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Distribution Characteristics of TikTok Vloggers in China and Their Influencing Factors: An Analysis at the Prefecture-Level Cities in China

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Contents

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Abstract: Entrepreneurship is recognized as the engine of innovation and regional economic development, and the link between entrepreneurship and economic geography is well-established. However, it is uncertain whether this connection persists in the context of the digital economy. Despite the growing prevalence of online entrepreneurship in many countries, the field remains under-theorized and spatially blind. Particularly, studies on fully online entrepreneurs (FOEs) are still lacking. Vloggers, referring to 'video bloggers' who create and upload short videos on online platforms, are a typical group of FOEs. This study employs data on TikTok vloggers in Chinese prefecture-level cities in 2023 to unveil the characteristics and influencing factors of their distribution. The results underscore the positive impact of mobile phone user base, talent power, policy, and the negative impact of per capita GDP on the scale of vloggers in a city. This study also reveals that for the highly influential vloggers, the technology power, high-quality amenities, and preferential policy are significantly correlated, while the impacts of the mobile phone user base and talent power become insignificant.

Keywords: TikTok vlogger, distribution pattern, influencing factor, fully online entrepreneur (FOE), digital economy

1. Introduction

Entrepreneurship is recognized as the engine of innovation and regional economic development and has garnered massive attention from scholars, policymakers, and practitioners. While the link between entrepreneurship and economic geography is well-established, it remains uncertain whether this connection persists in the context of the digital economy.

The prevalence of the digital economy has introduced a new dimension to entrepreneurship, creating a wide array of new demands and business opportunities. Meanwhile, online entrepreneurship has the potential to overcome traditional obstacles, such as high initial investment and regulatory barriers (Youssef et al., 2021). As a result, the rise of online entrepreneurship has revolutionized conventional patterns of economic activity and reshaped the economic geography. Despite the growing prevalence of online entrepreneurship in many countries, the field remains under-theorized and spatially blind (Kraus et al., 2019). Specifically, while there is a study on TikTok live-streaming commercial hosts in China (Peng & He, 2021), representing the entrepreneurs interacting both online and in the physical world, studies on fully online entrepreneurs (FOEs) are still lacking. With advances in information and communication technologies (ICT), internet infrastructure, and the widespread use of mobile devices, gaps in the digital environment across regions seem to be narrowing. However, does this mean that different regions have similar opportunities to incubate FOEs? The answer to this question is urgent to contemporary cities but has not been answered yet.

Vloggers, referring to ‘video bloggers’ who create and upload short videos on online platforms, are a typical group of FOEs. They create and upload videos to online platforms to increase their visibility and their follower base. Their activities fit the definition of entrepreneurship, which is defined as involving two key aspects: first, owning and managing a business at one’s own risk, and second, engaging in 'entrepreneurial behavior' by seizing economic opportunities (Sternberg & Wennekers, 2005). More importantly, vlogging can be conducted entirely online, free from geographic constraints. In this study, we focus on vloggers as a representative of FOEs, and aim to quantitatively clarify the distribution of vloggers in Chinese cities and examine the geographic determinants of vloggers. To achieve this objective, we examine the factors suggested by amenity theory and creative class theory, as well as other socioeconomic environmental perspectives.

This study employs data on TikTok (known as Douyin in the mainland of China, the largest online video platform there) vloggers in Chinese prefecture-level cities in 2023. First, visualization and autocorrelation analysis methods are utilized to unveil vloggers’ distribution patterns. Second, fixed-effect models are utilized for exploring the influencing factors of their distribution. The results underscore the positive impact of mobile phone user base, talent power, and preferential policy, as well as the negative impact of per capita GDP on the number of vloggers in a city. A series of rigorous robustness checks are also conducted and validate our primary findings. Third, this study compares the factors for the distribution of vloggers at different influential levels. The results reveal that for the number of highly influential vloggers, the technology power, high-quality amenities, and preferential policy are significantly correlated, while the impacts of the mobile phone user base and talent power become insignificant. Per capita GDP changed from significantly negative to insignificant.

This study contributes to the existing body of literature pertaining to entrepreneurs as well as the creative class in the following ways. First, we fill the gap of FOEs by incorporating vloggers. Second, we refine the existing research by revealing different mechanisms for the distribution of vloggers at varying influential levels. In this way, our empirical findings hold significant implications for policymakers. Cities in different development levels can take strategic steps accordingly, to foster fully online entrepreneurship and leverage the digital economy.

The remainder of this paper is structured as follows. Chapter 2 reviews the literature on the link between entrepreneurship and economic geography, and influencing factors of the distribution of creative class. Chapter 3 provides a general background on the development of short-video platforms and vloggers in China. Chapter 4 demonstrates the distribution patterns of vloggers. Chapter 5 reports the empirical analysis, including data, methodology, and findings. Chapter 6 presents a discussion and conclusions.

2. Literature Review

2.1 The link between geography and fully online entrepreneurship

Entrepreneurship is recognized as the engine of innovation and regional economic development and has garnered massive attention from scholars, policymakers, and practitioners. Traditionally, entrepreneurship research focused primarily on personal factors, with person-related entrepreneurship theory dominating the field for a long time. However, over the past two decades, a shift toward contextual factors has occurred (Zahra et al. 2014; Baker and Welter 2018). Researchers now argue that personal factors can only partially explain entrepreneurship events and that context factors, including geographical attributes, play a crucial role in influencing entrepreneurial activities (Sternberg, 2022). The influences of geographical attributes manifest in various ways, such as through knowledge spillover effects of entrepreneurship (Audretsch and Keilbach 2007, Mueller 2006), the impact of entrepreneurial ecosystems (Alvedalen and Boschma 2017; Stam 2015; Wurth et al. 2021), and the influence of regional-sectoral clusters (Klepper 2007, 2009, 2010). While the link between entrepreneurship and economic geography is well-established, it remains uncertain whether this connection persists in the context of the digital economy.

The prevalence of the digital economy has introduced a new dimension to entrepreneurship, creating a wide array of new demands and business opportunities. Meanwhile, online entrepreneurship has the potential to overcome traditional obstacles, such as high initial investment and regulatory barriers (Youssef et al., 2021). As a result, the rise of online entrepreneurship has revolutionized conventional patterns of economic activity and reshaped the economic geography. It has transformed the connections between online activities and physical spaces to varying degrees. On the one hand, some online businesses remain closely tied to geographical regions. For example, companies like Amazon, Alibaba, Airbnb, and Uber have altered the business model of internet-enabled commerce, allowing individual business owners to more easily access customers, while the flow of physical goods and offline services is reorganized. On the other hand, certain online entrepreneurial activities—such as vlogging, consulting, and education—can operate independently of geographical location.

Entrepreneurship is defined as involving two key aspects: first, owning and managing a business at one’s own risk, and second, engaging in 'entrepreneurial behavior' by seizing economic opportunities (Sternberg & Wennekers, 2005). Vloggers typically create and upload videos to online platforms to increase their visibility and their follower base. Their activities fit the definition of entrepreneurship and can be conducted entirely online, free from geographic constraints. As a result, vloggers are chosen to represent FOEs.

Despite the growing prevalence of online entrepreneurship in many countries, the field remains under-theorized and spatially blind (Kraus et al., 2019). Specifically, while there is a study on TikTok live-streaming commercial hosts in China (Peng & He, 2021), representing the entrepreneurs interacting both online and in the physical world, studies on fully online entrepreneurs (FOEs) are still lacking. Researching the geographic distribution of FOEs can deepen the discussion on how IT has changed geographical space and spatial interactions.

