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Catch-up Via Agglomeration: A Study of Township Clusters

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AGGLOMERATION AND INTER-FIRM COMPETITION AND COOPERATION: A STUDY OF CHINESE TOWNSHIP CLUSTERS

This study examines whether the premises of inter-firm competition and cooperation on cluster performance outcome hold true in the context of China. By examining 87 township clusters in Jiangsu Province, we find that cluster performance is co-determined by the intensity of inter-firm competition and cluster innovativeness. Our results also show that the cluster's competitive intensity mediates the relationship between cluster size and cluster performance, and that a cluster's R&D centers and inter-firm joint actions positively affect a cluster's innovativeness, which in turn contributes to cluster performance. These findings not only provide additional support for strategy theories about clusters in a new context, but also shed novel insights into the unique phenomenon of Chinese township clusters.

Keywords: township industrial cluster, agglomeration, China, cluster performance, innovation

INTRODUCTION

Clustering, or geographical agglomeration of firms in an industry sector, has become an increasingly important international economic phenomenon and has drawn increasing attention from global strategy scholars. Recent research has documented the role of clusters in affecting firm location choice (see review by McCann and Folta, 2008), regional innovation (see review by Breschi and Lissoni, 2001; Gordon and McCann, 2005), regional economic development (see reviews by Scott, 2000; Rocha, 2004), and regional entrepreneurship (Rocha and Sternberg, 2005).

With the development of cluster research in global strategy, scholars have started to shift their emphasis away from explaining where and why clusters exist toward the performance heterogeneity of clusters, of the firms within clusters, and of the performance outcomes for these clusters and firms (Tallman *et al*., 2004). For instance, as an extension of the knowledge-based view (KBV) of the firm at the cluster level, Arikan (2009) has developed a conceptual framework to explain factors determining a cluster's knowledge creation capability. Pouder and St. John (1996) have proposed an evolutionary perspective of cluster innovation performance. Tallman *et al*. (2004) have noted the importance of studying both cluster-level and firm-level competitive advantage, and laid down a knowledge-based framework to analyze factors affecting the competitive heterogeneity across clusters.

Most of the theory advancement on the subject of cluster competitive heterogeneity, however, has focused on a cooperation-based perspective. A central argument of this perspective is anchored on the effectiveness of inter-firm collaboration and knowledge exchange, which are facilitated by the geographic proximity of co-locating in the same cluster, and can help explain the differences in cluster performance, particularly for high tech clusters in developed economies.

The cooperation-based perspective has advanced our understanding on cluster heterogeneity; however, little is known about whether this rationale can be equally applied to manufacturing clusters in developing economies. Another important driving force within clusters, highlighted by Piore and Sabel (1984) and Porter (1990, 2000) and more recently Giarratana and Mariani (2014) and Alcacer and Zhao (2012), is based on internal competition. Will competitive forces be more effective than cooperative networks in determining the performance of manufacturing clusters, which tend to be more efficiency driven and less focused on innovation?

This study considers the perspectives of inter-firm competition and cooperation in clusters comprehensively and examines empirically how together they affect the competitive advantage of manufacturing clusters. As Maskell (2001) notes, a comprehensive understanding of cluster organization and performance needs to recognize and balance both competitive (or horizontal) and cooperative (or vertical) forces in them. In this sense, the cooperation and competition perspectives are two sides of the same coin in studying clusters. However, there have been few studies that use both perspectives to reach a more holistic view of cluster heterogeneity (see Gambardella and Giarratana, 2010, as an exception), and to our best knowledge, no empirical efforts have yet tested the simultaneous effects of competitive and cooperative forces on cluster performance.

We argue that the heterogeneity of cluster performance is determined by competitive forces such as the intensity of inter-firm competition and cooperative forces such as cluster-level innovativeness. Taking a competition-based perspective (Porter, 1990, 2000), we particularly contend that agglomeration effects on cluster performance are mediated by the cluster's competitive intensity. From a cooperation-based perspective, we argue that the knowledge stock and flows of a cluster positively affect a cluster's innovativeness, which in turn enhances cluster performance.

In addition, by utilizing a unique dataset based on township clusters in China, we are able to overcome the difficulty of observing and collecting cluster level performance variables to provide one of the first empirical studies on cluster performance heterogeneity. We test our hypotheses through the use of a survey of township industrial clusters in Jiangsu Province, one of the most industrialized provinces in China. As a driving force of the Chinese economic growth miracle, township clusters generate about $0.6 trillion toward China's GDP, accounting for about 10 percent of the total in 2010 (The People's Republic of China Yearbook, 2010). Township clusters are most developed in and account for about one-third of the GDP of the four coastal provinces of Jiangsu, Zhejiang, Fujian, and Guangdong, the most industrialized in China (The People's Republic of China Yearbook, 2010). Based on the Chinese central government's census, there were about 5,660 township industrial clusters in China by the end of 2007, and the number has increased since. Despite the growing importance of township industrial clusters, this phenomenon has been little studied in comparison with other types of clusters, such as Silicon Valley in the US and Emilia Romagna in Italy, so that their emergence and development over the last 30 years and whether they function differently from their counterparts in the developed economies has remained a mystery. Results from this study shed new light on the unique phenomenon of township industrial clusters in China and also provide important policy implications for industrial development.

THEORY DEVELOPMENT AND RESEARCH BACKGROUND

Theory development

According to Porter (2000: 16), a cluster or a geographical agglomeration can be defined as 'a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities.' Marshall's (1890/1920) seminal works note several primary benefits of geographical agglomeration for firms, including ready access to specialized labor, specialized inputs, technology spillovers, and greater consumer demand. Recent cluster researchers have advanced Marshall's work and recognized the driving forces of clusters in terms of the co-existence of competition and cooperation in clusters. (e.g., Maskell, 2001; see McCann and Folta, 2008 for a more comprehensive review). Based on the distinction of competition and cooperation, Pitelis (2012:1361) has extended the traditional definition by Porter (2000) to define clusters as 'geographical agglomerations of firms in particular, related, and/or complementary, activities, sharing a common vision, and *exhibiting horizontal, vertical intra- and/or inter-sectoral linkages, embedded in a supportive socio-institutional setting, and cooperating and competing in national and international markets*' (Italics by the authors to emphasize the incorporation of competition and cooperation in this definition).

Despite the fact that industrial clusters are global phenomena, observed across most countries, most cluster research has focused on clusters in developed economies and on the question of why firms tend to cluster geographically (Storper, 1995; McCann and Folta, 2008). Given the fact that most clusters in developed economies are high tech driven, existing studies largely subscribe to the cooperative perspective in investigating strategic issues of clusters. Not until recently have scholars started to pay greater attention to studying the competitiveness of the cluster itself. In a recent review article on the competitive dynamics of regional clusters, Ketchen, Snow, and Hoover (2004) call for future research to investigate why different types of clusters rise and decline.

