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How do subway stations encourage the vitality of urban consumption amenities in Shanghai: A perspective on agglomeration

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Abstract: Subway is an effective public transportation infrastructure that attracts many urban consumer amenities in developing countries. This paper uses points of interest (POI) data from Dianping.com in 2020 in Shanghai to measure the quantity, quality, and diversity of consumer amenities by six indices: numbers, types, comments, ratings, star ratings, and takeout rate. We find that subway stations have a positive spatial correlation with vitality of consumer amenities within a 2-km radius. In addition, subway stations attract more newly added consumer amenities with higher quality within a 2-km radius, and the results remain robust by using the propensity score matching method. There exists heterogeneity in the ridership of subway stations. Subway stations with higher ridership have a greater effect on the consumer amenities and newly added consumer amenities. In terms of mechanism, based on the perspective of agglomeration economy, this paper uses Baidu Street View big data to verify that pedestrian flow is the key mechanism. This study accurately evaluates the economic and social benefits of subway stations and provides fundamental policy implications for the spatial layout of subways and consumer amenities of large cities in developing countries.

Keywords: Subway stations, consumer amenities, street view, Shanghai

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1 Introduction

The high density of subway lines and stations in Shanghai not only alleviates the congestion of ground transportation but also attracts more commercial businesses and amenities. Subway and consumer amenities complement each other. More new and diverse consumer amenities are attracted by subway stations, which make nearby commercial activities more vital. It is worth noting that the stable pedestrian flow and concentration of consumer amenities are the main reasons for the high commercial vitality along subways, especially around the subway stations. Previous studies have found that, in large cities in developing countries, the interaction between subways and urban consumer amenities has become a critical driving force for urban economic growth and spatial layout optimization (Chen et al., 2022; Credit, 2018; Deng & Li, 2023; Haddad et al., 2015; Ibraeva et al., 2020; Sonnenschein et al., 2022). At present, the urbanization rate in China has exceeded 65%, and its urbanization has entered a new

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stage. On the one hand, after decades of development, subway has become an essential means of public transportation in China. As of October 2023, China has opened and operated 299 urban rail transit lines in 55 cities, with an operating mileage of 9862 kilometers[1]. Shanghai is the city in China with the largest and busiest rail transit system. By 2023, the length of operation lines reached 825 kilometers, and the volume of passenger traffic in 2023 hit 36.61 billion in Shanghai[2]. For a city with such a high-density and relatively complete subway network, it is crucial to maintain its subway's appeal to consumer amenities and to optimize the commercial layout around stations; On the other hand, the importance of urban consumer amenities is becoming increasingly visible to governments. Departments of urban planning are inclined to put more weight on creating vital places and various consumer amenities to enhance the livability and comfort of cities[3]. Therefore, studying the impact of subways on consumer amenities and newly added consumer amenities is crucial for understanding and exploring livable urban structures as well as formulating sustainable urban planning.

According to the theory of "Consumer City," cities are important centers of consumption as well as centers of production (Glaeser et al., 2001). Cities are the products of people's pursuit of high-density agglomeration. The agglomeration brought by cities not only enhances the productivity for urban residents but also offers them diversified social and consumption opportunities (Montgomery, 1998). Cities are also pursued for their abundant and various urban amenities (Chen & Rosenthal, 2008; Garretsen & Marlet, 2017). Scholars are increasingly recognizing the importance of transportation in shaping urban consumer amenities. Relevant research mainly discusses the impact of subways on the development of retail stores and the consumption behavior of residents (Castillo-Manzano & López-Valpuesta, 2009; Schuetz, 2015; Sonnenschein et al., 2022). Deng and Li (2023) is closely related to our study, which finds that subway stations in China could increase the number of consumer amenities nearby. However, they did not examine the impact of subway stations on the quality and diversity of consumer amenities and ignored the differences between the subway's impact on existing consumer amenities and new consumer amenities.

Shanghai is the study area in this paper. We collect data on stores from Dianping for Shanghai in 2020, match each store with its location, and conduct a micro-level study on the distribution of consumer amenities and newly added consumer amenities in 2020 in Shanghai. We quantitatively analyze the vitality of consumer amenities from Dianping and construct six indices for each 1-km^2 grid, including the number, type, comments, ratings, star ratings, and takeout rate of consumer amenities respectively. This paper empirically studies the impact of Shanghai subway stations on the vitality of consumer amenities and newly added consumer amenities within a 2-km radius. Propensity score

[1] Data source: Ministry of Transport of the People's Republic of China, and the website is https://www.mot.gov.cn/fenxigongbao/yunlifenxi/202311/t20231108_3940175.html.

[2] Data source: Urban Rail Transit Operation Data Short Report in 2023 issued by the Ministry of Transport of the People's Republic of China.

[3] The outline of the "14th Five-Year Plan" clarifies the task of promoting consumption and building cities as Centers of International Consumption. The "14th Five-Year Plan for the Development of Commerce" elaborates to cultivate several comprehensive international consumption center cities which are globally competitive and internationally influential, and those cities further drive surrounding cities to become distinctive centers of regional international consumption. In 2019, the Ministry of Commerce and other thirteen departments jointly published the "Guiding Opinions on Cultivating and Building an International Consumer Center City," which proposed a Five-Year plan for cultivating a group of cities as centers of international consumption. In July 2021, at the Conference for Cultivating Cities as Centers of International Consumption, Wang Wentao, Minister of Commerce, announced that with the approval of the State Council, Shanghai, Beijing, Guangzhou, Tianjin, and Chongqing will be the first cities to carry out the international consumption center experiments.

matching method is used to eliminate the self-selection bias. We want to explore: (1) What are the spatial characteristics of the distribution of consumer amenities and newly added consumer amenities in 2020 in Shanghai? (2) Do subway stations have a positive spatial correlation with the vitality of consumer amenities in their surrounding areas? (3) Do subway stations attract more newly added consumer amenities with higher quality in their surrounding areas? (4) What are the mechanisms? (5) Do subway stations with higher ridership have a greater impact on consumer amenities and newly added amenities?

