Creative China?

The University, Human Capital and the Creative Class in Chinese Regional Development

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Abstract

The relationships between talent, technology and regional development have been widely examined in the advanced economies. While there is a general consensus as to the important role talent plays in regional development, debate has emerged on two key issues. The first involves the efficacy of educational (i.e. human capital) versus occupational (i.e. the creative class) measures of talent; the second involves the factors affecting the distribution of talent. In this study, we have used structural equation models and path analysis. We employed both educational and occupational measures of talent to examine the relationships between talent, technology and regional economic performance in China, and to isolate the effects of tolerance, differing levels of consumer service amenities, and the location of universities on the distribution of talent. Contrary to the findings of empirical studies on the developed economies, we found the relationships between the distribution of talent and technology and between the distribution of talent and regional economic performance in China to be weak. We found the presence of universities – a factor highly influenced by government policy – and the actual stock of talent to be strongly related. We also found that tolerance, as measured by the "Hukou index," plays an important role in the distribution of talent and technology in China.

JEL: O3 P3 R1 R2 J24

Key words: China, Talent, Human Capital, Creative Class, Tolerance, Technology, Regional Development

Introduction

The role of human capital in economic development has been a focus of research for half a century. Ullman (1958) identified human capital as a key source of regional development. Barro's large-scale empirical tests of the human capital influence on national economic performance (1991, 1997) have been followed by several influential studies, including those by Rauch (1993), Simon and Nardinelli (1996), Simon (1998) and others. Further studies have shown that talent can serve as an attractor for the technology industry (Mellander and Florida, 2007; Florida et al, 2007).

Technology has been identified as the main source of productivity growth. Solow (1956) said that productivity growth – growth that is not based on increased input of labor and capital – could derive from technological improvements. This exogenous view of technology was later imbedded in the model by Romer (1990). Lucas (1988) demonstrated the role of human capital in economic growth. Based on the work of scholars such as Schumpeter (1934) and Baumol (1968) subsequent studies have improved our understanding of the role of human capital in relation to technology, technological innovation and entrepreneurship (Florida, 2002; Lee, Florida, and Acs, 2004; Acs and Armington, 2006; Audretsch, Keilbach, and Lehmann, 2006; Mellander and Florida, 2006). Research has also identified a growing divergence of human capital levels in U.S. regions over recent decades (Berry and Glaeser, 2005).

Though international in scope, most of these earlier studies were conducted in a Western context. Few scholars have examined the regional effects of talent and technology in a systematic manner in less developed countries. This paper attempts to add to our knowledge of the role of talent and technology in regional development by exploring their impacts in a Chinese regional context, using path analysis and structural equation modeling.

Our model enables us to test conventional human capital measurements against occupational or creative class definitions. It lets us test for the relationships between talent and technology and between talent and regional development as measured by GDP per capita. Finally, it allows us to test for the effects of regional institutional and cultural factors – such as the level of amenities, the presence of universities, and tolerance – on the distribution of talent, technology and regional development.

The relationship between talent, technology, tolerance and regional development has been successfully demonstrated in developed countries. However, there are good reasons to expect different results in China. China is a developing economy with a different industrial and urban structure. Importantly, the country has long restricted internal migration. The central government still holds enormous influence on the economic and social activity of Chinese people even after decades of decentralization. However, China's economic development has been oriented toward higher human capital and knowledge-based industries since the late 1990s. A top national policy priority has been to "build a creative country." Figure 1 illustrates the close relationship between the growth in human capital and high-tech industries since the late 1990s. This legitimizes our interest in China's talent and technology distributions.

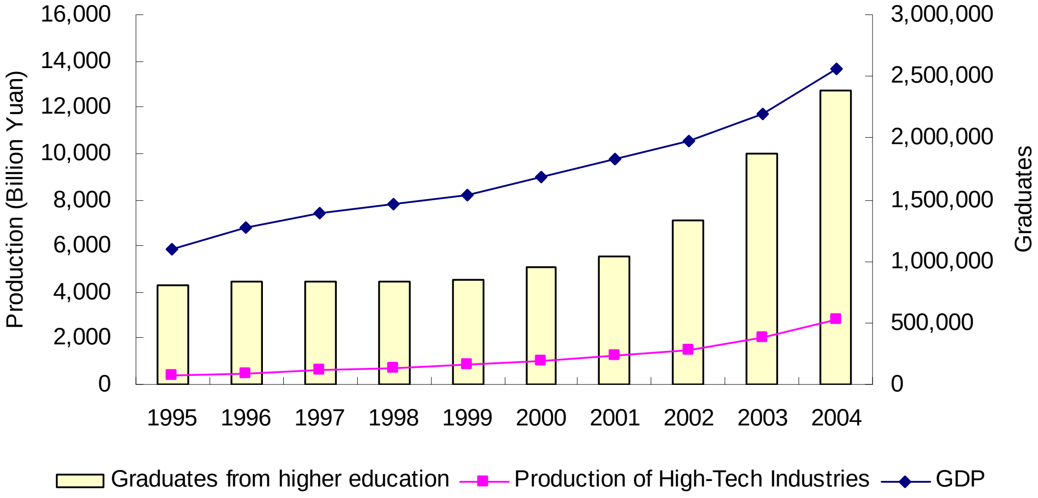


Figure 1: Graduates from higher education, production of high-tech industries and GDP (1995-2004)
Source: China Statistics Yearbook (2005).

Theories and Concepts

Nearly all regional studies to date have been conducted in developed countries where a transformation from traditional industrial society into a service or creative society has occurred. Based on this a vast literature has tried to explain the productivity gains observed during that transformation.

Solow (1956) highlighted the role of technology in the form of the error term, which is associated with productivity gains that cannot be explained by changes related to labor or capital. In other words he treated technology as an exogenous factor. Romer (1986, 1987, 1990) allowed technology to be explained endogenously within the model framework. Investment in R&D is thereby seen as a purposeful activity, one that generates technology and productivity improvements. Lucas (1988) let the human capital factor be embodied in individuals and investments in human capital that generate productivity gains and growth. He also stressed the role of cities as interactive places for human capital, places where knowledge is exchanged and created. By reducing the transaction cost of knowledge generation, cities become engines for economic growth.

The role of cities has also been identified by Jacobs (1964, 1969) who argued that a diversity of firms and individuals is associated with economic growth. She also illustrated the role of cities' scale and diversity in the generation of new ideas. Andersson (1985a, b) explored the subject of creativity in cities and metropolitan regions historically, stressing the importance of knowledge, culture, and communications in stimulating regional growth.

Given the role of talent in technological and regional development, attracting the creative, smart and highly educated has been a major task for regions in the past decade. Many approaches to doing this have been offered. The role of amenities was introduced in a neoclassical framework by Roback (1982). The traditional attractor for households in general is higher living standards through higher wages or lower living costs. In the Roback context, migration patterns not explained by those two factors could be explained by regional differences in amenity levels. Later, Glaeser et al. (2001) suggested that several factors help increase the competitiveness of the city: a variety of consumer services and goods; aesthetical and physical settings; good public services; and speed to make the city accessible. Florida (2002a, b, c) stressed the importance of lifestyle, culture, nightlife and entertainment as talent attractors. Shapiro (2006) illustrated the importance of quality of life over and above the employment growth effect of college graduates.

