that, with the exception of Russia and the UK, the Granger causality of research expenditure per researcher regarding value added was significant for the following seven countries: China, Germany, the USA, France, Japan, Italy, and Korea. The following three reasons can be suggested. First, the Granger causality of research expenditure per capita regarding value added was significant in at least four out of the five manufacturing industries for five countries. Second, in the case of Korea, research expenditure per researcher in the pharmaceutical industry significantly Granger-caused the number of papers, and the number of papers in the pharmaceutical industry significantly Granger-caused the number of patents in the pharmaceutical industry, as shown in Table 7. For the chemical industry, research expenditure per researcher significantly Granger-caused the number of patents, and the number of patents significantly Granger-caused the value added. Third, in the case of Japan, research expenditure per researcher significantly Granger-caused the number of patents, and the number of patents significantly Granger-caused the value added for the electrical and machinery industries, as shown in Table 7. Thus, the Granger causality was significant for research expenditure per researcher regarding the value added for the seven countries.

4.4. Research Funding as a Starting Segment

Table 8 shows the two results of the Granger causality tests and regression analyses in Tables 4–7. First, the countries where research expenditure per researcher significantly Granger-caused the value added of the knowledge/technology-intensive manufacturing and knowledge/technology-intensive services industries were China, the USA, Russia, Italy, and the UK. The countries where research expenditure per researcher was shown to be significant in a linear regression analysis on the value added of the knowledge/technology-intensive manufacturing and knowledge/technology-intensive service industries were Germany, France, Korea, and Japan. In short, the Granger causality of research expenditure per researcher regarding value added was significant for five countries, and the regression was significant for four countries.

Second, in the five manufacturing industries, the countries where research expenditure per researcher Granger-caused value added were China, Germany, the USA, France, Japan, Italy, and Korea.

The conclusion from the first and second results together is that research funding is the starting point for generating and creating value added, and that an increase in research expenditure per researcher leads to an increase in value added. The starting segment in the second stage of innovation is therefore the construction of a “research fund”.

Table 6. Regression analysis on manufacturing industries.

