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Explicit and tacit knowledge have diverging urban growth patterns

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This article utilizes an online job recruitment dataset of more than 4.6 million jobs in China to examine the urban scaling patterns of explicit and tacit knowledge. Knowledge complexity is considered essential for economic development and innovation, and recent studies find complex economic activities of many fields concentrate more in large cities. However, it remains unclear whether the urban concentration tendency would differ by explicit and tacit knowledge, given the latter is often argued as the hard core knowledge more difficult to transfer. We measure explicit/tacit knowledge in job descriptions regarding education/experience requirements. Our analysis reveals that knowledge of different natures differs to a great extent in their property of urban concentration. Specifically, jobs requiring greater explicit knowledge show higher urban scaling rates. This, however, is not true for tacit knowledge, as it demonstrates the exact opposite pattern. Our findings suggest that while cities are centers of knowledge and innovation, the engines of continued growth tend to become more biased towards explicit rather than know-how knowledge.

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INTRODUCTION

It has become increasingly recognized that economic productivity is intrinsically knowledge-related[1–6] and that economic growth essentially comes from the growth and sophistication of knowledge. In particular, recent studies have highlighted the role of knowledge complexity in explaining economic prosperity at both national and subnational levels[4,5,7,8]. Grounded spatially, knowledge accumulates and promotes the growth of productivity largely through aggregation in cities[9]. Ample evidence[10,11] has demonstrated the relationships between urbanization, economic development, and knowledge creation, highlighting superlinear urban scale effects of knowledge-intensive and innovative activities. More recent advances further understand the variation in the scaling rates and find that knowledge complexity is key in explaining varying degrees of urban concentration[12,13]. Complex knowledge tends to concentrate more in large cities, partly due to enlarged specialization[14] and increased atypicality of knowledge combinations[15].

However, given the importance of complex knowledge, it remains a challenge for researchers to understand the urban growth of complexity by considering knowledge of different natures. In particular, just as Michael Polanyi[16] famously noted—We can know more than we can tell – knowledge has long been recognized to differ in its nature and is commonly divided into two fundamental types—explicit knowledge, which is relatively easier to institutionalize, and tacit knowledge, which reflects mental understandings so ingrained and taken-for-granted that it cannot be easily expressed[17–19].

Scholars in the past few decades have carefully distinguished tacit knowledge and explicit knowledge from a variety of aspects[20–22]. Many descriptions of tacit knowledge stresses on its localness. Specifically, it is considered to be a set of historically derived beliefs[23], common practices or strategies for dealing with uncertainty, rather than a set of fixed techniques, rules, or plans[24,25]. Its cultural image is also described as traditional or indigenous[26] or romanticized as against scientific knowledge[24,26]. In this regard, tacit knowledge is often considered as the opposite of expert knowledge[27]. The former is derived from experience. By contrast, the latter refers to technical/professional knowledge based on academic training in school, and thus is also coined as academic knowledge[28]. In terms of acquirement, explicit knowledge can be relatively easily transmitted by reading texts or dialogs[5], whereas tacit or local knowledge can not. Learning tacit knowledge or know-how[14,29]essentially requires participation and doing[19,22,30], through informal acceptance of behaviors and procedures[31], and relies more on local trust[22,32,33]. The table below summarizes these diverse yet associated descriptions of the dual knowledge types (Table 1).

Despite these insightful distinctions, the lack of large-scale data has limited scholars' ability to investigate in detail how the two types of knowledge-tacit and explicit-affect innovation and economic development. However, the absence of extensive research does not imply that this question has gone unnoticed. In fact, tacit knowledge, or know-how, is often highlighted in scholarly discussions[8,34] as a key component for understanding why late-developing countries struggle to catch up quickly in technology and economic development. For instance[14], posits that the growth of tacit knowledge or know-how is more central to development. The classical example often cited is Adam Smith's pin factory, where increased task specialization fuels productivity growth. Meanwhile, the accumulation of explicit knowledge is also occasionally considered a strong indicator of knowledge complexity[12]. Despite the understanding that novel combinations of skills predominantly occur among individuals rather than within them, the social reward system still grapples with the ongoing challenge of properly identifying the value of different types of knowledge in jobs. Specifically, the specialization of labor[35] could theoretically involve specialization in explicit knowledge, tacit knowledge, or both. It remains unclear which type of specialization underlies Ricardian modes of economic development. Consequently, competing hypotheses can be formulated: H1: the Ricardian growth of the economy (namely, through labor specialization) in urban contexts relies primarily on the accumulation and continuous recombination of know-how; H2: alternatively, it relies on explicit knowledge; H3: both have equal importance.

