Localisation economies, intellectual property rights protection and entrepreneurship in China: A Bayesian analysis of multi-level spatial correlation

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Abstract

Entrepreneurship is an important determinant of innovation and growth with an uneven spatial distribution. In addition, the mechanism of entrepreneurship is affected by administrative hierarchies. However, the driving forces behind the spatial differences are not clear. Therefore, this study aims to examine the key determinants of entrepreneurship by clarifying the roles of localisation economies and intellectual property rights (IPRs) protection from 2008 to 2017 using a Bayesian analysis of multi-level spatial correlation. The empirical results indicate that localisation economies and IPRs protection have a major influence on entrepreneurship. In particular, the role of localisation economies at prefecture level is important, because the impact of supplier linkages at provincial level is negative, although it is insignificant. The effects of IPRs protection at both prefecture and provincial levels are significant in all the models, and its effect increases with the improvement in model performance. Moreover, these determinants vary across different spatial scales.

Keywords

Localisation economies, IPRs protection, entrepreneurship, multi-level models, spatial random effects

1 Introduction

Entrepreneurship is regarded as an important antecedent of innovation capacity and economic growth (Galindo and Mendez, 2014; Pagano, Petrucci and Bocconcelli, 2018). A high level of entrepreneurship leads to sustainable economic growth and radical technical change (Djankov et al., 2002; Fusari and Reati, 2013). In particular, in China, due to rapid economic development, entrepreneurship is regarded as a national priority, and, with effect from 2014, the Chinese government has put in place a nationwide strategic initiative to stimulate entrepreneurship and innovation in order to promote sustainable economic growth (Dou et al., 2019). However, the spatial distribution of entrepreneurship is uneven, which is a significant determinant of regional economic disparity (Stam, 2010), and some coastal cities seem to be more entrepreneurial than inland cities in China (Guo, He and Li, 2016). Meanwhile, government institutions also have an effect on the emergence of enterprises and innovation (Edler and James, 2015). Due to China's decentralisation process, local governments have considerable autonomy in terms of policy making without violating high-level government policies (Huang et al., 2015). Thus, administrative hierarchies have a significant impact on local entrepreneurship.

Localisation economies originate from a cluster of enterprises within the same industry in a local economy, and they create external economies for local businesses by means of labour market pooling and expertise spillovers, as well as input-output linkages (Marshall, 1920; Viladecans-Marsal, 2004). Theoretically, new firms have no strong links with local suppliers, and may lack knowledge about the local labour situation, management of business technology, and markets, meaning that they are unfamiliar with the local production network (Stinchcombe, 1965). Therefore, entrepreneurship is more dependent on localisation economies (Guo et al., 2016). Moreover, linkages between local suppliers/customers, professional labour pooling and knowledge spillovers can make it easier for potential entrepreneurs to deal with the initial debt that they incur in starting up a business (Ghani et al., 2013).

While the studies cited above have focused on the positive effect of localisation economies on entrepreneurship, our study introduces a new institutional context - that of intellectual property rights (IPRs) protection - to examine the relationship between localisation economies and entrepreneurship. IPRs protection, as an institutional driver of innovation, has mixed effects on local innovative activities and entrepreneurship (Bondarev, 2018). The conventional wisdom is that IPRs protection facilitates the dissemination of information, resulting in innovation and entrepreneurship (Allred and Park, 2007). However, sector monopolisation caused by strong IPRs regimes damages the potential for entrepreneurship and economic growth (Furukawa, 2007). Moreover, strong IPRs protection may reduce innovation, because it favours inventors rather than innovators (Workman, 2012). In addition, Autio and Acs (2010) suggested that strict IPRs protection has a negative impact on the relationship between educational levels and entrepreneurial intentions, and a positive influence on the relationship between income levels and entrepreneurial intentions. However, existing studies on the subject have some limitations. First, IPRs protection has not previously been incorporated into the framework for explaining how localisation economies affect entrepreneurship. Second, little effort has been made to explore the influence of administrative hierarchies and spatial factors on entrepreneurship.

Therefore, this study aims to examine the effects of localisation economies and IPRs protection on entrepreneurship by employing multi-level Bayesian spatial correlation analysis. Our study bridges the gaps in the existing studies as follows: first, we introduce IPRs protection into the framework via which localisation economies impact on entrepreneurship; second, by employing multi-level Bayesian models, this study distinguishes the effects resulting from different administrative levels. In China, various hierarchical levels of administration exist, which can therefore serve to demonstrate scale effects (Jiang et al., 2012). Second, using a single-level model may result in an overstatement of the statistical significance of variables (Subramanian et al., 2001). Multi-level analysis can help to capture unobserved heterogeneity between the intersections (Shi et al., 2016). Specifically, in this study, we create a multi-level model and a multi-level model with random parameters, and we also compare this with the classical negative binomial model (NB). We then evaluate the three models within the Bayesian inference framework. Third, we take spatial random effects into consideration. Spatial random effects are generally used with unrelated random effects terms to avoid inferences of inappropriate spatial correlation (Mitra, 2009). This type of analysis is ideal for entrepreneurship, because it allows us to include more descriptive predictors of regional differences in entrepreneurship.

The rest of this study is organised as follows. Section 2 provides a literature review that clarifies how localisation economies and IPRs protection affect entrepreneurship. Section 3 introduces the data and explains the methodology. Section 4 shows the empirical results obtained from the perspectives of multi-level analysis and spatial analysis. Conclusions and some important policy implications are presented in Section 5.

2 Literature review

2.1 Localisation economies and entrepreneurship

Localisation economies originate from enterprise clusters of the same type of industry within the local economy, and an external economy for local enterprises is created through labour market pooling, linkages between inputs and outputs and professional knowledge spillovers (Marshall, 1920). Enterprises in a spatially bounded region within the same industry benefit from knowledge and technology spillovers facilitated by information transfer, because sharing common capabilities can effectively disseminate knowledge or enable people to learn new knowledge, which calls for cognitive proximity between participants (Nooteboom, 2000). Moreover, localisation economies may also have advantages in terms of reducing transport costs, environmental costs and offering greater availability of highly specialised workers and input suppliers, as well as the emergence of external economies of scale, all of which represent a source of increased productivity for enterprises (Martin et al., 2011; Omri and Afi, 2020). Most of the relevant literature has come to the same conclusion that localisation economies have a significantly positive effect on enterprises' productivity (Beaudry and Schiffauerova, 2009).

