Discussion Papers In Economics And Business

Human capital spillovers from Special Economic Zones: evidence from Yangtze Delta in China

Zhaoying Lu

Discussion Paper 21-02

April 2021

Graduate School of Economics
Osaka University, Toyonaka, Osaka 560-0043, JAPAN

Human capital spillovers from Special Economic Zones: evidence from Yangtze Delta in China

Zhaoying Lu†

April 23, 2021

Abstract

This paper evaluates the effects of a place-based program in the Yangtze Delta of China—Special Economic Zones (SEZs). It takes into account spatial dependence to examine whether the human capital of SEZs exerts positive influences on the productivity of the local industry. The empirical results find that the local industry benefits from the human capital of SEZs. The spillover effects are not only confined to own counties but also neighboring counties. Indeed, SEZs contribute more to the productivity of neighboring counties than the one in the hosting county itself. Moreover, positive spillover effects of the human capital of SEZs still hold for the growth of productivity. Furthermore, the productivity of a region is similar to the one of the same industry in proximity.

Keywords: Special Economic Zone, Spatial Analysis, Human Capital, Spillovers, Yangtze Delta.
JEL classification: C21, C23, R10, O21

†Graduate School of Economics, Osaka University, 1-7, Machikaneyama-cho, Toyonaka, Osaka, 560-0043 , JAPAN. E-mail: u571686b@econ.osaka-u.ac.jp

1 Introduction

A growing number of "place-based" policies are implemented in geographically targeted areas to improve economic performances (Neumark and Simpson, 2015). For instance, Enterprise Zone programs in the US and the European Union; Special Economic Zone programs in developing countries. Such policies are thrown into doubt that they are simply a form of reallocating resources for arbitrage benefits (Glaeser and Gottlieb, 2008; Greenstone and Looney, 2010). On the other hand, some literature supports implementing the policies and provides rationales for them (Kline and Moretti, 2014).

The question arises whether rationales of the policies in developed countries such as knowledge spillovers still hold for developing countries. Knowledge spillovers are expected to produce positive effects on the local economy, more specifically, bringing additional people who have more skills can improve the other's productivity through sharing of knowledge and faster technology adoption (Moretti, 2010). Knowledge spillovers from additional human capital in targeted areas are crucial for policy-makers to understand the efficiency of the policies, especially for developing countries that have constraint resources to allocate.

Among developing countries, this paper focuses on place-based policies in China—Special Economic Zone (SEZ) program. China has been implemented SEZ program as a crucial part of Chinese economic reforms since 1978. In the last decades, the government has cost a huge amount of money and allocated millions of acres to set up SEZs for regional developments[1]. Empirical literature finds that implementing the policies has positive impacts for the firms located within SEZs or the cities hosting the SEZ program (Wang, 2013; Alder et al, 2013; Zheng et al, 2017; Lu et al, 2019). However, few attempts were made to study the extent of geography diffusion of the impacts in China, assuming that the spillovers of SEZs are only limited to their considered regions.

The relation of knowledge spillovers and regional growth can be investigated in a geographical dimension (see Döring and Schnellenbach, 2006). A common mechanism for a transfer of knowledge is the mobility of individuals and the trade of goods, which carry

[1] As of 2006, there were 1,568 SEZs in more than 270 cities that cover 9,949 square kilometers in total (Zheng et al, 2017).

production-related knowledge with them (e.g. Matusik and Hill, 1998), and notably, would also allow a spilling over of embodied knowledge. A particularly interesting mechanism of embodied knowledge spilling over is the transfer of human capital (i.e. a skilled worker commanding tacit knowledge) from one firm to another. We define the kind of spillovers as "human capital" spillovers in this paper. Human capital spillovers do not only occur within one particular region but also transfer to neighboring ones (Lopez-Bazo et al, 2004; Fischer et al, 2009).

In the context of the SEZ program, we need to consider spillover effects beyond the targeted zones. Some literature evaluates the impacts of place-based policies in the further scope (Rosenthal and Strange, 2008; Zheng et al, 2017). As a development policy widely accepted in many countries, the externalities from targeted zones to the local economy should also be included for policy-makers to do a cost-benefit analysis. Corresponding preferential policies such as tax deduction and subsidy are provided by the government to attract skilled labor in order to stimulate regional growth. However, entrants of targeted zones that have higher human capital may put local firms at disadvantage due to such policies. They may poach away locally trained talent, and crowd out firms outside the zones in the same industry.

This paper aims to address two important questions on human capital spillovers from SEZs to the local economy. First, does the human capital of SEZs diffuse positive externalities to local industries in the same region? Second, will the human capital of SEZs benefit the same industry in neighboring regions? Only considering the regions which hosting the SEZ program may overestimate the magnitude of the externalities of SEZs. Bringing additional skilled labor to SEZs is suspected to be simply a form of reallocating resources to another location. On the contrary, attracting firms that relatively have higher human capital is likely to spill over knowledge or advanced technology to stimulate the productivity of local industries.

This paper builds on the research estimating the human capital spillovers at the regional level. In many studies, they set the human capital of a state or of a county as an explanatory variable and confirm the existence of human capital externalities (Lopez-Bazo et al, 2004; Ramos et al, 2010). To evaluate the spillovers of SEZs to the local economy, we set the human capital of the firms within SEZs as an explanatory variable. In addition, we focus on the human capital spillovers in the same industry rather than across all the industries, supposing that the observation in proximity has high similarity in the same industry.

This study builds on the spatial econometric literature which allows us to examine spillovers in three channels (see LeSage and Pace, 2009; Elhorst, 2014)). Specifically, an increase in the human capital of a SEZ is likely to affect its own region (direct effect) and may affect the neighboring regions (indirect effect). Moreover, spatial regression can measure impacts passing through the neighboring regions and back to the region itself (feedback loops). These effects seek to investigate both intra- and inter-regional effects of human capital spillovers on regional productivity. In the context of the SEZ program, it should be examined that whether the externalities arising from a SEZ have impacts on the geographical proximal regions. However, to the best of the author's knowledge, existing literature focuses on the impacts of SEZs in an intra-region dimension that SEZs exert influences on the hosting regions in China. To fill this gap, the paper adds to the existing literature by considering spatial proximity. Both intra- and inter-regional examinations are necessary for policymakers to revise the cost-benefit analysis of the SEZ program.

