INDUSTRY CLUSTER USING CLUSTER ANALYSIS TO SUPPORT INDUSTRY CLUSTER POLICY OF THAILAND

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ABSTRACT

This research implies clustering into three clusters for five industries by means of *k*-Means clustering method. Agro-processing, textiles and clothing, petrochemicals and chemicals, electronics and telecommunications equipment *and* automotive and parts are selected for this study as they are main target promoting industries for Thailand. There were 23,628 firms in this study. From this study, we can identify different patterns of demanded resources in three different groups. One cluster required low level of resourced demands for all variables while the other two clusters required capital and manpower interchangeable between high and medium level. Only the electronics and telecommunications equipment sector showed high to medium demand for all variables. After all firms were divided into three clusters, we were able to define cluster regions by provinces, for particular types of clusters in order to evaluate the potential of each region and also define supporting policy for those firms to meet their demands following the regional economic development strategy.

INTRODUCTION

An industry cluster is defined broadly as a cluster of firms that are related economics actors and located near one another to gain competitive and productive advantages (Sureephong and Chakpitak 2007). Industrial policy generally determines for the future development by considering national development policies such as new motorway or new high speed trains through various areas. Different areas, such as a province, have been assigned as target areas under policies that lead to further growth. However, the policy makers may face limits of their understanding of the composition the cluster is and how to identify industry clusters in order to build economic development strategies around them. Therefore, cluster analysis can help to define a region's economic strength and to shape the regional economic future (Cortright 2006).

The regional economic development challenges are to identify and to inspire common economic strategies, for government, to shape the region's economic future and to harmonize with national development policies. The key policy success is to launch suitable policies for their region. Furthermore, the definition of a cluster is often seen in relation to the Boundaries of Governance Unit, but this is less important than the Boundaries of Economic Activities (Bennett 1997). As a result, a conflict of interest, between central agencies and local authorities to support different types of firms, may arise. Therefore, cluster analysis is a suitable tool for policy makers for three reasons (Cortright 2006):

1. To understand and improve the performance of regional economies,
2. To identify groups of firms, rather than individual firms, and
3. To build the unique strengths of particular regions, to develop different strategies for different clusters.

Furthermore, the concept of business or industry clusters is important: Porter (1998) presented the cluster concept to support the competition in three ways: increasing production efficiency of cluster firms, encouraging innovation in competition and encouraging new businesses in the industry.

The Thai government announced policies for industrial development, in the form of Cluster and Super Clusters, to follow the idea of leading entrepreneurs in the right direction; their policies led to the budget support or regulations for the target area. Business groups with geographic concentrations will be connected to each other in the relevant clusters. The integration aims to increase productivity and enhance competitiveness at the national and global level. Also, this integration is important in the perspective of strategic plans for industrial management in each group.

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An example of the success of cluster policy in Thailand, is the special economic development zone policy to promote the integration of investment clusters consistent with the potential of various areas. The Office of the Board of Investment (BOI) is a government agency, under the office of the Prime Minister. Its core roles are to promote valuable investment in Thailand and overseas, including implementation of the Cluster and Super Clusters policy, to create investment concentration in accordance with regional potential and to strengthen value chains (The Office of the Board of Investment (BOI) 2018). However, some policies may not suitable for all firms in all industries. The abilities and characters of firms in particular areas are different. If we can cluster firms with similar levels of resource requirements, they can guide suitable policies, to meet their demands, which can enhance their potential efficiently.

In this regard, we aimed to cluster Thai industrial firms with statistical techniques so as to understand the pattern of the cluster by considering their different demands for production resources. In the remainder of this paper: Section 2 is a brief overview of the literature. In Section 3, we introduce our material and methods. Section 4 shows the results of the analysis, before concluding and discussing further research.

LITERATURE REVIEW

Industry cluster research focuses on four areas (Smith 2003): 1) Workforce Development 2) Education 3) Economic Development and 4) Industry. Roelandt & Hertog (1999) proposed a cluster methodology framework that was implemented in organizing industry policy, based on research using four concepts:

1) Input-output analysis, by studying trade links between industry groups in value chains,
2) Graph analysis, using graph theory to define the connection of the network or industry group,
3) Correspondence analysis consists of various techniques such as factor analysis, Principal Component Analysis (PCA), aiming to define groups or classify factories or industries with similar patterns and
4) Qualitative case study by implementing the Porter framework in studies in several countries.

This study implements the third group to classify industry clusters in Thailand. Therefore the next section will focus on literature applying correspondence analysis.