To the best of our knowledge, no study has yet investigated the distribution of FOEs who are minimally constrained by physical locations. Research subjects related to—albeit not the same as—FOEs, include TikTok live-streaming commercial hosts, whose distribution in China is studied by Peng & He (2021). A live-streaming commercial host is an individual or organization that organizes and monitors live-streaming content broadcast via online platforms, primarily for selling products. Although these hosts are active online, their activities are also closely tied to physical locations, particularly areas with concentrated manufacturing factories. In their results, Peng & He (2021) uncover that e-commerce start-up agglomerations, cultural tourism resources, internet and transportation facilities, and natural environmental qualities have a strong explanatory power for the number of live-streaming commercial hosts in Chinese cities. They also found that the impact of technological power is significantly negative. Despite these findings, it remains uncertain whether the same factors apply to FOEs, whose activities are less dependent on physical space.

In general, apart from Peng & He (2021), studies on online entrepreneurs—whether partially connected to or entirely independent from the physical world—are scarce in the existing literature. Specifically, there are almost no empirical studies on the regional determinants of FOEs such as vloggers, a novel group of creative talents.

2.2 Potential factors influencing the distribution of creative talents

A rich body of literature has explored the regional determinants of creative talents. In the literature on economic geography and urban economics, the theories of amenities (Ullman, 1954) and the creative class (Florida, 2002) have been well-established to explain the concentration of creative talents, which drives regional economic development.

The theory of amenities is represented by Ullman (1954), who suggests that amenities surpass traditional economic components, to be more prominent factors in explaining regional population and economic growth in the USA. The definition of amenities has evolved across studies. Early research focused on natural amenities, such as the climate, mountains, lakes, and the sea (Ullman, 1954), which are typically not affected or created by humans (Mulligan & Carruthers 2011). Later studies broadened the concept to represent site- or region-specific goods and services that make certain locations particularly attractive for living and working, encompassing both natural and human amenities. Human amenities refer to things that are influenced by and created by people, such as culture (Mulligan & Carruthers 2011). These two types of amenities include climate, topography, proximity to mountains or coasts, cultivated landscapes, theatres, music halls, public parks, health and education services, public goods and services, and transportation facilities (Ballas, 2013; Nilsson, 2014). These factors have been empirically shown to influence the distribution and migration of creative talents in the knowledge economy (Florida, 2012; Frenkel et al., 2013; Zandiatashbar & Hamidi, 2018). Additionally, the built environment, including transit stations, malls, and parks, has also been found to attract the creative class (Mansury et al., 2012).

The theory of creative class, proposed by Florida (2002; 2012), defines 'scientists, engineers, university professors, poets, novelists, artists, entertainers, actors, designers, and architects' to be creative people, whose occupation are featured by 'the inherent human capacity to create new ideas, new technologies, new business models, new cultural forms, and, really important, entire new industries'. These specialists produce transferrable and useful new forms or designs (Oppert et al., 2023). Florida (2002) asserts that amenities inducive for creative talents' concentration include '3Ts', i.e., technology, talent, and tolerance. He points out that this spatial concentration in urban areas is the result of the local cultural climate, comfort, and technological development. Furthermore, he argues that tolerance and openness towards minorities, such as sexual orientation and place of origin, are factors that attract people to urban areas. Many factors influence the presence of the creative class, but Florida's 3Ts—tolerance, technology, and talent—are still considered key attractions (Cattivelli et al., 2023). On the contrary, there is also empirical evidence to support the idea that the geographical coincidence of diversity, openness, and tolerance does not necessarily attract the creative class (Barzotto & De

Propris, 2019; Haisch & Klöpper, 2015; Zhao et al., 2020). Based on the above, extant empirical research has not reached a consensus.

Meanwhile, empirical evidence shows that classic factors in residential decision-making, such as housing cost continue to be important (Lawton et al., 2013).

At present, most academic research on the distribution of talents in China discusses the geographical distribution of excellent talents at the national and regional levels and the reasons for this from the perspective of human resource geography (Ye, 2000). A review shows that most of the existing studies use qualitative research methods, with few empirical studies (Guo & Yang, 2018). Jiang et al (2005) found that since the 1990s, urbanization has become the main driving force for the concentration of talent. The capacity of higher education in a region is an important variable that affects the growth of talents density, and the combined effect of urbanization and income level is the most important factor in attracting talents. Fang (2014) used principal component analysis and multiple regression statistical methods to conduct an empirical analysis of the factors affecting the distribution of talents among regions within China. The main factors are indicators of economic development, which include the status of economic development, the level of educational development, and the level of urbanization.

Based on the above, we aim to examine the regional determinants of vloggers, a group of FOEs as well as a new creative class that emerged in the era of the digital economy, from the perspective of amenity, 3Ts, and other socioeconomic environments.

3. The development of short-video platforms and vloggers in China

Short video has become the mainstream of online video. Among all online videos in Chinese market, around 80% are less than 60 seconds (Newrank, 2024b). According to the data from China Internet Network Information Center (CNNIC, various year), the number of online short video users in China reached 1.039 trillion, accounting for 97.1% of all online video users and 93.8% of all internet users. This figure rose rapidly from 0.405 trillion in 2015, with an average annual growth rate of 17.4%—higher than the growth rates for all online video user (11.9%) and internet users (6.78%). It is important to note that the data of users for online (short) video indicate all viewers, with vloggers being a subset of this group.

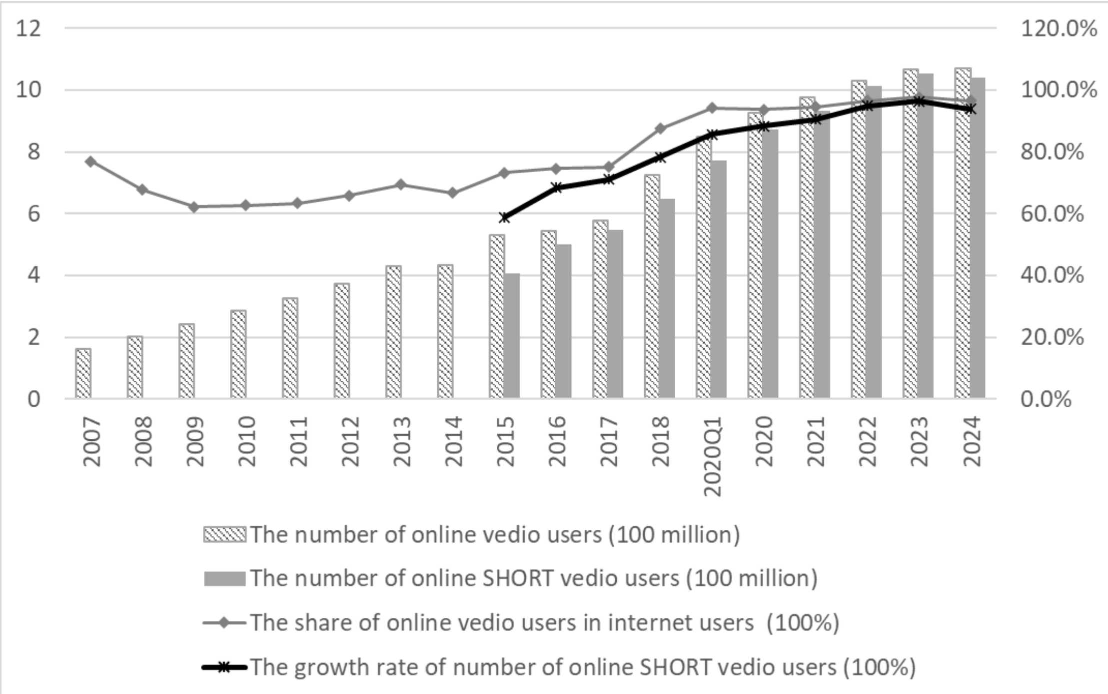


Figure 1. The trend of online video users and online short video users

Source: China Internet Network Information Center (various years)

TikTok is featured by displaying its videos on a vertical screen. Most of its videos are less than 15 seconds and are therefore called *short videos*, although it allows videos up to several minutes in length. The maximum video length is 60 minutes for Douyin and

10 minutes for TikTok overseas. It provides various tools to make video creation easy, such as adding captions, effects, or sounds to the video, and editing clips (splitting, combining, adjusting the speed, etc.). Also, it allows users to various ways to interact with people, such as liking, following, commenting, etc. The best part is its recommendation algorithm. That algorithm utilizes advanced machine learning techniques to accurately analyse users' past reaction patterns, and deliver relevant and personalized content to them accordingly. It is designed to learn from a user’s behavior and preferences over time, allowing it to provide a constantly evolving and engaging experience.