A second approach has focused on the role of diversity. Jacobs (1961) stressed the importance of a diversity of individuals. Quigley (1998) argued that we have a “taste for variety” and that firm-based diversity is associated with economic growth. The importance of diversity, as expressed in higher levels of tolerance and openness, has been demonstrated by Inglehart (2003, 2005) in the World Value Surveys. They examine the relationship between cultural attitudes and economic development. According to Inglehart, one of the best proxies for tolerance is openness toward gay and lesbian individuals. Studies by Florida and Gates (2001) found a positive relationship between gay concentrations and economic development in the US. Openness and tolerance may also be expressed in relation to immigrants. Florida (2002) demonstrated a relationship between the proportion of immigrants in a population and regional economic performance. Ottaviano and Peri (2005) showed how diversity, in the form of immigrants, increases regional productivity. Page (2007) found that diversity leads to better decision making, and that diversity within groups provides new perspectives. Florida (2002) has also argued that openness and tolerance lead to a lowering of regional barriers to entry.

A third factor with a strong influence on the distribution of talent is the location of universities which serve as talent producers. The value of such production depends on the mobility of graduates. If graduates are highly mobile and are insufficiently attracted to the region, universities may become talent exporters. This kind of migration is something several US regions have experienced and has been highlighted by Florida et al. (2006). When talent is less mobile or is restricted from migrating through various institutions, the role of universities may be of greater importance. In this case, the local universities are likely to be the key source of regional talent.

Since most literature on the geography of talent is based on observations in developed countries, it is unclear how these same factors affect the talent distribution of less developed economies. Zhang and Fan (2006) constructed a descriptive indicator system to explain the regional disparity of human capital in China. The system involves four categories of indicators: (1) economic performance, (2)education, science and education investments, (3) health system and medical care investments; and (4) communication investments. Jiang, Xu and Li (2005) mentioned the possible influences of urbanization, universities, national amenities, wage levels, and government policies on China's regional talent densities. Their statistical analysis reported significant and positive effects of universities and urbanization on talent distribution. Li and Florida (2006) examined the effects of non-market factors on talent production using city-level data and concluded that there was a positive impact of openness on the number of local universities. Compared with talent stock, however, talent production appears less important for regions, for at least two reasons. First, production does not necessarily lead to retention. Unless cities can retain university graduates or attract human capital from the outside, producing more or less talent does not influence regional innovation or economic growth much. Second, talent production in China is largely exogenous of regional characteristics and highly reliant on government policy. In most cases the government appoints university leaders and determines the scale of enrolment indirectly. Therefore, it is more meaningful to look at talent stock. Qian (2008) analyzed the impacts of both market factors (wage and employment) and non-market factors (universities, amenities and openness) on China's regional talent stock. He reported that the presence of universities had a strong influence on talent distribution and also highlighted the effects of openness on talent, innovation and regional economic performance.

Model, Variables, and Methods

A schematic picture of our general model of talent, technology, and regional development is provided in Figure 2. The model allows us to accomplish several useful analyses. First, it enables us to test conventional human capital measurements against occupational or creative class definitions. Second, it allows us to isolate the independent effects of talent and technology – Lucas versus Solow, if you will. The model also enables identification of regional cultural and institutional factors – namely, the presence of universities, level of amenities, and tolerance – as they affect the geographic distribution of talent in the first place. The arrows identify the hypothesized structure of relationships among the key variables.

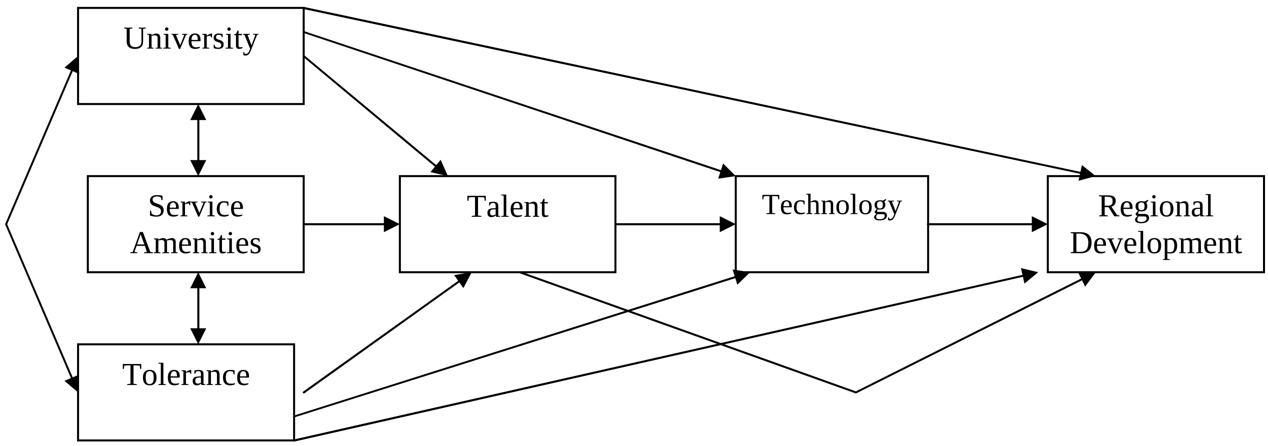


Figure 2: Path model of the regional development system

Variables

We now describe the variables used in the empirical model. Our analysis covers the 31 Chinese provincial-level regions in mainland China for the year 2004. Descriptive statistics for all measures and variables are provided in Table 1.

Table 1: Descriptive Statistics *

	Obs	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Regional institutional and cultural factors:					
University	31	16.06	11.202	5.50	62.04
Tolerance	31	.0914	.060	.01	.30
Service Amenities	31	1.03	.186	.70	1.56
Talent:					
Human Capital	31	.0769	.048	.01	.26
Creative Class	31	.0275	.015	.01	.10
Technology:					
High Technology	31	.7364	.825	.04	3.26
Patents	31	1.167	1.578	.08	6.10
Regional Development:					
GDP per Capita	31	13169.70	8427.79	4077.61	42768.48

* All the data in this paper, except specifically noted, are from the National Bureau of Statistics of China (2005).

Dependent Variable: Regional Development

Gross domestic product (GDP) is the most widely used indicator for economic performance. In China, while GDP is the single most important indicator for the promotion of local officials, GDP statistics are available at all the jurisdictional levels above county. Accordingly, we use 2004 GDP per capita as the measure of regional economic performance.

While some researchers use population or job growth as measures of development, those measures fail to control for the quality of development. Not all jobs are created equal; some pay better than others. Regions increasingly specialize in different kinds of economic activity, and therefore different kinds of jobs (Markusen 2004, 2006). By regional development, we mean the overall level of development and living standards. While GDP per capita is not a perfect measure of overall living standards, as it excludes the distribution of resources, it remains a reasonable proxy for regional development.

Independent Variables

Talent

Talent can be understood as human capital or as the creative class. Generally the former is associated with educational and the latter with occupational measures. We measure human capital as those graduating with a college or higher-level degree, standardized by the local population 15 years old or older. We measure the creative class as the proportion of professional and technical workers (*zhuanye jishu renyuan*) within the local population. Since specific occupational data are not available in China, an exact replication of the measurement methodology employed by Florida (Florida, 2002a, b, c) is not possible. However, China's *zhuanye jishu renyuan* mirrors Florida's creative class to a large extent. *Zhuanye jishu renyuan* includes scientists and engineers, university professors, teachers, agricultural and sanitation specialists, aviators and navigators, economic and statistical specialists, accountant, translators, librarians, journalists, publishers, lawyers, artists, broadcasts, athletes, etc. Both the human capital and the creative class measures are based on 2004 data.