Similarly, existing studies have indicated that localisation economies tend to foster entrepreneurship. First, entrepreneurs tend to start out in a familiar environment (Dahl and Sorenson, 2009; Renski, 2015). On the one hand, the decision to start a business depends on the founder's knowledge of local support networks and market potential, and few new businesses are committed to searching for a multi-regional, comprehensive location (Sorenson, 2003; Stam, 2007). On the other hand, new enterprises are more dependent on localisation economies than incumbent enterprises, because new enterprises lack local production networks, and access to local human resources, technologies, market and business management institutions, and have not yet established strong connections with local suppliers and customers (Stinchcombe, 1965). Thus, it is easier for entrepreneurs to deal with their initial liabilities by forming connections with local suppliers or customers, specialised workforce pooling and local knowledge spillovers (Ghani, Kerr and O'Connell, 2013). In addition, the evidence shows that scientists and/or engineers generally prefer to start up a new enterprise in a location near where they live (Dahl and Sorenson, 2010), because proximity to buyers and sellers in a familiar social and economic environment can facilitate the necessary trust relationships within the process of economic transactions and decrease transaction costs (Romero-Martínez and Montoro-Sánchez, 2008). Localisation economies also have the effect of lowering transport costs because it is easier for consumers to access local companies (Krugman, 1991).

Additionally, entrepreneurs are more inclined to start enterprises in fields in which they have acquired knowledge and experience (Shane, 2000). Most of this existing knowledge and experience comes from incumbent businesses (Renski, 2015). Thus, new enterprises tend to be set up in fields where there is already a concentration of specific industries (Feser, Renski and Goldstein, 2008; Renski, 2014; Reynolds, 2007). Meanwhile, new enterprises can also share local suppliers and clients with incumbent enterprises via localisation economies, thereby reducing the entry barriers (Guo, He and Li, 2016). Due to the pool of knowledge and experience available, new enterprises have better opportunities and more resources available to them with which to form links with local customers and suppliers. Moreover, proximity to suppliers and customers can promote innovation via local knowledge spillovers (Porter, 1990). More importantly, having access to a large number of suppliers and consumers in the same area can help entrepreneurs to find the most suitable suppliers and consumers more easily and effectively, thereby reducing the costs associated with searching for these (Stuart, 1979). Thus, localisation economies promote entrepreneurship through the existing established knowledge base and the fact that they provide entrepreneurs with a familiar environment.

2.2 IPRs protection and entrepreneurship

It has been found that the economies of nations with IPRs protection grow faster than those of nations without IPRs protection (Leblang, 1996). Strong IPRs protection may be beneficial to entrepreneurs in some economies, but harmful to entrepreneurs in other types of economies. In countries where there are mechanisms such as corruption, nepotism, and the caste system, strict IPRs protection may have a negative impact on entrepreneurs' use of technology, whereas IPRs protection may have a more positive impact on entrepreneurship in a more democratic system, as democratic processes often ensure greater participation by those who may be affected by legislation (Laplume, Pathak and Xavier-Oliveira, 2014). Thus, the IPRs regime may influence economic growth and help to explain differences in economic growth between nations (Goldsmith, 1995). However, technology policy issues relating to IPRs protection may have different implications for entrepreneurship. For example, existing suppliers with a superior technology portfolio prefer a strong monopoly to maximise their rent allocation (Teece, 1986), but in the case of new entrepreneurs seeking to use the latest technology, strong IPRs protection may be a barrier to entry, as well as reducing the effects of knowledge spillovers on entrepreneurs (Acs et al., 2009). Thus, existing studies have not reached a consistent conclusion about how IPRs protection affects entrepreneurship.

We first review the literature on strong IPRs protection hindering entrepreneurship. Entrepreneurial knowledge spillover theory states that endogenous forces first create knowledge and then knowledge spillover enables entrepreneurs to discover and take advantage of opportunities (Acs et al., 2009). Startups are more likely to introduce radical and disruptive innovations that are often overlooked by incumbents (Bower and Christensen, 1995). Taking advantage of existing knowledge base spillovers enables entrepreneurs to innovate (Acs and Audretsch, 1988). Meanwhile, the intensity of a country's IPRS protection determines the ease with which foreign companies can innovate in order for them to compete in that market. An institution that ensures easy access to resources may encourage entrepreneurial intent, while an overly strict institution may stifle entrepreneurial intent by lowering expectations regarding the net benefits of entrepreneurial behaviour (Pathak, Xavier-Oliveira and Laplume, 2013). Implementing strong IPRs protection would hinder entrepreneurship, as it would increase the cost of adopting technology for entrepreneurs seeking to leverage new combinations of patents or copyrighted components. For instance, in emerging economies, such as China, access to start-up capital is more restricted and human capital levels are lower, which may exacerbate technology licensing issues and make it more difficult to overcome problems associated with IPRs protection, thereby reducing the expected net benefits of entrepreneurship (Autio and Acs, 2010). Since most innovations in goods and services are based on knowledge and the imitation of existing resources (Glass and Saggi, 2002), strong IPRs protection will hinder entrepreneurship by hampering knowledge spillover, and thus reducing the potential for innovation and growth (Acs and Sanders, 2008). The resulting reduction in opportunities may make people think that the net benefits of engaging in entrepreneurial behaviour are not worth the effort, thereby stifling the incentive to start a business (Pathak, Xavier-Oliveira and Laplume, 2013). In addition, IPRs protection may hinder entrepreneurship and growth by increasing initial costs and reducing access to key technologies (Fleming, 2001). Therefore, strong IPRs protection may have negative effects on entrepreneurship.

However, some studies have also discussed the positive impacts of strong IPRs protection on entrepreneurship. IPRs protection influences entrepreneurs' search and response behaviours by changing the incentive structure of choosing an entrepreneurial career (Eckhardt et al., 2008; Krueger et al., 2000). IPRs protection affects transaction costs for access to and use of the latest available knowledge and related technologies (Williamson, 2000). When IPRs protection is strict, entrepreneurs know that their technology is protected from competitors (Acs and Sanders, 2008; Huarng, Mas-Tur and Yu, 2012). Implementing effective IPRs protection can also increase entrepreneurs' access to capital from risk-averse investors and other sources (Pathak, Xavier-Oliveira and Laplume, 2013). While the threat of alleged infringement can be much more serious, IPRs protection helps entrepreneurs by protecting their ideas from imitators (Lemley, 2012).

