

Food Consumption Vulnerability in a Shrinking City: Panel Evidence from Busan, South Korea

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Abstract

In shrinking cities, population decline and aging influence local food retail environments in ways that GIS-based accessibility measures cannot fully capture, because these measures record where outlets exist rather than how they are used. Using a balanced monthly panel of 205 sub-districts in Busan, South Korea (January 2023 to December 2025, 7,380 observations), this study estimates sub-district fixed effects from two-way panel models across three outcome dimensions, including total transaction value, transaction count, and mean transaction value, separately for food-specialized (Food) and general retail (Retail) establishments. Sub-districts in the lower 10th percentile of fixed effects are classified as consumption-vulnerable and cross-tabulated across channels into four categories, including Type A (Neither), Type B (Retail-only), Type C (Food-only), and Type D (Both). The results show three distinct formation pathways, including a simultaneous supply and demand collapse in Type D sub-districts concentrated in the old urban core of Busan, a demographic contraction pathway in Type C sub-districts, and a supply infrastructure gap in Type B sub-districts. These vulnerability patterns are spatially clustered rather than randomly distributed. This diagnostic framework provides shrinking cities with a screening tool to monitor early warning signals of food access vulnerability before conventional food desert conditions occur.

Keywords: urban shrinkage; food retail; offline transaction activity; payment-card transactions; small-area panel data; spatial screening

1. Introduction

Population decline and aging influence the geography of daily retail, but store inventories alone cannot show where recorded commercial activity is low. Two neighborhoods with equally low transaction activity may require different policy responses. For example, one neighborhood may face a limited local customer base, whereas the other may be served through adjacent centers or online channels. Therefore, the spatial problem is to identify low activity after controlling for observable differences, distinguish food-specialized patterns from general retail conditions, and determine which spatial signals require follow-up.

Transaction data offer a complementary observation layer unavailable in annual store inventories. Establishment-based card data capture recorded offline activity at merchant locations across detailed spatial and temporal scales. However, these data measure commercial activity rather than resident demand or food access, because they combine purchases by residents and visitors while omitting cash transactions and online orders. A neighborhood with low recorded activity may face a retail deficit, or it may export purchases to adjacent areas or online platforms. Distinguishing these cases requires controlling for observable differences across neighborhoods.

This distinction is important in shrinking cities, where population loss, aging, and retail disinvestment do not occur uniformly. Research on East Asian urban shrinkage identifies aging and service outflow as features of declining inner-city areas (Jeon & Kim, 2020), whereas studies on Japanese metropolitan suburbs document spatial gaps between changing food supply and the mobility of an aging population (Nakayama et al., 2024). Busan shows these conditions. The registered population of Busan declined from 3.733 million in 2000 to approximately 3.24 million in 2025, with 24.7% of residents aged 65 or older as of July 2025 (Busan Metropolitan City, 2025). These trends are severe in the old urban core districts of Jung-gu, Dong-gu, Seo-gu, and Yeongdo-gu, where retail withdrawal and demographic decline may reinforce each other in ways that store inventories alone cannot reveal.

Low offline activity is also difficult to interpret in the context of growing online grocery purchases. It may reflect a voluntary channel choice or an adjustment away from the preferred offline–online mix of households. However, offline channels still account for approximately 83.6% of primary food purchase locations in South Korea (KREI, 2024). Furthermore, elderly and single-person households face barriers to online substitution due to lower digital literacy and mobility constraints (Trude et al., 2022; Kim et al., 2025). These considerations motivate a focus on offline transaction activity as a signal of local food consumption vulnerability, particularly in aging neighborhoods.

This study develops a consumption-based diagnostic framework to identify sub-districts with structurally low offline food consumption in Busan and treats these areas as potential precursors to food desert formation. Using a balanced monthly panel of 205 sub-districts from January 2023 to December 2025, this estimate sub-district fixed effects across three outcome dimensions, including transaction value, transaction count, and mean value per transaction, separately for food-specialized (Food) and general retail (Retail) establishments. Cross-classifying the lower tails of Food and Retail fixed effects produces four consumption vulnerability types, and Global Moran's I and local indicators of spatial association are used to examine their spatial organization.

This study provides three contributions. First, it uses place-based offline transaction activity as a diagnostic layer between retail availability and household acquisition, treating structurally low consumption as a potential precursor to food desert formation. Second, it identifies distinct pathways to consumption vulnerability, where each pathway has different policy implications that a uniform intervention would obscure. Third, it provides a screening workflow for shrinking cities to monitor early warning signals of food access vulnerability before conventional food desert conditions occur.

2. Related Literature

2.1. Urban Shrinkage and the Spatial Restructuring of Everyday Retail

Urban shrinkage is not a uniform contraction of population and services. Evidence from East Asia shows locally contingent combinations of demographic aging, redevelopment, housing decline, and service outflow (Jeon & Kim, 2020). The main implication for this study is that metropolitan population loss can coexist with uneven neighborhood conditions, rather than forcing sub-districts in Busan into predetermined stages of decline.

