

Dining Opportunities in Transition: Restaurant Spending-Tier Recomposition in Beijing, 2019-2025

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Research Article

Keywords: Restaurants, Spending tiers, Dining opportunities, Urban commercial change, Spatial association, Beijing

Posted Date: July 4th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10190762/v1>

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Applied Spatial Analysis and Policy on September 12th, 2026. See the published version at <https://doi.org/10.1007/s12061-026-10011-4>.

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Abstract

As consumption choices become more cautious and differentiated, urban-scale longitudinal evidence remains limited on how the spending-tier composition of local restaurant supply changes over time. Using Dianping restaurant records from Beijing's six central districts in 2019 and 2025, this study classifies restaurants with fixed 2019 platform-recorded per-person spending thresholds and examines tier composition, state transitions, and spatial associations within 500 m units. The share of low-tier records rose from 21.3% to 26.7%, while the share of high-tier records fell from 19.6% to 12.8%, indicating an aggregate shift toward lower tiers. Yet local structures were largely continuous: 73.18% of comparable units retained their original dominant tier, and units that changed moved mainly toward middle-tier dominance or mixed-balanced states, suggesting gradual recomposition rather than direct substitution between the low and high ends. Spatial associations show that low-tier provision was more embedded in dense everyday living spaces, whereas high-tier continuity was concentrated in urban nodes able to support experiential, business-oriented, and recognizably higher-quality consumption. By grounding consumption adjustment in the spending-tier composition of local restaurant supply, the study shows how everyday dining opportunities are reconfigured through local structural continuity, middle- and mixed-state recomposition, and spatially differentiated supply outcomes.

Keywords

Restaurants; Spending tiers; Dining opportunities; Urban commercial change; Spatial association; Beijing

1. Introduction

Everyday commercial services are an important spatial medium through which socioeconomic change enters urban life. Many economies are facing weaker growth prospects and more fragile expectations amid slowing growth, demographic change, and rising uncertainty (International Monetary Fund, 2025). In China, these pressures overlap in the short term with continuing upgrading momentum, making a mixed condition of upgrading momentum and cautious consumption more prominent. This condition may lead residents to adjust everyday consumption across frequency, price bands, categories, and channels, while making differentiated choices between cautious spending and quality seeking (Rui & Xu, 2026; McKinsey & Company, 2024, 2025). Changes in consumption patterns can gain concrete spatial expression through the provision and layout of commercial service facilities. Understanding how these facilities change matters for commercial-system performance and for residents' everyday access to routine services, which shapes convenience and neighborhood life (Meltzer & Capperis, 2017; Kickert et al., 2020). Among everyday commercial activities, dining out is frequent and woven into social interaction and neighborhood life. Restaurants respond quickly to market adjustment: openings, closures, spatial distributions, and survival patterns become visible in the urban landscape, making them a useful lens on everyday commercial service restructuring (Wu et al., 2021; Wang et al., 2026).

Existing studies have widely examined the dynamics of dining service facilities as they change with broader urban systems. On the one hand, delivery platforms, e-commerce, and related changes have

produced new restaurant formats and spatial organization patterns. On the other hand, studies of restaurant openings and closures, online-to-offline food accessibility, and restaurant hotspots and deserts show that restaurant change remains embedded in urban spatial regularities, including centrality, local demand, and the morphology of commercial space (Wu et al., 2021; Li et al., 2023; Tian et al., 2023; Wood et al., 2025). These studies have explained where restaurants appear, how they cluster, and how their presence expands or contracts in cities. Yet behavioral and spatial change lie on a continuum rather than being only about presence and absence. Opening and closure are the most visible outcomes; between them are gradual processes such as business-positioning adjustment, consumption change, and the recomposition of supply tiers. Observing only restaurant presence, openings and closures, and counts therefore makes it difficult to capture cross-period changes in the internal tier composition of local restaurant markets.

Commercial tiers have social and spatial meaning. Research on commercial gentrification and related retail and food landscapes links higher-end retail and food spaces to higher-end consumption, commercial hierarchy, and neighborhood identity, often at the scale of streets, neighborhoods, and case areas (Zukin et al., 2009; Kosta, 2019; Bourlessas et al., 2022; Chang & Spierings, 2023). Business and market studies add a complementary view, showing how price segments, submarkets, and competition shape restaurant clustering and spatial spillovers (Jung & Jang, 2019; Park & Kim, 2026). Together, these literatures move the question beyond restaurant presence to differentiated provision, but they focus mainly on static distributions and specific places. However, in a context of differentiated consumption adjustment, restaurants are sensitive to market change but, as place-based service facilities, remain constrained by existing locations, premises, and market positioning (Wu et al., 2021; Tang et al., 2023). Urban-scale longitudinal evidence remains limited on how the spending-tier composition of local restaurant supply changes over time.

Platform records make this question empirically observable. Restaurant POI data locate dining establishments across the city (Wu et al., 2021; Li et al., 2023; Zhang et al., 2025), while user-reported average spending per person provides a basis for classifying restaurants by observable spending level (Zhai et al., 2015; Tang et al., 2023). This study treats the spending field as a per-person consumption experience attached to restaurants, uses it to classify spending tiers under a fixed reference, and diagnoses the composition of local restaurant supply.

Beijing is a valuable case because growth signals, market pressure, and post-pandemic adjustment coexist. In 2025, Beijing's gross regional product and service consumption continued to grow, while total retail sales of consumer goods and catering revenue both declined (Beijing Municipal Bureau of Statistics, 2026a, 2026b; Beijing Municipal Bureau of Statistics & NBS Survey Office in Beijing, 2026). This coexistence means that Beijing is not a simple growth or contraction setting, but a case for observing how the composition of everyday restaurant supply changes amid active demand, market pressure, and urban spatial differentiation. For restaurant supply, this tension can gradually appear in local service composition through numerous small decisions about location, format, and spending level.

Accordingly, this study uses platform-recorded average spending per person to construct restaurant spending tiers and examines the restaurant spending-tier structure in Beijing's six central districts from 2019 to 2025. By restaurant spending-tier structure, we mean the composition of local restaurant supply across spending tiers and its changes over time. We ask, first, how the aggregate spending-tier composition of restaurants changed; second, to what extent local dominant spending-tier states persisted

or shifted and through which transition pathways; and third, which urban spatial contexts were associated with changes in low-, middle-, and high-tier shares. This study extends research on restaurant dynamics from establishment presence, location, and counts to spending-tier composition, thereby providing a window for understanding urban commercial-service change under a complex transition context.

2. Methods

This two-period repeated cross-sectional study examined restaurant spending-tier change across Beijing's six central districts from 2019 to 2025. We classified restaurants into tiers, constructed unit-level compositions, identified annual states and transition pathways, and modelled associations with urban spatial characteristics. Sensitivity analyses tested threshold, sample, and model robustness (Fig. 1).