3 Data and methodology

3.1 Data and variables

As a form of innovation, entrepreneurship is treated as a dependent variable. Most studies use the number of new firms or the number of people employed in new firms with which to measure it (Delgado et al., 2010; Glaeser and Kerr, 2009). However, in transitional China, there are new kinds of firms, and entrepreneurs have different motivations and objectives for establishing new firms. For example, the choice of location and establishment of new foreign-owned firms depend on the international strategy of parent firms, rather than on entrepreneurship (Guo et al., 2016). In addition, state-owned enterprises are mainly established as part of national or regional government planning. Thus, we decided not to choose new firm formation as a measure of entrepreneurship. Instead, we chose privately owned start-ups as the proxy for manufacturing entrepreneurship, and calculated the number of start-ups in order to measure new enterprises in their early years (Guo et al., 2016). The entrepreneurship data were taken from the China Industry Statistical Yearbooks produced by the National Bureau of Statistics of China, which provides industrial economic statistics for all provinces, autonomous regions and municipalities directly under central government control, as well as historical data for the main indicators. In addition, our study also takes data at prefecture level into consideration, due to the high statistical calibre of China Industry Statistical Yearbooks, we collected the data at prefecture level from the provincial statistical yearbooks.

Localisation economies is used as an independent variable. We chose three variables with which to measure it, namely: location quotient (LOC), supply, and consumption. The LOC of employment was thought to be a suitable proxy for localisation economies (Delgado et al. 2010). In addition, the links to suppliers and consumpers are important features of localisation economies (Krugman, 1991; Marshall, 1920). Following Guo et al.'s (2016) study, we choose the following formulae with which to measure them:

$$Input_{ri} = \sum_{k \in I} input_{i \leftarrow k} \times Empl_{rk} \qquad (1)$$

$$Output_{ri} = \sum_{k \in I} output_{i \rightarrow k} \times Empl_{rk} \qquad (2)$$

Where, $i \leftarrow k$ is the share of sector *i* inputs coming from sector *k*; this value is also viewed as the weight, ranging from 0 (no input) to 1 (full input); $Empl_{rk}$ is the employment of sector k in prefecture r. $Input_{ri}$ represents the potential input relations offered by city r in new firms in section i. The equation $Output_{ri}$ has a similar meaning to that of $Input_{ri}$. We use the location quotient of $Input_{ri}$ and $Output_{ri}$ to test Supplier and Consumption. The data used are taken from China's 2002 input–output table for 122 industrial sectors, produced by the National Bureau of Statistics.

Another independent variable is IPRs protection (IPP). This study uses Han and Li's (2005) quantitative index to measure the intensity of IPP. The measure is based on Ginarte and Park's (1997) (G-P) IPRs index, but further develops and improves it. There are 5 sub-indexes in the G-P method. Each metric takes 1 point, and the points of each sub-indicator are such that the sum of the scores of each metric is divided by the number of metrics in this sub-indicator. The accumulated scores give a measure of quantified IPRs protection strength. However, the G-P method may not be suitable for China, because China's judiciary and legislature are not fully synchronised (Han and Li, 2005). Thus, Han and Li (2005) added law enforcement efforts to the G-P method to produce the following measure:

$$P^A(t) = F(t) * P^G(t) \qquad (3)$$

Where t means time; $P^A(t)$ denotes IPRs protection strength; $P^G(t)$ represents the IPRs protection strength measured by the G-P method; and $F(t)$ denotes law enforcement efforts. The value of $F(t)$ ranges from 0 to 1, where 0 indicates that the provisions of IPRs protection regulated by law have not been implemented at all and 1 that these provisions have been fully implemented. The following 4 indexes are employed to measure $F(t)$: lawyer ratio, legislative time, per capita GDP, and whether the country is a member of the WTO. The final $F(t)$ scores are the arithmetic mean of the 4 indicators. Using different data, we calculated the IPRs protection at provincial and prefecture levels.

Based on relevant studies, we also chose a series of control variables which may affect entrepreneurship. Incumbent firms' performance and local market prospects have an impact on whether an entrepreneur decides to develop a new firm (Guo, He and Li, 2016). Thus, the growth rate (GROWTH) and entry rate (ENTRY) of the three-digit sector at a city level are included in the model. Meanwhile, in order to control for the influence of policies on entrepreneurship, we added the following: subsidy rate (SUBSIDY), local R&D investments (RD), and number of patent applications (PATENT). Furthermore, all the independent variables are lagged by 2 years to avoid endogeneity issues. The IPP and control variables data were taken from a pkulaw Database search, Intellectual Property Yearbooks, China's City Statistics Yearbooks and the China Industry Statistical Yearbooks produced by the State Statistical Bureau of China. The time period for this data was from 2008 to 2017. The prefecture and provincial level analysis was conducted on the following basis: There are 31 provincial regions, consisting of 22 provinces, 5 autonomous regions and 4 municipalities[1]. In addition, according to China's Annual Survey of Industrial Firms, there are 286 prefecture-level cities, located in different provinces. Table 1 describes all the variables.

Table1. Definition and measurement of variables

Variables	Description	Measurement
Entrepreneurship	Dependent variable	The number of privately owned start-ups in their early years
Independent variables		
LOC	Localisation (Log)	The location quotient of employment at prefecture or provincial level
SUPPLIER	Suppliers (Log)	The sum of supply sector employment calculated by the percentage of supply sector inputs needed by a sector at prefecture or provincial level

[1] Municipalities are major cities that are on the same administrative level as provinces, consisting of Beijing, Shanghai, Tianjin and Chongqing.