TikTok was launched in China in September 2016 (under the name Douyin, i.e., 抖音) and quickly became popular. It is now the most representative online short video platform in the Chinese market, alongside Kwai (快手), RedNote (小红书), WeChat Video (微信视频号), and others. In China alone, it had a monthly active user base of over 755 million as of April 2024 (Statista, 2024).

Its international version was released in May 2017 under the name TikTok, targeting overseas markets of China. For viewers and content creators, the design, functions, algorithms are basically the same on both Douyin and TikTok, but the two applications do not share data. TikTok’s user base in countries and regions other than the mainland of China reached 1,582 million as of April 2024 (Statista, 2024). It has grown to be the largest online short video platform globally, holding the largest user base worldwide. The top 5 markets are the U.S., Indonesia, Brazil, Mexico, Pakistan as of February 2025 (Statista, 2025).

By 2022, the number of short video creators (the number of accounts that have uploaded short videos) surpassed 1 trillion (OPS-CAPA etc., 2023). Beyond this, data on the number of short video creators, including TikTok content creators, is unavailable. However, some information reveals the profile of TikTok content creators. For example, 51.5% of TikTok vloggers are female (Newrank, 2024a). 22.5% are below 25 years old, 13.9% are in the 25–30 age group, 11.6% are in the 31–35 age group, 10.1% are in the 36–40 age group, 9.0% are in the 41–45 age group, 11.3% are in the 46–50 age group, and 21.7% are 51 years old and above (Newrank, 2024a). Additionally, Figure 2 shows the distribution of TikTok vloggers by their number of followers. The top 5 categories with the highest number of videos are food (14.7% of the total number of videos), home decoration (14.5%), fashion (13.6%), automobiles (6.2%), and mother-infant, child care and parenting (4.9%) (Newrank, 2024a).

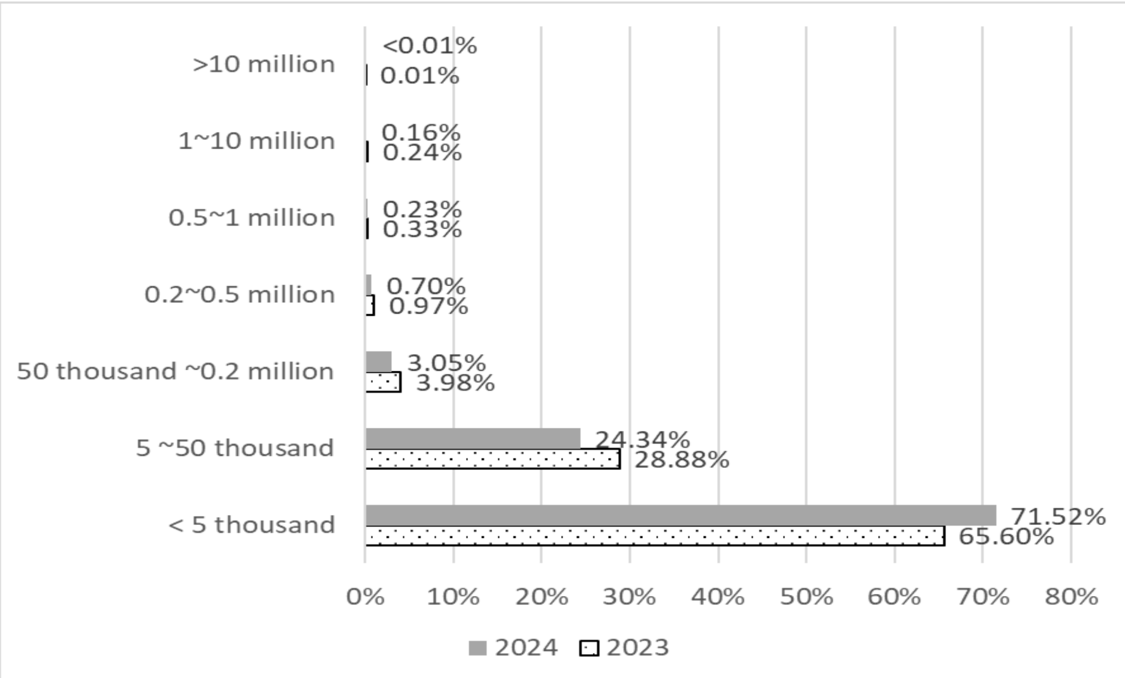


Figure 2. Distribution of TikTok vloggers by number of followers

Source: Newrank (2024b).

Note: the number of TikTok vloggers in each category was calculated based on vloggers who has uploaded at least one video during that year.

4. Analysis on the distribution patterns of vloggers

We used the data of the number of TikTok vloggers in each Chinese city. The information of TikTok vloggers' residences is self-reported by them on the online video platforms. In some cases, vloggers may provide false information about their self-reported city. Despite this possibility, the data can still largely approximate the actual distribution of vloggers. One reason is that the city registered on the online video platform serves as a label for a vlogger, and falsified information could damage their credibility and commercial value. Another reason is that their self-reported city is where they should pay taxes, provided their online income meets the tax threshold. Even if the address is false, the self-reported cities still represent where tax revenues generated by the concentration of vloggers will be directed.

This analysis only includes vloggers who have provided information about their city of residence, excluding all others. Since the app does not mandate users to report residence information, many vloggers have not revealed their city and are therefore not included in our study. Nevertheless, there are still many samples remaining, which are adequate for analysis.

The data on TikTok vloggers are as of October 2023. There are 367 cities included. They include municipalities directly under the Central Government, prefecture-level cities, and counties or cities directly administrated by provinces.

4.1 Descriptive analysis of vloggers' distribution patterns

We compare the distribution of vloggers with different levels of influence, represented by their number of followers. There are a total of 12.059 million vloggers across all levels of influence. The number of vloggers with more than 1 million followers is 28,903, while those with more than 10 million followers' number 667. By region, 42.2% of all vloggers live in the East Region. The Middle and West Regions each have approximately 27%, while the North East Region has only 4% (Figure 3). In the East Region, the share of vloggers with more than 1 million followers increases to 58.0%, and the share for those with more than 10 million followers rises to 66.0%. In the North East Region, the share increases from 4.1% to 6.8% and 6.3% respectively as vloggers' influence levels increase. Conversely, the shares for the Middle and West Regions decline as vloggers' influence levels up. It appears that the more influential vloggers are, the more they tend to be concentrated in the East Region, and to a lesser extent, the North East Region.

