THE IMPACT OF AGGLOMERATIVE INDUSTRIAL DYNAMIC EXTERNALITIES ON REGIONAL TECHNOLOGY GAPS: A CASE OF THE ICT INDUSTRY IN TAIWAN

Ku-Hsieh (Michael) Chen
Graduate Institute of Industrial Economics, Tamkang University, 151 Ying-Chuan Road, Tamsui 25137, Taipei County, TAIWAN.

ABSTRACT: All other things being equal, questions arise as to whether the location of firms in distinct regions will result in variations in their technology capabilities, and what the nature of the local industrial environment is that determines regional technology gaps. This study investigates these issues from a perspective of industrial agglomerative dynamic externalities, examining the roles played by three influential assertions on regional technology gaps, namely, the Marshall-Arrow-Romer (MAR), Porter and Jacobs hypotheses. The results tend to favour the contention of Porter hypothesis on the contribution of the nature of local industrial agglomeration to the production technologies of information and computer technology (ICT) firms.

1. INTRODUCTION

Over the past two decades, there has been some considerable resurgence in interest in the discussion of the phenomenon of industrial agglomeration. The attention of regional and industrial public policy has also been drawn to the successful development of so-called ‘new industrial districts’ or ‘industrial clusters’, such as the electronics industries in Silicon Valley in the US, the clothing industry in Northern Italy and the Hsin-chu Science-based Industrial Park in Taiwan. Theoretically, the agglomeration of firms would provide effects of external economic benefits. As the classic argument of Alfred Marshall (1920), the emergence and maintenance of agglomeration has at least three origins, comprising of the development of a local pool of specialized labour, the increased provision of local non-tradable specialized inputs, and the maximum flow of information and ideas (Krugman, 1991). Of these, in this era of the knowledge-based economy, the flow of information (knowledge spill-over) is particularly important.

The significant role played by knowledge spill-over has been empirically evidenced (Tsai and Yang, 1996; Adams and Jaffe, 1996) and is well-recognized and regarded as the ‘engine of growth’ in economic growth theory, from which the external effect relating to such knowledge spill-over is also distinguished as a ‘dynamic externality’ (Glaeser et al., 1992). At the aggregate level, such a mechanism leads to the knowledge accumulated by one firm having a beneficial effect for other firms without full compensation; however, since the nature of ideas and specific know-how is usually accompanied by high cost transfer, given its non-codified and tacit characteristics (see Desrochers, 2001), the diffusion of knowledge is not typically invariant to distance or geographically bounded to regions (Jaffe et al., 1993; Rosenthal and Strange, 2003). Therefore, if spatial proximity is vital for firms' access to the technology spill-overs, it is reasonable to hypothesize that the variations in the nature of local industrial environment will be the crucial dominating factor in technological capabilities of firms in different regions.

Referring to the nature of local industrial environment, Glaeser et al. (1992) embraced three competing hypotheses in relation to its impact on the stimulation of dynamic externality; i.e., the Marshall (1890)-Arrow (1962)-Romer (1986) (henceforth MAR), Porter (1990) and Jacobs (1969) hypotheses. Briefly, the MAR hypothesis stresses the contribution of local specialization and local monopoly. The Porter hypothesis favours the importance of local specialization and local competition, whilst the Jacobs hypothesis is based upon the argument that the effects of local competition and local diversification are preferable. In recent years, these three hypotheses have been adopted as the means of exploring the impacts of the local industrial environment on various elements of economic performance, such as productivity, innovativeness, cities' growth and industrial development. However, despite the studies in the literature, the relationships are invariably seen as indirect.

Henderson (2003) and Duranton and Puga (2001) argue that when knowledge spills over to firms, this is followed by the processes of sifting, fathoming, experimentation and trial. By virtue of these processes, firms' technologies are gradually accumulated and enhanced, then leading to a contribution to performance. Thus, whilst the volume, strength and speed of knowledge spill-over may not ultimately equate to achievement, it at least serves as a factor providing local firms with advantages in receiving technologies. In other words, the intensity of knowledge spill-over is associated with the technologies available to firms, which in turn directly influences firms' technological capabilities. Nonetheless, such linkage is still poorly evidenced. From a policy perspective, this issue is crucial.

Specifically, some commentators have asserted that nowadays, due to advancements in transportation and communication technologies, the 'death of distance' would render agglomeration economies obsolete; however, it is also argued that such a trend would tend to encourage, rather than discourage, geographical concentration (Desrochers, 2001). This is particularly so for innovative (ICT) industries, within which the most critical knowledge is the latest changes and specialized know-how, that usually is tacit and non-codified and not routine patterns, standardized information or public knowledge. Thus, the importance of the agglomeration effect should still be paid close attention to rather than cast away. Further, if the agglomerative effect actually exists and serves as an essential factor in firms' technologies, for different industries, there may be a variety of dependencies on the diverse nature of the local industrial environment. The identification and creation of the most suitable environment for each specific industry represent important tasks.

Accordingly, the aims of this study are twofold. Firstly, variations in firms' technological capabilities across regions need to be measured and examined. This work will be conducted by using the latest econometric technique to estimate regional technology gaps. Secondly, in addition to examining the impacts of firm- and industry-related characteristics, there is a need to determine the most effective nature of the local industrial environment, in terms of the enhancing effect on firms' technologies. This study also serves as a supplement to Battese et al. (2004) with respect to providing explanation of technology gaps from both industrial and regional perspectives for Taiwan.

The remainder of this paper is organized as follows. The basic concepts on the segmentation of economic regions are presented in Section 2, along with a description of the model specifications used to investigate the determinants of the regional technology gaps. Section 3 provides the data sources and construction of the variables, followed, in Section 4, by presentation of the empirical results. Finally some concluding remarks and policy implications are provided in Section 5.

2. MODEL SPECIFICATIONS AND MEASUREMENT ISSUES

2.1 Segmentation of Economic Regions

Despite metropolitan statistical areas (MSAs) often being regarded as one operational instrument for the segmentation of economic regions under limitations of data, it appears doubtful that the location of firms would be decided in accordance with artificial political boundaries, and indeed, identifying economic regions on the basis of factual deployment and agglomeration of economic activities would seem to be more desirable. For tackling this task, based upon the similarities between the notions of agglomeration and industrial clustering, operationally the identification of clusters could be considered as an appropriate reference material. However, given the multi-dimensional nature, it has proven extremely difficult to identify clear criteria for defining clusters. In any analysis of industrial clustering, as opposed to attempting to select an absolutely correct approach, it would be better to identify a path in keeping with the emphatic dimensions (Rosenfeld, 1997).

Conceptually, according to Jacobs and De Man (1996), three common broad definitions of clustering can be drawn from the literature, each of which emphasizes different dimensions: (i) the agglomeration of economic activities within related sectors at regional level; (ii) the gathering of production activities based on vertical production chains at industry level: and (iii) the large aggregation of connected sectors in an economy at national level. Further, Gordon and McCann (2000) also proposed three typical ideal models to define clustering based upon the nature of the structural characteristics: (i) the model of 'pure agglomeration'; (ii) the model of 'industrial-complex'; and (iii) the model of 'social-network'. In this study, in view of the major interest is in the effect of the nature of the local industrial environment, a more generalized definition would be more appropriate. Accordingly, this paper adopts the definitions of 'agglomeration of economic activities', the first category in Jacobs and De Man (1996), and 'pure agglomeration', the first type of model in Gordon and McCann (2000); thus, the segmentation of economic regions would be mainly focused on the phenomena of the raw spatial proximities of firms' location and employment activities.

