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Ren Lu
Jiangxi University of Finance and Economics

Min Ruan
Jiangxi University of Finance and Economics

Torger Reve
BI Norwegian Business School

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By
Ren Lu
Institute of Industrial Economics
Jiangxi University of Finance and Economics
Nanchang, China
luren@jxufe.edu.cn

Min Ruan (corresponding author)
Institute of Industrial Economics
Jiangxi University of Finance and Economics
Nanchang, China
ruanmin@jxufe.edu.cn

&
Torger Reve
Department of Strategy
BI Norwegian Business School
Oslo, Norway
torger.reve@bi.no

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Abstract

We study how industrial clusters in three different life phases both influence and moderate total factor productivity (TFP) of other co-located industries or clusters. A multilevel regression model is applied to panel data, 1993–2012, from the Pearl River Delta, China. Our empirical results show that emerging clusters have negative effects on other co-located industries' or clusters' TFP while mature clusters have positive effects. Emerging clusters positively moderate TFP, while mature clusters negatively moderate TFP of other co-located industries or clusters; declining clusters only have direct positive impact on TFP of other co-located industries or clusters.

Key words: cluster, co-located cluster effects, TFP, cluster life phase, moderating effect

JEL codes: R11, L00

1 Introduction

"No city is really a one-industry town, not even Hollywood or the Silicon Valley" (Helsley and Strange, 2014, p.1064). This is particularly true for big cities. In large metropolitan areas, several industrial clusters are co-located, generating jobs and creating wealth. This reality of multiple urban clusters represents the starting point for our research. Martin and Sunley (2006, p.431), argued that "in most regions there will be groups of interrelated or complementary industries and activities, linked either by direct input-output relationships, or by various indirect (or untraded) interdependencies and externalities". Sturgeon et al. (2008, p.301) added that there are few discussions about cluster relationships, and Cooke (2012) highlighted that building inter-industries is important.

Although it is unrealistic to assume that one region can only contain one cluster, co-located clusters represents a research void. Quickly reviewing the trajectory of cluster theory development over the last more than two decades: when studies about cluster phenomena emerged and flourished, the most famous paradigms—such as Porter's (1990) diamond model, Krugman's (1991) core-peripheral model, Asheim's (1996) learning region argument, Gertler's tacit knowledge approach (e.g., Gertler, 2003; Lawson and Lorenz, 1999) and network approach (Giuliani, 2007; Liu et al., 2013), etc.—paid more attention to the meso-level (that is, the individual cluster level). In other words, studies at meso-level are concerned about the mechanisms of how one individual cluster functions. Regarding the future study orientation, some scholars suggested that studying the micro-level, that is, checking cluster phenomena from the viewpoint of individual cluster firms, could be meaningful and valuable (Hervas-Oliver et al., 2015, p.25; and the Journal of Economic Geography, 2011, issue 2). In recent years, however, other scholars have embraced the macro-level (that is, multi-cluster level, or relation among clusters) studies. Departing from the business scholars' and geographers' viewpoint, Delgado et al. (2010), Bathelt and Li (2014), Li (2014), Lu et al. (2013), and Lu and Reve (2015) have shown that conducting studies at a multi-cluster level provides new insights. Some may question whether clusters have relations with one another since they are abstract phenomena (Martin and Sunley, 2003). We argue that just like microeconomics cannot replace macroeconomics, cluster relation summaries based only on the viewpoint of individual firms are insufficient. Furthermore, building on the viewpoint of regional policy makers, who cannot intervene in individual relations, but are interested in how various clusters contribute to economic development, how to balance various clusters' interests is a main issue in regional policy-making (Lu and Reve, 2015).

Fortunately, a few scholars have seen the value of studying relations among clusters. The first current approach focuses on clusters that are geographically distant from each other (clusters' global network). For instance, Bathelt and Li (2014) showed that Chinese and Canadian clusters were connected by FDI activities; Li (2014) reported that trade fairs are platforms to enhance cluster relations. Furthermore, Global Commodity Chains (GCC), Global Value Chains (GVC), and Global Production Networks (GPN) pay attention to the power-driven reasons that explain business relations among countries (Mahutga, 2014), although geography per se is not a key argument of GCC, GVC, and GPN (e.g., Barrientos, 2014; Henderson et al., 2002; Patel-Campillo, 2011). The second approach, by contrast, studies relations among clusters in geographic proximity or so-called co-located clusters. For instance, Delgado et al. (2010) and Lu et al. (2013) reported that when two or more clusters are in the same or a nearby location, local resources (for example, capital, talent, and knowledge) can flow among them, influencing their size. According to Mukim (2015), when industries are in geographic proximity, there are potentially at least four linkage types: labour-market, buyer, seller, and technological.

Though this paper is based on the second approach, it goes further by not only expanding prior discussions about relations among clusters, but also showing how they impact co-located **industries**[1] **or clusters**. The paper introduces two key factors: **total factor productivity** (hereafter, TFP) and **life phase**. TFP refers to the ability of an industry or a cluster to transfer its inputs to outputs efficiently. If TFP is high, the industry or cluster can input fewer resources to generate more outputs (Syverson, 2011). TFP as an indicator can reflect three key features of an industry or a cluster: technology progress, allocation of resources, and economies of scale (Ibid). The reason for choosing TFP as a dependent variable is that it shows the essence of cluster phenomena, as increasing productivity is its most attractive virtue (Krugman, 1996, chapter 1; Porter, 1998, chapter 7). Studies by Lee et al. (2013), Lin et al. (2011), and Widodo et al. (2014), for example, all empirically showed how important TFP is in cluster theory. On the other hand, because clusters of different "ages" may have different impacts on co-located industries or clusters, this paper divides them into three **life phases**, that is, emerging clusters, mature clusters, and declining clusters (Brenner and Schlump, 2011).

The key research question of this paper is two-fold as follows:

(1) Do clusters of different life phases directly impact the TFP of co-located industries or clusters?

(2) Do clusters of different life phases moderate the relations between co-located industrial or cluster size and industry or cluster TFP?

Figure 1 separates the research question into three relations:

(1) How industry or cluster size influences its own TFP (relation 1);

(2) How the size of co-located emerging clusters, mature clusters, and declining clusters directly influence the focal industry's or cluster's TFP (relations 2a, 2b, and 2c, respectively);

(3) How the size of co-located emerging clusters, mature clusters, and declining clusters moderates the focal industry's or cluster's TFP (relations 3a, 3b, and 3c, respectively).

<Insert Figure 1 about here>

This paper focuses on co-located cluster effects. In other words, relation 2 (including 2a, 2b, and 2c) and relation 3 (including 3a, 3b, and 3c) in Figure 1 fit the research question of this paper. Relation 1 per se is not the focus of this paper; it is nonetheless necessary to test it.

According to regression results, this paper detects that clusters in different life phases have different direct and moderating influences on TFP of co-located industries or clusters. Vis-à-vis theory, this paper expands the discussion of multi-cluster relations (the terms "multi-cluster

[1] Here industries as a term stand for "industries that are not big enough or dense enough to be clusters".

relations" and "relations among clusters" are used interchangeably), distinguishing between clusters and industries. By doing so, the results fit reality more closely, and give more details about how clusters impact other co-located economies. Moreover, this paper details the influence of cluster life phases by showing in which life phase clusters play roles in influencing other co-located economic activities. Empirically, this paper presents evidence to policy makers about whether, when, and how they should formulate policies. In countries where the government represents a strong central power, such as China and Singapore, understanding clusters and co-located effects aids making appropriate decisions. Such countries' economic policies may provide comparative insights with different economic developing trajectories.

The paper is organized as follows: relevant hypotheses are advanced in section 2; methodologies are presented in section 3; regression results, endogeneity tests, and discussions are provided in section 4; and a conclusion is presented at the end.

2 Hypotheses

As formulated in Figure 1 and stated in the research question, before raising the hypothesis, this paper has to briefly illustrate the cluster effect on TFP, which is relation 1 in Figure 1.

Marshall's classic (1890) argument analyzed the relation between an industry's or a cluster's size (hereafter, **focal size**) and its TFP (hereafter, **focal TFP**). Marshall argued that cluster size and TFP are positively related because of four mechanisms, namely job specialization, brokering (or input-and-output system), knowledge spillover, and reducing transportation costs. This paper draws on the first three mechanisms to illustrate the positive relation between focal size and focal TFP: (1) Job specialization refers to "breaking down jobs into narrow and repetitive tasks" (Robbins and Coulter, 2013, p.28). Common sense says that job specialization drives TFP up (Ibid). Geographic proximity also abets job specialization (Marshall, 1890). Cicoone and Hall's (1996) study of US national labour productivity offered a good argument that "doubling of employment density increases average labour productivity by around 6 percent" (Ibid, p.54). Gabe and Abel (2012) examined 284 US metropolitan areas, and argued that those jobs with strong specialized features are more easily geographically clustered. By the same token, firms are also specialized in certain business for maximizing TFP (Widodo et al., 2014); (2) Brokering means that after the manufacturing process is specialized, the marketing process, information process, service process, and so on, are all going to be specialized (Amin, 1989). Large focal size engenders mature brokering systems, which helps increase focal TFP by providing professional services. Kodama's (2008) study, for example, showed that the TAMA association (Japan) is important for increasing focal TFP; (3) Focal size may directly impact focal TFP by building local tacit knowledge and stimulating knowledge spillover (Gertler, 2003). Although firm access others' knowledge depends on other factors, such as absorptive capability (Giuliani, 2005; Kodama, 2008) and knowledge and technology distance (Huber, 2012a; 2012b), large focal size provides more alternatives (for example, bilateral links) to obtain local knowledge. Furthermore, knowledge spillover is limited by geographic distance. Following Jaffe's papers on technology and innovation spillover (Jaffe, 1986; 1989; Jaffe et al., 1993), local firms that are typically the main beneficiaries and receivers when patents are generated.