	China	Germany	US	Korea	France	Japan	Italy	Russia	UK
	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value
research expenses → VA	automobile	1.61 × 10 ⁹ ***	0.00000169 ***						
	chemical	8.31 × 10 ¹² ***	0.0000271 ***	6.79 × 10 ¹⁰ ***	0.00000011758 ***	0.00149 **	0.04323 *	1.73 × 10 ¹² ***	0.000131 ***
	electrocnics	2.58 × 10 ¹⁰ ***	0.00551 **	0.000000148 ***	4.50 × 10 ¹⁰ ***	0.0175 *			0.0068 **
	machinery	1.42 × 10 ¹¹ ***	0.00000743 ***	0.000000066 ***	2.83 × 10 ¹¹ ***	0.00185 **			
	medicine	0.0000000473 ***	0.001835 **	9.02 × 10 ¹⁰ ***	4.29 × 10 ⁸ ***				
research expense → paper	automobile	0.00000000924 ***	1.99 × 10 ¹¹ ***	0.0000871 ***	5.83 × 10 ¹¹ ***	1.91 × 10 ⁵ ***	0.0129 *	0.00184 **	0.000147 ***
	chemical	0.0000000132 ***	3.26 × 10 ¹⁰ ***	0.000868 ***	3.39 × 10 ¹⁰ ***	0.00158 **			0.0151 *
	electrocnics	0.0000000561 ***			0.00951 **		0.000772 ***	0.000754 ***	
	machinery	0.00000000924 ***	1.99 × 10 ¹¹ ***	0.0000871 ***	3.49 × 10 ¹¹ ***	1.91 × 10 ⁰⁵ ***	0.0274 *	0.00184 **	0.000147 ***
	medicine	0.00000000924 ***	0.000000152 ***	0.00171 **	9.79 × 109 ***	0.000763 ***	0.000224 ***	0.0000436 ***	
research expenses → patent	automobile	0.0000000157 ***	0.000689 ***		5.71 × 10 ⁸ ***	0.0000261 ***	0.00000000136 ***	0.00000245 ***	
	chemical	0.00001817 ***	0.00443 **	0.014 *	3.49 × 10 ¹¹ ***	2.65 × 10 ⁵ ***	0.00000000152 ***		
	electrocnics	0.000001463 ***	0.0000010531 ***	0.0000962 ***	2.01 × 10 ¹¹ ***	2.65 × 10 ⁶ ***	7.38 × 10 ¹⁰ ***	0.000193 ***	0.0000698 ***
	machinery	0.00003405 ***	0.000229 ***		6.99 × 10 ¹⁰ ***		2.01 × 10 ¹¹ ***		0.0368 *
	medicine	0.0000261 ***	4.04 × 10 ⁶ ***	0.0106 *	6.84 × 10 ¹⁰ ***	0.00429 **		0.00215 **	
patent → VA	automobile	1.7 × 10 ¹³ ***	0.00951 **			0.0261 *	0.0209 *	0.000182 ***	
	chemical	0.000000204 ***	0.000381 ***	0.0096 **	0.0000000658 ***	0.00411 **	0.0224 *	0.041 *	0.0000568 ***
	electrocnics	6.31 × 10 ¹¹ ***	0.00102 **		5.53 × 10 ¹⁰ ***				0.00129 **
	machinery	0.000000347 ***	0.00000725 ***	0.020193 *	0.0000000102 ***	0.0174 *	0.00693 **	0.000384 ***	
	medicine	6.5 × 10 ¹¹ ***			0.00000919 ***			0.000358 ***	0.0424 *
paper → VA	automobile	2.19 × 10 ¹⁰ ***	0.00000127 ***			0.03717 *			
	chemical	2.29 × 10 ¹¹ ***	0.000162 ***	0.000331 ***	0.0000000226 ***	1.33 × 10 ⁵ ***		0.00035 ***	
	electrocnics	2.06 × 10 ¹³ ***	0.000277 ***		0.00326 **	0.005891 **		0.000374 ***	
	machinery	3.02 × 10 ¹² ***	0.0000807 ***	0.0000221 ***	1.25 × 10 ¹⁰ ***		0.005101 **	0.0082 **	0.0112 *
	medicine	1.69 × 10 ¹⁴ ***	0.000126 ***	0.0156 *	0.0000395 ***			0.0231 *	

Table 6. Cont.

	China	Germany	US	Korea	France	Japan	Italy	Russia	UK
	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value	<i>p</i> -Value
paper → patent	automobile	5.01 × 10 ¹¹ ***	0.000197 ***	0.00000000479 ***	8.98 × 10 ¹¹ ***	0.0442 *	0.000000618 ***	0.0309 *	0.00492 **
	chemical	0.00000000647 ***	0.00862 **	8.89 × 10 ¹¹ ***	0.0138 *		0.00303 **		
	electronics	0.000000000040 ***	0.00331 **	0.0265 *		5.88 × 10 ⁵ ***	0.0018 **		0.0404 *
	machinery	0.00000000500 ***	0.000152 ***	4.78 × 10 ¹¹ ***			0.000173 ***		0.0324 *
	medicine	0.00000000188 ***	0.000161 ***	4.55 × 10 ¹¹ ***	0.00396 **		0.0250 *		

Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Source: Author's calculation.

Table 7. Granger causality on manufacturing industries.