The contributions of this paper are as follows: First, the existing research on consumer amenities and their vitality is usually conducted in cities of developed countries with traditional market economies, but Chinese cities differ significantly in urban form, public transportation needs and functions, and spatial layout of consumer amenities compared to the developed countries (Glaeser & Henderson, 2017; Wu, 2016). It is therefore necessary to study the impact of subways on the vitality of consumer amenities in China as a large emerging economy. Hence, this paper carries out a case study in Shanghai, a city with a developed subway system and high-quality consumer amenities. It can provide new empirical evidence and policy suggestions for the further improvement of subways and the vitality of both existing and newly added consumer amenities in Shanghai and other mega-cities. Second, the POI data from Dianping could objectively reflect the spatial distribution of urban consumer amenities and subjectively measure people's perceptions and evaluations of consumption. Based on the POI data of various stores in Dianping, we enrich the indices of the vitality of consumer amenities. We also distinguish between the existing and newly added consumer amenities in Dianping, thus helping to address the endogeneity issue between subway stations and consumer amenities. Third, the theoretical analysis and empirical testing of our mechanism are consistent with the hypothesis of agglomeration economy. Using Shanghai's street view big data and machine learning method to identify pedestrian flow on the street, our mechanism analysis shows that the subway station could increase the pedestrian flow within a 2-km radius and thus promote the vitality of nearby consumer amenities.

The remainder of this paper is organized as follows. Section 2 is the literature review and theoretical analysis. Section 3 describes the study area, data sources, and variables, and analyzes the spatial characteristics of consumer amenities and newly added consumer amenities in Shanghai. Section 4 introduces the econometric models and propensity score matching methods. Section 5 empirically tests the impact of subway stations on consumer amenities and newly added consumer amenities. Section 6 discusses the mechanism. Section 7 concludes the paper.

2 Literature review and theoretical analysis

2.1 Literature on subway stations, consumer amenities and economic effects

A growing literature has noticed the positive influence of subways and other public transportation on urbanization, to prove the rationality and sustainability of investment in public transportation infrastructure. The development of public transportation is not only an inevitable characteristic of urbanization but also plays a significant positive role in urban scale expansion, urban spatial layout optimization, and urban amenities and attractiveness enhancement (Deng & Li, 2023; Fielbaum et al., 2016; Matsunaka et al., 2013; Sonnenschein et al., 2022). This paper is related to two branches of literature:

The first branch of literature is about measuring the vitality of urban consumer amenities. Urban vitality is a key indicator of urban economic development (Jacobs, 1961; Lees, 2012), and scholars have conducted extensive studies on its definition and measurement. Jacobs (1961) first proposed the concept of urban vitality and defined it as the intensity of people's concentration. Although many scholars have since joined this research and haven been continuously expanding the meaning of urban vitality, the core of this concept has always been "the crowdedness of human activities" (Kim, 2020; Lynch, 1984; Montgomery, 1995; Ravenscroft, 2000; Ye et al., 2018; Yue et al., 2019). Therefore, various quantitative methods are proposed to make breakthroughs around this core concept. Urban consumer amenities are more than places for consumption, they also boost the city's economy and are closely linked with residents' welfare. Even though some scholars find that consumer amenities have potential negative side effects, such as gentrification (Smith, 1996), reasonable planning and policy guidance could promote the positive impacts of consumer amenities and boost urban vitality.

Early studies were limited by the unavailability of data, urban vitality was measured using data either from statistical yearbooks and economic censuses (Drewes & van Aswegen, 2011; Huang et al., 1998) or from interviews and surveys (Azmi & Karim, 2012). Currently, with the development of geographic information science (GIS) and the emergence of new databases, spatial big data mining and GIS analysis have been widely applied in the measurement of urban vitality. Examples include mobile phone signaling data (De Nadai et al., 2016; Jiang et al., 2019; Liu, Zhang et al., 2020), social media check-in data (He et al., 2018; Jin et al., 2017; Wu et al., 2018), GPS-based data (Wu et al., 2018; Yue et al., 2017), and night-light remote sensing image data (Huang & Wang, 2020; Yang et al., 2022). Compared to other types of spatial data, the advantage of data from Dianping is that, Dianping POI data includes the location of each store, making it convenient for us to match store POI data with subway station data spatially. Data from Dianping displays detailed reviews and rating information for each store, which can reflect consumers' perceptions and evaluations of their consumption. In recent studies, star ratings and online reviews have been used to measure the quality of consumer amenities (Luca, 2016; Raval et al., 2024). Local businesses with higher average ratings and more reviews are more likely to attract customers and offer a better consumer experience, although it is possible for sellers to manipulate the ratings and reviews. Finally, Dianping provides a detailed classification of various consumer amenities. In 2020, the categories with the largest number of stores included food, shopping, beauty & spas, local services, education, entertainment and hotels. Based on data from Dianping, we select stores of all categories, which can provide a more comprehensive portrayal of urban consumer amenities. However, POI data from Dianping also have limitations, such as they do not capture information about the scale of consumer amenities and their classifications of amenities are not detailed enough, which might introduce errors in the measurement of vitality of consumer amenities.

The second branch of literature is about the impact of subway stations on the vitality of urban consumer amenities. The economic effects of transportation have always been discussed in urban economics. Existing literature exploring the influence of highways, high-speed railways, and other inter-city means of transportation on urban growth is relatively abundant (Duranton & Turner, 2012; Garcia-López, Hémet et al., 2017; Garcia-López, Holl et al., 2015; Jiwattanakulpaisarn et al., 2009; Michaels, 2008). Some recent studies also highlight the active roles of intra-city means of transportation such as rail transit in shaping urban forms and improving welfare of residents (Yin et al., 2021). At present, the positive effects of subways on urban growth, factor productivity, wages and housing prices have been confirmed (Bollinger & Ihlanfeldt, 1997; Chen & Wu, 2024; Gonzalez-Navarro & Turner, 2018; Pasha et al., 2020; Redding & Turner, 2015; Tian et al., 2021; Zhang et al., 2019;), as well as the alleviation of air pollution and improvement of residents' health (Gendron-Carrier et al., 2022; Li et al., 2019; Zheng et al., 2019). Meanwhile, some literature supports the idea that rail transit could effectively facilitate the convenience of commuting and accessibility (Barnes, 2005; Currie et al., 2010; Foth et al., 2013; Guzman et al, 2017; Heblich et al., 2020; Severen, 2021), reduce traffic congestion (Gu et al., 2021; Yang et al., 2018), boost people's happiness (Leyden et al., 2011; Li et al., 2018; Moeinaddini et al., 2020). However, little research reveals the impact of subway stations on consumer amenities from the perspective of urban vitality under the background of China (Deng & Li, 2023), and mechanisms have not been discussed. Therefore, it is of great importance to investigate the impact of subway stations on the vitality of consumer amenities in big cities in China.