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Table 1. Two knowledge types.

	Terms	Acquisition
Tacit knowledge	Know-how, local knowledge, indigenous knowledge, informal knowledge, implicit knowledge	Doing, Experience, Trust
Explicit knowledge	Expert knowledge, academic knowledge, institutionalized knowledge, scientific knowledge	Academic training, Reading

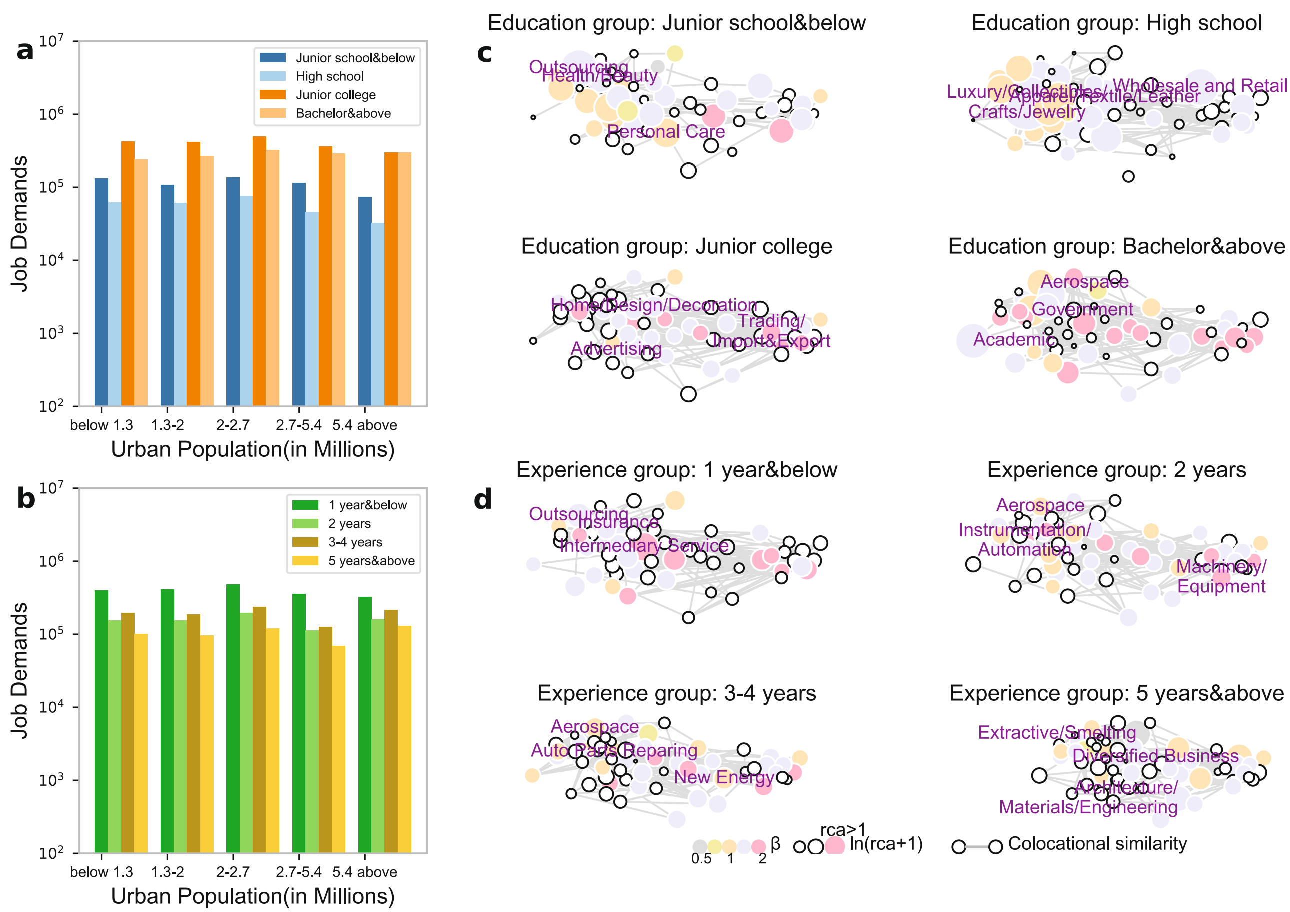

Fig. 1 Distributions of explicit and tacit knowledge. a The distribution of explicit knowledge (education) across different city sizes. **b** The distribution of tacit knowledge (experience) across city sizes. 288 cities are divided into four groups according to population size: below 1.3 million, 1.3–2 million, 2–2.7 million, 2.7–5.4 million, and 5.4 million or more. **c** The distribution of different levels of explicit knowledge across industries. In each educational group, nodes correspond to industries; links between nodes are set according to the collocational similarity between industries (See Supplementary Methods for more details); and node size indicates the revealed comparative advantage of different industries in the group, with empty nodes having RCA less than 1 (See Supplementary Methods). The color of a node is set according to the urban scaling coefficient (β) of each industry. Labeled industries are the most characteristic ones of their group. **d** The distribution of different levels of tacit knowledge in different industries. Nodes are drawn similarly as in **c**.