CONSUMPTION	Customers (Log)	The sum of demand sector employment calculated by the percentage of a sector's output sales which flow to demand sectors at prefecture or provincial level
IPP	Intellectual property rights protection	The measurement is derived from Han and Li (2005), see equation (3)
Control variables		
ENTRY	Entry rate	New enterprises as a percentage of all existing enterprises at prefecture or provincial level
GROWTH	Growth rate	The value in *t* year is the difference between the number of people employed in new firms in *t* and *t-1* years, divided by the number of people employed in new firms in *t* year at prefecture or provincial level
SUBSIDY	Subsidy	The percentage difference between gross output and subsidies at prefecture or provincial level
RD	Local R&D investment rate	Local R&D investment as a percentage of GDP at prefecture or provincial level
PATENT	Patent grant rate	Patent grant counts as a percentage of patent application counts at prefecture or provincial level

3.2 Methods

Due to the hierarchical data structure and complex estimation process, we employed Bayesian multi-level NB models and random parameters multi-level models. NB regressions and the Poisson model are most frequently chosen to study complex economic issues. When the Poisson model is replaced with the NB model, an error term of gamma distribution is included in order to account for the over-dispersion. Therefore, the NB model is also called the Poisson-gamma model. The NB model is as follows:

$$Y_{ij} \sim Poisson\left(\lambda_{ij}, \varepsilon_{ij}\right) \qquad (4)$$

Where Y_{ij} denotes the number of start-ups (entrepreneurship) in prefecture i belonging to province j, which obeys the Poisson distribution with an expected entrepreneurship frequency of λ_{ij}; ε_{ij} is the gamma distributed error term.

There are two kinds of Bayesian models: multi-level models that are used to estimate prefectures and provinces at different levels, and the random parameters multi-level model at both prefecture and province levels. Regarding the multi-level model, the expectation λ_{ij} of the NB distribution is:

$$\lambda_{ij} = e_{ij}^{\delta} \exp(\alpha + a_{ij} + \boldsymbol{\beta X_{ij}}) \qquad (5)$$

Where e_{ij} represents the exposure variable. We regard economic growth (GDP) at different levels as the exposure variable. $\boldsymbol{X_{ij}}$ denotes candidate factors at province and prefecture levels; $\boldsymbol{\beta}$ and α

represent the vector of the regression coefficients and intercept, respectively. In order to fully understand the effect, separate models are employed at the provincial and prefecture levels. The equation for the provincial level model is:

$$\log(\lambda_{ij}) = \alpha + \delta_l LogGDP_j + a_{ij} + \boldsymbol{\beta X_{ij}} \tag{6}$$

And for the prefecture level:

$$a_i = \delta_v LogGDP_i + \boldsymbol{U_i \gamma} \tag{7}$$

Where $\boldsymbol{U_i}$ and $\boldsymbol{\gamma}$ are the control variables and vector of regression coefficients at prefecture level, respectively; δ_l and δ_v are the coefficients of the exposure variables.

Regarding the random parameters multi-level model, the model specification at provincial level is as follows:

$$\log(\lambda_{ij}) = \alpha_j + \delta_{l_j} LogGDP_j + a_{ij} + \boldsymbol{\beta_j X_j} \tag{8}$$

And at prefecture level:

$$a_i = \delta_{v_i} LogGDP_i + \boldsymbol{U_i \gamma_i} \tag{9}$$

Where, α_j , δ_{l_j} , $\boldsymbol{\beta_j}$, δ_{v_i} , and $\boldsymbol{\gamma_i}$ are the coefficients of the random parameters. $\alpha, \alpha_j, \boldsymbol{\beta}, \boldsymbol{\beta_j}, \delta_l, \delta_{l_j}, \delta_v, \delta_{v_i}, \boldsymbol{\gamma}$ and $\boldsymbol{\gamma_i}$ follow non-informative priors of $N(0, 10^6)$. a_i follows a normal distribution; the variance obeys gamma (10^{-3}, 10^{-3}). According to Lord and Mannering (2010), the error term follows the gamma distribution of gamma (θ, θ), where $\theta = e^{\log(\theta)}$ and $\log(\theta) \sim N(0,\ 10^6)$. The study then used the Markov Chain Monte Carlo (MCMC) algorithm to construct the multi-level models. The structure of the Bayesian model is essentially hierarchical. As one of the most commonly used formulations for missing data predictions, the full Bayesian or information maximum likelihood approach constructs a joint normal distribution for all variables (Zaninotto and Sacker, 2017). Furthermore, based on the complete set of observed data, the Bayesian method or the maximum likelihood method is used to estimate the parameters of the distribution (Xu and Gardoni, 2020). In this study, in order to address the problem of missing data, the prior distribution of the model parameter with prior parameters can be seen as one level of hierarchy, and the likelihood α is regarded as the final stage of a Bayesian model. In addition, the posterior distribution can be obtained by the Bayes theorem (Ntzoufras, 2011). Also, based on Spiegelhalter et al.'s (2002) study, the model fit and complexity tests of Bayesian analysis employ the Deviance Information Criteria (DIC). The Bayesian Credible Interval (BCI) was chosen to test the variables' significance.

Furthermore, we introduced spatial effects into the multi-level Bayesian analysis, because regions in close geographical proximity affect each other. The effects of spatial correlation at regional level can be measured by the introduction of spatial random effects (Miaou and Song, 2005). Spatial random effects can explain some or all of the errors by measuring the impacts of neighbouring regions (Quddus, 2008). They are comprised of the following two levels: first order neighbours which share borders, and second order neighbours which are not adjacent to one another. The spatial random effects term u_i obeys a conditional autoregressive prior distribution as follows:

$$P(u|r) \propto \frac{1}{r^{\frac{m}{2}}} \exp\left(-\frac{1}{2r}\sum_i \sum_{j\in\delta_i}\left(u_i - u_j\right)^2\right), i \neq j \qquad (10)$$