This paper answers the question of whether the externalities of human capital in SEZs are able to raise local productivity. From the empirical results, we conclude that the human capital of SEZs contributes to diffusing knowledge and thus improving productivity in the same region. In addition, this paper further addresses whether the spillover effects of SEZs can benefit neighboring regions in spatial proximity as well. The positive spillovers to wider geographic scope imply that the rising proportion of college-educated workers in SEZs does not harm the firms in the proximity, instead, the driving effect of human capital to facilitate local firms to improve productivity is evident.

The rest of this paper is organized as follows. Section 2 presents related literature that mainly focuses on place-based policies in developing countries. Section 3 introduces the background of the SEZ program released in China. Section 4 describes the data. Section 5 and Section 6 present estimation models and empirical results. The conclusion is summarized in the last section.

2 Related Literature

2.1 Literature on Place-based Policies

Place-based policies in developed countries differ from those in developing countries on both policy goals and implement measures. To contrast empirical evidence for similar types, this paper directly relates to place-based policies operated in developing countries.

In developing countries, implementing place-based policies is a way to stimulate the local economy, as well as to promote development within the zones. Johansson and Nilsson (1997) find that SEZs have positive effects on exports in Hong Kong, Malaysia, Singapore, and Sri Lanka. In particular, they highlight the performances of SEZs in Malaysia for attracting foreign investors who transfer knowledge to local markets. Wang (2013) and Alder et al. (2013) find that SEZs exert positive influences on the local economy with respect to employment, export, and foreign direct investment in China. Since using macro-level data, they evaluate the influences on the whole SEZ-operating counties, do not separate firms in zones with those outside zones in a county. Zheng et al. (2017) and Lu et al. (2019) distinguish firms located within SEZs and those outside zones by using geocoded firm-level data. Zheng et al. (2017) find that in several major cities of China SEZs have positive spillovers with respect to wage, employment, and productivity for non-SEZ firms located nearby SEZs. Ciżkowicz et al. (2017) also find that implementing place-based policies creates jobs for the firms outside zones in Poland.

With regards to research methods, existing literature studying place-based policies can be divided into two types. One is literature that summarizes experiences and rationales of implementing place-based policies based on case studies and interviews. Zeng (2011) describes experiences in China and discusses keys of success and faced opportunities. Farole (2011) introduces experiences in Africa and possible reasons for those outcomes. The other one is literature that employs econometric models to estimate the effects of place-based policies. Many empirical studies evaluate the impacts of place-based policies by a quasi-experimental approach such as the difference-in-difference method (See Wang, 2013; Alder et al, 2013; Zheng et al, 2017; Lu et al, 2019). These studies that allow for comparisons of treatment groups and appropriate control groups make valid identification of causal effects. The quasi-experimental approach is broadly applied to investigate the impacts of place-based policies in both developing and developed countries (See Busso et al, 2011). Except for this kind of approach, spatial econometric models are used to assess the spillover effects of place-based policies by taking into account the geographical proximity of the observations (Ciżkowicz et al., 2017).

2.2 Literature on Human Capital Spillovers

Human capital spillovers and accumulation of knowledge are regarded as catalysts for the development of a city (Lucas, 1988). More generally, the human capital of others in close proximity can raise everyone's human capital and increase firm productivity, through sharing of knowledge and faster adoption of innovations (Moretti, 2010). Lots of literature measures human capital by the educational level, such as the share of workers with a college degree or comparable education, because positive spillovers are more likely to diffuse from more highly educated workers, due to the knowledge they possess and perhaps the work they do. Glaeser and Saiz (2004) find that human capitals benefit the local economy in the term of wage, patents, and economic growth rate. Human capital is used to estimate the spillover effects not only in its own region but also in the spatial dimension. Ramos et al. (2010) investigate the effects of human capital spillovers on regional productivity and growth, not only for the considered region but also for the neighboring ones. Baltagi et al. (2016) estimate firm-level productivity spillovers in China's chemical industry considering the neighbor's skilled labor ratio.

3 Background

This section introduces the background of SEZ programs implemented in China. SEZs are geographically designated areas by the government that is aimed to stimulate economic growth in their jurisdiction. They are subject to different regulations than other areas within the same country. Generally, the term "SEZ" is a zone that includes some common characteristics such as—it is located in geographically designated areas; it offers benefit to investors within the zone; it has separate customs areas; it has single administrations (World Bank, 2009).

The SEZ program has been implemented over the last 40 years as a crucial part of Chinese economic reforms since 1978. Before the reforms, China was an isolated socialist state dominated by central planning. Instead of carrying on previous policies, the creation of SEZs in the initial stage was an experiment to test for the market-oriented economy. By 1980, the first four SEZs were approved to set up in Shenzhen, Zhuhai, Shantou, and Xiamen. Since these regions were eastern coastal areas near Hong Kong, Macao, and Taiwan, the designation at that time took into account both economic and political factors. As the success of these regions, additional 14 coastal regions were designated as SEZs in 1984 to gain further access to foreign markets and investment. The next wave of SEZs in the 1990s gradually began to extend from eastern coastlines towards inland regions, especially after Deng Xiaoping's southern tour to SEZs in 1992. By 2001, SEZs were established one after another covering all provinces across China. As of 2006, SEZs account for 1,568 occupying 9,949 acres of land in total.

By administrative levels, SEZs are divided into two categories: national-level and provincial-level. The former one is conducted by the central government and the latter one is directed by the provincial governments. National-level SEZs grant more autonomy and enjoy more privileges than provincial-level SEZs. Only authorized by the central government or the governments which have provincial administrative level are legal SEZs in China. The others that were not approved by the central or provincial governments violated related laws and regulations were abolished in 2006.

Although there are some differences between specific privileges of national- and provincial-level, SEZs are all granted market-oriented freedom and offered preferential benefits. The SEZ program is given greater autonomy to adjust related regulations along the basic lines of national ones by removing some constraints within the scope of the zones. Also, the government provides a series of preferential policy packages for foreign and domestic investors which enter the zones as the following[2]:

1. *Tax deduction.* In General, the policy deducts corporate income tax rate to 15-24% for firms in SEZs relative to 33% for ordinary domestic firms outside SEZs. Also, customs

[2] See Wang (2013), Alder et al. (2013), Zheng et al. (2017) and respective provincial government websites for details.

duty is exempted and duty-free allowances of intermediate inputs are offered for the firms located in SEZs.

