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The impact of science parks on small- and medium-sized enterprises' productivity distributions: the case of Taiwan and South Korea

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Abstract In this article, the effectiveness of policy creating science parks is evaluated with respect to small- and medium-sized enterprises (SMEs). Science parks created to support innovation and regional growth often target productivity gains through agglomeration economies. However, spatial proximity of firms may also stimulate selection, less competitive firms being forced to exit, a cluster of high-productivity, surviving firms being observed at the regional level. Empirical studies also show that high- or low-productivity firms or both may spatially sort into a region. Using estimates of firm-level total factor productivity, the science park sorting and selection behavior of Taiwanese and South Korean SMEs is analyzed. The results indicate heterogeneity in location choice of SMEs arising from the economic environment of science parks. Overall, the empirical evidence suggests that science parks can generate real productivity improvements if the incentives are reinforced through national-level policies; otherwise, such incentives may end up protecting inefficient firms.

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1 Introduction

Establishment of science parks to stimulate technological innovation and regional growth is considered an important policy measure. Taiwan and South Korea are countries that have shown remarkable growth and whose policy instruments have included establishment of science parks. Both countries have placed great emphasis on small- and medium-sized enterprises (SMEs) as an engine of economic growth. However, the national-level economic models pursued by each country are quite different. The dominance of the SME-network model in Taiwan and the scale-based technological development model in South Korea has affected the efficiency of SMEs in a varied manner. The objective of the research presented in this article is to determine the impact of incentives offered through science parks on SME-level productivity.

The idea of developing regional innovation systems became popular in industrialized economies in the 1980s (Hassink 2002). These policies are unique as their implementation is region-specific, but they are formulated and enforced through national programs. A key feature of these policies is the institutional setup and infrastructural buildup manifested through creation of science parks and supported by financial incentives to help clustering of industries. The objective of science parks is to support regional potential by encouraging horizontal and vertical cooperation among universities, SMEs, and large firms through transfer of knowledge and diffusion of technology (Hassink 2002). Regional innovation-support systems, including those offering incentives to deal with financial constraints faced by small technology-intensive firms (Storey and Tether 1998), have been extensively studied for OECD and European countries (OECD 1996) but in a very limited manner for East Asian economies (Okubo and Tomiura 2012). However, none of these studies have specifically focused on SMEs. Therefore, the analysis presented in the current article examines the effectiveness of these policy instruments through comprehensive analysis of regional productivity distributions for SMEs in Taiwan and South Korea.

Firm-level productivity is a key performance indicator in the growing literature on heterogeneous firms, but additional analysis is required to understand the impact of science parks on the productivity distribution of firms. There is a consensus in regional economics that firms located in large cities are often more productive than those located elsewhere due to agglomeration benefits (Rosenthal and Strange 2004). However, contemporary progress in spatial economic analysis indicates that there may be other factors generating higher firm-level productivity in large cities. For example, observed higher average productivity of firms in large cities or industrial clusters may be due to competition-based selection (Combes et al. 2012). Alternatively, both low- and high-productivity firms may spatially sort into large cities in order to take advantage of the economic benefits of large markets (Forslid and Okubo 2014).

The main issues with the current literature on the effect of science parks on productivity are limitations due to site-specific methodologies and potential selection bias as pointed out by Siegel et al. (2003) and Phan et al. (2005). An attempt is made in the current article to overcome these shortcomings by adding a separate region housing science parks to the core-periphery analysis of the new economic geography model. The methodology is not restricted to a particular estimation model or specific park objective(s), but is instead based on a robust theoretical foundation that provides a basis for generalization and policy evaluation. From a policy perspective, the results from this study suggest that science parks do help in correcting innovation market failures and improving regional growth, but they may also turn out to provide protection against market competition, resulting in sorting by low-productivity firms. This latter kind of support does not lead to productivity growth, as is evident in the case of SMEs in South Korea. It can also be inferred from the results that tax credits and tariff exemptions for research and development (R&D) expenses generally favor large corporations and do little to support innovation by and growth of SMEs.

The article is structured as follows: in Section 2, the research contribution of the article is summarized, followed by a brief country-level analysis and a review of the relevant literature in Sections 3 and 4 respectively. The hypotheses, data, empirical analysis, and discussion of results are detailed in Sections 5 and 6, and a summary of the findings and some concluding observations are presented in Section 7.

2 Methodology and significance of the study

The overall methodology adopted in this article draws on Okubo and Tomiura (2012) and Forslid and Okubo (2014). As a first step in the analysis, productivity distributions for firms in cities and science parks are simultaneously analyzed to identify the impact of agglomeration and selection effects. This analysis is conducted for all manufacturing firms, SMEs, and large firms in both Taiwan and South Korea, where SMEs are defined as manufacturing firms with employment up to 250 people and independent management. Given that science park incentives are designed to support the growth of incumbent firms (Siegel et al. 2003) and that self-selection by firms into a region containing a science park(s) is very likely, a two-stage Heckman (1979) selection model is also used to evaluate regional firm-level productivity distributions. This is followed by an estimation of the impact of incentives on firm productivity using both regression and matching techniques. Finally, to control for the effect of unobserved heterogeneity and resultant productivity variations on spatial sorting behavior of firms, the percentile-wise probability of location is estimated for science parks in the two countries.

For the purpose of spatial analysis, the two countries are divided into three exclusive regions based on population density and location of science parks. These regions include urban areas with above median population density (large cities), urban areas with below median population density (small cities), and urban areas housing science parks (science park cities).[1] In order to avoid the possibility of the agglomeration benefits of large cities tainting the analysis, only science parks located in small cities are considered. Therefore, as the three regions are mutually exclusive there should be no potential for contamination of treatment. Urban areas refer to either a county, city, or metropolitan city depending upon the administrative division of the relevant country. Following Ahn's (2001) finding that a disproportionate amount of growth in Asia is due to increased inputs rather than improved efficiency, the current analysis digs deeper into the determinants of growth and the potential role of SMEs therein. Hall and Harvie (2003) point out that SMEs in South Korea have faced a more unfavorable business environment particularly in terms of access to finance, etc.; hence, it is reasonable to expect heterogeneity in SME performance across the two countries.

The key results of the study are as follows: first, at the aggregate manufacturing level, firms located in science parks in both Taiwan and South Korea have an average level of productivity lower than that for firms located in large cities but higher than that for firms located in small cities (Fig. 1). Second, SMEs located in science parks in Taiwan have the highest average productivity whereas those in South Korea have the lowest average productivity (Fig. 2). A similar analysis was also conducted for large firms, the results showing the differences in productivity of large firms in the two countries (Fig. 3). Specifically, large firms located in science parks in Taiwan have an average level of productivity lower than that for large firms located in small cities but higher than that for large firms located in large cities, the opposite being the case in South Korea.

Third, the policy analysis confirms that on average, after controlling for firm and industry characteristics influencing productivity, SMEs in Taiwanese science parks have higher productivity compared to SMEs located elsewhere in the country. Therefore, the productivity distributions indicate that regional policy interventions are much more effective in the case of Taiwan compared to South Korea. Fourth, the analysis of spatial sorting and competitive selection behavior indicates that both selection and one-sided sorting for SMEs occur in Taiwan, whereas two-sided sorting is prevalent in South Korea. However, analysis of the summary statistics for the log firm-level total factor productivity (TFP) distributions shows that, across the three markets in both Taiwan and South Korea, the selection effect is of a much lower order of magnitude than the agglomeration effect.