Technology

Since technological innovation is most likely to occur in high-tech industries, we have defined high technology as the location quotient of the value added for high-tech industries. In China the high-tech industries are officially defined as electronic and telecommunications, computers and office equipment, pharmaceuticals, medical equipment and meters, and aircraft and spacecraft. The high-tech value-added data are available from *China Statistics Yearbook on High Technology Industry (2005)*.

However, the high-tech industries are not necessarily high-tech based. In China, only 4.6% of the value added in the high-tech industries is used for R&D expenditures, much lower than in most developed countries. To better evaluate regional technology and innovation, we have used officially approved patents per capita in 2004 as a supplementary measure. In China three types of patents are granted: inventions; utility models; and designs. Innovation can be measured either from the input side, such as R&D expenditures, or from the output side, in the form of patents. The output side is more reliable in the sense that high input does not necessarily lead to high output.

Regional Institutional and Cultural Factors

Universities:

Universities are where most talent is produced. Regions with more universities and university students possess potential advantages in talent attraction, providing they can retain graduates. University students are often reluctant to seek a job in other places after graduation due to their well-established local network and the costs of adapting to a new environment. In China, institutional barriers (in the form of the inhabitant registration, or "Hukou," system) further prevent the flow of university students. As a result, the university is hypothesized to play an exclusively important role in China's talent distribution. This is measured by the number of university students in 2004 standardized by local population.

Amenities:

The term "amenities" in this paper refer to service amenities, as measured by the 2004 location quotient of employment in those service industries that directly contribute to human life and well-being. The service industries included in this measure are hotels and restaurants, environment and public-facility management, resident services, sanitation, social security, social welfare, culture, sports and entertainment.

Tolerance, Diversity, Openness:

Most research uses the diversity index or gay index to measure tolerance/diversity/openness (Florida, 2002a, b, c; Mellander and Florida, 2006; Florida et al., 2007). Not surprisingly, statistical data on gays are not available in China. As an alternative, we have adopted the “Hukou index” as a proxy for openness. In the case of China, it is a compelling measure, perhaps better than the gay index. The rules of Hukou (or the inhabitant registration system) are used by the central government to control internal migration. The system determines which city or county a person belongs to and whether she or he has rural or urban status. Those with a locally registered Hukou are always permanent residents and receive local economic, social and political benefits, such as social welfare, education, and voting rights. Those who live in a jurisdictional area without a local Hukou, however, are always “marginal” workers or visitors. If a large proportion of an area’s population is without a locally registered Hukou, this indicates that a large proportion of the population is from outside the region. The Hukou index of openness is defined as the proportion of the population without a locally registered Hukou. The higher the Hukou index, the more open the region. The statistical data used for this measure are for 2004.

Table 2: Regional distribution of key resources (2004)

Province Name	*GDP (Billion Yuan)*	*High-Tech Value Added (Billion Yuan)*	*Human Capital (Thousand)*	*Creative Class (Thousand)*	*Population (Million)*
Beijing	428.3	31.5	3,404.8	131.5	14.9
Tianjin	293.2	37.2	1,403.7	37.8	10.2
Hebei	876.9	7.8	3,786.7	62.6	68.1
Shanxi	304.2	2.4	1,648.0	45.4	33.4
Inner Mongolia	271.2	3.2	1,512.4	32.3	23.8
Liaoning	687.3	14.9	3,375.8	72.7	42.2
Jilin	295.8	6.3	1,798.1	35.0	27.1
Heilongjiang	530.3	5.0	1,724.6	59.2	38.2
Shanghai	745.0	60.1	3,106.6	80.6	17.4
Jiangsu	1,540.3	103.2	3,512.4	105.0	74.3
Zhejiang	1,124.3	31.4	3,339.5	100.3	47.2
Anhui	481.3	4.3	2,695.7	42.1	64.6
Fujian	605.3	29.0	1,512.4	56.0	35.1
Jiangxi	349.6	5.2	1,861.3	30.5	42.8
Shandong	1,549.1	35.9	4,731.9	110.8	91.8
Henan	881.5	8.1	4,017.6	80.2	97.2
Hubei	631.0	8.7	3,341.6	58.0	60.2
Hunan	561.2	6.2	3,290.9	51.3	67.0
Guangdong	1,603.9	188.0	3,892.3	177.1	83.0
Guangxi	332.0	3.5	2,371.6	35.2	48.9
Hainan	76.9	1.1	396.5	9.1	8.2
Chongqing	266.5	4.2	1,078.7	29.4	31.2
Sichuan	655.6	14.4	2,992.8	67.4	87.3
Guizhou	159.2	4.4	1,604.6	23.7	39.0
Yunnan	295.9	2.2	1,556.9	34.5	44.2
Tibet	21.2	0.3	23.8	4.5	2.7
Shanxi	288.4	13.5	2,554.9	41.6	37.1
Gansu	155.9	1.5	1,398.6	25.0	26.2
Qinghai	46.6	0.4	223.6	7.0	5.4
Ningxia	46.0	0.5	383.0	8.7	5.9
Xinjiang	220.0	0.3	1,794.0	35.6	19.6

Methods

We have used path analysis and structural equations to examine the relationships between variables in the model. Structural equation models (SEM) may be thought of as an extension of regression analysis and factor analysis, expressing the interrelationship between variables through a set of linear relationships, based upon their variances and covariances. In other words, structural equation modeling replaces a (usually large) set of observable variables with a small set of unobservable factor constructs, thus minimizing the problem of multicollinearity (further technical description in Jöreskog, 1973). The parameters of the equations are estimated by the maximum likelihood method.

It is important to stress that the graphic picture of the structural model (Figure 2) expresses direct and indirect correlations, not actual causalities. Rather, the estimated parameters (path coefficients) provide information on the relations between the variables. Moreover, the relative importance of the parameters is expressed by the standardized path coefficients, which allow for interpretation of the direct as well as the indirect effects. We do not assume any causality among the university, tolerance and service amenities factors but rather treat them as correlations.

From the relationships depicted in the model (Figure 2) we estimate three equations:

$$Talent = \beta_{11} University + \beta_{12} ServiceAmenities + \beta_{13} Tolerance + e_3 \quad (1)$$
$$Technology = \beta_{21} University + \beta_{23} Tolerance + \beta_{24} Talent + e_2 \quad (2)$$
$$RegionalDevelopment = \beta_{31} University + \beta_{33} Tolerance + \beta_{34} Talent + \beta_{35} Technology + e_1 \quad (3)$$