	1. China	2. Germany	3. US	4. France	5. Japan	6. Italy	7. Korea	Russia	UK
	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value	Time Lag <i>p</i> -Value
research expenses → VA	automobile	1 0.0005782	3 0.02033	5 0.004196	3 0.002152	5 0.001305	5 0.01123		
	chemical	1 0.002759	2 0.03582	1 0.007459	2 0.02098	1 0.01026	RE->Pt->VA	4 0.0104	
	electronics	1 0.02399	2 0.03627	1 0.00283	5 0.04121	5 0.01163	1 0.03791		
	machinery	3 0.007767	1 0.006289	2 0.05986	RE->Pt->VA	5 7.135 × 10 ⁵ ***	1 0.04528		
	medicine	1 0.004031	1 0.03299	1 0.036	4 0.05973	5 0.0005573	1 0.002347	RE->Pt->VA	
research expense → paper	automobile	4 0.0003871	2 0.007884	1 0.004823	1 0.0505	2 0.002166	5 0.02677	5 0.01668	
	chemical	5 0.04862	2 0.001778	4 0.004839	5 0.003421	3 0.04339	1 0.003932		
	electronics	4 0.04884	3 0.007929	3 0.007929					
	machinery	4 0.0003871	2 0.007884	1 0.004823	1 0.0505	2 0.002166	5 0.02677	5 0.01668	
	medicine	5 0.003375	5 0.003375	5 0.004823	5 0.5054	1 0.004201			
research expenses → patent	automobile		2 0.007197	1 0.007088	1 0.02797			3 0.04176	
	chemical		1 0.0103	3 3.898 × 10 ⁶ ***	3 0.0324	5 0.03486		2 0.05074	
	electronics	4 0.02162	1 0.02915	5 0.01908	1 0.05371	1 0.007952	1 0.006342		
	machinery	1 0.01026		2 0.000188	4 0.03953	4 0.00702			
	medicine		2 0.00945	2 0.00945	2 0.02193				

Table 7. Cont.

1. China		2. Germany		3. US		4. France		5. Japan		6. Italy		7. Korea		Russia		UK	
	Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value		Time Lag p-Value
patent → VA	5 0.007519			4 0.02923				5 0.006903		1 0.02506		5 0.01342		2 0.03777		1 0.03643	
chemical				1 0.02141		2 0.02057		3 0.01933								1 0.03595	
electronics machinery	1 0.03054	4 0.01941						3 0.002327								5 0.01725	
medicine	2 0.05268	2 0.001904						5 0.04556		3 0.03667						3 0.01199	
																1 0.007831	
paper → VA	3 2.026 × 10 ⁵ ***			5 0.000272		1 0.05596		5 0.04938						2 0.007205		1 0.03325	
chemical	2 0.01808	1 0.003124		4 0.05314		1 0.0008412				2 0.003245				3 0.007512			
electronics	1 0.0007995	1 1.301 × 10 ⁵ ***				4 0.00627				1 0.02881				2 0.001018			
machinery	2 0.0006962			1 0.01777				1 0.005931						3 0.004204		4 0.05634	
medicine	2 5.518 × 10 ⁵ ***	1 0.001744		5 0.7632				2 0.05489				4 0.0002894					
paper → patent				1 0.04935		1 0.003534		2 0.006062				1 0.01137				2 0.02453	
chemical				1 0.01655		4 0.001901				1 0.002241		2 0.01692		3 0.002075		1 0.001396	
electronics	3 0.0005932			1 0.01139		1 0.03994		1 0.0425		1 0.002947							
machinery				3 0.04288				1 0.04987				1 0.000234				5 0.05209	
medicine				1 0.04715		5 0.0151		1 0.0274				3 0.01562		1 0.05257			

Note: RE = Research expenses, Pt = Patents, VA = Value added. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Source: Author's calculation.

Table 8. Summary.