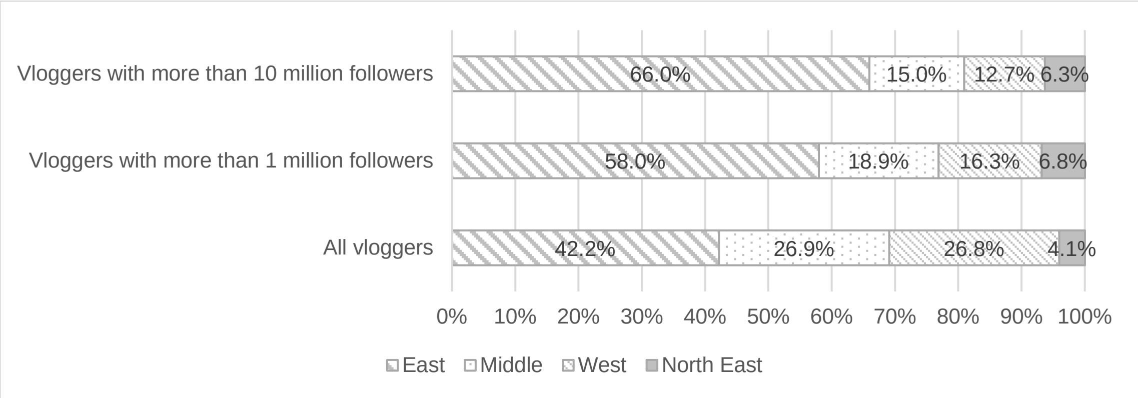
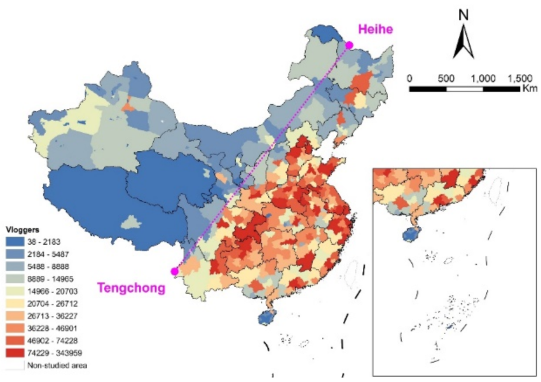


Figure 3. Distribution of vloggers at different influential levels, by region

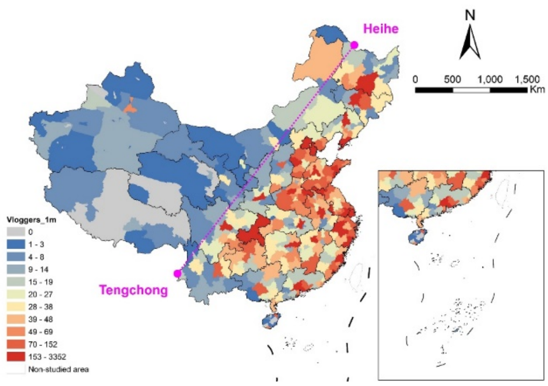
By province, vloggers are mostly distributed in Guangdong, Henan, Jiangsu, Zhejiang, and Sichuan, while Ningxia, Qinghai, and Tibet have the lowest numbers of vloggers. For vloggers with more than 1 million followers, the top three provinces in descending order are Guangdong, Beijing, and Zhejiang. For those with more than 1 million followers, the top three provinces are Beijing, Guangdong, and Zhejiang.

The lists of top 20 cities for all three categories of vloggers are listed in Table 1. The list of top 6 cities for vloggers with 1 million or 10 million and above followers are the same, although they differ from the top 6 cities for all vloggers.

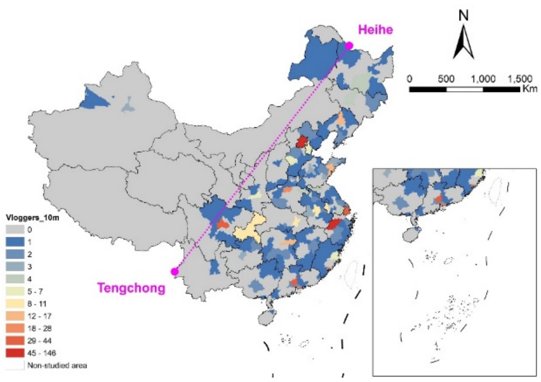
Figure 4 displays the decile maps for vloggers at different influential levels, with (a) for all vloggers, (b) for vloggers with more than 1 million followers, (c) for vloggers with more than 10 million followers.



(a)



(b)



(c)

Figure 4. Decile map of the number of vloggers: (a) all vloggers; (b) vloggers with over 1 million followers; (c) vloggers with over 10 million followers

Table 1. Top 20 cities for number of vloggers at different influential levels

Ranking	All vloggers		Vloggers who have more than 1 million followers		Vloggers who have more than 10 million followers	
	Top 10 cities	Number	Top 10 cities	Number	Top 10 cities	Number
1	Chongqing	343,959	Beijing	3352	Beijing	146
2	Guangzhou	298,466	Hangzhou	1811	Hangzhou	52
3	Beijing	281,399	Guangzhou	1693	Guangzhou	44
4	Shanghai	250,100	Chengdu	1300	Chengdu	39
5	Shenzhen	248,107	Shanghai	1289	Shanghai	38
6	Chengdu	236,026	Shenzhen	1162	Shenzhen	28
7	Hangzhou	193,210	Changsha	773	Zhengzhou	18
8	Zhengzhou	187,765	Chongqing	670	Xiamen	18
9	Xi'an	170,695	Zhengzhou	638	Qingdao	17
10	Suzhou	157,539	Suzhou	494	Shenyang	17
11	Dongguan	136,679	Shenyang	492	Changsha	16
12	Wuhan	129,507	Wuhan	477	Wuhan	11
13	Changsha	129,094	Xi'an	449	Nanjing	11
14	Quanzhou	117,596	Nanjing	434	Chongqing	10
15	Wenzhou	110,458	Qingdao	421	Hefei	8
16	Kunming	109,506	Xiamen	354	Xi'an	7
17	Zunyi	108,016	Hefei	344	Tianjin	6
18	Foshan	104,931	Jinan	298	Fuzhou	6
19	Jinhua	102,889	Haerbin	293	Shijiazhuang	5
20	Hefei	96,143	Tianjin	259	Shangqiu	4

4.2 Autocorrelation analysis of vloggers' distribution patterns

Moran's *I* index is a commonly employed metric for assessing global spatial autocorrelation, by examining whether there are any associations between the locations and the values of a variable. It was developed by Moran (1948) and popularized through the work of Cliff and Ord (1973). For an observation at location *i* with attribute *x*, we have the deviation calculated as $z_i = x_i - \bar{x}$, where $\bar{x}$ is the mean of variable *x*. Moran's *I* index is then expressed as:

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j / S_0}{\sum_i z_i^2 / n} \quad (1)$$

where w_{ij} is the element of the spatial weight matrix, $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all the weights, and *n* is the number of observations. The value of Moran's *I* index ranges from -1 to 1. A positive value indicates that similar cities are spatially clustered, a negative value indicates that similar cities are spatially dispersed, and an approximate 0 value reflects a truly random distribution. Cities are considered adjacent to each other if they share any side or vertex. In other words, the spatial weights of queen contiguity based on order 1 are used in the analysis. GeoDa software is utilized for calculation.

The results are reported in Table 2. Significant and positive autocorrelation is identified for all vloggers and no significant results are found for the other two cohorts.

Table 2. Global Moran's I index for vloggers at different influential levels

Groups	Global Moran's *I*	Significance level
All vloggers	0.259	0.1%
Vloggers who have more than 1 million followers	0.026	Insignificant
Vloggers who have more than 10 million followers	-0.036	Insignificant

Next, local Moran's *I* index are calculated to identify where similar or dissimilar cities are. This index is invented by Anselin (1995). For an observation at city *i*, its spatially lagged variable representing the weighted average of the neighboring values is:

$$L_i = \sum_{j=1}^{n} w_{ij} \frac{(x_i - \bar{x})}{\sqrt{\sum_{j=1}^{n}(x_j - \bar{x})^2/n}} \cdot \frac{1}{n} \quad (2)$$

where $\bar{x}$ is the mean of variable x, w_{ij} is the element of the spatial weight matrix, and *n* is the number of observations.