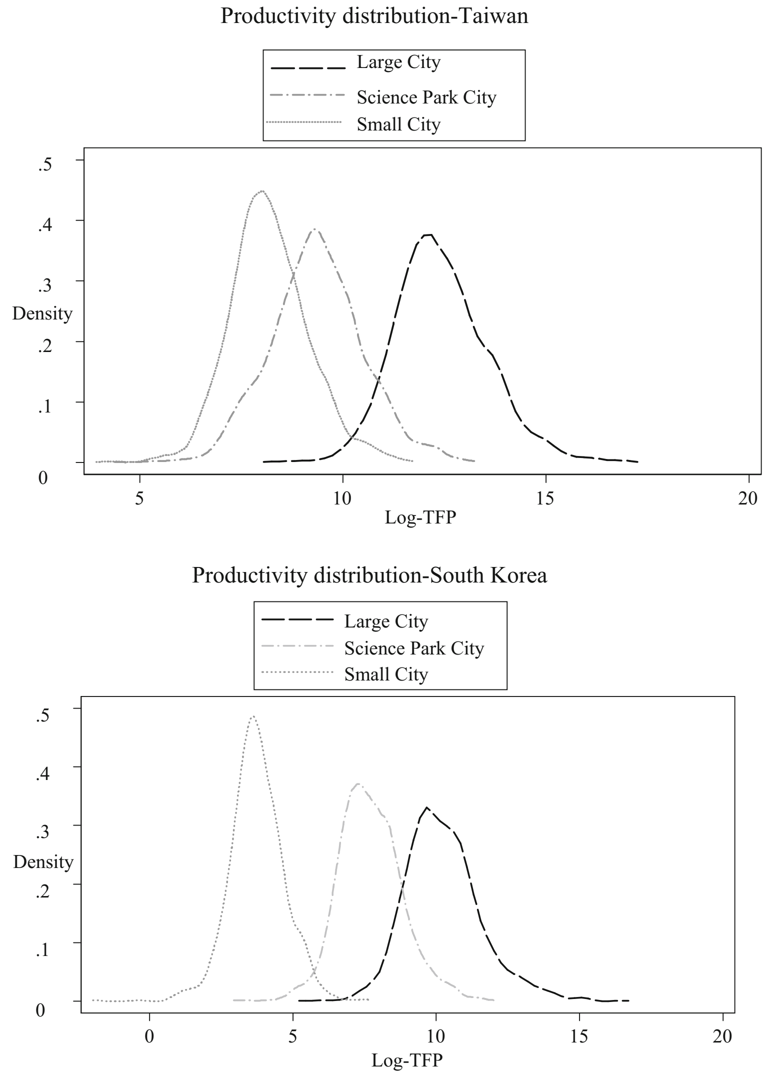
3 Economic growth and innovation policy in Taiwan and South Korea

Taiwan and South Korea have been widely recognized as countries representative of the successful developmental state-model based on export-oriented industrialization (Amsden 1989). Although the two countries both share a commitment to export-led growth, there are significant structural differences in their approaches. Taiwan has realized economic growth centered on SMEs and as a result, has been able to become successfully integrated with global production networks supplying parts and equipment (Ito and Krueger 1995). South Korea on the other hand has pursued an export-oriented strategy centered on large conglomerates in order to take advantage of capital intensity and scale economies in production processes. The outcome of differences in their national approaches is also manifested in the respective industries that they specialize in. Taiwan has been more successful in integrated circuits, personal computers, industrial machinery, and the cellular phone industry. South Korea, however, has strength in capital-intensive information-technology products, such as memory semiconductors and displays, as well as in traditional scale-intensive industries such as automobiles, shipbuilding, and steelmaking.

The observed differences in industry and product specialization can be analyzed using the national innovation systems approach. Nelson (1996) suggests that such variations are caused by differences in national institutional frameworks. At the national and industry level, diversity in innovation systems originates from government policies and the role of the public sector. Policies for selecting and promoting strategic industries and the development of relationships between industrial and national innovation systems are closely related; hence, design and development of innovation systems needs serious consideration. From a policy viewpoint,

[1] The definitions of large and small cities are based on those given in Combes et al. (2012).

Fig. 1 Region-wise productivity distribution plots for aggregate manufacturing in Taiwan and South Korea

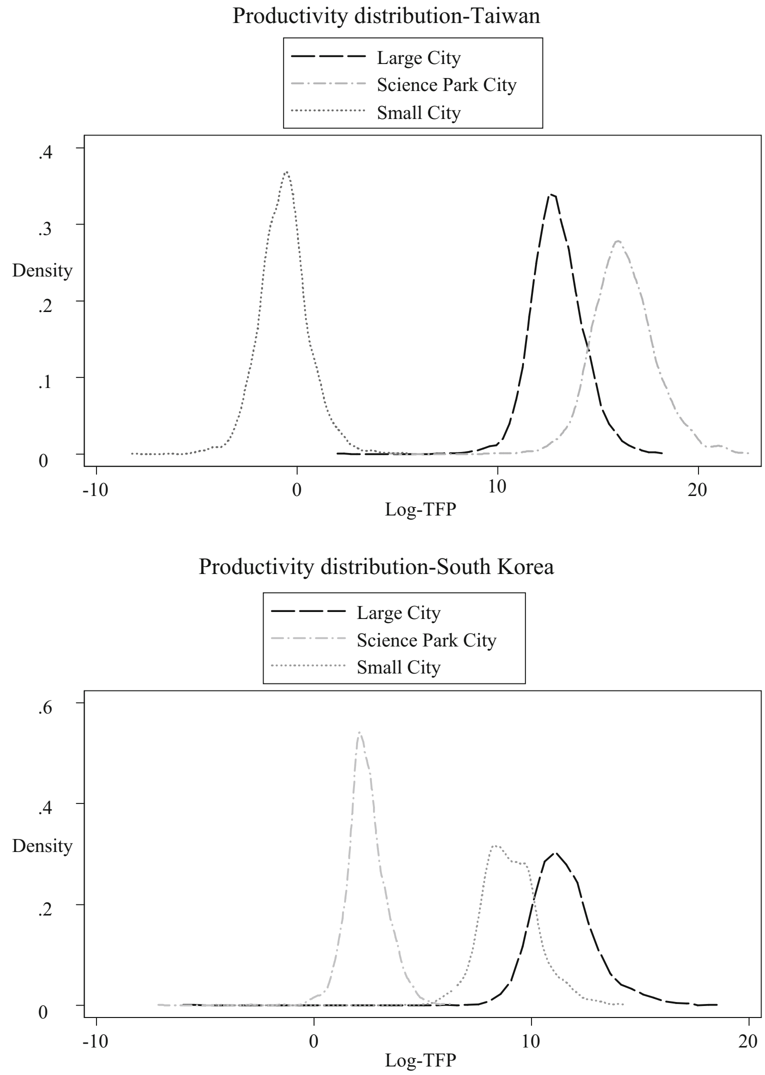


resource allocation is the key factor affecting the organization of R&D and pattern of industrial development.

According to Park (1998), for Taiwan and South Korea, it is reasonable to argue that their governments have contributed to their rapid growth and industrialization. Without direct intervention, it was highly unlikely that the private sector itself could have launched and maintained an investment and export-led development strategy. This viewpoint has been endorsed by Rodrik (1994) who argues that government was able to successfully subsidize and coordinate investment decisions. In the context of this article, policy for establishment of science parks is one of the state-sponsored measures to support R&D, as well as to promote the growth of SMEs.

Inspired by the success of California's Silicon Valley, the Taiwanese government embarked on upgrading its economy with technology and capital-intensive industries. In 1979, a statute was enacted for the establishment of science parks. The first park was established in December 1980 in Hsinchu City, which now stretches over both the city and county of Hsinchu. The park was a public project in its entirety, developed using public land and publicly-funded infrastructure. The central government provided strong policy regulations along with preferential fiscal and other investment incentives. Subsequently, similar science parks were established in central and southern Taiwan, with the objective of providing a favorable environment based on appropriate incentives to attract current technologies and skilled

Fig. 2 Region-wise productivity distribution plots for SMEs in Taiwan and South Korea



human resources. The primary policy tool in the case of science parks was provision of tax credits against R&D expenses (Lien et al. 2010). Taiwan has also had a long history of policy support for SME development (Seong 1995). However, in the wake of recent fiscal difficulties and revenue shortfalls, the policy tool of R&D tax credits has been widely criticized as being beneficial only for a few large firms, leaving behind the remaining 97% of SMEs in Taiwan.