2. *Land use discount.* The land is owned by the government and the land use right is strictly regulated in China. Different from many countries, officials can allocate land on large scale and convert agricultural land for industrial purposes when necessary. Land use rights for industrial purposes are granted for domestic and foreign investors which enter the SEZs. Besides land use rights, land use fees are discounted for entrants relative to the firms outside zones.

3. *Special treatment for a loan.* The state-owned bank looses lending policies and gives priority to the firms in SEZs to apply for a loan.

4. *Procedure simplification.* For potential investors who enter the zones, procedures are simplified and approved for high-speed.

5. *Property protection.* The government commits to the investors who enter the zones that all of their private properties are under-protected.

Besides these preferential policies, the government also makes a great effort to improve infrastructures of zones such as roads, ports, electricity, gas, water, telecommunications, and other service facilities. Furthermore, to attract skilled human capital, SEZs offer an extra personal income tax deduction, allowances, and Hukou registration priority benefit to a highly qualified individual[3].

Each SEZ has its administrative committee which performs management functions within its geographical scope. Administrative committees are not under the control of local governments, they are directly controlled by the state or the provincial governments. They direct and administer affairs of SEZs on the behalf of the government such as project approval, local taxation, land management, public facilities planning, financial revenue, personnel, environment protection, and so on. For example, administrative committees take responsibility to attract investors from domestic or abroad that meet the standards of local development. Each administrative committee has the right to decide which investors could enter the zone. They offer a bundle of preferential policies and negotiate with po-

[3] In China, each citizen is categorized by location of origin and further classified in a rural or urban Hukou.

tential entrants for details. After these negotiations, the investors decide whether to enter the zone or not.

4 Data

The main data is firm-level data from the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics of China (NBS). The ASIF data covers all state-owned firms and non-state-owned firms with an annual turnover exceeding five million yuan (approximately $700,000), and those firms occupy over 90% of the total industrial outputs of China in 2004. The ASIF data contains more than 100 variables, providing information on industrial output, intermediate input, total employment, industry affiliation, and geographic location. Since covering comprehensive variables, the data has been widely used in empirical literature such as Brandt et. al. (2011).

The ASIF data in 2004 is more comprehensive than other years' ASIF data. Besides the basic information, the data in 2004 include the level of employee education. To evaluate the spillover effects of human capital, we exclusively use the 2004 data. Our paper focuses on manufacturing firms in Yangtze Delta, which is made up of three province-level areas in east-central China: Shanghai City, Jiangsu, and Zhejiang Provinces. Yangtze Delta is the most industrially developed and wealthiest area in China. Although occupying about 2% of the total land area, Yangtze Delta contributes more than 21% of GDP in China. In this paper, we focus on manufacturing firms in Yangtze Delta which includes 84,290 firms.

The information of SEZs is from notices of the government. One is "The review of Special Economic Zones in China", which was published by the National Development and Reform Commission and the Ministry of Land and Resources in 2006. It contains authorized SEZ's name, type, authorized time, and occupied area. The other one is "the notice of four directions" which includes geographic information on SEZs released by the Ministry of Land and Resources of China. It has detail information on the geographic boundary of SEZs which covers specific villages, roads, or coasts. The data has been used to related research such as Zheng et al. (2017) and Lu et al. (2019).

The ASIF data does not report any information about SEZs, however, it contains each firm's address and geographic location code. The geographic location consists of a 12-digit geographic code, which provides location information at the most disaggregated level. It consists of district (or county), jiedao (streets or avenues), and juweihui (communities or villages). Following Zheng et al. (2017), each firm's geographic location code and the exact geographic boundaries of SEZs can be used to identify whether a firm is located in SEZs or not. By comparing geographic location code and boundaries, there are about 15% of the firms located in SEZs.

To investigate intra- and inter-regional spillovers from SEZs, we define *region* as a county in this paper. All variables are aggregated at the county-level by using firm-level data information. In particular, we define regional productivity as the log of value-added per employed worker of each industry in county i (y_{ik}). We assume that the regional productivity function depends on three factors. First, we employ the level of education as a measure of human capital. h_{ik} denotes the share of labor who have college degrees or above for the firms *located in the zones* of industry k in county i; edu_{ik} denotes the average numbers of schooling years for the firms *outside the zones* of industry k in county i. Second, we use physical capital into the function to describe regional productivity: the log of capital stock per employed worker of each industry in county i (cap_{ik}). Third, we control for competition index (com_{ik}) and industrial diversity index (div_{ik}). The strength of competition of an industry in a local market will influence regional productivity. Fierce competition may decrease regional productivity due to diminishing marginal returns. Meanwhile, intensive competition forces local firms to adopt advanced techniques to improve productivity. In this paper, we define a competition index as follows,

$$com_{ik} = ln(1/H_{ik})$$

where $H_{ik} = \sum_{f \in \Omega_{ik}} (\frac{revenue_{ikf}}{revenue_{ik}})^2$ denotes an Herfindahl index of sales revenue concentration of industry k in county i; $revenue_{ikf}$ is sales revenue of firm f belongs to industry k in county i; $revenue_{ikf}$ denotes the sum of sales revenue of industry k in county i.

Additionally, we control for industrial diversity index (div_{ik}). As noted by Jacobs, productivity of an industry in a region can be influenced by different industries and the more diverse the more likely to improve regional productivity. Following Marrocu et al. (2013) and Henderson (1997), an industrial diversity index is defined as the follows,

$$div_{ik} = ln(1/\sum_{k \neq k'}(\frac{emp_{ik'}}{emp_i - emp_{ik}})^2)$$

where emp_i denotes total employment in county i; emp_{ik} denotes the total employment of industry k in county i.

In Figure 1, we present the counties hosting SEZ program in Yangtze Delta. SEZ-hosting counties are mainly distributed on the east coast or along the Yangtze River. There are as many as 108 SEZ-hosting counties in Yangtze Delta in 2004, which means SEZ-hosting counties occupy about two-thirds of all the counties in the area.