In this study, we use online recruitment data from more than 4.6 million jobs in China to investigate this question. Following the notion that cities are centers of innovation and economic development, we examine the urban scaling patterns for jobs requiring the two knowledge types at different levels. We measure explicit and tacit knowledge in job descriptions based on education and experience requirements, respectively. Although both tacit and explicit knowledge scale with urban population growth, our analysis reveals that their growth tendencies differ significantly. Complex tacit knowledge tends to decrease the urban scaling rates of associated jobs, while complex explicit knowledge increases the rates. This pattern remains stable regardless of changes in the resolution of observation. Our findings suggest that in larger cities, the concentration of explicit knowledge and a reduced share of hard-core know-how knowledge are more likely to be the dominant drivers of economic growth. In this sense, local knowledge indeed assumes a nonurban character.

RESULTS

Spatial and industrial distribution of explicit and tacit knowledge

We first describe the spatial and industrial distribution of job demands for different levels of knowledge in 288 Chinese cities. On the left panel of Fig. 1a, b the histograms of explicit and tacit knowledge are plotted under different city-size groups. As can be seen, the cumulative amount of knowledge demands clearly differs by the knowledge level. Jobs requiring higher-level explicit knowledge are in greater demand in all city groups. In comparison, jobs requiring higher levels of tacit knowledge are less in demand than