Retail restructuring is one dimension of this unevenness. A spatial survival analysis across U.S. cities found sales volume to be the primary indicator of supermarket and convenience store survival (Warren & Gordon-Larsen, 2018). In the suburbs of Yokohama, declining resident mobility and the relocation of supermarkets toward station areas widened gaps between food supply and demand in locations farther from stations (Nakayama et al., 2024). Population change, purchasing power, urban centrality, store mix, and mobility may influence where commercial activity is sustained, without supporting a mechanical sequence from population loss to store withdrawal and food desert conditions.

Aging also complicates the connection between population composition and local transactions. Among older Japanese adults living alone, reported shopping difficulty was associated with car use, walking limitations, available help, and supermarket distance (Ishikawa et al., 2016). Store format can also be important. For example, higher neighborhood coverage by convenience stores was associated with shopping independence among older Japanese adults (Matsumoto et al., 2019).

In South Korea, studies have investigated food desert vulnerability using demographic variables, such as elderly population size, aging rates, and the presence of vulnerable older adults (Cho et al., 2024; Choi, 2025; Kim & Kim, 2025; Kim & Lee, 2025; Lee et al., 2024; Rhew & Moon, 2025; Seong & Lee, 2021). These studies indicate that urban food deserts are driven mainly by structural decay in old districts, where the outmigration of younger residents reduces local purchasing power and makes

retail operations unprofitable, leaving less mobile older residents in newly formed food deserts. However, this literature relies mainly on GIS-based supply metrics and does not capture actual consumption behavior. Purchasing patterns of older adults are influenced by mobility limitations that reduce shopping frequency (Iizaka et al., 2020). In addition, single-person elderly households often prefer small-portioned groceries, which affects unit prices and expenditures (Yang & Kim, 2020). Urban studies also suggest that shrinkage manifests in diverse trajectories rather than as a uniform process, often called varieties of shrinkage (Grossmann et al., 2013; Häußermann & Siebel, 1988). However, how these pathways of urban decline appear in food retail networks remains less understood.

2.2. From Food Environments to Place-Based Transaction Activity

The food access literature established an important policy concern that where people live may influence their ability to obtain affordable and healthy food. However, its empirical focus varies across outlet presence, distance, population characteristics, transportation, prices, and combinations of these measures. Alternative definitions identify different parts of the same city as vulnerable (Leete et al., 2012), and perceived access can diverge from objective proximity within the same population (Caspi et al., 2012). Lower transaction values alone do not constitute a diagnosis of food access problems.

The residential neighborhood is also an imperfect boundary for food acquisition. Disadvantaged residents often bypass nearby outlets for supermarkets elsewhere (LeDoux & Vojnovic, 2013), whereas participants in Minneapolis combined food shopping with everyday mobility and used destinations beyond their immediate neighborhoods (Shannon, 2016). Store availability, practical accessibility, affordability, and product suitability should therefore be treated as related but distinct characteristics, none of which is directly measured by transaction values at local establishments.

Neighborhood food systems can be examined through four related aspects, including the local supply environment, transactions recorded at establishments, household access and acquisition, and downstream dietary or welfare outcomes. This study examines the second aspect. The measured outcomes describe recorded offline activity at merchant locations, rather than the food purchases, access constraints, or food desert status of residents.

2.3. Out-Shopping, Online Grocery Services, and the Ambiguity of Low Offline Activity

Online grocery services expand shopping options beyond the residential neighborhood and weaken the relationship between local offline transactions and household acquisition. A review focused on low-income populations identifies cost, limited service availability, and low perceived control over product selection as barriers to online grocery use (Trude et al., 2022). Evidence from South Korea also shows that adding online grocery options does not eliminate spatial inequalities in food access (Kim et al., 2025). Therefore, low local offline activity can reflect either a voluntary choice of shopping channel or an adjustment away from the preferred offline–online mix of households, which imposes additional delivery, search, and product selection costs.

Nominal service availability is also different from practical digital access. In South Korea, offline channels still account for approximately 83.6% of primary food purchase locations (KREI, 2024), and elderly and single-person households face barriers to online substitution due to lower digital literacy and mobility constraints. Because the dataset does not record online orders or household acquisition, voluntary and constrained substitution remain competing interpretations.

2.4. Transaction Data, Merchant Categories, and Accounting-Linked Outcomes

Transaction data offer an observational layer that store directories and household surveys cannot provide alone. Credit card transaction data have been used to describe expenditure patterns and temporal commercial rhythms in urban areas (Carpio-Pinedo et al., 2022). The dataset from Busan provides an advantage over annual store counts by offering monthly observations of monetary activity recorded at establishments at the sub-district level.

This advantage depends on coverage. Card transaction data from a single provider do not constitute a comprehensive measure of local consumption. Differences across sub-districts in Busan can reflect actual commerce alongside differences in cardholder coverage, merchant acceptance, cash usage, and establishment location data. Moreover, aggregation at merchant locations combines purchases by residents, commuters, tourists, and other visitors.