Nagy & Ormos (2018) introduced the financial market implied industry classification standard, with a spectral clustering based quantitative methodology, to overcome the main drawback of current standards leading from qualitative classification techniques. They employed The Financial Market Implied Classification (FMIC) based on daily closing prices between 01/01/2007 and 01/03/2017. They showed that comparing market implied clusters with global industry classification provided better statistical results.

Zhu et al. (2010), with questionnaires from 334 respondents, analyzed the industry cluster from the concept of Circular Economy (CE) to examine Environmentally oriented Supply Chain Cooperation (ESCC) to classify industrial manufacturers in China. They used multivariate analysis of variance (MANOVA) among the four identified types of Chinese manufacturers, varying in environmental-oriented supply chain cooperation, to highlight the importance of intensifying cooperation with upstream and downstream supply chain partners for a CE initiative to succeed.

Arvanitis & Hollenstein (1998) used Swiss data to group similar firms into innovation types based on a cluster analysis of nine innovation indicators and 17 knowledge sources. Their study yielded five innovation types, which have been characterized by additional structural properties (e.g. firm size) and factors relevant for innovation (e.g. market conditions). They started with factor analysis to define four factors and then applied PCA, which led to a grouping of the firms in terms of innovation indicators into five categories. Their analysis had an overall $R^2 = 0.56$, i.e. a good fit of data to the underlying cluster model.

Kuo et al. (2002) compared cluster analysis methods for market segmentation with methods based on Self-organizing feature maps and *k*-Means methods. They compared a conventional two-stage method with a new two-stage method through the simulated data. Their simulation showed that their scheme was better than the conventional two-stage method based on the rate of misclassification by using simulated data based on t-test and ANOVA.

MATERIAL AND METHODS

Data

This research defined five target industries: agro-processing, textiles and clothing, petrochemicals and chemicals, electronics and telecommunications equipment, *and* automotive and parts. These five industries are currently the major Thai industries and also part of the cluster and super cluster government policy. Secondary data were acquired from the Thai Department of Industrial Works, to which registered companies submitted their essential data and obtained

business approvals. Data from individual registered firms were used for the cluster analysis completed by five focused Thai industries, distinguished by their Thailand Standard Industrial Classification (TSIC) code (Employment Promotion Division: Department of Employment 2009).

Variables

The defined variables are related to the demanded resources in the production for general industries as 10 variables. All variables are recorded and collected by the Thai Department of Industrial Works. According to the limitations of available recorded data, seven variables are used here: Horsepower (HP), Land Capital (CAPLAND), Building Capital (CAPBUID), Machinery Capital (CAPMACH), Working Capital (CAPWORK), Skilled Worker (Total Skill), and Total Worker (Total Worker).

***k*-Means**

k-Means is a well-known cluster analysis technique which is an unsupervised learning technique. Given a set of observations ($x_1, x_2, \ldots, x_n$), where each observation is a d-dimensional real vector, *k*-Means clustering aims to partition the n observations into k ($\leq$ n) so the objective of *k*-Means is to minimize the within-cluster sum of squares (WCSS) (i.e. variance) or to minimize total intra-cluster variance, Equation (1).

$$\sum_{j=1}^{k}\sum_{i=1}^{n}\left(x_i^{(j)} - c_j\right)^2 \qquad (1)$$

where:

k is number of cluster,

n is number of cases,

c_j is centroid for cluster j,

x_i is case i^{th}

j = 1, 2, 3, …, k

i = 1, 2, 3, …, n.

Because the total variance is constant, this is equivalent to maximizing the sum of squared deviations between points in different clusters (between-cluster sum of squares, BCSS), which follows from the law of total variance.

The *k*-Means algorithm is proposed of following steps,

(1) Define k points into the space represented by the objects that are being clustered. The k-points represent initial group of centroids.

(2) Assign each object the group that has the closest centroid according to the Euclidean distance function.

(3) After the assignment of centroids to each object, recalculate the positions of the k centroids:

$$c_j = \frac{\sum_{i=1}^{n_j} x_{ij}}{n_j} \qquad (2)$$

(4) Repeat steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups of the objects into groups from which the metric to be minimized can be calculated.

Since *k*-Means is unsupervised model, we employ the unsupervised evaluation so that it does not rely on external information. In this paper we evaluate the *k*-Means results of industry clustering by considering the p-value of F-test from ANOVA by comparing with inter-cluster (within cluster sum of squares) and intra-cluster (between cluster sum of squares) variances to decide whether the results were good enough.

