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China's Consumption Geography: A County-level Estimation of Daily Consumption Using Big Data

Yuqingyang Wang
Peking University
Tao Liu
liutao@pku.edu.cn

Peking University

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Abstract

Residents' daily consumption (RDC) levels provide an important indicator of regional development. However, existing research has largely examined consumption patterns either at coarse spatial scales or through localized case studies owing to data constraints, limiting our understanding of fine-grained spatial disparities in consumption. Using Baidu Population Profiling data, this study systematically examines the geography of RDC levels across county-level units in China and explores the socioeconomic factors underlying regional variation in consumption levels. We find that RDC levels exhibit pronounced east–west spatial disparities, with markedly higher RDC in coastal urban agglomerations. Regional RDC levels are closely associated with administrative levels and urbanization rate. A significant relationship can also be observed between urbanization and the upgrading of consumption structures. Both consumption market and consumption amenity play important roles in raising regional consumption levels. Improvements in consumption market primarily contribute to consumption upgrading by reducing the proportion of low-level consumption populations, whereas better consumption amenity is more strongly associated with an expansion of the high-level consumption population.

1 Introduction

Economic and social development has been accompanied by a continuous increase in the levels of residents' daily consumption (RDC). However, RDC remains unevenly distributed across space, exhibiting pronounced geographical disparities(Carrier and McC, 1997). The main advantage of cities is shifting from production to consumption, which not only indicates a wider gap in consumption levels between urban and rural areas, but is also reflected as disparities among cities of different levels and at different stages of development(Glaeser et al., 2001). Advanced and highly urbanized cities can offer more diverse and high-quality commodities and services with higher incomes for citizens, thereby boosting the level of RDC; By comparison, the disposable income of residents in rural areas or towns are likely to be lower than cities, and these less developed places also cannot concentrate large numbers of retailers or service-providers, resulting in a relatively lower level of RDC (Xu et al., 2025).

Existing literature has widely examined the geography of consumption and its influence factors. At the micro level, researchers have focused on individual consumers, examining how geographical factors such as spatial distance, travel costs or local conditions influence consumption preferences and behaviors(Bounie et al., 2023; Cevik, 2023). City case studies have further emphasized the effects of individual characteristics and the micro-scale distribution of consumption facilities, exploring the mechanisms through which geographical factors shape consumption behaviors, particularly through distance-related costs and accessibility to consumption opportunities. At broader spatial scales, research in the geography of consumption has adopted a macro perspective to systematically characterize the spatiotemporal patterns of consumption levels, linking regional consumption to processes such as urbanization and demographic change to explain spatial heterogeneity in consumption across regions(Arapova, 2018; Ding and Li, 2022; Pan, 2025). Despite the extensive body of

research on regional consumption levels, existing studies have largely been constrained by data availability. As a result, they have predominantly focused either on case studies of cities or on consumption measurement at relatively coarse spatial scales, with a lack of fine-grained analyses of the spatial patterns of consumption(Secondi, 2021). Besides, most research tends to focus on specific types of consumption, such as medical expenditure or tourism consumption(Aparicio et al., 2022; Jung and Tran, 2014), but relatively little attention has been paid to residents' comprehensive levels of daily consumption.

In China, the spatial distribution of consumption is also notably imbalanced along with the rapid process of urbanization(Le et al., 2023; Theurillat and Graezer Bideau, 2022). Since the Reform and Opening in 1978, the urbanization rate in China has increased from 17.92% to 63.89% in 2020. The high-speeded urbanization is accompanied by the rising spatial inequality across the country, especially in the urban-rural gap and distinctions among cities of different levels(Liu et al., 2015; Shi et al., 2023). Moreover, urbanization in China is mainly driven by the production side, manifested as the quick expansion of urban construction areas and huge investments in the development of infrastructure(Hugo, 2019). The emphasis on production may contribute to the incoordination between supply-side and demand-side, which is detrimental to the sustainable development of urban and rural areas. Faced with these problems accompanying rapid urbanization, the Chinese government has begun to shift its focus from the level of urbanization to its quality. In the 15th Five-Year Plan proposed in 2026, "expanding domestic demand" has become one of the key priorities of the government's future work(State Council of the People's Republic of China, 2026). Against this background, RDC serves as an important driver of domestic demand.

Based on these, this study aims to examine the spatial pattern of RDC across county-level units in China, by utilizing the 2021 Baidu Population Profiling dataset. It further seeks to explain the observed spatial heterogeneity in consumption by investigating the underlying determinants and mechanisms shaping RDC levels across regions. In doing so, the study contributes to the literature by providing a more comprehensive and fine-grained understanding of the spatial distribution of RDC levels in China. The remainder of the paper is organized as follows: The next section provides a brief review of relevant literature and proposes the basic framework to explain the regional differences of residents' daily consumption levels; Section 3 gives a detailed description of the data and methodology used in this paper. Section 4 reports the empirical results, followed by a conclusion and discussion in section 5.