1. China		2. US		3. Russia		4. Italy		5. UK		Germany		France		Korea		Japan	
	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag	p-value	Time lag
knowledge manufac- turing services	3	0.0003343 ***	5	0.00913 **	5	0.04261 *	5	0.00143 **	4	0.0635	0.000000312 ***	0.000128 ***	1.50 × 10 ¹¹ ***	RE->Pt- >VA			
knowledge services	3	0.002839 *	1	0.02544 *	2	0.0538	1	0.007579 **	2	0.001634 **	1.60 × 10 ¹² ***	0.0119 *	1.92 × 10 ¹⁰ ***	RE->Pt- >VA			
1. China																	
2. Ger- many																	
1. China																	
automobile	1	0.0005782 ***	1	0.0003931 ***	3	0.02033 *	5	0.004196 **	3	0.002152 **	5	0.001305 **					
chemical	1	0.002759 **			2	0.03582 *	1	0.007459 **	2	0.02098 *	1	0.01026 *					RE->Pt- >VA
electronics	1	0.02399 *			1	0.00283 **	5	0.04121 *		RE->Pt- >VA	5	0.01163 *	1	0.04			
machinery	3	0.007767 **	1	0.006289 **	2	0.0599		RE->Pt- >VA	5	0.00007135 ***	1	0.05					
medicine	1	0.004031 **	1	0.03299 *	1	0.036 *	4	0.05973 *	5	0.0005573 ***	1	0.002347 **					RE->Pt- >VA

Note 1: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Note 2: RE = Research expenses, Pt = Patents, VA = Value added. Source: Author's.

5. Summary and Conclusions

This study concerned innovation, which is Step II in cluster policy. Granger causality tests were conducted between research expenditure per researcher and each of the value added, patents, and papers for the knowledge/technology-intensive industries and the manufacturing industries in nine countries with lags of one to five years.

The hypothesis that research expenditure per researcher Granger-caused value added is significant, as shown by the results summarized in Table 8. Consequently, this study identified research funds as the initial segment for Step II. The conclusion is that the starting segment of innovation is the construction of a research fund.

This implication is critical for cluster policy. The outcome of research depends, in part, on funding, and one cannot initiate research activities without funding. The policy implication is that innovation begins with the establishment of research funds for researchers.

The amount of funding is a major determinant of research outcomes. According to Honjyo (2024), research related to the Nobel Prize in Medicinal Physiology will become increasingly expensive, making it difficult to collect funding. There were 26 Japanese Nobel laureates as of 2024, and many of them have relocated to the USA to improve their research environment, especially to raise funds for their research. Notably, the winner of the Nobel Prize in Physics, S. Manabe, changed his nationality to American.

This study contributes to the development of specific guidelines for cluster policies. First, we divided a cluster policy into two steps, namely agglomeration and innovation, and further divided the determinants, such as elements of Porter's diamond model, into segments for the step of innovation. Second, we sequenced these segments into the process of efficient construction by economies of sequences. It is important to note that the finalization of agglomeration is not automatically the starting segment that activates innovation. Step II (innovation) does not begin without building the starting segment of innovation, even after agglomeration is established. In order to initialize innovation, a research fund must be set up as the starting segment. Thus, the need to implement many policies at the same time is eliminated, and the feasibility of the policy's implementation is increased.

The contributions of this study are as follows. There are three theories of agglomeration: (i) spatial economics, (ii) construction sequencing in the industry, and (iii) sequencing economics. In this study, we linked construction sequencing in industries to sequencing economics, as shown in Table 1. Construction sequencing and start segment. We also integrated sequencing economics for cluster policy with the theory of Fujita and Thisse (2003), as shown in Figure 1. This study identified research funding as the starting segment of innovation.

However, there are many remaining issues. First, it is essential to re-examine our conclusions by examining other data and other methods such as causal inference tools, Bayesian causality, and behavioral economics. For example, causal inference tools would ensure that the observed outcomes were a direct result of the intervention and were not confounded by other variables. Bayesian causality provides a probabilistic framework for understanding how rational agents should update their beliefs and make decisions under uncertainty. Behavioral economics provides a theoretical foundation for understanding decision making.

Second, although "research funding" was identified as the starting segment, the existence of "human resources for researchers" was assumed. Although the data on research expenses were based on expenses per researcher and the factor of human resources was considered, it is necessary to further analyze the relationship between the human resources of researchers and research funding. Third, one study showed that university–industry–government links are effective in stimulating innovation. It is also essential to analyze the conclusions of this article regarding research expenditure. In addition, there are many other issues to be considered such as the identification of segments for cluster formation and their sequencing in the construction process.