This recent focus on cluster competitiveness has taken place largely from a knowledge-based viewpoint, seeking to understand how knowledge is shared among the firms in a cluster and how knowledge engenders competitive advantage among firms in a cluster and for the cluster as a whole. For instance, Tallman *et al*. (2004) proposed the ‘rail system and cargo’ metaphor to describe the stock and flow of knowledge in a cluster, and their implications for the competitive advantages of firms and of the cluster. The ‘cargo’ is component knowledge, moving among clustered firms quickly and freely along the ‘rail tracks’ of cluster-level architectural knowledge (Tallman *et al*., 2004: 266). The overall performance of the ‘rail system’, the cluster, is determined by both the quality of component knowledge and the effectiveness of architectural knowledge in facilitating inter-firm exchanges.

This KBV framework for cluster competitiveness has emphasized the cooperative side of inter-firm relationship in a cluster. The effects of agglomeration on cluster knowledge creation and competitive advantage, as viewed by Tallman *et al*. (2004) and Arikan (2009), are achieved through inter-firm cooperation based upon the variation and division of labor and on knowledge flows within a cluster through interdependencies. However, this cooperation-based perspective has not effectively incorporated the competitive side of inter-firm relationships in a cluster, which can be more commonly observed in manufacturing clusters in developing countries.

Indeed, competition plays an important role in the diamond model of cluster competitiveness (Porter, 1990, 1998, 2000). Porter’s work focuses on the effects of agglomeration on productivity and innovation through intensifying competition in the global economy. By co-locating with competitors, the pressure of competition intensity on performance will be amplified, the spillover effect will be expedited, and imitative threats will be more observable. Despite potential spillover effects and imitation fears, research shows that industry leaders can still benefit from the agglomeration effect. For instance, by studying clusters in the global semiconductor industry, Alcacer and Zhao (2012) found that when co-locating with direct market competitors, industry leaders will enhance their own knowledge appropriation mechanisms through intensifying internal linkages across locations to avoid knowledge expropriation. Similarly, Giarratana and Mariani (2014) found that firms tend to benefit from local competition and the spillover effect of clusters unless two contingencies simultaneously concur—that they run costly R&D projects and are surrounded by competitors with high absorptive capacity. As a result, firms in a cluster are likely to enhance productivity, to fuel future growth through innovation, and to spur the formation of new businesses (Porter, 1998). Accordingly, internal competitive intensity drives a cluster to be more competitive as a whole. Given its emphasis on inter-firm competition, we summarize this perspective as the competition-based perspective on clusters.

Having noted the differences between these two perspectives, we should not infer that they must oppose each other. Indeed, scholars from both perspectives have acknowledged works from the other perspective. For instance, although not emphasizing the 'common knowledge base' in a cluster, Porter (1998, 2000) explicitly noted the role of innovation in mutually reinforcing the competitive forces to determine a cluster's competitiveness. Similarly, in the classic KBV work on the theory of cluster, Maskell (2001) considered clusters as having both cooperative (vertical) and competitive (horizontal) dimensions in relation to knowledge creation. In a more recent study, Gambardella and Giarratana (2010) examined the distribution of rewards among 146 U.S. cities and found that both competitive and cooperative forces affect cluster economic characteristics, particularly managerial financial performance. However, their study only focuses on the distribution of managerial rewards in clusters, but not on overall cluster performance.

This study intends to extend the prior research to provide a more systematic examination of factors that determine cluster performance to provide a comprehensive perspective on cluster performance from both perspectives. Combining the competition-based and cooperation-based perspectives helps us to have a more complete answer to how agglomeration affects the innovation and performance of the cluster. In sum, the competition-based perspective suggests that agglomeration plays a role in amplifying internal competition to increase the external competitiveness of the cluster; the cooperation-based perspective suggests that agglomeration plays a role in fostering joint internal knowledge creation and knowledge flows to provide competitive advantage to the cluster. In the sections below, we will integrate the context of the township industrial clusters in China to develop testable hypotheses.

Research context—township industrial clusters in China

This study is set among the township industrial clusters of China. In China, since its adoption of the economic reforms and open door policy at the end of the 1970s, a variety of township industrial clusters, such as 'specialized towns' and 'single-product towns,' has mushroomed. Despite some differences regarding names, these township industrial clusters share three common characteristics: first, a large group of firms proximately located in a specific town; second, a clear leading industry, which has several leading firms, significantly contributing to the regional and national economies; and third, a supportive township government, providing necessary infrastructure elements and favorable policies to foster the development of the leading industry.

We should note that given the unique government structure in China, a town not only has a clear geographical territory but it also has clear administrative boundaries. For example, in Jiangsu Province in coastal China, there are 13 districts (each district has a capital city) under which there are 102 cities or counties, 956 towns and 15,656 administrative villages in 2011.[1] In addition, driven by the goal of increasing GDP growth, local township officials are motivated to provide supporting infrastructure and policies to their local companies, in order to promote the leading industry in their town and to differentiate their township industrial clusters from those of their neighboring towns. As a result, 57 percent of township and village enterprises are located in industrial clusters in Jiangsu Province, and there are more than 50 township clusters with an annual GDP of one billion US dollars or higher (The People's Republic of China Yearbook, 2010).

Furthermore, each town usually has its own leading industry and almost all the firms in the town engage in the leading industry or in vertically related industry sectors. For example, Daxin Town of Zhangjiagang City in Jiangsu Province specializes in hardware tools, with metallurgy and textiles as vertically supporting industries. The Daxin cluster had 36,000 employees in 2004. In 2003, its total industrial production value reached 2.4 billion RMB, one third of which was produced by the tools (hardware) industry with nearly 60 percent of the products exported abroad.

The production of hardware tools in Daxin Town dates back to 1958. From 1958 to 1979, the Second Medical Instrument Factory of Shazhou County (later renamed as Hongnao after privatization), established by merging several manual smithy workshops, produced medical

[1] The data come from the official website of People's Government of Jiangsu Province (http://www.js.gov.cn/zgjszjjs/jsgl/xzqh/), which were retrieved on Dec 30, 2012.

instruments according to the production plans issued by the central government. With the beginning of the economic reforms in 1979, the Factory started to seek and receive overseas orders to produce knives and scissors. At the end of 1980, due to booming overseas orders, the Factory helped eleven of twelve administrative villages in Daxin Town to set up supplementary plants. Since 1992, a growing number of hardware tool companies have set up their headquarters or manufacturing centers in Daxin town. In the late 90s, some leading companies, such as Hongbao, Tianda, and Zhongbao, have started to make heavy investments in technological development and brand management. In 2003, Daxin Town was named *The Hardware Town of China* by the Hardware Association of China.