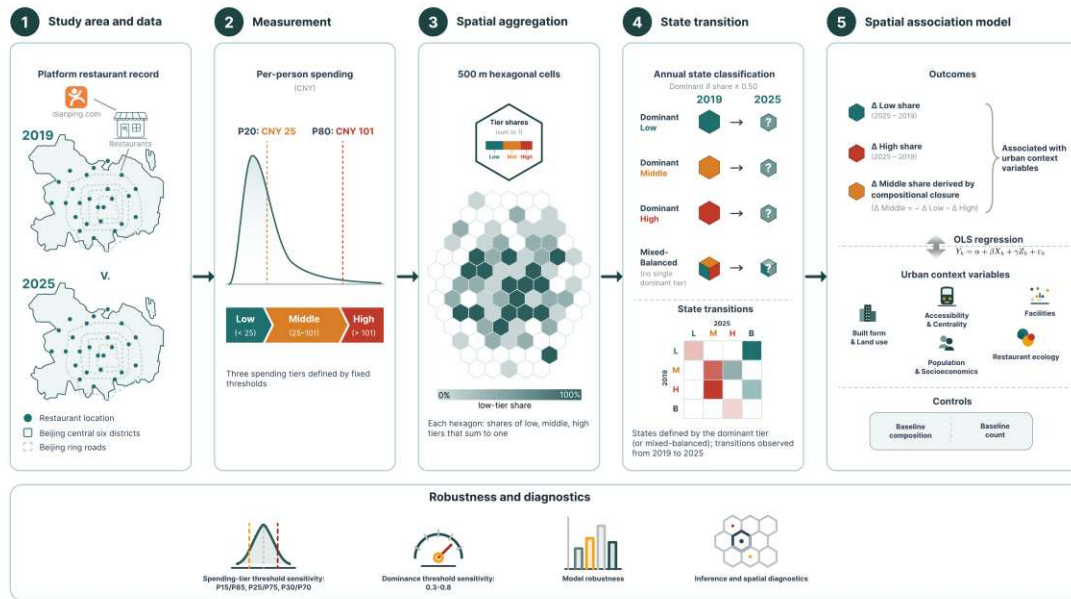


Fig. 1 Analytical framework. Platform restaurant records are classified by fixed spending-tier thresholds, aggregated to 500 m units, classified into annual states and transitions, and modelled for spatial associations; sensitivity checks and diagnostics are summarized.

2.1 Study area and data

The study area comprised Beijing's six central districts: Dongcheng, Xicheng, Chaoyang, Haidian, Fengtai, and Shijingshan. These contiguous districts span the historic core, major business and employment centers, high-density residential neighborhoods, and built-up areas toward the periphery, providing center-to-periphery, functional, and housing-market variation for comparing spatial changes across restaurant spending tiers.

Restaurant data were obtained from Dianping for 2019 and 2025 and included geographic location, restaurant category, user-reported spending per person, and review information. These platform records make large-scale restaurant supply and its spending tiers observable; similar data have been used to examine urban restaurant distributions, neighborhood socioeconomic disparities, and long-term spatial changes in commercial facilities (Zhai et al., 2015; Dong et al., 2019; Zhang et al., 2025). All restaurant

locations were standardized to the WGS84 coordinate system. After category screening and spatial restriction, the dataset contained 73,716 restaurant records in 2019 and 68,839 in 2025, of which 29,414 and 47,122, respectively, had valid spending-per-person values.

Restaurant points were aggregated into regular hexagonal units with a 500 m distance between opposite sides. The 500 m hexagonal grid provided consistent areas and adjacency relationships across administrative boundaries while balancing neighborhood-level spatial detail with sufficient restaurant records for estimating tier shares (Birch et al., 2007; Niu et al., 2025). The grid retained all complete hexagons intersecting the six central districts, for a total of 6,694 units; restaurants were assigned to units using point-in-polygon overlay.

2.2 Restaurant sample and spending-tier measurement

The restaurant sample included establishment types commonly serving breakfast, lunch, or dinner in China. We manually screened categories using consistent criteria, report the full list in Online Resource 1, and deduplicated records in both years. The platform spending-per-person field represents user-reported per-person spending experience aggregated at the restaurant level in RMB, and records were valid only when flagged by the platform and greater than 0.

We applied the 20th and 80th percentiles of the 29,414 valid 2019 records to establish fixed low, middle, and high spending tiers. This distribution-based approach avoids externally predefined monetary ranges while retaining adequate sample sizes at both ends; sensitivity analyses below assess alternative percentile cut points. For spending per person p , the thresholds were defined as follows: the low spending tier included $p \leq 25$ yuan, the middle spending tier included $25 < p \leq 101$ yuan, and the high spending tier included $p > 101$ yuan. The thresholds of 25 and 101 yuan were fixed nominal amounts, were not adjusted for the consumer price index (CPI), and were applied consistently to both 2019 and 2025, providing the same fixed 2019 reference for both periods.

For year t , hexagonal unit i , and spending tier k , the unit-level tier share was defined as

$$s_{itk} = \frac{n_{itk}}{n_{it,\text{valid}}}, \quad k \in \{L, M, H\},$$

where n_{itk} is the number of valid spending records in unit i and year t that belonged to tier k , and $n_{it,\text{valid}}$ is the total number of valid spending records in that unit and year. The three shares sum to 1 in every unit for which they can be calculated. The annual spending-data coverage rate for each unit was defined as

$$r_{it} = \frac{n_{it,\text{valid}}}{n_{it,\text{all}}},$$

where $n_{it,\text{all}}$ is the total number of included restaurants in the unit and year. Across the study area, spending-data coverage was $29,414/73,716 = 39.9\%$ in 2019 and $47,122/68,839 = 68.5\%$ in 2025. The 1,335 hexagons with at least 5 valid spending records in both 2019 and 2025 were defined as stable comparable units and used to compare changes in tier shares within the same spatial units. Fig. 2 shows the spatial distribution of restaurant records in both years, the 500 m hexagonal grid, and the stable comparable units.