Fourth, as stated above regarding the actions of Japanese Nobel laureates, outside of the USA, research funding per capita is low, and obtaining research funding is the first major obstacle for researchers in various research efforts. In this sense, it is essential to recognize that funding is the starting segment of research. For example, Nobel laureate Yamanaka (2024) also identified research funding activities in Japan as an important issue in his IPS cell research. However, further empirical research is needed on this point.

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Data Availability Statement: The following publicly available datasets were analyzed in this study: World Intellectual Property Organization (WIPO 2002–2019) (available online at <https://www.wipo.int/patentscope/en/data/forms/products.jsp>, accessed on 26 April 2024), the National Science Foundation (NSF 2002–2019) (available online at <https://www.nsf.gov/statistics/>, accessed on 26 April 2024) and UNESCO (2002–2019) (UNESCO Institute of Statistics) (<https://uis.unesco.org/>, accessed on 26 April 2024).

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Appendix A

Appendix A.1. The Segments of a Tourism Agglomeration in Osaka

Category	Segment
Infrastructure	1. Kansai International Airport: Low-cost carriers Railway Port Communication, Electricity, Water
Human resources	Population Unskilled labor Engineers Managers
Institutions	Laws and regulations Land ownership
Living conditions	2. Entertainment: Universal Studio Japan Hospitals and schools
Living conditions: Cultural aspects	Dynasty: Heian Dynasty Food: Octopus dumplings Music: Kawachi folk song History: Osaka Castle Textile: Senshu Towel Painting: the Korin school Nakamurahochu Resort: Kyoto, Kobe Alcoholic beverage: Local sake Akishika

Source: Author's Illustration based on Kuchiki (2020).

Appendix A.2. The Segments of a Manufacturing Industry Agglomeration

Category	Segment
Infrastructure	Transport: 1. Port, Highways, Railway, Airport 1. Industrial zone Electricity Water Communication
Human resources	2. Unskilled labor Engineers Managers
Institutions	3. Deregulation 3. Preferential treatments (tax incentives, etc.) 3. One-stop services Laws and regulations
Living conditions	Housing International schools Hospitals Entertainment & shopping

Source: Author's Illustration based on Kuchiki (2020).

Appendix B. Data Sources for Table 3

Patents: World Intellectual Property Organization (WIPO 2002–2019); available online at <https://www.wipo.int/patentscope/en/data/forms/products.jsp> (accessed on 26 April 2024);

Value-added: National Science Foundation (NSF 2002–2019); available online at <https://www.nsf.gov/statistics/> (accessed on 26 April 2024);

Number of published science and engineering articles: National Science Foundation (NSF 2002–2019); available online at <http://www.nsf.gov/statistics/> (accessed on 26 April 2024);

Research expenses: UNESCO (2002–2019) (UNESCO Institute of Statistics); available at <https://uis.unesco.org/> (accessed on 26 April 2024);

Material: Global Note; <https://www.globalnote.jp/post-17789.html> (accessed on 2 May 2024).

Samples of these data are shown in Appendices B.1 and B.2.