2.2 Mechanistic link between subway stations and consumer amenities

In China, prioritizing public transportation policies has driven the rapid development of public transportation. As one of the green and sustainable means of transportation, subways attract population and employment agglomeration along the lines and stations (AlQuhtani & Anjomani, 2021; Hurst & West, 2014; Lai et al., 2024; Yao & Hu, 2020). Consequently, newly established consumer amenities tend to locate near subway stations. Subways interact intimately with nearby urban amenities, and this interaction could be explained by the theory of agglomeration economy of transportation infrastructure (Krugman, 1991). The improvement of transportation infrastructure enables businesses and labor to concentrate in core areas with convenient access more easily, thus creating economic agglomeration effects. The lower transportation costs allow core areas to offer stronger economies of scale and network effects, while peripheral areas may develop relatively slower due to transportation disadvantages.

Enhanced transportation accessibility, reduced transportation costs, and shorter travel times ultimately contribute to increasing pedestrian flow in the surrounding areas of subways. On the one hand, subways make it easier for residents to travel to various consumer amenities and further increase their consumption frequencies, which can boost pedestrian flow around subway stations. On the other hand, subway stations stimulate the prosperous development of catering businesses and entertainment and leisure industries (Deng & Li, 2023; Lee & Sener, 2017). These consumer amenities serve nearby residents and attract consumers from surrounding areas, further increasing pedestrian flow around subway stations. As the key to the agglomeration of consumer amenities, pedestrian flow is important for the quantity, quality, and diversity of consumer amenities. Diversified consumer amenities meet the needs of residents and enhance their quality of life and happiness. Therefore, this paper posits that the increase in pedestrian flow of subway stations correlates with the vitality of consumer amenities. This paper proposes the following hypothesis:

Hypothesis 1: Subway stations have a positive spatial correlation with the vitality of consumer amenities in their surrounding areas.

Hypothesis 2: Subway stations attract more newly added consumer amenities with higher quality in their surrounding areas.

Hypothesis 3: From the perspective of the agglomeration economy, the increase in pedestrian flow is the key mechanism.

3 Study area, datasets and Kernel density estimation

3.1 Study area

As China's largest economic center and an emerging global city, Shanghai has strong international influence and is competitive worldwide[4]. Additionally, Shanghai is known to be the first city to be cultivated and constructed as a center of international consumption in China, and its level of urban amenities is at the forefront of China. Meanwhile, since the construction of Shanghai Metro Line 1 in 1990, Shanghai has entered the "Era of the Metro." Therefore, it is reasonable for us to regard Shanghai as the best area to conduct our study. Based on the administrative map of Shanghai, we set the 1-km^2 grid as the study unit and divided Shanghai into 8710 grids by ArcGIS 10.2. Figure 1 shows the study area, including the distribution of subway lines in Shanghai in 2020.

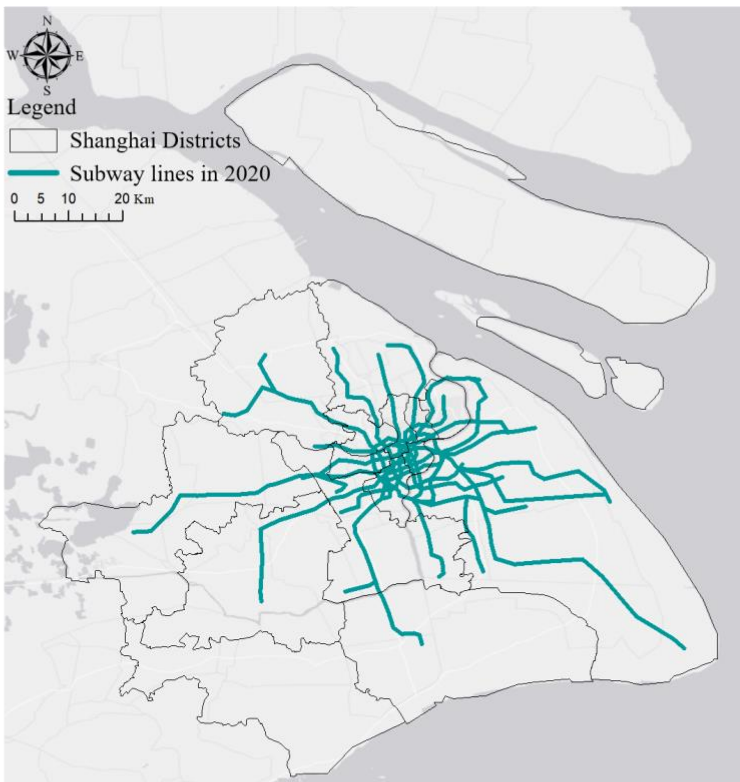

Figure 1. The distribution of subway lines in Shanghai in 2020

3.2 Datasets and variables

3.2.1 Subway vector data

We sort out the vector data of the subway lines and stations that were in operation in Shanghai in 2020, including line names, station names, station longitudes and latitudes, and opening years of stations. According to the statistics, 18 subway lines were in use in

[4] In 2023, Shanghai's administrative area was 6,340.50 km^2, with a permanent resident population of 24.8745 million. Data source is from the Statistical Bulletin of Shanghai's National Economic and Social Development in 2023.

Shanghai in 2020, and the total length reached 729.2 km. Notably, the number of stations reached 354, ranking 1st in China[5]. Referring to Gibbons et al. (2019) and Sonnenschein et al. (2022), we set each subway station as the center and define the buffer zones as 0-1 km, 1-2 km radii, represented by $ring_l$ (l-1, l km), respectively. Figure 2 shows the two buffer zones around a subway station as an example.