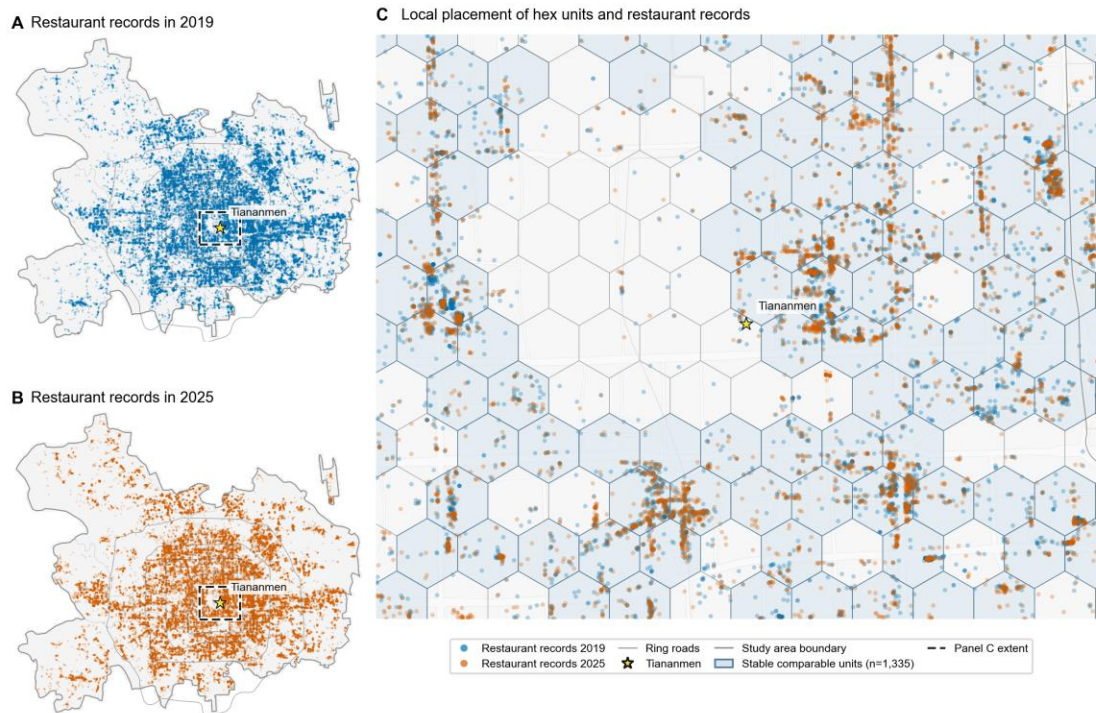


Fig. 2 Study area, restaurant records, and analytical units. Panels A-B map 2019 and 2025 records. Panel C shows local records, the 500 m grid, and stable comparable units. Ring roads and Tiananmen are references.

We tested alternative fixed thresholds (P15/P85, P25/P75, and P30/P70) and repeated tier-share comparisons under coverage-change restrictions: no increase and absolute changes within 5, 10, and 15 percentage points.

2.3 Spending-tier state classification and transitions

To identify local restaurant spending-tier structures and their changes over time, we classified each unit's annual structural state from its low, middle, and high spending-tier shares and then constructed state transitions between 2019 and 2025. An annual state was identified only when a unit contained at least 5 valid spending records in that year. This threshold reduced share instability from small samples while retaining spatial coverage. Under this criterion, 1,428 units in 2019 and 1,907 units in 2025 had identifiable annual states. Combining the two annual states across the full grid produced complete transition pathways that included the low-sample state. Analyses of comparable structural transitions among the low-tier-dominant, middle-tier-dominant, high-tier-dominant, and mixed-balanced states used the 1,335 stable comparable units defined above.

Among units with an identifiable annual state, a unit was classified as low-tier-dominant, middle-tier-dominant, or high-tier-dominant when the corresponding tier share reached 0.50 and was the unique maximum, indicating that the tier constituted an absolute majority. A unit was classified as mixed-balanced when the largest share was below 0.50 or when two or more tiers were tied for the largest share. Units that did not meet the annual record threshold were classified as low-sample. The combination of states across the two years described local structural persistence, shifts, and changes in identifiability. Transitions between low-sample and an identifiable state indicated that the tier structure became

identifiable or ceased to be identifiable. We further compared annual valid-record thresholds of $m = 3, 5, 10, 15, 20$ and varied the dominance-share threshold from 0.30 to 0.80 to assess the sensitivity of state classification and transition patterns to these choices.

2.4 Spatial association models and diagnostics

The spatial association analysis focused on within-unit changes in spending-tier composition among the stable comparable units. The dependent variables were changes in the low- and high-tier shares between 2019 and 2025:

$$\Delta L_i = L_{i,2025} - L_{i,2019}, \quad \Delta H_i = H_{i,2025} - H_{i,2019}.$$

The main analysis used a full linear change-score model that controlled for baseline composition:

$$\Delta s_{ik} = \alpha_k + \beta_{Lk} z(L_{i,2019}) + \beta_{Hk} z(H_{i,2019}) + \gamma_k z[\log(1 + N_{i,2019})] + X_i' \theta_k + \varepsilon_{ik}, \quad k \in \{L, H\}.$$

Here, $z(\cdot)$ denotes z-standardization. X_i is the vector of urban spatial explanatory variables listed in Table 1; all continuous variables were z-standardized, whereas the commercial-center level indicator retained its original coding. θ_k is the corresponding coefficient vector, and ε_{ik} is the error term. The dependent variables remained proportions on a 0-1 scale; for reporting, coefficients were multiplied by 100 and expressed in percentage points.

The change-score model captured shifts in tier composition within local restaurant markets. Baseline low- and high-tier shares controlled for each unit's initial composition and possible regression toward the mean, while the 2019 restaurant count controlled for differences in baseline local restaurant-market size. Because the three tier shares are compositionally closed, only the low- and high-tier equations were estimated independently. Middle-tier changes were derived from compositional closure as $\Delta M_i = -\Delta L_i - \Delta H_i$, and the corresponding middle-tier coefficients were obtained as the negative sums of the low- and high-tier coefficient estimates.

Drawing on prior studies of restaurant location and spatial change, we selected variables in five domains: centrality and transport accessibility, built form and land-use structure, urban functional facilities, the local restaurant ecology, and demographic and housing-market context. Where possible, explanatory variables were measured at or near baseline. Table 1 lists the variables included in the main specification, and Online Resource 1 provides standardization parameters and supplementary measurement details.

Centrality and transport accessibility characterized each hexagonal unit's relative position within the urban market system and the surrounding transport conditions. The city center and commercial centers correspond to concentrations of markets and activities at different spatial extents, while road and public transport networks affect access to local restaurants (Wu et al., 2021; Wood et al., 2025).

Built form and land-use structure characterized the physical and functional setting surrounding restaurant locations. Building coverage and development intensity captured the amount and intensity of built space available to accommodate restaurants, while land-use structure distinguished commercial, office, residential, and other urban environments with different activity profiles (Wu et al., 2021; Tian et al., 2023).

Urban functional facilities characterized the consumption, employment, leisure, tourism, and residential settings of each unit. Different facility types represent different activity settings; their category-specific densities, together with overall POI diversity, captured the local activity environment surrounding restaurants (Zhai et al., 2015; Tian et al., 2023).

The local restaurant ecology captured the type composition of restaurant supply at baseline and its platform-interaction context. Restaurant subtypes differ in their clustering patterns, making it necessary to account for the diversity of local supply categories (Jung & Jang, 2019). Platform review intensity was measured as the mean of $\log(1 + \text{review count})$ across restaurants in each unit.

Demographic and housing-market context represented the local population background and broader neighborhood setting. Population density and composition characterize the local population context, nearby housing prices capture the surrounding housing-market and socioeconomic setting, and the construction period of residential communities reflects the timing and planning context of neighborhood development (Wu et al., 2021; Tang et al., 2023).