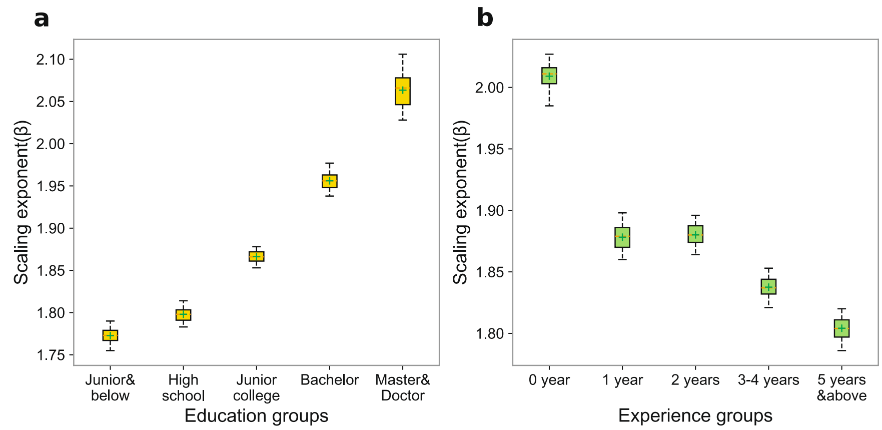

Fig. 2 Scaling of explicit and tacit knowledge (The scaling relationship between urban population and the size of jobs). a Urban scaling of jobs requiring varying levels of explicit knowledge: In the graph, the x-axis represents different education groups, while the y-axis displays the scaling exponent for each knowledge group. Box plots illustrate the median, interquartile range (IQR, as boxes), and 90% confidence interval(as rims) derived from 100 bootstrapping estimations, with each estimation resampling 600,000 job samples for a subgroup (with replacement). **b** Urban scaling of jobs requiring various levels of "tacit knowledge, plotted similarly to **a**.

lower ones in all city groups, reflecting the relative scarcity in demands of tacit knowledge in society.

The right panel of Fig. 1c, d describes a more nuanced structure of the characteristic industries for different levels of knowledge groups, separately by the type of knowledge. In particular, we first obtain the industry networks according to their collocational similarity (Supplementary Methods). Then we compute the revealed comparative advantage of industries with respect to each subgroup and highlight the most characteristic ones with labels. As shown in the figure, for explicit knowledge groups, industries such as hairdressing, personal care, and outsourcing are most characteristic of jobs with simple knowledge, while the most complex jobs are from aerospace, academic, and government-related industries. For tacit knowledge, the lowest level includes insurance and intermediary services, and the jobs that require the highest level of experience are those in fields such as smelting, diversified business, and architecture. These descriptive results are consistent with existing understandings of knowledge complexity in jobs[36–38], yet provide clearer images of the differences based on the nature of knowledge.

Figure 1c, d also displays the relationships between industries under different types of knowledge. A link between two nodes indicates whether two industries have high collocational similarity. It is possible that two industries have similar spatial distributions in one category but different distributions in another, resulting in the presence or absence of links between identical nodes in different categories (i.e., similarity or dissimilarity in geographical distribution). For instance, after classifying jobs according to education and experience level, we found that in the knowledge categories of junior and high school level, the computer services industry has geographic proximity to the automobile manufacturing and real estate industries, as these industries require similar management and operational skills. In knowledge categories of college and bachelor levels, the computer services industry is geographically correlated with industries such as computer software, finance, and telecommunications, as these industries require similar technical and professional knowledge that may be concentrated in specific regions or cities. Such enriched details demonstrate the value of breaking down jobs into knowledge categories and levels for analyzing their spatial distributions.

Urban scaling patterns of complex explicit and tacit knowledge

Urban scaling results can sometimes be sensitive to data size and randomness. To ensure the robustness of scaling patterns, we employ bootstrapping, a resampling method that involves drawing random samples of job post items from the pool to calculate the scaling exponents for knowledge-level groups. In every round, we sample 600,000 items for each subgroup for estimation. We repeat this process 100 times, obtaining 100 estimates for each subgroup. Box plots are used to indicate the confidence interval (90%), interquartile range (IQR), and median of the estimated scaling coefficients, illustrating the distribution and central tendency of the bootstrapped estimates. The results are shown in Fig. 2. As can be seen, for each knowledge group, the recruitment scale has a significant super-linear scaling relationship with the urban population (with R-squares averaging around 0.65). Despite this, when the nature of knowledge is taken into account, we find that the scaling displays a different pattern for explicit and tacit knowledge groups. Specifically, the scaling coefficient increases steadily as the explicit knowledge level increases from Junior School and below ($\beta = 1.77$) to Master degree or above ($\beta = 2.06$), indicating that jobs with higher levels of explicit knowledge tend to concentrate more in large cities. For jobs demanding tacit knowledge, however, the pattern is reversed. The scaling coefficient for the least experienced group (0 Year) is the highest ($\beta = 2.01$), then β drops down to around 1.87 for '1 year' and '2 years', and further down to 1.81 for '5 years or more'. We conducted additional robustness tests with varied sample sizes to confirm the patterns (See Supporting Information).