From the above example of the Daxin Township cluster, we can see that Chinese township industrial clusters indeed are ‘geographically proximate group(s) of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities’ (Porter, 2000: 16). In addition, from the above example of Daxin Township cluster, we can see that Chinese township industrial clusters present striking similarities to the industry-focused clusters noted by St. John and Pouder (2006), in that firms (a) compete in the same industry, (b) begin as one or several start-up firms that, as a group, grow more rapidly than other industry participants (sales and employment levels), and (c) have the same or very similar immobile physical resource requirements in the long run.

We should note that township clusters may differ from Silicon Valley or Bangalore in India regarding their origins, evolutions and structures, due partly to the nature of technology that fosters the clusters and partly to the different institutional environments in which these clusters are embedded. For instance, one unique distinction between Chinese township clusters and high tech clusters in developed economies is that the township or local governments play an important role in designing cluster strategies ex ante and managing, or at least overseeing, the development of township clusters. This process differs from cluster dynamics in most other countries, where the membership tends to be informal and common action is emergent, whereby the pattern of strategy can only be observed ex post. But the township clusters are good representatives of clusters that based on what Iammaraino and McCann (2006) called traditional social networks. As Iammarino and McCann (2006) note, the social network model of clusters is more typical for traditional manufacturing industrial clusters which tend to feature both competition and cooperation in their internal dynamics. These features are less likely to be observed in high tech clusters, such as Silicon Valley, which are more oriented to new innovation and based on more openness of innovation systems. In this sense, the context of Chinese township clusters provides a suitable context to study the coexistence of competitive and cooperative forces in determining cluster performance in traditional industrial clusters.

Finally, we should note that due to the unique governmental structures in China, these township industrial clusters have clear industry and geographic boundaries and specific administrative reporting requirements as compared to their counterparts in developed countries. These features help overcome the criticism that clusters typically lack clear industrial and geographical boundaries (Martin and Sunley, 2003), and thereby facilitate measuring and testing cluster performance.

HYPOTHESIS DEVELOPMENT

Extending the above theoretical argument to the context of Chinese township industrial clusters, we develop a set of hypotheses concerning the key determinants of cluster performance along the inter-firm competition and cooperation dimensions, respectively.

Inter-firm competition, agglomeration, and cluster performance

From the competition-based perspective, inter-firm competition will be amplified as a result of agglomeration effects (Porter, 1998, 2000). The agglomeration effect or 'economies of agglomeration' increases as a cluster increases its size (Folta, Cooper, and Baik, 2006). In other words, 'the net benefits to being in a location together with other firms increase with the number of firms in the location' (Arthur, 1990: 237).

This tenet of economies of agglomeration has been tested at the firm level. For example, using a sample of 806 U.S. biotechnology firms founded between 1973 and 1998, Folta *et al*. (2006) found that cluster size is associated with higher firm performance. Similarly, by analyzing a large sample of British manufacturing firms during the period 1997-1999, Beaudry and Swann (2001) showed that firm growth is positively related to total employment in clusters in the firm's industry. These studies suggest a positive relationship between cluster size and firm performance in a cluster. However, it is not clear that this tenet will also hold true at an aggregate cluster level of analysis. This is because individual firm performance can be built upon the sacrifice of its competitors and the deterioration of the competitive environment of the cluster. From a cluster life cycle perspective (Menzel and Fornahl, 2010), when a cluster becomes oversized, it will stagnate and enter a declining stage. Therefore, it is arguable that with the increasing size of a cluster, the overall effectiveness and efficiency of knowledge flow within the cluster may encounter the issue of diseconomies of scale, thus having an inverted U shape effect on cluster performance.

However, we note in the specific context of Chinese township cluster, where the geographic boundary is largely predetermined by the municipal government and economic activities are coordinated through the township government, a township cluster cannot expand its geographic boundary at will and its size may also be economically monitored by the planning power. In addition, most of the township clusters in China started to take off in the 1990s or the earlier 2000s. With only 10 to 15 years of development, these township clusters are relatively young compared with their overseas counterparts, thus more likely to still be in a growing stage. Hence, we argue that for Chinese township clusters increasing cluster size is less likely to cause diseconomies of scale, while the key resources of the cluster, such as skilled labor, technicians, and professionals with industry-specific knowledge, specialized service suppliers, and network ties that unite specific agents will increase accordingly. Thus, increasing size will lead to a higher possibility of variation and a greater degree of the division of labor in a cluster, which will in turn foster the overall competitiveness of a cluster. Indeed, by using qualitative evidence, Tsuji (2004) found that a key reason for the automotive and parts clusters around Shanghai areas to achieve the most success among automotive industry clusters in China is that it is 'the most heavily agglomerated in China'. Therefore, we hypothesize that:

Hypothesis 1: *In Chinese township clusters, cluster size is positively related to township cluster performance.*

The township cluster is a unique hybrid of top down government control and grassroots entrepreneurship activities (Zhao, 2013). As noted above, the township government has the power to coordinate, direct, and regulate economic activities, directly and indirectly affecting the size of clusters. A simple example is that the government can decide whether to allow the registration of a business or to issue land permits to set up a factory. This top down government control provides an institutional background for township cluster growth and development. An equally or more important factor in township cluster performance is free market competition at the grassroots of the cluster. This free market competition provides incentives for firms to appropriate value from the cluster, encouraging the mobility of labor and knowledge flows within the cluster. In this sense, the effect of cluster size on performance is realized through inter-firm competition, instead of top down government controls. In other words, inter-firm competition plays a mediating role in the relationship between cluster size and performance.

This mediating effect has also been observed in other types of clusters through qualitative research methods. By investigating the differences between leading European ceramic tile clusters, Hervas-Oliver & Albors-Garrigos (2007) find that during 1998 to 2002 the Castellon cluster in Spain had better overall financial performance than the Emilia-Romagna cluster in Italy. They attribute the superior performance of the Castellon cluster to its higher level of competitive intensity, as a result of the presence of more firms and skilled labor than that in the Emilia-Romagna cluster. These competitive forces in a cluster can be more critical for Chinese township clusters, as competition among Chinese firms tends to be driven by low cost strategies. As a result of agglomeration effects, competition will mobilize all member firms to be more efficient and effective, creating an overall competitive benefit for the cluster. Accordingly, we argue:

Hypothesis 2: *In Chinese township clusters, the effect of cluster size on cluster performance is partially mediated by the inter-firm competition in a cluster.*

Inter-firm cooperation, innovativeness and cluster performance

Clustering in a geographic proximate location allows firms to develop norms and common conventions to guide and coordinate business activities within the cluster. In this cooperation process, an emphasis on innovation is critical for the success (Tsuji and Ueki, 2008). By studying clusters in multiple countries in East Asia, Tsuji and Ueki(2008) note that a critical factor for clusters in that region to achieve sustainable growth is to develop endogenous innovation. From this perspective, we focus on two aspects of a township industrial cluster—the establishment of R&D centers as a proxy for cluster knowledge stocks and inter-firm joint actions as a proxy for cluster knowledge flows.