[Insert Figure 1 here]

5 Model Specification

In this paper, we introduce spatial dependence to analyze the spillover effects of the human capital of SEZs to their own counties and the neighboring ones. Considering spatial dependence to examine the effects of SEZs to intra- and inter-region is plausible because a positive shock on the productivity of an industry in a county could also be transferred to the same industry in the nearby counties. Moreover, the spatial lag of explanatory variables can also be included because externalities arising from neighbor's human capital or other neighbor characteristics could also play a role in determining the productivity of the local industry.

There are two advantages to employ spatial regressions. First, spatial regressions can take into account the spatial lag of the dependent variable and independent variables to describe the outcome of interest. The introduction of spatial dependence allows observations to have associations with each other and to explore the relationship between a county and the neighboring counties. In addition, spatial regression captures spillover effects through three channels. An increase in SEZs will affect the SEZ-hosting county itself (direct effect) and possibly affect the neighboring counties (indirect effect). Furthermore, spatial regression exploits impact passing through the neighboring counties and back to the counties themselves (feedback effect). The inclusion of spatial information makes it possible to assess the effects of the SEZ program more comprehensively through multiple channels.

In this paper, we divide manufacturing firms into 28 industries by 2-digit level classification, for the reason that the same industry clusters together and has similar characteristics in proximity. We estimate human capital spillovers of SEZs on the local economy via a Spatial Durbin Model (SDM) as follows,

$$\begin{aligned} \boldsymbol{y} = \ & \boldsymbol{\alpha} + \boldsymbol{W}\boldsymbol{y}\delta + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon} \\ & \boldsymbol{X} = [\boldsymbol{h} \quad \boldsymbol{edu} \quad \boldsymbol{cap} \quad \boldsymbol{com} \quad \boldsymbol{div}] \end{aligned} \tag{1}$$

where $\boldsymbol{y}$ is regional productivity for industry k in county i; $\boldsymbol{W}$ is row-standardized inverse weight matrix within 150 kilometers, otherwise zero; $\boldsymbol{h}$ denotes the share of labor who have college degrees or above for the firms *located in the zones* in county i; $\boldsymbol{edu}$ controls the average numbers of schooling years for the firms *outside the zones* of industry k in county i; $\boldsymbol{cap}$ is the capital stock per employed worker of each industry in county i; $\boldsymbol{com}$ and $\boldsymbol{div}$ denote competition index and industrial diversity index; $\boldsymbol{\varepsilon}$ is the error term, normally distributed by (0, σ^2).

The coefficient of $\boldsymbol{h}$ describes the spillover effects from the human capital of SEZs on regional productivity. If the coefficient of $\boldsymbol{h}$ is significantly positive, which means that a 1% increase in the human capital of SEZs stimulates regional productivity. Also, if the estimate δ is statistically significant, it implies that a spatial autocorrelation exists and employing spatially lagged dependent variable is meaningful. Furthermore, if the coefficient of $\boldsymbol{Wh}$ is significantly positive, it implies that the human capital of SEZ in a county is similar to the one in neighboring counties located in close distance.

With respect to the selection of models, we compare SDM models with other spatial regression models. As noted by LeSage and Pace (2009), SDM models nest most of the other specifications like Spatial Error Model (SEM) and Spatial Autoregressive Model (SAR). Hence, we estimate the SDM models and then compare them with SEM or SAR models by Likelihood Ratio (LR) test. The estimation results obtained from these models can be used to test the hypothesis:

$$H_0 : \boldsymbol{\theta} = \boldsymbol{0}$$

$$H_0 : \boldsymbol{\theta} + \delta\boldsymbol{\beta} = \boldsymbol{0}.$$

The former one examines the hypothesis of whether the SDM model can be simplified to forms of SAR model. If the null hypothesis is rejected, it demonstrates that the SDM model better describes the data; the latter one is used to examine between SDM and SEM model. If the null hypothesis is rejected, it means that the SDM model cannot be simplified to the SEM model. Since the SDM model is a generated form nesting the other two models, it is better favored than the two models in the case that either of the two hypotheses is rejected.

As suggested by LeSage and Pace (2009), we measure average direct and indirect effects to explain the marginal effects of the explanatory variable. Average direct effect, measured by taking an average of the own derivatives for the counties themselves, which captures the effects of SEZs to its own county. The average indirect effect is calculated by the average of derivatives with respect to neighboring counties, which measures the spillovers of SEZs to neighboring counties. To illustrate, we take the partial derivative of the dependent variable with respect to $\boldsymbol{h}$ as follows,

$$\frac{\partial \boldsymbol{y}}{\partial \boldsymbol{h}} = \boldsymbol{S(W)} = (\boldsymbol{I_n} - \delta \boldsymbol{W})^{-1}(\boldsymbol{I_n}\beta_1 + \boldsymbol{W}\theta_1) \quad (2)$$

where $\boldsymbol{I_n}$ are 3815×3815 idempotent matrices. From equation (4), the partial derivative is not only depends on β_1, but also θ_1, δ, and spatial weight matrix. By definition, the average indirect effect is calculated by the average of diagonal elements of $\boldsymbol{S(W)}$, and the average indirect effect is measured by the average of off-diagonal elements of $\boldsymbol{S(W)}$. From the above equation, we can capture spillover effects through three channels. An increase in human capital in SEZs will affect the firms in the considered county itself (direct effect) and arouse spillovers passing through neighboring counties and back to the counties themselves (feedback effect). Furthermore, growth in human capital in county i may affect the neighboring counties (indirect effect).

Some literature suggests that one needs to estimate the effects of human capital on growth rate (Lopez-Bazo, 2004; Ramos et al, 2010) because the human capital used in most literature is a stock variable which may arouse the problem of endogeneity. Criticize causality from productivity to human capital does not apply to the estimation of growth rate in this case. To investigate the relation of the growth of regional productivity, we transform equation (1) as follows[4],

$$\begin{aligned} \boldsymbol{\Delta y} = \ & \boldsymbol{\alpha} + \boldsymbol{W}\boldsymbol{\Delta y}\delta + \boldsymbol{y_{-1}}\gamma + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon} \\ \boldsymbol{X} = & [\boldsymbol{h} \quad \boldsymbol{edu} \quad \boldsymbol{cap} \quad \boldsymbol{com} \quad \boldsymbol{div}] \end{aligned} \tag{3}$$

where $\boldsymbol{\Delta y}$ denotes the growth rate of regional productivity from the period of 2003 to 2004 for industry k in county i; $\boldsymbol{y_{-1}}$ denotes the regional productivity for industry k in county i in 2003.