The divergent patterns of urban scaling are interesting, particularly because complex explicit knowledge and tacit knowledge are often viewed as complementary to each other. To further decompose them, we then control for both education and experience to examine the more fine-grained patterns of job scaling. Jobs are divided into sixteen groups. Just as before, we repeatedly sample data from each group 100 times to obtain robust estimates and compute the mean scaling rates for each group. The results are plotted in Fig. 3. After accounting for the requirement of explicit knowledge, high-experience jobs tend to scale more slowly than low-experience jobs at all education levels. The bottom education group (Junior school or below) shows the greatest downward trend (from $\beta = 1.76$ to $\beta = 1.36$). The scaling exponent in the top education group decreases from 2.03 (least experience demanding) to 1.87 (most experience demanding).

Finally, we investigate more fine-grained scaling exponents separately for 323 types of jobs ranging from 'intern', 'deliveryman' to 'software engineer' and 'financial manager', and use linear regression models to predict the variation of scaling in terms of knowledge levels. For each job type, we assigned values to and then averaged the requirements of education/experience levels in

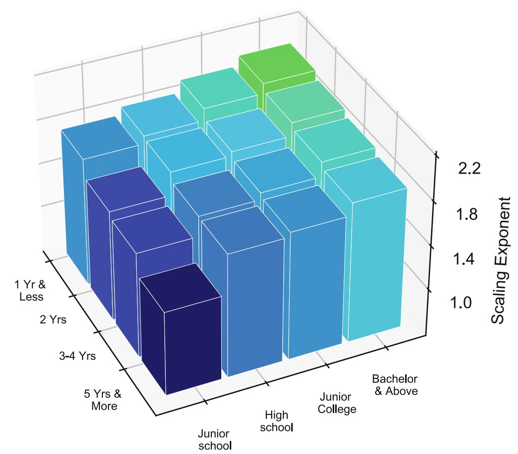

Fig. 3 The scaling relationship between urban population and the size of jobs by groups. Jobs are divided into 16 groups by the requirement of experience and education level. The vertical axis indicates the scaling exponent for each group.

Table 2. Linear regression: effects of knowledge levels (tacit and explicit) on urban scaling exponents of 323 job categories.

Y = urban scaling exponent	Model 1	Model 2
Level of tacit knowledge	−0.133*** (0.013)	−0.167*** (0.015)
Level of explicit knowledge	0.0425*** (0.009)	0.0299** (0.009)
Salary Level		0.0174*** (0.004)
R^2	0.26	0.3
N	323	323

*$p < 0.05$, **$p < 0.01$,***$p < 0.001$ (two-tailed t test).

the posts. Consistent with coarse-grained results, Table 2 shows that the coefficient for tacit knowledge is significantly negative (−0.133, $p < 0.001$), meaning that an increase in the tacit knowledge level will decrease the scaling exponent. By contrast, explicit knowledge shows a positive coefficient (0.0425, $p < 0.001$). A visual demonstration of regression can be found in Supporting Information. The divergent pattern holds after introducing salary level for control. Like in existing studies[39,40], high-income jobs tend to concentrate in larger cities.

DISCUSSION

Much remains to be learned about the concentration of knowledge complexity and its determinants[8]. Our research contributes to the ongoing effort of bridging urban scaling studies, knowledge studies, and studies of economic complexity together for a better understanding of innovation and development. Recent studies of explicit and tacit knowledge have gradually shifted from a pure dualism[41] to highlight the complementary roles for knowledge to work properly in the real context[42,43]. Yet, given that working knowledge is always a complex mixture, it is possible that the process of innovation may drive the two parts geographically apart from each other. This question becomes particularly interesting as scholars find highly-productive individuals become more attracted to large cities[44]. Existing studies, after successful demonstrations of complex knowledge as the key driver of economic development, often treat tacit knowledge (know-how) as more central to economic complexity. Here, we perform an empirical analysis by decomposing the patterns of urban scaling for jobs associated with tacit and explicit knowledge at different levels. We show that although both are essential components of knowledge, their growing tendencies in the urban context may not be consistent with each other.