Findings

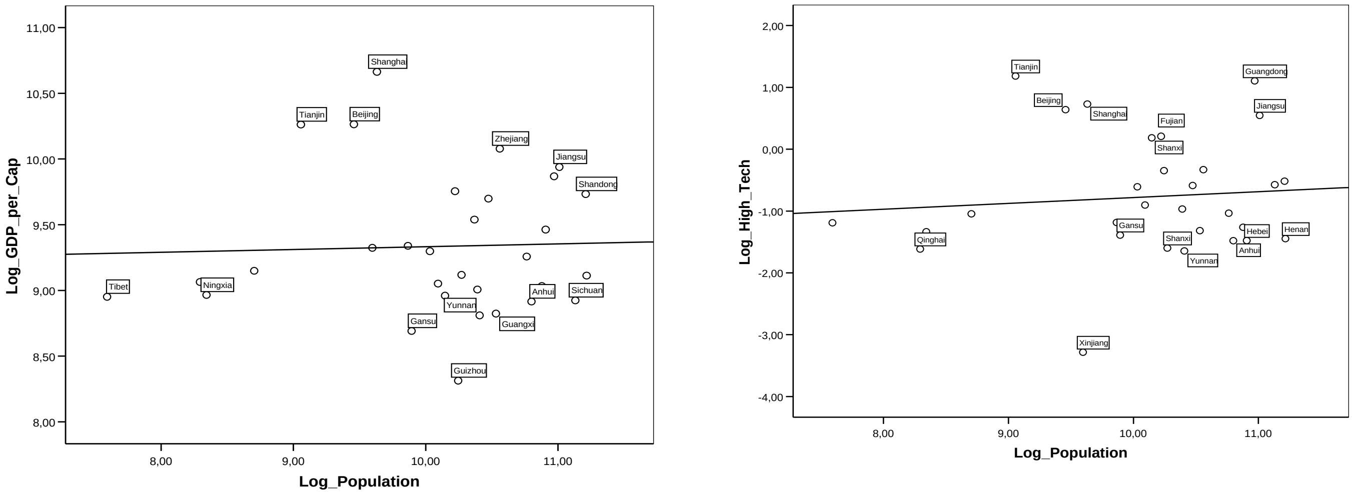
Table 3 is a correlation matrix for the major variables. According to this table, the presence of universities has a strong and significant correlation with talent, both in terms of human capital and of the creative class. It also presents a significant relationship with technology and patents. Relatively speaking, the university shows a stronger association with patents than with high-tech industries. This is not surprising, considering that university professors and students form one of the key groups that applies for patents and given the low level of R&D activity in China’s high-tech industries. Lastly the university is significantly associated with regional economic performance in terms of GDP per capita. There are no significant correlations between service amenities and any of the other variables. As with the presence of universities, tolerance is significantly associated with talent, technology and regional economic performance.

Table 3: Correlation Matrix

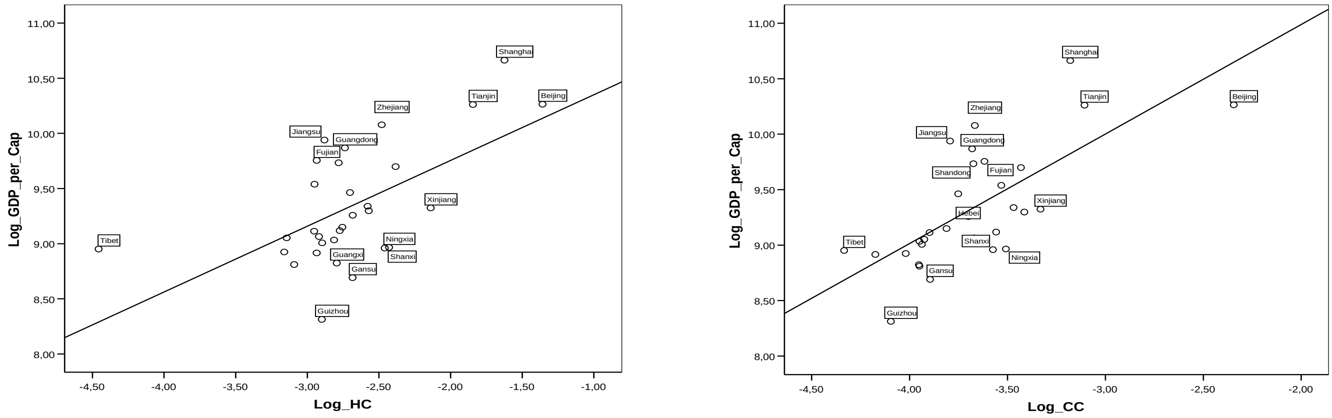
	University	Service Amenities	Tolerance	Human Capital	Creative Class	High-Tech	Patents	GDP per Capita
University	1							
Service Amenities	0.188	1						
Tolerance	0.636***	-0.113	1					
Human Capital	0.828***	0.142	0.738***	1				
Creative Class	0.860***	0.227	0.660***	0.856***	1			
High-Tech	0.571***	0.101	0.523***	0.344	0.366**	1		
Patents	0.795***	0.017	0.753***	0.662***	0.678***	0.721***	1	
GDP per Capita	0.761***	0.135	0.677***	0.594***	0.693***	0.614***	0.880***	1

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).

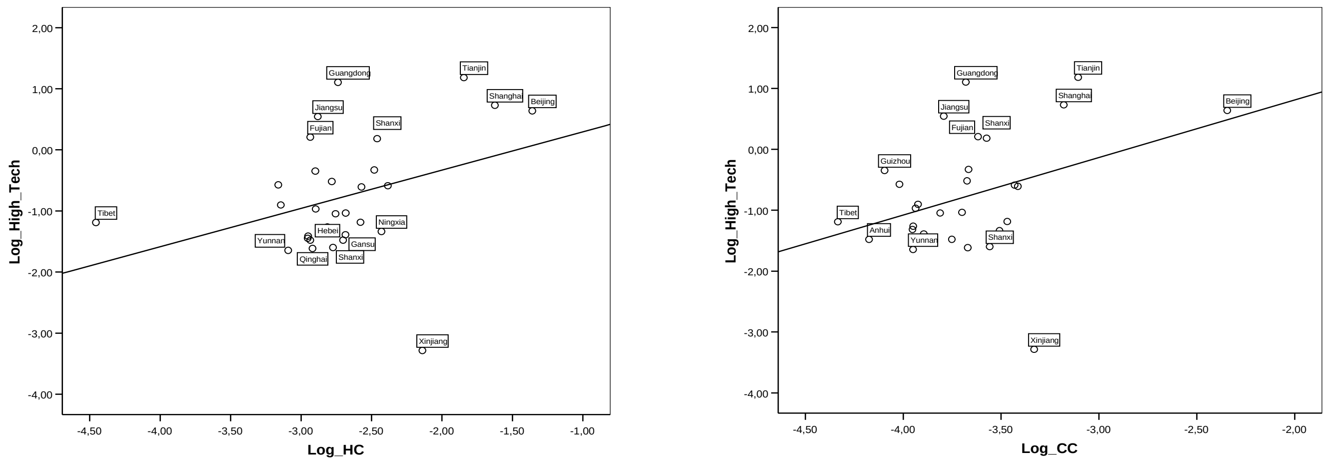
Figure 3 provides scatter-graphs that further compare the relationships between talent (both human capital and the creative class) and economic and technology performance in China. As some graphs shows, talent is unevenly distributed both in terms of human capital and of the creative class. Beijing, Shanghai and Tianjin, three of the four municipalities that answer directly to the central government, have the largest proportion of talent. Beijing takes the lead, with 26% of its population 15 years old or older holding a college or higher-level degree, and 9.6% of its population belonging to the creative class. Among all the provinces, only four have more than 10% of the population 15 years old or older holding a college or higher-level degree, and in only seven of them does the creative class represent more than 3% of the population.