In South Korea, the establishment of science parks began in 1997, as part of an effort by the central government to increase its support for enhancing the innovativeness of SMEs and development of inter-firm networks. The evaluation of South Korea's SME-oriented innovation-support indicates mixed results as is evident from the diverse views expressed in Kim and Nugent (1994), Park (1998), and Sung et al. (2016). Chung (1999), however, is of the opinion that the differences in these findings are largely due to lack of a systematic evaluation procedure. Although the World Development Indicators (World Bank 2014) indicate that over the period 2003–2011, R&D expenditure as a share of South Korean GDP rose from 2.5 to 4%, studies point out several weaknesses in its innovation system. These include a lack of interplay between universities and the private sector, as well as a dearth of diffusion mechanisms to transfer research results from public research establishments to industry and particularly to SMEs (Kim 1997). A recent review of SME-specific policy in South Korea indicates that the only consistent

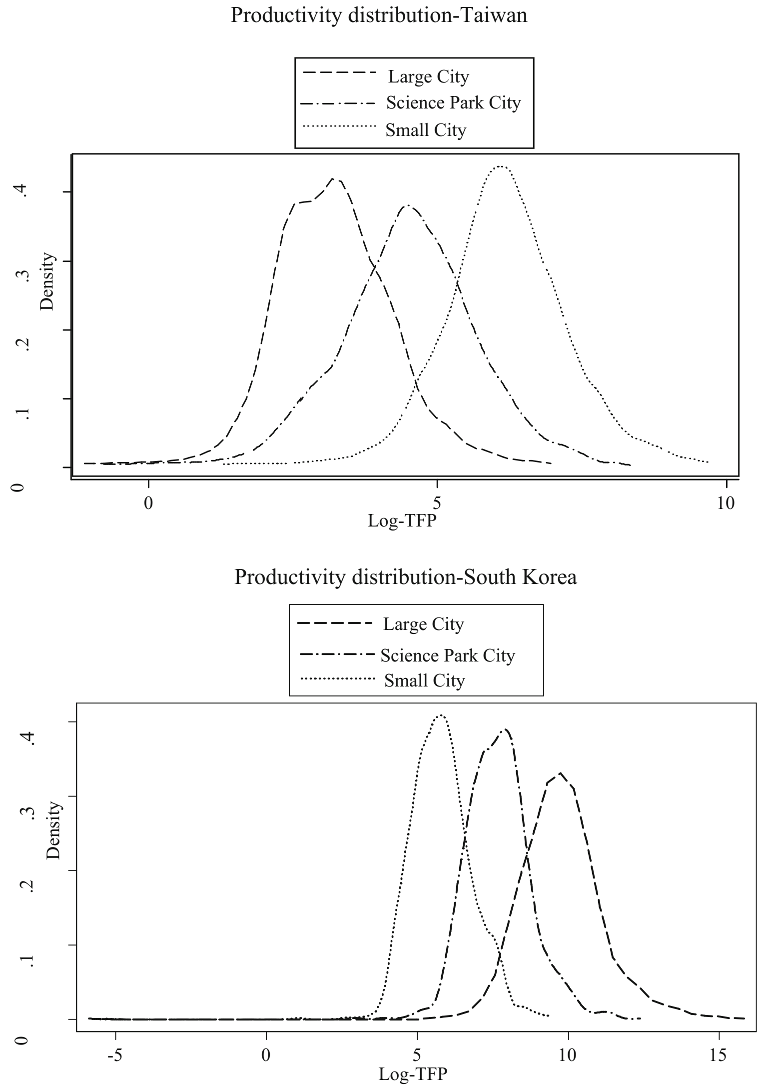


Fig. 3 Region-wise productivity distribution plots for large firms in Taiwan and South Korea

measure adopted since the 1960s has been the provision of financial assistance and removal of credit constraints facing SMEs (Sung et al. 2016). Even the recent focus on fostering growth through greater collaboration between SMEs and large companies is considered insufficient.

4 The impact of clustering on firm productivity

In the case of urban regions, externalities are generally attributed to agglomeration economies associated with firms located in large cities and industrial clusters, the theoretical underpinnings dating back to Marshall (1890). The agglomeration literature explains productivity gains resulting from labor market pooling, factor-sharing, and knowledge spillovers. Also, in the case of industrial clusters, a positive association between regional plant-density and productivity has been empirically confirmed by Ciccone and Hall (1996).

Apart from agglomeration economies, the high level of firm productivity observed in large cities has recently been explained in terms of competitive selection associated with large markets. Melitz and Ottaviano (2008) show that with heterogeneous firms, monopolistic competition and free entry, as markets get larger firms' markups on price over marginal cost go down due to an increase in demand for factors of production and congestion costs. As heterogeneity of firms is explained in terms of their productivity, firms exit the market when their productivity is below the market cut-off level, the surviving mass of firms having higher average productivity.

Another strand of literature that combines aspects of the new economic geography with an assumption of heterogeneous firms shows that high-productivity firms may sort into larger markets with trade liberalization. Baldwin and Okubo (2006) assume a setting with two regions, one small and one large, where capital is mobile between regions, subject to an adjustment cost, and units of capital in each region embody a particular level of labor productivity. Assuming monopolistic competition with fixed price–cost markups, decreasing trade costs cause the most efficient firms to relocate from the small to the large region. Baldwin and Okubo (2006) also establish that subsidizing firms to move from the large to the small region induces only the least productive firms to relocate.

Based on Melitz and Ottaviano (2008), as well as finding that decreasing trade costs lead to agglomeration of efficient firms in the large region, Okubo et al. (2010) also establish that less efficient firms relocate to the smaller region. However, as the two regions become increasingly integrated, inefficient firms eventually relocate to the larger region in order to access a larger pool of consumers. Finally, Forslid and Okubo (2014) use a structure similar to Baldwin and Okubo (2006), where higher capital intensity among more productive firms is also sector-specific. Their theoretical results generate two-sided sorting: firms with the highest return to capital have the strongest incentive to move from the small to the large region, which would include both the most productive firms and the least productive firms that are labor intensive. In other words, depending on the sector of production, such firms may lie at either tail of the productivity distribution.

The phenomenon of selection and spatial sorting clearly raises serious endogeneity concerns when evaluating the impact of spatial clustering policies on firm productivity. As noted by Baldwin and Okubo (2006), standard econometric analysis of agglomeration economies is very likely to overestimate the benefits of agglomeration on firm productivity. This is due to only the most productive firms either surviving in or relocating to larger and more competitive markets. In addition, as Forslid and Okubo (2014) point out, although agglomeration economies, selection, and sorting all result in higher than average productivity for firms located in a cluster, they also generate quite different shaped firm productivity distributions. In the case of agglomeration economies, all firms located in the core benefit, the productivity distribution shifting to the right. For the case of selection, the productivity distribution of firms in the core will be left truncated as the least productive firms exit the core, and for two-sided sorting, the productivity distribution will be wider as the least and most productive firms relocate to the core. While acknowledging the arguments of Okubo et al. (2010) and Forslid and Okubo (2014), selection of low-productivity firms into a specific region may also be the unintended consequence of loosely designed public policy (Shane 2009).

With respect to empirical evidence, Martin et al. (2011) found that French industrial cluster policy has had no significant effect on firm productivity, and Bernini and Pellegrini (2011) detected a decline in the productivity of firms subsidized by the Italian government. In the case of Japan, Okubo and Tomiura (2012) found that average plant-level productivity is significantly lower in regions targeted by policy. However, none of these studies investigated competitive selection and spatial sorting of SMEs when policy incentives are offered through a science park.