2 Literature review

2.1 The uneven geography of consumption and its influencing factors: consumption market and amenities

Scholars have long recognized the spatial heterogeneity of consumption levels, and considerable theoretical discussion as well as empirical investigation has been devoted to understanding the geographical patterns of consumption. Earlier literature mainly focused on the spatial distribution of

retailers and conceptualized consumption as the opposite of production, thereby the spatial distribution of consumption largely mirrored that of production(Mansvelt, 2005). Christaller's Central Place Theory proposes a theoretical model of the spatial pattern of retailers, assuming that high-level and larger-scale retailers are fewer in number and more widely spaced, whereas lower-level retailers providing daily goods and services are more numerous and geographically widespread(Christaller, 1933). This distribution gives rise to a hierarchically nested structure of market areas. The gravity model draws on population and distance to delineate the trade areas among different cities, which also assumes a high correlation between population and consumption levels(Converse, 1949; Huff, 1963; Reilly and others, 1929). Following this, regional consumption levels are largely determined by the market size, therefore densely populated areas tend to accommodate a larger number of producers and consumers and generally exhibit higher levels of consumption than sparsely populated areas. Although adopting a static perspective of supply and demand, these classical models have noticed the link between consumption and market size and provided important theoretical insights into understanding and explaining the spatial distribution of consumption levels.

With the development of transportation and industries, the geography of consumption is continuously evolving and the spatial disparity of consumption levels is becoming more pronounced, especially between urban and rural areas and among cities with different levels(Zheng et al., 2022). An important concept is Glaeser's "Consumer City", which argues that cities have increasingly derived their competitive advantage from consumption opportunities rather than production activities(Glaeser et al., 2001). This shift results from four types of "amenities" in urban areas: a rich variety of goods and services, better physical and cultural environment for consumption, high-quality public services and infrastructure, and less cost in consumption time or transportation(Zhang, 2015). The emergence of these amenities has contributed to sustaining high levels of consumption in economically advanced metropolitan areas. Such cities tend to attract a dense concentration of both firms and consumers and provide superior consumption infrastructures and services, which enhance market efficiency and further stimulate consumption(Yu, 2010). From this perspective, consumption amenities such as transportation conditions or agglomeration of facilities are playing an increasingly significant role in shaping regional consumption levels.

Compared with production activities, consumption has historically been less observable at fine spatial scales due to data limitations, hindering systematic investigations of the spatial distribution of consumption levels. The rapid diffusion of digital payment platforms and e-commerce, however, has created unprecedented opportunities to capture and analyze residents' consumption behaviors and consumption levels at a much finer spatial resolution(Jiang et al., 2024; Liu, 2023). Drawing on credit card transaction records and consumption data provided by third-party enterprises, a substantial body of research has examined consumers' behavioral patterns and the factors shaping consumption behavior(Di Clemente et al., 2018; Li, Li, et al., 2019; Wu et al., 2016). At the individual level, studies have explored the heterogeneity of consumption patterns across demographic and socioeconomic groups, revealing significant differences in expenditure levels, purchase sequences, mobility behaviors, and consumption preferences by age, gender, and income(Chai et al., 2015; de Montjoye et al., 2015;

Velaoras et al., 2025). Beyond individual behaviors, recent studies have also discussed the spatial organization of consumption, demonstrating that consumption activities exhibit pronounced spatial and temporal regularities and are closely associated with urban socioeconomic structures(Peng et al., 2023; Tan and Li, 2024). Besides, there are also numerous papers focusing on the broader socio-cultural transformations associated with consumption. This strand of literature investigates how marketing strategies, including branding, advertising and symbolic communication, shape consumers' aesthetic preferences, lifestyles and identities(Mansvelt, 2008; Park and Rabolt, 2009). Consumption is thus understood not merely as an economic activity but also as a process through which meanings are produced, communicated, and negotiated(Abratt and Motlana, 2002; Crewe, 2001). Particular attention has been paid to the cultural embeddedness and locality of consumer goods, exploring how local consumption practices interact with global cultural flows(Özsomer, 2012). Consequently, studies of consumption have become closely linked to broader debates surrounding globalization and modernity. However, the existing literature has largely concentrated either on individual-level consumption behaviors or on the cultural and societal implications of consumption within broader processes of globalization and modernity. As a result, the spatial distribution of consumption levels at fine spatial scales remains insufficiently documented and examined, highlighting a critical gap in consumption geography research.

2.2 The context of China

Since the Reform and Opening in 1978, the level of urbanization and productivity has largely increased in China. This rapid urbanization process is accompanied by a highly uneven pattern of economic development, especially for consumption(Cai et al., 2010). China's early urbanization strategy was predominantly production-oriented, characterized by rapid urban expansion, extensive infrastructure investment, and industrial development(Guan et al., 2018). Although this production-led growth model contributed substantially to economic growth, it also generated notable imbalances, including weak domestic consumption and a mismatch between economic expansion and improvements in living standards. As a result, RDC in China exhibit pronounced spatial disparities. Large cities with concentrated population and favorable market conditions tend to possess stronger consumer demand and greater purchasing power, whereas small towns and rural areas generally display much lower levels of consumption, with residents' expenditure patterns remaining relatively narrow and concentrated in a limited range of categories(Emran and Hou, 2013).

In recent years, the Chinese government has paid more attention to promoting the level of consumption, and RDC is considered as one of the most important areas. The central government has introduced a series of policies aimed at stimulating residents' consumption levels, including the issuance of consumption vouchers and subsidies for the replacement of old household appliances(Lardy, 2015). The rapid expansion of domestic tourism and cultural and recreational services has further helped unleash households' consumption potential. At the same time, the growing diffusion of digital payment technologies and e-commerce in China has provided consumers with more convenient purchasing channels and a broader range of product choices(Wang et al., 2023). Against this backdrop, big data generated from online consumption has provided a valuable data foundation for the study of residents'

consumption, overcoming the long-standing difficulty of monitoring daily consumption behaviors on a large scale.

