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# Spatial agglomeration and specialization in emerging markets

## Economic efficiency of clusters in Thai industries

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### Abstract

**Purpose** – The paper aims to investigate the role of specialization and agglomeration forces on industry performance in an emerging market, namely, Thailand. In particular, the impact of clusters and the influence of complexity will be tackled.

**Design/methodology/approach** – The methodology used is based on the work of Delgado *et al.* (2014). Industries and clusters are assigned to a certain category according to their respective level of specialization and complexity. Performance measures are then computed for each category.

**Findings** – It was found that the agglomeration of similar industries and co-located and related industries increase the performance of firms in terms of gross output per employee and remuneration per employee. Moreover, the increase of performance induced by the complexity level of an industry was closely related to the level of specialization.

**Originality/value** – Building on a cluster mapping, this study brings new insight on the effect of specialization and agglomeration on performance in emerging markets. In fact, the paper show how performance can be enhanced in less sophisticated and developed economies.

**Keywords** Performance, Agglomeration, Emerging market, Clusters

**Paper type** Research paper

### 1. Introduction

The aspect of economic performance has always aroused the interest, not only of economists but also of policymakers and academics. Whether at the firm, regional or national level, many studies have tried to explain the determinants of economic performance (Marshall, 1961; Porter, 2003). Porter has gained popularity in explaining performance and the role of locations in the creation of wealth. More specifically, he stressed the role of the

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microeconomic environment and introduced the concept of clusters, which, according to many studies, plays a role in shaping performance (Porter, 1998; Delgado *et al.*, 2014; Mendoza-Velazquez, 2017). Other ranges of studies have tried to explain the economic performance based on firm or industry characteristics (Hansen and Wernerfelt, 1989; Holmes *et al.*, 2010).

The attention to the cluster theory has increased in the past decades (Porter, 2000, 2003, 2008; Sölvell *et al.*, 2008; Delgado *et al.*, 2014). While clusters in developed economies have been widely studied through case studies (Konstantynova and Lehmann, 2017; Tödtling *et al.*, 2016; Valdaliso *et al.*, 2011), empirical analyses (Porter, 2003; Delgado *et al.*, 2014; Resbeut and Gugler, 2016) and cluster mapping (USA Cluster Mapping, 2014; Delgado *et al.*, 2015), research on this matter in developing economies is more scarce and has been mostly tackled through case studies (Rothenberg *et al.*, 2017; Newman and Page, 2017) even though a few empirical analyses and mapping have been conducted (Lu *et al.*, 2016; Mendoza-Velazquez, 2017).

Building on Porter (2003, 2008), a new generation of quantitative studies on the economic performance of clusters or on the impact of clusters on the economic performance of locations has been published (Spencer *et al.*, 2010; Delgado *et al.*, 2014; Resbeut and Gugler, 2016; Slaper *et al.*, 2016). Following these studies, the aim of the present paper is to scrutinize the impact of clusters in an emerging economy, namely, Thailand. In other words, it will take a closer look at the industry and cluster-based agglomeration that drives the performance of the firms and therefore of the industries and clusters in which they compete in. The angle of specialization of industries and of inter-related industries composing a cluster are investigated in terms of their role in shaping performance. As mentioned above, this approach on clusters has already been widely studied in developed economies but not in emerging ones. Therefore, someone may wonder if the observations and conclusions that were deduced in developed economies also hold in an emerging economy. Are the agglomeration forces between similar industries and related industries comparable in emerging economies? This would expand our knowledge on the matter and help decision-makers to design and implement the most appropriate policies.

The inclusion of a supplementary dimension, namely the level of technological complexity is added to the analysis. In fact, the gap in performance between technologically complex – so-called high-tech – industries or clusters and less complex ones may be greater in emerging economies and consequently lead to different conclusions.

Hence, this study would extend our knowledge on clusters in emerging economies. Thailand is considered as an efficiency-driven economy (Stage 2 out of 3) by the WEF (2012) and is ranked 39th of the GCI in 2012 (WEF, 2012, p. 15). In 2012, the GDP per capita of Thailand (in current US dollars) is US$5859.89 and is considered by The World Bank (2012a, 2012b) as an upper-middle-income economy in 2012.

After anchoring the problems within the existing literature in Section 2 of this paper, the methodology and data are introduced in Sections 3 and 4. Section 5 presents the results and Section 6 lays the foundation for the discussion, recommendations and further research.

## 2. Theoretical background and hypotheses

According to Porter (2000, p. 16), a cluster is: "[. . .] a geographic concentrations of interconnected companies, specialized suppliers, services providers, firms in related industries, and associated institutions [. . .] in a particular field that compete but also cooperate." A central component is the geographical concentration of firms, and therefore, of the underlying industries. These concentrations may vary from one location to another and from one industry to another. In fact, a firm may compete in an industry that is highly concentrated in a particular location. Put in other words, it can be said that the location is specialized in that industry.