5 Empirical analysis

5.1 Hypotheses

The empirical analysis described in this article draws on theoretical models developed in Combes et al. (2012) and Arimoto et al. (2014) (see the Appendix for the technical details), as well as the analysis of Baldwin and Okubo (2006) and Forslid and Okubo (2014) outlined in the previous section. Specifically, the following two hypotheses can be stated:

- Hypothesis 1 (*Agglomeration*): Policy incentives offered through science parks are likely to cause an increase in the mean of the log-TFP distribution for SMEs located in a region (see Combes et al. 2012 and Arimoto et al. 2014).
- Hypothesis 2 (*Sorting and selection*): Provision of public incentives through science parks results in two-sided sorting in the case of low mean firm-level productivity, compared to competitive

selection and one-sided sorting in the case of high mean firm-level productivity (Baldwin and Okubo 2006; Forslid and Okubo 2014; and Arimoto et al. 2014).

5.2 Data

Firm-level data, disaggregated at the urban area-industry level, are derived from the Emerging Markets Information Services (EMIS) (2017). EMIS is an aggregate database that provides information on emerging markets.[2] It aggregates and produces unique content including full-text news articles, financial statements, company information, industry analysis, equity quotes, macroeconomic statistics, and market-specific information, which are derived directly from more than 13,000 local and global publications.

The unbalanced panel data, at the 3-digit NAICS level, covers the period 2010–2012 for Taiwan and South Korea. The dataset has four main fields indicating physical location, industry, operational status of the firm, and its listing and trading status on the stock market. The dataset also provides information about financial indicators relating to firms' balance sheet and income statements, such as non-current assets and sales revenues along with data on profitability, liquidity and growth trend ratios. Information is extracted about each firm's total operating revenues, assets and number of employees to estimate the production function parameters. The dataset is supplemented with urban area-level income and industry price data, available at the website of the National Statistics Office (DGBAS) (2010), Taiwan, and Statistics Korea (KOSTAT) (2014). These data are used to deflate the revenue figures and construct instrumental variables to be used with the instrumental variables/two-stage least squares (IV/2SLS) estimation methodology.

The raw data were cleaned using several steps: first, revenue was deflated by industry-level prices for the year 1996; second, using box plots, the data were examined for outliers, firms with the top and bottom 1% TFPs being removed to avoid their influence on the results. Empirical analysis of heterogeneous firms often shows that the values of variables such as TFP are either much larger or smaller than other values in the sample. Usually, it is not possible to decide whether these observations actually represent clear noise or instead reflect the skewness of the TFP distribution. In both cases, however, these outliers, may have a large impact on the statistical analyses. Hence, the standard empirical approach in the literature has been to drop the outliers as per the method described above (Vogel and Wagner 2011). This resulted in a final dataset of 4646 observations for Taiwan and 5066 observations for South Korea.

As stated earlier the geographical unit for spatial analysis is the relevant urban area/region. This division is justified, due to the fact that for big cities, the market effects are likely to spill over to the entire urban area. In the case of science parks, most notably that in Hsinchu, ever increasing demand has forced a greater part of the relevant urban area being designated as the science park. The region-wise location of all firms and SMEs in the two countries is shown in Table 1, along with data describing their value of capital and amount of labor employed. Standard errors clustered at the regional level are used in the econometric analysis because the data indicate a significant presence of SMEs in all three regions.

For Taiwan, the urban areas categorized as science parks are Hsinchu County, Tainan City, Yunlin City, and Kaohsiung City, whereas for South Korea the cities of Ansan, Busan, Changwon, Chuncheon, Daegu, Daejeon, Gyeongsan, Jeju, Pohang, Ulsan, and Cheongwon County are categorized as science parks (Fig. 4). The firms located in the Seoul science park are not included in the analysis as Seoul is categorized as a large city. Therefore, all science parks in the empirical analysis are located in small cities. As a consequence, there is no contamination between any agglomeration benefits associated with firm-location in large cities and any benefits due to firm-location in science parks.

5.3 TFP estimation results

The econometric analysis conducted in this article hinges primarily on generating unbiased estimates of TFP. The log-TFP distribution of firms located in any region is then predicted from the residual of the equation. Firm-level TFP is calculated assuming that the

[2] EMIS, formerly known as ISI Emerging Markets, was founded in 1994 by Harvard Business School graduate Gary Mueller with the purpose of providing easy access to critical business information and research on emerging markets.

Table 1 Regional distribution of firms and SMEs in Taiwan and South Korea

Taiwan										
Region	All firms					SMEs				
	Number	Capital		Labor		Number	Capital		Labor	
		Mean	SD	Mean	SD		Mean	SD	Mean	SD
Small city	1090	7,262,650	2.89^{e7}	752	1868	503	1,159,935	1,242,428	132	65
Science park	1174	9,222,076	4.38^{e7}	786	2268	521	902,908	1,438,685	127	63
Large city	2382	9,752,043	4.48^{e7}	549	1368	1240	4,111,160	2.17^{e7}	106	62
South Korea										
Region	All firms					SMEs				
	Number	Capital		Labor		Number	Capital		Labor	
		Mean	SD	Mean	SD		Mean	SD	Mean	SD
Small city	987	204,564	875,075	489	1395	576	56,907	154,804	123	63
Science park	780	39,517	93,701	456	1211	391	19,318	45,995	112	72
Large city	3299	184,319	2,542,837	880	3989	1774	21,853	142,645	109	72

Capital—Taiwan (thousands of Taiwan dollars), South Korea (millions of Won)

technology for revenue generated is Cobb-Douglas in the inputs of capital and labor:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l}, \tag{1}$$

where, for firm i at time t, Y_{it} is physical output; K_{it} and L_{it} are the factors of production, capital, and labor; and$A_{it}$is the Hicks-neutral efficiency level of the firm which is unobservable to the researcher. Written in logarithmic form, (1) becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \psi_{it}. \tag{2}$$

From (1) and (2), it is observed that $\ln(A_{it}) = \beta_0 + \varepsilon_{it}$ where$\beta_0$is the mean efficiency-level, across firms over time, and ψ_{it} is the deviation from the mean, and which can be further decomposed into an observable and unobservable component:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + v_{it} + u_{it}. \tag{3}$$

In (3), firm-level log productivity is given by $\omega_{it} = \beta_0 + v_{it}$, and u_{it} is the independent and identically distributed (*i.i.d.*) measurement error. The productivity level can be obtained from (3) by taking the exponential of the estimated parameter ω_{it}.

Estimation of (3) by ordinary least squares (OLS) is likely to suffer from two problems: first, there may be simultaneity bias due to inputs not being exogenous and, second, there may be selection bias due to correlation between productivity and capital. The former problem can be addressed through using IV/2SLS, instrumental variables being used for the freely alterable inputs in the production function. Alternatively, Olley and Pakes (1996) have developed a semi-parametric estimation algorithm that takes both the selection and simultaneity problem directly into account.

The Olley and Pakes (1996) estimator solves the simultaneity problem by using the firm's investment decision as a proxy for unobserved productivity shocks. Selection issues are addressed by incorporating an exit provision into the model. At the start of each period, each surviving firm decides whether to exit or to continue its operations. If it exits, it receives a particular sell-off value. If it continues, it chooses an appropriate level of variable inputs and investment. The firm is assumed to maximize the expected discounted value of net cash flows and investment and exit decisions will depend on the firm's perceptions about the distribution of future market structure.

