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# Assessing the Attraction of Cities on Venture Capital From a Scaling Law Perspective

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**ABSTRACT** Cities are centers for the integration of capital and incubators of inventions. Attracting venture capital (VC) is of great importance for cities to advance in innovative technology and business models towards a sustainable and prosperous future. Yet we still lack a quantitative understanding of the relationship between urban characteristics and VC activities. In this paper, we find a clear nonlinear scaling relationship between VC activities and the urban population of Chinese cities. In such nonlinear systems, the widely applied linear per capita indicators would be either biased to larger cities or smaller cities depends on whether it is superlinear or sublinear, while the residual of cities relative to the prediction of scaling law is a more objective and scale-invariant metric. Such a metric can distinguish the effects of local dynamics and scaled growth induced by the change of population size. The spatiotemporal evolution of such metrics on VC activities reveals three distinct groups of cities, two of which stand out with increasing and decreasing trends, respectively. The taxonomy results together with spatial analysis also signify different development modes between large urban agglomeration regions. Besides, we notice the evolution of scaling exponents on VC activities are of much larger fluctuations than on socioeconomic output of cities, and a conceptual model that focuses on the growth dynamics of different sized cities can well explain it, which we assume would be general to other scenarios.

**INDEX TERMS** Venture capital investment, complex systems, urban scaling laws, scale-invariant indicator, growth.

## I. INTRODUCTION

Cities are centers for the integration of capital and incubators of invention, which have created more than 80% wealth [1] and 90% innovation [2] worldwide, mainly due to agglomeration and knowledge spillover effect [3]–[7], and played a crucial role in the development of science, technology, novel business models and culture. Partially due to the knowledge spillover effect and self-reinforcing process, cities with greater creation and higher concentration of both knowledge and capital would be more attractive to educated, highly-skilled, entrepreneurial, and creative individuals [3], [6]–[8], which has long been recognized as positive externalities generated from the increase of urban scale [9], [10].

Venture capital (VC) is a form of private equity financing that is provided by venture capital firms/funds to startups, early-stage, and emerging companies that have been deemed to have high growth potential or which have demonstrated high growth. Venture capital investment activities have been largely an urban phenomenon since its institutionalization around the 1980s [11]. Venture capital investment is usually regarded as the engine of inventions and wind indicator of emerging markets opened up by innovative technology or business model [12], which is of high potential returns, as well as of high uncertainties, risks, and failure rates. Attracting more venture capital investments in an industry is associated with significantly higher patenting rates and

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spurring of innovation [2], [13]. A quantitative understanding of the relationship between urban characteristics and venture capital activities would be important for the development of cities towards a sustainable and prosperous future.

From a physical perspective, the size of population would be the most important attribute as itself is a manifestation of the attraction and maintenance on financial and human capital [3], [14]–[16]. Various superlinear scaling laws have been discovered on socioeconomic related quantities, including gross metropolitan product (GMP), income, the number of patents, severe crime and HIV/AIDS cases, in different countries over different periods of time [14]–[19]. Yet currently, to our best knowledge, there has been no work focusing on urban scaling analysis of VC activities – e.g., whether the amount of VC investment will scale linearly or superlinearly with the urban population size. In addition, another compelling question is to ascertain what types of cities (or even more precisely, which features of urban systems) would attract more VC investments. An intuitive way might be looking at the total amount or the per capita value, yet such commonly used criteria assume the linearity of the system where the ensemble is just a linear sum of all its elements. However, we are well aware that cities are complex systems with nonlinear effects manifested as super- and sub-linear scaling relation with respect to the urban population. In such situations, it would be unfair and inherently biased to compare per capita value; for example, there has been a piece of strong evidence showing that the total weight can be lifted by champion weightlifters is in a 2/3 sublinear relation with their body mass [20], which means that if we compare per capita value, heavier weightlifters will be always underrated on a per capita basis [21]. This suggests that we have to come up with a more objective measurement if there are nonlinear effects in the system.

As the scaling law never appears by accident [22], it can be regarded as a baseline or null model, similar to the criterion of judging who is the strongest weightlifter [21], where the residual relative to the prediction by the scaling law is a more objective and scale-invariant indicator [23], [24]. Such an idea has been developed into a standard measurement named Scale-Invariant Metropolitan Indicator (SIMI) [23]–[25]. From the evolution of SIMI of cities, we can further identify groups of cities with similar performance to reveal possible relationships between cities or even developing modes and dynamics of cities, which can be beneficial to related regional and policy studies.

In this paper, we first look at some basic statistics on the Chinese venture capital industry, and then investigate the quantitative relationship between VC activity (both the number of investments and total investment amount) and the urban size (i.e., population) in China over roughly the last two decades. In particular, we identify a nonlinear scaling relation between them, which is a manifestation of emergent behavior of complex systems from general micro-level interactions among the system's constituent units [21]. The scaling exponents of VC activities are growing over time, and they larger than the ones of GMP (Gross Metropolitan Product) of cities in the last decade, which suggests that venture capital activities are more complex phenomena as indicated by recent advances [17], [26] and have a higher concentration in larger cities. Furthermore, we take the scaling relationship as a baseline to make a more objective evaluation on the attractiveness to venture capitals by exploiting the Scale-Invariant Metropolitan Indicator (SIMI) [23], [24] that controls the nonlinear size effect induced by agglomeration and ensuing nonlinear interactions between individuals. Different from the evolution of SIMI on GMP which is quite stable over decades, the evolution of SIMI on venture capital activities are undergoing larger fluctuations, and there are three groups of cities identified through their evolution patterns, two of which stand out with increasing (investment-enhancing cities) and decreasing trends (investment-declining cities) over decades, respectively. The gaining or losing momentum on attracting venture capital might reflect the impacts of local policies on attracting investment which still require further detailed investigation and we assume it also manifests a process of forming order and hierarchy in a not yet mature market. In addition, we also notice that though scaling laws hold over time, the scaling exponents of VC activities are changing non-trivially in past decades which can be explained via different growth dynamics of cities by a conceptual framework proposed by us, which are important for better understanding the indications of urban scaling laws. We assume that such a conceptual model would be general to other scenarios, including the evolution of scaling exponents on traffic congestion [27], built-up areas, the volume of urban road networks, electricity consumption [19].