Table 1. Variables used in the spatial association models

Variable group	Variable	Measurement / meaning	Source or construction
Baseline controls	Initial low-tier share (2019)	Low-tier valid spending records divided by all valid spending records in the unit	2019 Dianping restaurant records
	Initial high-tier share (2019)	High-tier valid spending records divided by all valid spending records in the unit	2019 Dianping restaurant records
	Restaurant supply (2019)	Number of included restaurant records in the unit	2019 Dianping restaurant records; $\log(1 + x)$ transformed
Centrality	Distance to Tiananmen	Straight-line distance from the hexagon centroid to Tiananmen	Tiananmen reference point
	Distance to nearest commercial center	Straight-line distance from the hexagon centroid to the nearest commercial center	Beijing Municipal Commission of Planning and Natural Resources & Beijing Municipal Commerce Bureau (2022)
	Nearest commercial center level: secondary vs. primary	Indicator for the nearest commercial center being secondary rather than primary	Beijing Municipal Commission of Planning and Natural Resources & Beijing Municipal Commerce Bureau (2022)
Transport accessibility	Distance to nearest metro station	Straight-line distance from the hexagon centroid to the nearest metro station	2020 Amap metro data
	Metro stations within 800 m	Number of metro stations within 800 m of the hexagon centroid	2020 Amap metro data
	Bus stops within 500 m	Number of bus stops within 500 m of the hexagon centroid	2020 Amap bus-stop data
	Road network density	Total road length in the unit divided by hexagon area	OpenStreetMap road network
Built form and land use	Building coverage ratio	Building footprint area divided by hexagon area	2019 Baidu building footprints
	Floor-area ratio (proxy)	Approximate floor area from footprint area and building-height proxy divided by hexagon area	2019 Baidu building footprints; $\log(1 + x)$ transformed

Variable group	Variable	Measurement / meaning	Source or construction
	Commercial-service land-use share	Commercial-service land area divided by hexagon area	2018 EULUC-China
	Business-office land-use share	Business-office land area divided by hexagon area	2018 EULUC-China
	Residential land-use share	Residential land area divided by hexagon area	2018 EULUC-China
Functional context	POI diversity	Shannon entropy of major POI categories in the unit	2018 Amap POIs
	Shopping POI density	Shopping POI count divided by hexagon area	2018 Amap POIs; $\log(1 + x)$ transformed
	Leisure-service POI density	Leisure-service POI count divided by hexagon area	2018 Amap POIs; $\log(1 + x)$ transformed
	Tourism-accommodation POI density	Tourism-accommodation POI count divided by hexagon area	2018 Amap POIs; $\log(1 + x)$ transformed
	Office-company POI density	Office-company POI count divided by hexagon area	2018 Amap POIs; $\log(1 + x)$ transformed
	Residential POI density	Residential POI count divided by hexagon area	2018 Amap POIs; $\log(1 + x)$ transformed
Restaurant context	Restaurant-category diversity	Shannon entropy of included restaurant categories in the unit	2019 Dianping restaurant records
	Platform review intensity	Mean $\log(1 + \text{review count})$ across restaurants in the unit	2019 Dianping restaurant records
Population and housing	Population density	100 m grid population aggregated to the unit and divided by area	2020 PopSE
	Floating-population share	Subdistrict floating-population share assigned to the unit	2020 Seventh National Population Census subdistrict data
	Population aged 60+ share	Subdistrict share of residents aged 60 or above assigned to the unit	2020 Seventh National Population Census subdistrict data
	Nearby median housing price	Median transaction unit price of nearby second-hand housing	2018-2019 Lianjia transactions; $\log(1 + x)$ transformed
	Median built year of nearby housing	Median built year of nearby transacted residential communities	2018-2019 Lianjia transactions

Note. Continuous variables were z-standardized before model estimation. The commercial-center level variable is an indicator with primary commercial centers as the reference category. The floor-area ratio measure is a proxy, not an official parcel-level FAR. Platform review intensity refers to platform-visible review activity based on review counts.

Continuous explanatory variables were z-standardized among the 1,335 stable comparable units; the commercial-center level indicator was not standardized. Models used complete cases, excluding 8 units with missing housing variables and leaving 1,327 units. The low- and high-tier equations were estimated by OLS with HC3 heteroskedasticity-robust standard errors; coefficients represent conditional associations in percentage-point changes after adjustment for the other variables.

Paired bootstrap resampling of hexagons with 5,000 replications generated percentile intervals, including for the derived middle-tier coefficients. Spatial HAC standard errors were calculated for the independently estimated low- and high-tier equations, using the eighth-nearest-neighbor bandwidth as the primary setting and fourth- and twelfth-nearest-neighbor bandwidths as sensitivity checks. Additional weighting, threshold, variable-definition, housing-exclusion, and baseline-composition comparisons are detailed in Online Resource 1.

Diagnostics covered multicollinearity, residual spatial autocorrelation, and prediction feasibility. Residual Moran's I used directed, row-standardized 8-nearest-neighbor weights with a zero diagonal and 999 two-sided permutations. Predicted changes were compared with each unit's feasible interval. Moran's I was diagnostic only; spatial-dependence robustness used spatial HAC standard errors. Further details are in Online Resource 1.

3. Results

3.1 Overall change in the restaurant spending-tier structure

Between 2019 and 2025, the restaurant spending-tier structure in central Beijing shifted toward the low spending tier. We used the 2019 P20/P80 thresholds of platform-recorded per-person spending as the fixed reference: records at CNY 25 or below were classified as low tier, those above CNY 25 and up to CNY 101 as middle tier, and those above CNY 101 as high tier. Under this definition, the share of valid spending records in the low tier increased from 0.213 to 0.267, a gain of 5.4 percentage points. The high-tier share declined from 0.196 to 0.128, a loss of 6.8 percentage points. The middle-tier share rose only slightly, from 0.591 to 0.605, a gain of 1.4 percentage points. The spending distribution also shifted downward: the mean fell from CNY 73.89 to CNY 60.68, the median from CNY 50 to CNY 38, P80 from CNY 101 to CNY 86, and P95 from CNY 180 to CNY 146 (Table 2).

Table 2. Record-level spending-tier composition and platform-recorded per-person spending distribution, 2019 and 2025

Year	Valid records (n)	Low-tier share	Middle-tier share	High-tier share	Mean (CNY)	Median (CNY)	P80 (CNY)	P95 (CNY)
2019	29,414	0.213	0.591	0.196	73.89	50	101	180
2025	47,122	0.267	0.605	0.128	60.68	38	86	146
2019-2025 change	+17,708	+0.054	+0.014	-0.068	-13.22	-12	-15	-34

Note. Spending tiers use fixed 2019 reference thresholds derived from platform-recorded per-person spending: low tier at CNY 25 or below, middle tier above CNY 25 and up to CNY 101, and high tier above CNY 101. The monetary summaries describe platform-recorded per-person spending among valid records.

At the unit level, the same pattern of rising low-tier shares and falling high-tier shares appeared in within-unit changes. Among the 1,335 500 m units with at least five valid spending records in both years, 835 units, or 62.55%, recorded an increase in the low-tier share, while the high-tier share declined in 836 units, or 62.62%. The median changes were +0.050 for the low-tier share and -0.045 for the high-tier share; only 338 units recorded an increase in the high-tier share. Changes in the middle tier were milder:

the share increased in 51.16% of units and decreased in 46.59%, with a median change of +0.010 (Fig. 3). These directions persisted under alternative fixed thresholds and coverage-change restrictions (Online Resource 1).