The specialization of a location in an industry or an array of interconnected industries may, therefore, have a positive influence on performance. Delgado *et al.* (2014) developed a model that estimates the influence of clusters on the economic performance of USA regions. The methodology disentangles convergence and agglomeration forces. They found that cluster-driven agglomeration increases employment growth (Delgado *et al.*, 2014, p. 1785). This study was the first to use clusters to control for agglomeration forces. The methodology was replicated in a study by Resbeut and Gugler (2016) on a particular cluster in Switzerland. Even though the conditions were modified, the hypotheses still hold: firms that are part of a strong cluster environment experience higher growth rates.

These two studies concentrated on developed economies, namely, the USA and Switzerland. In this study, the analysis will concentrate on Thailand, which is an emerging market, and therefore, the patterns of specialization and agglomeration, whether at the industry or cluster level, may diverge between these economies. Porter (2008, p. 246) argues that, while clusters are more clear-cut in developed economies, they may also be present in emerging markets. Porter (2008, p. 247) specified that clusters in emerging markets "tend to be shallow and to rely primarily on foreign components, services and technology." Additionally, many studies also highlight striking deficiencies in institutions, infrastructure or education (Porter, 2003, 2008; Lall *et al.*, 2004; Newman and Page, 2017). Mendoza-Velazquez (2017, p. 426) investigated the role of various types of externalities in Mexico. Using a database that included 41 industrial clusters, they assessed the impact of specialization, competition and diversity on employment growth. While they found a negative impact of specialization on average, they also identified clusters that created a positive effect on employment growth.

When studying Indian industries, Lall *et al.* (2004) highlighted the paradox that industries concentrate in large cities even if the negative externalities tied to urban areas (i.e. congestion, higher rent costs and wages) seem to outweigh the advantage of agglomerating (i.e. knowledge spillovers, the pool of specific workers, etc.). On the other hand, Balat and Casas (2018) found a positive impact of location economies on firm productivity in Colombia. They found that firms benefit from being clustered and from being located in cities that are specialized. In Chile, López and Südekum (2009) analyzed the impact of intra- and inter-industry linkages on productivity (TFP). While they found intra-industry effects, inter-industry externalities only appeared with the upstream sectors (López and Südekum, 2009, p. 15).

Overall, it appears that the benefits of agglomeration forces in emerging markets are mitigated. However, firms also show signs of potential gains of being localized in a specialized industry or in a cluster. In this paper, three hypotheses are presented regarding the relation between specialization and performance in emerging economies.

It has also been highlighted that in emerging economies, many industries agglomerate around big cities such as Bangkok in Thailand or Hanoi and Ho Chi Minh City in Vietnam (Porter, 2008; Newman and Page, 2017; Lall *et al.*, 2004). Consequently, the positive effects of concentration may be mitigated by the cost of urbanization, and therefore, the benefits of being agglomerated may be weakened in comparison to developed economies.

Building on the studies mentioned above, the relation between specialization and economic performance is expected to follow the same tendency in emerging economies as in developed ones. In fact, many drivers of the agglomeration of similar industries that are observed in developed economies may also be present in emerging economies (i.e. a pool of specific workers, common inputs, knowledge spillovers and increased competition).

Therefore, an industry that is specialized should experience a higher performance level than a similar industry located in a region, which does not show signs of specialization in that particular industry. Hence, the following hypothesis is proposed:

*H1*. The level of specialization of a location in a given industry is positively associated with the performance of that industry.

While the *H1* concentrates on the relation between industry specialization and performance, *H2* focuses on the cluster environment surrounding an industry. In fact, if the performance of an industry is expected to be positively influenced by the specialization of the location in that industry, cluster-driven agglomeration is also expected to increase performance. While the studies of López and Südekum (2009) or Mendoza-Velazquez (2017) did not find strong evidence of the positive externalities of inter-industry in relation to performance, specific examples tend to demonstrate the opposite, such as business services or processed food in Mexico (Mendoza and Velazquez, 2017, p. 426). Indeed, access to specialized inputs, the possibility of outsourcing and the multiplicity of knowledge spillovers across industries or the setup of associations have a beneficial impact on performance (Porter, 2008, p. 213). It has been shown in developed economies that the geographical agglomeration of related industries has a positive impact on performance (Hanson, 2000; Delgado *et al.*, 2014; Resbeut and Gugler, 2016). Even though the determinants of cluster-driven agglomeration that leads to higher performance are not as broad or sophisticated in emerging markets (Porter, 2008, p. 247), the cluster effect should improve the performance. Therefore, the following hypothesis is offered:

*H2*. The level of specialization of a location in a given cluster is positively associated with the economic performance of the industries that operate in the cluster.