## II. LITERATURE REVIEW

Since the proposition of urban scaling theory, it has been regarded as promising of developing into a unified quantitative theory that underpins the science of cities [21]. Scaling laws on cities state that the urban quantities $Y$ would be in a simple form with urban size (usually indicated as population $P$) as $Y \propto P^{\beta}$, where $\beta$ is the scaling exponent. Studies on urban scaling have been largely inspired by the scaling analysis in biological systems [21], Bettencourt *et al.* first systematically reveal the scaling laws on cities on various urban quantities across countries [14]. The scaling exponent falls into three categories: Linear scaling $\beta \approx 1$ for basic human needs; sublinear $\beta < 1$ for infrastructure related variables, which indicate the economies of scale; and superlinear $\beta > 1$ for socioeconomic related quantities, which signifies increasing returns to scale and reflects unique social characteristics with no equivalent in biological systems [14]. For example, the number of patents [3], crime, gross metropolitan product (GMP), income all scale superlinearly with the urban population [28]. Recent advances indicate that for more complex socioeconomic phenomena, $\beta$ is larger [17], [26], which can be explained from the complexity of activities and the cultural evolution. Such scaling laws have been verified on various urban quantities across continents, e.g., USA [14], countries in Europe [29]), China [24], India [30], and Brazil [31].

There are a few works looking at the investment related topics from an urban scaling perspective. Finance *et al.* looked at foreign direct investments in French cities, where the number of employment in every foreign-controlled establishment scales superlinearly with the urban population, while the number of employment in every new transnational investment scales sublinearly when considering those valid zero values (i.e., some cities host no new investment over the past a few years) [32]. Bettencourt *et al.* first revealed the superlinear scaling relation between the number of patents and the urban population [3]. The spurring effect of VC investments on patenting rate has been verified in the North American market [2], [13], but is still not systematically tested in the Chinese market. To our best knowledge, there has been no work looking precisely at the venture capital investments from an urban scaling perspective.

It is quite astonishing to discover such simple scaling relations behind complex urban systems. Over the past decade, there have been several important mechanistic models that try to open the black box of urban scaling. Bettencourt proposed that the nonlinear interactions between urban residents are the reason behind superlinear scaling on economic related quantities [15], which is supported by a hierarchical fractal transportation network that can reach every individual in the city. Gomez-Lievano *et al.* proposed a theory that unifies models of economic complexity and cultural evolution, which reveals that complex phenomena that require more factors will manifest a larger superlinear scaling exponent and larger variance across similar sized cities [17]. Li *et al.* unified urban scaling laws across cities and spatial scaling laws within cities from the interplay between spatial attraction and spatial constraint in a mechanistic dynamic growth model [16]. By exploiting geocoded microdata from Swedish population registers, Keuschnigg *et al.* pointed out that the differences in local population composition on education and cognitive ability, which is fueled by migration from smaller to larger cities, explains half of the superlinearity [33] which was mainly attributed to nonlinear interactions due to increases in social interconnectivity. Explaining the origins of urban scaling laws via mechanistic models is still an important topic of urban science.

The paradigm of urban scaling laws has an ambition of predicting an averaged growth trajectory of individual cities when they gain in population by assuming cities as self-similar scaled versions of an idealized one [14], [21]. Recently, the evolution of scaling exponent and its interpretation, as well as implications, have become a hot topic. Strano *et al.* discovered that rich and poor countries in Europe have different urban scaling exponents when looking at the GMP [34]. Rich west EU cities are relatively stable over time with an almost constant scaling exponent, which is close to 1. However, the scaling exponents of post-communist cities are almost always increasing from the year 2005 to 2010 [34]. Depersin *et al.* revealed that, though the urban scaling law on traffic congestion in American metropolitan areas holds over time, the scaling exponents are changing nontrivially. Their results pose challenges on the use of cross-sectional urban scaling laws to predict longitudinal growth of individual cities [27]. Similar discoveries on a variety of urban quantities have been made by Xu *et al.* on Chinese cities at almost the same time [19]. Evidences from Swedish cities showed that the exponent of longitudinal scaling on the average wage is much larger than its counterpart of cross-sectional scaling ($1.094\pm0.002$ v.s. $1.039\pm0.008$) after controlling several important aspects of socioeconomic changes [8]. Still, the relation between longitudinal and cross-sectional scaling is under hot debate [19], [35], [36].

## III. RESULTS

### A. DATASET AND PREPROCESSING

We get access to detailed venture capital investment records regarding the Chinese VC industry from the SiMuTong dataset (Zero2IPO Group) [37]. The dataset we purchased is the most authoritative VC industry dataset in China. Each record in the VC investment dataset gives us "the investor, the company that got invested, the registered industry of the company, the registration city of the company, the date of investment, amount, share, stage, and the round of investment".

Before 2018, there were 48,707 investment records in the raw dataset. 1932 noisy records were filtered, which are identical to other records but only with an unknown investment amount. Eventually, 46,775 investment records were adopted in our study. We also convert the investment amount that was in foreign currency into RMB. For simplicity and due to difficulty in getting access to reliable and comprehensive historical exchange rates, we use the exchange rate in the year 2017. Besides, for better consistency, we also map the industry category of the start-up company indicated by the SiMuTong dataset to the one in the Industrial Classification for National Economic Activities of China (ICNEAC, the version is GB/T 4754-2017).

For this study, we remove all records where the registration city of the company that got invested is not in China, which corresponds to 510 records. If the registration city is missing in the raw data, we query it from Qichacha (`www.qcc.com`), which provides comprehensive information of registered companies in China. Still, for 120 records in the dataset, we are unable to get the registration city of the company (only at province level), all of which, interestingly, are registered in Guizhou Province or Jiangsu Province. When connecting the investments with cities, we focus on 276 prefecture-level cities whose population and GMP (Gross Metropolitan Product) data are of high quality over the past two decades. The population and GMP data of prefecture-level cities in our study are collected from the China City Statistical Yearbook. Since the spatial resolution of the location of the company is limited, the city refers to the administrative definition. Note that there are 80 county-level cities that got VC investments, but due to the fact that we do not have access to their