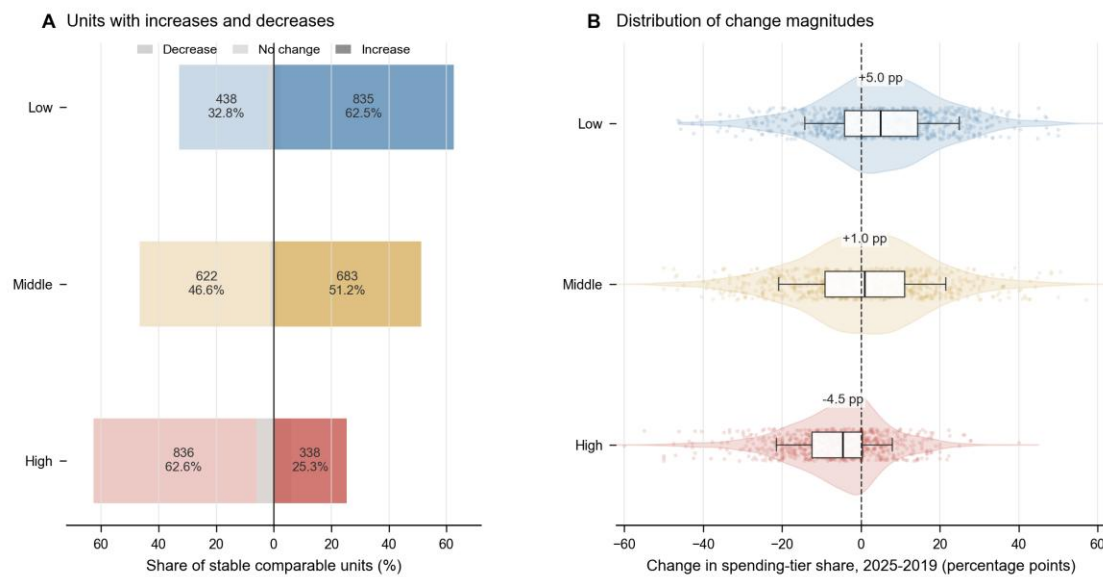


Fig. 3 Overall within-unit spending-tier share changes. Stable comparable 500 m units are hexagons with at least five valid platform-recorded per-person spending records in both years. Panel A reports units with increases, decreases, and no change; lighter and darker tier-colored bars indicate decreases and increases. Panel B shows change magnitudes using individual points, violins, interquartile boxes, P10-P90 whiskers, and median labels.

Spatially, the shift toward lower tiers was stronger in the outer ring-road zones. Units with increasing low-tier shares were distributed across the whole study area, but the increase was more pronounced toward the periphery. Across ring-road zones, median changes in the low-tier share were positive, with the largest increase beyond the Fifth Ring Road (+0.060), followed by the zone between the Fourth and Fifth Ring Roads (+0.057). Changes in the middle-tier share were weaker, with small increases mainly inside the Second Ring Road and between the Third and Fourth Ring Roads, rather than a clear outward expansion or clustering. The high-tier share declined across ring-road zones overall, but units with relatively large high-tier shares remained concentrated in central and northeastern areas. The high spending tier therefore remained locally concentrated while contracting in relative share (Fig. 4).

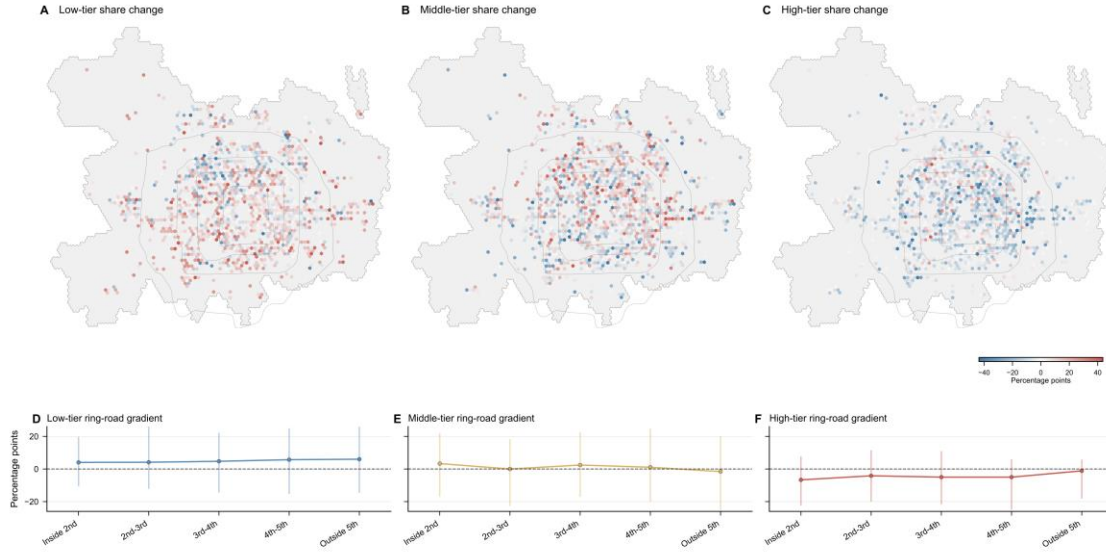


Fig. 4 Spatial pattern and ring-road gradient of tier-share changes. Panels A-C map low-, middle-, and high-tier share changes among stable comparable 500 m units on a shared zero-centered percentage-point scale. Panels D-F report ring-road gradients; markers show medians and vertical ranges show P10-P90. Ring roads are spatial references.

3.2 Persistence and recomposition paths of the spending-tier structure

Classifying each 500 m hexagonal unit by its dominant spending tier showed recomposition within a largely persistent 2019-2025 structure. Most existing structures were retained, and units that changed type mainly recombined around the middle spending tier rather than switching directly between the low and high tiers.

The annual type distribution showed a stronger middle-tier base in 2025, accompanied by a modest rise in low-tier-dominated units and a marked contraction of high-tier-dominated units. The number of identifiable units increased from 1,428 in 2019 to 1,907 in 2025. Middle-tier-dominated units remained the main type and increased from 72.9% to 77.0%, or from 1,041 to 1,468 units. Low-tier-dominated units increased from 6.5% to 8.3%, or from 93 to 158 units. The mixed-balanced type declined slightly in share, from 11.5% to 10.1%, although its count increased from 164 to 192 units. By contrast, high-tier-dominated units declined from 9.1% to 4.7%, or from 130 to 89 units.

Persistence was the dominant feature of the spending-tier structure. Among the 1,335 units whose structure could be identified in both years, 73.18% retained their original type (977 units), while 26.82% changed type (358 units). Persistent units were highly concentrated in the middle-tier-dominated type: among all units that retained their type, 89.5% were middle-tier-dominated (874/977). Thus, changes in the restaurant spending-tier structure occurred on top of an already stable middle-tier base.