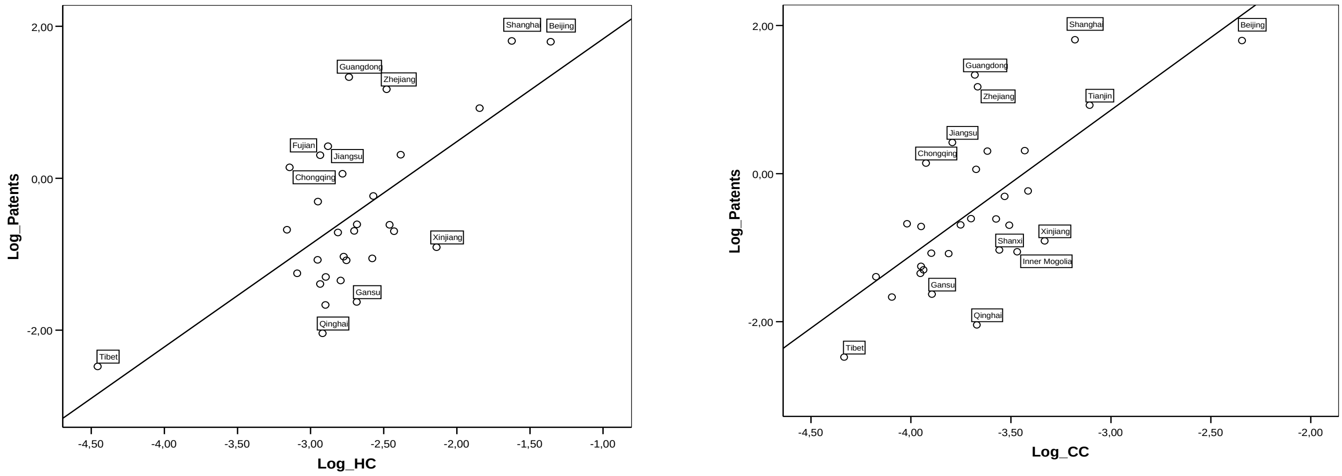
Population, GDP per capita and high technology



Human capital, creative class and GDP per capita



Human capital, creative class and high technology



Human capital, creative class and patents

Figure 3: Human capital versus the creative class

In those graphs depicting relationships between talent and technology or economic performance, the regions basically form two clusters, excluding Tibet and Xinjiang as lagging outliers in some cases. One cluster includes Beijing, Shanghai and Tianjin in the up-right corner. Those regions share several distinguishing features. First, they are all municipalities directly under the central government, with the highest political status among provincial-level regions. Second, they benefit from preferential (economic and social) central government policies. Third, they all have a high level of urbanization (with more than 70% of the population living in the cities). These commonalities shed light on the spiky distribution of talent in China.

Most other regions gather in the middle cluster, showing little connection between talent and economic performance or between talent and technology. This implies that China as a whole is a long way from being a talent-driven knowledge economy. Regional innovation and economic performance, where they exist, are likely to rely on something other than human capital or the creative class. Even so, the few talent-intensive regions (Beijing, Shanghai, and Tianjin) that make up the first cluster have better technology and economic performance than the others.

After comparing these plots with studies by Florida et al. (2007) and Mellander and Florida (2006), we can see that the economic geography of talent in China is more concentrated than in the West. In other words, talent distribution is spikier in China. This may be a result of the contrast between the more market-based economies of the West and a Chinese system in which the government and related non-market factors are at least as important as market factors. The enormous political, economic and social resources brought to bear by the central government render Beijing, Shanghai and Tianjin unbeatable in attracting talent and high-tech industries and in fostering economic growth. These hard-to-measure government factors have not been incorporated into our model.

Results from Path Analysis and Structural Equations Models

We now turn to the results of the SEM models and path analysis. Figure 4 and Table 4 show the statistical results when talent is measured by human capital and regional economic performance by GDP per capita. It can be seen that the university holds a significant association with human capital after keeping tolerance and service amenities constant. Tolerance is also significantly associated with human capital. But this relationship, according to the path coefficients, is not as strong as that between the university and human capital. In addition, there is no significant association between service amenities and human capital.

Model 1: Human Capital, High Technology and GDP per Capita

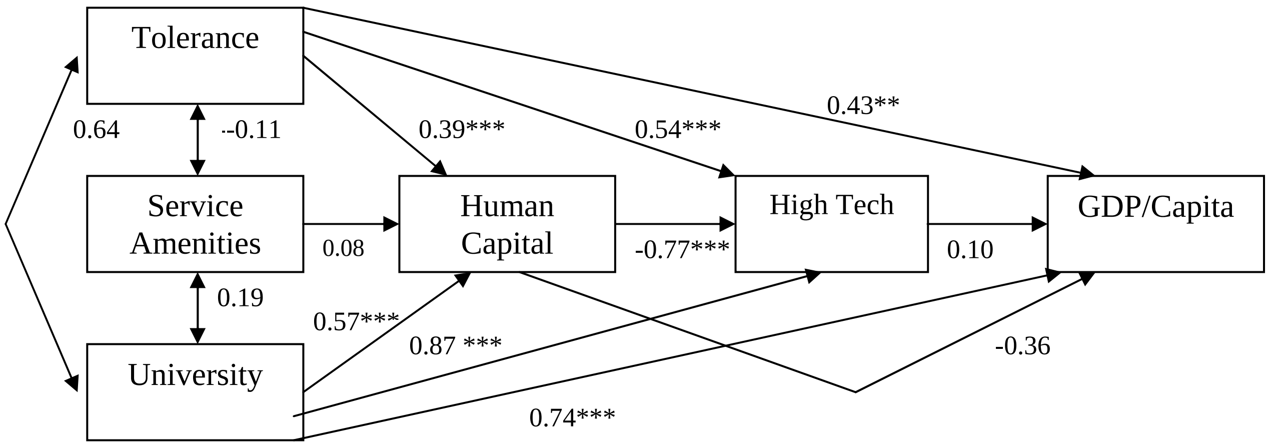


Figure 4: Path analysis for human capital, high technology and GDP per capita

Table 4: Regression results for human capital, high technology and GDP per capita

GDP per capita	Human Capital		
	Talent	**High Tech**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.304***	0.778***	0.337**
Service Amenities	0.242		
University	0.602***	1.676***	0.784***
Talent		-1.411***	-0.364
High Technology			0.053
Observations	31	31	31
R^2	0.619	0.513	0.691

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).

The results are different from those observed in the West. Amenities, which appear to be a significant contributor to human capital distribution in the US and Sweden (Florida, Mellander and Stolarick, 2007; Mellander and Florida, 2006), are not important in China. This reflects the difference between developing and developed economies. At this earlier stage of development, Chinese talent, while experiencing higher living standards than other Chinese people, does not use quality of life as a key factor in location choice.

The presence of universities plays the leading role in forming regional human capital stock. This is in line with findings by Qian (2008). According to his study, the university is the single most important factor affecting talent distribution in China, outweighing market and other non-market factors. This is also in accordance with findings in the Western context by Berry and Glaeser (2005), Florida (2006) and Mellander and Florida (2006). Even so, it is reasonable to say that the university is more important in China than in the West. Florida et al. (2006) point out that US cities with a good university system do not necessarily retain talent, partially due to labor market mobility. In China, by contrast, the government controls the local population through the Hukou system. Most employers in big cities, especially in star cities like Beijing and Shanghai, have quotas of local Hukous they can issue. The local university graduates, due to their networks and other advantages in accessing job information, are better able to find and compete for opportunities, and subsequently become locally registered. This process is much more difficult for graduates from outside the local area. Therefore talent in China is much less mobile than in the US. This reinforces the power of local universities in influencing the local talent stock. It also locks in place jurisdictional advantage and prevents efficient allocation of talent or resources.