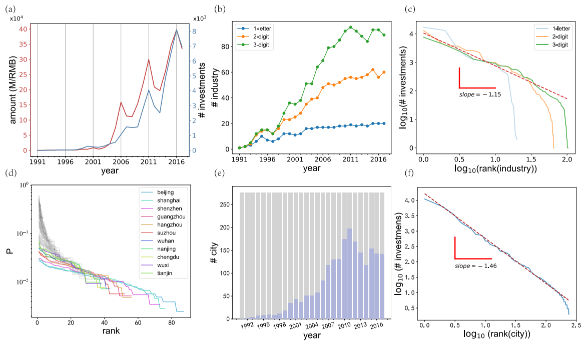


**FIGURE 1.** **Basic statistics of venture capital investment activities in China. (a) The size of annual investment amount (left Y axis) and the number of investment activities (right Y axis) from the year 1991 to 2017, both of which undergo fast increase after 2000, and manifest a roughly five-year cycle. (b) The number of industries got VC investment in each year at successive classification levels according to the Industrial Classification for National Economic Activities of China. At the first level (encoded by 1-letter), there are 17 categories; the second level (2-digit) has 97 categories; and the third level (3-digit) has hundreds of categories. (c) The Zipfian rank distribution on the number of VC investment activities on each industry at successive classification level. $\#investments \propto rank^{-1.15}$ at the third level, which indicates that the top ranking industry receives roughly twice of investments as of the second top ranking one, and triple of the third one, and so on. (d) The rank distribution of industries in each city, where each line represents an individual city, and the rank of each industry within a city is still calculated from the number of investments, and the Y axis corresponds to its fraction in each city. (e) The number of cities that receive VC investments every year (denoted by blue bars), which undergoes a fast increase since 2000. The number of cities that receive no VC investment in the year is denoted by the light grey bar. (f) The Zipfian rank distribution on the number of investments of each city over the past two decades, whose exponent is -1.46.**

population and GMP data over time and they take up a tiny fraction of the investment activities, we exclude these cities from our study, which corresponds to only 298 records in the raw dataset. A descriptive table of the data used in this paper can be found in Supplementary Table 1.

### B. BASIC STATISTICS OF VENTURE CAPITAL INVESTMENT ACTIVITIES IN CHINA

Since the origins of the modern private equity (PE) industry (VC is a type of PE) in 1946, there had been a first boom and bust cycle worldwide from 1982 to 1993 [38]. While in China, VC is still a relatively newly emergent industry. Until 1985, the first Chinese VC firm (the China New-tech Venture Capital Corporation, CNVCC) was established, which was fully-owned by the Ministry of Science and Technology [39]. And the first foreign VC that entered China was IDG in 1992. At very first there were quite a few VC firms and investment activities. The size of the annual investment amount and the number of investment activities undergo fast increase after 2000, and they both manifest a roughly five-year cycle (see Fig. 1(a)). The industry diversity of VC investments gradually reaches the most of first- and second-level industrial categories (see 1-letter and 2-digit classifications in Fig. 1(b)). According to the Industrial Classification for National Economic Activities of China (ICNEAC), there are 17 categories of first-level industry (encoded by 1-letter), 97 of second-level (encoded by 2-digits). There are four levels of classifications in ICNEAC, but due to the limitation on resolution and the nature of the VC investment dataset, the industry category can only be mapped to the third-level of classifications in ICNEAC (encoded by 3-digits). Furthermore, among all categories of industries that got VC investments over the past three decades, we find that the number of VC investment activities in all industries follows the Zipf's law at all three successive classification levels (see Fig. 1(c)) with an exponent approximately equals to -1.15, which indicates that the number of investments of the top ranking industry is roughly twice (more precisely, 2.2 times) of the second top ranking industry, and roughly triple (3.5 times) of the third one, and so on (see Supplementary Figure 1(a) for more details of industries at the third-level classification). While within each city, especially for big cities, their rank distributions on industries are similar, where the rank is calculated from the number of investments in each industry. We can observe that though the ranking of specific industries might vary in different cities, the whole distribution and the slope between big cities are quite comparable. For smaller cities (grey lines in Fig. 1(d)), the number of industries that got VC investments are smaller and the slope is much steeper than in big cities, which means that the top ranking industry in these small cities has a more dominant position (see Fig. 1(d)). The number of cities that have ever got involved with VC investments increase fast over the past decades. Before 2000, only a few (roughly four) new cities were reached by VC investments in each year, while after 2000, it increases much faster (roughly fifteen per year, see Supplementary Figure 1(b) for the cumulative distribution on the number of cities that got VC investments). We assume that the State Council issued Opinions on Establishing a Risk Investment Mechanism in 1999 might trigger the boom in VC investment activities. In addition, China made an important agreement on joining the WTO at the end of 1999, and officially became a member in 2001, which we assume had great impacts on foreign venture capital investments in China, which worth future investigations. Up to 2018, only 22 out of 276 prefecture-level cities have not received any VC investment (see Supplementary Figure 1(b)). In each year, VC activities appear in just tens of cities in the 1990s, most of which are big cities (see Fig. 1(e)). While after 2006, there are more than 100 cities that receive VC investments every year (see Fig. 1(e)). Among all the cities that got VC investments, urban hierarchy exists. The Zipfian rank distribution on the number of investments in cities over the past two decades indicates that most investments concentrate in a few big cities (see Fig. 1(f)). The Zipfian exponent is -1.46 and it means that the top ranking city is roughly three times of the second top ranking city, and five times of the third top ranking city, and so on.

### C. SCALING LAW ON THE VENTURE CAPITAL ACTIVITIES AND EVALUATION ON THE ATTRACTION OF VENTURE CAPITAL

After a glance at the Chinese venture capital industry, we then investigate the relation between the venture capital