Equation (3) evaluates the effects of human capital on the growth of regional productivity controlling for the neighbors, lagged value of the productivity, and other variables. If the estimate δ is significantly positive, it implies that the growth of regional productivity depends on the one in the neighbors. Also, the coefficient of $\boldsymbol{h}$ describes the spillover effects from the human capital of SEZs on the growth of regional productivity when controlling for lagged productivity and other explanatory variables. Furthermore, if the coefficient of $\boldsymbol{Wh}$ is significantly positive, it implies that the human capital of SEZ in a county is similar to one another that is located in close distance.

6 Empirical results

[Insert Table 1 here]

Table 1 reports the results of spatial regression models using regional productivity as the dependent variable. To diagnose the existence of spatial dependence, we first estimate equation (1) using linear ordinary least squares (OLS) models without spatial effects. The estimated coefficients of the spatially lagged dependent variable in the SAR and SDM model are significant at the 1% significance level, which suggests the existence of spatial dependence. In addition, estimated coefficients of $\boldsymbol{h}$ from (1) to (3) are all significantly positive. In the third column, the coefficient of $\boldsymbol{h}$ amounts to 0.7936, which implies that a 1% increase in the human capital of SEZs will lead to 0.7936% improvement in regional productivity. Furthermore, the spatial lag of $\boldsymbol{h}$ shows significantly positive in the third

[4] See Ramos et al (2010) and Lopez-Bazo (2004) for the derivation of the equation (3).

column, which implies that the human capital in a zone is similar to the one in the neighbor zones.

Likelihood ratio (LR) tests are proceeded to compare the SDM model with SAR and SEM models. As presented in Table 1, the first hypothesis whether the SDM model can be simplified to the SAR model should be rejected at the 1% significance level; the second hypothesis whether the SDM model can be replaced by the SEM model should also be rejected. Thus, we come to a conclusion that the SDM model best describes the data and the remains of this paper employs the SDM model to calculate average direct, indirect effects, and robustness checks.

[Insert Table 2 here]

Table 2 reports direct, indirect, and total effects of the SDM model in equation (1). As noted in the previous section, one cannot interpret the estimate $\boldsymbol{\beta}$ as a partial derivative with respect to the explanatory variable, one should calculate the estimates of direct, indirect, and total effects to interpret the marginal effects. In particular, the direct effect of the human capital of SEZs on regional productivity is positive and similar to the coefficient of $\boldsymbol{h}$. In addition, the feedback loops calculated by the difference between them are insignificantly different from zero, so that feedback loops can be neglected. The result implies that the regional productivity benefits from the human capital of SEZs in the considered counties, however, the spillovers from SEZs pass through neighboring ones are not back to the considered counties.

From the second column, we find that the indirect effect of the human capital of SEZs on the neighboring counties is significantly positive. The estimation result indicates that a 1% increase in the human capital of SEZs will lead to a 1.7844% increase in the regional productivity of the neighbors. The neighboring counties benefit from the human capital of SEZs more than two times the one in the considered counties. Because the indirect effects are cumulative impacts from all other neighboring counties, aggregating indirect effects from the neighborhood would lead to a larger magnitude than the direct effect itself.

[Insert Table 3 here]

Table 3 presents sensitivity checks of our estimates with alternative spatial weight matrices. We employ alternative weight matrices based on cut-off distance from 160 kilometers to 200 kilometers respectively. In particular, we present the derivative with respect to the variable $\boldsymbol{h}$ and compare it with the results in Table 2 which used the cut-off distance as 150 kilometers. The direct effect estimates are not affected by alternative weight matrices, and the indirect effect estimates are relatively constant with alternative weight matrices.

[Insert Table 4 here]

The empirical results of equation (4) using OLS, SAR, as well as SDM models are shown in Table 4 respectively. As the estimates of equation (1), the ones of the spatially lagged dependent variable in SAR and SDM model are significant at the 1% significance level and suggest the existence of spatial lag of the growth of productivity. Also, the estimates of human capital are significantly positive at a 5% significance level. The magnitude of the coefficient for human capital accounts for 0.5634 in the SDM model, which means a 1% increase in the human capital of SEZs will lead to a 0.5634% improvement in the growth of regional productivity when controlling for the lagged value of the productivity and other variables. Moreover, the spatial lag of human capital is significantly positive as the one in Table 1.

[Insert Table 5-Table 8 here]

From Table 5 to Table 8, we present the estimated results of the alternative explanatory variable: entrants of SEZs. Firms located within SEZs include entrants and incumbent firms. Since incumbent firms were established before SEZs were introduced, they strictly were not supposed to be called "additional" firms or people to the zones. In addition, the incumbent firms are unable to enjoy preferential policies like the entrants (see Zheng et al). For these reasons, we drop them from the sample and focus on the entrants to evaluate whether human capital spillovers of SEZs have positive effects on regional productivity.

In Table 5, we report the estimates of equation (1) replaced $\boldsymbol{h}$ with the human capital of entrants in SEZs, and find that the magnitude of the estimates remains virtually unchanged relative to the ones in Table 1. In Table 6 and Table 7, we report average direct, indirect effects and the estimates with alternative weight matrices based on the results of the SDM model in Table 5. In Table 8, we present the estimates of equation (3) with the human capital of entrants in SEZs. From Table 5 to Tables 8, the estimates of the human capital of entrants are a little smaller than the ones from Table 1 to Table 4 because the number of entrants occupies 77% of all the firms in SEZs. Since entrants are a subsample of all the firms in SEZs, it is reasonable that the estimates are smaller than the ones in previous estimation results.

To sum up, our results find that local firms benefit from the human capital of SEZs in the same industry. Positive spillover effects are not only confined to own counties but also neighboring ones. In addition, we find that the human capital of SEZs benefits the growth of regional productivity. Moreover, positive externalities of human capital still hold for the sample of entrants.