2.1 Cluster life phase and TFP: Direct impact of co-located clusters

Prior studies showed that financial resources are positively related to TFP (e.g., O'Mahony and Vecchi, 2009; Wakelin, 2001) via investments in R&D, innovation, manufacturing and information technology, education and training (e.g., see Vieira et al., 2011). Since industries and clusters compete, distribution of financial resources across various industries and clusters in geographic proximity influences focal TFP. Emerging clusters have more growth and profit opportunities, and will attract financial resources from other industries (e.g., Grundy, 2006); when emerging clusters appear in geographic proximity, they influence focal TFP by attracting financial resources from outside the region in addition to those belonging to co-located industries or clusters. Unlike with emerging clusters, some declining cluster financial resources migrate to co-located industries or clusters play an opposite role when it comes to co-location cluster effects. Because declining clusters are in the process of shrinking in size, it means that declining clusters loose resources, including financial resources finding new investment opportunities. Thus, some financial resources migrate to co-located industries or clusters. Regarding mature clusters, on the one hand they could attract financial resources from other local industries or clusters. On the other hand, financial resources may also leave mature clusters for new investment opportunities in co-located industries or clusters. The net TFP effect of mature clusters on co-located focal TFP remains ambiguous.

Similar to financial resources, human resources influence focal TFP. From the salary perspective, it is the nature of human beings to choose promising industries with good salaries, good working conditions and dynamic business environments (Florida, 2002; Lopez-Bazo and Motellon, 2012, p.1348). Thus, emerging clusters attract other local people, providing a good future for talents. Otto and Fornahl's (2010) research on the media clusters in Germany empirically showed that emerging clusters attract labour, both from locally and nationally. This argument is also seen in Wang et al.'s (2014) study of Ontario, Canada's wine industry. Declining clusters are in the opposite situation, where people leave to search for good jobs and better lives. Regarding mature clusters, it is hard to judge how people flow in and out: on the one hand, some people are attracted by mature clusters and flow in. In Dauth's (2013) paper, for example, cluster and regional employment are positively related; on the other hand, some people who work for mature clusters may be tired of their jobs and decide to leave, as Klepper (2001, p.646) pointed out: "founders of spinoffs will have been frustrated with their prior employers' unwillingness to pursue ideas they perceived to be promising."

Economies of scale are another way that clusters can influence the focal TFP. "Economies of scale are features of a firm's technology that make average total cost fall as output increases" (Parkin, 2014, p.262). Economies of scale also work at the industry level due to new infrastructure investments, reducing transportation and logistics costs to all industries in a city region. In other words, forming large economies of scale means that less input can generate higher TFP. Though emerging clusters, as mentioned, attract both financial resources and human resources from other co-located industries or clusters, mobility makes it hard for them to form economies of scale. Declining clusters, by contrast, benefit other co-located industries or clusters because the former provides resources to the latter. Regarding mature clusters, they can play the same roles as either emerging or declining clusters or both, again making their net effect uncertain.

Hypothesis 1a: Co-located emerging clusters negatively impact focal TFP.
Hypothesis 1b: Co-located mature clusters impact focal TFP ambiguously.
Hypothesis 1c: Co-located declining clusters positively impact focal TFP.

2.2 Cluster life phase and TFP: Moderating effects of co-located clusters

This section discusses how co-located clusters in different life phases moderate the relation between focal size and focal TFP. A moderator "is a qualitative or quantitative variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable" (Baron and Kenny, 1986, p.1174). Mathematically, it could be described as "the relationship between X and Y is a function of the level of Z" (James and Brett, 1984, p.310). In this paper, co-located emerging, mature, and declining clusters are moderators; that is, they are Z variables. Moderating effects are the mechanisms through which moderators play roles. X*Z is the math form of moderating effect (Sharma et al., 1981). Since section 2.1 discussed how moderators directly influence focal TFP (that is, Z→focal TFP), and since one of questions that moderating effects frequently help answer is "under which environment" (e.g., see Kirkman et al., 2004), this section studies moderating effect (that is, X*Z→focal TFP) through two arguments: cluster identity and lock-in effect.

"Cluster identity is defined as the shared understanding of the basic industrial, technological, social, and institutional features of a cluster" (Staber and Sautter, 2011, p.1350). Different clusters contain different identities, which influence not only participants, but also stakeholders. Previous studies noted that cluster identity influences regional economies. For example, a "stable identity offers reliability that helps to attract new resources and secure long-term economic success" (Ibid, p.1350). Local firms, regardless of whether or not they are clustered, are involved in the local environment by responding to changing identities. Lock-in effect is an innovation theory term (e.g., see Behrens, 2007). "Lock-in can occur in a geographical location, particularly where a cluster of firms exists with a particular specialization, the entire cluster can be 'locked-in' technologically to specific paradigms. That is, the self-reinforcing interaction between firms and infrastructure perpetuates the use of a specific technology or technologies, or production of specific products, and/or through specific processes" (Narula, 2002, p.798). Lock-in effect is a double-edged sword. On the one hand, because of specialization, cluster TFP may improve. On the other hand, over-specialization causes clusters to decline (e.g., Grabher, 1993). To sum up, cluster identity and lock-effects are two regional environment factors. The former concerns shared understanding and the latter concerns technology development.

Cluster identity and lock-in effects take time to develop. This paper argues that cluster identity and lock-in effects apply at the regional level (e.g., Brun and Jolley, 2011), and not only at the cluster level. When a region simultaneously contains more than one cluster, the social environment is a set of various identities of different clusters. In other words, a cluster's identity is not only a function of its own environment, but also of that of other co-located industries or clusters (Staber and Sautter, 2011). Lock-in effects play similar roles, particularly in mature and declining clusters, where they strongly influence local institutions and atmosphere. This paper gives more examples below.

Emerging clusters bring positive moderating effect. On the one hand, the negative roles of lock-in effects do not show up because the technology and institutions have not yet been built (Grundy, 2006). On the other hand, and probably more importantly, prior papers (e.g., Menzel and Fornahl, 2010; Neffke et al., 2011) have shown that emerging clusters are driven by innovations. For firms in emerging clusters, "shared identity evolves in response to knowledge heterogeneity stemming from variable resource and social legitimation pressure. The key…is to build a core identity to facilitate cooperation and knowledge sharing" (Staber and Sautter, 2011, p.1358). In the early 1990s, several high-tech clusters, such as IT and medicine, appeared in Shenzhen, China (Yuan et al., 2010). In addition to rapid inflow of the capital and technology, the emerging clusters also brought new ideas and created a new business environment. Under such an environment, Shenzhen citizens, regardless of whether or not they worked for emerging clusters, got a chance to learn advanced western ideas and new management methods. Therefore, both labour-intensive industries and technology-intensive industries were influenced by the environment (Lu et al., 2013; Yuan et al., 2010). In such an environment, fixed focal size could generate higher focal TFP, strengthening the relationship.

Declining clusters have negative influences on the regional economic environment, with lock-in effects that "develop rigidities in the defence of established interests" (Popp and Wilson, 2007, p.2977). Under such conditions, local policies tend to protect the old industries, rather than embracing the new ones, because "vested interests in political economic realm (conservative coalitions of large firms, labour unions and public authorities) may actively oppose the required changes when their dominant positions are threatened" (Boschma and Lambooy, 1999, p.416). Empirically, Bologna's silk industry is a compelling case: "all the community interests from entrepreneurs and workers to the clergy and peasants joined together to reserve their local silk monopoly, thus foreclosing alternative choices and bringing about the collapse of the entire district" (Alberti, 2006, p.475). The Bologna silk cluster was in the declining phase that contained strong identity and lock-in effect. Under such environment, the silk cluster "blocked" the innovations of other co-located industries or clusters, leading to declining focal TFP. In other words, the relation between focal size and focal TFP becomes weaker.

Mature clusters contain features of both emerging clusters and declining clusters. It depends on cluster development trajectory: either to update or go to decline (Shin and Hassink, 2011). If mature clusters manage to transform and innovate, they face a situation similar to emerging clusters; if they don't, they would encounter the same situation as declining clusters. Tuttlingen medical instrument cluster (Germany) is an example of a successful update cluster (Staber and Sautter, 2011), while the Black Forest clock-making cluster (Germany) is an example of unsuccessful cluster (Ibid). Therefore, moderating effects belonging to mature clusters are depend.

Hypothesis 2a: Co-located emerging clusters positively moderate relation between focal size and focal TFP.

Hypothesis 2b: Co-located mature clusters moderate relation between focal size and focal TFP

ambiguously.

Hypothesis 2c: Co-located declining clusters negatively moderate relation between focal size and focal TFP.

3 Methodology

3.1 Research Context

This paper gathered data from six Chinese city regions, namely Guangzhou, Shenzhen, Dongguan, Zhuhai, Foshang, and Huizhou, in the Pearl River Delta (PRD). The PRD, one of the most vigorous economies in China, was the first region in China that opened its doors to the world in 1978. Over more than three decades, its GDP growth was about 10 percent per year. Accordingly, the PRD cultivated a number of clusters, offering an ideal context to examine the research question for this article. Yuan et al. (2010), for instance, detailed Shenzhen's experience of building clusters, while Liang (2006, p.60) introduced Dongguan's miracle of building IT clusters in the 2000s: more than 2,800 firms set up factories there, seizing more than 10 percent of the world market share and becoming the biggest IT part manufacturing base in the world. Furthermore, the six city regions comprise more than 40 million people totally. Therefore, it is quite normal that two or several clusters are co-located in the same city region.

This paper relied on annual statistical data, starting as far back as 1993, the year after the Chinese former leader Deng Xiaoping had his "Southern Tour", which initiated China's so-called social market economy. After 1992, the official statistical data became more formal and consistent. We gathered data for this study from two sources: (1) Annual Year Statistical Books (1993–2012), which provide relevant industry data; and (2) The EPS Database, which provides educational data.