Where, r means the prior knowledge of a spatial region; m indicates the number of neighbours in the adjacency matrix; j is the neighbour of i region, and δ_i represents the neighbourhood of i region. The first and second order spatial correlations were quantified for comparison. For the second order neighbours, the model was run using two weight systems: in the first, the two order neighbours are equally weighted, and in the second model, second order neighbours have half the weight of the first order neighbours (Aguero-Valverde and Jovanis, 2010; Wang et al., 2009). These weight systems indicate that the first order neighbours are more closely linked to every region. In addition, uncorrelated random effects are usually clarified with spatial random effects (Mitra, 2009). They prevent spatial random effects from inferring non-existent spatial correlations. The results can lead to increased confidence in the estimates of spatial random effects and fixed effects parameters, and they cannot make the model even more complex (Aguero-Valverde and Jovanis, 2008). The uncorrelated random effects are given a normal distribution as follows:

$$v_i \sim Normal\ (0, \tau_v) \qquad (11)$$

Where, τ_v represents the inverse variance of the uncorrelated random effects (v_i), and it follows a diffuse gamma prior distribution. Moreover, the spatial correlation coefficients were evaluated to test the importance of spatial correlation. Based on the following equation, the spatial correlation coefficients can explain the ratio of the model errors which can be specified by uncorrelated random effects and spatial random effects:

$$\eta = \frac{\sigma_u}{\sigma_u + \sigma_v} \qquad (12)$$

Where, σ_u and σ_v are the standard deviation of the spatial random effects (u) and uncorrelated random effects (v). In this case, the aforementioned statistical approach makes the spatial random effects more influential (Flask and Schneider IV, 2013). Before taking spatial effects into consideration, the Bayesian approach can help to avoid potential problems caused by missing data, but it does not consider spatial correlation in the estimation. Moreover, there is a lack of information about the effects of neighbouring conditions between different variables in similar research. Thus, in the process of spatial estimation, our study incorporates spatial correlation into the missing data prediction by employing the autoregression model. The estimation process in this study is able to model the statistics for the missing data in one area as functions of the observations in neighbouring areas (Xu and Gardoni, 2020).

4 Empirical results

Table 2 presents the descriptive statistics regarding the relationships between localisation economies, IPRs protection and entrepreneurship. LOC, SUPPLIER and CONSUMPTION were selected to show the effects of localisation economies. The LOC values show that there is a lack of labour capable of driving innovation. The statistics for SUPPLIER and CONSUMPTION indicate that supply is greater than consumption. This may also suggest that entrepreneurship would only have a limited potential to transform the market. However, more in-depth analysis would be required to test this finding. Because the model includes data at prefecture level, there are greater disparities in the IPP values and IPRs protection in Chinese cities appears to have become stronger. In addition, the difference between the maximum and minimum GROWTH values indicates that independent entrepreneurship has become a common phenomenon in China, and this is a growing trend. The differences in the values of financial subsidies show that not all cities or regions attach great importance to entrepreneurship. This could be because more advanced technology may not be suitable for the development of all cities and/or regions. Lastly, the overall percentage of innovation input (RD) in Chinese cities is relatively small. The following subsections discuss the analysis of the modelling results in greater depth, based on our research design.

Table 2 Descriptive statistics showing relationships between localisation economies, IPRs protection and entrepreneurship

Variables	Minimum	Maximum	Median	Standard Deviation
LOC	0.37	1.29	0.54	4.573
SUPPLIER	0.58	1.87	1.04	5.923
CONSUMPTION	0.21	1.19	0.43	4.324
IPP	0.24	4.29	1.96	8.009
ENTRY	0.19	0.45	0.21	3.981
GROWTH	0.05	0.51	0.19	2.781
SUBSIDY	0.03	0.39	0.12	1.975
RD	0.004	0.083	0.013	0.562

4.1 Results of multi-level random parameters framework

Table 3 depicts the estimation results of the multi-level random parameters model. The variables at prefecture and provincial level were estimated simultaneously. We calculated the mean of the estimated coefficients, standard deviation, 95% BCI and t-values. When the parameter distribution is 95% BCI, it does not contain a 0, and the variable is significant. Regarding localisation economies, at prefecture level, the three variables (LOC, SUPPLIER and CONSUMPTION) all have significant effects on entrepreneurship. Specifically, the effects of LOC and CONSUMPTION are positive, whereas that of SUPPLIER is negative. At provincial level, the effects of LOC_P and CONSUMPTION_P are positive and significant. Although the effect of SUPPLIER_P is negative, it is insignificant. Therefore, localisation economies can significantly impact on the development of entrepreneurship, particularly at prefecture level, because of their significance. Regarding LOC and LOC_P, most studies have concluded that they play a positive role in entrepreneurship (Combes et al., 2004; Glaeser et al., 2010). Based on data from the USA, Glaeser et al. (2010) obtained a 0.996 effect of localisation economies on entrepreneurship. Although the results demonstrate that LOC can help to understand variations in entrepreneurship in China, the degree of influence is smaller than in the USA as the values are 1.161 at prefecture level and 0.513 at provincial level. In addition, the results also suggest that localisation economies still have great potential for positively influencing entrepreneurship (Guo et al., 2016). The significant effects of supplier and consumption linkages at prefecture level suggest that industrial linkages play an important role in localisation economies on a small regional scale, and that proximity to consumers can reduce the transport and search costs of new firms (Guo et al., 2016). However, the negative effect of SUPPLIER at prefecture level also indicates that the supply of entrepreneurship resources is not closely connected with the consumer market. To some extent, this also shows that not all entrepreneurship can necessarily be transformed into actual productivity. In other words, the consumer market needs high-quality entrepreneurship. In addition, the results at both prefecture and provincial levels are significantly larger for CONSUMPTION than for SUPPLIER. However, the consensus in the existing literature is that suppliers are more important in promoting entrepreneurship (Glaeser and Kerr, 2009). A possible explanation for this is that, in the case of start-ups, sufficient consumption can ensure that they have more money to reinvest. Proximity to a large market and customers not only allow start-ups to recover costs quickly, but also to better understand the market direction and consumer demand. Regarding IPP, it is significant and positive both at prefecture and provincial levels, indicating that stronger IPRs protection promotes entrepreneurship. In particular, the median IPP value at provincial level is greater than that at prefecture level by 0.9, indicating that the effect of the IPRs institution is stronger at provincial level. Thus, the institutional quality of China's higher administrative levels has a greater impact on economic activity such as entrepreneurship, and it also reflects the fact that China is a highly centralised country.