Operationally, some approaches are available for identifying the segmentation of economic regions, including political territories, location quotients and mapping techniques, as well as the cluster analysis of multivariate analyses. Nevertheless, there is also no definitive rule for comparing the appropriateness of these approaches, but judging by the emphasized purposes and dimensions (Rosenfeld, 1997). Of these, essentially as a result of the advantages in concisely distinguishing agglomeration and delineating the profiles of economic regions, the cluster analysis of multivariate analyses is adopted as being consistent with the aims and objectives of this study.

Generally, a cluster analysis is a quantitative approach with a logical process which can segment observations into certain significant groups on the basis of distance (similarities) with no prior assumptions with regard to the number of groups (Johnson and Wichern, 1992). In practice, a two-stage analytical procedure is commonly adopted. In the first stage, using raw information, the Euclidean distance and Wald's minimum variance method of 'agglomerative hierarchical procedures' are adopted to repeatedly explore the most reasonable number of groupings, K, which can be judged by the 'cubic clustering criterion' (CCC) statistic based upon reliable stabilization. In the second stage, the K-means 'non-hierarchical procedure' method is then adopted to determine the appropriate members of the K clusters.

2.2 Estimation of the Regional Technology Gaps

To estimate the regional technology gaps, the idea of stochastic meta-frontier production function model recently proposed by Battese, *et al*. (2004) is introduced while briefly illustrated as follows. Briefly, consider an industry in which there are N firms located in R regions, such that there are n_r firms in region r and $\Sigma_r n_r = N$. The stochastic frontier production function model in log linear form can be expressed as:

$$y_{ir} = e^{x_{ir}\beta_r + V_{ir} - U_{ir}}, \text{ and } i = 1,2,...n_r,\ r = 1,2,...R \tag{1}$$

where y_{ir} represents output and x_{ir} represents a vector of inputs for firm i in region r, all taken in logarithmic form; β_r denotes a vector of unknown parameters for region r; V_{ir} denotes the random error term and is assumed to be *iid* $N(0, \sigma^2_{vr})$; and U_{ir} denotes the technical inefficiency of firm i in region r which is assumed to comprise of non-negative random variables truncated at zero and *iid* $N|(\mu_{ir}, \sigma^2_{ur})|$.

We know from Equation (1) that the maximum output level y'_{ir} on the respective production frontier for firm i in region r can be expressed as equation (2) whilst the meta-frontier production function model is expressed as equation (3):

$$y'_{ir} = f(x_{ir}, \beta_r) = e^{x_{ir}\beta_r} \tag{2}$$

$$y^*_{ir} = f(x_{ir}, \beta^*) = e^{x_{ir}\beta^*} \tag{3}$$

where y_{ir}^{*} represents the potential meta-frontier output level for firm i in region r; and β^{*} denotes a vector of unknown parameters for this function. Based upon the meta-frontier as an envelope curve for the respective frontiers of all regions, the following condition must be met:

$$y^{*}_{ir} \geq y'_{ir}\text{, or } x_{ir}\beta^{*} \geq x_{ir}\beta_{r} \tag{4}$$

Subsequently, the concept of Equation (3) can be further incorporated into an alternative expression of Equation (1) as shown in Equation (5):

$$\frac{y_{ir}}{e^{x_{ir}\beta^{*}+V_{ir}}} = e^{-U_{ir}} \times \frac{e^{x_{ir}\beta_{r}}}{e^{x_{ir}\beta^{*}}} \tag{5}$$

In Equation (5), the term on the left-hand side is the technical efficiency of the i^{th} firm on the basis of a meta-frontier function (TE^{*}_{ir}). The first term on the right-hand side is the technical efficiency of the i^{th} firm based upon the respective regional production frontier function (TE_{ir}). The second term on the right-hand side is just the technology gap ratio (*TGR*) targeted by this study which is measured by the potential output level for the i^{th} firm on the regional production frontier function relative to that on the meta-frontier function. Thus, it is clear that when TGR_{ir} are larger, the technology operated by firm i will be superior.

In practice, the maximum likelihood estimate β_{r}^{m} can stand for β_{r}. Furthermore, according to Battese *et al*. (2004), β^{*} can be obtained by solving the linear programming (LP) problem, Equation (6), or the quadratic programming (QP) problem, Equation (7). The standard errors for the parameters of the meta-frontier model can be obtained using the bootstrap method:

$$LP\text{: } Min\ L \equiv \sum_{i=1}^{n}\sum_{r=1}^{R}\left|x_{ir}\beta^{*} - x_{ir}\beta_{r}^{m}\right| \tag{6}$$

$$s.t.\text{: } x_{ir}\beta^{*} \geq x_{ir}\beta_{r}^{m}$$

$$QP\text{: } Min\ Q \equiv \sum_{i=1}^{n}\sum_{r=1}^{R}\left(x_{ir}\beta^{*} - x_{ir}\beta_{r}^{m}\right)^{2} \tag{7}$$

$$s.t.\text{: } x_{ir}\beta^{*} \geq x_{ir}\beta_{r}^{m}$$

2.3 Model Specifications

Intuitively, the censored (or truncated) Tobit regression can be regarded as a suitable analytical approach to the investigation of the determinants of regional technology gaps, since the *TGR* measures are restricted to non-negativity and are not greater than 1. Nevertheless, based upon methodological considerations to the consistency in logic and estimation, this study simultaneously considers an alternative approach, adopting the ‘censored least absolute deviations’ (CLAD) regression model. The non-parametric CLAD, first proposed by Powell (1984), is a generalization of the ‘least absolute deviations’ (LAD) estimator. According to Powell (1984), a censored regression model can be written as:

$$g_i = \max\left\{0, z_i'\theta + \zeta_i\right\},\ i = 1...N \tag{8}$$

where g_i and z_i represent the dependent variable and regression vector for each firm i ; and θ and ζ_i denote the unobserved desired parameter vector and error terms, respectively. Conceptually, the CLAD is set out from the notion of LAD. Suppose that g_i is some known function $m(z_i, \theta)$ of the regressor z_i and unknown parameters θ, the LAD estimator for this model will be based on the conditional median which can be defined by choosing θ_M, so that the function $(1/N)\Sigma| g_i - m(z_i, \theta)|$ is minimized at the value $\theta = \theta_M$. In the context of CLAD, the median function for g_i then takes a specific form $m(z_i, \theta) = \max\{0, z_i'\theta\}$ as the non-negativity of g_i; for which, the median of g_i is $z_i'\theta$ when $z_i'\theta > 0$, and all the medians of g_i are zero when $z_i'\theta \leq 0$. Thus, for those values of z_i with $z_i'\theta \leq 0$, there is no one-to-one relationship between the median of g_i (zero) and the value of $z_i'\theta$, implying that g_i is unrelated to θ. Hence, the LAD can be performed only for those points with $z_i'\theta \geq 0$.

Powell (1984) demonstrated the strong consistency and asymptotic normality of the CLAD estimator. Under the condition that there are sufficient sample points with $z_i'\theta > 0$, the minimization of the linear programming objective function $S(\theta)$ of the CLAD is written as:

$$S(\theta) \equiv (1/N)\sum_{i=1}^{N}\left|g_i - \max\{0, z_i'\theta\}\right| \tag{9}$$

Since the *TGRs* are between zero and one, the concept of the CLAD estimator can easily be extended to the ground $0 \leq z_i'\theta \leq 1$. In this study, CLAD is performed with the bootstrap estimates of the standard errors, as proposed by Rogers (1993), for robustness to violations of homoscedasticity. Consequently, our empirical CLAD model for explaining the causes of *TGRs* can be specified as:

$$TGR_{ir} = f(R_{ir}, F_{ir}, I_{ir}) \tag{10}$$

where the dependent variable TGR_{ir} represents the *TGR* estimates for each firm i in region r; and R_{ir} denotes a vector of regional specific characteristics which is the main determinant focused in this study. Operationally, so as to ensure that all other things are equal, and to ensure the pureness and robustness of the influences of these region-specific characteristics, the potential effects of other factors should be simultaneously considered. Thus, F_{ir} and I_{ir}, respectively representing the vectors of the firm- and industry-specific characteristics, are also incorporated into the model. All of these variables are constructed and illustrated in the next section.