Appendix B.1. Data of Main Countries: Knowledge Industries

China						US				
Manufacturing			Service			Manufacturing			Service	
Year	re	pt	va	pt	va	re	pt	va	pt	va
2002	58,839	7	203,326	44	19,857	58,839	7	203,326	1655	300,333
2003	65,749	16	244,588	52	20,286	65,749	16	244,588	1567	312,111
2004	75,031	18	275,052	91	23,378	75,031	18	275,052	1412	340,318
2005	76,833	22	323,745	132	29,921	76,833	22	323,745	1581	360,619
2006	85,391	33	391,773	288	37,831	85,391	33	391,773	1792	384,845
2007	86,448	50	497,876	427	50,613	86,448	50	497,876	2097	405,546
2008	90,888	93	643,951	499	66,448	90,888	93	643,951	2180	451,098
2009	159,202	103	688,103	623	79,820	159,202	103	688,103	1453	465,210
2010	174,634	122	852,641	615	94,812	174,634	122	852,641	1162	508,349
2011	186,388	308	1,033,982	810	122,088	186,388	308	1,033,982	1014	562,385
2012	205,220	554	1,148,147	1043	150,561	205,220	554	1,148,147	1038	589,059
2013	217,178	609	1,283,720	843	174,833	217,178	609	1,283,720	1337	632,570
2014	226,412	757	1,397,329	996	205,027	226,412	757	1,397,329	1397	675,251
2015	225,475	844	1,460,433	1093	215,576	225,475	844	1,460,433	1195	734,204
2016	231,550	1053	1,514,143	1369	215,915	231,550	1053	1,514,143	1226	789,795
2017	241,078	1057	1,702,829	1630	243,712	241,078	1057	1,702,829	1319	847,116
2018	248,868	1426	1,937,445	1993	288,090	248,868	1426	1,937,445	1441	940,907
2019	249,066	2060	1,981,928	1854	285,503	249,066	2060	1,981,928	1333	1,034,456

Russia						Italy				
Manufacturing			Service			Manufacturing			Service	
Year	re	pt	va	pt	va	re	pt	va	pt	va
2002	29,658	4	22,362	15	5475	248,420	12	74,413	13	33,066
2003	35,394	6	26,002	8	6895	250,990	17	88,214	13	40,211
2004	35,580	5	37,228	13	8978	247,710	13	101,182	13	44,437
2005	39,081	9	47,419	16	10,938	220,673	9	101,347	13	45,911
2006	49,351	10	59,821	12	14,662	230,886	21	108,612	15	48,350
2007	56,585	10	79,587	21	18,924	241,215	25	125,988	13	55,535
2008	66,612	6	104,859	9	25,576	252,185	24	134,670	13	60,984
2009	78,335	10	66,800	10	21,233	243,992	34	109,634	13	58,795
2010	74,825	10	83,694	10	28,360	244,914	31	114,957	13	57,301
2011	73,890	13	108,645	18	37,365	245,670	29	123,018	16	60,468
2012	80,598	17	118,015	20	41,991	247,346	34	111,185	16	55,354
2013	87,145	19	124,589	22	48,530	244,851	40	115,973	14	57,863
2014	90,627	18	111,060	31	44,012	249,278	28	115,650	16	58,832
2015	86,286	9	61,512	22	27,083	238,546	32	104,291	16	50,733
2016	90,830	2	60,373	16	24,617	247,586	22	110,645	14	52,970
2017	102,793	12	69,912	20	29,621	245,951	18	117,112	15	56,813
2018	103,200	6	73,316	25	30,774	243,441	30	125,224	12	59,600
2019	114,013	13	78,565	13	32,672	241,240	26	113,710	14	60,483

Note 1: re: research expenditures per researcher, pr: papers, pt: patents, va: value added. Note 2: Program R 4.3.3. is used for Granger causality test. source: Appendix B.