Even in China, where mobility is restricted, tolerance or openness plays a significant role in the distribution of talent. This is consistent with the research on developed countries (Florida, Mellander and Stolarick, 2007; Mellander and Florida, 2006) and further proves the indispensable role of tolerance in attracting talent.

Similarly, the university and tolerance are both significantly associated with high technology and GDP per capita. High-tech firms like to locate themselves near universities which provide technologies, scientists and engineers. It is also possible that open and diversified regions can better attract high-tech industries than relatively closed and homogenous regions.

Interestingly enough, there are some non-intuitive relationships between human capital, high technology and GDP per capita, once the university and tolerance factors are controlled. Human capital exhibits a significant but negative relationship with high technology. The equilibrium between talent supply and demand is distorted and the market forces “disappear”. Moreover, compared with the correlation matrix, the significant and positive associations between human capital or high technology and GDP per capita no long exist. This is not in line with the empirical results from analysis on developed economies. Why does this happen for China?

One possible explanation is that the restriction of population mobility decreases the role of talent in high-tech industries and economic performance. Because of the Hukou system, talent cannot freely migrate to those places with high-tech industries. Talent demand by high-tech industries and the supply by talent itself thus cannot reach market equilibriums.

Another possible explanation lies in the characteristics of China’s high-tech industries. Those so-called high-tech industries are primarily based on manufacturing, processing and assembling, rather than on innovation and service. Compared with developed countries, innovative activity in the Chinese high-tech industries is very limited. Specifically, R&D expenditures in 2004 accounted for 4.6% of the total value added of the high-tech industries, much lower than 27% in the US in 2002 and 18.2% in Korea in 2003. According to Table 5, this percentage for knowledge economies is generally above 20%. With limited innovative opportunities, the link between human capital and high-tech industries is weakened. A negative sign in our results suggests that the high-tech firms would rather locate themselves in places with less talent. This is reasonable in that the total costs of production (including, for instance, land use costs) in those places are likely to be low.

Table 5: International comparison on R&D expenditures as a percentage of value added of high-tech industries

	China 2004	US 2002	Japan 2002	Germany 2002	France 2002	UK 2002	Italy 2002	Korea 2003
Total high-tech industries	4.6	27.3	29.9	24.1	28.6	26	11.6	18.2
Pharmaceutical products	2.4	21.1	27	-	27.2	52.4	6.6	4.4
Aircraft and spacecraft	16.9	18.5	21.6	-	29.4	23.8	23.4	-
Electronic and telecommunications equipment	5.6	25.4	20.4	39.2	57.2	23.6	19.4	23.4
Computers and office equipment	3.2	32.8	90.4	18.1	15.8	5.9	8.8	4.4
Medical equipment and meters	2.5	49.1	30.1	14	16.1	8.3	6.4	10.7

Source: China Statistics Yearbook on High Technology Industry 2005; OECD STAN Database 2005; OECD, Research and Development Statistics 2005. Available at: http://www.sts.org.cn/sjkl/gjscy/data2006/2006-1.htm

A third possible explanation is the role of government. Although implementing economic policies of liberalization and decentralization, Chinese governments, both central and local, still exert tremendous influence on economic and social activity. For instance, Beijing is home to the nation’s best education institutions and health systems, which serve as talent magnets, and benefits considerably from housing the central government. National Economic and Technology Development Zones (NETDZ) in China are the most attractive places for high-tech firms, largely because of preferential policies approved by the central government. Tianjin and Beijing have two of the largest and best such zones in China. Shanghai is the home of four such zones and the only city with more than two. In addition, Shanghai, as the economic center of China, receives economic development support from the central government in all possible forms. The government, to sum up, might affect talent, technology and economic growth in ways that diminish their intrinsic relationships.

Statistically, the negative relation between talent and technology may be partly a result of the very close correlation between the university and talent. To see whether talent, the university and tolerance include the same information, we ran an OLS separately, letting high technology be explained by these three variables, including a VIF test for multicollinearity. The VIF values are distributed between 2 and 5, indicating that they to some extent include the same information. But with values less than 5 we concluded that they did not include identical information. Instead, to further explore the relation between talent and innovation, we substituted patents for high technology in the original model.

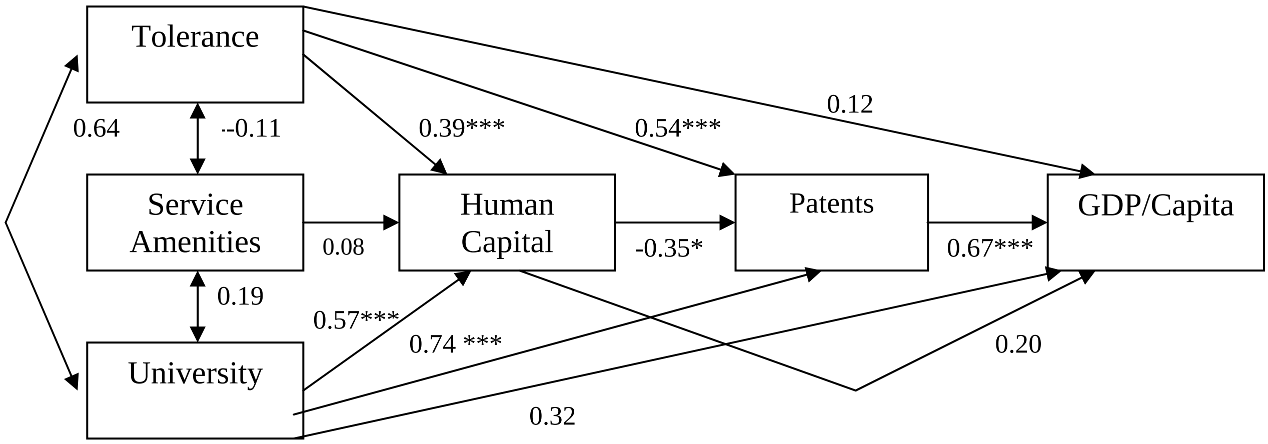


Figure 5: Path analysis for human capital, patents and GDP per capita

According to the results shown in Figure 5 and Table 6, the relationship between talent and patents is still negative and weakly significant. However, patents have a stronger explanatory value in relation to GDP per capita. Consistent with our explanation for the high technology case, patents in China are not necessarily innovation-based. As mentioned before, patents consist of three types: inventions; utility models; and designs. Inventions, which are the most likely to be high-tech or innovation-based, accounted for only 12% of the total number of patents in 2004. In contrast, the less innovation-based utility models and designs represented 46% and 42% respectively.

Table 6: Regression results for human capital, patents and GDP per capita

GDP per capita	**Human Capital**		
	Talent	**Patents**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.304***	0.868***	0.091
Service amenities	0.242		
University	0.602***	1.606***	0.340
Talent		-0.715*	-0.202
Patents			0.053***
Observations	31	31	31
R^2	0.766	0.764	0.793

*** Significant at the 0.01 level (2-tailed).
* Significant at the 0.10 level (2-tailed).

To make sure this isn't driven by outliers (which the scatter plots assume) we re-ran this path/SEM, excluding the very obvious outliers, Beijing, Shanghai and Tibet (the regressions are therefore basically towards the second cluster). The negative and significant relation between human capital and high technology is no longer significant at all (see Figure 6 and Table 7).