2.3 Analytical framework

Based on existing literature and the empirical context of China, we develop the analytical framework of this study as shown in Fig. 1. The level of RDC is affected by both the consumption market and consumption amenity. For the consumption market, (1) regions at different administrative levels exhibit disparities in factor agglomeration, functional specialization and economic development. As such, administrative level constitutes an important dimension for understanding spatial heterogeneity in RDC across regions. (2) Urbanization rate reflects the degree of regional urban development. In urban areas with high population concentration, consumer markets are correspondingly larger, and cities with higher levels of economic development and income tend to exhibit stronger capacity for resource agglomeration, which in turn is associated with higher levels of consumption(Li, Cheong, et al., 2019). The spillover of consumption-related information and the diffusion of cultural practices driven by population agglomeration further contribute to the continuous expansion of consumer demand. Regions with higher urbanization rates therefore typically possess more mature consumer markets, and the comparative advantage of cities over rural areas is also reflected in the spatial concentration of consumption activities. (3) Regional per capita GDP and employment reflect the average consumption capacity of residents and jointly affect the general level of RDC(Yang et al., 2018).

For the consumption amenity, (1) one type of consumption facility refers to retail facilities where consumption directly takes place, such as shopping malls and stores. These facilities constitute important carriers of material consumption. A dense and diversified distribution of such retail facilities not only better meets consumers’ demand but also stimulates consumption activities and enhances consumption propensity, thereby shaping regional consumption levels(He et al., 2025). (2) Another type of consumption facilities consists of indirect service infrastructures that support the operation of the consumption chain, such as logistics and transportation systems. These infrastructures extend consumption activities in space by enhancing accessibility. Regions with higher accessibility can effectively reduce transportation and mobility costs associated with consumption, thereby promoting higher consumption levels and a more diversified consumer market(Li and Gong, 2024).

3 Data and Methodology

3.1 Data

The RDC data used in this study are derived from 2021 Baidu Population Profiling data. Baidu is one of China's largest internet companies and operates across multiple sectors, including search engines, mapping services, and technology manufacturing. Baidu Population Profiling data are generated primarily through big data technologies and machine learning models that integrate information from multiple sources. By collecting users' behavioral records, device information, and location data, and combining them with third-party sources such as publicly available government data, e-commerce

platforms and social media, the system extracts user attributes including occupation and consumption capacity. Pattern recognition techniques are then applied to users' clickstreams and browsing behaviors to generate a wide range of individual profile labels. The database covers an exceptionally broad user population. Its coverage extends beyond users of Baidu's own applications to include users of any applications that incorporate Baidu Map services, yielding a sample size of more than one billion individuals. As a result, it represents one of the most comprehensive and up-to-date individual-level databases currently available in China. Moreover, individual consumption behavior is difficult to measure through conventional statistical surveys. With the widespread adoption of online shopping and mobile payment systems, as well as the increasing specialization and diversification of e-commerce platforms, a growing share of household consumption activities is conducted through digital channels. Big data sources such as Baidu Population Profiling can capture these online consumption behaviors with high sensitivity, thereby effectively complementing the limitations of traditional data sources in measuring everyday consumption.

Baidu Population Profiling data classify RDC levels into three categories—low, medium, and high—corresponding to average weekly expenditures of less than CNY 110, CNY 110–506, and more than CNY 506, respectively. The data represents the total amount of routine expenditures, including spending on clothing, food, and transportation, but excludes major purchases and housing rent. The numbers of individuals belonging to each consumption level are aggregated to the county level, yielding the population sizes associated with low, medium, and high consumption levels in each county.

Using the population sizes of the three consumption groups as weights, we construct a per capita weekly RDC indicator to characterize the average consumption level of each county. Group midpoints are employed to quantify the interval variables. Since the high-consumption category is represented by an open-ended interval without an upper bound, estimating its midpoint using the equal-interval approach would be inappropriate, given the long-tailed distribution of household income and expenditure(Cowell and Flachaire, 2007; Han and Cheng, 2019). Instead, we assume that the midpoints of adjacent consumption categories increase geometrically, which better reflects the underlying distribution. Accordingly, the representative weekly expenditures for the low-, medium-, and high-level consumption groups are estimated to be CNY 55, CNY 308, and CNY 1724.8, respectively, and are used to represent the average weekly consumption of individuals in each category. The county-level per capita weekly RDC is calculated as follows:

$$WRDC_i = \frac{Low_i \times 55 + Medium_i \times 308 + High_i \times 1724.8}{Low_i + Medium_i + High_i} \#$$

$WRDC_i$ is the per capita weekly RDC level in county i, Low_i, $Medium_i$ and $High_i$ represent the population size of low-, medium- and high-level consumption in county i, respectively.

To investigate the determinants of spatial disparities in household daily consumption, several auxiliary socioeconomic datasets are incorporated. Employment and GDP data are obtained from the *China City Statistical Yearbook 2021* and the *China County Statistical Yearbook 2021*. Urbanization level, average

educational attainment, and age composition are derived from the Seventh National Population Census of 2020. Road network data are obtained from the national road network dataset released by the Chinese Academy of Sciences in 2020. POI data are sourced from Amap in 2021, from which POIs belonging to the “shopping facilities” category are extracted to characterize the distribution of consumption facilities.

3.2 Methods and Study area

Based on the analytical framework proposed above, we construct a series of multiple linear regression models to examine the determinants of regional consumption levels. The dependent variables are per capita weekly RDC level and the shares of the population belonging to the high-, medium-, and low-level consumption groups. The independent variables include county-level administrative level, the share of urban population, per capita GDP, employment size, the number of shopping facilities, and road network density.