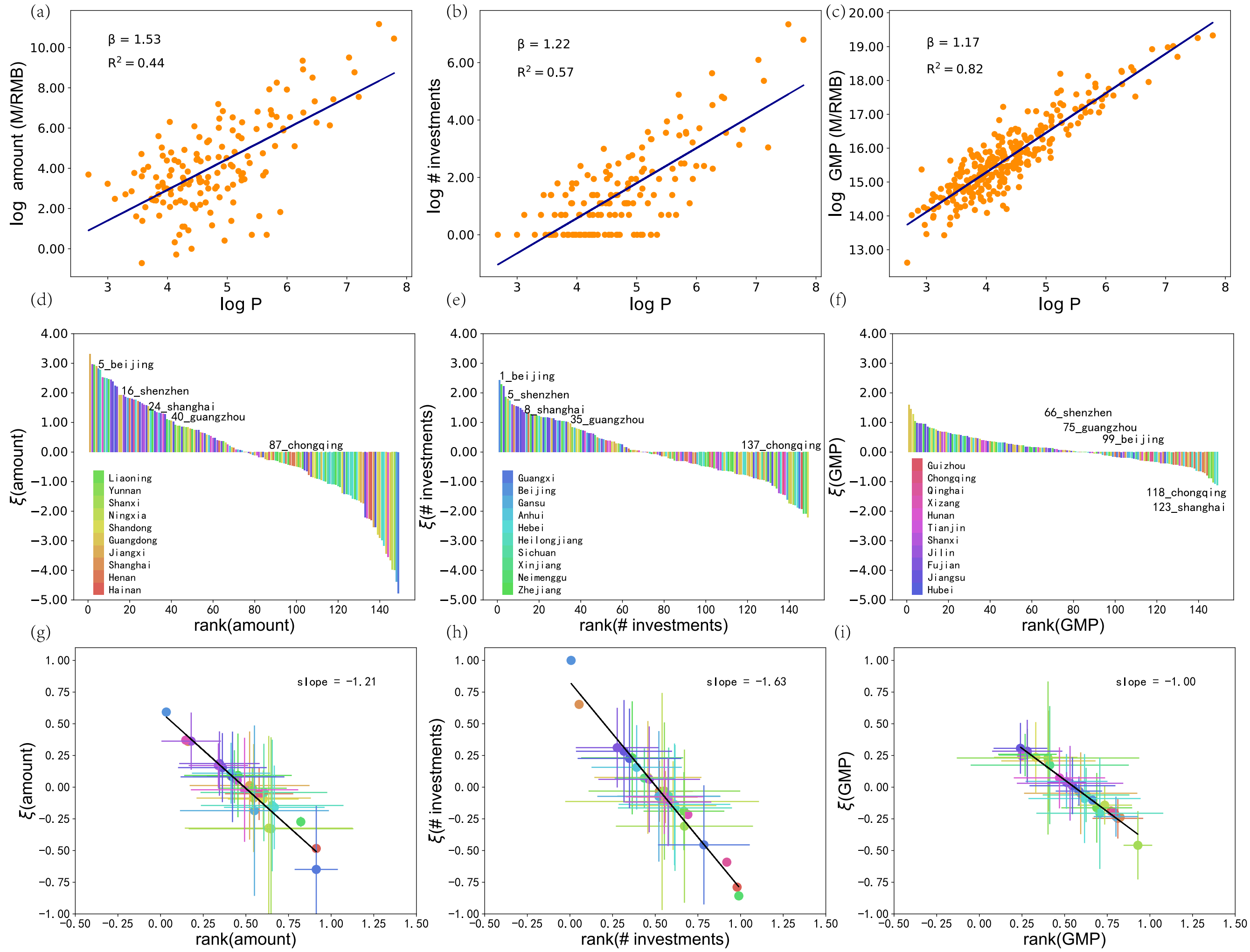


**FIGURE 2. Urban scaling Laws on venture capital activities and the corresponding Scale-Invariant Metropolitan Indicators (SIMI). (a) The total investment amount, (b) The number of investments, (c) Gross Metropolitan Product (GMP) and population for Chinese cities in 2015. The unit of population is 10,000. Each dot represents a city, and the solid line is obtained from ordinary least squares (OLS) fitting from the data. (d-f) The corresponding SIMI plots as of (a-c). Cities are ranked according to their SIMI values. The five largest cities (measured by population) are labeled with the number indicating its rank, and cities in the same province are in the same color. The color legend is displayed in the left bottom of (d-f). (g-i) The corresponding provincial average as of (d-f). The mean and standard deviation (indicated by vertical and horizontal line attached to the node) of normalized SIMI values and ranks, where $\xi_j(t) = \xi_j(t)/\max \xi_j(t)$ and $rank_j(t) = rank_j(t)/\max rank_j(t), j \in [1, N]$. The color coding of (d-f) and (g-i) is the same. We can clearly observe that the difference between provinces are more significant on VC activities (especially on the number of investments) than on GMP, as indicated by a larger absolute magnitude of the slope.**

activities and urban population, and identify a power law relation between measures of venture capital activities $Y$ and population size $P$:

$$Y_i(t) = Y_0(t)P_i(t)^{\beta} e^{\xi_i(t)}, \tag{1}$$

where $Y_i(t)$ is the concerned urban quantity of city $i$ at time $t$ (such as the total amount of investment, the number of investments), $Y_0(t)$ is the intercept characterizing the baseline quantity per capita in the system, $P_i(t)$ is the population of city $i$, $\beta$ is the scaling exponent (or elasticity in the language of economics) which tends to be approximately independent of city size $P_i$, and $\xi_i(t)$ is the residual term. From Fig. 2(a-c), we can observe that venture capital activity (for both of the total amount of investment and the number of investments) scales superlinearly ($\beta > 1$) with respect to urban population size, which exhibits increasing returns to scale and higher concentration in large cities. From the perspective of econometrics, the scaling coefficient $\beta$ that there will be $\beta$ percent of the growth in VC investment induced by one percent of the growth in population [40]. Such scaling laws span several magnitudes, covering small cities with tens of thousands residents to mega-cities inhabited by more than tens of millions. In comparison with the scaling analysis on Gross Metropolitan Product (GMP, see Fig. 2(c)), the scaling exponents of VC activities are much larger (1.53 and 1.22 for the total amount and number of investments, respectively, compared to 1.17 for GMP). While a larger scaling exponent means a higher concentration in big cities, and it might also reflect that the complexity of VC activities are higher [17], [26]. Regressions in our study are performed by using ordinary least squares (OLS), which is adopted after comparing it with sophisticated regression models. Though OLS has a few disadvantages [41], we find that OLS model is the most compatible one with the data over time (see Supplementary Table 2). But it is worth noting that some cities are of zero values (i.e., a city that receives no VC investment, see Fig. 1(e)), and these zero values are valid observations and are as important as those non-zero ones [32], which presents an interesting fact that some cities are not touched by VC investments while many others are. However, OLS cannot handle valid zero values as computing log(0) is impossible. To overcome this problem, we employ a more sophisticated maximum likelihood estimation (MLE) model with Gaussian fluctuations [41], which reveals that the superlinearity always holds over time (see Supplementary Table 2).

As shown in Fig. 2(a, b) and Supplementary Table 2, the system is nonlinear, thus traditional per capita value is not suitable for evaluating the attraction of cities on venture capital, as the per capita value will be biased to larger cities due to the super-linearity effect (i.e., $\beta > 1$). For example, let's assume two cities of population $P_1$ and $P_2$, where $P_2 = 2P_1$, and some concerned quantity $Y$ scales superlinearly with the population (i.e., $Y \propto P^{\beta}, \beta > 1$). Then the per capita value $\langle m_1 \rangle$ of the smaller city would be $\langle m_1 \rangle = Y_1/P_1 = P_1^{\beta-1}$, as for the larger city $\langle m_2 \rangle = Y_2/P_2$. As $Y_2 \propto P_2^{\beta}$ and $P_2 = 2P_1$, so $\langle m_2 \rangle = (2P_1)^{\beta}/(2P_1) = 2^{\beta-1}P_1^{\beta-1} = 2^{\beta-1}\langle m_1 \rangle$. Since $\beta > 1$, averagely speaking, $\langle m_2 \rangle$ will always be larger than $\langle m_1 \rangle$ due to the nonlinear effect, i.e., when the system is superlinear, the per capita value will be inherently biased towards bigger cities; while, if the system is sublinear, then it's biased towards smaller cities. This indicates that per capita value is not objective in making comparisons between entities in a nonlinear system.