Olley and Pakes' (1996) technique is based on three key assumptions. First, the only unobserved state variable is the firm's productivity which evolves as a first-order Markov process. Second, investment is monotonically related to productivity and hence during econometric analysis, non-negative values of the investment variable are required. This investment is shown as a function of capital and productivity, $i_{it} = i_t(k_{it}, \omega_{it})$. The monotonicity assumption allows its inversion as $\omega_{it} = h_t(k_{it}, i_{it})$, so that productivity can be expressed in terms

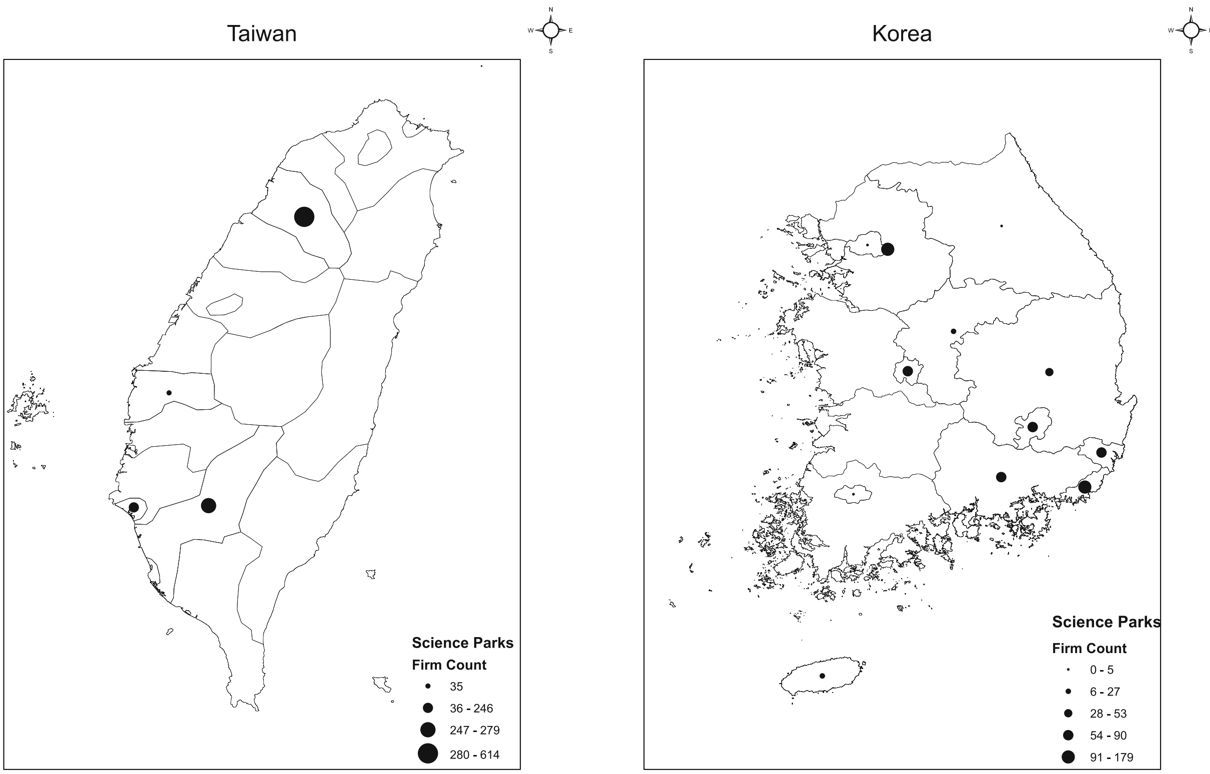


Fig. 4 Science park location in Taiwan and South Korea along with firm count

of capital and investment. Third, deflation on the basis of industry-level prices implies that all firms face the same prices.

The Olley and Pakes (1996) technique proceeds in two stages. In the first-stage regression, using the relationship in (3), the free input variable(s) coefficients are derived. The second stage evaluates the temporal productivity level to compare it with the lower bound or the threshold. Using coefficients from the first stage and the survival probability and by applying a non-linear least squares method, the coefficient on the capital variable is estimated. However, in adopting this method, observations are lost when information on the firm's investment decision is missing.

The estimated input coefficients from (3) are reported in Table 2. In all cases, the coefficients on capital and labor sum to less than one, indicating decreasing returns to scale at the firm-level in both countries. In the case of Taiwan, the OLS and Olley and Pakes (1996) estimates indicate the coefficient on capital is biased downward for Taiwan, and in the case of South Korea, the coefficient is biased upward for the OLS and IV/2SLS estimates and biased downward for the Olley and Pakes (1996) estimates.

To test the reliability of the OLS estimates, the Durbin-Wu-Hausman (DWH) test of endogeneity is performed. The small p values indicate that the estimates are not reliable for either Taiwan or South Korea. To avoid simultaneity bias, IV/2SLS is also used, the Sargan test indicating that the instruments (county-level wages and population density) are not correlated with the residual term. Although the estimates shown in columns 3 and 6 of Table 2 overcome the simultaneity bias, they still do not take care of the selection problem.

Keeping in mind the shortcomings of the techniques used above, TFP was predicted using the method proposed by Olley and Pakes (1996). The standard errors of all estimation routines are bootstrapped using 200 replications to derive appropriate standard errors. From the results, log-TFP distributions were drawn for each region in each country. Here, the return on capital is used as a proxy for investments made by the firm along with control variables such as the number of employees to control for size.

Table 2 Production function coefficients for firms

Model/variables	Taiwan			South Korea		
	OLS	IV/2SLS	OP	OLS	IV/2SLS	OP
Capital	0.37***	0.56***	0.29**	0.66***	0.56***	0.13*
	(0.0118)	(0.017)	(0.101)	(0.019)	(0.021)	(0.203)
Labor	0.56***	0.21***	0.47***	0.18***	0.21***	0.39***
	(0.0158)	(0.0108)	(0.029)	(0.012)	(0.014)	(0.018)
R-squared	0.62	0.57		0.42	0.57	
Sargan test (*p* value)		0.72			0.54	
DWH (*p* value)	0.003	0.245		0.022	0.457	

OLS ordinary least squares, *IV* = instrumental variables, *2SLS* two-stage least squares, *OP* Olley and Pakes, *DWH* Durbin-Wu-Hausman
*Significant at 10% level, **significant at 5% level, ***significant at 1% level

The summary statistics of the log-TFP distribution estimates by region for Taiwan and South Korea are detailed in Table 3. Large cities have the highest mean value of firm-level log-TFP, followed by that of science park firms which suggests firms in large cities continue to benefit the most from agglomeration economies, and the impact of science park intervention is not enough to overcome this. An estimate for competitive selection is made using the value of minima and the tenth percentile of the distributions in each region. Increasing values of these parameters as one moves from small city to science park, and then to large city, indicate that low-productivity firms cannot survive in a more competitive environment.

5.4 Policy evaluation

Three approaches are taken to analyze the impact of policy intervention on SME productivity. First, a simple regression equation is estimated where the potential effect of a science park is captured through a dummy variable. Second, a matching technique is used to estimate the average treatment effect of science parks on SME productivity through comparing similar firms.[3] Third, a Heckman (1979) selection model is used to control for self-selection bias.

5.4.1 Policy impact analysis

Following the methodology outlined in Okubo and Tomiura (2012) the following reduced form regression model is estimated:

$$TFP_{it} = \alpha Policy + \boldsymbol{K}_{it} + \varepsilon_{it}, \tag{4}$$

where *TFP* refers to the log-TFP of SME *i* in year *t*, $\boldsymbol{K}_{it}$ is a vector of SME control variables in logarithmic form such as size and capital, and ε_{it} is the *i.i.d.* error term. Robust standard errors are used to correct for measurement errors in the dependent variable. The main variable of interest is the *Policy* dummy. If *Policy* has a statistically significant positive coefficient, it implies that SMEs located in science parks have a higher level of TFP on average compared to SMEs located elsewhere. However, it is important to note that the results from estimating Eq. (4), which are reported in Table 4, are likely to suffer from reverse causality on account of either competitive selection or sorting, and should therefore be interpreted as indicating correlation only.