Regarding control variables, we primarily account for the effects of individual characteristics and regional contexts on consumption behavior. Consumers of different ages and educational attainment levels may exhibit distinct consumption preferences. The influence of age may operate through both life-cycle and cohort effects. From a life-cycle perspective, individuals at different stages of life face different consumption needs(Gourinchas and Parker, 2002); for example, younger consumers tend to spend more on entertainment and leisure, whereas middle-aged consumers may allocate a larger proportion of expenditure to durable goods and other household necessities. Age-related differences may also arise from cohort effects, as consumers from different birth cohorts may differ in their consumption attitudes and values(Goss, 2006). Educational attainment reflects consumers’ human capital and is associated with heterogeneous consumption preferences and behavioral patterns(Fraser et al., 2000). These differences are likely to be manifested in consumption behavior. Accordingly, average years of schooling and the population shares of different age groups are included as control variables. In addition, three spatial indicators—eastern, central, and western China; urban agglomeration status; and the hierarchical level of central cities—are incorporated to control for the influence of regional context on consumption levels. After excluding county-level units with missing data, the final dataset comprises 2,827 county-level units. In the regression analysis, all municipal districts within the same prefecture-level city are aggregated into a single analytical unit. Consequently, the regression models are estimated using a sample of 2,125 units. The municipal districts of each prefecture-level city are merged into one unit. Detailed information about each variable is listed in Table 1.

Table 1
Description of independent variables

Variables	Description
Consumption Market	
Admin	The administrative level of county-level units (County = 1; County-level city = 2; Municipal district = 3)
Urb	The proportion of urban population in total population of the county-level units (%)
GDPC	The ratio of regional GDP to the total regional population (10,000 yuan), log-transformed
Emp	The total size of the employed population of county-level units, log-transformed
Consumption Amenity	
Fac	The number of POIs classified under the “shopping services” category within county-level units, log-transformed
Road	The ratio of total road length to administrative area within each county-level unit
Control variables	
Age	The shares of population in different age cohorts (0–14, 15–24, 25–34, 35–44, 45–54, 55–64, 65+)
Edu	Average years of schooling per capita in each county-level unit
Region	Geographical location of county-level units (West = 1; Middle = 2; East = 3)
City_size	The size class of the prefecture-level city to which each county-level unit belongs (Small = 1; Medium = 2; Large = 3; Megacity = 4; Super-large city = 5)
Urb_agglo	Whether a county-level unit is located within an urban agglomeration (Yes = 1; No = 0)

4 Results

4.1 The spatial pattern of RDC across county-level units

RDC levels in China exhibit a pronounced east–central–west gradient, with substantially higher consumption levels observed within urban agglomerations. Figure 2(a)-(c) depict the spatial distributions of the proportions of low-, medium-, and high-consumption populations across county-level units using standard deviation classification. Overall, the three consumption groups display a stepwise pattern from east to west. Low-consumption populations are concentrated primarily in western China, particularly in the southwest; medium-consumption populations account for the largest shares in central China; and most high-consumption populations are clustered in the more developed eastern regions. Consumption levels are markedly higher in urban agglomerations than elsewhere, with coastal urban agglomerations exhibiting the strongest concentration of high-consumption populations. These regions generally possess more favorable socioeconomic conditions and stronger administrative resource

endowments, providing ample market conditions for consumption activities. In addition, provinces with high population densities, such as Shandong, Henan, Jiangsu, Zhejiang, Fujian, and Guangdong, generally exhibit above-average consumption levels, possibly because larger populations generate stronger market demand and thereby sustain higher aggregate consumption.

The spatial pattern of average weekly RDC per capita closely resembles the distribution of economic factors and administrative resources in China. Figure 2(d) illustrates the spatial distribution of per capita weekly consumption expenditure across county-level units. Regional disparities are characterized primarily by an east–west divide, with eastern China exhibiting the highest levels of per capita weekly consumption expenditure, followed by central China, whereas western China remains at a substantially lower level. Provincial capitals and coastal cities are characterized by particularly high levels of consumption, and urban agglomerations serve as the principal clusters of high-consumption areas.

Consumption levels vary substantially across county-level units with different administrative levels. From rural counties to municipal districts which are characterized by the highest degree of urbanization, the RDC levels increase steadily, as reflected by a rising share of high-consumption populations and a declining share of low-consumption populations. Figure 3 presents the proportions of the three consumption groups across different types of county-level units. The differences in consumption patterns are primarily manifested at the two extremes of the consumption distribution. Compared with counties, county-level cities exhibit a reduction of about five percentage points in the proportion of low-level RDC population, whereas the corresponding decline from county-level cities to municipal districts is less than two percentage points. Relative to predominantly rural counties, the advantage of county-level cities lies mainly in their lower concentration of low-consumption populations, while municipal districts, which are predominantly urban, exhibit the highest share of high-consumption populations.