In this study, the role of complexity will also be tackled. Complexity refers to the technological degree of an industry. According to Hausmann *et al.* (2014, p. 18): "the complexity of an economy is related to the multiplicity of useful knowledge embedded in it." This interaction and combination of multiple sources of knowledge (i.e. design, technology, operation management, etc.) may, therefore, be considered as the basis of the creation and production of goods and services. The more complex the interactions and combinations of these sources of knowledge are, the more complex the underlying goods will be. The technological complexity dimension is also used in the growth theory (Romer, 1990). Based on Balland and Rigby (2017), Broekel (2017, p. 2) argues only few "are capable of mastering complex technologies that lay the foundation for their future growth." According to these authors, the technological complexity plays an important role.

Hence, there may be greater differences in terms of performance between technologically complex industries and clusters that benefit from the above-mentioned conditions on the one hand and less technologically complex industries or clusters, on the other hand. Therefore, the following hypotheses are offered:

*H3a*. The level of technological complexity of an industry within a region is positively associated with the performance of that industry within the degree of specialization.

*H3b*. The level of technological complexity of a cluster within a region is positively associated with the performance of the industries operating in the cluster within the degree of specialization.

## 3. Methodology

### 3.1 Measures of specialization and concentration

A common tool for identifying industry specialization and concentration is the use of the location quotient (LQ) (Crawley *et al.*, 2013, p. 1854; Delgado *et al.*, 2014; Lall *et al.*, 2004). Although the LQ approach has some limitations (i.e. relative measure and use of a threshold), it is a straightforward tool to compute and analyze the concentration of an industry in a particular location (Resbeut and Gugler, 2016, p. 189; Isserman, 1977, p. 33).

We assume an industry ($i$) in a particular region ($r$) of a certain nation ($n$). $E$ stands for employment and it is used as the input variable. For example, $E_{i,r}$ represents the employment for industry ($i$) in region ($r$). The employment-based LQ shows the concentration of the industry ($i$) in the region ($r$) compared to the concentration of that same industry ($i$) in the nation ($n$) (Delgado *et al.*, 2012, p. 21; Strotebeck, 2010, p. 3; Isserman, 1977, p. 34). The LQ can be written as follows:

$$LQ_{i,r} = \frac{E_{i,r}/E_r}{E_{i,n}/E_n} \tag{2.1}$$

The equation (2.1) is simply the ratio between the concentration of industry ($i$) in region ($r$) and the concentration of that same industry ($i$) in the nation ($n$). When the LQ is above one, it means that the industry has a higher share of employment in the given region compared to the national level. In this study, employment is defined as the number of employees in each industry and does not take into account the number of hours worked by each employee.

The employment-based LQ is used to compute the *Industry Spec*, *Cluster Spec outside i* and *Cluster Spec* variables. The *Industry Spec* variable measures the degree of specialization of a region-industry, namely, a particular industry in a given region. It is computed following the equation 2.1. Therefore, if the variable *Industry Spec* takes a value above one, it means that the region-industry is specialized:

$$Industry\ Spec_{Employ,i,r} = \frac{E_{i,r}/E_r}{E_{i,n}/E_n} \tag{2.2}$$

Similar to the first variable, the *Cluster Spec outside i* variable estimates the degree of specialization of a cluster outside the industry ($i$). It is an indicator of the cluster environment surrounding an industry ($i$) and takes into account the specialization of the cluster when excluding a core industry. The higher the value of the variable, the stronger (i.e. the more specialized) will the cluster environment be (Delgado *et al.*, 2012, p. 21). The calculation is similar to equation 2.1:

$$Cluster\ Spec\ {}^{outside\ i}_{Employ,c,r} = \frac{E^{outside\ i}_{c,r}/E_r}{E^{outside\ i}_{c,n}/E_n} \tag{2.3}$$

Using the same logic as for the previous variable, the *Cluster Spec* variable also gives a measure of the cluster environment. However, attention is, here, given to the region-cluster level, which is a particular cluster ($c$) in a given region ($r$). A value above one means that the cluster is more specialized in the region ($r$) than at the national level ($n$). Hence, this measure takes into account all industries of the cluster:

$$Cluster\ Spec_{Employ,c,r} = \frac{E_{c,r}/E_r}{E_{c,n}/E_n} \tag{2.4}$$

*3.2 The technological complexity of industries and clusters*

Each industry and cluster, both in the secondary and tertiary sectors, has its proper technological level. Some industries may be considered as more technologically complex than others. The manufacture of food products may be seen as technologically less advanced than the manufacture of computers, electronic and optical products. According to Tani and Cimatti (2008, p. 6), the concept of technological complexity is difficult to define, as it is not physically tangible and supposes subjective consideration. This leads to challenges in measuring it (Broekel, 2017, p. 2). The OECD has classified manufacturing industries according to the intensity of the technology into four groups ranging from high to low technology industries. The classification is based on research and development (Hatzichronoglou, 2007).