As scaling laws reported in Eq. (1) never appear by accidents [22], it can be regarded as an important null/reference model where the deviation from it can be a scale invariant evaluation on the attraction of cities on venture capital. In Eq. 1, $\xi_i(t)$ is the residual term (i.e., the deviation) to the expectation from the scaling relation, where

$$\xi_i(t) = \ln Y_i(t) - \ln Y_0 - \beta \ln P_i(t). \tag{2}$$

An important feature of residual $\xi_i$ are that they are independent of city size $P_i$ and dimensionless, which makes them a great Scale-Invariant Metropolitan Indicators [24] (previously known as "Scale-Adjusted Metropolitan Indicators (SAMI)" [23]) on evaluating the performance of cities. A positive residual ($\xi_i > 0$) signifies over-performance with respect to its population size, while a negative value indicates under-performance. SIMI can separate the growth induced by the increasing of population and by other local policies or features, which allow us to make a direct comparison between any two cities of different size and provide meaningful rankings across the whole urban system. From Fig. 2(d-f), we can observe that though the largest cities are under-performing or having a much lower ranking on GMP (Fig. 2(f)), they are generally over-performing on venture capital activities (Fig. 2(d, e)). This indicates that though their performances on GMP are not that good, big cities still attract more than expected VC investments with respect to their size. For example, Beijing is the top ranking city on the number of investments, but only ranked around 100 on GMP.

In addition, we also look at the average situation of each province whose SIMI is obtained from averaging all its cities on both SIMI values and ranks, which are all normalized by the maximum value in the year (i.e., $\xi_i(t) = \xi_i(t)/\max \xi_j(t)$ and $rank_i(t) = rank_i(t)/\max rank_j(t), j \in [1, N]$). We can observe that the difference between provinces are more significant on VC activities (especially on the number of investments) than on GMP, as indicated by a larger absolute magnitude of the slope (see Fig. 2(g-i)).

### D. THE EVOLUTION OF SIMI AND CLASSIFICATION OF CITIES

In addition, the temporal evolution of scale-invariant metropolitan indicators (SIMIs) on venture capital activities displays larger fluctuations than on GMP (see lighter lines in Fig. 3(a-c), each of which represents a city). A larger fluctuation might indicate a fast evolving phase, while a much smoother temporal evolution also means a long-term memory.

To infer possible connections between cities, the spatial correlation between two cities is a good indicator, which is calculated based on the cosine similarity of their SIMI time series

$$C_{ij} = \frac{\sum_t \xi_i(t)\xi_j(t)}{|\xi_i||\xi_j|} = \frac{\sum_t \xi_i(t)\xi_j(t)}{\sqrt{\sum_t \xi_i(t)^2}\sqrt{\sum_t \xi_j(t)^2}}. \tag{3}$$

$C_{ij}$ takes off size effect and is normalized to [-1,1], where a larger positive value indicates a higher similarity (or a positive relation), and 0 means no correlation, -1 refers to the extreme case of dissimilarity (or a negative relation). Fig. 3(d-f) show the correlation between cities on the time series of the amount of investment, the number of investments and GMP, respectively.

We can further define a corresponding distance matrix $D_{ij} = (1 - C_{ij})/2$, where two cities that are changing in a perfect positive trend (i.e., $\xi_i(t) = a\xi_j(t), a > 0$) will be the closest with $D_{ij} = 0$ (since $C_{ij} = 1$); while for the two changing in a perfect negative trend (i.e., $\xi_i(t) = a\xi_j(t), a < 0$), $C_{ij} = -1$ and their distance will be the longest $D_{ij} = 1$. If two cities are of no correlation (i.e., $C_{ij} = 0$), then the distance between them will be $D_{ij} = 1/2$. Based on the distance matrix $D_{ij}$, we can group cities into clusters with higher similarity (shorter distance) by standard hierarchy clustering algorithm. There are three groups of cities can be identified through their evolution patterns on VC investment activities (see thicker and darker lines in Fig. 3(a, b) and Fig. 3(g, i) for their spatial distribution), and we can observe that all first-tier cities (i.e., Beijing, Shanghai, Guangzhou, Shenzhen) and the majority cities in Yangtze River Delta (comprising the