Regional consumption levels exhibit a clear association with the share of the urban population. Figure 4 presents scatter plots based on county-level RDC and urban population shares. A significant relationship can be observed between urbanization and the upgrading of consumption structures. As the proportion of urban residents increases, the share of the low-consumption population declines, whereas the share of the high-consumption population rises. In contrast, the share of the medium-consumption population follows an inverted U-shaped pattern, increasing initially and subsequently declining. The fitted curves reveal a dynamic process underlying the transformation of consumption structures along the course of urbanization. At lower levels of urbanization, the decline in the low-consumption population is accompanied by a transition toward medium- and high-consumption groups. As urbanization proceeds, this transition gradually slows. In the later stages of urbanization, the upgrading process is driven primarily by the shift from medium- to high-consumption groups, while the proportion of low-consumption populations stabilizes at a relatively low level. To some extent, this pattern reflects the evolving pathway through which urbanization exerts its poverty-reducing effects. Average weekly RDC per capita is also positively associated with the share of the urban population. As the proportion of urban residents increases, average weekly consumption expenditure rises accordingly, with a correlation coefficient of 0.43.

4.2 The influencing factors of regional RDC levels

Table 2 reports the results of the OLS regression models described above. Model 1 takes average weekly RDC per capita as the dependent variable. The coefficients of all major explanatory variables are statistically significant, and the model achieves an R^2 value of 0.7148, providing further evidence for the strong association between regional consumption levels and the urbanization process identified in the preceding analysis. The share of the urban population exhibits a significant positive relationship with per capita weekly consumption expenditure, confirming the co-evolution of urbanization and consumption levels at both the local and regional scales. By contrast, the coefficients associated with county-level administrative categories fail to reach statistical significance, possibly because their explanatory power is absorbed by other covariates included in the model. RDC levels are strongly and positively associated with regional per capita GDP, whereas the coefficient on employment size is significantly negative. One possible explanation is that some regions accommodate large numbers of migrant workers whose consumption activities are not fully realized in their places of employment. Instead, a considerable share of their expenditures may be directed toward their places of origin through remittances or consumption during return visits(Fan, 2007). As a result, regions with large inflows of migrant workers and correspondingly large employment populations may exhibit relatively lower local consumption levels despite their substantial labor force. Both road network density and the number of shopping facilities have significantly positive coefficients, indicating that regions with better consumption amenity conditions tend to exhibit higher levels of consumption.

Table 2
OLS regression models of regional RDC levels

Dependent variables	Model 1	Model 2	Model 3	Model 4
	WRDC	Low-level	Medium-level	High-level
Admin	0.116	-0.221*	0.090	0.131
	(0.88)	(-1.66)	(0.62)	(0.74)
Urb	1.495**	-3.853***	2.342***	1.511*
	(2.20)	(-4.23)	(2.61)	(1.67)
GDPC	2.529***	-2.049***	-1.313***	3.361***
	(12.05)	(-9.90)	(-5.83)	(11.79)
Emp	-0.759***	0.481**	0.551***	-1.033***
	(-4.99)	(2.20)	(2.73)	(-5.15)
Fac	0.949***	-0.661***	-0.619***	1.280***
	(6.47)	(-3.15)	(-3.28)	(6.64)
Road	0.333***	0.215***	-0.745***	0.529***
	(4.38)	(2.63)	(-8.64)	(5.15)
Control variables	Yes	Yes	Yes	Yes
Constant	0.910	33.441***	81.028***	-14.470***
	(0.27)	(8.60)	(19.64)	(-3.20)
N	2125	2125	2125	2125
F	321.50	452.05	102.82	268.54
Adjusted R^2	0.7148	0.8325	0.4804	0.6713
Note: *t* values in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.				

To further explore the mechanisms through which explanatory variables affect regional consumption levels, Models 2, 3, and 4 take the shares of the low-, medium-, and high-level consumption populations as dependent variables, respectively. Overall, the results suggest that the effects of consumption capacity and consumption amenity are heterogeneous across mechanisms. An increase in per capita GDP is associated with an overall upgrading of regional consumption levels. In contrast, the effect of urbanization on consumption improvement is mainly realized through a reduction in the share of low-

level consumption populations, highlighting the role of both core cities and county-level development in poverty reduction. An increase in road network density is often associated with a polarization of regional consumption structures, characterized by simultaneous increases in both low- and high-level consumption population shares and a decline in the medium-level consumption share. By contrast, the expansion in the number of shopping facilities is beneficial to the release and fulfillment of consumption demand and significantly increases the share of high-level consumption populations within a region.

5 Conclusion and Discussion

Using household daily consumption data derived from Baidu Population Profiling, this study systematically examines the spatial pattern of RDC across county-level units in China and investigates the determinants and underlying mechanisms of regional consumption disparities. The main findings are as follows. (1) RDC levels exhibit pronounced east–west spatial disparities. Consumption levels are markedly higher in urban agglomerations than elsewhere, with coastal urban agglomerations exhibiting the strongest concentration of high-consumption populations. (2) Regional RDC levels are closely associated with administrative levels. Counties exhibit relatively high shares of low-level consumption populations, whereas municipal districts, on average, concentrate a substantially larger proportion of high-level consumption populations. (3) RDC levels are positively associated with the urbanization rate. A significant relationship can also be observed between urbanization and the upgrading of consumption structures. (4) Both consumption market and consumption amenity play important roles in raising regional consumption levels while through different pathways. Improvements in consumption market primarily contribute to consumption upgrading by reducing the proportion of low-level consumption populations, whereas better consumption amenity is more strongly associated with an expansion of the high-level consumption population.