R&D centers help increase cluster innovativeness by preserving both component and architectural knowledge in the cluster (Tallman *et al*., 2004). First, R&D centers can provide important component knowledge to a cluster. Although most R&D centers reside in individual companies, they tend to be subsidized by the local government with the goal of facilitating the distribution of the knowledge about technology, products, and marketing created by these centers. Thus, these R&D centers become part of the common knowledge base of the cluster through spillovers and intentional knowledge sharing with supplier firms. In a parallel qualitative research initiative on township clusters, the founder of a lead company in a township cluster noted the role of R&D centers as 'a public service platform to serve small and medium sized enterprises in this specific industrial cluster.' This component knowledge moves among the firms quickly and freely in a township industrial cluster because of interdependencies and the shorter cognitive distance inside the cluster (Marshall, 1890/1920; Tallman *et al*., 2004).

Second, R&D centers can also help the creation of cluster architectural knowledge. Treating a cluster as an organizational field, scholars have noted that clusters are also subject to isomorphic pressure (Pouder and St. John, 1996). It is through learning, trying and improving that technology-oriented identity and conventions can be created in a cluster. The more firms that are engaged in establishing technology centers in a cluster, the more likely the cluster will form technology-oriented identities and conventions. Such conventions create the cluster's reputation (Maskell, 2001). Conventions and reputations are part of the cluster-level architectural knowledge that helps boost cluster innovativeness (Tallman *et al*., 2004). In sum, we argue:

Hypothesis 3: *In Chinese township clusters, the number of R&D centers in a cluster is positively related to the innovativeness of the cluster.*

Inter-firm joint actions refer to formal cooperation between firms in a cluster, such as joint production, joint R&D, marketing, etc. While coordination can be done by market and other informal mechanisms, such as conventions, informal rules, etc., inter-firm joint actions may formally help to resolve problems caused by information asymmetries, which impede the division of labor and specialization in the value chain in a cluster (Young, 1928; Maskell, 2001). As division and specialization of labor are the foundations of vertical knowledge exchange in a cluster, inter-firm joint actions will facilitate knowledge flows and sharing within a cluster. This can be particularly true for Chinese township clusters, which tend to evolve around the leading firms' vertical value chains. Active interactions among cluster members foster a learning environment that facilitates the development of innovative solutions and intermediate products along the value chain. In other words, the more inter-firm joint actions, the higher the growth of indirect methods of production in clusters, and thus the more rapid the knowledge flows in a cluster. In turn, the knowledge flows and sharing, facilitated by inter-firm joint actions, will foster knowledge creation in a cluster. Therefore, we argue:

Hypothesis 4: *In Chinese township clusters, the number of inter-firm joint actions in a cluster is positively related to the innovativeness of the cluster.*

At the aggregated cluster level, the innovativeness of a cluster reflects the extent of inter-firm cooperation within a cluster. From a KBV perspective, clusters are considered as venues of enhanced knowledge creation (Lawson and Lorenz, 1999; Lorenzen and Maskell, 2004; Maskell, 2001; Maskell and Malmberg, 1999). From this perspective, the innovativeness that results from knowledge creation efforts serves as a critical function to create competitive advantages for the cluster and the firms within (Arikan, 2009; Tallman *et al*., 2004). More specifically, the greater the innovativeness of the cluster, the more likely the firms in the cluster will enjoy the premium benefits resulting from competitive differentiation (Porter, 1998; Tallman *et al*., 2004). As most Chinese township clusters are based on manufacturing, the improvement of innovation will translate into more differentiated products or more efficient production process. In this sense, the competitive differentiation or cost advantages created by innovativeness within the cluster will help the focal cluster as a whole to increase sales growth and market share when competing with firms or other clusters in the same industry. Accordingly, we argue:

Hypothesis 5: *In Chinese township clusters, a cluster's innovativeness is positively related to its performance.*

METHOD

Data collection

The sample was collected from 87 township industrial clusters in Jiangsu Province, China. A province-wide interview survey was undertaken in October 2005. The questionnaire comprised two parts to be completed in separate personal interviews by two different respondents: one part included the information to produce the two outcome variables of cluster performance and innovativeness, which were reported by the director of the industrial department of the local town government; the other part contained predictive variables including information on inter-firm joint actions, the number of cluster leading brands, and cluster R&D centers, reported by the chairman or secretary of the local chamber of commerce of the industry. This multiple-source strategy minimizes common method problems and improves the internal validity of our results (Podsakoff *et al*., 2003; Chang, van Witteloostuijn, and Eden, 2010). In addition, we conducted Harman's one-factor analysis to examine whether a single factor or a general factor accounts for the majority of the covariance in the measures. The result showed that three distinct factors explain 58.996 percent of the total variance, and the first factor accounted for 28.837 percent. Therefore, it suggested little effect of common method variance and supported our measures' validity.

Sampling. First, we obtained a list of 800 township clusters from the Small and Medium Enterprise Bureau of Jiangsu (now the Bureau is merged into Jiangsu Economic and Information Technology Commission). The list gave a concise description about each township cluster. Second, we visited all town government web homepages in the list and read each city's statistical yearbooks to get each town's data of GDP and populations and to understand the history of each township cluster's development.

Recruitment of interviewers. We surveyed the senior undergraduates at the School of Business of a leading national university in Nanjing City. The purpose of this survey was to identify which students' homes were either located in or adjacent to these 800 towns. Among the total of 710 students, about half were from Jiangsu Province. We matched the students' homes with the 800 towns, and found matches for 101 towns. Forty-eight students' homes were located in or adjacent to these 101 towns. We recruited these 48 students as interviewers.

The training of interviewers. Each student was responsible for the survey work in two towns on average (one industrial cluster in each town). We presented the same three-hour training session to each interviewer. After all interviewers were trained, we gave two follow-up two-hour sessions for discussions with the 48 interviewers.

Coordination of the interviewing process. We maintained contact with the forty-eight interviewers to discuss any unanticipated problems in the field and to provide help when necessary. We had to drop five locations according to discussions with interviewers in the field and we finally completed interviews in 96 industrial township clusters. Five of the 96 industrial clusters had to be deleted upon further analysis because they belonged to the agriculture, forestry and fisheries industry, while the other 91were all in manufacturing industries. Four of the 91clusters lacked some key data, such as cluster performance and inter-firm joint actions. Therefore, the final sample consisted of 87 industrial clusters. The 87 towns were compared with the 713 towns that were not included in the study to explore possible sampling biases. No significant differences were found in the average populations and average GDP in the two sets of towns for 2001 to 2003. The descriptive statistics of the sample towns and clusters are presented in Table 1.