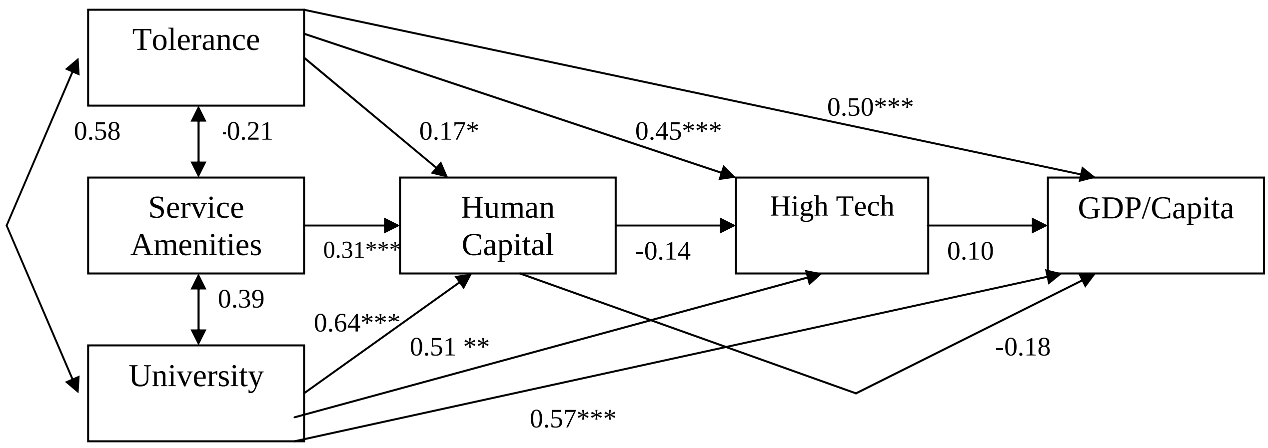


Figure 6: Excluding outliers – path analysis for human capital, high technology and GDP per capita

The role of high technology in relation to GDP per capita does not change with the exclusion of outliers. Again it is not significant. The association between tolerance and talent is now drastically weakened. However, the role of service amenities in relation to talent has become significant and is the second strongest after the university. Tolerance remains important for high technology and GDP per capita. The university plays a weaker role in relation to high technology but is still strong in relation to GDP per capita. As a summary, the key relations still hold after excluding outliers: the university and tolerance are still significantly associated with human capital, high technology and GDP per capita; and the relationships between human capital, high technology and GDP per capita are again anti-intuitive.

Table 7: Regression results for human capital, high technology and GDP per capita excluding outliers

GDP per capita	**Human Capital**		
	Talent	**High Tech**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.136*	0.737***	0.513***
Service Amenities	0.812***		
University	0.561***	0.913**	0.643***
Talent		-0.292	-0.232
High Technology			0.065
Observations	31	31	31
R^2	0.844	0.542	0.779

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).
* Significant at the 0.10 level (2-tailed).

We also re-ran these regressions, substituting patents for high technology and excluding the outliers. In this case, the relationship between talent and patents remains negative and significant.

Model 2: Creative Class, High Technology and GDP per Capita

Earlier research (Mellander and Florida, 2006; Florida, Mellander and Stolarick, 2007) has shown that talent when viewed in the form of the creative occupations may reveal a different role in this economic context. We therefore substituted the creative class for human capital and re-ran the same regressions as for Model 1 above. The results are presented in Figure 7 and Table 8.

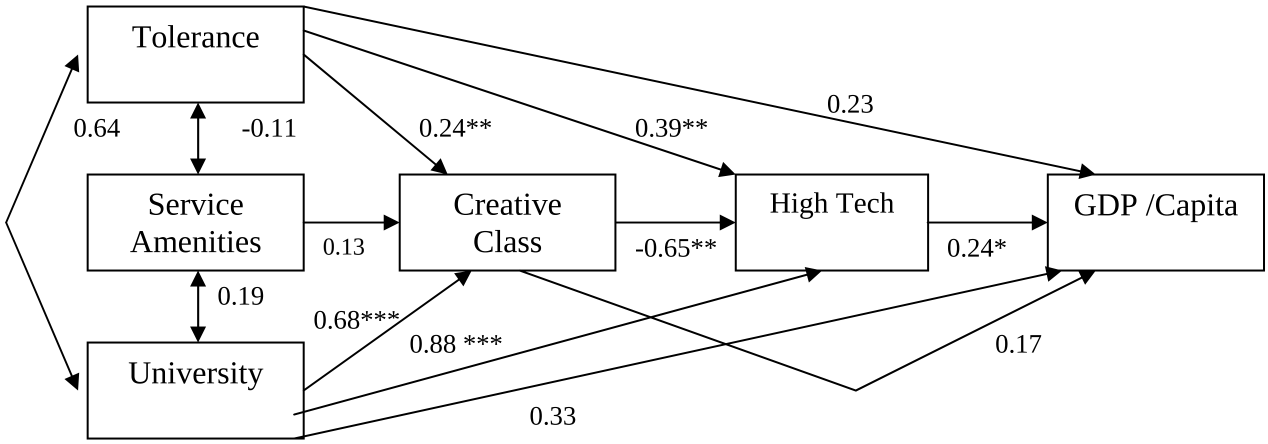


Figure 7: Path analysis for creative class, high technology and GDP per capita

The effects of the university, service amenities and tolerance on the creative class here follow a similar pattern to the human capital case. The university again shows its dominance in determining the distribution of the creative class. Its relative power over tolerance is even stronger. The university and tolerance are still significantly associated with high technology, but no longer with GDP per capita. The confusing relationships between talent (now the creative class), technology and GDP per capita still hold, though high technology now shows a significant and positive association with GDP per capita (but at the 0.1 level). The creative class, consistent with the human capital case, demonstrates a significant and negative effect on high technology.

Table 8: Results for creative class, high technology and GDP per capita

GDP per capita	**Creative Class**		
	Talent	**High Tech**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.133**	0.560**	0.178
Service Amenities	0.272		
University	0.512***	1.700***	0.355
Talent		-1.671**	0.400
High Technology			0.240*
Observations	331	331	331
R^2	0.774	0.469	0.673

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).
* Significant at the 0.10 level (2-tailed).

As in the human capital case, we substituted patents for high technology to get closer to innovation.

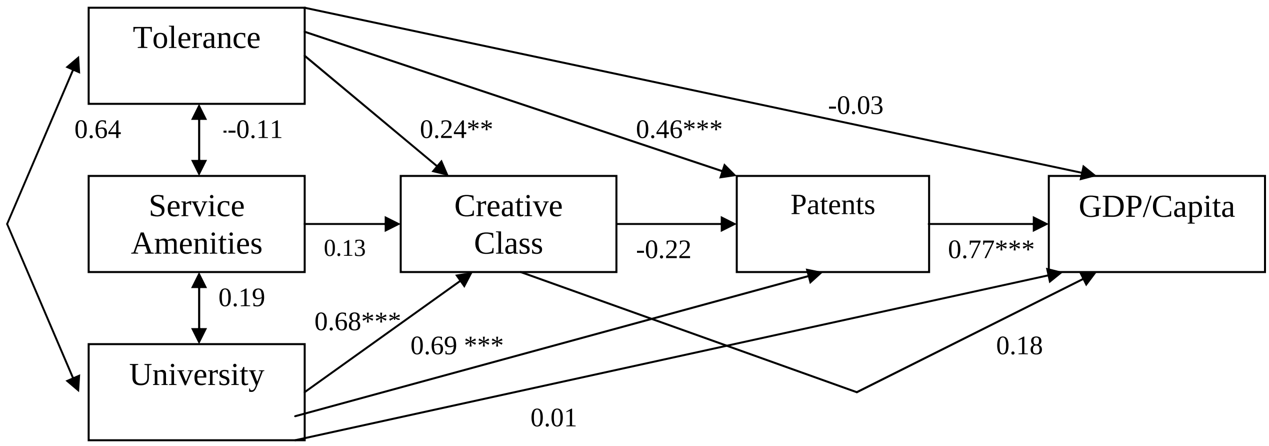


Figure 8: Path analysis for creative class, patents and GDP per capita

The significant and negative relation between the creative class and innovation now becomes non-significant (as shown in Figure 8 and Table 9). This is in line with what occurred when patents were substituted for high technology in the human capital case.