5.4.2 Treatment effect

In order to control for unobserved heterogeneity between firms located in science parks and outside, a matching technique is used. Matching has been used in previous studies in this context, including Martin et al. (2011) and Okubo and Tomiura (2012). The current dataset is a sample of SMEs from a population of firms, some of whom received a "treatment" based on a policy premium and the agglomeration benefits of being located in a science park, and the remaining SMEs located

[3] Siegel et al. (2003) highlight the importance of matching in the evaluation of science parks.

Table 3 Region-wise log-TFP distribution statistics

Statistics	Taiwan			South Korea		
	Small city	Science park	Large city	Small city	Science park	Large city
N	1090	1174	2382	987	780	3299
Mean	4.106923	8.32283	11.76685	3.74814	7.700501	10.23615
Max	8.708421	12.10286	17.08633	7.668521	12.15671	16.47615
Min	−2.43337	1.005013	4.605112	−1.97747	2.925614	5.438199
Range	11.14179	11.09784	12.48122	9.645994	9.231099	11.03795
Variance	1.089898	1.201957	1.247379	0.898821	1.250404	1.734177
p10	2.932698	6.96137	10.49661	2.673442	6.423069	8.733301
p25	3.461043	7.634048	11.01647	3.192485	6.961631	9.353257
p50	4.063416	8.291471	11.66475	3.713572	7.623936	10.11305
p75	4.691591	8.983652	12.43476	4.324795	8.39128	10.9753
p90	5.439116	9.73185	13.19089	4.945438	9.115471	11.89248
p95	5.90151	10.1574	13.67761	5.36431	9.66293	12.70057
p99	6.822562	11.15639	14.81686	5.999806	10.62025	14.02616
IQR	1.230548	1.349604	1.418283	1.13231	1.429649	1.622047

elsewhere in the country did not get "treatment." The interest is in finding out if the "treatment" influences an outcome variable, i.e., an SME's TFP. The quality of matching is estimated through the Mahalanobis metric which is used to calculate the similarity of two firms in terms of covariate values.

In an ideal world, TFP would be observed when an SME is treated, denoted as y^1, and TFP would also be observed when the same SME is not treated, denoted as y^0, so that the only difference is the presence or absence of the treatment. Based on these observations, the difference between the two outcomes across all the subjects in the dataset could be used to obtain a measure of the average impact of science park policy. However, as this ideal experiment is not possible, randomized treatment is adopted instead. The defining characteristic of

Table 4 Regression and matching results

Dependent variable	Log-TFP					
Variables	Taiwan			South Korea		
	OLS	Average treatment effect	Treatment effect	OLS	Average treatment effect	Treatment effect
Science park	0.08*	0.124*	0.086*	0.05	−0.003	0.131*
	(0.05)	(0.074)	(0.0478)	(0.05)	(0.051)	(0.074)
Log employment	0.039*			0.186		
	(0.020)			(0.039)		
Log capital	0.276***			0.396***		
	(0.015)			(0.023)		
R-squared	0.20			0.35		
Mahalanobis metric		−0.051			−0.048	
		(1.213)			(1.498)	
Observations	1933			2502		

Robust standard errors in parenthesis, clustered on industry. Sample size affected by removal of outliers and missing values for investment

*Significant at 10% level, **significant at 5% level, and *** significant at 1% level observational data is that treatment status is not randomized, implying that the outcome and treatment are not necessarily independent. The goal of the estimators employed here is to utilize covariates to make treatment and outcome independent, once conditioned on those covariates.

Therefore, to control for heterogeneity in the changes in TFP resulting from being located in a science park (treatment) across SMEs, a Mahalanobis nearest-neighbor matching algorithm is used to construct a refined control group of SMEs, those not experiencing incentives offered through a science park, by matching characteristics with those that experienced the incentives (Abadie and Imbens 2006). The matching algorithm selects comparable SMEs with similar levels of employment, capital investment and return on capital as matching covariates. The causal effect of the treatment is estimated as the mean difference in productivity between the treated and the untreated groups. The average effect of the treatment on the treated group is given by $E(y^1 - y^0|Policy)$, where $Policy = 1$ if plants are treated and 0 if otherwise. This estimation is useful for explicitly evaluating the effects on those SMEs, for whom the science park program was actually intended, the results being reported in Table 4. The values of the Mahalanobis metric indicate that SMEs located in either science parks or both types of city are closely matched.

5.4.3 Firm sorting and type of regional productivity distribution

To determine presence of spatial sorting by SMEs in science parks, the Heckman (1979) two-step estimator for selection models is used. The statistical significance of the coefficient of the inverse Mill's ratio indicates if there is any selection bias. To identify the process through which either low or high-productivity firms sort into science parks or large cities, a selection equation is used in conjunction with Eq. (4). Considering firm's sorting into science parks the relevant selection equation is as follows:

$$z_{it}^* = \alpha_0 + \alpha \boldsymbol{C}_{it} + \upsilon_{it}, \tag{5}$$

where $z_{it} = 1$ if $z_{it}^* > 0$ implying Policy = 1, and $z_{it} = 0$ if otherwise.z_{it} is the dependent variable of the selection equation which is binary in nature and $\boldsymbol{C}_{it}$ is a vector of self-selection (sorting) choice variables. The choice variables may include firm size, capital investments, and expected return indicators. For Eqs. (4) and (5), ε_{it} and υ_{it} are error terms which are assumed to be bivariate normal, with mean zero and covariance matrix $\begin{bmatrix} \sigma & \rho \\ \rho & 1 \end{bmatrix}$, where ρ is the correlation between the two error terms and σ is the variance of the error term from Eq. (4).

The results of using the Heckman (1979) selection model are shown in Table 5. The selection equation includes two variables namely capital and return on equity, the latter being excluded from the regression equation. The choice of the capital variable is in line with Forslid and Okubo's (2014) findings that capital intensity of the production process may determine sorting into a region. As the definition of an SME used in this article is based on the number of employees in the firm, labor is not used as a variable in the selection equation.

The variation in the sign of ρ indicates that the unobserved correlation between the selection and regression equations is negative in the case of Taiwan

Table 5 Heckman selection model

	Variable	Dependent variable: log-TFP	
		Taiwan	South Korea
Regression equation	Log capital	0.439***	0.449***
		(0.019)	(0.028)
	Log employment	0.032	0.0121
		(0.033)	(0.051)
	Science park	0.102*	0.175*
		(0.056)	(0.091)
	Constant	5.692***	2.597***
		(0.232)	(0.347)
Selection equation	Log capital	0.167***	1.136***
		(0.022)	(0.084)
	Return on equity	0.252***	0.043**
		(0.048)	(0.017)
	Constant	2.014***	8.484***
		(0.351)	(0.688)
	ρ	− 0.412***	1.141***
		(0.108)	(0.221)
	$\ln \sigma$	− 0.159***	− 0.0841***
		(0.022)	(0.024)
	Observations	1918	2502

*Significant at 10% level, **significant at 5% level, ***significant at 1% level and positive in the case of South Korea. Therefore, for Taiwan, sorting into a science park is negatively related to unobserved factors such as the business environment, but positively related to firm productivity. In the case of Korea, sorting behavior is positively correlated with both the business environment and firm productivity.