Units that changed type moved mainly toward the middle spending tier, with almost no direct exchange between the low and high ends. Among the 358 changing units, about 52.5% became middle-tier-dominated (188/358). By initial type, 49.5% of low-tier-dominated units became middle-tier-dominated (46/93), as did 34.6% of high-tier-dominated units (45/130) and 59.1% of mixed-balanced units (97/164). By contrast, only 2.5% of changing units became high-tier-dominated (9/358). No low-tier-dominated

unit became high-tier-dominated, and only one high-tier-dominated unit became low-tier-dominated. Recomposition therefore mainly involved movements through middle-tier or mixed-balanced states, rather than direct replacement between low- and high-tier-dominated areas (Fig. 5). Under alternative dominance thresholds, structural persistence, the prevalence of middle-tier-oriented paths, and the rarity of direct low-high switching remained stable. Detailed results are presented in Online Resource 1.

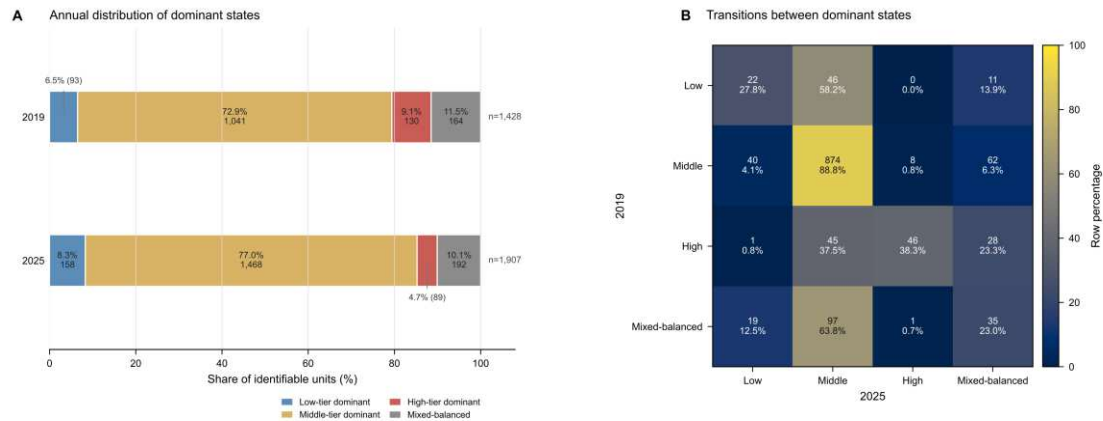


Fig. 5 Persistence and transitions of dominant spending-tier states. Panel A compares annual identifiable states, excluding low-sample units from annual denominators. Panel B reports transitions among units identifiable in both years; cell colors are row percentages and labels report counts and row percentages. Low-sample observability transitions are reported in Online Resource 1.

3.3 Spatial associations in changes in spending-tier shares

After controlling for the initial 2019 spending-tier structure, we modelled changes in the low-tier and high-tier shares separately. The middle-tier change follows directly from compositional closure. Primary inference used HC3 robust standard errors, and paired-bootstrap intervals were based on 5,000 resamples. This specification separated the spatial correlates of low-tier expansion and high-tier contraction, with the middle-tier association derived from the two estimated equations. Online Resource 1 checks showed similar directional associations.

The low-tier model had an adjusted R^2 of 0.406 and a residual Moran's I of -0.006 ($p = .677$); the high-tier model had an adjusted R^2 of 0.364 and a residual Moran's I of 0.055 ($p = .001$), using directed, row-standardized 8-nearest-neighbor weights and 999 two-sided permutations. All low- and high-tier associations that met the HC3 evidence criterion retained $p < .05$ under symmetric Gaussian spatial-HAC inference using bandwidths calibrated to the fourth, eighth, and twelfth nearest neighbors. Out-of-range predictions were rare in the low-tier model (0.08%) but more frequent in the high-tier model (7.91%), so the coefficients are interpreted as average conditional associations rather than bounded unit-level predictions (Table 3).

Table 3. Model performance and diagnostics

Outcome	N	Parameters (k)	R ²	Adjusted R ²	RMSE	Residual Moran's I (permutation p)	Out-of-range predictions
Low-tier share change	1,327	29	0.419	0.406	0.120	-0.006 (.677)	1 (0.08%)

Outcome	N	Parameters (k)	R ²	Adjusted R ²	RMSE	Residual Moran's I (permutation p)	Out-of-range predictions
High-tier share change	1,327	29	0.377	0.364	0.101	0.055 (.001)	105 (7.91%)

Note. The low- and high-tier equations were independently estimated by OLS with HC3 robust standard errors. RMSE is expressed on the 0-1 share scale. Residual Moran's *I* used directed, row-standardized 8-nearest-neighbor weights; values in parentheses are p-values from 999 two-sided random permutations. Out-of-range predictions were compared with the feasible interval implied by each unit's 2019 baseline share.

Table 4. Main spatial association estimates for spending-tier share changes

Variable	Low-tier change	Middle-tier change	High-tier change
Baseline controls			
Initial low-tier share (2019)	-11.20***	+11.19†	0.00
Initial high-tier share (2019)	-2.03***	+10.67†	-8.64***
Restaurant supply (2019)	-0.14	+0.97	-0.83
Centrality			
Distance to Tiananmen	-0.82	+0.86	-0.04
Distance to nearest commercial center	+1.01	-0.16	-0.85
Nearest commercial center level: secondary vs. primary	+1.14	-0.95	-0.20
Transport accessibility			
Distance to nearest metro station	-0.27	+0.50	-0.22
Metro stations within 800 m	-0.07	+0.52	-0.45
Bus stops within 500 m	+0.11	-0.11	0.00
Road network density	-1.01*	+0.68	+0.32
Built form and land use			
Building coverage ratio	-0.77	+0.96†	-0.19
Floor-area ratio (proxy)	+0.37	-0.81	+0.44
Commercial-service land-use share	-0.38	-0.10	+0.48
Business-office land-use share	-0.63	-0.36	+0.99*
Residential land-use share	+0.19	-0.23	+0.05
Functional context			
POI diversity	+0.69	-0.03	-0.66
Shopping POI density	+0.17	-0.01	-0.16
Leisure-service POI density	-0.28	-1.01†	+1.29**
Tourism-accommodation POI density	-1.00*	+1.28†	-0.28
Office-company POI density	+0.44	-0.73	+0.29

Variable	Low-tier change	Middle-tier change	High-tier change
Residential POI density	+0.57	-0.65	+0.08
Restaurant context			
Restaurant-category diversity	-0.65	+0.81	-0.15
Platform review intensity	-2.38***	+1.41†	+0.96*
Population and housing			
Population density	+1.17**	-0.01	-1.17***
Floating-population share	-0.36	-0.12	+0.47
Population aged 60+ share	+0.16	-0.71	+0.55
Nearby median housing price	-0.86	-0.24	+1.10*
Median built year of nearby housing	+0.51	+0.29	-0.80*

Note. All cells report estimated coefficients in percentage points. Stars for the low- and high-tier equations use HC3 robust p-values: * $p < .05$, ** $p < .01$, *** $p < .001$. The middle-tier association is derived from compositional closure; † indicates that the paired-bootstrap 95% interval excludes zero. Middle-tier cells do not use HC3 significance stars. Continuous-variable coefficients are percentage-point changes in tier share per one-standard-deviation increase; the commercial-center-level coefficient compares secondary with primary nearest commercial centers. Models control for initial 2019 low- and high-tier shares. All low- and high-tier associations that met the HC3 evidence criterion retained $p < .05$ under symmetric Gaussian spatial-HAC inference using bandwidths calibrated to the fourth, eighth, and twelfth nearest neighbors. Complete confidence intervals and p-values are reported in Online Resource 1.