Table 9: Regression results for creative class, patents and GDP per capita

GDP per capita	**Creative Class**		
	Talent	**Patents**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.133**	0.734***	-0.025
Service Amenities	0.272		
University	0.512***	1.498***	0.015
Talent		-0.630	0.255
Patents			0.380***
Observations	331	331	331
R^2	0.774	0.746	0.792

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).

We learn from the scatter plots that the linear relation may very well be driven by a few outliers. To correct for this, we re-ran the same regressions without the most extreme outliers, Beijing, Shanghai and Tibet, as we did in the human capital case.

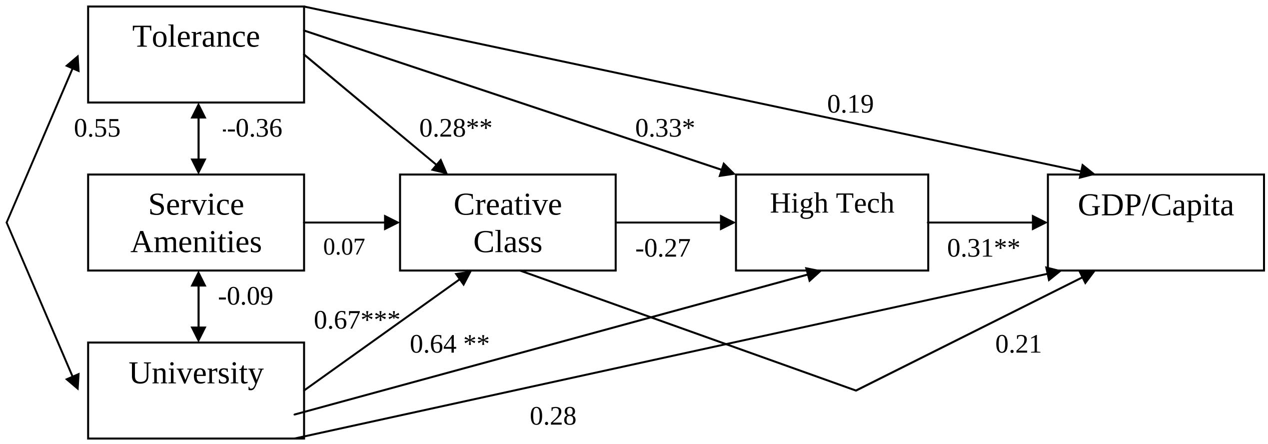


Figure 9: Path analysis for creative class, high technology and GDP per capita, excluding outliers

Without the outliers the connection between the creative class and high technology becomes insignificant and the roles of the university and tolerance are weaker than before (as shown in Figure 9 and Table 10). The relationship between high technology and GDP per capita is slightly stronger.

Table 10: Regression results for creative class, high technology and GDP per capita, excluding outliers

GDP per capita	**Creative Class**		
	Talent	**High Tech**	**GDP/capita**
Variables	Eq 1	Eq 2	Eq 3
Tolerance	0.120**	0.427*	0.156
Service Amenities	0.127		
University	0.439***	1.242**	0.335
Talent		-0.794	0.392
High Technology			0.191**
Observations	331	331	331
R^2	0.714	0.430	0.677

*** Significant at the 0.01 level (2-tailed).
** Significant at the 0.05 level (2-tailed).
* Significant at the 0.10 level (2-tailed).

We also re-ran the regressions with the outliers excluded and patents substituted for high technology. Here too the relation between the creative class and patents is not significant.

Discussion

Our research focuses on talent, technology (or innovation) and regional economic development in the developing context, using China as an example. We used path analysis and structural equation approaches and established a three-stage model. In the first stage, we explored the institutional and cultural factors affecting the distribution of talent. Second, we examined the impact of talent distribution on regional technology. Third, we investigated the effects of the university, tolerance, talent and technology on regional economic performance. Our path/SEM model allowed us to test for the direct, indirect, separate and joint effects of those factors on regional economic performance, while minimizing the problem of multicollinearity.

To achieve solid conclusions, we tried different measures for talent (human capital versus the creative class), technology (high-tech value added versus patents) and regional development (GDP per capita), and we examined the effects of outliers. No matter how we changed the model, the different path/SEM analyses produced several common findings. First, the role of universities in shaping the economic geography of talent and innovation is extremely important in China. Second, tolerance/openness/ diversity, although not as strong a determinant as universities, appears to be another significant factor in talent location, echoing findings from developed countries. Third, talent distribution does not exert significant and positive effects on the spatial variations of technology and economic performance.

In line with the empirical findings for developed economies, the university is critical to talent and technology concentrations in China. Universities not only supply educated talent to the region, but they produce new knowledge and technology through their professors, scientists and even students. However, university graduates do not necessarily stay put. A region's ability to retain and attract talent plays an even more important role in determining its talent stock. In China, mobility restrictions imposed by the inhabitant registration system make talent migration more difficult than in the West. Thus the region in China has an easier time retaining local university graduates. This indicates that the university is even more important for talent concentration in the Chinese context.

Tolerance, openness and diversity are significant factors in attracting talent and high-tech firms in China. This is another finding consistent between developed economies and China – along with the role of universities – suggesting the strong explanatory power of tolerance. Tolerance is likely to increase educational and occupational skill in a region by lowering the barriers to entry for talented people across gender, race, and sexual orientation. A tolerant and open social climate also nurtures new knowledge and entrepreneurial activity which in turn underpin innovation-based economic growth. To build a knowledge-based creative economy China will have to recognize the role of such social factors, and further socially "emancipate the mind (*jiefangsixiang*)."

The non-intuitive findings in the relationships between talent, technology and regional development for China contrast with those for the West. This implies that China is still far from being a knowledge economy, notwithstanding its efforts to build a creative country and promote higher education. China's high-tech industries, given their poor R&D expenditures, are not innovation-based. Also, most patents granted in

China are of the less innovation-based utility model and design varieties. By contrast, high-tech industries in developed countries lead technological innovation. To gain competitiveness high-tech firms generally invest tremendous resources in R&D and require plenty of talent to perform innovative activity. In China, however, R&D expenditures in high-tech industries are very low compared with the West. Without mature platforms for innovative activity, the Chinese talent pool, though growing rapidly, makes a limited contribution to technological and economic development.

Even if the high-tech firms have a high demand for talent, they may not be able to recruit what they need, since the spatial supply and demand of talent has been distorted by the government. China’s inhabitant registration system prevents talent from migrating to locations where its utility can be maximized. The government also intervenes into the talent market by bestowing upon a few regions, such as Beijing and Shanghai, enormous social, economic, and political resources. This has hyper-concentrated human capital and the creative class in these places. These regions are obviously talent-intensive, but not necessarily knowledge-based.

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