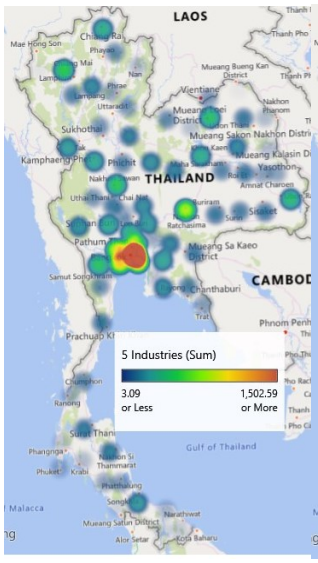
The algorithm is extremely sensitive to the initial randomly selected cluster centers. The *k*-Means algorithm can be run iteratively to minimize this effect. Furthermore, SPSS software is selected for analyzing data of this research.

RESULTS

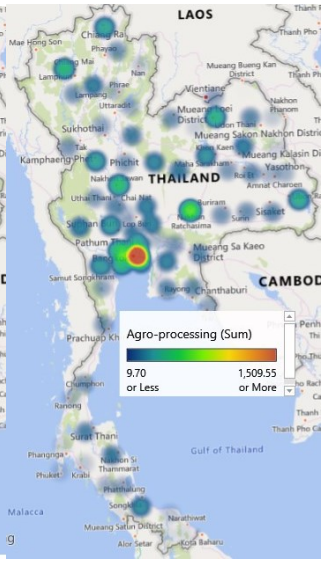
Current Firm Distribution in Thailand

Data for registered firms, distributed around the 77 provinces in Thailand, is divided into five regions: Northern, Northeastern, Central, Eastern and Southern area. Figure 1 shows density of firms represented by color for all five industries. It shows that the major firms are in Central Thailand. Agro-processing is the major industry, 13,851 firms in a total of 23,628 firms. As figures 1(a) and (b) show the distribution of agro-processing industries is similar to the distribution of all industries.

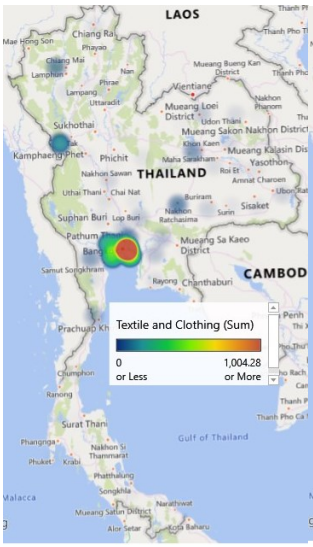
Agro-processing firms are mainly concentrated in the Bangkok Metropolitan Region (BMR), which covers five provinces (Samutprakarn, Patumthani, Samutsakorn, Nakornpatom and Nonthaburi), with high density and also in the northeastern region (e.g. Nakhon Ratchasima and Ubon Ratchathani) and the northern region (e.g. Chiang Mai and Chiang Rai). Textiles and clothing firms are mainly located in the BMR and Tak province. Petrochemical and chemical firms are mainly found in the BMR and Ratchaburi, Chiang Mai and Surat Thani provinces. Electronics and telecommunications equipment firms are mainly found in the BMR and Ratchaburi, Samut Prakan and Ayuttaya Provinces. Automotive and parts firms are found in the BMR, Samut Prakan, Pathum Thani and Ratchaburi Provinces.