Insert Table 1 about here

Measures

Cluster performance. Cluster performance has been measured as growth in the number of firms or growth in employment (e.g., Häussler and Zademach (2007), or as measured by Return on Assets (ROA) and Return on Equity (ROE) (e.g., Hervas-Oliver and Albors-Garrigos, 2007). These measures have advanced from the measures in prior research, such as using the sum of overall firm performance or regional economic development as a proxy, as they focus on cluster-level competitiveness as a whole, rather than cluster-firm or region-firm cross-levels. However, a single dimension of assessment of cluster performance may not provide a comprehensive evaluation of the strategic competitiveness of a cluster nor be able to tease out the potential industry influences.

To address these concerns, we gauged a cluster's performance on the four dimensions of profitability, sales growth, market share, and overall competitive position. These have been widely used to assess firm competitive advantage (e.g., Luo, 2002; Tan and Litschert, 1994) and have been recognized as major strategic goals in Sino-foreign joint ventures (e.g., Luo, 2002) and in Chinese companies (e.g., Tan and Litschert, 1994). We then asked the director of industrial department of the local town government and the chairman or secretary of the local chamber of commerce of the industry for an assessment of cluster performance relative to similar clusters in China, using a seven-point Likert scale (from 1 very low to 7 very high).

The dimensionality and reliability of this construct are validated by the high loadings in our exploratory factor analysis (≥0.72) and on Cronbach's α coefficient (0.83). The correlation was $r = 0.73$ ($p < 0.001$) between the two respondents for each cluster, suggesting that the performance measure was reliable. The assessment for 2005 by the director of the industrial department was calculated as the cluster performance in the final analysis.

Cluster innovativeness. Previous agglomeration research measured cluster innovativeness from the total number of technologically significant and commercially successful innovations (Baptista and Swann, 1998), or from the number of patents (Beaudry and Breschi, 2003). However, the industrial township clusters in China pursue process and product innovations, rather than producing non-commercializable patents (St. John and Pouder, 2006). This study therefore measured cluster innovativeness as the ratio of new product sales to total sales in year 2004. The data were provided by the director of the industrial departments of the local town governments based on the annual report of the cluster. We used the new product sales ratio because it has been used to represent firm innovativeness in organization theory and strategic management studies (e.g., Dougherty and Hardy, 1996; Collins and Smith, 2006).

Cluster size. Following prior research (McCann and Folta, 2008; Rocha and Sternberg, 2005; Folta *et al*., 2006), we measured cluster size as the total number of firms in a cluster to capture the pool of specialized labor and inputs and the effect of agglomeration. The data were provided by the director of the industrial department of the local town government based on the annual report of the cluster.

Cluster competitive intensity was measured as the ratio of the number of leading brands over total sales in a cluster. In China, each brand was evaluated by governments of quality supervision, inspection and quarantine at national, province and city levels to be categorized as world-class, national-class, province-class, city-class, and other brands based on its reputation and geographic influence. These brands and their class levels are registered mandatorily at the local chamber of commerce. The scope or level of each brand was reported by the chairman or secretary of the local chamber of commerce (see Table 1). To determine the relative weight of these different class levels, we sent a survey to 61 experts on technology centers (21 university professors, 26 middle managers and 14 top managers in different firms). We asked them to give a relative score to each of the different brand classes. The benchmark of a world-class brand was 10 points. The average scores of the 61 respondents on nation-, province-, city-level, and other brands were 6.90, 5.07, 3.63, and 2.41, respectively. An ANOVA indicated that there was no significant difference among professors', middle managers' and top managers' assessments. We then calculated the score of each cluster by multiplying the mean score of the 61 experts of each class of brand by the number of each class of brand in the cluster and then summing them. Therefore, the number of competing brands in the leading industry in a given cluster reflects the level of the competition in the cluster. We used the ratio of the weighted sum over the total sales of a cluster to capture the intensity of competition within a cluster.

Inter-firm joint actions captures the formal network ties that bind some firms together in a cluster. Answers to the six-item measure of *inter-firm joint actions* were provided by the chairman or secretary of the local chamber of commerce of the industry. A five-point Likert scale (from 1 not any cooperation to 5 very frequent and close cooperation) was used to determine the extent to which the firms in a cluster cooperated with each other with respect to the following actions: (1) production and manufacturing; (2) R&D and product design; (3) product sales; (4) purchase of raw and auxiliary materials; (5) marketing research; (6) personnel training. The Cronbach's α coefficient (0.82) confirmed the internal consistency of this construct, and the factor analysis demonstrated high loading for each item ($\geq$0.67).

Cluster R&D centers were measured as the weighted number of technological centers in a cluster. In China, there are four levels of technological centers, the national level, province level, city level, and firm level. In general, the level represents the capability in R&D and scientific experiments, with the national level as the highest. The data on different levels of centers in the cluster were provided by the chairman or secretary of the local chamber of commerce (see Table 1). In the same survey of the 61 experts described above, we asked them to give a relative score to each of different levels of the centers. The benchmark of a national level center was 10 points. The average scores of the 61 respondents on province-, city-, and firm-level centers were 7.17, 5.25, and 4.78, respectively. An ANOVA indicated that there was no significant difference among professors', middle managers' and top managers' assessments. We then calculated the cluster's technology center score by multiplying the mean score of the 61 experts for each level of center by the number of each level of center in a cluster, and then summed the four numbers. The final sum was log transformed.

Industry type was controlled because of different developments of the industrial infrastructure and different intensities of competition (Folta *et al*., 2006). The 87 clusters were categorized into nineteen two-digit SIC manufacturing industries. [2] Using data on 'industry' and 'profession' from *The Fifth Nationwide Census* in 2000, we calculated the distribution of 64 professions across the twenty-nine two-digit SIC manufacturing industries. Following Farjoun's (1998) procedures, we sort the twenty-nine two-digit SIC manufacturing industries into four similarity-in-skill groups. Industries in each group are similar to one another with regard to the intensity by which certain professions are required. Industry was thus measured by four dummy variables—category 1 as industries related to food and beverage processing; category 2 as heavy industries; category 3 as light industries (except for textile manufacturing); category 4 as textile manufacturing industries, which serve as the referent base.

Analyses

The partial least squares structural equation modeling (PLS-SEM) technique was employed for analysis. PLS-SEM is a second-generation data analysis technique that combines factor analysis with linear regression. It is an appropriate technique when sample sizes are small, when data normality and interval-scaled data cannot be assumed, and when the goal is to predict outcomes or to identify key drivers from the independent variables (Hair *et al*., 2013). We selected the PLS-SEM technique for three reasons. First, given the relatively small sample size in our study, PLS-SEM is more suitable than alternative statistical techniques in data analysis. Second, as our research design is to identify the cooperative and competitive determinants of cluster performance, PLS-SEM allows us to produce consistent parameter estimates. Third, the PLS-

[2] The SIC code is according to '*Industrial Classification of National Economy of China (GB/T4754-2002)*' issued by The National Council of People's Republic of China in 2002.