In this study, the methodology used to measure the levels of technological complexity is based on the product complexity index (PCI) (Simoes and Hidalgo, 2011). More precisely, the PCI uses both concepts of diversity; namely, "how many different types of products a country is able to make" and ubiquity, which refers to "the number of countries that are able to make a product" (Atlas of Economic Complexity, 2017). Mathematically, the complexity of a product is "determined by calculating the average diversity of countries that make a specific product and the average ubiquity of the other products that these countries make" (Atlas of Economic Complexity, 2017a). Based on this methodology, the Atlas of Economic Complexity (2017) assigns a value to each product.

As each product has its own complexity index, one could link the product to the corresponding industry and then compute the complexity index of the industry. However, one obstacle arises: the product classification system differs from the industry classification. The clustering of products into industry classification then can become a balancing act. The difference between product and industry classification is accentuated by the wide variety of industry classifications, such as Standard Industrial Classification (SIC), statistical classification of economic activities in the European Community, North American Industry Classification System, Thailand Standard Industrial Classification (TSIC), etc., and product classifications such as harmonized system codes (HS) and Standard International Trade Classification and their respective revisions. The data on exportation used in this study were based on the HS92 nomenclature, while the data on employment were based on the TSIC. The World Integrated Trade Solution (WITS) (2012) has developed a product concordance with various industry classifications. As the TSIC shares the same structure as the SIC, both nomenclatures are very close. Therefore, the concordance between HS92 and SIC was used.

Two Complexity variables were created to capture the technological complexity level of each industry and cluster. The technological complexity level of an industry is simply the PCI's value-weighted average of each good assigned to a particular industry:

$$Industry\ Technological\ Complexity_i = \sum_{p=1}^{n} w_p \times PCI_p \tag{2.5}$$

Where $w_p$ is the value-based weight of product ($p$) in the industry ($i$) and $PCI$ is the complexity index of product ($p$).

Regarding the cluster level, the technological complexity level of cluster is simply the PCI's value-weighted average of each good assigned to a particular cluster. In equation 2.6, the reasoning is similar as equation 2.5: $w_p$ is the value-based weight of product ($p$) in cluster ($c$) and $PCI$ is the complexity index of product ($p$):



$$Cluster\ Technological\ Complexity_c = \sum_{p=1}^{n} w_p \times PCI_p \tag{2.6}$$

*3.3 Explaining performance at the industrial and cluster level*

Various methodologies have been used to assess the performance of firms, industries and clusters (Delgado *et al.*, 2014; Mendoza-Velazquez, 2017; Balat and Casas, 2018). The methodology used in this study will be based on the work of Delgado *et al.* (2014).

The applied methodology is straightforward. Region-industries and region-clusters are categorized according to their respective degree of concentration and complexity. The degree of specialization and complexity (at the industrial and cluster level) defines the category to which a region–-industry or a region-cluster will be assigned. This methodology enables the comparison of the characteristics (here performance measures) of groups of industries/clusters depending on certain variables.

In this study, the variables used for the categorization are *Industry Spec*, *Cluster Spec outside i*, *Cluster Spec*, *Industry Technological Complexity* and *Cluster Technological Complexity*. There are two categories for each variable: above and under the cutoff. The implementation of an arbitrarily defined cutoff is always subject to discussion. In this study, the cutoff is set at 1.10 for all specialization variables. O'Donoghue and Gleave (2004, p. 421) give several examples of possible cutoffs: a study by Miller *et al.* (2001) use a cutoff of 1.25, Isaksen (1996), who uses a cutoff of 3 or the study of Puig *et al.* (2014) apply a cutoff of 1.4. O'Donoghue and Gleave (2004, p. 421) also propose a standardized location quotient, but to this end, the LQ needs to be normally distributed, which is not the case in this study. A cutoff of 1.10, reflects the fact that a region-industry or a region-cluster that is specialized will generate an LQ above 1. By adding a margin of 0.10, it accounts for the fact that the observed LQ is statistically different from 1. In fact, a confidence interval could not be implemented as the LQs are not normally distributed.

Regarding the complexity variables (*Industry Technological Complexity* and *Cluster Technological Complexity*), the cutoff is set to 0.087, which represents the PCI median when considering all goods exported in the world in 2012 (computation based on Simoes and Hidalgo, 2011). Therefore, an industry or cluster with a value above the cutoff is considered as complex or in other words, technologically more advanced.

When every region-industry and region-cluster is categorized, the average of each performance indicator is computed and the comparison of the performance between the categories is then analyzed.