The results reveal that, in terms of the number of vloggers and their agglomeration, city hierarchies deviate from the traditional urban hierarchical structure in China. While the three traditional economically developed regions—Beijing-Tianjin-Hebei region, Yangtze River Delta, and Pearl River Delta—maintain a strong presence, some inland agglomerations have also emerged, including cities around Chongqing (i.e. cities along the borders of Sichuan Province, Guizhou Province, Hubei Province, Shaanxi Province and Chongqing City), and in the middle of Henan Province.

Table 3. Local Moran's I result for vloggers

High High Clusters	
Province	City
Tianjin	Tianjin
Hebei	Langfang
Henan	Kaifeng
Henan	Pingdingshan
Henan	Xuchang
Shanghai	Shanghai
Zhejiang	Huzhou
Zhejiang	Jiaxing
Zhejiang	Shaoxing
Jiangsu	Nantong
Jiangsu	Jiangsu
Jiangsu	Taizhou
Shaanxi	Ankang
Hubei	Enshi
Hubei	Shiyan
Sichuan	Dazhou
Sichuan	Luzhou
Guizhou	Tongren
Guizhou	Zunyi
Guangdong	Dongguan
Guangdong	Foshan
Guangdong	Guangzhou
Guangdong	Huizhou
Guangdong	Shenzhen
Guangdong	Zhongshan

Low High Outliers	
Province	City
Sichuan	Guang'an
Sichuan	Neijiang
Sichuan	Ziyang
Sichuan	Suining
Hunan	Xiangxi
Guangdong	Qingyuan
Guangdong	Shaoguan
Hubei	Shennongjia

High Low Outliers	
Province	City
Heilongjiang	Haerbin
Gansu	Lanzhou
Liaoning	Shenyang
Xinjiang	Wulumuqi

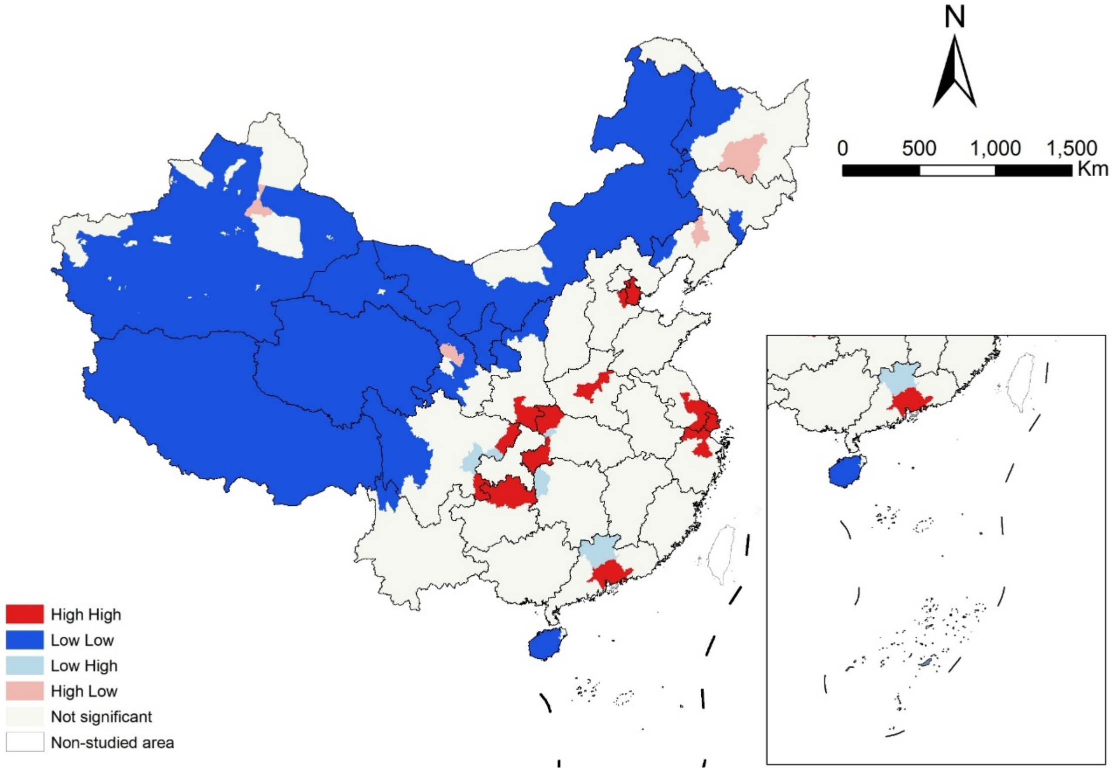


Figure 5. Analysis result of Local Moran's *I*

5. Analysis on the influencing factors of vloggers' distribution

5.1 Data and variables

Table 4 displays the descriptions and summary statistics of the variables.

Independent variables are generated based on the number of TikTok vloggers in each Chinese city. They include the logarithm of the number of vloggers at different influential levels, encompassing all vloggers (*VLOGGERln*), vloggers with more than 1 million followers (*VLOGGER1mln*), vloggers with more than 10 million followers (*VLOGGER10mln*). There is also a variable representing the number of vloggers per 10,000 population (*PVLOGGER*).

The dependent variables are a year prior to the independent variable, that is, in 2022, unless otherwise specified. First, we include a series of variables to represent '3T' power of the cities. They include the technology-power variables represented by the number of inventions (*INVENT*, *PINVENT*), the talent-power variable represented by the population's average years of schooling (*AASCH*), the openness variables represented by foreign trade dependence (*FTD*) and whether the city had a high-speed railway station in operation (*HSR*).

Next, a series of variables are included to represent urban amenities, which include medical amenities such as hospitals (*Hosp3A*, *PHosp3A*), cultural amenities such as museums (*MUSEUM*, *PMUSEUM*), felicities for the aged (*AGEDBEDln*, *PAGEDBED*). Among these amenities, the variables for hospitals represent both the best levels of amenity and the total supply of hospital beds. Specifically, the variable *Hosp3A* represents the number of tertiary hospitals—i.e. San Jia Yi Yuan in Chinese—the highest level according to Chinese hospital classification, while *PHosp3A* indicates the average number of tertiary hospitals per 10 million population.

The variables related to natural amenities include *GCOVER*, which represents the proportion of green space in the city, and *AQG*, which represents the air quality.

Other variables include economic factors such as per capita GDP (*PGDP*) and average housing price (*HOUSPRln*), to approximate the perspective income level and living cost in a city.

There is also a dummy variable for preferential policy, i.e., China's Big Data Comprehensive Pilot Zone（i.e. ‘Guo Jia Da Shu Ju Shi Yan Qu’ in Chinese）policy. This policy was initiated in 2016. Guizhou Province, Beijing-Tianjin-Hebei region, Pearl Delta Region, Shanghai City, Henan Province, Chongqing City, Shenyang City, and Inner Mongolia Autonomous Region are approved to be the Pilot Zones. For cities in these Pilot Zones, the dummy variable of *POLBIGDATA* is assigned a value of 1; otherwise, it receives a value of 0.

Finally, there are also vlogger-specific variables representing cities’ mobile phone user bases, both in terms of total volume (*MOBILEln*) and average level (*PMOBILE*).