3.2 Variables

3.2.1 Independent variables and moderators: How to quantify clusters and how to identify cluster life phase

There is no consensus on how to clearly identify a cluster (Sternberg and Litzenberger, 2004). In terms of quantitative methods, Keeble and Wever (1986) defined a cluster by applying the Lorenz curve and the Gini coefficient to measure regional distribution of industries. Krugman (1991) used a similar method. Sternberg and Litzenberger (2004, p.779) applied the cluster index. Furthermore, the Herfindahl indicator (Aiginger and Pfaffermayr, 2004; Mano and Otsuka, 2000) and the E-G indicator (Ellison and Glaeser, 1997) are also applied. In terms of qualitative method, Porter's diamond model, which analyzes clusters from six factors, is popular in business research (e.g., Chobanyan and Leigh, 2006). This paper employs the **Location Quotient (LQ**) to quantify clusters, as it shows cluster size simultaneously from regional and industrial levels (Beaudry and Schiffauerova, 2009). The LQ is calculated as follows (firm numbers as an example):

$$LQ = \frac{\text{(regional firm numbers sector X/total regional firm numbers)}}{\text{(national firm numbers sector X/total national firm numbers)}}$$

A cluster appears when the LQ is greater than 1. Delgado et al. (2010) and Bathelt and Li (2014) serve as examples. This paper uses firm numbers to calculate LQ (hereafter, LQf refers to LQ measured by firm numbers). This paper gathered data about all industries in the six city regions between 1993 and 2012; the total sample size was 3,470. We removed data related to mining, oil and gas, electricity production, and water, since they did not belong to manufacturing and the latter two are heavily related to city populations rather than to the cluster effect. Moreover, because there are missing values for some industries in some years, there were only 2,661 valid samples. We calculated the LQf for all 2,661 samples.

Before articulating how to identify emerging, mature, and declining clusters, we need to detail the validity of the LQ indicator. We realize that it is hard for some scholars to accept that "when LQ is greater than 1, a cluster appears", although such a standard has been employed in many prior studies. Someone may challenge that the LQ indicator does not sufficiently reflect the argument of "clusters contain cross-industry" and setting 1 as the cut-off is arbitrary; intuitively, LQ may only identify industries that are over-represented and cannot reflect related suppliers, customers, and intermediates, etc. This paper takes these views into account, and then conducts two steps. First, the results are compared to prior studies. For example, Isaksen (1997, p.68), who set the cut-off at 3, found 143 industries that fit the requirements for being defined as clusters in 1990 (imagining that if Isaksen set the cut-off at 1, Norway would absolutely contain much more than 143 clusters). Norway has a population of only about 5 million, which is less than half of Guangzhou. Compared to Isaksen's study, this paper argues that even employing a more flexible standard that sets the cut-off at 1, the number of clusters in the PRD region is much lower than Norway's. In other words, setting the cut-off at 1 is still conservative for the PRD data. Second, and probably more important from the qualitative perspective, projects such as "European Cluster Observatory" or "US Cluster Mapping Project" may be more popular in Porter's (1990; 1998) competitive advantage paradigm. A qualitative cluster mapping study of the PRD is seen in Gao and Lin's (2010) book, in which the authors pointed out which town (or community, or city), in their opinion, contained which cluster. By comparing the LQf indicator with Gao and Lin's study, this paper finds that more than 75 percent of clusters are defined when the standard is LQ>1. Although the LQf indicator reveals that more clusters existed than the number Gao and Lin mapped, as they (2010, p.68) mentioned, their study had uncertainty. Because of incomplete data, and because qualitatively mapping clusters can be labeled "arbitrary", it is reasonable to believe that more clusters exist. We argue that there are no perfect measures that accommodate everyone's understanding of clusters, which are fuzzily defined (Martin and Sunley, 2003). Such fuzziness shows the beauty of cluster theory and how it "spanned over time through a wide range of disciplines, changing, adapting and gaining theoretical power by finding application to different fields" (Lazzeretti et al., 2014, p.22). In other words, applying LQ to measure clusters does not violate cluster theory; moreover, adopting LQ to show clusters and setting the cut-off at 1 is appropriate for solving the research question of this paper.

How to identify a cluster's life phase is problematic, as Maskell and Malmberg (2007, p.611) argued. Drawing on Klepper's (2010), Agarwal and Gort's (2002), and McGahan and Silverman's (2001, p.1144) idea of applying growth rate to industrial life phase, this paper sets the following standards to assess a cluster's life phase:

Emerging Clusters

(1) At the time of measurement, there must be one identifiable point in time (time threshold) when the LQf changes from smaller than 1 to greater than 1;
(2) After the LQf crosses the threshold of 1, it should consistently be greater than 1 in the next five years;
(3) If a cluster's LQf fits the above two points, the emerging cluster appears in five years before the time threshold and five years after the time threshold.

Mature Clusters

(1) At the time of measurement, more than 80 percent of LQf should be greater than 1. Requiring that all LQf>1 yields a stable and strict set of samples of mature clusters, but it shrinks the number of samples dramatically. Our standard allows for accepting more samples; after all, "outliers" appear in realistic data[2].
(2) If there are LQfs smaller than 1 (as noted above, such that LQf<1 in a maximum of four cases), such LQf<1 should not appear in more than two consecutive years. This requirement ensures that the LQs<1 are real statistical outliers; in other words, LQf<1 should be randomly distributed in the measurement occasion.

Declining Clusters

The standard for judging a declining cluster is the opposite of that used for judging emerging clusters.

Again, we admit that the above standards are not perfect. For example, there is no reason to say that "greater than 1 in the next five years" is absolutely better than "in the next three years" or *n* years. Although the standard employed by this paper is imperfect, by drawing on Otto and Fornahl's (2010) and McGahan and Silverman's (2001) standards, we argue that the above standards fit the PRD data well. Before scholars reach a consensus on judging cluster life phases, the current method provides opportunities to understand this paper's research question, and offers insights that can initiate even better standards of measurement. Based on the rationality of LQf and life phase judging standard, Table 1 shows the details on clusters in each life phase in each city region.

<Insert Table1 about here>

There are four additional points that need emphasis. First, according to the above standards, clusters could not always be defined into different life phases within the period of observation. In particular, emerging clusters and declining clusters may "exist" only for a few years during the observation period. Although an emerging cluster normally goes into the mature phase, we must be more precise in defining the transition period between emerging and mature phase. Thus, when defining cluster life phases, we have to make some arbitrary decisions. We argue that the above standards are conservative. If readers agree with us, giving a detected cluster a fixed phase is acceptable. If readers disagree, there is no consensus about how to define cluster life phase in empirical studies. Our standards are adapted to answer our research question and to provide

[2] Actually, more than 90 percent of mature clusters' LQf is greater than 1 during the observation period. The remaining clusters are LQf<1 (max 4 times), but such "outliers" would not influence regressions since they are few.

insights for other scholars. Second, we chose an absolute number of firms to represent industrial or cluster size. This was meant to show two types of size: relative size, measured by LQf, and absolute size. However, as Wennberg and Lindqvist (2010) pointed out through studies of various industries in Sweden, LQ is not a good indicator for reflecting how cluster effects occur among firms. Frenken et al. (2015, p.13) concluded that "localization economies are best captured by absolute counts rather than by location quotients as benefits of co-location in clusters are expected to rise with the absolute number of co-located firms in the same industry irrespective of the country-wide distribution of firms." In fact, we once analyzed both LQf and absolute size with regressions, but the LQf fit Wennberg and Lindqvist's empirical results well, implying that a focal industry's or cluster's LQf does not relate to its TFP. In order to avoid confusion, this paper summarizes LQ as an indicator used to identify which industry is a cluster and which is not. The absolute number of firms (or GDP, or employment) is more powerful to show the cluster effect. Third, in spite of it being possible to check how one certain cluster impacts focal TFP, this can complicate the problem unnecessarily. Therefore, we use the average size of clusters as the independent variable. For example, assume that region A contains three mature clusters; this paper calculates their average size, and then imports it into the regressions. Though one may raise the question of why to prefer the average to the aggregate size, since the absolute number of firms is applied here, we argue that the average size[3] is better because, compared to the aggregate size, the average size actually controls for number of clusters. Therefore, the average size is comparable in the six city regions; further, the average size fits cluster effect better than the aggregate size. To give a simple example: there are two regions, region A and region B, and both regions contain 100 cluster firms. However, region A consists of two clusters and region B consists of three clusters. From the aggregate size viewpoint, the two regions are the same. However, region A's cluster effect is more apparent because the average size is big. Last but not least, this paper does not intend to answer more complex research question by introducing concepts of "related industries," "spatial autocorrelation," and other measures of clusters. Such issues need to be addressed in future papers.

3.2.2 Dependent Variables: How to Measure Total Factor Productivity (TFP)

This paper employs a very mature method to calculate TFP (Fare et al., 1994; Felipe, 1999; Solow, 1957): first we build a Cobb-Douglas production function, as

$$Y_{it} = A_{it} e^{\lambda t} K_{it}^{\alpha} L_{it}^{\beta} \qquad (1)$$

where α and β stand for elasticity of capital and elasticity of labour, respectively. Y_{it} stands for production level; K_{it} and L_{it} refer to the capital investment and labour investment of industry i in time point t.

Because α + β =1, setting logarithm at both sides of equation (1), and adding statistical error, generates the following:

[3] When focal TFP belongs to a cluster, the average size excludes focal size.

$$\ln(\frac{Y_{it}}{L_{it}}) = \ln A_{it} + \lambda t + \alpha \ln(\frac{K_{it}}{L_{it}}) + \varepsilon_{it} \qquad (2)$$

Therefore, to a certain industry i at time point t, its TFP is:

$$TFP_{it} = Y_{it} / (K_{it}^{\alpha} L_{it}^{\beta}) \qquad (3)$$

We use industrial value added, which is deflated by the consumer price index (set to 1990 as the benchmark) to measure production. Labour investment is measured by each industry's employment level. Capital investment is measured by the stock of capital of each industry.