There are two possible explanations for the estimated results. Both of them are beyond the scope of this paper and should be carefully investigated in further research. First, most firms that enter SEZs are engaged in new productive activities rather than simply reallocating capital and labor from elsewhere. Those firms bring additional people especially relatively highly skilled labor to the local industry. They generally have their own competitive advantages and do not compete with lower technology firms. Positive spillovers which are from higher-skilled labor to lower ones lead to faster new technology adoption. In addition, unlike a few multinational firms which have little connection with the local industry, the firms in SEZs establish strong linkages with the local industry like subcontracting (Zeng, 2011). This would facilitate interactions with skilled labor of SEZs and technical upgrades for local firms, and thus seems likely to improve productivity.

7 Conclusion

This paper evaluates the spillover effects of SEZs in Yangtze Delta using 2004 manufacturing data. Taking into account spatial proximity, this paper quantifies the spillover effects of the human capital of SEZs on regional productivity. One major finding is that local firms benefit from the human capital of SEZs in the same industry. The spillover effects are not only confined to own counties but also neighboring counties. Indeed, SEZs contribute more to the regional productivity of neighboring counties than the one in the hosting county itself. Moreover, positive spillover effects of the human capital of SEZs still hold for the growth of regional productivity.

This paper answers the question of whether the externalities of human capital in SEZs are able to raise regional productivity. From the empirical results, we conclude that the human capital of SEZs contributes to improving productivity. In addition, this paper further answers whether the spillover effects of human capital can benefit neighboring regions in spatial proximity as well. The positive spillovers to wider geographic scope imply that the rising proportion of college-educated workers in SEZs does not harm the firms in the proximity, instead, the driving effect of human capital to facilitate local firms to improve productivity is evident.

Although this paper sheds light on the spillover effects of human capital in SEZs, there are remaining issues for further research. We can make an extension to firm-level data which would enable us to analyze inter-firm issues in spatial econometric models that have been discussed in recent literature (Baltagi et al, 2016; Hashiguchi and Tanaka, 2015). In addition, we can identify spatial spillovers of human capital in own- and other industry sectors as Autant-Bernard and LeSage (2011) examining for MAR and Jacobs knowledge externalities. The magnitudes of them are crucial for understanding the spillover effects of human capital in SEZs on local productivity. The experience in the Yangtze Delta region needs to be carefully examined and put into the specific situation of other countries and regions whereas the evidence of the region has positive spillovers towards the local economy. We leave the remaining issues to further research and evaluate whether the conclusion still holds.

References

Alder, S., Shao, L., Zilibotti, F. 2016. "Economic Reforms and Industrial Policy in a Panel of Chinese Cities," *Journal of Economic Growth*, 21(4), 305-349.

Anselin, L. 1988. *Spatial Econometrics, Methods and Models*. Boston, U.S.: Kluwer Academic.

Anselin, L. 2001. "Spatial econometrics," *A Companion to Theoretical Econometrics*, 310-330.

Autant-Bernard, C., LeSage, J. 2011. "Quantifying Knowledge Spillovers using Spatial Econometric Models,". *Journal of Regional Science*, 51(3), 471-496.

Baltagi, B., Egger, P., Kesina, M. 2016. "Firm-Level Productivity Spillovers in China's Chemical Industry: A Spatial Hausman-Taylor Approach," *Journal of Applied Econometrics*, 31(1), 214-248.

Brandt, L., Van Biesebroeck, J., Zhang, Y. 2012. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of development economics*, 97(2), 339-351.

Busso, M., Gregory, J., Kline, P. 2013. "Assessing the Incidence and Efficiency of a Prominent Place Based Policy," *American Economic Review*, 103(2), 897-947.

Ciżkowicz, P., et al. 2017. "The Effects of Special Economic Zones on Employment and Investment: A Spatial Panel Modeling Perspective," *Journal of Economic Geography*, 17(3), 571-605.

Döring, T., Schnellenbach, J. 2006. "What do we know about Geographical Knowledge Spillovers and Regional Growth?: A Survey of the Literature," *Regional Studies*, 40(03), 375-395.

Elhorst, J. 2014. *Spatial Econometrics: from Cross-sectional Data to Spatial Panels*. Heidelberg, Germany.: Springer.

Farole, T. 2011. *Special Economic Zones in Africa: Comparing Performance and Learning from Global Experiences.* The World Bank.

FIAS. 2008. *Special Economic Zones in Africa: Comparing Performance and Learning from Global Experience.* The World Bank.

Fischer, M., Bartkowska, M., Riedl, A., Sardadvar, S., Kunnert, A. 2009. "The Impact of

Human Capital on Regional Labor Productivity in Europe," *Letters in Spatial and Resource Sciences*, 2(2), 97-108.

Glaeser, E., Saiz, A., Burtless, G., Strange, W. C. 2004. "The Rise of the Skilled City," *Brookings-Wharton Papers on Urban Affairs*, 47-105.

Greenbaum, R., Engberg, J. 2004. "The Impact of State Enterprise Zones on Urban Manufacturing Establishments," *Journal of Policy Analysis and Management*, 23(2), 315-339.

Greenstone, M., Looney, A. 2010. *An Economic Strategy to Renew American Communities.* Hamilton Project, Brookings Institution.

Hashiguchi, Y., Tanaka, K. 2015. "Agglomeration and Firm-level Productivity: A Bayesian Spatial Approach," *Papers in Regional Science*, 94, S95-S114.

IFC. 2016. *The World Bank Group's Experiences with SEZ and Way Forward: Operational Note.* The World Bank.

Johansson, H., Nilsson, L. 1997. "Export processing zones as catalysts," *World Development*, 25(12), 2115-2128.

Kline, P., Moretti, E. 2014. "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs," *Annu. Rev. Econ*, 6(1), 629-662.

LeSage, J., Pace, R. K. 2014. "The Biggest Myth in Spatial Econometrics," *Econometrics*, 2(4), 217-249.

LeSage, J., Pace, R. K. 2009. *Introduction to Spatial Econometrics*. Florida, U.S.: CRC Press.

López-Bazo, E., Vayá, E., Artis, M. 2004. "Regional Externalities and Growth: Evidence from European Regions," *Journal of regional science*, 44(1), 43-73.

Lu, Y., Wang, J., Zhu, L. 2019. "Place-Based Policies, Creation, and Agglomeration Economies: Evidence from China's Economic Zone Program," *American Economic Journal: Economic Policy*, 11(3), 325-60.