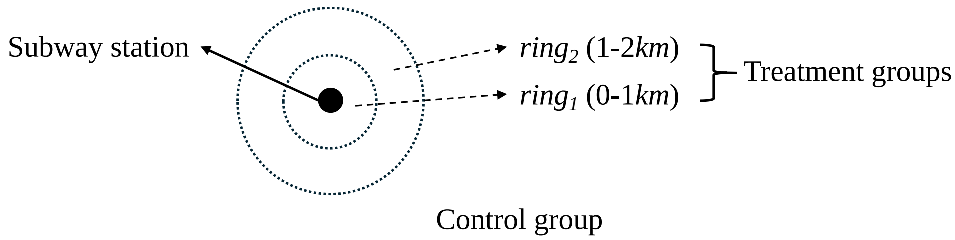

Figure 2. The treatment groups and the control group of one subway station

3.2.2 POI data of consumer amenities in Shanghai

Dianping is China's most extensive website for urban living guides and the earliest third-party platform globally to collect and publish consumer reviews[6]. It is committed to providing consumers with comprehensive and reliable online store information and consumer evaluations. Dianping has more than 290 million active users and over 5 million active businesses, covering more than 2800 cities in China (Liu, Song et al., 2020). We obtain detailed information on 297282 consumer amenities in Shanghai in 2020 from Dianping, including the name, longitude, latitude, number of reviews, overall rating, star ratings, and whether takeout service is provided, among other details. After deleting the outliers, including stores with missing values, duplicates, or abnormal operating status, we geocode each consumer amenity on ArcGIS 10.2 in each 1-km^2 grid. Then, we sort the number of consumer amenities, types, the average number of reviews, the average ratings, the average star ratings, and the average takeout rate of each 1-km^2 grid as proxies for its quantity, quality, and diversity of consumer amenities. The descriptive statistics of consumer amenities in Shanghai in 2020 are presented in Table 1.

[5] Data source: Urban Rail Transit Operation Data Short Report in 2023 issued by the Ministry of Transport of the People's Republic of China.

[6] As of December 2015, the trading volume of the Dianping.com platform exceeded 50 billion yuan, the number of active users exceeded 200 million, and the cumulative number of mobile users reached 250 million. At present, the expanded branches of Dianping cover more than 250 cities and employ more than 6000 workers.

Table 1. The descriptive statistics of consumer amenities from Dianping in Shanghai in 2020

Amenity	N	Reviews	Ratings	Star ratings	Takeout rate
Food	118206	265.45	3.75	3.55	0.42
Shopping	58062	43.87	3.70	3.55	0.09
Beaty & Spas	29245	119.64	3.96	3.71	0.00
Local Services	26982	13.30	3.68	3.34	0.01
Education	21381	36.03	3.80	3.54	0.00
Entertainment	15633	140.63	4.11	3.95	0.00
Hotel	10283	68.97	3.54	3.35	0.00
Autos	6332	22.56	3.68	3.43	0.00
Fitness	3264	72.29	4.12	3.99	0.00
Pets	3120	68.80	4.20	4.05	0.10
Parent & child Activities	2190	64.39	4.03	3.80	0.00
Health & Medical	1500	172.24	4.14	3.88	0.00
KTV	471	432.80	4.07	3.88	0.00
Movies & Performances	385	1779.66	4.24	4.38	0.00
Scenic spots	228	85.56	4.03	3.84	0.00
Total	297282	145.87	3.78	3.57	0.19

3.2.3 Ridership of subway stations data in Shanghai

We collect the daily average ridership of 313 subway stations from April 1 to April 7 in 2015 to calculate the average ridership volume of subway stations, denoted as ln*volum*e. The data is sourced from the Shanghai Public Transportation Card data, which is provided by the SODA Competition[7]. They include the information of the ID, swiping date, swiping time, and swiping station of each card.

3.2.4 Street view data in Shanghai

Machine learning algorithms for object detection are used to identify street pedestrian flow in Baidu Street View images of Shanghai from 2019. First, we obtain the vector data of Shanghai's road network from OpenStreetMap[8]. Sampling points are set every 100 meters along the road network, and panoramic street view images for each sampling point are retrieved from Baidu Maps[9]. Second, using the PaddleDetection framework with the YOLOV7 object detection model, we identify pedestrians in the street view images. Finally, we calculate the average number of pedestrians in the grid within a 0-2km radius around each subway station, denoted as ln*pedestrian*.

3.2.5 Control variables

We further control for other variables that may affect consumer amenities, including: (a) Population. Human activities bring urban vitality, and the agglomeration of people naturally increases the demand for consumption. Hence, we set the population of each grid as a control variable, denoted as ln*pop*. The population data is sourced from Landscan population data, a high-definition raster dataset provided by Oak Ridge

[7] http://shanghai.sodachallenges.com/data.html
[8] https://www.openstreetmap.org/
[9] https://map.baidu.com

National Laboratory[10]. (b) Economic development level. We use NPP-VIIRS nighttime lighting of each grid in 2020 (ln*light*) and historical nighttime lighting of each grid in 2001 (ln*light*_2001) to present the recent development level and historical development level. Nighttime lighting data is provided by the Earth Observation Group (EOG) of the National Oceanic and Atmospheric Administration (NOAA)[11]. (c) Historical number of amenities. To control the effect of existing amenities, we add the number of all amenities (ln*poi*). It is derived from the Amap[12]. (d) Geographic factors. The shortest Euclidean distance from each grid to the CBD, airports, railway stations, and highways are represented by ln*dist_CBD*, ln*dist_airp*, ln*dist_rails* and ln*dist_hwy*, respectively. (e) Historical subway planning. In 1958, a subway planning with three rings and eight lines based on the direction of urban traffic flow was published. To control the effect of historical construction of subways, we add a dummy variable, denoted as *dum_plan*. If a grid located in the 0-2km range of subway planning lines in 1958, *dum_plan* takes a value of 1; otherwise, it takes a value of 0. (f) Historical land use status. We use the land use status in 1980 (*dum_land*) to control the historical consumption levels of each grid. If the grid was built-up areas in 1980, *dum_land* takes a value of 1; otherwise, it takes a value of 0. Land use status data in 1980 is from the Resource and Environmental Science Data Platform[13].

3.3 Kernel density estimation on vitality of urban consumer amenities

We construct the kernel density graph of the consumer amenities in Shanghai (Figure 3a) and the kernel density graph of the newly added consumer amenities in Shanghai (Figure 3b) to show the distribution of consumer amenities and newly added consumer amenities, respectively. As shown in Figure 3a, the area with the largest kernel density overlaps with the traditional downtown of Shanghai. Figure 3a also shows that various consumption hotspots are distributed along subways. With the extension of subway lines to the outskirts of the city, the accessibility of the surrounding areas has greatly improved, attracting a large number of commercial and consumer amenities along the lines. Noticeably, each new district has a subway line that connects itself to the downtown, providing convenience and accessibility for the agglomeration of consumer amenities in new districts[14]. According to Figure 3b, newly added consumer amenities are located around subway stations, and consumer clusters have formed around the subway stations. Subways attract more new consumer amenities around their lines and stations. In sum, the layout of subway lines and stations can optimize the allocation of amenities in Shanghai spatially, promoting the optimization of amenity resource allocation and improving residents' living standards.