Regarding the control variables, ENTRY, RD and PATENT all have significant effects on entrepreneurship, while GROWTH and SUBSIDY are insignificant, indicating that financial subsidies and existing entrepreneurship are not strong motivators for the establishment of new firms. The positive impact of patent applications indicates that both new and existing firms benefit from IPRs protection. The positive effects of ENTRY demonstrate that local knowledge spillover is more likely to happen between a large number of enterprises. By contrast, the negative effects of GROWTH suggest that newly-established companies are very diverse, which is not conducive to local knowledge spillovers and entrepreneurship, because a greater variety of businesses, selling different types of products, would result in fierce competition for local inputs (Boschma and Frenken, 2011). In addition, R&D promotes local entrepreneurship by enhancing technological advancement and creating jobs in related infrastructure-producing industries (Anwar and Sun, 2015). In the case of SUBSIDY, the current credit assistance projects in the form of subsidies have a strong impact on the allocation of credit to targeted entrepreneurs, but at the expense of non-targeted entrepreneurs (Li, 2002). Thus, SUBSIDY cannot increase local entrepreneurship overall, even if it widens the entrepreneurship gap by accentuating spatial differences between those areas where subsidies are more generous and those where subsidies are lacking.

Table 3. Estimation of multi-level random parameters framework

Variables	Median	SD	95% BCI	t-value
Intercept	-1.043	0.416	(-2.217, 0.132)	-0.326

Prefecture level				
LOC	1.161	1.214	(0.003, 2.323)	0.714
SUPPLIER	-0.101	1.698	(-0.198, -0.003)	-1.002
CONSUMPTION	2.279	3.217	(0.225, 4.337)	1.916
IPP	1.704	2.553	(0.191,3.218)	0.993
Provincial level				
LOC_P	0.513	0.993	(0.001, 1.005)	1.013
SUPPLIER_P	-0.461	0.693	(-1.212, 0.293)	-0.846
CONSUMPTION _P	1.775	2.305	(0.334, 3.227)	2.006
IPP_P	2.605	3.869	(1.203, 4.004)	1.989
Control variables				
ENTRY	1.064	1.712	(0.006, 2.131)	1.192
GROWTH	-0.478	0.403	(-3.869, 2.914)	-1.438
SUBSIDY	-0.447	0.555	(-1.211, 0.329)	-0.798
RD	1.797	1.693	(0.728, 2.916)	1.227
PATENT	0.548	3.997	(0.003, 1.092)	0.813
Model performance				
DIC			683.214	

4.2 Results of NB, multi-level, and multi-level random parameters models

The study applied the multi-level NB model and multi-level random parameters NB model to compare the models' performance. The multi-level method can effectively evaluate the variables at their own levels, and the unobserved heterogeneity between the observed data can be flexibly resolved by the use of random parameters multi-level models (Shi et al., 2016). Table 4 summarises the estimation results for the simple NB, multi-level NB and multi-level random parameters NB models. The values for model performance indicate that the multi-level random parameters NB model performs most effectively. The results demonstrate that the fit of our models has been improved significantly by considering heterogeneity and the hierarchical data structure across the observations. Regarding the DIC, the multi-level models have a better fit than the simple NB model as the DIC decreased by 52. Furthermore, we also assigned the random parameters of LOG (GDP) and Average Education to the multi-level model (not reported), resulting in the fit of the multi-level random parameters NB model being further improved.

Most of the parameter estimations of variables that affect entrepreneurship are consistent for the three models in Table 3. In general, the direction of the effects of these variables for each of the three models are in agreement with each other. The effects of localisation economies at prefecture level are significant, whereas the effect of suppliers at provincial level is still insignificant. IPP is significant at both provincial and prefecture levels. With the improvement in model performance, the impact of IPP increases. The effect of IPP at provincial level is greater than at prefecture level. Regarding the control variables, ENTRY is insignificant in the simple NB model, but it becomes significant in the multi-level NB and multi-level random parameters NB models, indicating that hierarchies do have an impact on the results. RD and PATENT retain their significant effects, and the effects increase with the improved fit of the models. Although the effects of GROWTH and SUBSIDY on entrepreneurship are mixed, they are not significant. In addition, the number of significant variables shown in Table 4 increased as a result of assigning variables with random parameters and estimating variables at multi-levels. Thus, when we assess regional or geographical economies using hierarchically structured data, the trade-off in terms of of model complexity has to be considered, although the multi-level model and random parameters analysis are more accurate and feasible than the simple NB framework (Shi et al., 2016).

Table 4. Estimation and model comparison of NB, multi-level, and multi-level random parameters models

Variables	**Simple NB**				**Multi-level NB**				**Multi-level Random Parameters NB**			
	Median	SD	95% BCI	t-value	Median	SD	95% BCI	t-value	Median	SD	95% BCI	t-value
Intercept	-0.689	1.375	(-1.376, -0.005)	-2.981	-0.937	1.179	(-2.146, 0.273)	-3.189	-0.604	1.227	(-1.213, 0.006)	-2.763
Prefecture level												
LOC	2.129	6.329	(0.265, 3.992)	3.297	1.005	7.387	(0.005, 2.004)	0.996	1.067	5.989	(0.132, 2.001)	2.205
SUPPLIER	1.546	2.284	(0.119, 2.994)	2.038	1.186	4.235	(0.206, 2.165)	1.009	1.567	3.427	(0.129, 3.008)	0.973
CONSUMPTION	2.113	4.352	(1.203, 3.002)	1.992	1.586	5.867	(0.166, 3.005)	2.283	1.193	3.847	(0.009, 2.376)	2.043
IPP	1.563	3.679	(0.221, 2.873)	0.997	2.351	4.832	(1.003, 3.698)	2.217	1.344	2.998	(0.132, 2.556)	2.117
Provincial level												
LOC_P	0.514	1.734	(-0.076, 1.103)	2.121	0.499	2.417	(0.005, 0.992)	2.261	0.951	1.943	(0.006, 1.895)	1.452
SUPPLIER_P	-0.576	1.864	(-1.007, -0.143)	-1.879	-0.437	2.221	(-1.291, 0.411)	-1.623	-0.118	1.601	(-1.109, 0.873)	-0.992
CONSUMPTION _P	0.115	2.516	(0.025, 0.204)	1.095	0.485	5.402	(-0.011, 1.001)	0.995	1.291	3.427	(0.003, 2.591)	2.687
IPP_P	1.605	8.075	(0.008, 3.201)	2.193	1.139	7.913	(0.004, 2.273)	3.193	1.676	6.586	(0.124, 3.227)	0.669
Control variables												
ENTRY	0.401	2.115	(-0.215, 1.016)	1.281	1.085	4.009	(0.018, 2.176)	0.779	1.614	2.885	(0.106, 3.121)	2.197
GROWTH	-0.155	1.512	(-0.318, 0.008)	-1.761	-0.483	1.821	(-2.002, 1.034)	-0.942	-0.534	1.411	(-2.005, 0.937)	-1.262
SUBSIDY	-1.516	1.442	(-2.001, -1.034)	-0.889	-0.247	2.117	(-1.281, 0.783)	-1.009	0.477	2.073	(-0.112, 1.065)	1.206
RD	0.702	3.291	(0.394, 1.009)	1,713	0.651	4.556	(0.007, 1.295)	2.225	0.631	3.023	(0.025, 1.236)	1.371