3.3 Regression Models

Since each industry or cluster has its own features, this paper applies multilevel analysis (MLA) to build the regression models. Stone and Hollenbeck (1984) argued that MLA is an appropriate method for estimating moderator and moderating effect. Compared to OLS and panel data regressions (such as fixed effect and random effect models), MLA has three advantages: (1) MLA can easily trace how "time" influences the dependent variable (here TFP); (2) MLA identifies the differences among industries or clusters; (3) as Snijders and Bosker (1999, p.166) pointed out, MLA has the "flexibility to deal with measurement occasions where the data for (or all) individuals is incomplete, or longitudinal data where some or even all individuals are measured at different sets of time points." Empirically, MLA frequently appears in regional studies (for example, see Environment and Planning A, 1997, special issue 4). Since the data of this paper are unbalanced, applying the MLA to run regression avoids further discussion about this issue.

Therefore, the regression models are set as follows:

$$TFP = \beta_{oj} + \beta_{1j} * Time + \varepsilon \qquad (4)$$

where Time refers to when the observation is taken and ε refers to error. Clearly, Equation (4) shows that a focal TFP is only decided by time. After (4) is set down, two equations can be built:

$$\begin{aligned}\beta_{0j} &= \gamma_{00} + \gamma_{01} Size + \gamma_{02} ECbar + \gamma_{03} ECbar * Size + \gamma_{04} MCbar + \gamma_{05} MCbar * Size \\ &+ \gamma_{06} DCbar + \gamma_{07} DCbar * Size + \gamma_{08} Control\ Variable + u_{0j} \qquad (5)\end{aligned}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} Size + u_{1j} \qquad (6)$$

where Size refers to focal size; MCbar, ECbar, and DCbar refer to the average size of local mature clusters, emerging clusters, and declining clusters, respectively; MCbar*Size, ECbar*Size, and DCbar*Size refer to the moderating effect; u_{oj} and u_{1j} refer to standard deviation of residuals for intercept and for slope at cluster level. Equation (5) shows how other factors influence the intercept of TFP, and Equation (6) shows how other factors influence the slope of TFP. Therefore, replacing (5) and (6) with (4), we easily arrive at a new equation:

$$
\begin{aligned}
TFP = (&\gamma_{00} + \gamma_{01}Size + \gamma_{02}ECbar + \gamma_{03}ECbar * Size + \gamma_{04}MCbar + \gamma_{05}MCbar * Size \\
&+\gamma_{06}DCbar + \gamma_{07}DCbar * Size + \gamma_{10} * Time + \gamma_{11}Time * Size + \gamma_{08}Control\ Variables) \\
&+(u_{0j} + u_{1j} * Time + \varepsilon) \quad (7)
\end{aligned}
$$

The first bracket in Equation (7) is called the fixed effect, and the second bracket measures random effect. It is possible that more factors are included in Equation (6); by doing so, Equation (7) invokes Rabe-Hesketh and Skrondal's (2008, p.172) suggestion that "the overall message is that random slopes should be included only if strongly suggested by the subject-matter theory related to the application". This paper then does not integrate more factors into Equation (6).

We have followed Angrist and Pischke's suggestion to set control variables. Angrist and Pischke (2009, section 3.2.3) argued that "more control is not always better … bad controls might just as well be dependent variables too. Good controls are variables that we can think of as having been fixed at the time the regressor of interest was determined." We control two variables. The first is the number of local universities. On one hand, many papers have argued that local education conditions impact innovations and competitiveness (e.g., Abramovsky and Simpson, 2011; Link and Rees, 1990; Lucas et al., 2009). On the other hand, such numbers are decided by government city planning rather than by local technology and economic development — in China, establishing a new university is not as easy as opening a new firm. Second, the city level is controlled. In China, four cities (Beijing, Shanghai, Guangzhou, and Shenzhen) are classified as first-tier cities, and all other cities are classified as second- or third-tier cities (Tan et al., 2015). This classification is not determined by local cluster size and local TFP. We argue that both the number of universities and the city level are good control variables because they are fixed and are not influenced by other variables in equation (7). Finally, in order to compare the influence of emerging clusters, mature clusters, declining clusters, and industries, three dummy variables are introduced. Tables 2a, 2b and 3 provide more descriptive details on all variables.

<Insert Table 2a, 2b and Table 3 about here>

4 Regression Results and Discussions

4.1 Regression results

Before conducting regressions, it is necessary to make sure that MLA can be applied in this situation; in other words, that the TFP of each industry or cluster differs from that of others. Following Rabe-Hesketh and Skrondal's (2008) as well as Snijders and Bosker's (1999, p.46) method, this paper first builds the "empty model", which is the simplest version of Equation (7). The statistical software Stata version 12.0 is applied for testing the empty model:

$$TFP = \gamma_{00} + u_{oj} + \varepsilon$$

Model A in Table 4 shows the regression results.

<Insert Table 4 about here>

Following Rabe-Hesketh and Skrondal's suggestion (2008, p.69), we conducted a likelihood-ratio test to Model A. The result has a very small p-value (that is, 0.0000), which implies that TFP varies significantly among industries or clusters. MLA applies here appropriately.

Among the remaining regressions shown in Table 4, Model B contains focal size (that is, an independent variable) and all control variables. Model B shows that focal size is positively related to focal TFP. Comparing Model B with other models in Table 4 shows that control variables are stable in the regressions. Three variables – the number of local universities, city level, and time – are positively related to the TFP of focal industries or clusters. This result fits common sense. Prior studies have shown that local universities contribute to focal TFP through providing knowledge (Owen-Smith et al., 2002) and developing research platforms (Benneworth et al., 2009), etc. First-tier cities provide better innovation policy and environment to local industries or clusters. In addition, the PRD achieved great economic success during the observation period, which created the necessary conditions for augmenting TFP (Zeng, 2010). D3 as a dummy variable is negative related to TFP, which implies that if the focal cluster is declining, its own TFP will be lower than other types. This may be because declining clusters lose resources to other regions and industries.

Built on Model B, Models C and D go further. Model C takes all three moderators into account. Model D adds not only all moderators, but also three moderating effects. Models C and D provide some interesting insights: in Model C, all moderators are related to focal TFP, but focal size and focal TFP is not related. Unlike Model C, Model D exhibits three realities: first, focal size and focal TFP are positively related, which again, supports Model B. Second, focal TFP is directly influenced by the size of co-located clusters. To be more specific, the size of co-located emerging clusters negatively impacts focal TFP (-0.236), buth the size of co-located mature clusters and declining clusters have positive impact (that are 0.7 and 0.084 individually). Third, two moderating effects are significant and oppose direct effect. In this case, the size of the co-located emerging clusters has a positive moderating effect (0.041), but the size of the co-located mature clusters has a negative moderating effect (-0.123). The size of the co-located declining clusters does not play any moderating role.

As a general rule, a good regression should be efficient, unbiased, and consistent. This paper primarily focuses on the following endogenous issues: multicollinearity, reversal causality, and unobservable factors.

Regarding multicollinearity, as Jaccard and Turrisi (1990, p.27-28) argued that it is not important whether interacting items (XZ) would or would not be multicollinear with an independent variable (X) or with moderator (Z). We then calculated Variance-Inflating Factor (VIF), shown in Table 5, among all our variables, except interacting items (Gujarati and Porter, 2009, p.328). Generally, according to the textbook (Ibid), VIF value is acceptable if it is less than 10. Since all

VIFs in Table 5 are less than 10 and the mean VIF is 1.55, the collinearity between variables in the regression will not influence the results.

<Insert Table 5 about here>

This paper creates several models to examine reversal causality and unobservable factors. Reversal causality in this paper concerns whether the dependent variable will impact the independent variable (e.g, see Brulhart and Mathys, 2008). Model E introduces the concept of "lag period": when the dependent variable is set in t, the independent variables are figured from the year t-1. Comparing Model E to Model D, the role that emerging clusters, mature clusters and declining cluster play does not change much. Furthermore, we check the possible endogeneity that may be caused by the between groups reasons (Hanchane and Mostafa, 2012, p.1105). Mathematically speaking, in Equation (7), u_{0j} (or u_{1j}) as residuals may relate to independent variables. Mundlak (1978) attempted to solve this problem. Building on Mundlak (1978), Model F goes a step further by including the group mean variables. Comparing Models F and D, in terms of significances and signs, nothing changes. Additionally, it is necessary to check the possible endogeneity problem that may be caused by level 1 independent variables and the level 1 error term; that is mathematically ε may be correlated to the independent variables in Equation (7). Building on Mukim's idea (2015, p.343), Model G further controls city fixed effects and industrial fixed effects. Checking Model G clarifies that the significances and signs of each variable do not experience essential changes. Furthermore, this paper conducts three-level model, which sorts the data as follows: city region (level 3) – industry or cluster (level 2) – TFP in each observation time (level 1). Last but not least, as Model H shows, compared to Model D, all significances and signs remain the same and even the regression values do not change considerably.

<Insert Table 6 about here>

4.2 Discussions

This paper initiates discussions about regression results from both a mathematical perspective and a theoretical perspective. Mathematically, comparing Models B, C, and D is necessary because these three models bring us different information. The key issue is which model is more convincing and realisable. Compared to Models B and C, Model D controls more variables that are statistically significant. Therefore, Model D reduces more unobserved errors and appears to be more efficient, consistent, and unbiased. The indicator loglikelihood, shown at the bottom of Table 4, supports the above argument. For example, while Model C's loglikelihood is -3927.911, Model D's is -3904.284. Because loglikelihood fits χ^2 distribution (Cox and Hinkley, 1974), Model D is clearly significantly different from and better than Model C. If checking Model B, it seems that focal size and focal TFP are positively related, but such a relation actually includes both direct and moderating effects caused by co-located clusters. Furthermore, the changing process of variables from Model B, to Model C, and to Model D shows that the independent variable and the dependent variable are positively related only when taking moderating items into account.