3. DATA SOURCES AND VARIABLE CONSTRUCTIONS

3.1 Data Sources

The empirical data used in this study is mainly obtained from the 'Industry, Commerce and Service Census' (ICS) for the year 2001 undertaken by the Directorate-General of Budget, Accounting and Statistics in Taiwan. The ICS census, which provides detailed information on the volume or value of economic activities, such as sales or expenses and labour employment. This data enables us to construct the variables concerning the production function and the firm-, industry- and region-specific characteristics required for our empirical estimations. Furthermore, this dataset also provides information on the locations of firms at village, township and district level (sub-areas), thereby enabling us to contour the economic regions in accordance with the definition adopted in this paper. The ICT industry designated in this study is aggregated from the four-digit Standard Industrial Classification (SIC) industries, as listed in Table 1, and comprises of a total of 7,590 firms.

Table 1. ICS Census of ICT-related Industries in Taiwan, 2001

SIC	Industries	No. of firms
2548	Electronics and Semi-conductor Equipment Manufacturing	165
2611	Computer Manufacturing	157
2612	Monitor and Terminal Manufacturing	80
2613	Computer and Peripheral Equipment Manufacturing	386
2614	Electronic Parts and Components Manufacturing	584
2619	Other Computer Peripheral Equipment Manufacturing	251
2621	Wired Communication Equipment Manufacturing	275
2622	Wireless Communication Equipment Manufacturing	303
2631	Visual Electronic Product Manufacturing	22
2632	Audio Electronic Product Manufacturing	488
2639	Other Audio and Video Electronic Product Manufacturing	285
2640	Data Storage and Media Electronic Product Manufacturing	100
2710	Semi-conductor Manufacturing	532
2720	Passive Electronic Component Manufacturing	1,111
2730	Printed Circuit Board Manufacturing	677
2791	Electronic Tube Manufacturing	82
2792	Optical Instruments and Equipment Manufacturing	220
2799	Other Electronic Parts and Components Manufacturing Not Elsewhere Classified	1,872

Note: Data compiled for this study.

3.2 Variable Constructions

We begin by discussing the variables prepared for the segmentation of economic regions. Suppose that the longitude and latitude coordinates (T2-degree transverse Mercator), $L_{ijr} = (L_{ijr}^{long}, L_{ijr}^{lat})$, signifies the geographical location for firm i of industry j in region r. There are H sub-areas in region r; thus, $L_{hjr} = (L_{hjr}^{long}, L_{hjr}^{lat})$ represents the longitude and latitude coordinates for the center of sub-area h, and $h = 1, 2,\ldots, H$, whilst E_{hjr} denotes the employment level of industry j in sub-area h in region r. Given the lack of accurate information on the location of firms, in this paper L_{hjr} is used as a proxy for L_{ijr} if firm i located in sub-area h and the employment within the ICT industry in these sub-areas E_{hjr} is used to profile the labour deployment.

As to the production function variables for estimating the *TGRs* of firms, following the commonly adopted approach, in this study, the output variable y in Equation (1) is value-added, measured as the sum of operating income minus the sum of expenses on raw materials, energy and electricity. The input variables x in Equation (1) are capital inputs and labour inputs, respectively measured as the net amounts of fixed operating assets and the annual total wage bill. All of these variables are taken in natural logarithmic form.

Variables describing the firm-, industry- and region-specific characteristics also need to be constructed on the basis of the fundamental setting in Equation (10). In this paper, for the region-specific characteristics, we place the main focus on the impacts of the local industrial environment relevant, in a regional context, to the conditions encouraging or discouraging the intensity of dynamic externalities. The three measures of the local industrial environment commonly used in the literature, responding to the MAR, Porter and Jacobs hypotheses, are described as follows. Firstly, local specialization can be measured as:

$$Local\ specialization_{jr} = \frac{E_{jr} / E_r}{E_j / E} \tag{11}$$

where E_{jr} denotes the employment of industry j in region r; E_r denotes the employment of all industries in region r and $E_r \equiv \Sigma_j E_{jr}$; E_j denotes the employment of industry j in the country and $E_j \equiv \Sigma_r E_{jr}$; E signifies the employment of all industries in the country and $E \equiv \Sigma_j \Sigma_r E_{jr}$. In this paper, industry j is specific to the ICT industry. As in Glaeser *et al*. (1992), Equation (11) is designed as an indicator measuring the extent of specialization in regions relative to the random scattering of employment within the industry across regions. Subsequently, the measurement of local competition is specified as:

$$Local\ competition_{jr} = \frac{N_{jr} / E_{jr}}{N_j / E_j} \tag{12}$$

where N_{jr} denotes the number of firms of industry j in region r; N_j denotes the number of firms of industry j in the country and $N_j \equiv \Sigma_r N_{jr}$, whilst E_{jr} and E_j are the same as in Equation (11). Equation (12) is an indicator representing the extent of the competition in the different regions, measured as the number of firms per worker in industry j in region r relative to the number of firms per worker in industry j in the country. A greater value signifies fiercer competition for industry j in region r. Further, Local diversification is measured as:

$$Local\ diversification_{jr} = \frac{1}{\sum_{k \neq j}^{l} \left[E_{kr} \Big/ \left(E_r - E_{jr} \right) \right]^2} \Bigg/ \frac{1}{\sum_{k \neq j}^{l} \left[E_k \Big/ \left(E - E_j \right) \right]^2} \tag{13}$$

where E_{kr} denotes employment in industry k outside of industry j in region r and $k = 1 \ldots l$; E_k denotes employment in industry k outside of industry j in the country and $E_k \equiv \Sigma_r E_{kr}$; E_{jr}, E_r, E_j, E are all the same as in Equation (11). This indicator was defined by Combes (2000), with the construction being based upon the Hirshmann-Herfindal index (HHI). Conceptually, it is measured by the square sum of the employment share of each industry outside of industry *j* in region *r* relative to that of the country. For a given region, a larger square sum of employment share outside of industry *j* signifies that the economic activities are highly concentrated in a limited number of industries, suggesting lower diversity; thus, the inverse of the HHI measure is adopted. A larger value therefore implies a greater degree of diversification in region *r*.

Additionally, as suggested by the 'first law of geography' proposed by Tobler (1970), "everything is related to everything else, but near things are more related than distant things". In order to capture the intensity of external agglomerative effects more effectively, along with the three measures of the local industrial environment, a key factor, geographical distance, should also be further considered. Referring to Van Soest (2002), three extended distance-weighted (DW) measures of the local industrial environment are constructed to subsume the effect of inter-locational knowledge spillovers. The three prototypical measures of the local industrial environment, Equation (11), (12) and (13) are further modified as:

$$DW\ Local\ Specialization_{jr} = \frac{\sum_{i'\neq i} D_{i'i}^{-1} E_{i'jr} / \sum_{i'\neq i} D_{i'i}^{-1} E_{i'r}}{E_j / E} \tag{14}$$

$$DW\ Local\ competition_{jr} = \frac{\sum_{i'\neq i} D_{i'i}^{-1} N_{i'jr} / \sum_{i'\neq i} D_{i'i}^{-1} E_{i'jr}}{N_j / E_j} \tag{15}$$

$$DW\ Local\ diversification_{jr}$$

$$= \frac{1 \Big/ \sum_{k\neq j}^{l} \left[\sum_{i'\neq i} D_{i'i}^{-1} E_{i'kr} \Big/ \left(\sum_{i'\neq i} D_{i'i}^{-1} E_{i'r} - \sum_{i'\neq i} D_{i'i}^{-1} E_{i'jr} \right) \right]^2}{1 \Big/ \sum_{k\neq j}^{l} \left[E_k \Big/ \left(E - E_j \right) \right]^2} \tag{16}$$

where *i* denotes the i^{th} firm and *i'* denotes firms other than firm *i*; $D_{i'i}$ represents the distance-weighted variable matrix calculated by the Euclidean distance between the locations of firms *i'* and *i*, and *i'*, $i \in h$. All of the other variables and notations are the same as in Equations (11) to (13). Furthermore, five variables of relevance to the firm-specific characteristics are also considered; namely, *Size*, *Age*, *RDR*, *Export* and *Subcontract.*