Table 4. Descriptions and summary statistics of the dependent variables and potential determinants

Category	Variable	N	Mean	SD	Min	Max	Definitions and descriptions of the variables
Vlogger	*VLOGGERln*	288	10.081	1.029	7.33	12.75	Logarithm of the number of vloggers
	PVLOGGER	288	76.417	30.308	11.25	167.91	Number of vloggers per 10,000 population
	VLOGGER1mln	288	3.501	1.285	0	8.12	Logarithm of the sum of the number of vloggers with over 1 million followers and one
	VLOGGER10mln	288	0.519	0.789	0	4.99	Logarithm of the sum of the number of vloggers with over 10 million followers and one
Technology	*INVENT*	288	0.234	0.752	0	8.81	Number of patented inventions (10,000 pieces)
	PINVENT	288	2.759	4.811	0.01	40.35	Number of patented inventions per 10,000 population (piece)
Talent	*AASCH*	288	9.299	0.823	6.89	12.21	Average years of schooling for the population aged 15 and over, in 2020 (year)
Tolerance (Openness)	*FTD*	288	18.384	26.288	0.01	205.34	Foreign Trade Dependence Degree (%)
	HSR	288	0.851	0.357	0	1	Whether any high-speed rail station had been opened: 1=Yes; 0= Otherwise
Urban amenities	*Hosp3A*	288	5.951	9.893	0	85	Number of tertiary hospitals (unit)
	PHosp3A	288	12.123	14.166	0	131.56	Number of tertiary hospitals per 10 million population (unit)
	MUSEUM	288	21.122	26.559	1	215	Number of museums (unit)
	PMUSEUM	288	5.020	4.491	0.16	43.68	Number of museums per 1 million population (unit)
	AGEDBEDln	288	9.381	0.973	5.69	11.89	Logarithm of the number of beds in institutions for the aged
	PAGEDBED	288	4.118	2.175	0.26	13.67	Number of beds in institutions for the aged per 100 thousand population (bed)
Natural amenities	*GCOVER*	288	43.158	3.349	30.05	64.64	Green covered area as % of completed area (%)
	AQG	288	85.653	11.163	50.28	100	The proportion of days with good air qualities (%)
Economic factors	*PGDPln*	288	11.143	0.458	10.01	12.46	Logarithm of per capita GDP
	HOUSPRln	288	8.935	0.494	7.64	11	Logarithm of average housing price
Policy	*POLBIGDATA*	288	0.122	0.327	0	1	Dummy variable for the policy of National Big Data Comprehensive Pilot Zone: 1=Yes; 0= Otherwise
Vlogger-specific variables	*MOBILEln*	288	5.989	0.791	3.22	8.40	Logarithm of the number of subscribers of mobile telephones (10,000 households)
	PMOBILE	288	1.176	0.176	0.55	1.94	Number of subscribers of mobile telephones for every person (household)

Sources: Data of *AASCH* is from China's seventh national population census. Data of *FTD* and *POLBIGDATA* are self-collected by the authors. Data of *Hosp3A*and *PHosp3A* are collected from yyk.99.com.cn. Data of *HOUSPRln* are the average housing price of two major online real estate sales platform – anjuke.com and 58.com. Data of other variables are from China City Statistic Yearbook 2023 or provincial-level statistic yearbooks.

5.2 Model specification

We use province-fixed effect models for analysis.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Province_i + \varepsilon_i \quad (3)$$

Y_i denotes the number of vloggers in city *i*. In this study, we utilize *VLOGGERln*, *PVLOGGER*, *VLOGGER1mln*, and *VLOGGER10mln* as proxies for numbers of vloggers. X is the vector of explanatory variables. Additionally, we incorporate province-fixed effects β_2 and $Province$ is the dummy variable for each province. β_0, β_1 and β_2 are unknown coefficients. ε_i is an error term.

5.3 Main results

5.3.1 The significant factors of vloggers' distribution

This section reveals the significant factors of vloggers' distribution and $VLOGGERln$ is utilized as the dependent variable here. Table 5 presents the estimated results using four alternative methodologies. To determine the most suitable empirical methodology, we conduct two statistical tests to choose from pooling regression, random-effect regression, and fixed-fixed regression. The first test is the Lagrangian Multiplier (LM) test, which is performed within the random-effect regression. The null hypothesis for LM test posits that the province effect equals zero. As presented in Table 5, the Chi-square statistic equals 161.78 and rejects the null hypothesis at the 0.1% significant level. This result proves that the province effect is not zero and therefore the pooling regression is unsuitable. The second test is the Hausman test, which is conducted to compare the fixed-effect and the random-effect regressions. The obtained Chi-square statistic is 39.02 and the null hypothesis is rejected at the 0.1% significant level. This finding indicates that the fixed-effect regression is more suitable than the random-effect one. Lastly, a Breusch and

Pagan (BP) test method is employed to detect whether heteroscedasticity exists in the fixed-effect model. The Chi-square statistic is calculated to be 15.41 and we reject the null hypothesis at the 0.1% significant level. This finding underscores that fixed-effect regression using heteroscedasticity robust standard errors is the most appropriate and robust methodology.

Overall, we demonstrate that the mobile phone user base (*MOBILEln*), average years of schooling (*AASCH*), and the dummy of big data policy (*POLBIGDATA*) are positively and significantly correlated with the number of vloggers (*VLOGGERln*).

TikTok platform is designed in a way that content creators can make short videos on smartphones easily. In China, the majority of mobile phones are smartphones in current days unless on very few occasions such as illiterate elderly. So, the mobile phone user base can represent the user base of smartphones, which serves as suitable equipment for video creation and upload. Our result shows that the larger the mobile phone user base, the more vloggers there are likely to be in a city. Specifically, every 1.72 times (the natural number e minus 1, e-1) increases in the mobile users, the number of vloggers will increase by 1.63 times ($e^{0.966}$-1). This proves that mobile phone user penetration and sufficient equipment provide a basis for a city to incubate vloggers.

The other finding is that a unit increase in the average years of schooling results in 21% ($e^{0.192}$-1) increase in a city’s number of vloggers, indicates the significance of the talent power in a city. Video creation is a creative task requiring a certain level of literacy, learning abilities, and knowledge basis. The higher a city’s talent power is, the more its population is likely to overcome the obstacles and start to make videos.

We also find that a city incubates 53% ($e^{0.423}$-1) more vloggers if designated as Big Data Comprehensive Pilot Zones. This implies that such approvals likely create an ecosystem that supports digital innovation and content creation. Governments in these zones typically invest in fostering the development of the big data industry and promoting data sharing within the region (Wang et al., 2023). Other measures include improving infrastructures, organizing events, and encouraging collaborations, all of which contribute to a vibrant digital economy. This, in turn, provides local vloggers with better access to high-quality data, a wider range of business partnerships, opportunities to interact with world-class content creators, and so on

Additionally, per capita GDP is found to be negatively associated with the number of vloggers. More vloggers seem to emerge in less developed cities. This may be explained by the observation that the emerging digital and platform economy provides opportunities for low-educated and marginalized people, among others, to participate as producers in China's creative economy (Lin & de Kloet, 2019). In cities where economic prosperity and job opportunities are limited, individuals can find a new way of living through online entrepreneurship, such as vlogging, due to the digital economy.