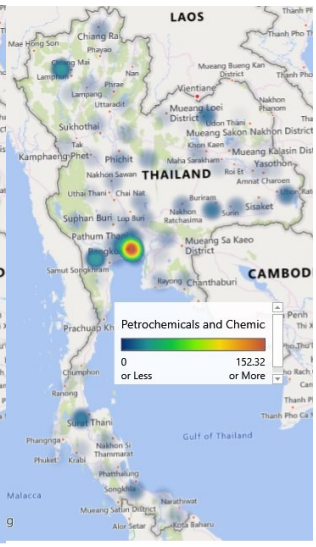
(a) All five industries



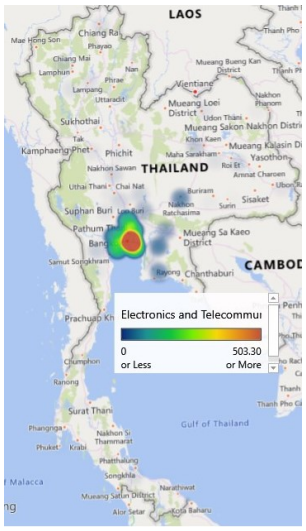
(b) Agro-processing



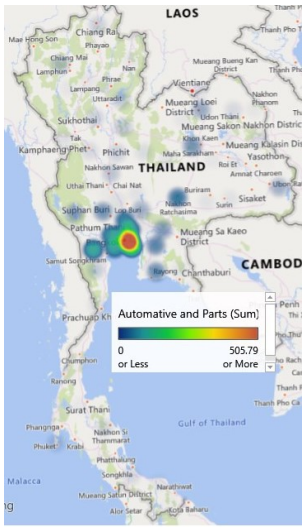
(c) Textiles and Clothing



(d) Petrochemicals and Chemicals



(e) Electronics and telecom-munications equipment



(f) Automotive and parts

Figures 1: Current Firms Distribution

Results of *k*-Means Cluster Analysis

We defined three clusters for *k*-Means cluster analysis in order to classify firms into three groups of demanded resources into three levels: high, medium, and low groups. Results of analysis for particular industries are presented in table 1 and table 2.

Agro-processing Industry

Most agro-processing firms are clustered in Cluster 2 which had negative mean of standardized (z) scores of all resourced variables, i.e. less than average required resources. Furthermore, there are similar number of firms in the other two clusters which are 184 firms and 158 firms respectively. The characteristics of Cluster 1 show high and positive mean z scores for both capital variables (CAPLAND, CAPBUID and CAPMACH). Cluster 3 shows high and positive mean z score for number of skilled and total workers, 2.177 and 3.228 i.e. values of those variables are significantly greater than the overall mean ~2.177 and 3.228 σ. In addition, HP for Cluster 1 and Cluster 3 showed similar mean z scores.

Textile and Clothing sector

In the textile and apparel sector, most firms are in Cluster 3 (4,643 of 5,019 firms) with the lowest and negative mean z scores for all resourced variables. Firms in Cluster 1 spend the highest amounts of investment and horsepower, while Cluster 2 contains the least number of firms, but they use the highest labor resources. The mean z score for number of skilled workers and total workers of Cluster 2 are the highest compared to other factors, 3.557 and 3.390.

Petrochemicals and Chemicals

Most firms in the petrochemicals and chemicals industry were established in Cluster 1 and followed by Cluster 2 and Cluster 3. Cluster 1 contains 571 firms with the lowest mean z score for all resourced variables. Only 2 firms are assigned in Cluster 3. The highest mean z score for working capital in Cluster 3 is 7.674. Cluster 2 contains 17 firms which spend the highest mean z score in various factors.

Electronics and Telecommunications Equipment

Most of firms in Electronics & telecommunications equipment sector are allocated in Cluster 3 (2,089 firms) while the least firms are assigned in Cluster 2. The highest mean z scores of all resource and investment variables are in Cluster 2 (18 firms). The top two mean z scores are Building capital and Machine capital.

Table 1: Mean z Scores for Resourced Variables for Three Clusters of Five Industries

z score	Cluster		
	1	2	3
Agro-processing			
HP	0.606	-0.070	0.699
CAPLAND	1.345	-0.054	0.320
CAPBUID	3.197	-0.108	0.550
CAPMACH	2.088	-0.087	0.558
CAPWORK	0.536	-0.033	0.208
Total Skill	0.540	-0.080	2.177
Total Worker	0.867	-0.097	3.228
Textiles and Clothing			
HP	1.849	0.209	-0.145
CAPLAND	1.062	0.272	-0.091
CAPBUID	2.140	0.726	-0.175
CAPMACH	1.697	0.209	-0.143
CAPWORK	1.077	0.427	-0.127
Total Skill	0.160	3.557	-0.155
Total Worker	0.807	3.390	-0.183
Petrochemicals and Chemicals*			
HP	-0.101	0.711	1.420
CAPBUID	-0.069	0.254	-0.078
CAPMACH	-0.083	0.661	-0.098
CAPWORK	-0.086	0.070	7.674
Total Skill	-0.110	1.300	-0.260
Total Worker	-0.167	3.460	3.488
Electronics and Telecommunications Equipment			
HP	1.055	3.376	-0.150
CAPLAND	1.547	2.855	-0.169
CAPBUID	0.685	4.168	-0.138
CAPMACH	0.647	3.864	-0.128
CAPWORK	1.126	2.725	-0.152
Total Skill	0.722	2.043	-0.130
Total Worker	1.136	3.650	-0.172
Automotive and Parts			
HP	0.871	-0.179	4.464
CAPLAND	0.077	-0.048	0.934
CAPBUID	0.213	-0.072	1.135
CAPMACH	0.348	-0.097	1.562
CAPWORK	0.568	-0.099	0.988
Total Skill	1.355	-0.148	0.886
Total Worker	1.824	-0.194	1.797