PATENT	1.022	4.007	(0.219, 1.823)	3.004	1.033	6.112	(0.017, 2.048)	0.947	2.028	3.991	(1.202, 2.853)	2.109
Model performance												
DIC	825.435				773.324				639.293			

4.3 Results of adding spatial considerations

Table 5 summarises the parameter estimates and results of the Bayesian analysis of the multi-level spatial models. The first order neighbours, unweighted second order neighbours, and weighted second order neighbours were modelled at prefecture and provincial levels. The goodness-of-fit characteristics of the models can be seen from the DICs. The results of the DICs suggest that adding spatial random effects to the models results in a significant improvement, indicating that spatial correlation is important in regard to local entrepreneurship. Moreover, when we weight the second order neighbours, the performance of the model improves significantly, and this model performs the best out of all the models. Thus, spatial correlation is a significant factor that has direct neighbourhood effects (Flask and Schneider IV, 2013). Adding spatial random effects can help to avoid the effects of unknown or unobserved predictors that are inadvertently ignored in the model. Regions that directly share borders at prefecture and provincial levels have spatial similarities, which can reveal information about patterns of local entrepreneurship. As the distance from a city or province with strong entrepreneurship increases, more cities or provinces are considered to be neighbours and are introduced into the analysis.

The impact of LOC is positive in all cases, and its positive effects at prefecture level are greater than at provincial level, indicating that the impact of localisation economies on entrepreneurship at a smaller spatial scale is more obvious, because the speed of knowledge transmission and knowledge spillover will be faster in a relatively small space with similar spatial characteristics. The SUPPLIER parameter is positive at prefecture level, whereas it is negative at provincial level. The results indicate that proximity to suppliers at prefecture spatial scale can promote entrepreneurship, while proximity to suppliers at provincial spatial scale cannot accelerate entrepreneurship. This may be because proximity to suppliers on a larger spatial scale would increase the search costs, production costs and transport costs for a start-up. By contrast, the positive effects of CONSUMPTION at provincial level are greater than at prefecture level, suggesting that a vast market and large consumer population are of great significance for start-ups during the early stages. Meanwhile IPP has the highest values for positive effects in all cases, demonstrating that an appropriate intellectual property rights institution can strongly promote entrepreneurship and that China is currently operating a suitable intellectual property protection system. Moreover, the existence of a greater positive impact at provincial level reflects the fact that policies from a high-level of the administrative hierarchy have a greater impact on entrepreneurship.

Regarding the control variables, ENTRY, PATENT and RD are positively related to local entrepreneurship at both prefecture and provincial levels. The difference is that the effects of ENTRY are more obvious at prefecture level, while the effects of RD and PATENT are greater at provincial level. The explanation for this is that because knowledge spillovers and transfers are more likely to occur in relatively small spaces, ENTRY can play a greater role in entrepreneurship at the prefecture level. In addition, RD comes mainly from government fiscal allocation and budgets. Although China's decentralisation process has made considerable progress, the fiscal power of prefecture governments still cannot violate that of high-level governments, but governments at provincial level do have considerable autonomy to adjust R&D investments within their jurisdiction. With regard to PATENT, patent authorisation is managed by the central government, and higher-level governments exercise greater restraint on the marketisation process of local patents. Thus, the effects of PATENT are greater at provincial level. GROWTH and SUBSIDY have a negative effect on entrepreneurship at both prefecture and provincial levels. The negative effects of GROWTH may be due to the fact that new entrants are irrelevant, and unrelated firms cannot promote local knowledge spillovers and increase agglomeration externalities (Zhang et al., 2014). The negative impact of subsidies shows that subsidies have not been used to promote entrepreneurship, which is partly due to local political and fiscal corruption

In order to check the robustness of our estimation, and following the previous research carried out by Guo et al. (2016), our study uses the number of people employed by privately owned start-ups to replace the number of privately owned start-ups, as the dependent variable. Similarly, panel Tobit models were estimated and the same procedure used in our study because of the excess of zero values. The final results still hold for our research design.

Table 5. Parameter estimation results when spatial effects are taken into consideration

Variables	First order neighbours				Second order neighbours				Weighted second order neighbours			
	Median	SD	2.5% CI	97.5% CI	Median	SD	2.5% CI	97.5% CI	Median	SD	2.5% CI	97.5% CI
Prefecture level												
LOC	0.008	0.007	0.006	0.009	0.012	0.004	0.007	0.015	0.021	0.005	0.005	0.009
SUPPLIER	0.004	0.003	0.002	0.005	0.003	0.001	0.002	0.005	0.002	0.001	0.001	0.005
CONSUMPTION	0.025	0.009	0.011	0.038	0.017	0.012	0.013	0.021	0.036	0.008	0.017	0.039
IPP	0.499	0.074	0.323	0.674	0.461	0.067	0.312	0.609	0.501	0.057	0.372	0.663
ENTRY	0.013	0.078	0.009	0.017	0.013	0.022	0.008	0.017	0.023	0.016	0.009	0.027
GROWTH	-0.002	0.002	-0.004	0.000	-0.003	0.001	-0.005	0.0001	-0.003	0.001	-0.004	-0.0002
SUBSIDY	-0.002	0.009	-0.017	0.014	-0.002	0.008	-0.016	0.013	-0.002	0.009	-0.018	0.014
RD	0.478	0.209	0.301	0.655	0.441	0.275	0.303	0.576	0.145	0.253	0.354	0.617
Intercept	-1.718	1.006	-2.431	-1.004	-2.029	1.012	-2.325	-1.732	-1.215	1.007	-2.221	-1.009
σ_u	0.296	0.197	0.145	0.449	0.456	0.257	0.161	0.752	0.319	0.125	0.152	0.638
σ_v	0.335	0.117	0.164	0.564	0.336	0.105	0.175	0.557	0.309	0.106	0.157	0.541
DIC	601.287				584.342				554.472			
Provincial level												