Compared with production-related activities, data on household consumption have long been scarce due to the difficulty of monitoring individual consumption behavior. Most existing studies rely either on small-scale survey data or on aggregate statistics at relatively coarse spatial scales. Consequently, regional consumption data at fine geographic scales remain largely unavailable. The emergence of big data has substantially alleviated this limitation. By mapping the spatial distribution of RDC levels across county-level units in China, this study reveals a close association between consumption levels and the urbanization process. This relationship stems not only from the larger consumer markets found in highly urbanized areas but also from their superior conditions of consumption amenity(Jalan and Ravallion, 2002). While larger market size contributes to greater consumption capacity, well-developed consumption amenity appears to play a particularly important role in stimulating high levels of consumption(Zhang et al., 2021). In addition, we find a negative relationship between employment size and consumption levels. This pattern is likely attributable to the spatial separation of work and consumption among migrants. Many migrants work in destination regions while consuming in their places of origin. Such geographically separated consumption behavior has been widely documented in studies of migrants in China.

Despite these contributions, the present study represents only an initial exploration of regional consumption levels and is subject to several limitations that warrant further investigation. First, our measure of regional consumption is limited to routine, small-scale expenditures and does not capture major purchases or other forms of large-value consumption. As a result, the indicator provides only a partial representation of regional consumption levels and is more reflective of daily consumption behavior. Also, it cannot distinguish different types of consumption such as survival consumption, development consumption or enjoyment consumption. Second, the big data of consumption may be affected by potential measurement errors and selection biases(Kitchin, 2013). Baidu Population Profiling data are generated from users' smartphone location information and online behavioral records, making data coverage and quality closely dependent on smartphone penetration. Since smartphone adoption varies considerably across regions, the resulting consumption estimates may contain systematic biases(Zhao and Gao, 2024). Moreover, potential errors arising from multiple-device usage by the same individual cannot be completely eliminated, and consumption patterns observed in the data may be subject to age-related selection effects. Third, the geographically separated consumption behavior of migrants may generate situations in which some regions appear to exhibit relatively low income but high consumption. This finding highlights the importance of adopting the household, rather than the individual, as the primary unit of analysis when examining consumption levels and consumption behavior. Future research could further investigate how household consumption patterns vary across different family structures and life-cycle stages, and how such variations are linked to regional disparities in consumption levels.

Declarations

Author Contribution

Y. W.: Data curation, Formal analysis, Visualization, Methodology, Writing – original draft. T. L.: Conceptualization, Methodology, Data curation, Funding acquisition, Supervision, Writing – review and editing

Data Availability

The data that support the findings of this study are derived from Baidu Population Profiling data and are subject to licensing and confidentiality restrictions. Therefore, the data are not publicly available. Researchers interested in accessing the data should contact Baidu or the corresponding author regarding data availability, subject to the relevant data use agreements.