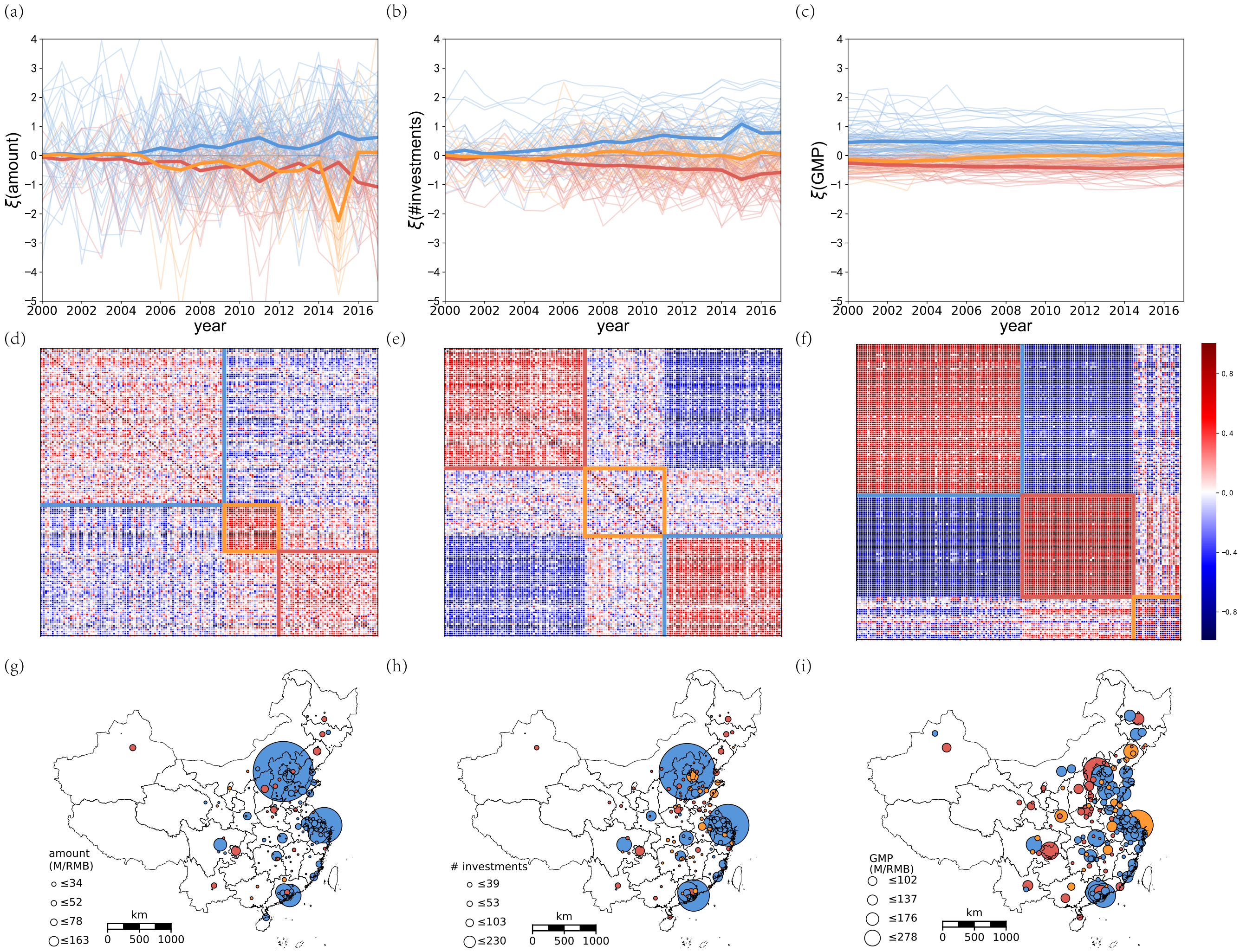


**FIGURE 3. The temporal evolution of scale-invariant metropolitan indicators (SIMIs) on (a) the total amount of investment, (b) the number of investments, (c) GMP from the year 2000 to 2017. The thicker and darker line indicates the average of the group, and each thinner and lighter line represents an individual city, and the color of the line signifies the group classification results. (d-f) The corresponding correlation matrix $C_{ij}$ calculated from the time series in (a-c). Each pixel represents the correlation $C_{ij}$ between city $i$ and $j$, i.e., each row/column stands for a city. Colored rectangle corresponds to a group obtained from standard hierarchical clustering algorithm based on the corresponding distance matrix $D_{ij} = (1 - C_{ij})/2$. (g-i) The spatial distribution of cities in different groups. The size of the circle is proportional to the cumulative value of concerned quantities from the year 2000 to 2017 (i.e., the total amount of investment, the number of investments, and GMP, respectively). Note that the color coding of subfigures is only consistent in each column (e.g., subfigures (a, d, g)), not between columns.**

areas of Shanghai, southern Jiangsu province and northern Zhejiang province) are in the same group. These cities have an increasing over-performance trend on the amount of investment (see Fig. 3(d, g)) as well as on the number of investments (see Fig. 3(e, h)). These uprising groups on the amount of investment and the number of investments have a large fraction of overlapping (with a Jaccard Index equals 0.55, see Supplementary Fig. 2 for more comparisons between clustering results). Generally, there are three groups of cities: investment-enhancing city, investment-stable city and investment-declining city, two out of which stand out with increasing (investment-enhancing cities) and decreasing trends (investment-declining cities) over decades, respectively. The gaining or losing momentum on attracting venture capital might reflect the impacts of local policies on attracting investment which still require further detailed investigation and we assume it also manifest a process of forming order and hierarchy. Generally speaking, tax exemption or reduction, subsidies on VC investment and practitioners training or the establishment of Innovative Industry Incubation Parks are pro-VC investment policy; while, strong and inappropriate interventions (sometimes pecuniary) from the local government and intense information asymmetries would harm VC activities there [42]. In comparison, there is almost no up and down of the average situation on SIMIs of GMP, where three groups are above-, on- and under-average from the prediction of scaling laws for decades, respectively.

In addition, from Fig. 3(g, h), we can clearly observe that over the past two decades, those megacities (such as Beijing, Shanghai, Guangzhou, Shenzhen) received far more investments than other cities (no matter on the total amount or the number of investments), and we find that cities in Yangtze River Delta (comprising the areas of Shanghai, southern Jiangsu province and northern Zhejiang province) and Pearl River Delta (comprised by nine cities including Shenzhen, Guangzhou and Zhuhai) are in a positive relationship and of relatively similar size (indicated by the size of the circle which represents the cumulative value from the year 2000 to 2017), however, the situation in Jing-Jin-Ji region (comprising Beijing, Tianjin and all of cities in Hebei province) is totally different, where Beijing takes an overwhelming dominant position, cities in Hebei province are of much smaller size, and have just an average-performance or even an under-performance with a declining trend on venture capital investments (see Fig. 3(a, g) and Fig. 3(b, h)). In comparison, the differences between cities on GMP in these regions are seemingly relatively smaller (see Fig. 3(i)), while researchers have already gained similar impressions about cities in these regions. For example, Beijing has a strong "siphon effects" over cities in Hebei or even over Tianjian [43], [44]; while between Shanghai and other cities in Yangtze River Delta, where the flows of high-skilled labors are more frequent, there is a stronger spatial spillover effect and coordinated development [6]. In addition, first-tier cities and the majority of cities in the Yangtze River Delta might take advantage of developed transportation infrastructure, including highways, high-speed rails, and convenient air travel, which also play an essential role in facilitating intercity VC inflows [45]. Further comparative analysis might reveal a deeper interacting relationship between cities on venture capital activities in these large urban agglomeration regions, and reveal more fundamental urban growth dynamics. Such regional imbalance on VC investments in Jing-Jin-Ji might harm sustainable urban developments in the future, as city-specific comparative advantages of many cities might not be utilized efficiently. Improving the local business environment, loosening some restrictions of other cities, and promoting inter-city innovation cooperation might be imperative. Instead, the current regional developing blueprint of Jing-Jin-Ji might focus too much on the environmental issues of Beijing and lack considerations on these aspects. In addition, establishing Venture Capital Government Guidance Fund, which is unique in China, to make direct VC investment in start-ups or invest in VC funds in investment-declining cities might also be helpful, which still require careful future investigations.

