Financial Economics Research; Vol.3, No.2; 2026
E-ISSN: 3006-3663 P-ISSN: 3006-3655
DOI: https://doi.org/10.70267/fer.250302.407412
Published by: Zeus Press

Heterogeneous Analysis of RMI on Urban Consumption Vitality: An Empirical Study Based on Panel Data of 50 Cities

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Abstract

Deepening domestic demand drives high-quality urban development. However, some lower-tier cities blindly introduce high-end brands, causing a spatial mismatch. This creates a severe gap between commercial supply and local purchasing power. Based on the Spatial Mismatch and Bottom of the Pyramid (BOP) theories, panel data from 50 Chinese cities (2022-2024) and spatial data of retail stores are utilized. A "Relative Mass-market Index" (RMI) is innovatively constructed. A Pooled OLS model is adopted to test how supply structure fit affects macro consumption. It is found that this activation effect is highly asymmetric. In lower-tier markets, the "downward compatibility" of mass-market retail generates a strong "filling effect," significantly increasing per capita retail sales. In mature markets, due to a saturated retail ecosystem, the index adjustment exhibits "elasticity desensitization." The conclusion confirms that high-quality mass-market retail acts as "new infrastructure" for lower-tier markets. It provides an important decision-making basis for local governments to abandon blindly upgrading commercial districts and to implement city-specific policies to unleash long-tail consumption benefits.

Keywords

spatial mismatch, lower-tier market, relative mass-market index, consumption vitality

1. Introduction

1.1 Background

China is currently focusing on building a new development pattern of 'dual circulation'. Under this macro background, promoting consumption and deepening domestic demand has become the core driving force for the high-quality development of urban development. The traditional commercial markets in first- and second-tier cities are currently gradually reaching saturation. However, China still has vast "lower-tier markets" that remain to be explored. These areas have enormous consumption resilience and consumption vitality, and are at a critical stage of consumption upgrading. In some low-tier cities, high-end brands are blindly introduced, causing spatial mismatch and resource waste. This phenomenon has led to a serious disconnect between the supply of physical businesses and the actual purchasing power of local residents. To face these problems,

which is more effective: simple capital expansion, or the structural fit of commercial supply (the relative ratio of mass-market to high-end formats)?

1.2 Literature Review

Recently, the relationship between retail space evolution and macro consumption vitality has been deeply explored. The relevant research framework mainly follows from “agglomeration size” to “spatial structure match.”

Early research mostly focused on the scale expansion and density of commercial resources. Couture & Handbury proved that the spatial agglomeration of non-tradable services attracts population return and reshapes urban vitality [1]. Baviera-Puig et al. proved that the spatial layout of retail formats is directly driven by local demographics [2]. Wang et al. revealed significant heterogeneity in the spatial clustering of commercial facilities; blind layout easily causes a mismatch between objective supply and local foot traffic [3].

However, with the complexity of urban spatial structure, Scholars are gradually shifting their focus toward the spatial mismatch of resources. The “Spatial Mismatch Hypothesis” was first proposed by Kain to explain unemployment caused by spatial disconnection [4]. Sun et al. revealed the negative impact of housing-job mismatch on urban efficiency in Shanghai [5]. Gobillon et al. systematically summarized the micro-mechanisms of spatial mismatch, pointing out that physical disconnection causes severe market exclusion [6]. This classic analytical framework provides an excellent theoretical anchor for analyzing the detachment between retail networks and local consumption bases.

At the level of supply-demand matching between the commercial supply structure and heterogeneous markets, Schiff confirmed that high-end retail relies heavily on large demand networks in core cities [7]. Tang et al. revealed a significant spatial mismatch between service supply and real local demand [8]. Glaeser et al. pointed out that commercial gentrification accelerates local retail churn, but weakening the loss of the original unique local businesses [9]. London and Hart expanded the BOP theory, noting that transnational models cannot blindly copy the existing models of the high-end market [10]. It is necessary to leverage the advantages of the existing market environment and provide customized solutions that align with the actual purchasing power locally.

Overall, existing literature lays a solid foundation for understanding urban retail agglomeration and spatial mismatch. Most studies focus on total store numbers or job-housing mismatch. Few studies explore the filling mechanism of mass-market retail in lower-tier markets from a supply structure perspective. This paper aims to fill this academic gap through empirical testing.

1.3 Research Content

To fill the above research gap, Spatial Mismatch and BOP theories are used as the core logical thread, and innovatively extends them to the field of physical business supply. Panel data from 50 key cities (2022-2024) are utilized. “Chabaidao” (mass-market) and “Starbucks” (high-end) are selected to construct the RMI. The City Commercial Charm Ranking is used as the standard for city commercial levels. Since offline stores are slow-moving variables, a Pooled OLS with Year Effects is constructed. Cluster-Robust Standard Errors (SE) are adopted to ensure the Reliability of Statistical Inference. A one-period lagged independent variable is introduced in robustness tests to alleviate endogeneity bias caused by reverse causality.