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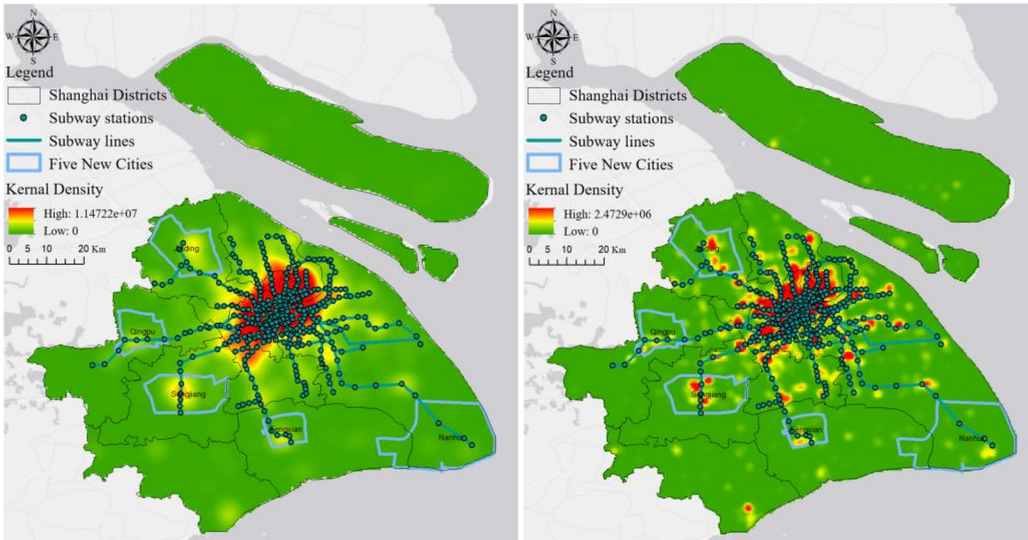
[10] https://www.ornl.gov/

[11] https://eogdata.mines.edu/products/vnl/

[12] https://ditu.amap.com/

[13] https://www.resdc.cn/DOI/DOI.aspx?DOIID=129

[14] According to the 2021 Shanghai Government Work Report, there are five new districts in Shanghai that will be given key cultivation, which are Jiading District, Qingpu District, Songjiang District, Fengxian District, and Nanhui District (https://www.shanghai.gov.cn/nw12336/20210201/ca9e963912cc4c30be7b63799374cd86.html).



(a) Consumer amenities (b) Newly added consumer amenities

Figure 3. The distribution of consumer amenities (a) and newly added consumer amenities (b) in Shanghai in 2020

4 Econometric models and propensity score matching methods

4.1 Baseline models specification

We estimate the following econometric models (1) and (2) to empirically test the correlation of subway stations and consumer amenities and newly added consumer amenities, respectively. Equation (1) verifies that subway stations positively attract more consumer amenities with higher quality around them. Equation (2) verifies that subway stations positively attract more newly added consumer amenities with higher quality around them.

$$\ln amenity_i = \alpha_0 + \sum_{l=1}^{2} \alpha_1^l \times ring_l + \alpha_2 X_i + \lambda_i + \varepsilon_i \quad (1)$$

Where i is the 1-km^2 grid. $\ln amenity_i$ represents the vitality of consumer amenities of grid i, which is illustrated by six indices: number of consumer amenities (ln*number*), types of consumer amenities (ln*type*), the average number of reviews (ln*review*), the average ratings (ln*score*), the average star ratings (ln*star*), and the average takeout rate (ln*takeout*). $ring_l$ is a dummy variable that is represented by the two treatment areas: 0-1 km ($ring_1$), and 1-2 km ($ring_2$) radii. Grids in $ring_1$-$ring_2$ are treatment groups, while grids beyond a 2-km radius are the control group. X_i represents all control variables, λ_i indicates the street or town fixed effects of grid i[15]. α_0 is the constant term, and ε_i is the error term.

$$\ln amenity\_n_i = \alpha_0 + \sum_{l=1}^{2} \alpha_1^l \times ring_l + \alpha_2 X_i + \lambda_i + \varepsilon_i \quad (2)$$

Where $\ln amenity\_n_i$ presents the vitality of newly added consumer amenities in 2020, which is also illustrated by the above six indices in Equation (1). Other variables in

[15] According to the administrative division in 2022 issued by the Shanghai Civil Affairs Bureau, there are 107 streets and 106 towns in Shanghai.

Equation (2) are the same as in Equation (1). Descriptive statistics of the variables in Equation (1) and (2) are presented in Table 2.

Table 2. Variables and descriptive statistics

Variable	N	Mean	SD	Min	Max
ln*number*	8423	1.4128	1.8110	0	7.7952
ln*type*	8423	0.8698	0.9426	0	2.7726
ln*review*	8423	1.4451	1.6923	0	8.8918
ln*score*	8423	0.8368	0.7664	0	1.7772
ln*star*	8423	0.8123	0.7445	0	1.7918
ln*takeout*	8423	0.0414	0.0848	0	0.6931
ln*number_n*	8423	0.5197	1.0665	0	5.7398
ln*type_n*	8423	0.2019	0.3550	0	1.3863
ln*review_n*	8423	0.6272	1.2636	0	6.6299
ln*score_n*	8423	0.3951	0.6737	0	1.7352
ln*star_n*	8423	0.3819	0.6513	0	1.7047
ln*takeout_n*	8423	0.0792	0.1767	0	0.6931
$ring_1$ (0-1*km*)	8423	0.1085	0.3110	0	1
$ring_2$ (1-2*km*)	8423	0.1121	0.3155	0	1
$ring_{12}$ (0-2*km*)	8423	0.2206	0.4147	0	1
ln*pop*	8423	6.5431	2.1732	0	10.8527
ln*light*	8423	1.6580	1.4346	0	5.9250
ln*light*_2001	8423	0.5621	1.0205	0	4.8122
ln*poi*	8423	0.5462	1.0883	0	5.8522
ln*dist_CBD*	8423	3.3647	0.5489	-1.4028	4.1157
ln*dist_airp*	8423	3.1396	0.6320	-2.6255	4.0550
ln*dist_rails*	8423	2.8760	0.9040	-3.9404	4.1459
ln*dist_hwy*	8423	0.7030	1.3388	-8.2410	3.2544
dum_plan	8423	0.0361	0.1865	0	1
dum_land	8423	0.0385	0.1923	0	1

4.2 Propensity score matching

Nearest neighbor propensity score matching is employed to address possible endogeneity of subway stations and consumer amenities and newly added consumer amenities. Same as the baseline regression models (1) and (2), grids located within 2 km of subway stations are the treatment groups, and grids located beyond 2 km of subway stations is the control group. Based on the control variables, we cluster grids with similar population (ln*pop*), nighttime lighting (ln*light*), historical nighttime lighting (ln*light*_2001), historical number of all amenities (ln*poi*), geographic factors (ln*dist_CBD*, ln*dist_airp*, ln*dist_rails*, ln*dist_hwy*), historical subway planning (*dum_plan*), historical built-up land use status (*dum_land*), thus pairs of treated and untreated grids are formed, matched girds have similar values of the propensity score. By applying propensity score matching, we reduce the bias introduced by the non-random assignment of the treatment, thereby ensuring that the observed differences in consumer amenities between treated and untreated groups can be attributed to the subway stations rather than to other confounding variables.