For the *Size* variable, representing firm size, we adopt the critical scale of 200 employees as the threshold to categorize firms into large enterprises (LEs) or small and medium enterprises (SMEs). Cohen and Klepper (1992) discussed the influence of firms scale on technology and suggested that to LEs, the advantages in production, financial resources and market share provide the sufficient conditions and incentives to innovate. Nevertheless, the even greater adjusted costs involved in adopting radically new technologies gives rise to an effect similar to adhesion, which would, to some extent, limit the scope of the technologies adopted by LEs to the extension of their customary technological trajectory. Conversely, whilst the resources for use in innovation and internal scale economies in production are relatively scarce for SMEs, their inherent characteristics of nimbleness, flexibility and lower adjusted costs in facing changes and challenges in the market create advantages for them to adopt new technologies, or to successively improve on their existing technologies, in order to compete effectively with other market players.

The *Age* variable denotes the operating age of the firm, measured as the sum of the value of 2001 minus the starting year of the firm, plus the ratio of 12 minus the starting month to 12. This variable represents the effect of operational experience or inertia in the adoption of technologies by individual firms. As the learning effect posited by Jovanovic (1982), abundant operational experience helps older firms to grasp the available advantages through improvements in, and the selection of, the requisite technologies. On the other hand, however, inertia in the adoption of technologies would be a weakness for older firms. Indeed, in recent years, the entrepreneurship literature has emphasized the relative capabilities of younger firms in absorbing and ameliorating technologies.

Further, the three variables *RDR*, *Export* and *Subcontract* are incorporated to control for the other possible sources of acquisition of technologies by individual firms. *RDR* signifies the intensity of a firm's research and development (R&D) activity, measured as the ratio of R&D and expenditure on technology to sales. *Export* denotes the exporting intensity of a firm and is defined as the share of exporting sales to total sales. *Subcontract* is also included to capture the impact of subcontracting activity, measured as the ratio of subcontracting revenue to sales.

As for the industry-specific characteristics, the potential influences of two variables, namely *MES* and *Profitability*, are controlled at the four-digit industry level. The 'minimum efficiency scale' is indicated by the *MES* variable, measured as the ratio of the average size of the largest fifty percentile of firms to the average size of all firms, in terms of employee numbers. This variable is used to capture the degree of barriers to entry, with a higher *MES* indicating that the industrial environment is such that it is more difficult for potential entrants, which may enable incumbents to pay less attention to improving their current technologies. The *Profitability* variable represents the average profitability of the four-digit industry to which the firms belong. Two possible influences may exist here. A higher *Profitability* could provide a slack market condition for an industry, which would moderate the incentives for firms to improve technologies, or indeed, loosen the financial constraints.

4. EMPIRICAL RESULTS

4.1 Economic Regions of the ICT Industry in Taiwan

The two-stage method of cluster analysis is adopted to identify the economic regions of the ICT industry in Taiwan. In the first stage, the CCC, computed by the SAS statistics software, is used to determine the optimal number of regions K; the numerical results are presented in Table A1 and Figure A1 in the Appendix, with three economic regions clearly being suggested by CCC. In the second stage, the *K*-means method is conducted to determine the members (sub-areas) of the three economic regions; these results are presented in Table 2.

Table 2. The ICT Industry Distribution in Taiwan

Northern Region		Central Region	
Taipei City	**Miaoli County**	**Taichung City**	**Yunlin County**
Shihlin District	Jhunan Township	North District	Dabi Township
Datong District	Nanjhuang Township	Beitun District	Yuanchang Township
Daan District	Toufen Township	West District	Douliou City
Jhongshan District	**Taoyuan County**	Situn District	Dounan Township
Jhongjheng District	Bade City	East District	Shueilin Township
Neihu District	Dayuan Township	South District	Beigang Township
Wunshan District	Dasi Township	Nantun District	Sihhu Township
Beitou District	Jhongli City	**Taichung County**	Siluo Township
Songshan District	Pingjhen City	Dajia Township	Huwei Township
Sinyi District	Taoyuan City	Daan Township	Lunbei Township
Nangang District	Fusing Township	Dadu Township	Cihtong Township
Wanhua District	Sinwu Township	Dali City	**Chiayi City**
Taipei County	Yangmei Township	Daya Township	West District
Bali Township	Longtan Township	Taiping City	East District
Sanjhih Township	Gueishan Township	Waipu Township	**Chiayi Country**
Sanchong City	Lujhu Township	Shihgang Township	Jhongpu Township
Sansia Township	Guanyin Township	Houli Township	Taibao City
Tucheng City	**Keelung City**	Shalu Township	Shueishang Township
Jhonghe City	Cidu District	Dongshih Township	Minsyong Township
Wugu Township	Jhongshan District	Wurih Township	Puzih City
Yonghe City	Jhongjheng District	Shengang Township	Meishan Township
Sijhih City	Renai District	Wuci Township	Singang Township
Linkou Township	Anle District	Cingshuei Township	**Changhua County**
Banciao City	Sinyi District	Sinshe Township	Erlin Township
Jinshan Township	Nuannuan District	Tanzih Township	Dacun Township
Taishan Township	**Hsinchu City**	Longjing Township	Yongjing Township
Danshuei Township	North District	Fongyuan City	Tianwei Township
Shenkeng Township	East District	Wufong Township	Shengang Township
Sindian City	Siangshan District	**Hualien County**	Sioushuei Township
Sinjhuang City	**Hsinchu County**	Hualien City	Hemei Township
Rueifang Township	Beipu Township	**Nantou County**	Shetou Township
Shulin City	Jhubei City	Mingjian Township	Fangyuan Township
Shuangsi Township	Jhudong Township	Nantou City	Huatan Township
Lujhou City	Cyonglin Township	Puli Township	Fenyuan Township
Yingge Township	Hukou Township	Caotun Township	Yuanlin Township
Yilan County	Sinpu Township	**Miaoli County**	Pusin Township
Sansing Township	Sinfong Township	Dahu Township	Puyan Township
Wujie Township	Hengshan Township	Gongguan Township	Bitou Township
Dongshan Township	Guansi Township	Sihu Township	Lugang Township
Jhuangwei Township	Baoshan Township	Houlong Township	Sijhou Township
Yilan City		Miaoli City	Sihu Township
Yuanshan Township		Yuanli Township	Changhua City
Toucheng Township		Tongsiao Township	Fusing Township
Jiaosi Township		Tongluo Township	Siansi Township
Luodong Township		Touwu Township	
Suao Township			

Table 2 (continued)

Southern Region			
Taitung County	**Tainan County**	**Pingtung County**	**Kaohsiung County**
Taitung City	Cigu Township	Jiouru Township	Dashe Township
Tainan City	Siaying Township	Neipu Township	Daliao Township
North District	Shanshang Township	Jhutian Township	Dashu Township
Anping District	Rende Township	Jiadong Township	Renwu Township
Annan District	Yongkang City	Fangliao Township	Yongan Township
West District	Anding Township	Donggang Township	Gangshan Township
East District	Sigang Township	Changjhih Township	Linyuan Township
South District	Jiali Township	Pingtung City	Alian Township
Central District	Guantian Township	Kanding Township	Meinong Township
	Houbi Township	Wandan Township	Jiading Township
	Liouying Township	Wanluan Township	Zihguan Township
	Madou Township	Chaojhou Township	Niaosong Township
	Shanhua Township	**Kaohsiung City**	Hunei Township
	Sinhua Township	Sanmin District	Lujhu Township
	Sinshih Township	Siaogang District	Cishan Township
	Sinying City	Zuoying District	Fongshan City
	Gueiren Township	Cianjin District	Ciaotou Township
	Guanmiao Township	Cianjhen District	Yanchao Township
		Lingya District	**Chiayi County**
		Sinsing District	Lucao Township
		Nanzih District	
		Gushan District	

Note: Data compiled for this study.