In this study, two performance indicators are used. The first indicator is labor productivity, namely, the value added per employee computed at the region-industry level. The second indicator is the remuneration per employee computed at the region-industry level. In fact, the remuneration per employee reflects the standard of living and is, therefore, a measure of performance and competitiveness (Porter, 2003, p. 569; Delgado *et al.*, 2014). Porter (2003, p. 564) also found that a particular cluster, that is present in distinctive regions, may experience differences in average remuneration. He posited the explanation of differences in sophistication, unionization, cost of living and productivity. In fact, higher remuneration per employee may be the result of a higher level of productivity (Klein, 2012). Therefore, both measures are scrutinized in this study. There are other measures of performance when looking at the cluster theories such as innovation through patenting rates, firm creation or firm's survival (Porter, 2003; Delgado *et al.*, 2014). However, the database used for this study does not include such measures of performance.

## 4. Data

Two databases are used in this study: Thailand's 2012 Business and Industrial Census and the BACI International Trade Database.

The 2012 Business and Industrial Census was conducted by the National Statistical Office of Thailand (NSO). The data were collected by the NSO through interviews (NSO, 2012). In this regard, the database might be subject to missing values. However, as the NSO itself uses it for its own studies and publications, we considered it good enough for use.

This study uses three different variables from the 2012 Business and Industrial Census, namely, number of persons engaged, remuneration and value added. Remuneration is the annual remuneration distributed to employees and the value added is the difference between gross output and intermediate consumption and is directly computed by the NSO. Remuneration and value-added are in 1,000 baht. For readability purposes, the term of employment or employee is used to refer to the number of persons engaged.

The NSO computed the data at the provincial level, in this case, the three variables described above. There are 77 provinces, including Bangkok. Moreover, industries are classified at 2-digit of the TSIC nomenclature. As this study focuses on the secondary sector, the 28 industries of the secondary sector were considered. Examples of industries defined at 2-digit of the TSIC nomenclature are the manufacture of food products, manufacture of wearing apparels or manufacture of textiles, which are the three biggest industries of the secondary sectors in terms of employment. Only industries that were of sufficient size in terms of employment and gross output were kept. Consequently, five small industries were put aside as they represented only a remote proportion of the secondary sector's total employment and gross output (i.e. sewerage or remediation activities and other waste management services). Taken together, they represent less than 1 per cent of the gross output of the secondary sector.

The 2012 Business and Industrial Census was used to create a cluster mapping of industries of the secondary sector in Thailand. The results of the cluster mapping were presented in a joint study of the Center for Competitiveness (2018) of the University of Fribourg (Switzerland) and the NIDA Business School in Bangkok. The mapping was developed following the methodologies of Delgado *et al.* (2015) and Ketels (2017). The cluster mapping in Thailand revealed that 20 industries could be regrouped in 8 clusters, namely, food; textiles; wood and furniture; paper and printing; chemicals and pharmaceuticals; metals; electronic appliances and machinery; and automotive. Additionally, nearly each of the 77 provinces hosted a cluster.

The Observatory of Economic Complexity (OEC) used data on trade to compute the PCI of each good (Simoes and Hidalgo, 2011). To match the data on employment (2012 Business and Industrial Census), data for 2012 were downloaded directly from the OEC's website. The PCI was already computed by the OEC. Therefore, the following two variables were of interest and downloaded: export value and PCI (Simoes and Hidalgo, 2011) (Table I).

## 5. Results

In the first analysis, the focus is put on the level of specialization at the industrial and cluster level. As explained in Section 2, the threshold between low and high was set at 1.10 both at

**Table I.** Variable definitions and descriptive statistics

| | Definition | Mean (Standard deviation) |
|---|---|---|
| *Variable* | | |
| Industry Spec. | Region-industry employment-based LQ in 2012 | 0.824 (1.361) |
| Cluster Spec. outside i | Region-industry employment-based LQ outside industry i of cluster c in 2012 | 0.791 (1.180) |
| Cluster Spec. | Region-cluster employment-based LQ in 2012 | 0.829 (1.055) |
| Industry Technological Complexity | PCI's value-weighted average of all goods in each industry | −0.147 (0.741) |
| Cluster Technological Complexity | PCI's value-weighted average of all goods in each cluster | −0.098 (0.704) |
| *Performance variables* | | |
| Value added per employee | Region-industry value added divided by the number of employee in that particular region-industry | 252 (419) |
| Remuneration per employee | Region-industry remuneration divided by the number of employee in that particular region-industry | 62 (46) |

**Source:** Based on NSO (2012), Observatory of Economic Complexity (2012) and WITS (2012)

the industrial and cluster level. While the value added per employee is used in Table II as a performance indicator, the remuneration per employee is employed in Table III.

The results presented in Tables II and III meet the expectations. In fact, when moving from low industry specialization to high specialization, both the value added per employee (Table II) and remuneration per employee (Table III) increase, irrespective of whether the industry is in a strong cluster environment. A strong cluster environment is characterized by a cluster LQ above the threshold, namely, an LQ of 1.10. *H1* stated that the higher the specialization of the industry is, the greater the performance should be. It can also be seen that the increase in performance is bigger when the industry is in a strong cluster environment than when the industry is not in a cluster. When the industry is in a strong cluster environment, the value added per employee increases by 116 per cent and the remuneration per employee by 67 per cent[1]. When the industry is not in a strong cluster, the increase is lower: 81 per cent for value added per employee and 45 per cent for remuneration per employee.