5 Main estimation results

5.1 Benchmark regression results

Table 3 reports the benchmark regression results. Columns (1) - (6) are the results of Equation (1), and columns (7) - (12) are the results of Equation (2). In columns (1) - (12) of Table 3, the coefficients of $ring_1$-$ring_2$ are statistically significant at the 1% level, and these coefficients descend with the distances from subway stations. It shows that subway stations can significantly attract more and new consumer amenities with higher quality and diversity within a 2-km radius. Besides, the effect decreases with distance, with a bigger effect on the consumer amenities in $ring_1$ than in $ring_2$. Therefore, we can see that subways are the urban arteries that bring the commercial prosperity effect around them. The regression results for control variables meet our expectations. Population (ln*pop*), nighttime lighting (ln*light*), historical nighttime lighting (ln*light*_2001), and historical number of all amenities (ln*poi*) are significantly and positively correlated with the vitality of consumer amenities in all columns, whereas the coefficients of ln*dist_CBD* are significantly negative except for the column (6). The coefficients of ln*dist_airp*, ln*dist_rails*, ln*dist_hwy*, *dum_plan* and *dum_land* are not all significant. It can be seen that the population size and level of economic development of a grid and its distance from the CBD directly affect the vitality of consumer amenities, the larger the population, the higher level of development the grid has and the closer it is to the CBD, the greater the demand and supply for quantity and diversity of consumer amenities.

Table 3. Results of subway stations on vitality of consumer amenities and newly added consumer amenities

	ln*number*	ln*type*	ln*review*	ln*score*	ln*star*	ln*takeout*
	(1)	(2)	(3)	(4)	(5)	(6)
$ring_1$ (0-1*km*)	0.8674***	0.3598***	0.7967***	0.1198***	0.1160***	0.0469***
	(0.0688)	(0.0338)	(0.0723)	(0.0258)	(0.0251)	(0.0049)
$ring_2$ (1-2*km*)	0.5032***	0.2297***	0.4133***	0.0885***	0.0841***	0.0267***
	(0.0554)	(0.0292)	(0.0604)	(0.0245)	(0.0238)	(0.0041)
ln*pop*	0.5032***	0.2297***	0.4133***	0.0885***	0.0841***	0.0267***
	(0.0554)	(0.0292)	(0.0604)	(0.0245)	(0.0238)	(0.0041)
ln*light*	0.1240***	0.0873***	0.1303***	0.0940***	0.0915***	0.0039***
	(0.0060)	(0.0036)	(0.0072)	(0.0038)	(0.0037)	(0.0004)
ln*light*_2001	0.0993***	0.0550***	0.0594***	0.0386***	0.0369***	0.0053***
	(0.0176)	(0.0088)	(0.0176)	(0.0066)	(0.0064)	(0.0013)
ln*poi*	0.7391***	0.3180***	0.3467***	0.1263***	0.1226***	0.0326***
	(0.0185)	(0.0092)	(0.0176)	(0.0068)	(0.0066)	(0.0014)
ln*dist_CBD*	-0.5657***	-0.3082***	-0.5643***	-0.1446**	-0.1393**	0.0012
	(0.1115)	(0.0614)	(0.1359)	(0.0628)	(0.0612)	(0.0077)
ln*dist_air*	0.0973	0.0462	0.1360*	-0.0516	-0.0457	0.0071
	(0.0697)	(0.0349)	(0.0813)	(0.0369)	(0.0357)	(0.0051)
ln*dist_rail*	0.0111	0.0350	0.0616	0.0338	0.0332	0.0002
	(0.0433)	(0.0234)	(0.0453)	(0.0256)	(0.0250)	(0.0029)
ln*dist_hwy*	0.0132	-0.0018	-0.0011	-0.0137*	-0.0132*	0.0012
	(0.0128)	(0.0072)	(0.0149)	(0.0073)	(0.0071)	(0.0009)
dum_plan	-0.0536	-0.0767	-0.0065	-0.0572	-0.0535	-0.0031
	(0.1550)	(0.0776)	(0.1432)	(0.0563)	(0.0544)	(0.0080)
dum_land	0.0523	0.0145	-0.0465	-0.0214	-0.0194	-0.0077
	(0.0850)	(0.0406)	(0.0804)	(0.0305)	(0.0297)	(0.0055)
Constant	1.4055***	0.7322***	1.3858***	0.5798**	0.5437**	-0.0479*
	(0.3861)	(0.2191)	(0.4726)	(0.2267)	(0.2206)	(0.0278)
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	8,423	8,423	8,423	8,423	8,423	8,423
Ad-R^2	0.7305	0.6560	0.5115	0.4135	0.4118	0.3780
	ln*number_n*	**ln*type_n***	**ln*review_n***	**ln*score_n***	**ln*star_n***	**ln*takeout_n***
	(7)	(8)	(9)	(10)	(11)	(12)
$ring_1$ (0-1*km*)	0.6651***	0.1705***	0.7897***	0.3237***	0.3106***	0.0972***
	(0.0553)	(0.0187)	(0.0721)	(0.0355)	(0.0343)	(0.0107)
$ring_2$ (1-2*km*)	0.3110***	0.1030***	0.3921***	0.1971***	0.1887***	0.0568***
	(0.0404)	(0.0152)	(0.0539)	(0.0293)	(0.0282)	(0.0085)
Constant	0.5511**	0.1775*	0.7204**	0.2816	0.2633	-0.0748
	(0.2776)	(0.1050)	(0.3672)	(0.2036)	(0.1966)	(0.0580)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	8,423	8,423	8,423	8,423	8,423	8,423
Ad-R^2	0.6590	0.5367	0.5737	0.4869	0.4867	0.3980

Notes: (1)***, **, and * represent estimated coefficients significant at 1, 5, and 10 confidence levels, respectively. (2)Robust standard errors clustered by 1km^2 grids are shown in parentheses. Unless otherwise specified, the following tables are the same.