Lucas Jr. 1988. "On the Mechanics of Economic Development," *Journal of Monetary Economics*, 22(1), 3-42.

Matusik, F., Hill, W. 1998. "The Utilization of Contingent Work, Knowledge Creation, and Competitive Advantage," *Academy of Management Review*, 23(4), 680-697.

Moretti, E. 2010. “Local Labor Markets,” *Handbook of Labor Economics*, vol. 4B. Elsevier, Amsterdam.

Moretti, E. 2012. *The new geography of jobs*. Houghton Mifflin Harcourt.

Neumark, D., Simpson, H. 2015. “Place-based Policies,” *Handbook of Regional and Urban Economics*, 5, 1197-1287.

Ramos, R., Suriñach, J., Artís, M. 2010. “Human Capital Spillovers, Productivity and Regional Convergence in Spain,” *Papers in Regional Science*, 89(2), 435-447.

Rosenthal, S., Strange, W. 2008. “The Attenuation of Human Capital Spillovers,” *Journal of Urban Economics*, 64(2), 373-389.

Wang, J. 2013. “The Economic Impact of Special Economic Zones: Evidence from Chinese Municipalities,” *Journal of Development Economics*, 101, 133-147.

World Bank. 2009.“Clusters for Competitiveness: A Practical Guide and Policy Implications for Developing Cluster Initiatives.” International Trade Department, PREM Network, Report, Washington, DC.

Zeng, D. Z. 2011. *How Do Special Economic Zones and Industrial Clusters Drive China’s Rapid Development?* The World Bank.

Zeng, D. Z. 2016. “Special Economic Zones: Lessons from the Global Experience,” *PEDL Synthesis Paper Series*, 1, 1-9.

Zheng, S., et al. 2017. “The Birth of Edge Cities in China: Measuring the Effects of Industrial Parks Policy,” *Journal of Urban Economics*, 100, 80-103.

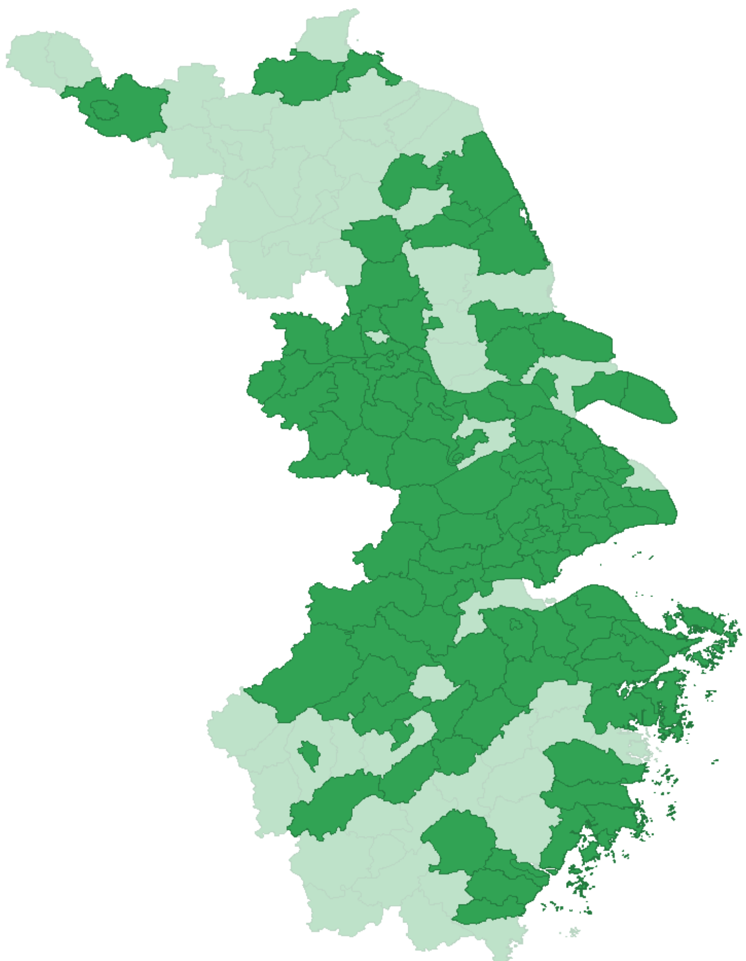

Figure 1: SEZ-hosting counties in Yangtze Delta

Table 1. Estimation Results for Regional Productivity

	OLS	SAR	SDM
	(1)	(2)	(3)
h	0.9407	0.8035	0.7936
	(9.9236)	(9.0136)	(2.6442)
edu	0.1180	0.1151	0.1335
	(8.4971)	(8.8304)	(1.4495)
cap	0.4788	0.3759	0.3993
	(41.1389)	(31.6789)	(24.2615)
com	-0.0001	0.0021	-0.0134
	(-0.0043)	(0.2141)	(-0.7696)
div	0.0576	0.0249	-0.0019
	(2.4902)	(1.1462)	(-0.1518)
W*h			0.3890
			(15.4114)
W*edu			-0.1369
			(-0.4929)
W*cap			-0.1358
			(-4.7920)
W*com			0.0095
			(0.4294)
W*div			0.1518
			(7.0856)
W*y		0.4419	0.5449
		(22.1670)	(8.8201)
R squared	0.4275	0.4330	0.4499
Std. error	0.6270	0.5882	0.5803
LR test spatial lag			71.60
			(0.00)
LR test spatial error			58.63
			(0.00)
No. of obs.	3,815	3,815	3,815

Note: t-statistics are reported in parentheses.

Numbers in parentheses for LR tests are p-values.

Table 2. Average Direct, Indirect, and Total Effects Estimates

	Direct	Indirect	Total
	(1)	(2)	(3)
h	0.8292	1.7844	2.6137
	(2.7129)	(4.3177)	(4.0456)
edu	0.1272	-0.1621	-0.0349
	(1.3693)	(-0.2643)	(-0.0551)
cap	0.4029	0.1875	0.5904
	(23.3717)	(1.7817)	(5.2583)
com	-0.0128	0.0050	-0.0077
	(-0.7410)	(0.1129)	(-0.1602)
div	0.0048	0.3288	0.3336
	(0.3883)	(5.5349)	(5.5227)

Note: t-statistics are reported in parentheses.