Theoretically, regressions results uncover and contribute new knowledge to understand the relation between focal size and focal TFP. As mentioned earlier, scholars have provided a body of evidence to prove that Marshall's specialization argument is right (see section 2 of this paper). The present paper uncovers a crucial mechanism that helps explain how focal size and focal TFP establish relations; that is, co-located clusters create a local environment that cannot be ignored. Taking co-located cluster moderating effects into consideration is more close to reality, and it is clear that the focal size and focal TFP relation exists because of the environment created by co-located clusters.

Building on the above arguments, the empirical results are summarized in Figures 2a and 2b, showing the moderating effects of co-located emerging/mature clusters on focal TFP. Co-located declining clusters are excluded because no significant moderating effect is detected. Because moderating effect is a continuous variable, which stands for many various situations, it is infeasible to draw all situations into one figure. Therefore, this paper takes the maximum, mean, and minimum values to show how moderating effect occurs (min value of co-located emerging clusters is 0; it is therefore excluded from Figure 2a). Figure 2a shows that, assuming any one industry or cluster in our database is co-located with the largest emerging cluster and emerging cluster with mean size, respectively, the largest emerging cluster size would lower the intercept, but significantly increase the slope of the diamond line that shows relations between focal size and focal TFP. However, this is an extreme example. In a normal case, for example when co-located clusters are in mean size, the slope of the diamond line has only a slight change. Figure 2b reflects the reality of co-located mature clusters. In terms of intercept, enlarging the size of the co-located mature clusters would increase the focal TFP. Regarding slope, when the size of co-located mature cluster is small (for example, LQ is just a slightly bigger than 1), the slope is still positive. However, when size of co-located mature cluster is at the mean value, the slope becomes negative. When the size of the co-located mature clusters is assumed to be at maximum value, the slope is steeply negative.

<Insert Figures 2a and 2b about here>

In sum, building on the PRD data, this paper finds that co-located emerging clusters or mature clusters actually influence focal TFP through the moderating effect. In other words, a focal TFP is determined not only by its only size, but also by other co-located clusters that influence the local environment.

5. Conclusions

This paper has empirically investigated how clusters influence Total Factor Productivity (TFP) of co-located industries and clusters. The study utilized an extensive statistical data set, 1993–2012, from the Pearl River Delta (PRD) in China. The influence of co-located clusters could be direct, moderating, or both. After testing and re-checking two sets of hypotheses on TFP in co-located clusters, hypotheses 1a and 2a, which argued that the direct emerging cluster impact should be negative and moderating effect should be positive, received empirical support. Although the direct influence and moderating effects that mature clusters bring to co-located industry or cluster TFP are theoretically ambiguous, in the research context of this study, mature clusters had a positive direct impact and a negative moderating effect on focal TFP. Regarding declining clusters, hypothesis 1c, which argued that the direct impact should be positive, received support; but hypothesis 2c, which argued that the moderating effect should be negative, did not receive any empirical support.

This paper first shows that the size of an industry or a cluster is positively related to its own TFP. This finding simply restates the original cluster argument, and it again proves Marshall’s classic (1890) argument—when many firms in the same or similar industries are in geographic proximity, cluster effects augment TFP (e.g., Lee et al., 2013).

Emerging clusters as a new economic power may attract resources and attention from other local industries and clusters (Frenken et al., 2015), pushing focal TFP down. However, by changing the viewpoint from the moderating effect, it is obvious that other local industries or clusters could benefit from the increasing average size of local emerging clusters. This finding follows the real economic development situation of the PRD during last three decades, which has been characterized by upgraded industrial structure. Emerging clusters are good representatives of such changes.

This paper finds that mature clusters have a positive direct impact, but a negative moderating effect, on co-located industry or cluster TFP. These two findings are similar to previous studies (e.g., Brenner and Gildner, 2006), and also follow the developing process of the PRD (e.g., Yang and Liao, 2010). Particularly in terms of negative moderating effects, the PRD is transforming from labour-intensive to capital-intensive industries (Hu and Lin, 2011). The industry update process is difficult; as time passes, the existing regional environment created by mature clusters does not benefit other co-located industries or clusters.

Declining clusters have a positive direct impact on focal TFP, but no moderating effect. These results have two meanings. In the PRD, it may be that not all resources of declining clusters leave to other distant regions. Some resources may leave from declining clusters to co-located focal industries or clusters. Thus, such resources increase focal TFP. However, declining clusters have few influences on local environment. This may be because other co-located industries or clusters were not interested in learning lessons from declining clusters.

This paper has several limitations. A weakness is the way of defining clusters and identifying cluster life phases. As Shin and Hassink (2011, p.1399) argued, a cluster can have many features, and it is hard to judge a life phase only from one or several features. This paper only gives one feasible approach, and scholars may apply other ways to define clusters, such as only using the “US cluster mapping project”, or employing a more flexible time period. This paper only investigated the data from the PRD, which is an economically prosperous region with several world-class clusters, most notably in ICT and equipment. In the future, scholars should compare cluster development in prosperous and poor regions, encompassing a variety of industries and clusters. Because this paper only tested the co-located effects with multilevel analysis of a number of firms, scholars should test the co-located cluster effects by applying different models (such as spatial regression models) with different variables (such as employees).

The findings of this study have important implications for industrial policy regarding multi-cluster city regions, especially vis-à-vis the large-scale industrial development that has taken place in China. Emerging clusters and mature clusters seemed to have opposite effects on TFP of co-located economies, while declining clusters did not empirically moderate TFP of co-located economies according to our data. Thus, declining clusters do not seem to slow down the transition and modernization of Chinese industries, as we have sometimes observed in Europe and North America (e.g., Alberti, 2006). Industrial policy needs to take a multi-cluster approach, taking into account the economic interdependencies between co-located industries and clusters. This requires more empirical studies of co-located clusters, not just more studies of single clusters, single cluster development and single cluster performance.

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Figures and Tables

Figure 1: Research questions of this paper

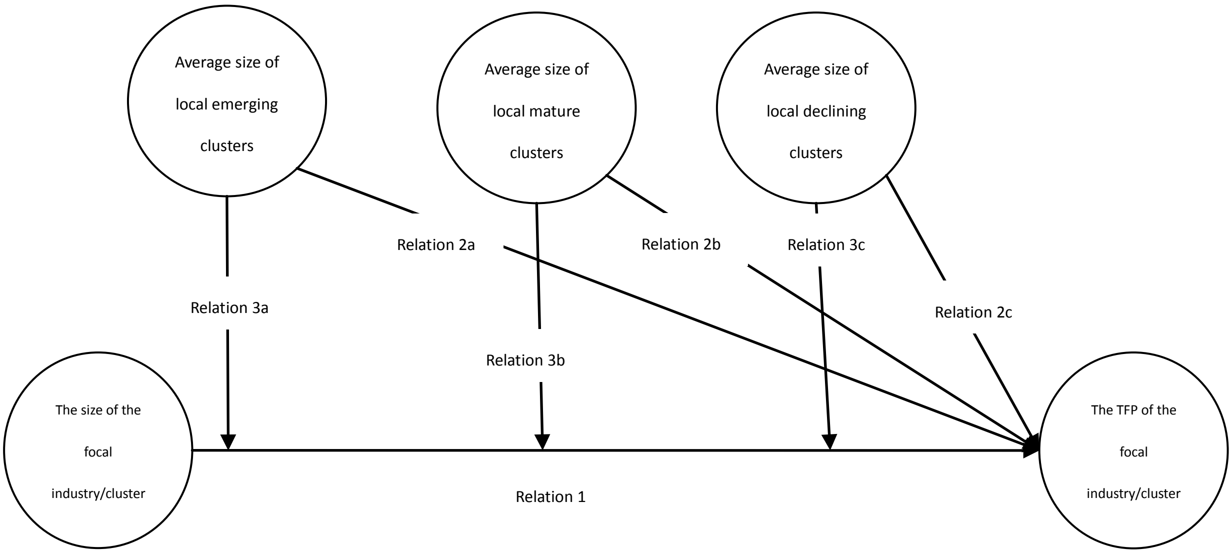


Table 1: Statistics about clusters in various life phases in the six city regions

City	City population (2013)	Emerging clusters	Mature clusters	Declining clusters	Total
Foshang	About 7.2 million	3	9	2	14
Dongguan	About 1.8 million	2	7	3	12
Guangzhou	About 12.92 million	1	9	4	14
Huizhou	About 4.7 million	1	3	1	5
Shenzhen	About 10.62 million	1	4	1	6
Zhaoqin	About 3.98 million	3	8	1	12
Total		11	40	12	

Note: The PRD contains seven city regions, but because data for calculating Zhongshang city region TFP is missing, it is excluded. Since the number of clusters may change yearly, this table provides an estimation; therefore, it may not match the precise number of clusters in each city in each year.