Funding Declaration

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Figures

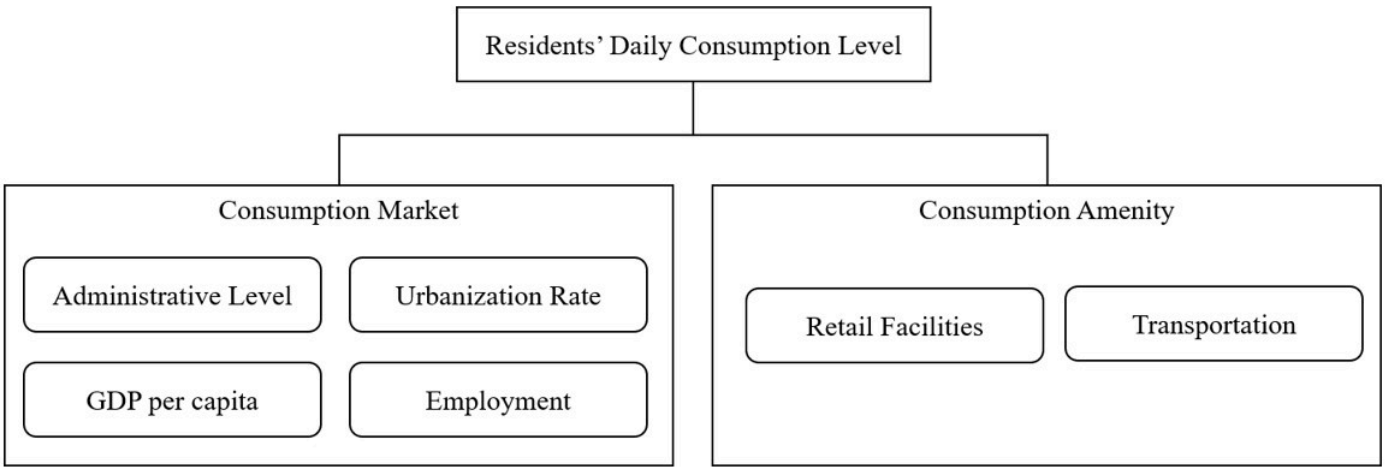


Figure 1

Analytical Framework

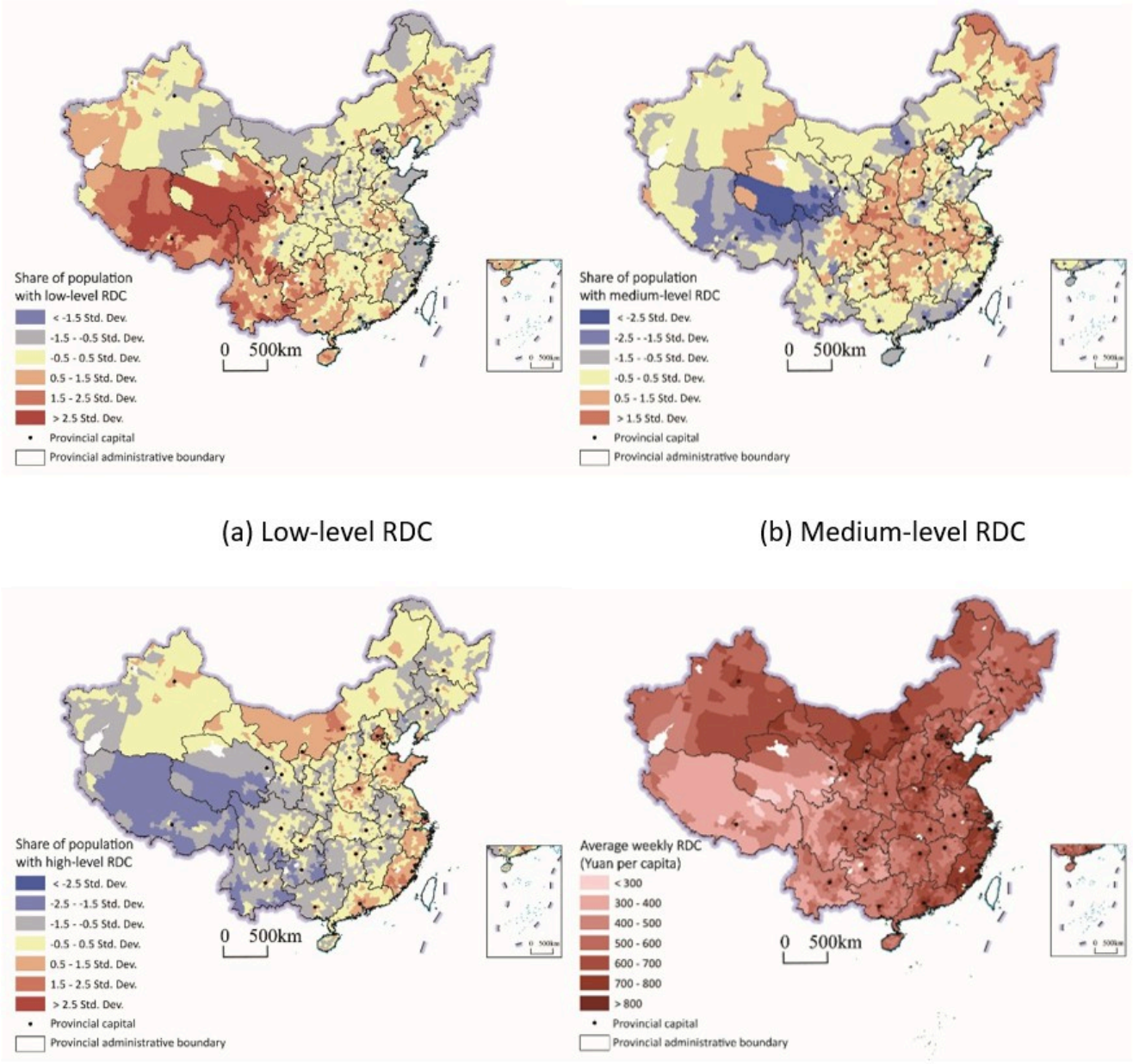


Figure 2

Spatial distribution of RDC levels in 2021