### *E. THE EVOLUTION OF SCALING EXPONENTS AND ITS EXPLANATION*

Apart from the larger fluctuations of SIMI values over time, we also notice a considerable change in the scaling exponents of VC activities (for both of the amount of investment and the number of investments, see Fig. 4(a)). Compared to GMP, which is relatively stable over time, the evolution of scaling exponents $\beta$ on VC activities are of much larger fluctuations, where the overall trend is increasing and the scaling exponent grows from below one to above one. Such a trend also reveals

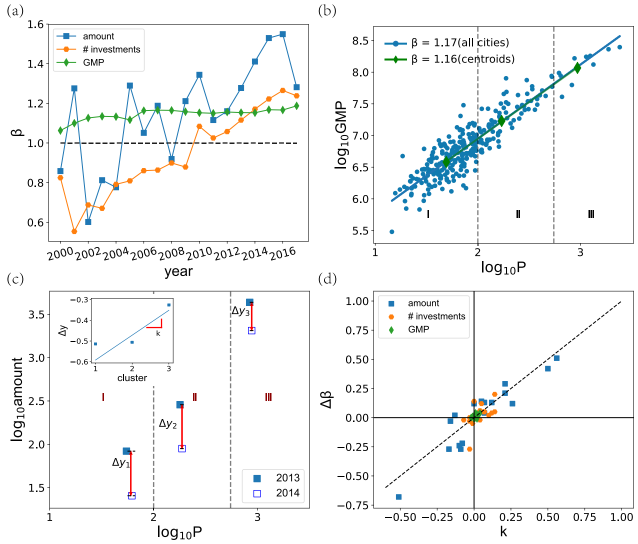


**FIGURE 4. (a) The temporal evolution of scaling exponent $\beta$ on the total amount of investment, the number of investments, GMP from the year 2000 to 2017. $R^2$ of fittings in each year are shown in Supplementary Fig. 3. (b) The scaling exponents estimated from the ensemble of the data and three centroids (denoted as green diamonds) of cities with different size, which is the average of both population and concerned variable. The estimated exponents are quite close. So, when coming to explain the evolution of scaling exponents, we exploit such a centroid view. (c) The dynamic change measured by centroids between two consecutive years on the amount of VC investment from the year 2013 to 2014, where the population growth is relatively small and thus we focus on the difference on Y-axis $\Delta y(t)$s. (inset) The fitting slope $k(t)$ of $\Delta y(t)$s of centroids for groups of cities with different size, where $\Delta y(t) = y(t) - y(t-1)$. (d) Correlation between the change of scaling exponent $\Delta\beta(t) = \beta(t) - \beta(t-1)$ and the slope $k(t)$ on the total amount of investment, the number of investments, GMP from the year 2000 to 2017, where each marker represents the result from two consecutive years. We can observe that most of the data are around the diagonal, which indicates that the growth dynamics of different sized cities can well predict the change of scaling exponent $\beta$.**

that the concentration of venture capital activities in big cities is becoming stronger. Though VC activities reach many small cities over the past two decades (also see the Supplementary Figure 1(b)), the increasing scaling exponent over time indicates that VC firms are making more investments in bigger cities that are at urban hierarchy (or at least maintaining more investments in bigger cities, as we can see in Fig. 4(c) that VC investments might decrease in most cities in the next year). Over the past two decades, the concentration of venture capital in bigger cities is becoming more obvious.

In order to explain the dynamics leading to such evolution, we propose a conceptual model where cities are divided into three groups – small, middle, and large sized cities, and the centroids of each group are regarded as averaged representative [25] (see Fig. 4(b) where larger diamond-shape markers are the centroids, whose value on GMP and population is the average of all cities in each group, respectively). And we find that the scaling exponent estimated from the centroids is in good agreement with the one estimated from all cities (see Fig. 4(b)). So, thereafter, we utilize such centroid representation to explain the change of scaling exponents. We assume that if smaller cities have a larger increase than

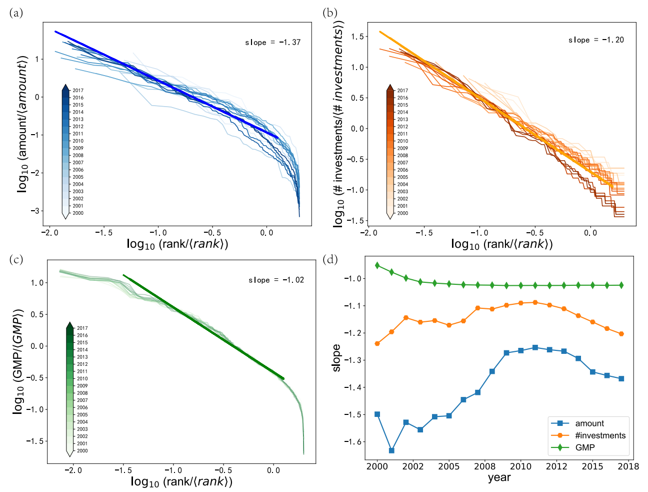


**FIGURE 5.** **Mean normalized Zipf's Law over past decades on (a) the total amount of investment, (b) the number of investments, (c) GMP from the year 2000 to 2017, and (d) the evolution of exponents of Zipfian distribution in (a-c). The average exponent is indicated by the line and value of the slope in (a-c). Corresponding Zipfian plots before normalization are shown in Supplementary Fig. 4.**

bigger cities, then the scaling exponent would decrease in the next year, and vice versa.

In Fig. 4(c), we take the situations of the year 2013 and 2014 on the amount of investment as an example, where the scaling exponent in the year 2014 is larger than the one in 2013 (see Fig. 4(a)). It's worth noting that different from GMP of cities or other common socioeconomic quantities [46], which is usually increasing (i.e., with a positive $\Delta y$ value, where $\Delta y(t) = y(t) - y(t-1)$), the situations for the total amount of investment or the number of investments can be negative, see the example in Fig. 4(c) where the average value is smaller than previous year. In this example, although all cities are decreasing, smaller cities are dropping at a larger magnitude than bigger ones – $|\Delta y_1(t)| \approx |\Delta y_2(t)| > |\Delta y_3(t)|$), so the scaling exponent is still increasing from the year 2013 to 2014 ($\Delta\beta(2014) = \beta(2014) - \beta(2013) > 0$) which is in agreement with a positive slope $k(2014)$ regressed from $\Delta y(t)$s as shown in the inset of Fig. 4(c).

And more importantly, from Fig. 4(d), we find that $k(t)$ can be quite close to the change of scaling exponent ($\Delta\beta(t) = \beta(t) - \beta(t-1)$), this further indicates that the growth dynamics of different sized cities can well explain the evolution of scaling exponents, which we assume would be able to apply to other scenarios [19], [27], [34].