Table 2a: Descriptive information on variables: names

Variable name	Kind of variable	Remarks
Focal TFP	Dependent variable	TFP of each focal industry or cluster
lnsizes	Independent variable	Focal size: number of firms of each focal industry or cluster (logarithm)
lnECbar	Moderator	Average size of co-located emerging clusters (logarithm)
lnMCbar	Moderator	Average size of co-located mature clusters (logarithm)
lnDCbar	Moderator	Average size of co-located declining clusters (logarithm)
d1	Control variable	Dummy, d1=1 if the focal is an emerging cluster, otherwise d1=0
d2	Control variable	Dummy, d2=1 if the focal is a mature cluster, otherwise d2=0
d3	Control variable	Dummy, d3=1 if the focal is a declining cluster, otherwise d3=0
lnuni	Control variable	Number of local universities (logarithm)
citylevel	Control variable	Dummy, d=1 when it is Guangzhou or Shenzhen, otherwise d=0
Time	Control variable	It is an integer between 1 and 20, standing for Year 1993-2012
constant	intercept	γ_{00} in the equation (7)
sd(time)	error	Standard deviation of u_{1j} in the equation (7)
sd(cons)	error	Standard deviation of u_{0j} in the equation (7)
sd(resid)	error	Standard deviation of ε in the equation (7)

Table 2b: Descriptive information on variables: mean, min, max values

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Focal TFP	2661	2.337	3.011	0.028	41.672
lnsizes	2661	3.919	1.395	0.000	7.287
ECbar	2661	2.869	2.060	0.000	5.991
MCbar	2661	5.060	0.741	2.959	6.658
DCbar	2661	3.317	2.260	0.000	6.452
d1	2661	0.038	0.192	0.000	1.000
d2	2661	0.241	0.427	0.000	1.000
d3	2661	0.044	0.205	0.000	1.000
lnuni	2661	1.481	1.351	0.000	4.382
citylevel	2661	0.366	0.482	0.000	1.000

Table 3: Correlation Table (sample size: 2661)

	Focal TFP	*lnsizes*	*ECbar*	*MCbar*	*DCbar*	*d1*	*d2*	*d3*	*lnuni*	*citylevel*
Focal TFP	1.000									
lnsizes	-0.233	1.000								
ECbar	0.002	0.020	1.000							
MCbar	0.182	0.429	0.096	1.000						
DCbar	-0.019	0.094	0.461	0.092	1.000					
d1	-0.002	0.000	-0.074	-0.041	0.068	1.000				
d2	-0.014	0.382	0.048	0.031	0.082	-0.112	1.000			
d3	-0.068	0.140	0.081	-0.002	-0.007	-0.043	-0.121	1.000		
lnuni	0.157	0.330	-0.212	0.281	0.082	-0.051	0.116	0.021	1.000	
citylevel	0.067	0.217	-0.144	0.289	0.227	-0.071	0.032	0.027	0.707	1.000

Table 4: Regression results (Dependent variable: Focal TFP)

	Model A	*Model B*	*Model C*	*Model D*
lnsizes		0.075*	-0.056	0.306*
		(0.041)	(0.054)	(0.185)
lnECbar			-0.060***	-0.236***
			(0.011)	(0.037)
lnMCbar			0.241***	0.700***
			(0.082)	(0.169)
lnDCbar			0.032**	0.084**
			(0.013)	(0.041)
*lnECbar*lnsizes*				0.041***
				(0.008)
*lnMCbar*lnsizes*				-0.123***
				(0.038)
*lnDCbar*lnsizes*				-0.009
				(0.008)
*Time*lnsizes*				0.015**
				(0.007)
d1		0.068	0.045	0.068
		(0.168)	(0.168)	(0.167)
d2		-0.490*	-0.361	-0.276
		(0.275)	(0.278)	(0.279)
d3		-0.454***	-0.345**	-0.389***
		(0.151)	(0.151)	(0.150)
lnuni		0.169***	0.157***	0.185***
		(0.056)	(0.058)	(0.059)
citylevel		0.618**	0.560**	0.493*
		(0.263)	(0.267)	(0.268)
Time		0.159***	0.157***	0.100**
		(0.025)	(0.026)	(0.039)
constant	2.466***	-0.095	-0.720**	-2.032**
	(0.207)	(0.231)	(0.350)	(0.794)
sd(time)		0.318	0.320	0.324
sd(cons)	2.641	2.056	2.157	2.216
sd(residual)	1.712	0.835	0.827	0.818
Loglikelihood	-5512.406	-3949.254	-3927.911	-3904.284
Number of groups	168	168	168	168
Sample size	2661	2661	2661	2661

Hereafter, standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: VIF indicator

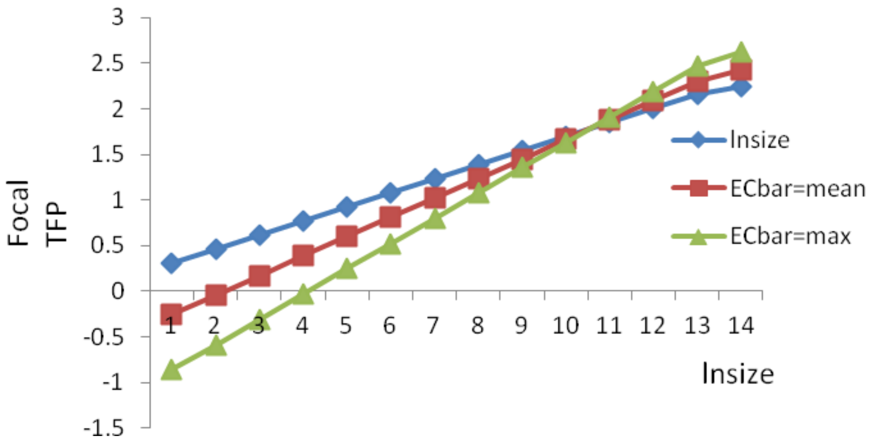
Variables	*VIF*	*1/VIF*
citylevel	2.25	0.445061
lnuni	2.22	0.450521
lnfirms	1.64	0.608215
lnECbar	1.50	0.668445
lnDCbar	1.48	0.673740
lnMCbar	1.37	0.727304
d2	1.29	0.774001
d3	1.09	0.917358
d1	1.06	0.943728
Mean VIF	1.55	0.689819

Table 6: Endogenous and robust tests (Dependent variable: Focal TFP)

	Model E		*Model F*	*Model G*	*Model H*
laglnsizes	0.620**	*lnsizes*	0.525***	0.381**	0.395**
	(0.194)		(0.191)	(0.181)	(0.186)
laglnECbar	-0.166***	*lnECbar*	-0.236***	-0.249***	-0.234***
	(0.038)		(0.036)	(0.037)	(0.037)
laglnMCbar	0.821***	*lnMCbar*	0.707***	0.543***	0.752***
	(0.175)		(0.177)	(0.164)	(0.171)
laglnDCbar	0.190***	*lnDCbar*	0.093**	0.074*	0.093**
	(0.042)		(0.041)	(0.040)	(0.041)
*laglnECbar*laglnsizes*	0.029***	*lnECbar*lnsizes*	0.041***	0.043***	0.041***
	(0.008)		(0.008)	(0.008)	(0.008)
*laglnMCbar*laglnsizes*	-0.134***	*lnMCbar*lnsizes*	-0.135***	-0.099***	-0.134***
	(0.039)		(0.038)	(0.035)	(0.038)
*laglnDCbar*laglnsizes*	-0.029***	*lnDCbar*lnsizes*	-0.009	-0.006	-0.010
	(0.009)		(0.008)	(0.009)	(0.009)
Number of groups	168		168	168	168
Sample size	2464		2661	2661	2661
Industry fixed effect	X		X	√	X
City fixed effect	X		X	√	X
2 levels or 3 levels	2		2	2	3

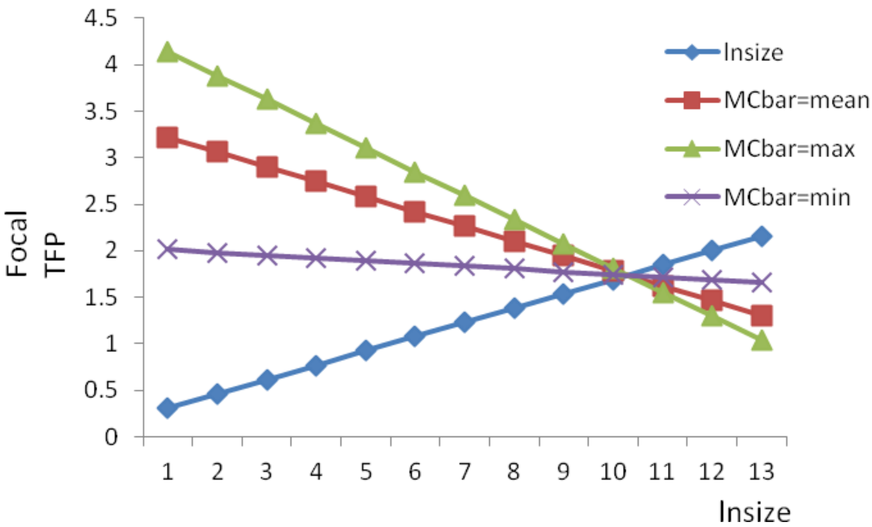
Models E, F, G, and H all have the same control variables as Model D. However, Model E takes lagged values as independent variables; Model F further includes the group mean value of lnsizes, lnECbar, lnMCbar, lnDCbar; Model G controls the industry fixed effect and city region fixed effect; Model H is a 3-level analysis, which takes city region at the level 3.

Figure 2a: Moderating effect of emerging clusters on focal TFP



Note: All lines refer to the relation between lnsize and focal TFP. Without considering the moderating effect of emerging clusters, the slope is the diamond line; when considering the moderating effect of emerging clusters, the incept becomes lower and slope becomes steeper than the original line.

Figure 2b: Moderating effect of mature clusters on focal TFP



Note: All lines refer to the relation between lnsize and focal TFP. Without considering the moderating effect of mature clusters, the slope is the diamond line; With the size of co-located mature cluster increasing, the incept increased, but slope decreases.

References

Abramovsky, L. and Simpson, H. (2011), "Geographic proximity and firm-university innovation linkages: evidence from Great Britain", *Journal of Economic Geography,* Vol. 11 No. 6, pp. 949-77.

Agarwal, R. and Gort, M. (2002), "Firm and product life cycles and firm survival", *American Economic Review,* Vol. 92 No. 2, pp. 184-90.