SEM technique uses structural equation modeling of specified latent factors to simultaneously estimate the structural and measurement model. It may thus have lower type-II errors than would the use of a single indicator (Boyd, Gove, and Hitt, 2005). We used SmartPLS 2.0 developed by Ringle, Wende, and Alexander (2005) in analyzing the data.

Results

Table 2 provides the basic statistics of the key variables and their correlation. As shown in Table 2, two competition-based proxies, i.e., cluster size and intensity of competition within cluster, are positively related to cluster performance (r = .22 and .25, all *ps* < .05, respectively); two cooperation-based predictors, measured by inter-firm joint actions and cluster R&D centers, are positively related to cluster innovativeness (r = .21 and .21, all *ps* < .05, respectively).

Insert Table 2 about here

Table 3 reports the regression results of the PLS model0. Model 1 only has industry control variables and cluster size included, while Model 2 presents the full model. As Model 1 shows, cluster size has a positive effect on performance (H1: $\beta = 0.26$, $p < 0.05$). This result supports Hypothesis 1 that argues the direct effect of agglomeration on cluster performance. When we add competitive intensity in Model 2, w see that, first, the intensity of competition has a positive effect on performance ($\beta = 0.19$, $p < 0.01$); and second, the direct effect of cluster size is still significantly positive ($\beta = 0.23$, $p < 0.05$) with a small decrease of .03 (from 0.26 to 0.23) which lends support to Hypothesis 2.

Model 2 in Table 3 also demonstrates that two cooperation-based proxies, i.e., cluster R&D centers and inter-firm joint actions, have positive effects on cluster innovativeness (β =

0.18, $p < 0.05$ for the former; $\beta = 0.18$, $p < 0.05$ for the latter). These results support Hypotheses 3 and 4. In addition, cluster innovativeness, measured as the ratio of new product sales to total sales, has a positive effect on performance ($\beta = 0.12$, $p < 0.10$), which supports Hypothesis 5. The results in Model 2 are illustrated in Figure 1.

Insert Table 3 and Figure 1 about Here

Post hoc analysis

The above results show that both inter-firm cooperation and competition affect cluster performance. We then conducted two post hoc tests to examine whether the cooperative or the competitive forces have a greater effect on cluster performance. First we followed Cohen *et al*. (2003) to test the distinctiveness between competition intensity and innovativeness by comparing the correlations between each of these variables with cluster performance. Although the competitive intensity-cluster performance correlation is 0.25 and innovativeness-cluster performance is 0.14, the z-statistic for the difference between these two was not significant (z = 0.74, $df = 84$). Second, we separately entered the two variables into a regression model to predict cluster performance. Competitive intensity accounts for 4.9 percent (effect size $f^2 = 0.06$) of the variance of cluster performance, while innovativeness accounts for 2.2 percent (effect size $f^2 = 0.02$) of the variance of performance. These tests suggest that competitive effects appear to have a greater impact on driving economic performance in our sample of township clusters.

Robustness tests

To better test the mediation effect of competitive intensity, we followed Hair *et al.* (2013) in using the bootstrapping procedure. Bootstrapping analysis is similar to the Sobel test, but relaxes the assumption that the mediated effect has to be normally distributed, thus is more suitable for testing for mediation in a smaller sample (Shrout and Bolger, 2002). The bootstrapping result shows that intensity of competition has a significant mediation effect between cluster size and cluster performance (mediation effect = 0.03; t = 1.43, $p < 0.10$, one-tailed test). Together with the PLS-SEM results, it suggests that competitive intensity has a positive effect on cluster performance, as well as partially mediating the effect of cluster size on cluster performance.

In addition, we sought to investigate the robustness of our results by using alternative measures of cluster performance (details on testing the model are available from the authors). We used the township GDP as an alternative to supplement the measure based on the 4 items of performance evaluation from the director of the town industrial department. By doing that, we can better assess whether cluster performance can be translated into regional economic development, and whether inter-firm cooperation and competition will have the same hypothesized effects on regional development. As shown in Table 4, when using town GDP as the performance criterion, the results were qualitatively similar to those reported above.

Insert Table 4 about here

DISCUSSION

Our study contributes to research on clusters in several ways. First, we provide a systematic examination of Chinese township cluster performance from both the cooperation-based and the competition-based perspectives. We also extend the cooperation- and competition-based perspectives, which have been largely applied to explain the existence of a cluster, to investigate their implications for cluster competitive advantage. We show that in our sample of 87 township industrial clusters competitive intensity partially mediates the effects of agglomeration on cluster performance. On the other hand, the number of R&D centers and the extent of inter-firm joint actions contribute to the innovativeness of a cluster, which in turn leads to superior cluster performance, as predicted by the cooperation-based perspective.

In addition, we further explore the differentiation between the effects of cooperative and competitive forces on cluster performance. Our post hoc analysis suggests that while both cooperation and competition are significant, competitive effects appear to a stronger driver of economic performance in our sample of township clusters. Two reasons may help explain this result. First, due to the lack of intellectual property rights protection in China, a cluster's innovativeness may not be effectively translated into superior performance; second, as Chinese firms tend to focus on low cost strategy, competitive intensity may help boost cluster sales and market shares, at least in a short run.

This finding sheds light on the development of a theory of cluster strategy by differentiating the effects of cooperation- and competition-based perspectives on cluster performance. Our empirical findings show that spatial agglomeration affects cluster innovation and performance by amplifying competition and through the medium of cooperative interdependencies. To our knowledge, this is the first study of this kind. However, we should also interpret the result with some cautions, as our study only focused on one type of cluster—township clusters in China over a short period time. Given the unique institutional environment in China, it is questionable whether a stronger effect of competitive forces on cluster performance can be generalized to the other types of clusters around the world. Also, given the relatively short window of observation in our study, our results may not be sufficient to conclude whether competitive forces are always preferable than cooperative forces in leading cluster competitive advantage in the long run.

Second, this study contributes to a better understanding of township industrial clusters in China. Existing cluster research tends to focus on clusters in developed countries, such as Emilia Romagna in Italy (Piore and Sabel, 1984) or the Silicon Valley IT cluster in the U.S. (Saxenian, 1994). More recently, greater attention has been paid to high tech clusters in developing countries, such as Bangalore in India (Bresnahan, Gambardella, and Saxenian, 2001; Dossani and Kenney, 2007), and the emerging science clusters around Moscow and St. Petersburg in Russia (AT Kearney 2004; Global Services, 2008). However, little previous research has addressed the more manufacturing driven township industrial clusters in China.