On the other hand, when moving from a low to a high cluster environment, the performance also increases for both performance indicators, when the industry is highly specialized. This is true for both performance indicators. However, the result should be

**Table II.** Average value added per employee (in 1,000 baht) by the level of specialization in 2012 at the region-industry level

| | *Industry Spec* | |
|---|---|---|
| | Low | High |
| *Cluster Spec outside i* | | |
| Low | *196* (672) | *354* (174) |
| High | *221* (172) | *477* (112) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Industry Spec* and *Cluster Spec outside i* is 0.448 and significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a *z*-test for mean differences, all averages are significantly different from each other at a 5% level except between 196 and 221
**Source:** Based on NSO (2012), Observatory of Economic Complexity (2012) and WITS (2012)

mitigated when the industries are not specialized. In fact, the difference in means between 196 and 221 is not statistically significant when using the value added per employee variable. Nonetheless, when focusing of the remuneration/employee variable, the difference in average is significant. In three out of four scenarii, the hypothesis is validated by the results. Therefore, the *H2*, which expresses the fact that the cluster environment is positively related to performance, is partially validated by the results in Tables II and III. Industries that are specialized experience a higher increase in performance (35 per cent in value added per employee and 45 per cent in remuneration per employee) than non-specialized industries (13 per cent for value added per employee and 25 per cent for remuneration per employee).

On average, the increase in performance is higher when moving from low to high industry specialization than from low to high cluster specialization. A firm is expected to increase its performance by 77 per cent on average when moving to a strong industrial environment and by 30 per cent when moving to a strong cluster environment.

One last observation is the repartition of region-industries in the four categories. In fact, 60 per cent of all region-industries are located in a low industry specialization and a weak cluster environment. The remaining region-industries are distributed in according to an almost equal share (15, 15 and 11 per cent).

A limitation that can be noted is the fact that both categorical variables are positively correlated. This is because of the fact that clusters are mostly composed of few industries because of the level of aggregation of the data. Therefore, parts of the clustering effect may be included in the industry-driven agglomeration; therefore, mitigating the results of the cluster-driven agglomerations.

After looking at the influence of industry and cluster specialization, the effect of technological complexity is tackled. The same methodology is used; however, the variables are changed. *Industry Technological Complexity* and *Cluster Technological Complexity* are added to the analysis and the variable *Cluster Spec outside i* is replaced by *Cluster Spec*. Tables IV and V look at the effect of the technological complexity of industries while Tables VI and VII focus on the effect of the technological complexity of clusters.

The first observation that can be made in Tables IV and V is that specialized industries outperform those that are not specialized, which is consistent with the previous analysis. Second, the industries that have a high technological complexity index and that are specialized have the highest performance both in terms of value added per employee and remuneration per employee.

| | *Industry Spec* | |
|---|---|---|
| | Low | High |
| *Cluster Spec outside i* | | |
| Low | *51* (660) | *74* (175) |
| High | *64* (172) | *107* (112) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Industry Spec* and *Cluster Spec outside i* is 0.441 and significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a *z*-test for mean differences, all averages are significantly different from each other at a 5% level except between 51 and 64
**Source:** Based on NSO (2012); Observatory of Economic Complexity (2012) and WITS (2012)

**Table III.** Average remuneration per employee (in 1,000 baht) by the level of specialization in 2012 at the region-industry level

More interestingly, the increase in performance, when moving from low to high industry specialization, is greater for technologically complex industries. In fact, the value added per employee increases by 156 per cent and the remuneration per employee increases by 130 per cent, when the industry is considered as technologically complex. On the other hand, the increase is only 63 per cent (value added per employee) and 25 per cent (remuneration per employee) for industries that are categorized as having low technological complexity.

Based on these observations, the third hypothesis can be partially confirmed. In fact, it was stated that both the level of concentration and complexity is positively related to the performance of industries and clusters. Here, *H3a* is observed at the region-industry level, however only when the industry has a high specialization level. When the industry specialization is low, the level of technological complexity does not seem to increase the performance (9 per cent for value added per employee and 0 per cent for remuneration per employee) and the difference in average performance is not statistically significant. This observation is true for both performance variables. Consequently, when the level of specialization is low, there is no difference in performance between so-called high- and low-tech industries. The difference in performance is only observed when the specialization is high. Therefore, an industry that is technologically complex but not specialized may have a lower performance than a non-complex industry that is specialized. This is true for both performance indicators.

Finally, most region-industries are considered as having a low technological complexity level (73 per cent), which is not surprising for the secondary sector of an emerging country.