The low-tier share increased more in areas with higher population density, and less in areas with stronger platform review intensity, denser road networks, and more tourism-accommodation POIs. In the model, platform review intensity had the largest negative association: a one-standard-deviation increase corresponded to an approximately 2.38 percentage-point smaller increase in the low-tier share. The positive association with population density was about +1.17 percentage points. Road network density and tourism-accommodation POI density corresponded to changes of about -1.01 and -1.00 percentage points, respectively. The relative increase in the low spending tier was spatially differentiated, with stronger growth in units with higher population density, lower platform review intensity, and fewer tourism-accommodation POIs.

Changes in the high-tier share were more positive where leisure-service POIs, nearby median housing price, business-office land use, and platform review intensity were higher. These four variables showed positive associations with high-tier share change, with standardized effects of about +1.29, +1.10, +0.99, and +0.96 percentage points, respectively. Population density and the median built year of nearby residential communities were negatively associated with high-tier share change, with effects of about -1.17 and -0.80 percentage points. Overall, more positive high-tier changes were concentrated in specific consumption- and work-related areas rather than simply tracking population density.

The derived middle-tier change was larger in areas with stronger platform review intensity, more tourism-accommodation POIs, and higher building coverage ratios, with standardized associations of +1.41, +1.28, and +0.96 percentage points, respectively. It was smaller where leisure-service POI density was

higher (-1.01 percentage points). These are closure-derived associations rather than estimates from an independently fitted middle-tier equation.

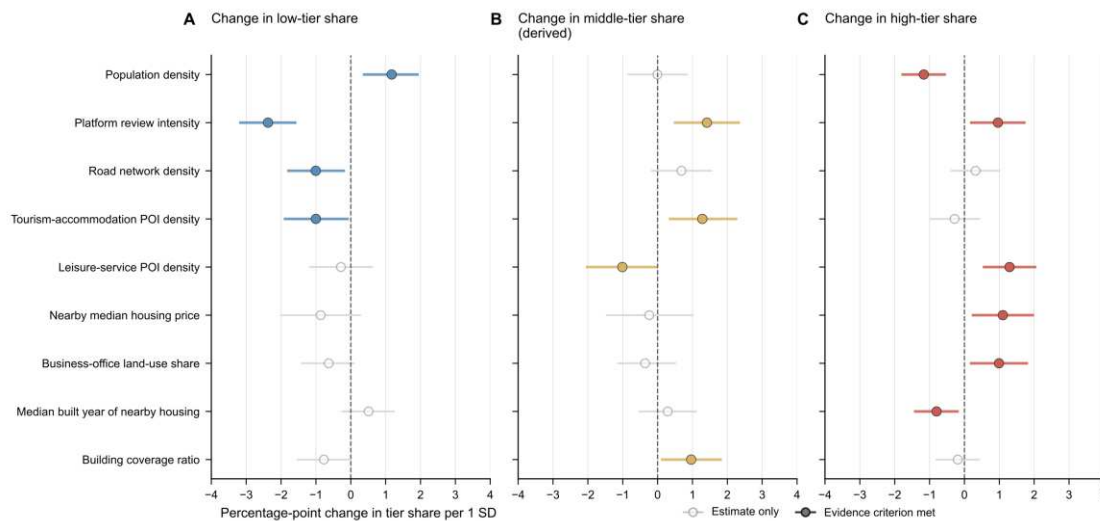


Fig. 6 Spatial associations with changes in spending-tier shares. Panels A-C report low-, middle-, and high-tier associations under the main specification. Points are standardized percentage-point coefficients per one-standard-deviation covariate increase; whiskers show paired-bootstrap 95% intervals. Filled tier-colored points meet the evidence criterion; hollow grey points do not. Low- and high-tier panels use HC3 criteria from independently estimated equations, whereas the middle-tier panel is derived from compositional closure and uses whether the paired-bootstrap interval excludes zero. Table 4 reports all model variables. Platform review intensity refers to the 2019 platform review-count measure.

Taken together, the three spending tiers formed a layered set of spatial associations, with population density, platform review intensity, tourism-accommodation POIs, leisure-service provision, business-office land use, and nearby housing-market context marking different parts of the recomposition. The restaurant spending-tier structure therefore varied by spending tier and urban setting.

4. Discussion

From 2019 to 2025, restaurant supply in Beijing's central urban area shifted overall toward lower spending tiers, but local dominant states did not generally flip, and different tiers remained embedded in differentiated urban spatial contexts. This result provides a window for understanding how everyday commercial supply adjusts in a mixed consumption environment. Existing studies of restaurant dynamics have mostly examined the spatial reconfiguration of dining landscapes through restaurant appearance, clustering, and accessibility change (Wu et al., 2021; Li et al., 2023; Wood et al., 2025). Building on this work, this study shows that the internal spending-tier composition of local restaurant supply is also part of urban commercial change. When the relative mix of low-, middle-, and high-tier restaurants changes within the same spatial unit, the everyday restaurant supply encountered by residents and urban users is also reconfigured in tiered terms.

The aggregate shift toward lower spending tiers can be read as a spatial expression of more cautious consumption. While upgrading momentum remained present (Beijing Municipal Bureau of Statistics & NBS Survey Office in Beijing, 2026), cautious consumption, price sensitivity, and changing income expectations (McKinsey & Company, 2024, 2025; Rui & Xu, 2026), together with January-July 2025

evidence of operating pressure in the catering market, lower market prices, and stronger preference for value-for-money meals (Beijing Municipal Bureau of Statistics, 2025), form the concrete background in which restaurant markets place greater emphasis on lower-priced and value-for-money provision. The observed increase in the low-tier share and decline in the high-tier share show that this change has entered the tier composition of local restaurant supply and become an observable structural change in urban commercial space.

In the face of this lower-price trend, path dependence in local restaurant structures remained evident, qualifying binary narratives of upgrading and downgrading. Compared with faster shifts in price expectations and consumption preferences, restaurant supply is embedded in specific locations, adjacent business environments, and existing commercial agglomerations, and therefore has stronger spatial stickiness. The type persistence observed here is consistent with this interpretation: most units retained their existing dominant spending tier. This also aligns with retail-centre and street-level business research that emphasizes pre-existing diversity, critical mass, agglomeration, and neighborhood context (Wrigley & Dolega, 2011; Meltzer & Capperis, 2017; Kickert & vom Hofe, 2018; Kickert et al., 2020). In this sense, upgrading and downgrading can summarize broad directional change, but they do not describe how local units are reorganized on top of existing commercial foundations.