Given that firm-level productivity distributions are simultaneously affected by agglomeration economies, competitive selection, and sorting, it is important to segregate each effect before determining the type of productivity distribution. The Heckman procedure mentioned above confirmed the sorting behavior by firms. In order to filter out sorting from agglomeration and selection effects, the methodology of Forslid and Okubo (2014) is employed. First, the firm-level productivity distributions are demeaned to remove the agglomeration effect. Second, a region-specific regression equation is used to determine the likelihood of any firm lying within a certain percentile of the firm-level productivity distribution as indicated by the coefficient of a regional dummy variable, D_{region}:

$$Percentile = \beta_p D_{region} + \mu. \tag{6}$$

A positive value for the coefficient β on the regional dummy variable, with robust standard errors to correct for deviations from the *i.i.d.* assumption, indicates the likelihood of sorting within the given percentile of the log-TFP distribution. Conversely, a negative value for β implies dominance of the selection effect. Therefore, the estimated βs for various percentiles pick up the difference between selection and sorting effects on the firm-level productivity distribution of the region under consideration in contrast to the rest of the country. For example, a negative (positive) estimate of β at low percentiles implies a dominant selection (sorting) effect at the lower tail of the productivity distribution. In order to estimate the β coefficient, regression analyses based on Eq. (6) are performed for all three regions (large city, science parks, and small city) utilizing the joint probability distribution of all SMEs, the results being reported in Table 6. Due to the β coefficients being significant both at low and high percentiles, they are used to develop profiles to identify the dominance of either selection or sorting, i.e., one-sided or two-sided effects on a region's firm-level log-TFP distribution. The results indicate that for lower percentiles, selection is more dominant in the case of Taiwanese SMEs compared to sorting in the case of South Korean SMEs.

6 Discussion of empirical results

Given the two hypotheses outlined in the preceding section, analysis of the empirical results is divided into five parts as follows:

(i) Non-parametric comparisons are made of the firm-level log-TFP distributions in the aggregate manufacturing sector located in the three identified regions. This analysis helps in understanding the extent to which policy intervention may act as a productivity shock and disturb the equilibrium where more productive firms are supposedly always located in large cities. Here, the highest mean log-TFPs are for firms located in large cities and the lowest mean log-TFPs are for firms located in small cities with the mean log-TFPs for science park firms lying between the two (see Fig. 1). This shows that factors driving productivity gains of firms located in large cities are not affected by policy incentives elsewhere, although the establishment of science parks does lead to regional productivity growth, providing support for hypothesis 1.

(ii) A comparison is made between the inter-regional productivity distributions for SMEs. The results show that science park incentives are not sufficient to increase significantly the productivity of SMEs. Due to the national-level economic model having such a strong influence, regional policies have only a weak impact. The log-TFP distribution for SMEs and the regional spread are shown in Fig. 2, indicating that policy supporting SMEs is much more effective in the case of Taiwan as most SMEs are in high-productivity regions, i.e., large cities or science park cities. Moreover, the creation of science parks has the greatest influence on the productivity of SMEs in Taiwan where they have the highest mean productivity level. This finding is in sharp contrast to similar analysis for South Korea where SMEs located in science parks have the lowest mean productivity level. Overall, these results provide support for both hypotheses 1 and 2.

(iii) With respect to the impact of agglomeration versus selection, a region-wise comparison of the summary log-TFP distribution statistics is made for both Taiwan and South Korea. Following Syverson (2004), the mean and minimum of the log-FTP distributions are used as indicators of rightward shift and left truncation. Based on the

Table 6 β coefficients for science park SMEs in Taiwan and South Korea

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
Country									
Taiwan	− 0.00956*	− 0.00137*	0.00209*	0.00233**	0.00301*	− 0.00032	− 0.00025	0.000246	− 0.00162*
South Korea	− 0.00463*	0.00246*	0.000862	3.86-e5	0.000351	0.00139	0.000822	− 0.0015*	0.00376*

results reported in Table 3, it is consistently found that although firms located in large cities benefit most from agglomeration economies, they also face the highest level of competitive selection. The results also indicate that the creation of science parks raises the level of TFP by a factor of four as compared to small cities, without causing a proportionate increase in the level of competition, evidence supporting hypothesis 1.

(iv) The empirical methods used to determine the policy premium of science park intervention on SMEs, using regression estimates and matching techniques confirm two points (see Table 4). The regression results indicate a correlation between higher levels of firm productivity and choice of location in a science park, which is positive for both Taiwan and South Korea, but only statistically significant in the case of Taiwan, providing support for hypothesis 1. The results from using the matching technique indicate that in Taiwan the average treatment effect is statistically significant, SMEs located in a science park having 12% higher TFP and the treatment effect is also statistically significant, TFP being 8% higher. By contrast in South Korea, the average treatment effect is negative but not statistically significant, while the treatment effect is positive and statistically significant, indicating that treated SMEs exhibit 13% higher TFP.[4] As the literature considers the average treatment effect on the treatment less restrictive than the average treatment effect (Caliendo and Hujer 2006), the support mechanism for Korean science parks can be interpreted as more rewarding than for their Taiwanese counterparts.

(v) The competitive selection and spatial sorting patterns indicate how far incentives offered through science parks are able create a competitive or a protective economic environment for science park incumbent SMEs. In the case of Taiwan, high-productivity SMEs sort into science parks and low-productivity SMEs are forced to exit due to competitive selection. The situation is quite different in the case of South Korea where both low- and high-productivity SMEs self-select into science parks indicating a double-sorting pattern similar to that described in Forslid and Okubo (2014). Based on these findings, it can be concluded that science parks in Taiwan generate a competitive environment whereas in South Korea the policy incentives act as a shield from market competition for low-productivity SMEs (Baldwin and Okubo 2006), evidence supporting hypothesis 2. A review of the results in Table 6, which show the β coefficients for various percentiles estimated using Eq. (6), supplements these findings. The inverted S shape observed in case of South Korea indicates prevalence of double sorting as highlighted in Forslid and Okubo (2014). By contrast, the profile for Taiwan is different in shape, both one-sided sorting by high productivity SMEs, and competitive selection for low-productivity SMEs being observed, providing support for hypothesis 2.

[4] The analysis reported in this article focuses only on the impact on SMEs located in science parks in small cities. In the case of Taiwan, no large cities contain science parks; however, 8 out of 21 large cities in South Korea do contain science parks. Therefore, for completeness, in the case of South Korea the TFP of SMEs located in large cities with science parks was compared to the TFP of SMEs located in large cities without science parks. The average treatment effect implies that SMEs located in the former have 16% higher TFP, the treatment effect being positive and statistically significant (the results are available from the authors on request). However, due to the potential for contamination, it is not possible to separate out the effect on SME productivity of science parks from the agglomeration effect in large cities.

7 Summary and conclusion

The overwhelming success of a few science parks across the globe has convinced policymakers to provide for state-sponsored support to overcome innovation market failures. As this support has been made available from public funds, it is critical that policy for establishment of science parks be subject to an appropriate evaluation process. More importantly, the gap in the available literature on a uniform methodology for performance evaluation of science parks indicates that the debate on effectiveness of science parks is still considered to be open (Salvador and Rolfo 2011). Therefore, the research presented in this article is an attempt to bridge the gap and to develop a consistent methodology for policy evaluation to ensure that empirical findings are objective and can form the basis for substantive policy recommendation(s).

In summary, there are four key findings reported in this article. First, at the aggregate manufacturing level, firms located in science parks in both Taiwan and South Korea have an average level of productivity lower than that for firms located in large cities but higher than that for firms located in small cities (Fig. 1), and across the three markets in both Taiwan and South Korea, the selection effect is of a much lower order of magnitude than the agglomeration effect (Table 3). Second, SMEs located in science parks in Taiwan have the highest average productivity whereas those in South Korea have the lowest average productivity (Fig. 2). Third, the policy analysis confirms that on average, after controlling for firm and industry characteristics influencing productivity, SMEs in Taiwanese science parks have higher productivity compared to SMEs located elsewhere in the country (Table 4). Therefore, the productivity distributions indicate that regional policy interventions are much more effective in the case of Taiwan compared to South Korea. Fourth, the analysis of spatial sorting and competitive selection behavior indicates that both selection and one-sided sorting for SMEs occur in Taiwan, whereas two-sided sorting is prevalent in South Korea (Table 6).