**Table IV.** Average value added per employee (in 1,000 baht) by the level of complexity and specialization in 2012 at the region-industry level

| | *Industry Technological Complexity* | |
|---|---|---|
| | Low | Low |
| *Industry Spec* | | |
| Low | *209* (358) | *228* (176) |
| High | *341* (331) | *584* (78) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Industry Spec* and *Industry Complexity* is −0.253 significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a z-test for mean differences, all averages are significantly different from each other at a 5% level except between 209 and 228

**Source:** Based on NSO, 2012; Observatory of Economic Complexity (2012) and WITS (2012)

**Table V.** Average remuneration per employee (in 1,000 baht) by the level of complexity and specialization in 2012 at the region-industry level

| | *Industry Technological Complexity* | |
|---|---|---|
| | Low | High |
| *Industry Spec* | | |
| Low | *56* (353) | *56* (176) |
| High | *70* (324) | *129* (78) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Industry Spec* and *Industry Complexity* is −0.240 and significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a z-test for mean differences, all averages are significantly different from each other at a 5% level except between 56 and 56

**Source:**Based on NSO (2012); Observatory of Economic Complexity (2012) and WITS (2012)

A couple of observations made at the industrial level are also observed at the cluster level. Similar to the industrial level, high cluster specialization outperforms low cluster specialization in three out of four scenarii, which is consistent with the previous analysis. Additionally, firms competing in a strong cluster environment and in a technologically complex cluster experience the highest performance, both in terms of value added per employee and remuneration per employee (Tables VI and VII). Further, the increase in performance when moving from low to high cluster specialization is more important when the technological complexity is high (the value added per employee increases by 219 per cent and the remuneration per employee by 139 per cent). On the other hand, when the technological complexity is low, the increase in value added per employee is only 9 per cent and 24 per cent for the remuneration per employee indicator and the difference in average are not statistically significant for the value added/employee variable. Nonetheless, when focusing on the remuneration/employee variable, the difference in average is significant.

Similarly, to the industrial level, the technological complexity level has a positive influence on performance only when the cluster is specialized (139 per cent for value added per employee and 93 per cent for remuneration per employee). On the other hand, when the cluster environment is weak, the technological complexity level has no influence. In fact, the difference in average between high- and low-tech industries is not statistically significant when the cluster environment is weak.

Similar to the industrial level, industries in technologically complex clusters only outperform industries in technologically non-complex clusters when the latter is specialized.

| | *Cluster Technological Complexity* | |
|---|---|---|
| | Low | High |
| *Cluster Spec* | | |
| Low | *233* (494) | *191* (246) |
| High | *255* (311) | *610* (79) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Cluster Spec* and *Industry Complexity* is −0.418 and significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a z-test for mean differences, all averages are significantly different from each other at a 5% level except between 233 and 191; and 233 and 255

**Source:** Based on NSO (2012); Observatory of Economic Complexity (2012) and WITS (2012)

**Table VI.** Average value added per employee (in 1,000 baht) by the level of complexity and specialization in 2012 at the region-industry level

| | *Cluster Technological Complexity* | |
|---|---|---|
| | Low | High |
| *Cluster Spec* | | |
| Low | *54* (495) | *54* (246) |
| High | *67* (299) | *129* (79) |

**Notes:** In parentheses are the numbers of region-industries for each category. The Spearman correlation coefficient between *Cluster Spec* and *Industry Complexity* is −0.407 and significant at an alpha of 1%. A chi-squared test of independence reveals that both categorical variables are not independent at an alpha of 5%. Using a z-test for mean differences, all averages are significantly different from each other at a 5% level except between 54 and 54

**Source:** Based on NSO (2012); Observatory of Economic Complexity (2012) and WITS (2012)

**Table VII.** Average remuneration per employee (in 1,000 baht) by the level of complexity and specialization in 2012 at the region-industry level

According to Tables VI and VII, a firm that produces non-complex goods may have higher productivity levels when it is located in a strong cluster environment than a firm that manufactures technologically complex products and is located in a weak cluster environment.

Finally, 71 per cent of all region-industries are operating in a low technologically complex cluster, while only 7 per cent of them compete in a technologically complex and specialized cluster.

Based on these observations, it can be stated that *H3b* is partially confirmed. In fact, firms that produce complex goods only perform better when the cluster environment surrounding the firms is strong.

## 6. Discussions, limitations and further research

The results provide new perspectives for emerging economies. In fact, it has been proved in many developed economies that the specialization and cluster-driven agglomeration are beneficial for the performance of firms. However, only a few studies have found such relationships in emerging markets. In this paper, it was found that both the agglomeration of similar industries and the co-location of related industries are positively related to the two productivity measures; namely, the value added per employee and remuneration per employee. The region-industries with the highest performance measures were the ones that were specialized and that competed in a strong cluster environment. These results were consistent with *H1* and *H2* and they may have consequences for policy issues by providing a solid basis for the development of cluster-oriented policies.