Aiginger, K. and Pfaffermayr, M. (2004), "The single market and geographic concentration in Europe", *Review of International Economics,* Vol. 12 No. 1, pp. 1-11.

Alberti, F.G. (2006), "The decline of the industrial district of Como: recession, relocation or reconversion?", *Entrepreneurship & Regional Development,* Vol. 18, pp. 473-501.

Amin, A. (1989), "Flexible specialisation and small firms in Italy: myths and realities", *Antipode,* Vol. 21 No. 1, pp. 13-34.

Angrist, J.D. and Pischke, J.-S. (2009), *Mostly Harmless Econometrics: An Empiricist's Companion,* Princeton University Press, USA.

Asheim, B.T. (1996), "Industrial districts as 'learning regions': a condition for prosperity", *European Planning Studies,* Vol. 4 No. 4, pp. 379-400.

Baron, R.M. and Kenny, D.A. (1986), "The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations", *Journal of Personality and Social Psychology,* Vol. 51 No. 6, pp. 1173-82.

Barrientos, S. (2014), "Gendered global production networks: analysis of Cocoa-Chocolate sourcing", *Regional Studies,* Vol. 48 No. 5, pp. 791-803.

Bathelt, H. and Li, P.-F. (2014), "Global cluster networks -- foreign direct investment flows from Canada to China", *Journal of Economic Geography,* Vol. 14 No. 1, pp. 45-71.

Beaudry, C. and Schiffauerova, A. (2009), "Who's right, Marshall or Jacobs? The localization versus urbanization debate", *Research Policy,* Vol. 38 No. 2, pp. 318-37.

Behrens, K. (2007), "On the location and lock-in of cities: geography vs transportation technology", *Regional Science & Urban Economics,* Vol. 37, pp. 22-45.

Benneworth, P., Coenen, L., Moodysson, J. and Asheim, B.T. (2009), "Exploring the multiple roles of Lund University in strengthening Scania's regional innovation system: towards institutional learning?", *European Planning Studies,* Vol. 17 No. 11, pp. 1645-64.

Boschma, R.A. and Lambooy, J.G. (1999), "Evolutionary economics and economic geography", *Journal of Evolutionary Economics,* Vol. 9 No. 4, pp. 411-29.

Brenner, T. and Gildner, A. (2006), "The long-term implications of local industrial clusters", *European Planning Studies,* Vol. 14 No. 9, pp. 1315-28.

Brenner, T. and Schlump, C. (2011), "Policy measures and their effects in the different phases of the cluster life cycle", *Regional Studies,* Vol. 45 No. 10, pp. 1363-86.

Brulhart, M. and Mathys, N.A. (2008), "Sectoral agglomeration economies in a panel of European regions", *Regional Science and Urban Economics,* Vol. 38 No. 4, pp. 348-62.

Brun, L.C. and Jolley, G.J. (2011), "Increasing stakeholder participation in industry cluster identification", *Economic Development Quarterly,* Vol. 25 No. 3, pp. 211-20.

Chobanyan, A. and Leigh, L. (2006), "The competitive advantages of nations applying the 'diamond' model to Armenia", *International Journal of Emerging Martets,* Vol. 1 No. 2, pp. 147-64.

Ciccone, A. and Hall, R.E. (1996), "Productivity and the density of economic activity", *American Economic Review,* Vol. 86 No. 1, pp. 54-70.

Cooke, P. (2012), "From clusters to platform policies in regional development", *European Planning Studies,* Vol. 20 No. 8, pp. 1415-24.

Cox, D.R. and Hinkley, D.V. (1974), *Theoretical Statistics,* Chapman and Hall, New York.

Dauth, W. (2013), "Agglomeration and regional employment dynamics", *Papers in Regional Science,* Vol. 92 No. 2, pp. 419-35.

Delgado, M., Porter, M.E. and Stern, S. (2010), "Clusters and entrepreneurship", *Journal of Economic Geography,* Vol. 10 No. 4, pp. 495-518.

Ellison, G. and Glaeser, E.L. (1997), "Geographic concentration in U.S. manufacturing industries: a dartboard approach", *Journal of Political Economy,* Vol. 105 No. 5, pp. 889-927.

Fare, R., Grosskopf, S., Norris, M. and Zhang, Z. (1994), "Productivity growth, technical progress, and efficiency change in industrialized countries", *American Economic Review,* Vol. 84 No. 1, pp. 66-83.

Felipe, J. (1999), "Total factor productivity growth in East Asia: a critical survey", *Journal of Development Studies,* Vol. 35 No. 4, pp. 1-41.

Florida, R. (2002), "The economic geography of talent", *Annals of the Association of American Geographers,* Vol. 92 No. 4, pp. 743-55.

Frenken, K., Cefis, E. and Stam, E. (2015), "Industrial dynamics and clusters: a survey", *Regional Studies,* Vol. 49 No. 1, pp. 10-27.

Gabe, T.M. and Abel, J.R. (2012), "Specialized knowledge and the geographic concentration of occupations", *Journal of Economic Geography,* Vol. 12 No. 2, pp. 435-53.

Gao, Y. and Lin, P. (2010), *Innovation and Update of Industrial Clusters: the Case of Guangdong,* Press of South China University of Technology, Guangzhou (in Chinese).

Gertler, M. (2003), "Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there)", *Journal of Economic Geography,* Vol. 3 No. 1, pp. 75-99.

Giuliani, E. (2005), "Cluster absorptive capacity: why do some clusters forge ahead and others lag behind?", *European Urban and Regional Studies,* Vol. 12 No. 3, pp. 269-88.

Giuliani, E. (2007), "The selective nature of knowledge networks in clusters: evidence from the wine industry", *Journal of Economic Geography,* Vol. 7 No. 2, pp. 139-68.

Grabher, G. (1993), "The weakness of strong ties: the lock-in of regional development in the Ruhr area", in Grabher, G. (Ed.) *The Embedded Firm*, Routledge, London.

Grundy, T. (2006), "Rethinking and reinventing Michael Porter's five forces model", *Strategic Change,* Vol. 15 No. 5, pp. 213-29.

Gujarati, D.N. and Porter, D.C. (2009), *Basic Econometrics (fifth edition),* McGraw-Hill Irwin, Boston.

Hanchane, S. and Mostafa, T. (2012), "Solving endogeneity problems in multilevel estimation: an example using education production functions", *Journal of Applied Statistics,* Vol. 39 No. 5, pp. 1101-14.

Helsley, R.W. and Strange, W.C. (2014), "Coagglomeartion and the scale and composition of clusters", *Journal of Political Economy,* Vol. 122 No. 5, pp. 1064-93.

Henderson, J., Dicken, P., Hess, M., Coe, N. and Yeung, H.W.-C. (2002), "Global production networks and the analysis of economic development", *Review of International Political Economy,* Vol. 9 No. 3, pp. 436-64.

Hervas-Oliver, J.-L., Gonzalez, G., Caja, P. and Sempere-Ripoll, F. (2015), "Clusters and industrial districts: where is the literature going? identifying emerging sub-fields of research", *European Planning Studies,* Vol. Forthcoming, DOI:10.1080/09654313.2015.1021300, pp. 1-46.

Hu, F.Z.Y. and Lin, G.C.S. (2011), "Situating regional advantage in geographical political economy: transformation of the state-owned enterprises in Guangzhou, China", *Geoforum,* Vol. 42 No. 4, pp. 696-707.

Huber, F. (2012a), "Do clusters really matter for innovation practices in information technology? questioning the significance of technological knowledge spillovers", *Journal of Economic Geography,* Vol. 12 No. 1, pp. 107-26.

Huber, F. (2012b), "On the role and interrelationship of Spatial, social and cognitive proximity: personal knowledge relationships of R&D workers in the Cambridge information technology cluster", *Regional Studies,* Vol. 46 No. 9, pp. 1169-82.

Isaksen, A. (1997), "Regional clusters and competitiveness: the Norwegian case", *European Planning Studies,* Vol. 5 No. 1, pp. 65-76.

Jaccard, J. and Turrisi, R. (1990), *Interaction Effects in Multiple Regression,* Sage Publications, Newbury Park, CA.

Jaffe, A.B. (1986), "Technological opportunity and spillovers of R & D: evidence from firms' patents, profits, and market value", *American Economic Review,* Vol. 76 No. 5, pp. 984-1001.

Jaffe, A.B. (1989), "Real effects of academic research", *American Economic Review,* Vol. 79 No. 5, pp. 957-70.

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993), "Geographic localization of knowledge spillovers as evidenced by patent citations", *Quarterly Journal of Economics,* Vol. 108 No. 3, pp. 577-98.

James, L.R. and Brett, J.M. (1984), "Mediators, moderators, and tests for mediation", *Journal of Applied Psychology,* Vol. 69 No. 2, pp. 307-21.

Keeble, D. and Wever, E. (1986), *New Firms and Regional Development in Europe,* Croom Helm, London.

Kirkman, B.L., Rosen, B., Tesluk, P.E. and Gibson, C.B. (2004), "The impact of team empowerment on virtual team performance: the moderating role of face-to-face interaction", *Academy of Management Journal,* Vol. 47 No. 2, pp. 175-92.

Klepper, S. (2001), "Employee startups in high-tech industries", *Industrial & Corporate Change,* Vol. 10 No. 3, pp. 639-74.

Klepper, S. (2010), "The origin and growth of industry clusters: the making of Silicon Valley and Detroit", *Journal of Urban Economics,* Vol. 67 No. 1, pp. 15-32.

Kodama, T. (2008), "The role of intermediation and absorptive capacity in facilitating university-industry linkages--an empirical study of TAMA in Japan", *Research Policy,* Vol. 37 No. 8, pp. 1224-40.

Krugman, P. (1991), *Geography and Trade,* The MIT Press, London.

Krugman, P. (1996), *Pop Internationalism,* Mass:MIT Press, Cambridge.