Table 5. Estimation results

Variable	*VLOGGERln*			
Model	(1) Pooling	(2) RE	(3) FE	(4) FE_r
MOBILEln	1.057***	0.966***	0.964***	0.966***
	(0.068)	(0.061)	(0.058)	(0.070)
INVENT	0.008	-0.042	-0.045	-0.042
	(0.062)	(0.057)	(0.050)	(0.050)
AASCH	-0.163***	0.192***	0.146***	0.192**
	(0.047)	(0.047)	(0.044)	(0.058)
FTD	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
HSR	0.051	0.034	0.030	0.034
	(0.079)	(0.058)	(0.058)	(0.073)
Hosp3A	-0.001	-0.003	-0.002	-0.003
	(0.005)	(0.004)	(0.004)	(0.003)
MUSEUM	-0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
AGEDBEDln	0.058	0.060	0.063	0.060
	(0.040)	(0.038)	(0.036)	(0.048)
GCOVER	0.024**	0.011	0.012*	0.011
	(0.008)	(0.006)	(0.006)	(0.006)
AQG	-0.000	-0.001	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)

Variable		VLOGGERln		
Model	(1) Pooling	(2) RE	(3) FE	(4) FE_r
HOUSPRln	0.185	0.136	0.173	0.136
	(0.095)	(0.099)	(0.092)	(0.106)
POLBIGDATA	0.132	0.423	0.308	0.423***
	(0.086)	(0.303)	(0.195)	(0.114)
PGDPln	0.226**	-0.260***	-0.201**	-0.260*
	(0.087)	(0.074)	(0.072)	(0.108)
Constant	-0.505	3.150**	2.472**	3.207**
	(0.990)	(0.982)	(0.927)	(1.035)
Province-fixed effects	YES	YES	YES	YES
N	288	288	288	288
R^2	0.838	0.868		0.939
LM test	Chi2(01) =161.78***			
Hausman test	Chi2(14) =39.02***			
BP test	Chi2(1) =15.41***			

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.3.2 Robustness check

We perform robustness checks on our key findings.

First, we utilized the spatial regression method to detect the potential associations between the factors and the number of vloggers. Since we found significantly positive—albeit minor—autocorrelation for vloggers' distribution (with a Global Moran' *I* of 0.259, significant at the 0.1% level, as shown in Table 2), the spatial regression method is suitable for the analysis. To construct the spatial weight matrix, we first use the queen contiguity method (QC weight), where cities that share either a boundary or a vertex are considered proximate to each other. We also use the inverse distance method (ID weight), which resorts to the inverse of the distance to each city ('amount of proximity') when assigning weights.

We conduct the Lagrange Multiplier (LM) Test to choose the appropriate spatial regression model and present the results in Table 6. While using QC weight, the estimated value of LM-Error is statistically significant, while LM-Lag is insignificant, indicating that the spatial error model (SEM) is an appropriate strategy. When using ID weight, although both sets of the LM-Error and LM-Lag are significant, the former is much larger. Juxtaposing these two sets of results, it can be determined SEM strategy is applicable.

The SEM model can be specified as:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Province_i + u_i \tag{4}$$

$$u_i = \lambda W u_i + v_i \tag{5}$$

where λ is the spatial lag parameter, W is the spatial weight matrix, u_i and v_i are the error terms.

Adhering to SEM methodology, we replicate the estimation. We employ the QC weight in Model (6) and the ID weight in Model (7). The estimation results are reported in Table 7. Notably, the significant factors identified in Table 5—mobile user base, talent power, and the big data policy—are also found positively and significantly correlated with the magnitude of vloggers here.

Table 6. Estimation results for the Lagrange Multiplier (LM) Test

Spatial weight method	Queen Contiguity		Inverse Distance	
Test	Value	p	Value	p
LM (lag)	0.005	0.943	20.391	0.000
Robust LM (lag)	1.802	0.179	15.947	0.000
LM (error)	211.062	0.000	259.745	0.000
Robust LM (error)	212.859	0.000	255.302	0.000

Table 7. Estimation results of the spatial errors model

Variable	VLOGGERln	VLOGGERln
Model	(6) SEM_ QC	(7) SEM_ID
MOBILEln	0.979***	0.970***
	(0.063)	(0.062)
INVENT	-0.047	-0.048
	(0.039)	(0.038)
AASCH	0.176***	0.188***
	(0.048)	(0.049)
FTD	-0.000	-0.000
	(0.001)	(0.001)
HSR	0.025	0.044
	(0.065)	(0.065)
Hosp3A	-0.003	-0.002

Variable Model	VLOGGERln (6) SEM_ QC	VLOGGERln (7) SEM_ID
	(0.003)	(0.003)
MUSEUM	0.000	0.000
	(0.001)	(0.001)
AGEDBEDln	0.032	0.048
	(0.043)	(0.043)
GCOVER	0.009*	0.010*
	(0.005)	(0.005)
AQG	0.000	0.001
	(0.003)	(0.003)
HOUSPRln	0.165	0.121
	(0.090)	(0.092)
POLBIGDATA	0.549***	0.463***
	(0.119)	(0.106)
PGDPln	-0.224**	-0.207*
	(0.086)	(0.086)
_cons	2.931***	3.098***
	(0.828)	(0.885)
Coefficient on the spatially correlated errors (λ)	0.702***	3.471**
	(0.116)	(1.076)
Province-fixed effects	YES	YES
N	288	288
Pseudo R squared	0.9353	0.9203
Wald test of spatial terms	Chi2(2)=36.30***	Chi2(2)=10.40**

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Second, we revisit our preliminary findings using an alternative measure of vloggers, ensuring the findings remain unaffected by variations in variable definitions or the estimated forms of the estimation model. The variables are changed from those representing the total scale to the average level. They include the dependent variable representing the number of vloggers, and the independent variables representing the number of mobile phone subscribers, patented inventions, hospitals, museums, and beds in facilities for the aged. We employ a fixed-effect model in Model (8) and SEMs in Model (9) and (10). Model (9) and (10) differ in the method used to generate their spatial weight matrix, with the former using the QC weight and the latter using the ID weight.

The estimation results are presented in Table 8. The results reinforce our main findings that the mobile phone user base, talent power, and policy dummy of a city are positively associated with the share of vloggers in the population.

Table 8. Estimation results for robustness check

Variable Model	*pVLOGGER* (8) FE_r	*pVLOGGER* (9) SEM_QC	*pVLOGGER* (10) SEM_ID
PMOBILE	46.456***	41.733***	44.026***
	(11.932)	(10.716)	(10.404)
PINVENT	-0.388	-0.234	-0.251
	(0.563)	(0.470)	(0.482)
AASCH	11.019**	9.944**	10.628***
	(3.592)	(3.041)	(3.074)
FTD	0.069	0.036	0.049
	(0.083)	(0.072)	(0.076)
HSR	2.986	2.050	3.083
	(3.733)	(3.171)	(3.248)
PHosp3A	-0.009	-0.013	-0.006
	(0.085)	(0.065)	(0.068)
PMUSEUM	0.519*	0.493*	0.534*
	(0.260)	(0.206)	(0.243)
PAGEDBED	1.617	1.060	1.116
	(0.831)	(0.704)	(0.743)
GCOVER	0.381	0.296	0.298
	(0.333)	(0.266)	(0.271)
AQG	-0.032	-0.017	0.020
	(0.177)	(0.160)	(0.174)
HOUSPRln	20.013***	19.007***	16.657***
	(5.467)	(4.713)	(4.806)
POLBIGDATA	16.228***	19.576***	17.719***
	(4.142)	(4.633)	(4.429)
PGDPln	-22.283***	-18.546***	-17.955***
	(6.127)	(5.155)	(4.898)
Constant	-61.221	-75.622	-58.321
	(69.382)	(57.296)	(56.651)
Coefficient on the spatially correlated errors (λ)		0.641***	3.075**
		(0.108)	(1.131)
Province-fixed effects	YES	YES	YES
N	288	288	288
R2	0.735		
Pseudo R squared		0.7239	0.6444
Wald test of spatial terms		Chi2(2)=35.26***	Chi2(2)=7.39**

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 Heterogenous effects

To obtain comparative results for vloggers at different influential levels, we replicate Model (4) FE_r by replacing the dependent variable with the variable of vloggers who have a larger follower base. The thresholds are set at 1 million and 10 million followers, respectively. The outcomes of these estimations are detailed in Table 9. By comparison, some interesting results are yielded.