Additionally, the agglomeration of similar industries was seen to have a bigger impact than the clustering effect. The reason for this trend may be the fact that the breath and sophistication of the economy in an emerging economy may not be as important as in a developed economy. Another reason may be the limitation of the cluster mapping, which relies on data that are not as precise as other types of cluster mapping, such as the US cluster mapping.

The second part of the analysis tackled the possible effect of the complexity of goods produced on performance. It was shown that the potential increase of performance induced by the complexity of produced goods was closely related to the level of specialization of the industries and clusters. In fact, technologically complex industries only perform better than technologically non-complex ones when they are specialized. More interestingly, technologically non-complex firms located in specialized industries and/or clusters outperform technologically complex ones when the latter are not specialized or are not part of a strong cluster. Therefore, the *H3a* and *H3b* was only partially valid – the complexity of an industry or cluster positively influences performance only when the specialization is high.

This last observation is interesting not only from an academic point of view but also from a policy perspective. Many politicians chase and try to create high-tech industries from ground zero. However, the results showed here that low-tech industries also gain from being in a strong cluster environment and perform better than high-tech industries that are not part of a cluster. Therefore, fostering and improving the cluster environment of low-tech industries may yield a higher level of productivity and therefore remuneration than creating a high-tech cluster.

The results provide a good starting point for further research in emerging markets. Do other emerging countries show similar results? As the analysis was based on cluster mapping that comprised only industries of the secondary sector, would the results be similar when including industries from the tertiary sector? Do service activities behave in the same way? Another further research opportunity would be to analyze the performance over time as is done in developed economies (Delgado *et al.*, 2014; Resbeut and Gugler, 2016). Would the results be similar? A further research is the inclusion of a regression to investigate more deeply the causality between specialization and performance.

However, the present study does not lack limitations. As already mentioned, the first limitation concerns the cluster mapping. In fact, the accuracy of the results depends on the degree of the precision of the cluster mapping. In fact, a more precise database would have diminished the correlation between industry and cluster specialization by increasing the number of industries in a cluster, and therefore, lessen the effect of each one in the cluster. The second limitation is the use of the LQ as measure of specialization. In fact, the use of an arbitrary threshold, the independence from the absolute size or the number of firms reduces the precision of the analysis (Puig *et al.*, 2009; Strotebeck, 2010). Another limitation is the compatibility of the TSIC and the HS nomenclature and the definition of technological complexity of industries and clusters. Finally, the data were based on the year 2012, which may differ from the actual situation in 2017. However, it does provide a chance for a comparison when an update of the data is available.

## 7. Conclusion

The study has contributed to the literature to the extent that the methodology applied to developed economies has been reproduced in another context that is an emerging economy, namely, Thailand. Building on a cluster mapping conducted for the secondary sector in Thailand, three hypotheses regarding the relationships among concentration/specialization, performance and complexity were tested. While *H1* and *H2*, linking specialization and performance at the industrial level (*H1*) and cluster level (*H2*) were confirmed, *H3a* and *H3b*, which was rather provocative, was only partially confirmed. In fact, the complexity did not necessarily create higher performance levels.

From an academic perspective, this study brings new facts to the debate around clusters and their impact on performance. By testing agglomeration forces at the cluster level and between similar industries using a cluster mapping in an emerging economy, the study was able to show how performance may also be enhanced in less sophisticated and developed economies. Moreover, it brings quantitative proof of in a context (i.e. emerging economies) where more qualitative results were found. This study also contributes to academic knowledge in the way that the results are consistent with theories on externalities whether input–output, knowledge spillovers, etc. In this case, clusters account for those externalities. This has also been noted by Delgado *et al.* (2014, p. 1785). However, the present study has extended the results in the context of an emerging economy. More generally, this study provides insight into the behavior of industries and clusters in an emerging economy.

From a political point of view, the results shown in this study provide an interesting basis for policymakers, not only in Thailand but also in other emerging and Asian economies. Economic policies need to be consistent with the economic landscape and behavior of the concerned country. Delgado *et al.* (2014) have highlighted the fact that performance varies across regions in the USA, which has also been observed in this study, namely, in an emerging economy. Therefore, policy implications may be similar to developed economies.

Policies should encourage the strengthening of the microeconomic environment and help the development of complementarities between specialized co-located industries. In light of the results, the allocation of grants, development of institutions and subsiding of specific skills and training should be oriented toward industries that have comparative advantages. These policies would be more efficient than targeting high-tech industries that do not benefit from such advantages. By strengthening the microeconomic environment around such industries, competitive advantages may be sustained and the prosperity of the different regions can be increased and brought to higher levels. It is also important to note that these policy recommendations do not overshadows the importance of macroeconomic policies, but it highlights the role of the microeconomic environment in the development of prosperity in emerging economies.

## Note

1. Growth rates were computed using the following formula $(x_f - x_i)/x_i$.

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