We can see from Table 2 that with the omission of 130 sub-areas with no ICT firms, a total of 229 sub-areas are subsumed into the three economic regions; 80 sub-areas in the Northern region, 82 sub-areas in the Central region and 66 sub-areas in the Southern Region. Interestingly, such segmentation is similar to the three megalopolitan regions which emerged from the National Land Use Plan produced by the Council for Economic Planning and Development at the Executive Yuan in Taiwan. The basic descriptive statistics of the three regions are presented in Table 3.

Whether in terms of area, the number of firms or employment in the ICT and non-ICT industries, it is clear that the Northern region is the largest, with the Central region being the second largest (with the one exception that it has the smallest employment level in the overall ICT industry). The number of firms and employment divided by area is calculated to represent the average density and employment level of firms. As Table 3 shows, within the ICT industry, these two measures are at their highest in the Northern region and at their lowest in the Central region. In the non-ICT industries, these two measures are also at their highest in the Northern region; however, the density of firms is higher in the Central region than in the Southern region, whilst the density of employment is higher in the Southern region than in the Central region. Intuitively, from a perspective of agglomeration, we may presume that the relative prosperity and dense economic activities in the Northern region may prove to be a more substantial external effect for firms in that region, although the effects in the Central and Southern regions are somewhat ambiguous.

Table 3. Basic descriptive statistics, by northern, central and southern regions

Items \ Regions	Northern Region	Central Region	Southern Region
Square Measure km^2 [1]	4,510.85	4,479.41	2,787.25
ICT industry			
Number of Firms [2]	6,088	807	695
Number of Employment [3]	424,906	34,057	62,283
Average Density of Firms [2]/[1]	1.35	0.18	0.25
Average Density of Employment [3]/[1]	94.20	7.60	22.35
Non-ICT industry			
Number of Firms [4]	66,663	53,375	27,210
Number of Employment [5]	1,235,022	675,658	527,453
Average Density of Firms [4]/[1]	14.78	11.92	9.76
Average Density of Employment [5]/[1]	273.79	150.84	189.24
Number of Sub-Areas	80	82	66

Note: Data compiled for this study.

4.2 TGRs of ICT Firms across Regions

In this sub-section, we discuss the measures of the *TGRs* of firms, beginning with the estimation of the stochastic production frontier models for the firms in the three regions. Table 4 reports the basic summary statistics of the output and inputs variables, from which we can see that the means and standard deviations of these variables in the different regions seem heteroscedastic. When we divide capital inputs by labour inputs, it will be found that the capital labour ratios are distinct for the different regions. Further, given the output level, it will be revealed that firms in the Northern region use more capital; however, firms in the Central region use more labour. Overall, Table 4 seems to suggest the dissimilar structures of production activities across the different regions.

Table 4. Summary statistics on ICT industry firms in Taiwan

	Northern Region	Central Region	Southern Region
Number of Observations	6,088	807	695
Output (NT thousand)			
Mean	125,032.94	42,055.30	95,970.93
Standard Deviation	1,326,967.15	307,557.62	538,974.75
Capital (NT thousand)			
Mean	289,626.58	96,415.52	70,787.48
Standard Deviation	3,964,109.40	878,057.23	767,910.36
Labour			
Mean	69.79	42.20	89.62
Standard Deviation	370.29	280.50	392.32

Note: Data compiled for this study.

Table 5. Maximum-likelihood estimates of the stochastic frontier models

Variables	Northern Region					Central Region			
	Coef.		Std. Err.	t value		Coef.		Std. Err.	t value
Constant	1.293	***	0.156	8.305		1.438	***	0.350	4.115
Capital	0.199	***	0.045	4.457		-0.123		0.094	-1.305
Labor	0.699	***	0.047	14.933		1.032	***	0.109	9.467
$Capital^2$	0.079	***	0.010	7.771		0.090	***	0.016	5.505
$Labor^2$	0.101	***	0.011	9.569		0.041	**	0.021	1.911
Capital x Labor	-0.165	***	0.019	-8.939		-0.123	***	0.029	-4.244
$Sigma^2$	0.847	***	0.022	37.735		0.719	***	0.049	14.727
Garma	0.821	***	0.010	81.424		0.882	***	0.017	52.131
Number of Observations	6,088					807			
Likelihood Ratio [$\chi 2(0.01, 5)=15.09$][b]	-5757.3122***					-643.9182***			

Variables	Southern Region					All firms[a]			
	Coef.		Std. Err.	t value		Coef.		Std. Err.	t value
Constant	1.407	***	0.380	3.707		1.287	***	0.132	9.759
Capital	0.246	***	0.112	2.191		0.153	***	0.037	4.125
Labor	0.637	***	0.136	4.679		0.754	***	0.041	18.615
$Capital^2$	0.078	***	0.029	2.704		0.080	***	0.008	9.696
$Labor^2$	0.123	***	0.033	3.664		0.092	***	0.009	10.312
Capital x Labor	-0.185	***	0.055	-3.360		-0.159	***	0.015	-10.537
$Sigma^2$	0.926	***	0.067	13.786		0.841	***	0.020	41.973
Garma	0.862	***	0.022	39.150		0.826	***	0.009	95.914
Number of Observations	695					7,590			
Likelihood Ratio [$\chi 2(0.01, 5)=15.09$][b]	-659.9139***					-7112.8421***			
Likelihood Ratio [$\chi 2(0.01,18)=34.81$][c]	103.3960***								

Notes:
***, ** and * denote coefficient significant at 1%, 5% and 10%, respectively.
a: All firms are used to estimate the stochastic frontier regardless of the segmentation of the economic regions.
b: Likelihood ratio test; H0: all the $\beta = 0$; H1: at least one of the β is not 0.
c: Likelihood ratio test; H0: the frontiers of firms in all regions are identical; H1: the frontiers of firms in different regions are distinct. The LR statistic is defined by $\lambda=-2\{\ln[L(H0)]-\ln[L(H1)]\}$. Where ln[L(H0)] is the value of the log likelihood function for the frontier estimated by pooling all the firms, while ln[L(H1)] is the sum of the values of the log likelihood functions for the three regional frontiers.

The maximum likelihood estimates for the stochastic frontiers of the firms in the three regions are then obtained using the Frontier 4.1 program (Coelli, 1996). The translog production function is adopted as the stochastic production frontier model and the results are presented in Table 5. Most of the coefficients reveal statistical significance at least at the 10 percent level. The question of whether firms in the different regions actually operate under different technology frontiers is of particular relevance at this stage. If the firms' frontiers were identical across regions, which imply identical technology, it would be extremely unreasonable to estimate the *TGRs* across the different regions; a likelihood-ratio (LR) test is therefore necessary to deal with this issue, and as we can see from Table 5, the LR statistic 103.3960 is significant at the 1 percent level. Such a result strongly infers that the stochastic frontiers for the ICT firms in the Northern, Central and Southern regions do indeed differ, as expected, and that they should therefore be estimated separately.

The meta-frontier production function is further estimated according to Equations (6) and (7) using the GAUSS programming language. The bootstrap method is also used to calculate the standard deviations as the standard errors for the meta-frontier estimators under a 5,000 re-sampling process; the results are shown in Table 6 with the LP and QP estimates respectively presented in Panels A and B. From Table 6, we can see that the differences between the LP and QP parameters are small.