Our analyses reveal nuanced insights into the urban growth of complex activities. While we confirm that complex explicit knowledge exhibits higher rates of urban scaling, in line with current understandings, our study challenges prevailing assumptions when it comes to tacit knowledge. Contrary to existing wisdom, we discovered that the concentration of complexity does not hold true for tacit knowledge. Specifically, jobs requiring deeper tacit knowledge are found to scale much more slowly than the shallower ones in urban environments, and the pattern also stays significant after we fix the level of explicit knowledge. This means tacit knowledge is likely to take a smaller share as the complex economy grows, especially in larger cities. This result may have important implications for the theory of innovation. It indicates that, innovation, given its combinatorial feature and urban concentration tendency, is likely to hinge more and more on the combination of explicit, academic, and institutionalized knowledge if economic complexity keeps growing and the urban economy continues to scale. It also indicates that larger cities may increasingly distinguish themselves from smaller ones in their composition of System-II thinking and System-I thinking, as they are closely associated with explicit and tacit knowledge[45,46].

There may be several reasons behind the diverging scaling patterns of explicit and tacit knowledge. Although a detailed explanation is beyond the scope of this study, we offer a potential reason. Specifically, the findings might be related to the combinatorial nature of innovation. Previous studies have shown that larger cities exhibit greater diversity of activities[47] as well as more atypical combinations of activities[15]. This increased diversity might not apply as much to jobs requiring higher experience levels, as these workers may be more likely to stay in their current positions for longer periods. In other words, in large cities, economic activities may not only grow faster in numbers but also in the proportion of recombination of knowledge from different areas. While this gives large cities more opportunities for trial and error in innovation, it may also affect the social functioning of experience-based knowledge, as this type of knowledge is more sticky and heavy[48] and thus may be less movable to join the recombination process. In other words, the increase in complexity of this type of knowledge likely requires more time to settle down. As urban centers grow in size and complexity, those with extensive experience may face greater difficulties in adapting their specialized knowhows to the ever-changing landscape, potentially limiting their contributions to the cross-fertilization of ideas and creative problem-solving. In addition, it is possible that our findings are related to the specific industrial and urban structures in China. Although many previous studies of urban scaling have relied on observations of Chinese cities[10,49,50], none have examined the differences in knowledge nature. Therefore, we cannot exclude the possibility that our results are specific to the Chinese context. That said, further research is needed to provide a comprehensive understanding of these dynamics across different geographical and cultural contexts.

METHODS

Knowledge is known to be geographically sticky[12,51], and the presence of activities carries with it the accumulated information about the locational structure of the knowledge associated with those activities[5,48]. In light of this, we propose that the employment structure of a region, particularly the demand for relevant jobs and capabilities, can largely reflect the knowledge structure of the region[12,52–54]. A region's job demands serve as direct indicators of the spatial diversity and density of its knowledge stocks. Comparisons of the demands for various types of jobs between regions with different population sizes can reveal how knowledge tends to scale and concentrate in urban contexts.

Recent findings that small cities tend to follow a common pathway of large cities[55] also support the validity of using scaling methods to understand economic development. Therefore, we explore the general patterns of urban scaling for knowledge of different natures based on a large-scale dataset of online urban job recruitments and examine how the nature of knowledge, city size, and complexity interact with one another.

Data

Our data consists of two parts. The first part comes from an online job recruitment website, Carefree Future, which is currently the largest open online job recruitment platform in China, where companies nationwide can post job vacancies daily. We obtained recruitment posts over a period of 3 months, from December 2021 to February 2022, through web scraping. After cleaning, the collected data contains more than 4.6 million individual posts spanning 61 industries and 332 job types distributed across 284 prefecture-level cities (Supplementary Figs. 1–4. Supplementary Table 2). For each post, we retain key recruitment information such as firm name, firm size, industry, city, salary range, working experience requirements, and education requirements. Additionally, we randomly sampled 120,000 posts to further obtain detailed job descriptions, which we later used to cross-validate our distinction between explicit and tacit knowledge (Supplementary Fig. 12).