Appendix B.2. Data of Main Countries: Manufacturing Industries

China																
	Automobile			Chemistry			Electronics			Machinery			Medicine			
Year	re	pr	pt	va	pr	pt	va	pr	pt	va	pr	pt	va	pr	pt	va
2002	58,839	20,188	22	5695	8,427	11	36,714	9651	44	27,719	20,188	11	33,564	4939	154	14,497
2003	65,749	22,897	28	6001	9,452	25	43,679	11,183	83	32,094	22,897	12	41,002	6405	83	16,186
2004	75,031	32,328	24	6189	12,304	29	56,156	14,185	64	36,381	32,328	13	46,834	7991	121	16,141
2005	76,833	46,084	34	7341	15,361	24	62,765	18,731	107	46,107	46,084	20	59,684	10,792	132	19,658
2006	85,391	54,332	49	7749	17,496	39	74,288	22,142	176	57,244	54,332	28	75,317	13,597	171	22,349
2007	86,448	58,085	79	9815	20,295	65	100,067	23,530	201	74,419	58,085	54	100,212	16,259	169	28,052
2008	90,888	65,792	109	13,392	21,163	110	120,194	26,429	323	102,628	65,792	72	144,758	18,597	238	37,488
2009	159,202	75,839	113	14,427	23,653	81	127,064	27,841	368	113,041	75,839	95	150,615	21,202	220	41,334
2010	174,634	82,537	135	17,594	23,613	103	163,643	30,222	485	133,301	82,537	93	186,474	22,725	254	47,335
2011	186,388	94,564	229	21,187	26,914	180	214,757	31,686	743	157,116	94,564	132	231,110	25,862	329	58,692
2012	205,220	87,752	261	25,071	29,197	231	221,443	33,860	1056	174,714	87,752	217	254,584	28,992	414	73,290
2013	217,178	96,347	305	27,759	32,438	211	242,156	37,497	1265	196,140	96,347	226	280,127	33,943	411	84,314
2014	226,412	101,202	289	34,107	37,288	269	250,309	40,457	1395	214,155	101,202	238	292,900	38,387	479	95,166
2015	225,475	109,652	368	36,230	40,449	230	256,040	42,152	1577	225,875	109,652	252	297,394	42,579	502	106,325
2016	231,550	116,023	351	37,089	41,604	291	246,983	42,202	1900	236,717	116,023	342	304,797	45,802	707	116,085
2017	241,078	124,888	372	41,092	43,428	418	273,074	49,105	2328	266,149	124,888	343	344,290	46,204	919	133,259
2018	248,868	142,832	457	44,959	48,912	556	325,928	55,110	2972	297,886	142,832	560	391,636	52,618	1017	153,450
2019	249,066	162,746	557	46,628	54,517	676	326,874	63,921	3031	318,792	162,746	746	401,285	63,007	1233	158,924

US																
	Automobile			Chemistry			Electronics			Machinery			Medicine			
Year	re	pr	pt	va	pr	va	re	pr	pt	va	pr	pt	va	pr	pt	va
2002	271,089	38,525	520	126,710	14,098	110,416	271,089	28,125	1488	43690	38524.61	596	99,340	53,624	2646	97,432
2003	266,650	42,144	513	134,318	13,530	110,060	266,650	30,363	1526	45545	42144.05	632	98,027	54,912	2725	100,571
2004	285,183	48,874	540	130,398	12,939	121,101	285,183	29,314	1484	42063	48873.55	612	105,023	58,238	2743	105,686
2005	309,764	55,197	570	127,477	12,432	119,214	309,764	36,575	1723	43212	55197.17	730	115,150	57,833	3411	103,758
2006	327,198	51,147	713	125,912	12,330	135,907	327,198	37,758	1933	51425	51146.9	752	122,686	59,030	3604	117,857
2007	353,780	50,178	761	116,358	11,493	144,841	353,780	35,904	2099	50296	50178.1	807	130,345	60,257	3570	123,086
2008	362,201	52,871	838	83,586	14,519	141,608	362,201	33,810	2245	55513	52870.54	770	132,905	60,006	3779	124,050
2009	346,088	52,689	793	44,165	13,096	144,211	346,088	34,498	2018	50640	52688.63	640	119,158	61,045	3165	143,751
2010	369,856	56,708	844	83,384	13,410	172,146	369,856	33,986	2082	50777	56708.15	584	127,752	60,600	3141	131,150
2011	371,421	56,620	949	97,966	14,220	175,458	371,421	36,123	2162	48309	56619.69	603	145,307	62,712	3052	130,502
2012	375,894	57,024	958	108,729	14,180	180,983	375,894	34,330	2297	52152	57023.54	591	152,625	65,477	2942	123,990