Table 6. Meta-frontier production function estimates

Panel A: Linear Programming (LP) Estimates				
Variables	Metafrontier [a] Coefficients	Bootstrapping Approach [b] Mean	Std. Dev.	Skewness
Constant	1.6300	1.8212	0.2756	0.5768
Capital	0.0739	0.0551	0.0726	-0.1545
Labor	0.7764	0.7537	0.0808	-0.4562
Capital^2	0.1085	0.1195	0.0178	0.3681
Labor^2	0.1193	0.1339	0.0220	0.5826
Capital x Labour	-0.2091	-0.2299	0.0366	-0.4582
Panel B: Quadratic Programming (QP) Estimates				
Variables	Metafrontier [a] Coefficients	Bootstrapping Approach [b] Mean	Std. Dev.	Skewness
Constant	1.6507	1.8091	0.2615	0.4926
Capital	0.0748	0.0637	0.0689	-0.1832
Labor	0.7717	0.7466	0.0781	-0.4049
Capital^2	0.1052	0.1147	0.0167	0.3220
Labor^2	0.1159	0.1298	0.0205	0.7898
Capital x Labour	-0.2021	-0.2210	0.0330	-0.5195

Notes:
a: The meta-frontier production model estimates are obtained using LP and QP.
b: The standard errors of the parameters are obtained using the bootstrap method with 5,000 re-sampling process.

We now have the necessary parameters for calculating the *TGRs*, with the values for the firms in the three regions being computed according to the basic setting in Equation (5). The basic summary statistics are shown in Table 7 where the respective LP and QP estimates are presented in Panels A and B. Using the results of LP for the purpose of discussion (the results obtained by QP are very similar), the means of the *TGRs* vary across regions, from 0.8667 in the Central region to 0.9754 in the Northern region. Such values imply that, given the technology available to the industry as a whole, firms in the Central region produce about 86.67 percent of their potential output, whilst those in the Northern region produce about 95.74 percent of their potential output. Furthermore, the maximum values of the *TGRs* show that in all regions, the respective production frontiers are tangential to the meta-frontier. The frequency distributions for the *TGR* estimates are provided in Figure A2 in the Appendix.

Table 7. Summary statistics of TGRs and technical efficiency of ICT firm

Panel A: *Linear Programming (LP) Estimates*				
Regions/Statistics	Mean	Minimum	Maximum	Std. Dev.
Northern Region				
Technology Gap Ratio	0.9754	0.7861	1.0000	0.0251
Regional TE	0.5838	0.0075	1.0000	0.1670
Metafrontier TE*	0.5693	0.0071	0.9797	0.1634
Central Region				
Technology Gap Ratio	0.8667	0.5347	1.0000	0.0809
Regional TE	0.6055	0.0082	0.9311	0.1727
Metafrontier TE*	0.5253	0.0072	0.8537	0.1604
Southern Region				
Technology Gap Ratio	0.9475	0.6073	1.0000	0.0434
Regional TE	0.5691	0.0400	0.9383	0.1838
Metafrontier TE*	0.5393	0.0381	0.8927	0.1760

Panel B: *Quadratic Programming (QP) Estimates*				
Region / Statistic	Mean	Minimum	Maximum	Std. Dev.
Northern Region				
Technology Gap Ratio	0.9746	0.7875	1.0000	0.0254
Regional TE	0.5838	0.0075	1.0000	0.1670
Metafrontier TE*	0.5689	0.0071	0.9772	0.1631
Central Region				
Technology Gap Ratio	0.8661	0.5525	1.0000	0.0774
Regional TE	0.6055	0.0082	0.9311	0.1727
Metafrontier TE*	0.5249	0.0072	0.8517	0.1594
Southern Region				
Technology Gap Ratio	0.9462	0.6078	1.0000	0.0427
Regional TE	0.5691	0.0400	0.9383	0.1838
Metafrontier TE*	0.5385	0.0380	0.8889	0.1756

4.3 Determinants of the TGRs of Firms across Regions

In this sub-section, we present the empirical results of the determinants of *TGRs* (calculated under the LP approach), in accordance with the basic specification of Equation (10). The two sets of estimates obtained using the Tobit and CLAD regression models are reported in Tables 8 and 9 respectively. The results of regressions (I) to (IV) of the Tobit model (Table 8) are discussed first.

Table 8. Tobit regression estimates of the determinants of TGRs[a]

Variables	Tobit regression [b]			
	(I)	(II)	(III)	(IV)
Constant	0.95634 ***	0.95687 ***	0.95634 ***	0.95687 ***
	(0.00076)	(0.00326)	(0.00076)	(0.00326)
Local- specialization	0.00356 ***	0.00353 ***		
	(0.00016)	(0.00016)		
Local- competition	0.03877 ***	0.03836 ***		
	(0.00196)	(0.00196)		
Local- diversification	-0.14938 ***	-0.14782 ***		
	(0.00736)	(0.00736)		
DW local- specialization			0.00151 ***	0.00150 ***
			(0.00008)	(0.00008)
DW local- competition			0.01411 ***	0.01390 ***
			(0.00092)	(0.00092)
DW local- diversification			-0.05627 ***	-0.05548 ***
			(0.00340)	(0.00341)
Size		-0.01333 ***		-0.01333 ***
		(0.00221)		(0.00221)
Age		0.00021 ***		0.00021 ***
		(0.00007)		(0.00007)
RDR		0.01425 **		0.01425 **
		(0.00587)		(0.00587)
Export		0.01254 ***		0.01254 ***
		(0.00178)		(0.00178)
Subcontract		-0.00028		-0.00028
		(0.00136)		(0.00136)
MES		-0.00098 *		-0.00098 *
		(0.00059)		(0.00059)
Profitability		-0.00013		-0.00013
		(0.00020)		(0.00020)
No. of observations	7590	7590	7,590	7,590
Pseudo R^2	-0.0827	-0.08670	-0.0827	-0.0867
Likelihood Ratio	12934.55 ***	12982.66 ***	12934.55 ***	12982.66 ***

Notes: ***, ** and * denote coefficient significant at 1%, 5% and 10%, respectively.
a: The TGRs are obtained by using the linear programming approach (the estimated results obtained under the quadratic programming approach are similar).
b: Figures in parentheses are standard errors.

In regression (I), only the region-specific characteristics are incorporated as the explanatory variables, with no consideration of any other control variables. The estimated parameters of the local industrial environment indicators clearly reveal that both local specialization and local competition are positively correlated to *TGRs*, whilst local diversification is negatively correlated to *TGRs* and statistically significant at the 1 percent level. In contrast to regression (I), the empirical results obtained from regression (II) simultaneously consider all of the firm-, industry- and region-specific characteristics. We can see from regression (II) that the local industrial environment coefficients vary only slightly, with the signs and statistical significance remaining unchanged.

Regression (III) provides the estimations of the DW local industrial environment indicators, but as in regression (I), only the region-specific characteristics are considered. The estimated parameters of the DW local specialization and DW local competition indicators demonstrate significant positive contributions to the *TGRs* of firms across regions, whereas the DW local diversification indicator reveals a notable negative impact. Regression (IV) again jointly incorporates all of the variables, with the coefficients of the three DW indicators also varying only slightly relative to regression (III). The implication is therefore that, essentially as a result of the significantly positive contributions of local specialization and local competition, the Tobit regression appears to favor the Porter hypothesis.

The results of the CLAD model are presented in Table 9 as regressions (V) to (VIII). Firstly, regression (V) provides the estimated parameters of the three local industrial environment indicators with no consideration of the control variables. From these results, which are statistically significant at the 1 percent level, we can see that local specialization and local competition have positive influences on *TGRs*, whereas local diversification has a negative effect. In contrast to regression (V), regression (VI) presents the estimations when simultaneously considering all of the other control variables, from which we can see that the coefficients of the three local industrial environment indicators are very similar to those in regression (V).