LOC_P	0.009	0.004	0.007	0.011	0.01	0.005	0.008	0.011	0.019	0.004	0.005	0.01
SUPPLIER_P	-0.002	0.002	-0.005	0.001	-0.002	0.002	-0.004	0.000	-0.004	0.001	-0.003	-0.001
CONSUMPTION_P	0.126	0.107	0.114	0.139	0.129	0.109	0.114	0.146	0.129	0.108	0.114	0.144
IPP_P	0.533	0.146	0.395	0.67	0.536	0.156	0.405	0.667	0.679	0.158	0.453	0.625
ENTRY	0.005	0.003	0.003	0.007	0.005	0.003	0.003	0.006	0.005	0.003	0.003	0.007
GROWTH	-0.277	0.051	-0.384	-0.173	-0.258	0.053	-0.364	-0.157	-0.37	0.049	-0.373	-0.169
SUBSIDY	-0.026	0.039	-0.096	0.043	-0.016	0.036	-0.081	0.050	-0.026	0.037	-0.088	0.048
RD	0.347	0.431	0.213	0.472	0.339	0.442	0.208	0.481	0.306	0.399	0.232	0.491
PATENT	0.411	0.527	0.277	0.573	0.407	0.518	0.269	0.571	0.413	0.534	0.272	0.575
Intercept	-0.534	1.081	-0.867	-0.207	-0.543	1.083	-0.869	-0.218	-1.951	1.076	-0.861	-0.202
σ_u	0.806	0.016	0.57	1.044	1.514	0.115	0.831	2.198	1.429	0.127	0.809	2.127
σ_v	0.267	0.036	0.261	0.296	0.288	0.041	0.265	0.292	0.267	0.039	0.263	0.295
DIC		583.112				519.791				483.297		

5 Conclusions

In this study, we have investigated how localisation economies and IPRs protection affect entrepreneurship by employing multi-level Bayesian analysis and taking spatial random effects into consideration. The study is among the first to examine the effects of localisation economies within the framework of the IPRs institution in China by highlighting the roles of administrative hierarchies and geographical space. Using official data from 2008 to 2017 provided by the State Statistical Bureau of China, we found that localisation economies and IPRs protection are good predictors of entrepreneurship. Regarding localisation economies, links to suppliers and consumers at prefecture level play a significant and positive role in shaping entrepreneurship, while supplier linkages are insignificant at provincial level. IPRs protection, can positively impact on entrepreneurship at both prefecture and provincial levels, but the mechanism is stronger at provincial level. The multi-level NB model and the multi-level random parameters NB model were applied to compare the fitness performance against that of the simple NB model, and we concluded that multi-level and random parameters models are more suitable than the simple NB model for modelling entrepreneurship with hierarchically structured data. We also examined some control variables and found that patent applications and R&D can significantly contribute to entrepreneurship, whereas the effects of financial subsidies and firms' growth rate are insignificant. The impact of the entry rate becomes significant with the improvement in model performance. In addition, when we introduced spatial factors into the multi-level Bayesian analysis, the effects of these predictors varied over different spatial scales. The positive influences of LOC and SUPPLIER were more apparent at prefecture level than at provincial level, whereas CONSUMPTION and IPP had greater effects at provincial level. Similarly, the control variables also exhibited spatial variations. In addition to the negative effects of GROWTH and SUBSIDY, the positive effects of ENTRY at prefecture spatial scale were greater, while RD and PATENT had more pronounced impacts on entrepreneurship. Taking spatial random effects into consideration helped to avoid the effects of unknown or unobserved predictors that could be inadvertently ignored in the multi-level Bayesian analysis. These results also demonstrate that spatial correlation is a significant factor with regard to neighbour effects.

The results also offer some important policy implications for promoting local entrepreneurship. Our methodology indicates that administrative hierarchies and geographical space play an important role in entrepreneurship. Thus, vertical and horizontal cooperation between government sectors and bodies should be valued in planning and promoting entrepreneurship. The results relating to localisation economies showed that knowledge spillovers and transfers are more likely to occur on small spatial scales, and that unrelated firms cannot form an agglomeration economy, and thus cannot promote entrepreneurship. Therefore, regional governments should implement a clear industrial layout strategy to attract investment, rather than just trying to attract any type of enterprise. The significantly positive effects of IPRs protection highlight the important role that the IPRs institution plays in entrepreneurship, particularly with regard to high-level government policies. Thus, high-level governments should focus on achieving an appropriate balance when allocating IPRs resources within their jurisdiction. In addition, the negative effects of SUBSIDY also suggest potential corruption issues.

In addition to spatial effects, temporal effects may also have an impact on the results. The definition of entrepreneurship refers to a kind of internal strength accumulated by entrepreneurs throughout the process of entrepreneurship after a long period of precipitation to further their progress, which indicates that entrepreneurship may also be affected by temporal considerations. Thus, future studies could consider the effects of relevant issues, as well as testing whether the hierarchical Bayesian spatiotemporal model based on spatial multi-scale joint analysis is better than a single spatial scale type of analysis. One possible approach could involve identifying and adding instrumental variables into the multi-level random parameters NB model to carry out the spatial estimation. Moreover, the instruments used to assess localisation economies and institutional protection should be based on exogenous geographical and historical characteristics of different spatial scales, because they are unlikely to change over time. In methodological terms, future studies could attempt to refine how missing data is dealt with. Although our study employs the Bayesian approach and autoregression formulation to address the problem of missing data, they are not applicable to point data, because further areal statistics and boundary conditions would be needed. Moreover, in dealing with the issue of missing data, our study only highlights neighbouring effects in the estimation of spatial dependency, while inter-level dependencies are not taken into account. Thus, future studies could suggest and try new approaches to address the estimation of missing multi-level spatial data.

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