Lawson, C. and Lorenz, E. (1999), "Collective learning, tacit knowledge and regional innovative capacity", *Regional Studies,* Vol. 33 No. 4, pp. 305-17.

Lazzeretti, L., Sedita, S.R. and Caloffi, A. (2014), "Founders and disseminators of cluster research", *Journal of Economic Geography,* Vol. 14 No. 1, pp. 21-43.

Lee, Y., Chyi, Y.-L., Lin, E.S. and Wu, S.-Y. (2013), "Do local industrial agglomeration and foreign direct investment to China enhance the productivity of Taiwanese firms?", *Journal of International Trade & Economic Development,* Vol. 22 No. 6, pp. 839-65.

Li, P.-F. (2014), "Global temporary networks of clusters: structures and dynamics of trade fairs in Asian economies", *Journal of Economic Geography,* Vol. 14 No. 5, pp. 995-1021.

Liang, Q. (2006), *On Industrial Clusters (in Chinese),* The Commercial Press, Beijing.

Lin, H.-L., Li, H.-Y. and Yang, C.-H. (2011), "Agglomeration and productivity: firm-level evidence from China's textile industry", *China Economic Review,* Vol. 22 No. 3, pp. 313-29.

Link, A.N. and Rees, J. (1990), "Firm size, university based research, and the returns to R&D", *Small Business Economics,* Vol. 2 No. 1, pp. 25-31.

Liu, J., Chaminade, C. and Asheim, B.T. (2013), "The geography and structure of global innovation networks: a knowledge base perspective", *European Planning Studies,* Vol. 21 No. 9, pp. 1456-73.

Lopez-Bazo, E. and Motellon, E. (2012), "Human capital and regional wage gaps", *Regional Studies,* Vol. 46 No. 10, pp. 1347-65.

Lu, R. and Reve, T. (2015), "Relations among clusters", *European Planning Studies,* Vol. 23 No. 4, pp. 828-45.

Lu, R., Zhang, R. and Reve, T. (2013), "Relations among clusters in six Chinese city regions", *European Planning Studies,* Vol. 21 No. 8, pp. 1189-209.

Lucas, M., Sands, A. and Wolfe, D.A. (2009), "Regional clusters in a global industry: ICT clusters in Canada", *European Planning Studies,* Vol. 17 No. 2, pp. 189-209.

Mahutga, M.C. (2014), "Global models of networked organization, the positional power of nations and economic development", *Review of International Political Economy,* Vol. 21 No. 1, pp. 157-94.

Mano, Y. and Otsuka, K. (2000), "Agglomeration Economies and Geographical Concentration of Industries: A Case Study of Manufacturing Sectors in Postwar Japan", *Journal of the Japanese and International Economies,* Vol. 14 No. 3, pp. 189-203.

Marshall, A. (1890), *Principles of Economics,* Macmillan, London.

Martin, R. and Sunley, P. (2003), "Deconstructing clusters: chaotic concept or policy panacea?", *Journal of Economic Geography,* Vol. 3 No. 1, pp. 5-35.

Martin, R. and Sunley, P. (2006), "Path dependence and regional economic evolution", *Journal of Economic Geography,* Vol. 6 No. 4, pp. 395-437.

Maskell, P. and Malmberg, A. (2007), "Myopia, knowledge development and cluster evolution", *Journal of Economic Geography,* Vol. 7 No. 5, pp. 607-18.

McGahan, A.M. and Silverman, B.S. (2001), "How does innovative activity change as industries mature?", *International Journal of Industrial Organization,* Vol. 19 No. 7, pp. 1141-60.

Menzel, M.-P. and Fornahl, D. (2010), "Cluster life cycles--dimensions and rationales of cluster evolution", *Industrial & Corporate Change,* Vol. 19 No. 1, pp. 205-38.

Mukim, M. (2015), "Coagglomeration of formal and informal industry: evidence from India", *Journal of Economic Geography,* Vol. 15 No. 2, pp. 329-51.

Mundlak, Y. (1978), "On the pooling of time series and cross section data", *Econometrica,* Vol. 46 No. 1, pp. 69-85.

Narula, R. (2002), "Innovation systems and 'inertia' in R&D location: Norwegian firms and the role of systemic lock-in", *Research Policy,* Vol. 31 No. 5, pp. 795-816.

Neffke, F., Henning, M., Boschma, R., Lundquist, K.-J. and Olander, L.-O. (2011), "The dynamics of agglomeration externalities along the life cycle of industries", *Regional Studies,* Vol. 45 No. 1, pp. 49-65.

O'Mahony, M. and Vecchi, M.M.V. (2009), "R&D, knowledge spillovers and company productivity performance", *Research Policy,* Vol. 38 No. 1, pp. 35-44.

Otto, A. and Fornahl, D. (2010), "Origins of human capital in clusters: regional, industrial and academic transitions in media cluster in Germany", in Fornahl, D., Henn, S. and Menzel, M.-P. (Eds.), *Emering Clusters: Theoretical, Empirical and Political Aspects of the Cluster Evolution*, Edward Elgar Publishing Ltd, Jena, Germany.

Owen-Smith, J., Riccaboni, M., Pammolli, F. and Powell, W.W. (2002), "A comparison of US and European university-industry relations in the life sciences", *Management Science,* Vol. 48 No. 1, pp. 24-43.

Parkin, M. (2014), *Economics (11 edition),* Pearson Education Limited, England.

Patel-Campillo, A. (2011), "Transforming global commodity chains: actor strategies, regulation, and competitive relations in the Dutch cut floweer sector", *Economic Geography,* Vol. 87 No. 1, pp. 79-99.

Popp, A. and Wilson, J. (2007), "Life cycles, contingency, and agency: growth, development, and change in English industrial districts and clusters", *Environment and Planning A,* Vol. 39 No. 12, pp. 2975-92.

Porter, M.E. (1990), *The Competitive Advantage of Nations,* Macmillan, London.

Porter, M.E. (1998), *On Competition,* Harvard Business School Press, Boston.

Rabe-Hesketh, S. and Skrondal, A. (2008), *Multilevel and Longitudinal Modeling Using Stata,* A Stata Press Publication, Texas, America.

Robbins, S.P. and Coulter, M. (2013), *Management (11th edition),* Tsinghua University Press, Beijing.

Sharma, S., Durand, R.M. and Gur-Arie, O. (1981), "Identification and analysis of moderator variables", *Journal of Marketing Research,* Vol. 18 No. 3, pp. 291-300.

Shin, D.-H. and Hassink, R. (2011), "Cluster life cycles: the case of the shipbuilding industry cluster in South Korea", *Regional Studies,* Vol. 45 No. 10, pp. 1387-402.

Snijders, T.A.B. and Bosker, R.J. (1999), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling,* SAGE publications Ltd, London.

Solow, R.M. (1957), "Technical change and the aggregate production function", *Review of Economics and Statistics,* Vol. 39 No. 3, pp. 312-20.

Staber, U. and Sautter, B. (2011), "Who are we, and do we need to change? cluster identity and life cycle", *Regional Studies,* Vol. 45 No. 10, pp. 1349-61.

Sternberg, R.G. and Litzenberger, T. (2004), "Regional clusters in Germany -- their geography and their relevance for entrepreneurial activities", *European Planning Studies,* Vol. 12 No. 6, pp. 767-91.

Stone, E.F. and Hollenbeck, J.R. (1984), "Some issues associated with the use of moderated regression", *Organizational Behavior and Human Performance,* Vol. 34 No. 2, pp. 195-213.

Sturgeon, T., Biesebroeck, J.V. and Gereffi, G. (2008), "Value chains, networks and clusters: reframing the global automotive industry", *Journal of Economic Geography,* Vol. 8 No. 3, pp. 297-321.

Syverson, C. (2011), "What determines productivity?", *Journal of Economic Literature,* Vol. 49 No. 2, pp. 326-65.

Tan, K.G., Nie, T. and Baek, S. (2015), "Empirical assessment on the liveability of cities in the Greater China region", *Competitiveness Review,* Vol. 26 No. 1, pp. 2-24.

Vieira, E., Neira, I. and Vazquez, E. (2011), "Productivity and innovation economy: comparative analysis of European NUTS II, 1995-2004", *Regional Studies,* Vol. 45 No. 9, pp. 1269-86.

Wakelin, K. (2001), "Productivity growth and R&D expenditure in UK manufacturing firms", *Research Policy,* Vol. 30 No. 7, pp. 1079-90.

Wang, L., Madhok, A. and Li, S.X. (2014), "Agglomeration and clustering over the industry life cycle:

toward a dynamic model of geographic concentration", *Strategic Management Journal,* Vol. 35 No. 7, pp. 995-1012.

Wennberg, K. and Lindqvist, G. (2010), "The effect of clusters on the survival and performance of new firms", *Small Business Economics,* Vol. 34 No. 3, pp. 221-41.

Widodo, W., Salim, R. and Bloch, H. (2014), "Agglomeration economies and productivity growth in manufacturing industry: empirical evidence from Indonesia", *Economic Record,* Vol. 90 No. special issue, pp. 41-58.

Yang, C. and Liao, H. (2010), "Industrial agglomeration of Hong Kong and Taiwanese manufacturing investment in China: a town-level analysis in Dongguan", *Annals of Regional Science,* Vol. 45 No. 3, pp. 487-517.

Yuan, Y., Guo, H., Xu, H., Li, W., Luo, S., Lin, H. and Yuan, Y. (2010), "China's first special economic zone: the case of Shenzhen", in Zeng, D.Z. (Ed.) *Building Engines for Growth and Competitiveness in China: Experience with Special Economic Zones and Industrial Clusters*, The World Bank, Washington DC, pp. 55-86.

Zeng, D.Z. (2010), *Building Engines for Growth and Competitiveness in China: Experience with Special Economic Zones and Industrial Clusters,* The World Bank, Washington, D.C.