5.2 Propensity score matching results

Regression results of propensity score matching for Equation (1) and (2) in Table 4 show that all consumer amenities and newly added consumer amenities agglomerate around subway stations in Shanghai. These results suggest that the correlation between subway stations and the vitality of consumer amenities and newly added consumer amenities, as presented in the baseline regressions, remains valid after controlling for endogeneity by propensity score matching.

Table 4. Results of propensity score matching

	ln*number*	**ln*type***	**ln*review***	**ln*score***	**ln*star***	**ln*takeout***
	(1)	(2)	(3)	(4)	(5)	(6)
$ring_{12}$ (0-2*km*)	0.6286***	0.2560***	0.4464***	0.0742**	0.0720**	0.0338***
	(0.0770)	(0.0399)	(0.0802)	(0.0312)	(0.0303)	(0.0056)
Constant	-0.5416	0.3400	4.1047***	1.0007**	0.9867**	-0.1878**
	(1.1263)	(0.5876)	(1.1901)	(0.4669)	(0.4534)	(0.0919)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	1,592	1,592	1,592	1,592	1,592	1,592
Ad-R^2	0.5585	0.5091	0.3350	0.3034	0.3032	0.2629
	ln*number_n*	**ln*type_n***	**ln*review_n***	**ln*score_n***	**ln*star_n***	**ln*takeout_n***
	(7)	(8)	(9)	(10)	(11)	(12)
$ring_{12}$ (0-2*km*)	0.4505***	0.1299***	0.5208***	0.2478***	0.2378***	0.0771***
	(0.0588)	(0.0227)	(0.0765)	(0.0439)	(0.0424)	(0.0126)
Constant	-1.4853*	-0.1242	0.0771	-0.5583	-0.5408	-0.3362*
	(0.8644)	(0.3245)	(1.0981)	(0.6326)	(0.6109)	(0.1844)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	1,592	1,592	1,592	1,592	1,592	1,592
Ad-R^2	0.4225	0.3470	0.3538	0.3255	0.3265	0.2888

5.3 Robustness checks of replacing explanatory variables

In Table 5, we replace the core explanatory variable with the shortest distance between each grid and its nearest subway station (ln*dist_point*). The results in columns (1) - (12) of Table 5 show that the nearer the grid is to a subway station, the higher the vitality of consumer amenities and the number of newly added consumer amenities. This result verifies the fact that commercial amenities feature along subway lines and stations.

Table 5. Results of robustness checks

	ln*number*	ln*type*	ln*review*	ln*score*	ln*star*	ln*takeout*
	(1)	(2)	(3)	(4)	(5)	(6)
ln*dist_point*	-0.2415***	-0.1143***	-0.2328***	-0.0620***	-0.0598***	-0.0121***
	(0.0190)	(0.0096)	(0.0208)	(0.0080)	(0.0077)	(0.0014)
Constant	1.2806***	0.6804***	1.1946**	0.5117**	0.4762**	-0.0482*
	(0.3952)	(0.2213)	(0.4792)	(0.2269)	(0.2207)	(0.0279)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	8,423	8,423	8,423	8,423	8,423	8,423
Ad-R^2	0.7282	0.6555	0.5105	0.4151	0.4133	0.3735
	ln*number_n*	ln*type_n*	ln*review_n*	ln*score_n*	ln*star_n*	ln*takeout_n*
	(7)	(8)	(9)	(10)	(11)	(12)
ln*dist_point*	-0.1589***	-0.0405***	-0.1956***	-0.0796***	-0.0765***	-0.0249***
	(0.0158)	(0.0051)	(0.0216)	(0.0098)	(0.0095)	(0.0031)
Constant	0.6009**	0.2039*	0.7673**	0.3224	0.3018	-0.0674
	(0.2892)	(0.1071)	(0.3778)	(0.2072)	(0.2001)	(0.0586)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	8,423	8,423	8,423	8,423	8,423	8,423
Ad-R^2	0.6525	0.5320	0.5676	0.4826	0.4824	0.3932

5.4 Heterogeneity analysis of subway station's ridership

The effect of subways on consumer amenities and newly added consumer amenities could vary with the ridership of subway stations. We add the interaction term of the ridership of subway stations (ln*volume*) and $ring_{12}$ in the baseline regressions. The coefficients of the interaction term in columns (1) - (6) of Table 6 show that subway stations with higher ridership have a larger effect on the quantity and takeout rates of consumer amenities but have a smaller effect on the ratings and star ratings of consumer amenities. In columns (7) - (12) of Table 6, the coefficients of the interaction term show that subway stations with higher ridership have a higher effect on the quantity, quality, and diversity of the newly added consumer amenities in 2020. Transportation with higher ridership breeds more new commercial districts and stores. With the expansion of subway lines, the siphon effect of subways is becoming stronger with higher ridership.

Table 6. Results of subway station ridership heterogeneity analysis

	ln*number*	ln*type*	ln*review*	ln*score*	ln*star*	ln*takeout*
	(1)	(2)	(3)	(4)	(5)	(6)
$ring_{12}$ (0-2*km*)	0.5907***	0.2486***	0.5769***	0.1009***	0.0978***	0.0274***
	(0.0637)	(0.0332)	(0.0707)	(0.0281)	(0.0273)	(0.0048)
ln*volume*×$ring_{12}$	0.1829***	0.0132	0.0904	-0.0610**	-0.0597**	0.0114***
	(0.0534)	(0.0277)	(0.0593)	(0.0242)	(0.0235)	(0.0039)
ln*volume*	0.1369***	0.0879***	0.1502***	0.0724***	0.0718***	0.0054*
	(0.0344)	(0.0199)	(0.0433)	(0.0197)	(0.0192)	(0.0028)
Constant	1.2627***	0.7383***	1.2830**	0.5547**	0.5334**	-0.0154
	(0.4693)	(0.2583)	(0.5615)	(0.2642)	(0.2572)	(0.0324)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	5,399	5,399	5,399	5,399	5,399	5,399
Ad-R^2	0.7682	0.6972	0.5706	0.4541	0.4522	0.4035
	ln*number_n*	**ln*type_n***	**ln*review_n***	**ln*score_n***	**ln*star_n***	**ln*takeout_n***
	(7)	(8)	(9)	(10)	(11)	(12)
$ring_{12}$ (0-2*km*)	0.4126***	0.1150***	0.5066***	0.2194***	0.2099***	0.0646***
	(0.0481)	(0.0180)	(0.0646)	(0.0342)	(0.0330)	(0.0098)
ln*volume*×$ring_{12}$	0.2392***	0.0377**	0.2054***	0.0550*	0.0535**	0.0187**
	(0.0413)	(0.0149)	(0.0539)	(0.0282)	(0.0272)	(0.0086)
ln*volume*	0.0563**	0.0326***	0.0978***	0.0656***	0.0636***	0.0080
	(0.0231)	(0.0090)	(0.0293)	(0.0183)	(0.0177)	(0.0052)
Constant	0.3884	0.1183	0.7537*	0.2102	0.2006	-0.0181
	(0.3525)	(0.1288)	(0.4573)	(0.2414)	(0.2336)	(0.0674)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Control group	>2km	>2km	>2km	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	5,399	5,399	5,399	5,399	5,399	5,399
Ad-R^2	0.7033	0.5823	0.6245	0.5350	0.5353	0.4276