Indeed, township industrial clusters play a significant role in the development of Chinese economy. By the end of 2010, there were about 1.1 million firms located in township industrial clusters and other parks in China, generating $ 2.4 trillion total output value (The People's Republic of China Yearbook, 2010). In Jiangsu Province alone, township clusters produced about 42 percent of the province's GDP of $ 608 billion.[3] In China, clusters provide an arena for companies to share common conventions, informal rules, and habits that can coordinate economic agents under conditions of uncertainty. A relevant consequence of the administration of these clusters by a government entity is that Chinese township clusters do demonstrate at least the potential for cluster-level strategic direction. How well a combination of local government and party officials and company managers actually succeed in providing direction to the cluster of firms as a group is only hinted at in our study, but may begin to provide some insight into the

[3] The data also come from the official website of the Central People's Government of the People's Republic of China (http://www.gov.cn/gzdt/2008-02/04/content_882785.htm), which was retrieved on Dec 30, 2012.

value of actively coordinating the actions of a group of clustered firms even in the more informally administered settings in most industrialized countries.

Our research also extends and complements prior agglomeration studies in China, which tend to analyze national technology development zones but not township industrial clusters (Tan, 2006; Zhang, Li, and Schoonhoven, 2009). Results from this study contribute to knowledge on agglomeration from a new angle and also have important policy implications for industrial development in rural towns in China. For instance, to improve the innovativeness of a township cluster, the town governments should encourage the development of R&D centers and the inter-firm joint actions. On the other hand, encouraging competition within a cluster helps to promote the overall health and competitiveness of the cluster. Using regional GDP as an alternative dependent variable, we found similar result patterns, which suggest that the cooperative and competitive forces in a township cluster will also benefit to the local economic development. Some of our findings are consistent with prior research predictions based on clusters in the Western countries, while some of our results may be more specific to Chinese township clusters and less generalizable to the other types of clusters. We hope that future research can better compare and contrast the similarity and differences between township clusters and other types of clusters around the world in order to better understand the heterogeneity of clusters.

Third, our paper provides new evidence toward the development of a theory of the strategy of clusters. Prior research has focused on the existence of clusters (Maskell, 2001), or the implication of clusters for regional economic development (Porter, 1998, 2000), but little effort has been spent on investigating why clusters differ regarding performance (with some notable exceptions, such as Tallman *et al*., 2004 or Arikan, 2009). Prior research on cluster performance has advanced the horizon of cluster research, but has largely stayed at the conceptual level. Although there is a research stream investigating the role of clusters in regional economic development, relatively little effort (Häussler and Zademach, 2007; Hervas-Oliver and Albors-Garrigos, 2007 are notable exceptions) has been made in the management research to directly study the strategic performance of clusters and its managerial implications.

Due to the lack of empirical evidence, the conceptual development of a theory of the strategy of clusters has not been sufficiently advanced. Our paper utilizes evidence from Chinese township industrial clusters to support some basic propositions of a strategic theory of cluster from both the cooperation-based and competition-based perspectives. We hope that our study provides useful evidence for the further advancement of a more comprehensive theory of cluster heterogeneity.

We would like to note several limitations of this study, which can provide some directions for future research. First, this study focuses on the township industrial clusters in one region. Although this single province research design helps mitigate the influence of the variation of provincial policies on the performance of cluster, we should note that township industrial clusters have boomed in the Yangtze River Delta, the Pearl River Delta, and other regions in China. We hope that future research can be extended to including samples from multiple provinces and even to going beyond a single country study to compare different models of clustering around the world.

Second, our study may have touched upon how to examine comprehensively the cooperation- and competition-based perspectives on cluster performance, but given the limitations of our data we may not be able to draw a deeper insight into how these two perspectives interact with each other in affecting cluster performance. Although some preliminary post hoc tests suggest that inter-firm competition has a stronger effect on cluster performance than cooperation in our sample, we hope that future research can take more rigorous method to compare and contrast the differences between the cooperation and competition forces. In addition, in this paper, we did not have a chance to examine how the forces of inter-firm cooperation and competition interact in determining cluster performance. For instance, the intensity of competition may contribute to cluster innovativeness through horizontal competition (Maskell, 2001). We hope that future research can further investigate the interaction effects of cooperation and competition within a cluster.

Third, as one of the first attempts to investigate Chinese township clusters, the research design and variable measurement may not be refined enough to provide deeper insights into the important phenomenon. This study is at the cluster-level and uses a cross-sectional design. The impact of cluster-level agglomeration on micro-level longitudinal firm behaviors – skills and knowledge accumulation, for example – is not explored. The effect of cluster evolution on innovation and performance, which is stressed by Pouder and St. John (1996), is also not a focus of this study. In addition, as a pilot study of township clusters, we are still exploring how to better proxy key constructs, such as the competition level within cluster, cluster performance, etc. We hope that this study can provide a stepping stone for future research to better examine township clusters. Further studies that use a cross-level and/or longitudinal model to probe the mechanism of cluster-level effects on firm-level conducts and to determine the effect of cluster evolution on innovation and performance would be fruitful.

In conclusion, our study extends agglomeration and cluster studies to include a new cluster form (a township industrial cluster) and a new context (an emerging market). The findings demonstrated that agglomeration, arising from similar firms within a particular industry located together in a town, by and large accounts for the phenomenal growth and success of the township industrial clusters in China. We hope that this study provides insights on the township clustering phenomenon in China, contributing to the extant knowledge on clusters in general.

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Table 1. Descriptive statistics of the sample: towns, industrial clusters, cluster technology centers, and cluster brands (N=87)

	N	Min	Max	Mean	S. D.
Towns †					
Average GDP of 2001-2003 (in billion RMB)	87	0.02	4.72	1.04	1.11
Industrial clusters ‡					
Number of employees in the cluster	87	260	133965	14573	22977
Number of total firms in the cluster	87	10	2300	287	437
New product sales in 2004 (in million RMB)	87	0	30	3.41	6.00
Total sales in 2004 (in million RMB)	87	.21	230.27	25.48	41.40
New product sales ratio in 2004 (%)	87	0	89.30	17.95	19.22
Average export ratio of 2002-2004 (%)	87	0	100	24.54	27.27
Cluster technology centers (N) §					
National-level center	87	0	4	.30	.68
Province-level center	87	0	16	.75	1.89
City-level center	87	0	36	2.39	5.44
Firm-level center	87	0	108	12.32	18.43
Cluster product brands (N) §					
World-class brand	87	0	2	0.06	0.28
Nation-class brand	87	0	16	0.91	2.15
Province-class brand	87	0	36	3.48	5.99
City-class brand	87	0	80	9.08	14.59
Other brand	87	0	5	0.06	0.54

† The data were from each city's yearbook.

‡ The data were from the director of the industrial department of the local town government.

§ The data were from the chairman or secretary of the local chamber of commerce of the industry.