2013	381,462	57,692	1340	115,383	14,808	188,356	381,462	33,453	2512	58104	57691.66	666	157,927	64,708	3023	133,114
2014	386,076	57,357	2175	124,645	14,864	190,056	386,076	32,158	2846	54430	57357.06	884	161,014	65,487	3590	139,962
2015	403,409	55,321	1460	137,621	14,512	185,619	403,409	31,158	2341	63672	55321.34	700	152,509	64,344	2971	147,636
2016	425,626	56,514	883	146,182	15,107	198,603	425,626	29,545	2382	58462	56513.88	610	143,771	62,188	3327	158,446
2017	433,359	55,110	837	149,114	15,870	200,788	433,359	30,860	2391	60773	55110.26	556	153,411	61,451	3478	162,136
2018	436,492	57,812	912	148,207	15,601	210,273	436,492	29,001	2340	65061	57811.96	641	161,374	60,767	3593	165,487
2019	470,389	57,514	708	149,391	16,058	208,576	470,389	29,058	2174	65004	57514.43	654	166,982	61,092	3777	182,383

Germany																
	Automobile			Chemistry			Electronics			Machinery			Medicine			
Year	re	pr	pt	va	pr	pt	va	pr	pt	va	pr	pt	va	pr	pt	va
2002	220,716	6456	776	1436	5214	472	33,644	11,086	782	29,792	6456	388	58,328	9902	584	12,504
2003	227,275	7215	697	1971	5143	446	38,923	10,981	725	35,556	7215	450	70,504	10,040	573	16,793
2004	233,090	7622	818	1877	5371	417	43,474	10,651	689	41,595	7622	407	82,263	10,426	489	19,629
2005	235,349	8973	801	2363	5554	414	43,546	12,530	882	40,314	8973	542	84,181	10,929	589	22,044
2006	248,649	9449	861	2428	5500	473	44,210	12,555	996	45,485	9449	532	91,901	11,320	638	23,545
2007	252,496	9977	923	3078	5655	523	51,349	12,967	1240	48,176	9977	579	110,715	11,389	594	26,982
2008	268,147	11,080	951	2800	5662	598	55,032	12,625	1591	53,982	11,080	655	122,913	11,659	568	31,294
2009	260,556	11,804	1105	3002	5879	533	47,314	13,836	1552	46,511	11,804	651	90,526	11,946	520	28,523
2010	265,020	12,804	966	2854	6003	523	53,121	13,641	1380	51,679	12,804	559	100,372	11,985	474	27,198
2011	282,688	12,912	1119	3163	6152	575	56,488	14,526	1581	57,312	12,912	659	118,306	12,204	459	29,602
2012	284,915	15,023	1339	2852	6408	586	51,141	13,938	1879	52,290	15,023	741	111,598	12,969	483	28,403
2013	290,067	14,103	1224	2695	6591	535	53,014	14,044	2034	54,474	14,103	653	116,588	12,819	457	29,553
2014	310,912	15,338	1247	3446	6452	515	55,584	13,774	1688	57,259	15,338	607	122,054	13,441	391	31,318
2015	293,701	16,147	1118	3411	6685	527	50,551	12,901	1698	45,899	16,147	607	104,313	13,076	357	25,351
2016	305,915	17,555	1120	3273	6575	503	52,828	12,571	1594	47,618	17,555	594	106,957	12,724	340	28,475
2017	318,006	16,628	1082	3068	6687	523	56,173	12,979	1660	50,541	16,628	620	115,919	12,906	370	25,004
2018	327,878	17,486	1087	3605	6814	589	58,734	11,722	1877	52,206	17,486	698	129,240	12,545	380	30,865
2019	324,563	17,282	961	3600	6734	537	50,973	12,591	1996	42,432	17,282	684	120,827	12,881	362	24,796

Source: Author's.

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