In comparison, we can observe that fluctuations of the exponent of Zipfian distributions (see Fig. 5(d)) are relatively smaller than the cases on scaling law exponents reported in Fig. 4(a). This further indicates that though the growth dynamics of cities can be quite different, yet the hierarchical structure of all cities is relatively stable. The relation between the evolution of Zipf's Law and scaling law requires further investigations. In addition, we can observe that after performing a mean normalization, the Zipfian distributions are well collapsed (see Fig. 5(a-c)). This also indicates that such hierarchical structure is also relatively stable over time and not very sensitive to the size of the whole system.

## IV. CONCLUSION

Though relatively new to China, the venture capital industry has been coming to a booming phase with both the size and diversity increasing over the past two decades. In this paper, we first identify a significant nonlinear scaling law between VC activities and the urban population in China, which is unclear before our study. In recent years, the scaling exponents of VC activities are much larger than the exponents of GMP, which indicates that there is a stronger concentration in bigger cities, and VC activities are of higher complexity as indicated by a larger scaling exponent.

The discovered non-linearity is important for evaluating the urban attractiveness of venture capital, as in such nonlinear systems, the widely applied linear per capita indicators would be biased to larger cities if the system is superlinear, or biased to smaller cities if it is sublinear. So the SIMI of cities relative to the prediction of scaling laws is a more objective and size independent metric, which provides a more meaningful ranking and is able to distinguish the effects of local dynamics and change induced by the change of population size. We find that different from GMP, where big cities are usually under-performance, big cities are usually over-performing on attracting VC investments. Besides, the evolution of SIMIs on VC activities undergoes much larger fluctuations than the case of GMP, which indicates that there is no long-term memory on attracting VC investments. In addition, the spatiotemporal evolution of SIMI on VC activities reveals three distinct groups of cities (investment-enhancing, -declining, and -stable cities), two of which stand out with an increasing and a decreasing trend, respectively. And the taxonomy results also signify different development modes between large urban agglomeration regions. As we can observe that in the Jing-Jin-Ji region, Beijing takes an overwhelmingly dominant position with "siphon effect" over cities in Hebei province and even Tianjian; In comparison, cities in Hebei province are of much smaller size, and have just a normal performance relative to their population size on the number of investments or even under-performance with a declining trend on the amount of investment. While in Yangtze River Delta and Pearl River Delta, cities are generally in a positive relationship and of relatively similar size. Such discoveries would be informative and beneficial to related regional and policy studies. Note that in those large urban agglomeration regions, the administrative boundary of cities fails to capture the ever-increasing inter-city connectivity. A percolation theory based method on defining the city can be more appropriate, as the definition of the boundary of the city has a great impact on urban scaling analysis [47].

In addition, we observe that the scaling exponents of VC activities are changing non-trivially in past decades, with an overall increasing trend and much larger fluctuations compared to the situation of GMP. Explaining the origins and implications of the evolution of scaling exponents, which is still under hot debate, is of great scientific value to develop a science of cities. We find that such evolution can be well explained via different growth dynamics of cities by a conceptual model proposed by us. The idea behind our model is simple: if smaller sized cities have a larger increase (or smaller decrease) than bigger cities, then in the next year, the scaling exponent would be smaller, and vice versa. We find that with the simple measure developed by us, the change of scaling exponents can be reasonably well predicted by our model, which focuses on the growth dynamics of different sized cities. We assume that our model would be general to other scenarios, including the evolution of scaling exponents on traffic congestion, built-up areas, the volume of urban road networks, electricity consummations. In comparison, the evolution of Zipfian distributions are smoother, which indicates that the hierarchical structure between cities is relatively stable over time.

## V. DISCUSSIONS

Apart from human flows, capital flows are fundamental to the development of cities. Yet most of the previous works only focus on the growth of the urban population, thus an important future work would be integrating identified scaling relationships on venture capital into a predictive theory of endogenous (population and economic) growth model of cities. In addition, technology is critical for sustainable urban development, thus the relationship between venture capital activities and patenting, which is regarded as a proxy of technology innovation, in Chines cities worth closer investigation in the future.

It is also of great importance to make comparative analysis across countries with more and more open accessed datasets in the future and study the relation between foreign venture capital investments and local ones, and their impacts on urban development, innovation, and prosperity.

## VI. METHODS

### A. REGRESSION ANALYSIS

In this paper, we employ ordinary least square (OLS) to investigate urban scaling laws, which takes the following mathematical form $y = y_0 x^\beta$. In urban scaling context, we generally write it as the one reported in Eq. (1). The OLS is usually performed on the log-transformed data $\ln y$, $\ln x$, then the parameters $y_0$, $\beta$ are determined as the ones that minimize $\sum_{i=1}^{N}(\ln y_0 x_i^\beta - \ln y_i)^2$, where $N$ is the sample size. After determining the two parameters, the residual term $\xi_i = \ln y_0 x_i^\beta - \ln y_i$. The quality of the fitting is quantified by the coefficient of determination $R^2 = 1 - (\sum_i(\ln y_i - \ln y_0 x_i^\beta)^2)/(\sum_i(\ln y_i - \sum_j \ln y_j/N)^2)$. The fitting agrees better with data when $R^2$ is closer to 1.

Yet, it is worth noting that OLS has a few disadvantages [41], e.g., it cannot handle valid zeros values as computing log(0) is impossible. Still, after making comparisons between regression results with five sophisticated models in the framework of maximum likelihood estimation (MLE) [41], we find that the OLS model, which coincides with the lognormal model with fix fluctuations in the MLE framework, is the most compatible one with the data over time (see Supplementary Table 2). The best model is identified by a p-value higher than 0.05. When none of the models is accepted, then it is judged according to the Bayesian Information Criterion (BIC). BIC$= -2\ln\mathcal{L} + k\ln N$, where $\mathcal{L}$ is the maximum-likelihood of the model, $k$ is the number of free parameters and $N$ the number of observations.

### B. DATA AND CODE ACCESSIBILITY

All data needed for reproducing our analysis are available at `https://github.com/UrbanNet-Lab/Urban\Scaling_VentureCapital/tree/master/data`. The raw data on venture capital investments is purchased from SiMuTong dataset of Zero2IPO Group (`www.pedata.cn`), for which we cannot disclose. The population and GMP data of prefecture-level cities in our study are collected from the China City Statistical Yearbook. Since the spatial resolution of the location of the company is limited, the city refers to the administrative definition. Complemented information of start-up companies can be queried from Qichacha (`www.qcc.com`). The code for reproducing our analysis can be found at `https://github.com/UrbanNet-Lab/UrbanScaling_VentureCapital/tree/master/code`.

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