Table 2. Descriptive statistics and Pearson's correlation matrix (*N*=87)

	Mean	S.D.	1	2	3	4	5	6	7	8
1. Cluster performance	4.68	0.89	*0.82*§							
2. Cluster Innovativeness	17.95	19.22	0.14							
3. Cluster size	4.73	1.40	0.22**	0.01						
4. Intensity of competition	0.25	0.14	0.25**	0.10	0.15					
5. Inter-firm joint actions	2.55	1.09	-0.04	0.21**	-0.06	*0.*28***	*0.75*§			
6. Cluster R&D centers	3.41	1.76	0.33***	0.21**	0.39***	0.39***	0.19*			
7. Industry category 1 †, ‡	0.25	0.44	0.08	0.14	-0.15	-0.12	0.01	-0.16		
8. Industry category 2	0.34	0.48	0.15	-0.09	0.03	0.20*	-0.09	0.17*	-0.42***	
9. Industry category 3	0.18	0.39	-0.06	-0.11	-0.03	-0.05	0.10	-0.06	-0.28***	-0.34***

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

† Industry category 1 as food and beverage related industries; category 2 as heavy manufacturing industries; category 3 as light manufacturing industries (except for textile manufacturing).

‡ The other 19 clusters which engage in textile manufacturing serve as the referent industry category.

§ The diagonal entries in bold are squared roots of average variance extracted (AVE) for the two multi-item constructs.

Table 3. PLS results of inter-firm competition and cooperation on cluster performance (N=87)

	Model 1		Model 2	
Hypothesized path	β	**s.e.**	B	**s.e.**
Control paths				
Industry category 1 to cluster performance	0.28^{*}	(0.16)	0.23^{*}	(0.13)
Industry category 2 to cluster performance	0.31^{**}	(0.14)	0.24^{*}	(0.14)
Industry category 3 to cluster performance	0.13	(0.11)	0.10	(0.10)
Hypothesis 1				
Cluster size to cluster performance	0.26^{**}	(0.12)	0.23^{**}	(0.10)
Hypothesis 2				
Intensity of competition to cluster performance			0.19^{***}	(0.08)
Cluster size to intensity of competition			0.15^{*}	(0.09)
Hypothesis 3				
Cluster R&D centers to cluster innovativeness			0.18^{**}	(0.08)
Hypothesis 4				
Inter-firm joint actions to cluster innovativeness			0.18^{**}	(0.08)
Hypothesis 5				
Cluster innovativeness to cluster performance			0.12^{*}	(0.07)

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The entries are standardized path coefficients (standardized errors).

Table 4. PLS results of inter-firm competition and cooperation on local economy (N=87)

Town GDP				
	Model 1		**Model 2**	
Hypothesized path	$\boldsymbol{\beta}$	**s.e.**	***B***	**s.e.**
Control paths				
Industry category 1 to town GDP	-0.27^{***}	(0.10)	-0.27^{**}	(0.13)
Industry category 2 to town GDP	-0.07	(0.09)	-0.11	(0.12)
Industry category 3 to town GDP	-0.10	(0.09)	-0.10	(0.11)
Hypothesis 1				
Cluster size to town GDP	0.23^{***}	(0.09)	0.20^{***}	(0.08)
Hypothesis 2				
Intensity of competition to town GDP			0.19^{***}	(0.07)
Cluster size to Intensity of competition			0.15^{*}	(0.09)
Hypothesis 3				
Cluster R&D centers to cluster innovativeness			0.18^{***}	(0.08)
Hypothesis 4				
Inter-firm joint actions to cluster innovativeness			0.18^{**}	(0.07)
Hypothesis 5				
Cluster innovativeness to town GDP			0.15^{*}	(0.09)

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The entries are standardized path coefficients (standardized errors).

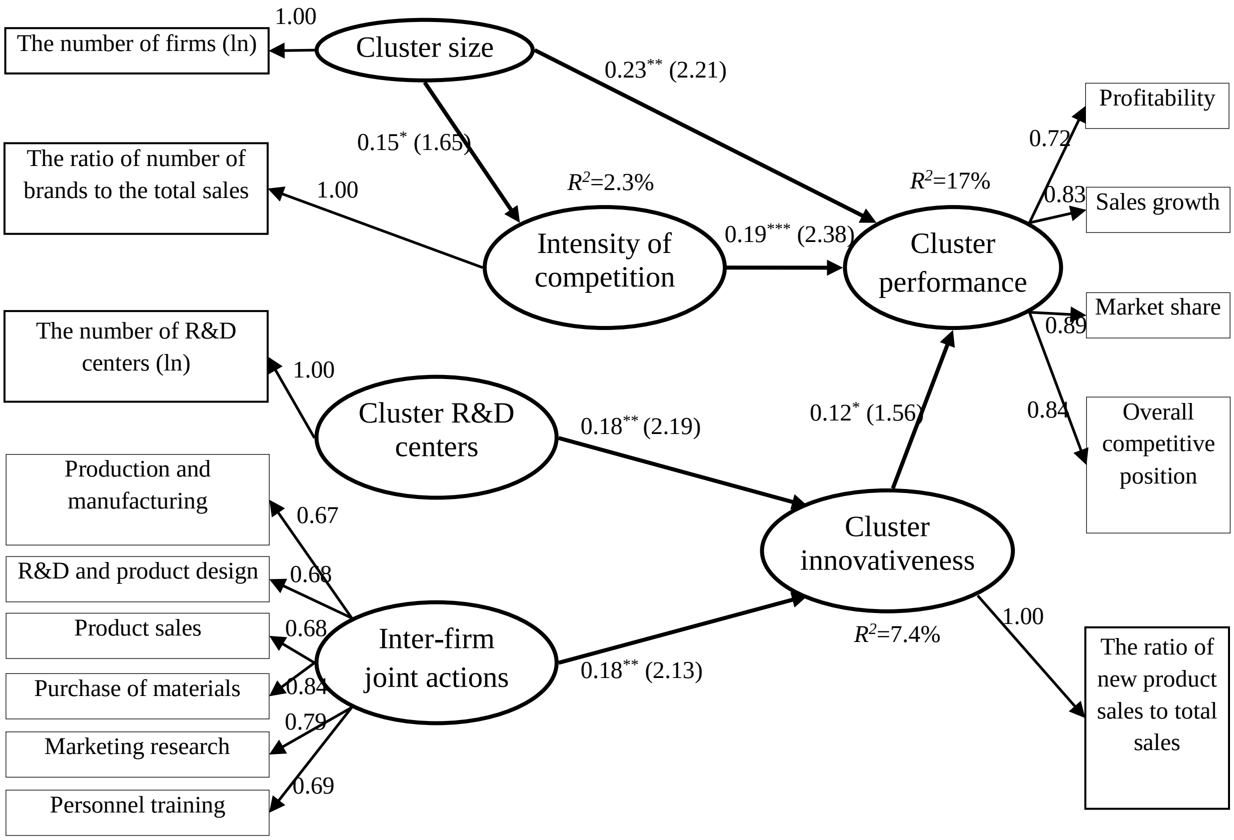

Figure 1. Performance implication of inter-firm competition and cooperation in Chinese township industrial clusters: Partial Least Squares Latent Variable Modeling (N=87) †

† All factor loadings are significant at the 0.001 level. The entries on the paths are standardized coefficients (T values).