6 Mechanism analysis

The results of the mechanism analysis are in Table 7. The core explanatory variables in column (1) are $ring_1$ and $ring_2$, and the core explanatory variable in column (2) is $ring_{12}$. In column (3), we set the explanatory variable as the shortest Euclidean distance of each grid to the nearest subway station (ln*dist_point*). The results in columns (1) - (3) of Table 7 indicate that subway stations significantly attract the pedestrian flow on the surrounding streets. Based on the perspective of the agglomeration economy, this paper verifies that subway stations have a positive spatial correlation with the vitality of urban consumer amenities in their surrounding areas, and pedestrian flow is the key mechanism. Subways bring more foot traffic to commercial areas, which boosts the commercial prosperity around subways.

Table 7. Results of the mechanism analysis

	ln*pedestrian*	ln*pedestrian*	ln*pedestrian*
	(1)	(2)	(3)
$ring_1$ (0-1*km*)	0.0775***		
	(0.0175)		
$ring_2$ (1-2*km*)	0.0308**		
	(0.0142)		
$ring_{12}$ (0-2*km*)		0.0465***	
		(0.0131)	
ln*dist_point*			-0.0177***
			(0.0052)
Constant	0.8101***	0.8275***	0.8273***
	(0.1434)	(0.1436)	(0.1442)
Controls	Yes	Yes	Yes
Control group	>2km	>2km	>2km
Street fixed	Yes	Yes	Yes
N	5,362	5,362	5,362
Ad-R^2	0.6193	0.6186	0.6185

7 Conclusions

The high-density subway network, along with the commercial features along the subway lines and stations, together paint a vibrant picture of Shanghai as an international metropolis. This study, focusing on consumer amenities, assesses the spatial relationship between subways and the vitality of consumer amenities and newly added consumer amenities. Specifically, we take Shanghai as a typical example, use POI data from Dianping to depict the vitality of urban consumer amenities in each 1-km^2 grid, and reveal the positive impact of subway stations on the vitality of consumer amenities and newly added consumer amenities. It is found that subway stations in Shanghai have a positive spatial correlation with the vitality of consumer amenities within 0-2km radius. Besides, subway stations attract more newly added consumer amenities with higher quality within 0-2km radius. Notably, this positive effect exhibits heterogeneity in that the impact of subway stations is greater at stations with higher ridership. From the perspective of the agglomeration economy, we use the street view big data of Shanghai in the mechanism analysis and prove that the subway stations attract pedestrians to gather in the vicinity to facilitate the development of nearby consumer amenities and newly added consumer amenities. Our findings shed light on the policymaking of Shanghai and other mega-cities in developing countries with high-density subway systems and great demand for consumer amenities. Therefore, this paper proposes the following policy suggestions:

First, though Shanghai subways started relatively late in the 1990s, its length and stations are now among the highest in the world. How to maintain the long-term prosperity of commercial areas around subway stations and continuously increase the subway's attractiveness to consumer amenities is a practical issue that deserves attention. Therefore, above all, policymakers need to notice and have a deep understanding of the active role of subways in shaping urban consumer amenities and vitality. New subway stations should be organically integrated with surrounding commercial areas, residential buildings, and public service facilities to create multifunctional commercial complexes that attract foot traffic. By combining commercial amenities with transportation, urban functions can be further optimized, providing a more convenient consumer experience. Second, in urban planning, the layout of commercial areas should ensure seamless connections between commercial amenities and subway stations to enhance the attractiveness and convenience of commercial amenities. Commercial development should prioritize transportation hubs or intersections within the subway network, such as locations where multiple lines converge, to maximize the foot traffic and transportation advantages that subway stations bring, thereby promoting the sustainable growth of consumer amenities. Additionally, big data analysis of passenger flow can be utilized to optimize the layout of consumer amenities around subway stations. Finally, pedestrian flow is the path through which subway stations affect consumer amenities. Therefore, cities that prepare to or currently build subways should explore transit-oriented development, design high-density, multi-functional urban complexes and other urban spaces around subway stations to encourage crowd gathering, boost economic and social benefits of subways, and contribute to sustainable cities. To conclude, in the context of rapid urbanization in China, integrating urban rail transit more effectively with the consumption potential it brings will be crucial for enhancing urban vitality in the future. This study provides new practical insights to guide the coordinated development of urban rail transit with urban spatial structure and the layout of urban consumer amenities.

This paper provides a case study of the spatial relationship between subways and urban consumer amenities, but it has several limitations. First, measuring the vitality of urban consumer amenities is worth exploring in the future. For example, how to combine POI data with the scale of consumer amenities could improve the accuracy of the results. Second, this paper is based on Shanghai, and the above policy suggestions are customized for Shanghai. Further research can expand the study sample. For cities that are planning subways, it is important to take commercial development into account. For cities that are just starting to construct their subway systems, a Difference-in-Differences (DID) analysis can be conducted to explore the causal effects of subway construction on consumer amenities.

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Author contribution

The authors confirm contribution to the paper as follows: Investigation, methodology, supervision: Meixia Meng; data curation, software, formal analysis, writing–original draft, writing–review and editing: Zihan Zeng; conceptualization, data curation, software, formal analysis, visualization, writing–original draft, writing–review and editing: Zhe Huo.

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