* only 5 factors were used for this model

Automotive and Parts

Most firms in Automotive and parts sector established in Cluster 2 (1,780 firms) and followed by Cluster 1 (109 firms) and Cluster 3 (32 firms) respectively. Mean scores of all resourced variables in Cluster 2 are the lowest. Whereas the highest mean z scores of horsepower and capital variables are in Cluster 3, the mean z scores of two worker variables are on Cluster 1. The highest mean z score of all variables is 4.464 of horsepower in Cluster 3.

Table 2: Number of Firms Represented by Cluster and Type of Industry

Cluster	Agro-processing	Textiles and clothing	Petrochemicals and chemicals	Electronics and telecommunications equipment	Automotive and parts
1	184	236	571	140	109
2	13,509	140	17	18	1,780
3	158	4,643	2	2,089	32
Total	**13,851**	**5,019**	**590**	**2,247**	**1,921**

Average Distance from Centroid

Computing centroids of each cluster are essential for center-based clustering in *k*-Means analysis. The average of all objects in each cluster is represented as the centroid. In these results, the average distance between centroid of each cluster in particular industries are shown in Table 3.

Table 3: Distances between Cluster Centroids

Cluster	Cluster		
	1	2	3
Agro-processing			
1		4.434	4.332
2	4.434		4.216
3	4.332	4.216	
Textiles and Clothing			
1		5.115	4.072
2	5.115		5.296
3	4.072	5.296	
Petrochemicals and Chemicals			
1		4.061	8.712
2	4.061		7.838
3	8.712	7.838	
Electronics and telecommunications equipment			
1		6.340	3.121
2	6.340		9.146
3	3.121	9.146	
Automotive and parts			
1		2.858	4.045
2	2.858		5.739
3	4.045	5.739	

Table 4: ANOVA

Factors	ANOVA			
	Df 1	Df 2	F	P-value
Agro-processing				
HP	2	13,848	994.669	0.000
CAPLAND	2	13,848	1,829.923	0.000
CAPBUID	2	13,848	9,033.274	0.000
CAPMACH	2	13,848	5,247.654	0.000
CAPWORK	2	13,848	1,082.858	0.000
Total Skill	2	13,848	4,784.224	0.000
Total Worker	2	13,848	8,790.757	0.000
Textiles and Clothing				
HP	2	5016	1,243.658	0.000
CAPLAND	2	5016	622.476	0.000
CAPBUID	2	5016	1,909.216	0.000
CAPMACH	2	5016	1,709.992	0.000
CAPWORK	2	5016	834.731	0.000
Total Skill	2	5016	4,051.716	0.000
Total Worker	2	5016	3,182.784	0.000
Petrochemicals and& Chemicals*				
HP	2	587	46.563	0.000
CAPBUID	2	587	37.737	0.000
CAPMACH	2	587	27.301	0.000
CAPWORK	2	587	1,241.612	0.000
Total Skill	2	587	200.751	0.000
Total Worker	2	587	763.812	0.000
Electronics and& Telecommunications Equipment				
HP	2	2,244	640.378	0.000
CAPLAND	2	2,244	680.216	0.000
CAPBUID	2	2,244	1,743.421	0.000
CAPMACH	2	2,244	1,383.371	0.000
CAPWORK	2	2,244	569.258	0.000
Total Skill	2	2,244	436.677	0.000
Total Worker	2	2,244	1,001.742	0.000
Automotive & Parts				
HP	2	1,918	2,528.218	0.000
CAPLAND	2	1,918	225.367	0.000
CAPBUID	2	1,918	327.219	0.000
CAPMACH	2	1,918	514.801	0.000
CAPWORK	2	1,918	205.950	0.000
Total Skill	2	1,918	543.099	0.000
Total Worker	2	1,918	1,073.262	0.000

CONCLUSIONS AND FURTHER RESEARCH

This paper summarizes the different patterns of spending demanded resources into 3 clusters of firms by using *k*-Means technique as shown in Table 5. When we know requirements of particular clusters, we can specify suitable resources needed for production. Therefore, policy makers can provide suitable policy to meet their demands in particular clusters.