As regards the estimation results of the DW local industrial environment indicators in regression (VII) and (VIII), it is quite clear that the coefficients of the two regressions are quite similar. The DW local specialization and DW local competition indicators again reveal positive effects on the *TGRs* of firms across regions, whilst the DW local diversification indicator again reveals a negative effect. It is manifested that the CLAD regression again tends to provide support for the Porter hypothesis. Moreover, we can also learn from Table 8 that the signs of the (DW) indicators estimated under the Tobit maximum likelihood method are indeed similar to those estimated under the CLAD approach, irrespective of whether the control variables are considered. Accordingly, Table 8 also suggests that the signs of the impacts of these indicators are robust to the model specifications.

We now go on to check the influences of the firm- and industry-specific characteristics, and indeed, we find that the estimated results under the Tobit and CLAD models are different. The variables in the Tobit model (Table 8), including *Size*, *Age*, *RDR*, *Export* and *MES* are significant at least at the 10 percent level; however, in the CLAD model (Table 9), only *Size* and *Export* reveal statistical significances, whilst *RDR* is only significant at the 10 percent level in regression (VI), but insignificant in regression (VIII). Thus, we have two noteworthy and relatively unambiguous results.

Table 9. Tobit regression estimates of the determinants of TGRs[a]

Variables	CLAD regression [b]			
	(V)	(VI)	(VII)	(VIII)
Constant	0.97450 ***	0.97514 ***	0.97450 ***	0.97514 ***
	(0.00102)	(0.00260)	(0.00066)	(0.00219)
Local- specialization	0.00485 ***	0.00483 ***		
	(0.00095)	(0.00146)		
Local- competition	0.05461 ***	0.05440 ***		
	(0.01089)	(0.01703)		
Local- diversification	-0.20890 ***	-0.20801 ***		
	(0.04130)	(0.06430)		
DW local- specialization			0.00021 ***	0.00210 ***
			(0.00028)	(0.00034)
DW local- competition			0.02187 ***	0.02187 ***
			(0.00313)	(0.00387)
DW local- diversification			-0.08493 ***	-0.08480 ***
			(0.01181)	(0.01460)
Size		-0.00602 ***		-0.00602 ***
		(0.00182)		(0.00189)
Age		-0.00007		-0.00007
		(0.00005)		(0.00005)
RDR		0.00765 *		0.00765
		(0.00458)		(0.00562)
Export		0.00910 ***		0.00910 ***
		(0.00117)		(0.00159)
Subcontract		-0.00140		-0.00140
		(0.00092)		(0.00113)
MES		-0.00025		-0.00025
		(0.00039)		(0.00037)
Profitability		0.00020		0.00020
		(0.00020)		(0.00021)
No. of observations	7590	7590	7590	7590
Pseudo R^2	0.02990	0.12240	-0.45390	0.12240
Likelihood Ratio				

Notes: ***, ** and * denote coefficient significant at 1%, 5% and 10%, respectively.
a: The TGRs are obtained by using the linear programming approach (the estimated results obtained under the quadratic programming approach are similar).
b: Figures in parentheses are standard errors.

Firstly, the negative effects of firm size on the *TGRs* are consistently revealed in regressions (II), (IV), (VI) and (VIII). To some extent, this implies that to an industry with a rapidly-changing business environment and rapidly-changing technologies, such as the ICT industry, flexibility and nimbleness are essential to the adoption of production technologies. Such firms would rather seek out a suitable scale than monotonously pursue the inordinate growth of their firm size.

Secondly, the *Export* variable also provides a significant positive contribution to *TGRs*, which also confirm the importance of export activity in channelling foreign technologies and know-how for those firms in the ICT industry.

5. CONCLUSIONS AND POLICY IMPLICATIONS

All other things being equal, with the local industrial environments which are heterogeneous in nature, the question arises as to whether the differences in the locations of firms in distinct regions will result in different levels of achievement. If the answer is positive, the critical role of the nature of the local industrial environment is a matter of course. The main interest of this study is the dimension of the production technologies operated by firms; we nevertheless also attempt to explain the nature of the local industrial environment that may be beneficial to firms' technologies. Consequently, our empirical study favours the contributions of local specialization and local competition, consistent with the Porter hypothesis.

As for why local specialization and local competition would facilitate knowledge spill-over and then be conducive to firms' technological level in a region. First, local specialization implies the gathering of technical and research staff who are equipped with similar knowledge and research backgrounds within a specific industry. As indicated in Glaeser et al. (1992), through the behaviour of spying, imitation and reverse engineering, as well as gossip and the movement of skilled labour across firms, technological barriers may be broken through quite accidentally. Thus, in a local specialized industrial environment, key ideas could be adopted and diffused more easily and rapidly across neighbouring firms to serve as the basis of further technological improvements (Glaeser et al., 1992). On the other hand, Porter (1990) had indicated that a business environment with ruthless local competition would serve as a driving force for firms to rapidly absorb knowledge and strive to continuously enhance their technological capabilities. Firms have no choice but to mutually refer, study, learn and rapidly trace the new knowledge created by others. The proceeding actions are necessary in order to improve the firm's own technologies, ensure their market niche and to avoid being displaced from the market. Fierce competition pushes forward the process of creative destruction (Schumpeter, 1934) which invariably spurs firms to improve. The alternative is to cease to exist.

Based on this empirical work, this study concludes that a policy initiative toward achieving a local industrial environment condition with local specialization and local competition would serve as a beneficiary blueprint for a productive economic region, within which production knowledge could interact most frequently among firms. For high-tech industries, such as the ICT industry, it is suggested that if they are to rival all other firms throughout the world, especially those firms at the global cutting edge of technologies, then there is a requirement for trans-administrative boundaries capable of incubating an environment with adequate physical and intangible channels, platforms for communicating professional ideas and specific know-how, and reasonable stimulants and incentives to encourage technological improvements.

With particular emphasis on certain developing economies, such as that of

Taiwan, economic growth has, for quite some time, been largely sustained by their subcontracting activities. However, the recent emergence of mainland China, as well as a number of Southeast Asian countries, all of which are equipped with labour cost advantages, actually poses a serious threat, and simultaneously raises a challenge to the phenomenon of 'industry emigration'. The type of strategy which would be a prerequisite to a policy of 'rooted in Taiwan' would comprise of inspiring advantages in technological capabilities in order to make up for the loss of labour cost competitiveness, along with the need to catch up with the production quality and technology levels of the advanced industrialized nations.

Additionally, with regard to Taiwanese technological development, one important concept also worthy of concern is the local effect of lack of globalization exposure due to the conflicts with mainland China. Taiwan's current economy is transforming from an investment-driven phase to an innovation driven phase, the foreign linkage is very critical. As stressed in productivity studies literature (e.g.: Chen and Shu, 2000, or Aw and Betra, 1998), the international trade and technological interflow are factors that predominate not only the scope of market, but also the tempo, level and source of technological development. Indeed, in recent years, the political constraints mandated by Mainland China in the global arena have created a blockade in Taiwan's global linkage. A significant case can be seen in China's actions curtailing Taiwan in its bid to join the Association of Southeast Asia Nations (ASEAN) or China's actions of obstructing Taiwan's proposals to establish free trade areas (FTA) with other countries (such as Singapore, Japan and US). The impact of this political dilemma on technological development should be better incorporates into the development policies of Taiwan.