From the perspective of research direction, the research broadens the research boundaries of the 'spatial mismatch effect'. It is found that the activation effect of commercial supply structure on domestic demand is significantly asymmetric. In low-tier cities, mass-market retail presents a strong “filling effect”, significantly boosting the local macro consumption vitality. In mature markets, adjustments to this single structure show “elasticity desensitization.” Standardized mass-market retail is confirmed as “new infrastructure” for lower-tier markets.

2. Theoretical Framework and Hypotheses

Spatial Mismatch and Bottom of the Pyramid (BOP) theories are combined to analyze the internal mechanism of RMI stimulating domestic demand from the perspective of structural adaptation, and propose the corresponding research hypotheses.

Spatial mismatch indicates that efficiency loss occurs when high-end brands detach from demand capacity. BOP theory emphasizes that standardized supply for low-income markets can effectively activate overlooked consumer potential. These two together constitute the fundamental mechanism through which RMI affects domestic demand.

In lower-tier markets, commercial infrastructure is weak. The main contradiction consumers face is the mismatch between the growing demand for quality and the backward local supply. An increase in RMI means a higher proportion of mass-market brands. This "downward compatibility" corrects spatial mismatch, producing a "Filling Effect" and driving retail sales. Therefore, the following is proposed:

H1: In lower-tier markets, RMI has a significant positive activation effect on urban domestic demand.

By contrast, the business ecosystem of mature markets has nearly reached saturation. Micro-adjustments in single formats are often zero-sum games, making the city insensitive to RMI changes. This shows an "elasticity desensitization" feature.

H2: In mature markets, RMI does not have a significant pull effect on urban domestic demand.

3. Research Design and Data Description

3.1 Data Sources and Sample Screening

To ensure the scientific nature of empirical research and the rigor of statistical inference, macro urban economic data, micro spatial data, and city level classifications are included. The specific sources of the core data are as follows:

(1) Macro economic data: Retail sales, GDP, and industrial structure data are manually matched from official statistical yearbooks.

(2) Micro spatial data (POI): Spatial data for "Starbucks" and "Chabaidao" are accurately extracted via the Gaode Map Open Platform with the authoritative domestic Narrow Gate Restaurant Brand Business Database. This reflects real commercial spatial structures.

(3) City grouping data: The City Commercial Charm Ranking is used as the measurement baseline. This list is currently the most widely recognized industry benchmark in China for the level of commercial infrastructure in cities.

The dataset was strictly cleaned. Cities with border changes, missing data, or too few stores were removed. Continuous macro variables were logarithmized. Ultimately, 150 observations of Strongly Balanced Panel Data were obtained. It laid a solid data foundation for subsequent causal inference.

3.2 Variables Selection and Measurement

Four types of indicators are established to comprehensively examine the impact of supply structure. The specific basis for selecting each variable and the measurement methods are shown in Table 1.

Table 1: Variable Definitions and Measurements

Variable Type	Variable	Symbol	Measurement
Dependent variable	Macro Consumption Vitality	Ln_sales_{it}	$Ln\ (per\ capita\ retail\ sales)$
Independent variable	Relative Mass-market Index	RMI_{it}	$RMI_{it} = \frac{N_{chabaidao,it}}{N_{starbucks,it} + N_{chabaidao,it}}$
Controls	Macro Economic Level	Ln_GDP_{it}	$Ln\ (per\ capita\ GDP)$
Controls	Industrial Structure	Ind_Struct_{it}	Tertiary industry GDP share (%)
Grouping Variable	City Commercial Level	$Grade_i$	Divided into mature markets and lower-tier markets

Dependent variable: Ln_sales_{it} is selected to measure consumption scale. The natural logarithm is executed to alleviate heteroscedasticity problem.

Independent variable: RMI_{it} is constructed from an internal structure fit perspective. "Starbucks" is chosen as the anchor for high premium thresholds. "Chabaidao" is chosen as the anchor for mass-market purchasing power. RMI ranges from 0 to 1. An index closer to 1 indicates the supply structure tends to align with mass purchasing power. Conversely, if it approaches 0, it indicates a tendency for high-end vacancies in the city's commercial supply.

Control variables: Ln_GDP_{it} controls the natural pull effect of basic wealth. Ind_Struct_{it} controls the interference of service sector development.

Grouping variable:$Grade_i$ divides the sample into mature markets and lower-tier markets based on the City Commercial Charm Ranking.

3.3 Model Specification

The specific econometric equation specification is as follows:

$$Ln\_sales_{it}=\beta_0+\beta_1 RMI_{it}+\gamma_1 Ln\_GDP_{it}+\gamma_2 Ind\_Struct_{it}+\mu_t+\varepsilon_{it} \quad (1)$$

Where the subscript *i* and *t* represent the city and year, respectively; β_0 is the intercept term; μ_t is the year fixed effect;$\varepsilon_{it}$is the random error term.

RMI is a "Slow-moving Variable." If City-specific fixed effects are forcibly controlled, valuable cross-sectional variance is irreversibly removed, causing the estimated coefficients to exhibit severe downward bias. Therefore, Pooled OLS is adopted. Cluster-Robust SE clustered at the city level is uniformly adopted to ensure the consistency and unbiasedness of statistical inference.