Table 5: Summary Industry Patterns from Cluster Analysis

Industry	Cluster 1	Cluster 2	Cluster 3
Agro-processing	High demand of investment	Low horsepower, demand of investment, and manpower	High horsepower and manpower
Textiles and Clothing	High horsepower and demand of investment	High manpower	Low horsepower, demand of investment, and manpower
Petrochemicals and Chemicals	Low horsepower, demand of investment, and manpower	High demand of machinery capital, and manpower (Skilled workers)	High horsepower, demand of working capital, and manpower (total workers)
Electronics and telecommunications equipment	Moderate horsepower, demand of investment, and manpower	High horsepower, demand of investment, and manpower	Low horsepower, demand of investment, and manpower
Automotive and parts	High manpower	Low horsepower, demand of investment, and manpower	High horsepower and demand of investment

This research presents one of the usefulness of defining patterns for particular clusters in each industry by *k*-Means analysis. The further analysis can define clusters by provinces in order to represent potential of particular provinces by considering the regional clusters. According to the results of analysis above, there are many firms required low level of resources, so all available resources in the region should be sufficient to support their production. However, a few firms require high level of resources; we need to provide the special supports for potential firms. For example, some clusters required general workers but another requires skilled workers so this can help to decide for setting a skilled labor development center for particular regions. We believe that classify provinces as regional cluster by considering only number of firms without consider the other factors such as level of resource demands may lead to the difficulty because potential firms can be overlooked.

In addition, we can compare between significant provinces, which are defined by current demanded resources in particular clusters, and the target provinces determined by Thailand policy such as the Cluster and Super Cluster Policy or the S-curve policy. The results of the comparison can help the policy makers to identify provinces that comply with the policy, provinces that need to be promoted to achieve their goals, and provinces that can reduce benefit supports.

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REFERENCES

Arvanitis, Spyros, and Heinz Hollenstein. 1998. "Innovative Activity and Firm Characteristics - A Cluster Analysis with Firm-Level Data of Swiss Manufacturing." Pp. 1–28 in *25th Annual Conference of the European Association for Research in Industrial Economics*.

Bennett, Robert J. 1997. "Administrative Systems and Economic Spaces." *Regional Studies* 31(3):323–36. Retrieved April 11, 2019 (http://www.tandfonline.com/doi/abs/10.1080/00343409750134728).

Cortright, Joseph. 2006. *Making Sense of Clusters: Regional Competitiveness and Economic Development*.

Employment Promotion Division: Department of Employment. 2009. *Thailand Standard Industrial Classification TSCI 2009*.

Kuo, R. J., L. M. Ho, and C. M. Hu. 2002. "Cluster Analysis in Industrial Market Segmentation through Artificial Neural Network." *Computers & Industrial Engineering* 42(2):391–99.

Michael E. Porter. 1998. "Clusters and the New Economics of Competition." *Harvard Business Review* 76(6):77–90. Retrieved April 11, 2019 (https://hbr.org/1998/11/clusters-and-the-new-economics-of-competition).

Nagy, Laszlo, and Mihaly Ormos. 2018. "Review Of Global Industry Classification." Pp. 66–73 in. Retrieved February 28, 2019 (http://www.scs-europe.net/dlib/2018/ecms2018acceptedpapers/0066_fes_ecms2018_0840.pdf).

Roelandt, J. A. Theo, and Pim den Hertog. 1999. "Cluster Analysis and Cluster-Based Policy Making in OECD Countries: An Introduction to the Theme." in *Boosting Innovation the Cluster Approach: The Cluster Approach*, edited by Organisation for Economic Co-Operation and Development (OECD).

Smith, Rachel V. 2003. "Industry Cluster Analysis: Inspiring a Common Strategy for Community Development." P. 296 in *Central Pennsylvania Workforce Development Corporation Report*.

Sureephong, P., and N. Chakpitak. 2007. "Knowledge Management System Architecture for the Industry Cluster." in *Industrial Engineering and Engineering Management*. Retrieved March 14, 2016 (http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4419536).

The Office of the Board of Investment (BOI). 2018. "What We DO." Retrieved (https://www.boi.go.th/index.php?page=what_we_do2).

Zhu, Qinghua, Yong Geng, and Kee-hung Lai. 2010. "Circular Economy Practices among Chinese Manufacturers Varying in Environmental-Oriented Supply Chain Cooperation and the Performance Implications." *Journal of Environmental Management* 91(6):1324–31.

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