The shift in local restaurant structures is better understood as gradual recomposition, with almost no leapfrog substitution between low- and high-tier dominance. In this study, the decline in high-tier-dominant units occurred mainly through transitions into middle-tier or mixed states, while the expansion of low-tier-dominant space also came mainly from middle-tier or mixed states. Almost no direct conversion occurred between low- and high-tier-dominant units, indicating a clear boundary between supply structures at the two ends. Work on restaurant segmentation and quality differentiation helps interpret this boundary: restaurants differentiated by segment or perceived quality often differ in locational needs, service occasions, and clustering patterns (Jung & Jang, 2019; Mossay et al., 2022). In this sense, the change in Beijing's restaurant spending-tier structure was closer to partial absorption and boundary adjustment within a differentiated market than to spatial exchange between the low and high ends.

The spatial association results further show that changes in different spending tiers were embedded in different urban spatial contexts: large peripheral residential areas more often absorbed lower-price provision, while spaces with stronger centrality and consumption scenes continued to support the persistence of the high tier. The low-tier share increased more strongly in peripheral zones and was positively associated with population density. These spaces contain large commuting residential populations and stable everyday meal needs, with consumption scenes closer to convenience, frequency, and price sensitivity; lower-price supply adjustment therefore fits more readily into high-density everyday living spaces. This pattern connects lower-price supply adjustment with neighborhood population composition and everyday service foundations (Meltzer & Capperis, 2017; Tang et al., 2023). By contrast, although the high-tier share declined overall, it remained locally concentrated; more positive high-tier changes appeared in spaces with stronger leisure services, business-office land use, nearby housing-market context, and platform review intensity. This suggests that the retention of high-tier restaurants depends more on urban scenes that can support experiential, business-oriented, and recognizably higher-quality consumption. It also echoes studies of upscale restaurant environmental perception, service experience, quality differentiation, centrality, and same-quality clustering (Ryu &

Jang, 2007; Mossay et al., 2022), as well as research on consumer cities and the quality of local consumption amenities (Glaeser et al., 2001; Berry & Waldfogel, 2010; Kuang, 2017). Thus, in a more cautious consumption context, restaurant supply adjustment retained urban commercial hierarchy and highlighted the dependence of different spending tiers on different spatial foundations.

The association with platform review intensity also reflects this differentiation. In the models, higher review intensity was associated with more negative low-tier share change and more positive middle- and high-tier share changes. This result indicates that restaurant spending-tier differentiation also has a platform-visibility dimension: one type of provision serves frequent, proximate, and price-sensitive everyday dining needs and may not rely on strong platform exposure, while another type depends more on visibility formed through search, review, and comparison. Studies of online reviews, word of mouth, and platform reputation show that digital evaluations shape consumer choice and restaurant market performance, giving restaurants searchable, reviewable, and comparable digital visibility beyond physical location (Zhang et al., 2010; Lu et al., 2013). Accordingly, spaces with stronger review intensity are more likely to support middle- and high-tier provision that depends on recognizability, accumulated evaluations, and cross-place comparison. Related research on Chinese cities also shows that platform restaurant records are not only digital representations of establishment locations; they can reflect neighborhood socioeconomic attributes and the horizontal expansion and vertical differentiation of physical commercial space in the digital era (Dong et al., 2019; Zhang et al., 2025).

The increase in the middle spending tier reveals another mode of supply adjustment: an intermediate band of moderately priced and recognizably higher-quality provision was strengthened in specific urban spaces. Middle-tier share change was larger in units with stronger platform review intensity, more tourism and accommodation POIs, and higher building coverage ratios. In the context of cautious consumption, middle-price provision may be supported in these spaces because it can meet needs for acceptable prices, recognizable quality, and cross-group use at the same time. Spaces with stronger platform visibility, more short-stay users, and compact built environments often require dining provision that can be searched and compared, fit multiple use scenes, and does not depend on a strong experiential premium. This interpretation is consistent with restaurant-market research that treats restaurant supply as differentiated across quality tiers and submarkets rather than as a single homogeneous market (Berry & Waldfogel, 2010; Park & Kim, 2026).

Two limitations constrain the interpretation of these results. First, platform records are selective. Dianping data provide an observational window into broad restaurant locations, review activity, and platform-reported per-capita spending experience (Zhai et al., 2015; Dong et al., 2019; Zhang et al., 2025), but the restaurants covered by the platform and their spending records cannot represent all restaurants or all residents' dining choices. Second, the two-period repeated cross-sectional design can compare composition and states in 2019 and 2025, but it cannot reconstruct the continuous process of change or distinguish restaurant entry, exit, incumbent business adjustment, and changes in platform records.

Overall, this study grounds the relationship between consumption adjustment and urban commercial space in the spending-tier composition of local restaurant supply. The results show that changes in local restaurant supply involve aggregate shift, local persistence, intermediary-state absorption, and differentiated spatial contexts. This perspective moves broad narratives of consumption upgrading or downgrading to the level of local commercial-structure adjustment. Bringing aggregate change together with local structural transition pathways helps interpret the adaptation of urban commercial space from

the supply side and how everyday dining opportunities are reconfigured with it (Meltzer & Capperis, 2017; Kuang, 2017).

5. Conclusion

From 2019 to 2025, the spending-tier composition of local restaurant supply in Beijing's six central districts shifted overall toward lower tiers, a direction that can be read against the background of more cautious consumption choices. At the local scale, most spatial units retained their original dominant tier, while the smaller set of changing units moved mainly toward middle-tier dominance or mixed-balanced states. The result points to gradual recomposition organized by structural continuity and recombination through middle-tier and mixed-balanced states. Low-tier provision was more closely embedded in dense everyday living spaces, whereas high-tier provision remained more concentrated in urban nodes able to support experiential, business-oriented, and recognizably higher-quality consumption. Consumption adjustment therefore corresponded to differentiated supply outcomes across urban spatial contexts.

The contribution of this study is to move research on urban restaurant dynamics beyond establishment location, counts, openings, closures, and accessibility toward the tier composition within local supply. Through this perspective, the relationship between consumption adjustment and urban commercial-space change can be understood as local continuity and recombination through middle-tier and mixed-balanced states in restaurant supply structures. The spending-tier composition of local restaurant supply therefore offers an important dimension for examining how everyday commercial services take spatial form through local supply structures.

These findings suggest that one-way upgrading, one-way downgrading, or direct substitution between the low and high ends cannot adequately describe the gradual recomposition of local commercial space. Everyday dining opportunities are reconfigured through the tier composition, structural persistence, and local shifts of specific places. Attending to this configuration helps place commercial-space adaptation, service availability, and differences in everyday dining opportunities within the same local supply structure.

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