4. Empirical Results and Analysis

4.1 Descriptive Statistics

Before performing the estimation of measurement parameters, this paper conducts descriptive statistical analysis on various key macroeconomic and microeconomic variables (see Table 2).

Table 2: Descriptive Statistical Analysis of Major Variables

Variable	Obs	Max	Min	Mean	Std.Dev.
RMI_{it}	150	0.860	0.146	0.474	0.157
Ln_GDP_{it}	150	12.237	10.867	11.664	0.337
Ind_Struct_{it}	150	84.800	40.800	55.327	9.343
Ln_sales_{it}	150	9.063	7.674	8.386	0.302

From the statistical results in Table 2, it can be seen that Ln_sales_{it} shows a reasonable span in maximum and minimum values with a standard deviation of 0.302, indicating that there is indeed significant heterogeneity in the consumption base among different cities. The mean of RMI is 0.474, with a standard deviation of 0.157, providing rich cross-sectional variance to capture the "downward compatibility" effect.

4.2 Baseline and Heterogeneity Regression Analysis

According to the empirical estimation results in Table 3, this article provides the following analysis on the internal mechanism by which the optimization of commercial supply structure drives urban consumption vitality:

In lower-tier markets, the RMI estimation coefficient is 0.5353, highly significant at the 1% level. A 0.1-unit increase in RMI drives Ln_sales_{it} up by about 5.35%. H1 is verified.

In mature markets, the RMI coefficient is only 0.124 and fails the significance test (P=0.547). This asymmetric performance perfectly proves H2. High-tier cities are highly saturated; increasing mass-market proportions cannot produce substantial influence.

Ln_GDP_{it} is extremely significant in both models. It further confirms that the economic fundamentals and household income are the fundamental cornerstones driving retail prosperity. The R-squared values exceed 0.62. Cluster-Robust SE effectively eliminates endogenous interference from serial correlation.

Table 3: Analysis of Regression Results

Variable	Model 1 (Lower-tier markets)	Model 2 (Mature markets)
RMI_{it}	0.5353***	0.1238
Ln_GDP_{it}	0.7641***	0.8366***
Ind_Struct_{it}	0.0049	-0.0002
Year FE	YES	YES
Cluster	YES	YES
Obs	93	57
Constant	-1.0700	-1.3931
R^2	0.642	0.625

*Note: *** represents significance at the 1% level.*

4.3 Robustness and Endogeneity Tests

In the preceding baseline and heterogeneous group regressions, this paper confirms that RMI has a strong positive driving effect on urban macro consumption vitality in the sinking market. However, this empirical result may be subject to potential interference from endogeneity issues, particularly the challenge of reverse causality. Specifically, lower-tier cities with stronger overall consumption vitality and a more stable foundation of residents' purchasing power, may naturally attract more mass-market standardized restaurant chain brands, thereby passively raising the RMI index.

To overcome potential reverse causality, a one-period lagged independent variable is executed. Past supply structure determines current consumption ecosystems, but current consumption cannot reversely intervene in past brand locations, meeting the “cause-and-effect” chronological feature. The estimation results of the one-period lag robustness test are shown in Table 4:

Table 4: Robustness Test

Variable	Model
RMI_{it-1}	0.576***
Ln_GDP_{it}	0.7809***
Ind_Struct_{it}	0.006*
Year FE	YES
Cluster	YES
Obs	62
Constant	-1.339
R^2	0.654

*Note: *** represents significance at the 1% level, * represents significance at the 10% level.*

After excluding endogeneity, the lagged RMI coefficient reaches 0.576. The R-squared stabilizes at 0.654. It is strongly proven that the activation effect of “downward compatibility” remains stably present.

5. Conclusion

This paper empirically examines the impact of the physical commercial supply structure on urban consumption vitality. It is found that “downward compatibility” produces an extremely significant pull effect on lower-tier markets, effectively filling the supply-demand gap. Mature markets show obvious “system resilience” due to saturated facilities. Accordingly, it is suggested that low-tier cities should abandon blind high-end tendencies and increase support for high-quality mass-market formats. High-tier cities should focus on stock optimization and experiential retail, promoting the transformation of commercial supply from total expansion to refined structural adaptation.

There are still some shortcomings in this article. Specifically reflected in the following three aspects. Firstly, due to the difficulty of obtaining micro level store spatiotemporal big data, the RMI constructed in this paper only selected two benchmark freshly made beverage brands as measurement benchmarks. In the future, efforts can be made to expand the full category chain format to enrich the indicator dimensions; Secondly, the study

period of this article is from 2022 to 2024, which belongs to typical short panel data and fails to fully capture the dynamic time lag effects of the evolution of physical business networks under longer macroeconomic cycles; Finally, this article mainly focuses on the aggregation effect at the macro level of cities. In the future, it can further explore the spatial mismatch and micro mechanism of commercial resource distribution within cities by combining micro geographic grid data.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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