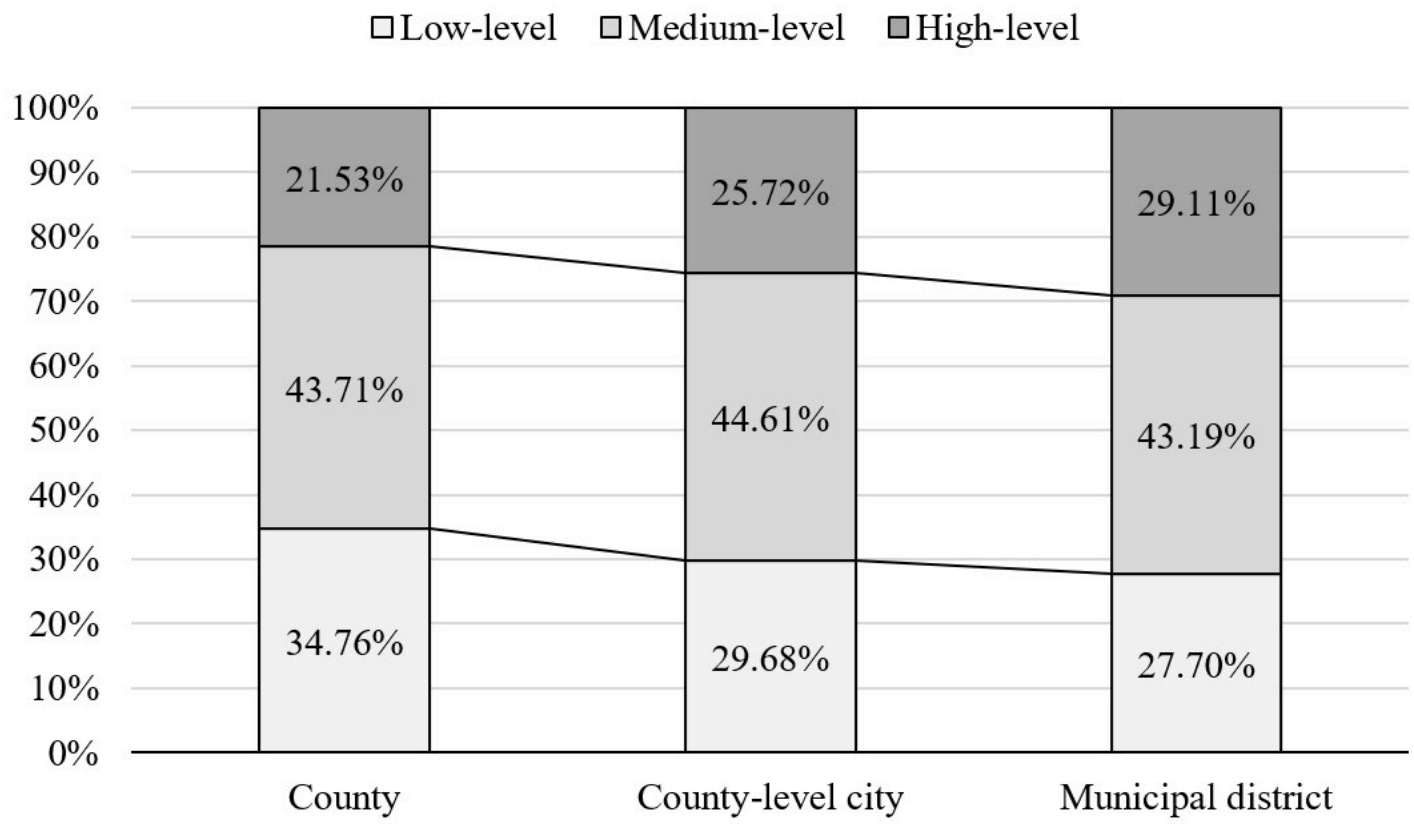


Figure 3

Share of population with different levels of RDC by administrative levels

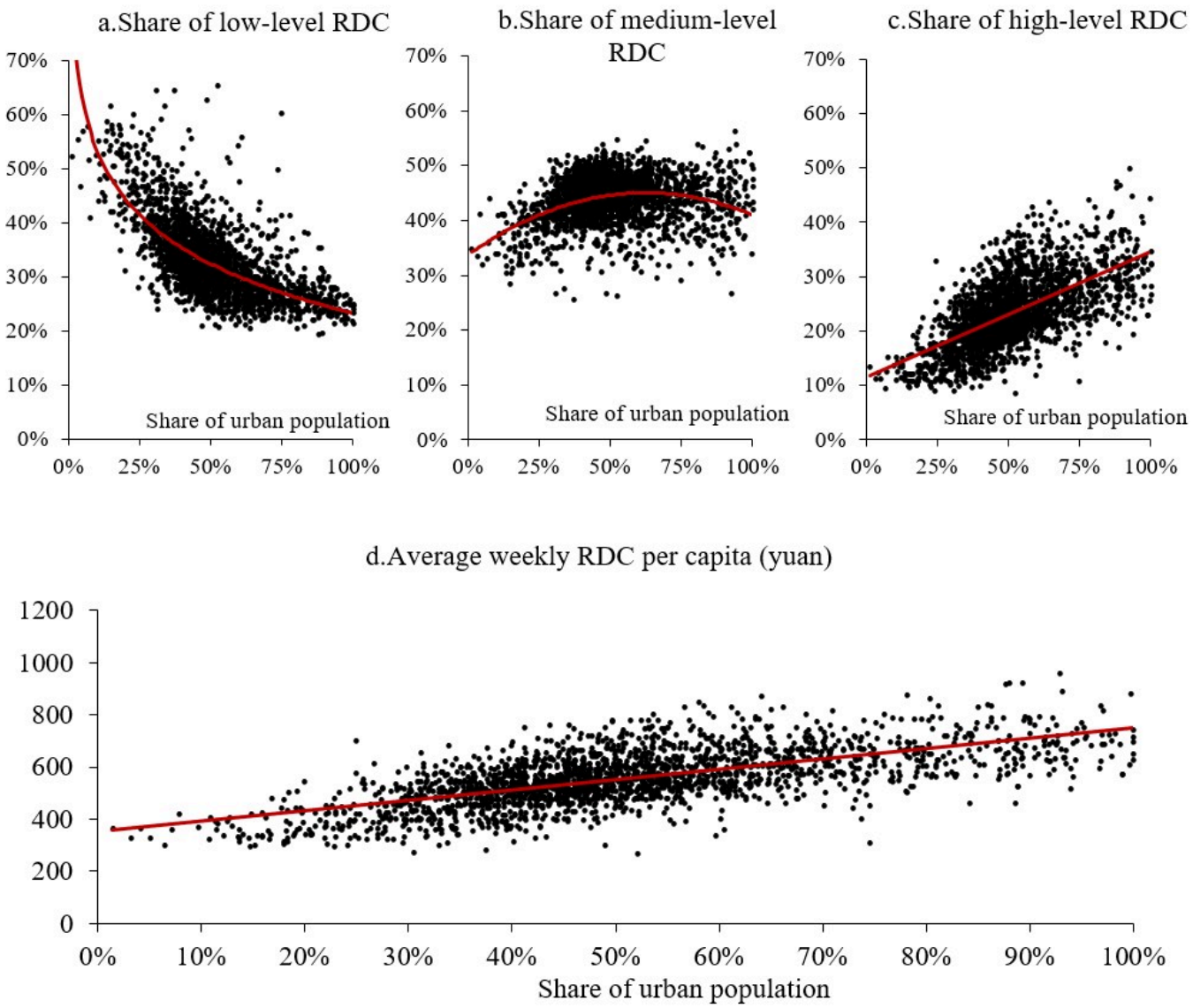


Figure 4

Correlation of county-level RDC and urbanization