There are two limitations to this study worth noting. Firstly, the policy implications as noted above should be treated with caution, since this study was aimed at an industry characterized by a rapidly-changing business environment and rapidly-changing technologies. For other industries, such as the manufacturing, finance, commerce, and service and retail industries, it remains to be seen whether the same conclusions could be drawn. In other words, it may be quite interesting to examine whether, in industries other than the ICT industry, the MAR or Jacobs hypotheses might hold sway over the Porter hypothesis. Further empirical works will be necessary in order to complete the whole picture on this theme. Secondly, in this study, the segmentation of economic regions was based mainly upon the concept of 'pure agglomeration'; however, there are also clearly other perspectives and approaches to the identification of economic regions. Given the multi-dimensional characteristics of this topic, each and every methodology adopted in future studies dealing with this particular theme should prove to be of significant interest.

Furthermore, in this empirical study, it is acknowledged that there are some potential concerns that could influence the significance of the results. First, in this paper, the Taiwan's ICT industry is segmented into three regions: the Northern region, the Central region and the Southern region, which are mainly based on the actual deployment of labour and firms, and information inherently embedded in the dataset. Nonetheless, for a long time, the industrial and employment dynamics of ICTs and other sectors in Taiwan are much more developed in the west-coast than in the east-coast, due to the difference in natural geographical conditions, public policies and historical factors. The potential effect of industrial disparity between the west-coast and the east-coast is not taken into account in the empirical work. This would be an important differentiation for policy purposes and worthy of consideration in future studies.

Second, this study is static in nature and does not analyze the potential impact of urban dynamics. Indeed, urban dynamics dominate the pattern of a city's development, which has influence on the locations and high technology absorption of firms. In the Northern region, Taipei is not only the capital, but also the most key financial position of Taiwan. Wherein, the co-location of the financial services firms implies the accessibility of financial support that could explain the high concentration of ICT firms and their greater technological orientation, especially regarding the high-tech corridor or the ICT knowledge precinct around the Taipei 101 tower. Relatively speaking, the Central and Southern regions of Taiwan have a higher concentration of manufacturing firms which could impact the businesses conducted being of lower knowledge intensity and which may be more oriented to personal computing services for low intensity firms requiring more deployment of labour. Thus, the role of urban dynamics in the economic regions represents another critical factor for determining the technological capability in a region which is also ill-considered in this empirical work.

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APPENDIX TABLES

Table A.1. Cubic clustering criterion and number of regions

No. of Clusters	CCC	No. of Clusters	CCC	No. of Clusters	CCC	No. of Clusters	CCC
-	-	11	9.8697	21	11.2495	31	12.0577
2	-2.4458	12	10.0126	22	11.3363	32	12.1347
3	**5.6687**	13	10.2613	23	11.3981	33	12.1802
4	4.7748	14	10.4058	24	11.4055	34	12.2009
5	6.7126	15	10.7362	25	11.4169	35	12.2407
6	7.8806	16	11.0703	26	11.4708	36	12.3054
7	8.3733	17	11.1752	27	11.5657	37	12.2785
8	9.9175	18	11.1872	28	11.7100	38	12.1619
9	10.2279	19	11.1513	29	11.8964	39	11.9471
10	9.8933	20	11.2067	30	11.9591	-	-

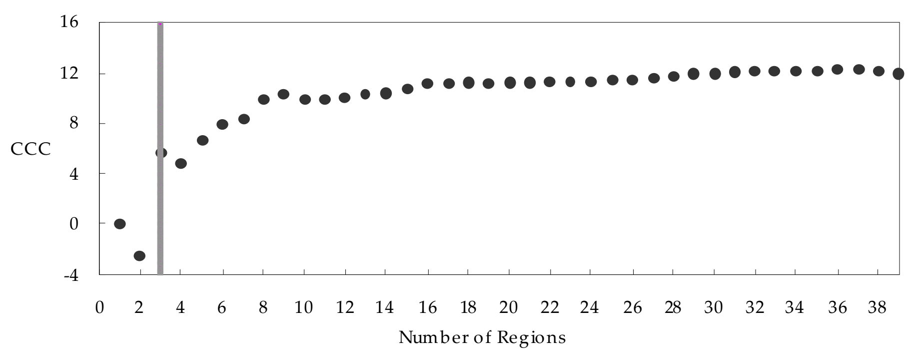

Figure A.1. Cubic Clustering Criterion

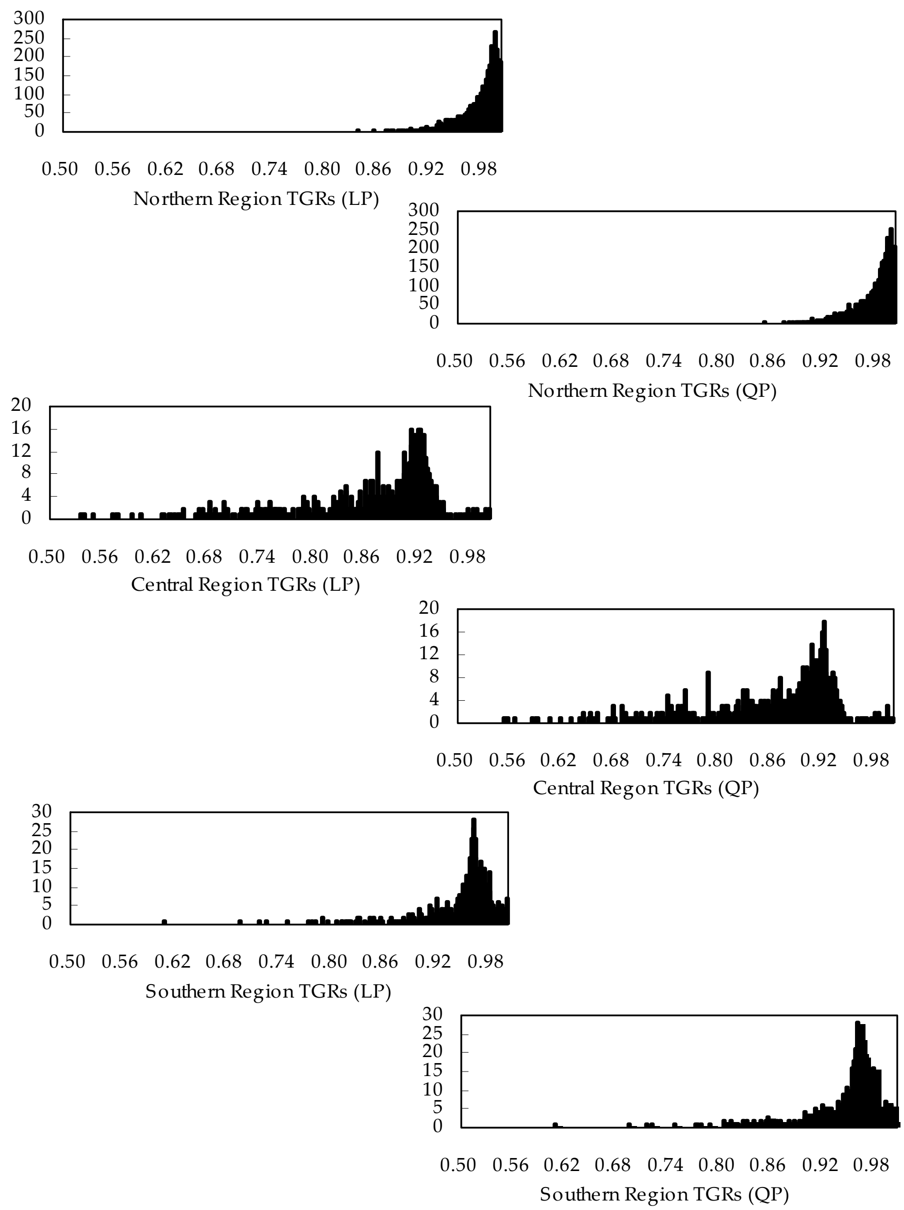

Figure A.2 Frequency Distributions of TGRs for ICT firms in different regions of Taiwan