Table 3. Robustness checks with alternative spatial weight matrices
partial derivatives with respect to human capital

	Direct	Indirect	Total
	(1)	(2)	(3)
160 kilometer	0.8259	1.8798	2.7058
	(2.2841)	(3.5512)	(3.3450)
170 kilometer	0.8208	2.0949	2.9157
	(2.3427)	(3.6255)	(3.4873)
180 kilometer	0.8097	2.1802	2.9900
	(2.1759)	(3.6839)	(3.4007)
190 kilometer	0.8253	2.5176	3.3429
	(2.1373)	(3.6122)	(3.4160)
200 kilometer	0.8338	2.6302	3.4641
	(2.7775)	(3.6747)	(3.5306)

Note: t-statistics are reported in parentheses.

Table 4. Estimation Results for Growth of Regional Productivity

	OLS	SAR	SDM
	(1)	(2)	(3)
h	0.5914	0.5967	0.5634
	(7.0428)	(7.1602)	(2.2175)
edu	0.0509	0.0551	0.0666
	(3.9129)	(4.2719)	(0.5722)
cap	0.3663	0.3545	0.3407
	(31.9542)	(31.1575)	(6.0845)
com	-0.0056	-0.0067	-0.0160
	(-0.5996)	(-0.7204)	(-0.2643)
div	0.0543	0.0522	0.0232
	(2.6740)	(2.5907)	(1.7109)
y_{-1}	-0.5438	-0.5537	-0.5655
	(-37.7554)	(-38.7224)	(-6.0849)
W*h			0.5889
			(3.2629)
W*edu			-0.0780
			(-0.2871)
W*cap			0.0409
			(1.5522)
W*com			0.0042
			(0.1916)
W*div			0.1747
			(5.2314)
W*y		0.2159	0.1770
		(103.8699)	(3.2380)
R squared	0.3574	0.3367	0.3485
Std. error	0.5274	0.5234	0.5214
LR test spatial lag			29.88
			(0.00)
LR test spatial error			37.54
			(0.00)
No. of obs.	3,459	3,459	3,459

Note: t-statistics are reported in parentheses.

Numbers in parentheses for LR tests are p-values.

Table 5. Estimation Results for Regional Productivity
replace with the human capital of entrants

	OLS	SAR	SDM
	(1)	(2)	(3)
h	0.8553	0.7324	0.7236
	(9.1292)	(8.3205)	(2.4393)
edu	0.1164	0.1137	0.1317
	(8.3480)	(8.6950)	(1.4570)
cap	0.4844	0.3804	0.4048
	(41.8230)	(32.1716)	(24.7774)
com	0.0000	0.0022	-0.0139
	(0.0024)	(0.2271)	(-0.8167)
div	0.0662	0.0329	0.0067
	(2.8699)	(1.5189)	(0.5311)
W*h			0.3297
			(13.5335)
W*edu			-0.1281
			(-0.4669)
W*cap			-0.1375
			(-4.8362)
W*com			0.0134
			(0.6095)
W*div			0.1564
			(7.2730)
W*y		0.4439	0.5469
		(22.2332)	(8.9368)
R squared	0.4253	0.4304	0.4468
Std. error	0.6282	0.5890	0.5812
LR test spatial lag			70.58
			(0.00)
LR test spatial error			56.02
			(0.00)
No. of obs.	3,815	3,815	3,815

Note: t-statistics are reported in parentheses.

Numbers in parentheses for LR tests are p-values.

Table 6. Average Direct, Indirect, and Total Effects Estimates
replace with the human capital of entrants

	Direct	Indirect	Total
	(1)	(2)	(3)
h	0.7553	1.5809	2.3362
	(2.4954)	(3.9907)	(3.6479)
edu	0.1258	-0.1412	-0.0153
	(1.3803)	(-0.2326)	(-0.0245)
cap	0.4085	0.1928	0.6014
	(23.9274)	(1.8346)	(5.3778)
com	-0.0132	0.0129	-0.0003
	(-0.7767)	(0.2855)	(-0.0064)
div	0.0140	0.3509	0.3649
	(1.1222)	(5.6364)	(5.7503)

Note: t-statistics are reported in parentheses.

Table 7. Robustness checks with alternative spatial weight matrices
partial derivatives with respect to human capital of entrants

	Direct	Indirect	Total
	(1)	(2)	(3)
160 kilometer	0.7497	1.6790	2.4287
	(2.1065)	(3.3197)	(3.0532)
170 kilometer	0.7450	1.8699	2.6150
	(2.1552)	(3.3179)	(3.1437)
180 kilometer	0.7342	1.9009	2.6352
	(1.9955)	(3.1498)	(2.9280)
190 kilometer	0.7480	2.1362	2.8843
	(1.9755)	(3.4030)	(3.1002)
200 kilometer	0.7567	2.3084	3.0652
	(1.9988)	(3.3872)	(3.1613)

Note: t-statistics are reported in parentheses.

Table 8. Estimation Results for Growth of Regional Productivity

replace with the human capital of entrants

	OLS	SAR	SDM
	(1)	(2)	(3)
h	0.5305	0.5361	0.5138
	(6.3964)	(6.5122)	(2.0380)
edu	0.0495	0.0537	0.0650
	(3.7936)	(4.1489)	(0.6978)
cap	0.3700	0.3582	0.3442
	(32.3987)	(31.6024)	(10.1529)
com	-0.0055	-0.0066	-0.0163
	(-0.5895)	(-0.7112)	(-0.4542)
div	0.0601	0.0580	0.0282
	(2.9635)	(2.8837)	(2.2371)
y_{-1}	-0.5420	-0.5520	-0.5636
	(-37.6190)	(-38.5840)	(-10.2150)
W*h			0.5361
			(5.5386)
W*edu			-0.0752
			(-0.2980)
W*cap			0.0427
			(1.6886)
W*com			0.0056
			(0.2640)
W*div			0.1876
			(7.3179)
W*y		0.2159	0.1780
		(103.8232)	(3.2749)
R squared	0.3558	0.3349	0.3485
Std. error	0.5280	0.5241	0.5214
LR test spatial lag			29.58
			(0.00)
LR test spatial error			37.23
			(0.00)
No. of obs.	3,459	3,459	3,459

Note: t-statistics are reported in parentheses.

Numbers in parentheses for LR tests are p-values.