Because the job data comes from online websites, it naturally differs from more conventional employment data and may contain a higher proportion of certain job types than others. In response to this issue, we conducted a series of robustness tests by utilizing employment statistics from Chinese statistical yearbooks (Supplementary Figs. 9–11) and testing the results under perturbations of job distributions. We found our findings to be very robust under different kinds of stability tests. Nevertheless, it is necessary to note that some unknown biases may still be present, and therefore the findings may need to be examined using more comprehensive data in the future.

To collect population data, we rely on the most recent national census-China's Seventh Population Census. The results of the census were published separately on each city government website since 2020. We manually obtained files from the websites and then combined them. As some cities did not publish their census results, a final set of 288 prefecture-level cities were obtained. Following Zünd and Bettencourt[49], we consider urban permanent residents (rather than registered population) as a more accurate estimate of urban population to mitigate bias issues due to large-scale migration in China. We then matched the urban population with the job recruitment data by city, and ultimately, more than 4.6 million unique recruitment posts from 288 cities were included in the analysis.

Measurement of explicit and tacit knowledge

As discussed previously, the two different types of knowledge-explicit knowledge and tacit knowledge[16,21]—are also referred to as expert knowledge and local knowledge[23,27] or academic knowledge and everyday knowledge[28]. To facilitate analysis, we treat local knowledge and daily knowledge as synonymous with tacit knowledge and consider expert knowledge and academic knowledge to be equivalent to explicit knowledge. We maintain the essential notion that explicit knowledge is based on academic theories, abstract concepts, and scientific structures, while tacit knowledge is derived from life experience and practice, contextualized, cross-derived, daily, practical reasoning that deviates from established or legitimized disciplinary frameworks and is informally disseminated among smaller local groups[24,27,28]. Therefore, the stated educational requirements (knowledge acquired through the educational system) in a job recruitment can be reasonably regarded as a measure of its demand for explicit knowledge, while we consider the working experience requirements (knowledge accumulated in practice) as a measure of tacit knowledge.

In measuring the depth of different kinds of knowledge, we assume that it will increase with the requirements for educational or experience levels. Specifically, we divide education (explicit knowledge) into five groups: Junior school or below, High school, Junior college, Bachelor, and Master or above. Similarly, experience (tacit knowledge) is also divided into five groups-No experience, 1 year, 2 years, 3–4 years, and 5 years or above. The higher the requirement, the more demanding the knowledge. While this treatment of explicit and tacit knowledge is simple and intuitive, we also further examine the lexical diversity of job descriptions for different educational or experience job groups (Supplementary Figs. 12–14). We find that, unlike explicit knowledge, whose level of complexity can be directly reflected in its lexical diversity, the lexical diversity for tacit knowledge does not increase with knowledge levels. This finding highlights the inherent difficulty of expressing the associated knowledge of a job verbally in written language.

Urban scaling

The new science of cities emphasizes the law of urban scaling as a simple and powerful way to understand the various spatial patterns of urban activity[56,57]. Following this exciting shift, we further explore the urban scaling patterns for different types of knowledge. As pointed out by Hausmann[14], increased specialization and complexity of knowledge are reflected in the expanded cooperation among a growing number of people. Thus, the urban scaling of jobs and the growth of knowledge are two sides of the same coin. Similar to previous studies[55,58], we assume the following scaling model:

$$K_i = K_0 N^{\beta} \tag{1}$$

Where K_i is the number of jobs demanding a certain kind of knowledge at a certain level. K_0, the intercept, refers to the base number. N is the population size, and β is the scaling coefficient. In the follow-up analysis, we will fit the scaling exponents for both tacit and explicit knowledge jobs and compare their urban growth patterns.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this article.

DATA AVAILABILITY

The data that support the findings of this study are available at https://github.com/linzhuoliSOC/Explicit_and_tacit_knowledge.

CODE AVAILABILITY

The code for analysis in the current study can be found at https://github.com/linzhuoliSOC/Explicit_and_tacit_knowledge.

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AUTHOR CONTRIBUTIONS

L.L. designed the research. L.L. and N.Z. collected the data, performed the analysis, wrote the paper, and revised the paper.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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