These findings confirm that the impact of industrial clusters such as science parks is not homogenous across firms and the resultant productivity shock at the aggregate level of manufacturing is weak. The results of the current article clearly point out that purposeful utilization of the policy is only possible if science park incentives are offered to firms that have strong production linkages with industries considered to be on the "national comparative advantage" list. Clusters managed in this way will add to the productivity of the region and contribute substantially in removing regional disparities. The evidence that this has only been partially achieved is the lagging productivity distribution of science park firms.

The growth and productivity of SMEs depends on the level of their integration in the overall economy. In this article, the impact of science parks on SME performance has been examined. Using firm-level TFP, and controlling for spatial heterogeneity and possible contamination of the policy treatment, productivity differences are explained in terms of national economic approaches. As there have been systemic differences between Taiwan and South Korea in the utilization of SMEs for nationally competitive industries, the heterogeneous impact on policy can be explained.

For SMEs, the research indicates that provision of a protective environment or tax credits, etc., is not sufficient to stimulate growth and development. Therefore, it can be seen in the case of South Korea that even after considerable time, the productivity level of SMEs is not competitive. As the national model in South Korea has supported growth of large conglomerates, an alternative approach might be to develop a network of support between conglomerate firms and SMEs so that SMEs benefit from the growth of large firms. Otherwise, science park incentives will continue to insulate firms from the competition they might face in open markets.

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Appendix

Model

Agglomeration effects impart higher productivity to cluster incumbents through the transfer of knowledge and innovative ideas among workers, improvement in labor matching, and sharing of commonly needed services among firms. These agglomeration effects, also termed as external economies of scale, offer benefits that are shared by all firms located in the cluster. On the other hand, owing to selection effects in clusters, intensification of competition shakes out less productive firms.

To distinguish between agglomeration and selection effects, the theoretical analysis presented in Combes et al. (2012) and Arimoto et al. (2014) is followed. The model is designed to examine the implications for these two effects on the distribution of firm-level productivity in a given region. Intuitively, the agglomeration effect will shift the log-total TFP distribution to the right by improving the productivity of all firms in the region, but at the same time keeping the shape of the distribution unchanged. On the other hand, the selection effect will drive less productive firms out of the market, resulting in left truncation of the log-TFP distribution. Therefore, it is possible to identify the two effects by comparing the characteristics of the distribution of firm-level productivity among various regions. The salient features of the model are outlined as follows, along with some key results.

Preferences and demand

First, the general framework of the model is introduced. A consumer's utility is given as follows:

$$U = q^o + \alpha \int_{i\in\Omega} q^i di - 1/2\gamma \int_{i\in\Omega} \left(q^i\right)^2 di - 1/2\eta \left(\int_{i\in\Omega} q^i di\right)^2, \quad \text{(A1)}$$

where q^i denotes the consumption of variety i from a set Ω of differentiated varieties of manufactured goods and q^0 is the numeraire good. Using the demand function for variety i the utility maximization problem is solved subject to a budget constraint. Taking P as the average price of varieties with positive consumption, the demand function for variety i can be written as follows:

$$q^i = \left\{ \begin{array}{l} \frac{1}{\gamma+\eta\omega}\left(\alpha + \frac{\eta}{\gamma}\omega P\right) - \frac{1}{\gamma} p^i \ \text{ if } \ p^i \le \overline{h}, \\ 0, \ \text{ otherwise} \end{array} \right\}, \quad \text{(A2)}$$

where $\overline{h}$ is the cut-off price at which demand becomes zero.

Production

The numeraire is produced under constant returns to scale using one unit of labor per unit of output which implies that the cost to firms of hiring one unit of labor is always unity. Differentiated products are produced under monopolistic competition. By incurring a sunk-entry cost s a firm manufactures a product using h units of labor per unit of output. The value of h differs across firms depending on their productivity and is randomly drawn, from a distribution with known probability density function $g(h)$ and cumulative density function $G(h)$ common to all regions. The total sales of a firm are $Q(h) = Cq(h)$, where C is the mass of consumers. Firms maximize their profit as follows:

$$\pi(h) = [p(h) - h]Q(h). \quad \text{(A3)}$$

In the monopolistically competitive industry with free entry firms enter until ex ante profits can no longer offset the sunk-entry cost:

$$\frac{C}{4\gamma} \int_o^{\overline{h}} \left(\overline{h} - h\right)^2 dG(h) = s. \quad \text{(A4)}$$

Using the optimal pricing rule, the zero cut-off profit condition is derived as:

$$N \equiv \omega = \frac{2\gamma}{\eta} \frac{\alpha - \overline{h}}{\overline{h} - H} \quad \text{(A5)}$$

where N is the mass of surviving firms, which is equivalent to the number of varieties produced, and H is the average cost of surviving firms.

Agglomeration effect

Combes et al. (2012) assume in their model that each worker supplies a single unit of labor. If the agglomeration effect is present, it is assumed that workers' productivity increases with the number of firms within a region. That is, effective labor supply by a single worker is $a(N)$, $a' > 0$, $a'' < 0$ and $a'(0) = 1$. On the other hand, if agglomeration of firms does not improve workers' productivity, for any value of N, $a(N) = 1$. It is also assumed that if the agglomeration effect is present, it benefits workers across both the differentiated good and numeraire good sectors.

Given agglomeration effects, a firm of unit labor requirement h hires labor such that $l(h) = Q(h)h/a(N)$. Taking logs of both sides, firm's log productivity is obtained as $\phi = \ln(Q/l) = \ln[a(N)] - \ln(h)$. With $A \equiv \ln[a(N)]$ firm's log productivity is given as:

$$\phi = A - \ln(h) \tag{A6}$$

Using the change of variable theorem, the probability density function of firms' log productivities is given as follows:

$$f(\phi) = \begin{cases} 0 & for\ \ \phi \leq A - \ln\left(\overline{h}\right) \\ \dfrac{e^{A-\phi} g\left(e^{A-\phi}\right)}{G\left(\overline{h}\right)} & for\ \ \phi > A - \ln\left(\overline{h}\right) \end{cases}, \tag{A7}$$

The numerator in (A7) follows from use of (A6) and the change of variables theorem, while the denominator $G\left(\overline{h}\right)$ takes care of the fact that firms with a unit labor requirement above $\overline{h}$ exit. Thus, the gain in productivity caused by external economies of scale due to the presence of N firms in the region as indicated by the term A shifts the distribution of firms' log productivity to the right. This is referred to as the agglomeration effect.

Selection effect for different regions in Taiwan and South Korea

To adopt the model for regional location of firms, one more assumption is imposed. For any region, $r \in \{1\ldots R\}$, it is assumed that fixed sunk-entry costs s_r, vary across regions based on the intensity of factor demands and provision of public policy incentives. The free entry condition for any region r is given by Arimoto et al. (2014) as follows:

$$\frac{C_r}{4\gamma} \int_o^{\overline{h}_r} \left(\overline{h}_r - h\right)^2 dG(h) = s_r. \tag{A8}$$

where for firms located in a region, a unit increase in the entry cost raises the cut-off labor requirement, $\frac{\partial h_r^d}{\partial s_r} > 0$. Hence, if the entry costs are lower either because of some policy incentive or due to less competition in factor demands, this lowers the cut-off labor requirement of surviving firms. Reversing the argument, the cut-off productivity level in a region goes up as more firms compete for the available supply of factors of production such as land and labor. This higher cut-off level is observed as the left truncation of the log total factor productivity distribution. This phenomenon is referred to as competitive selection. The proportion of firms that fail to survive product market competition in region r is denoted by:

$$S_r \equiv 1 - G\left(\overline{h}_r\right). \tag{A9}$$

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