First, we observe that the impacts of mobile phone user bases and average years of schooling change from significantly positive to insignificant as vloggers' influence increases. The impact of per capita GDP changed from significantly negative to insignificant.

Second, the coefficients of two factors turn from insignificant to significantly positive. They include high-quality amenities (represented by the number of tertiary hospitals, i.e. 'San Jia Yi Yuan' in Chinese, the highest rank in the classification of Chinese hospitals), and technology power (represented by the number of patented inventions). These two findings suggest that, for cities aiming to enlarge their base of vloggers, increasing mobile phone penetration and average education level are beneficial. However, those with more ambitious goals of incubating the most influential vloggers, need to be equipped with high-quality amenities and higher technology powers. Less developed cities may have a higher chance of incubating ordinary vloggers, but are less likely to incubate successful ones.

A third noteworthy finding is related to policy. The dummy variable for China's Big Data Comprehensive Pilot Zone consistently showed significant and positive effects across all three models. The results indicate that the Big Data Comprehensive Pilot Zone can facilitate the incubation of vloggers by utilizing high-quality data and fostering the development of big data industries.

The fourth finding of note concerns those insignificant variables. Both variables representing cities' openness are insignificant, which are the variable of foreign trade dependence and the dummy variable of high-speed railway stations. Although exploring other variables to represent the 'tolerance' of cities in future research might be necessary, our results still provide valuable empirical evidence that these two dimensions of urban openness are not significantly related to the incubation of online content creators. Additionally, no significant results are found for natural-amenity-related variables, including air quality and green spaces in cities. Similarly, housing prices are not found to be associated with vloggers in cities.

Table 9. Estimation results for comparative analyses

Variables Model	VLOGGERln (4) FE_r	VLOGGERW1mln (11) FE_r	VLOGGERW10mln (12) FE_r
MOBILEln	0.966***	1.011***	-0.004
	(0.070)	(0.096)	(0.096)
INVENT	-0.042	0.254**	0.569***
	(0.050)	(0.088)	(0.150)
AASCH	0.192**	0.312***	0.131
	(0.058)	(0.068)	(0.069)
FTD	0.000	-0.002	0.003
	(0.001)	(0.003)	(0.002)
HSR	0.034	0.065	-0.014
	(0.073)	(0.092)	(0.061)
Hosp3A	-0.003	0.014**	0.024***
	(0.003)	(0.005)	(0.007)
MUSEUM	0.000	-0.001	0.002
	(0.001)	(0.002)	(0.003)
AGEDBEDln	0.060	0.000	0.062
	(0.048)	(0.065)	(0.058)
GCOVER	0.011	-0.001	0.000
	(0.006)	(0.008)	(0.010)
AQG	-0.001	0.005	0.004
	(0.003)	(0.004)	(0.004)
HOUSPRln	0.136	0.302	0.074
	(0.106)	(0.170)	(0.178)
POLBIGDATA	0.423***	0.338*	1.091***
	(0.114)	(0.153)	(0.206)
PGDPln	-0.260*	-0.334**	-0.192
	(0.108)	(0.114)	(0.105)
_cons	3.207**	-6.735***	-3.799*
	(1.035)	(1.607)	(1.534)

Variables Model	VLOGGERln (4) FE_r	VLOGGERW1mln (11) FE_r	VLOGGERW10mln (12) FE_r
Province-fixed effects	YES	YES	YES
N	288	288	288
R^2	0.939	0.915	0.768

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6. Discussion and Conclusions

This study delves into the distribution of FOEs and the factors influencing their distribution, with FOEs represented by TikTok Vloggers in China. We have unveiled significant findings. First, this study identifies a distribution pattern among vloggers that deviates from the traditional urban hierarchy in China, demonstrating that the digital economy has created online opportunities for inland cities. Second, this study underscores the positive impact of mobile phone userbase, talent power, and preferential policy, and the negative impact of per capita GDP on the number of vloggers in a city. These results are validated through the FE model and a series of rigorous robustness tests, including the use of alternative variables in FE models and spatial analysis methods. Third, this study compares the factors influencing the distribution of vloggers at different influential levels. The results reveal that, for highly influential vloggers, the technology power, high-quality amenities, and preferential policy are significantly correlated with their numbers in cities, while the effects of mobile phone user base and talent power become insignificant. The impact of per capita GDP changes from significantly negative to insignificant.

This study contributes to the existing body of literature pertaining to entrepreneurs as well as the creative class in the following ways. First, we fill the gap of FOEs by incorporating vloggers. Second, we refine the existing research by revealing different mechanisms for the distribution of vloggers at different influential levels.

Our empirical findings hold significant implications for policymakers. The conclusions drawn from vloggers may also apply to other FOEs, including digital nomads, Internet-based freelancers, remote consultants, and others, whose relocation could influence the redistribution of technologies and innovations across regions.

The findings suggest that cities follow two distinct patterns in the vlogger incubation process, each linked to different mechanisms. In economically less developed cities, a larger vlogger pool is likely to emerge, if all other conditions are equal. This pattern may be attributed to the limited job opportunities in these cities, demonstrating how the digital economy can empower less developed cities. To foster this growth, actions such as expanding the mobile phone user base, and increasing the talent power could be effective. Cities can expand their mobile phone user base by providing a larger proportion of the population with access to new IT technologies, through improving communication infrastructures and enhanced signal coverage. Additionally, a larger and higher-quality talent base in a city indicates that more residents possess the knowledge and skills necessary for online entrepreneurial activities. Strategies such as enhancing access to education, promoting adult education, and offering more scholarships could help increase the average educational attainment and support the growth of human resources in cities.

On the other hand, in more developed cities, more influential vloggers are likely to emerge, even though the total number of vloggers is smaller, holding all other conditions constant. Economic prosperity in these cities provides residents with more job options beyond online entrepreneurial activities. As a result, fewer vloggers may emerge, but more top-tier vloggers are likely to appear. Higher technology powers and more high-quality medical amenities help to foster the growth of top-tier vloggers. One reason for this could be that the most creative and innovative FOEs tend to gather in developed cities. Another possibility is that cities with these attributes contribute to the success of vloggers, allowing them to embrace new ideas, increase productivity, and access supportive services and facilities more easily.

Regarding the preferential policy, the provinces and cities that have set up Big Data Pilot Zones are encouraged to firmly and continuously implement their big data development strategies. This is important not only from the perspective of agglomeration of the big data industry, but also from the perspective of agglomeration of new types of creative talents—particularly FOEs—in the digital age.

However, we hesitate to conclude that cities should pursue the aforementioned measures solely for the benefit of vloggers. Rather, the emergence of a larger base of vloggers is more like one of many potential rewards from those measures. Anyway, in less developed cities, investing in improving IT infrastructure, enhancing internet access, and investing in education are crucial for fostering the emergence of FOEs, including vloggers. Similarly, the emergence of influential vloggers in developed cities serves as an added benefit of these cities' overall excellence, especially due to their high technology power and affluent high-quality medical amenities. In any case, incubating vloggers, as well as other FOEs, is a relatively long-term strategy. The findings of this study can guide policymakers in making informed decisions to foster FOEs and leveraging the digital economy more effectively.

For future research on FOEs, we suggest exploring the impact of job market dynamics, such as the unemployment rates. Second, although the results regarding housing prices are not robust in this study, we recommend that future research investigate other indicators of living or business costs. Additionally, examining other types of FOEs and comparing the results with those of vloggers could yield interesting insights.

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