Merchant categories create a second measurement boundary. In the data from Busan, Food and Retail are establishment classifications rather than mutually exclusive product baskets. Food bought at a general retailer is recorded under Retail, which also includes non-food purchases. Therefore, Retail provides a comparison for the local retail base, rather than a second food transaction outcome. The three outcomes, including recorded transaction value, transaction count, and mean value per transaction, are linked by an accounting identity and are not independent behavioral tests.

2.5. Panel Comparison, Relative Screening, and Spatial Diagnostics

Panel fixed effects address one source of ambiguity while leaving others intact. In food environment research, estimates can differ across ordinary least squares, random effects, and fixed effects specifications (Rummo et al., 2017), and retail supply, demographic composition, and transactions may be jointly determined. In this study, coefficients on time-varying covariates are interpreted as conditional associations within sub-districts. The estimated sub-district fixed effects summarize period-average conditional differences under specified covariates and time effects. They do not represent causal place effects or direct measures of unmet food needs.

Classification requires additional caution. The categories from Type A to Type D produced by cross-classifying the lower tails of Food and Retail are cutoff-specific overlaps rather than observed trajectories. Global Moran's I summarizes whether similar values are located near one another (Moran, 1950), whereas local indicators of spatial association decompose global association into local clusters and spatial outliers (Anselin, 1995). This study uses these metrics as exploratory descriptions of estimated place effects. A positive global statistic indicates that similar effects tend to cluster geographically, and Low-Low clusters identify below-average values surrounded by below-average

neighbors. Combining panel conditioning, cross-category comparison, and spatial diagnostics provides an initial map of low recorded activity. This framework treats the spatial concentration of low consumption as a potential precursor to food desert formation, which supports follow-up investigation of resident mobility, online purchasing, prices, and household outcomes.

3. Data and Methods

3.1. Data and Measures

This study uses public administrative and commercial datasets covering 205 sub-districts in Busan from January 2023 to December 2025. This dataset yields a panel of 7,380 monthly observations at the sub-district level.

Dependent variables are based on offline credit card transaction data provided by Shinhan Card and distributed by the Busan Big Data Wave platform.¹ This dataset contains the monthly average of daily approved card transactions and the corresponding expenditure amounts by industry category and sub-district. The data are aggregated to protect individual privacy. This study analyzes two industry categories, food and grocery (the Food channel) and general retail distribution (the Retail channel). This classification is based on the type of business establishment rather than the specific goods purchased. Therefore, food spending at large retail outlets is recorded under the Retail channel, which creates an overlap between the channels regarding actual food consumption.

Using these two variables, three outcome measures are calculated for each channel, including total expenditure, the number of transactions, and expenditure per transaction. Expenditure per transaction is defined as the ratio of total expenditure to the number of transactions. The three outcomes are linked by an accounting identity (recorded value equals count multiplied by mean value) and do not represent independent behavioral tests. All outcome variables are log-transformed before estimation.

¹ Busan Metropolitan City Big Data Wave: <https://data.busan.go.kr>

Because transaction data are aggregated at the business establishment level within each sub-district, the metrics include all transactions at establishments in the sub-district, regardless of consumer residence. Therefore, the data provide an establishment-based measure of consumption rather than a household-based measure. Differences across sub-districts may reflect commercial activity, along with differences in cardholder coverage, merchant acceptance, and cash usage. Because this dataset captures transactions at physical establishments, it reflects only offline food purchasing activity and excludes online grocery purchases. Because offline channels represent the primary mode of food purchasing in South Korea (KREI, 2024), this metric provides a valid basis for assessing structural food consumption vulnerability at the sub-district level.

Demographic variables are obtained from two sources. Annual data for the total population and the elderly population at the sub-district level are collected from Statistics Korea. The number of elderly residents living alone is obtained from the resident registration database of the Ministry of the Interior and Safety, which provides annual counts of single-person households by age and sex. Two demographic covariates are calculated. The first is the elderly rate, defined as the proportion of residents aged 65 or older in the sub-district population. The second is the elderly living alone rate, defined as the proportion of elderly single-person households among all elderly residents. To control for consumption by non-residents at local establishments, the monthly average visiting population is included. This variable is derived from mobile network signal data collected from telecommunications base stations by the Busan Big Data Wave platform. It identifies individuals in a sub-district who are not registered residents or commuters.²

Supply variables are divided into large and small retail formats. Large retail format variables include the number of hypermarkets, mid-size marts, and registered traditional markets. These data are obtained from the annual large-scale retail establishment registry of the Ministry of the Interior and

² Ministry of the Interior and Safety, Resident Registration Database: <https://jumin.mois.go.kr>

Safety, published on the Public Data Portal.³ Small retail format variables include the number of small supermarkets, convenience stores, and specialty grocery stores. These data come from the commercial establishment registry of the Korea Federation of Small and Medium Business, distributed on the Public Data Portal.⁴ All supply variables are measured annually and matched to the monthly observations. For the Retail channel models, two additional control variables are included: log expenditure on living goods and log expenditure on clothing and accessories. These variables capture co-moving general retail activity recorded at merchant locations and help distinguish food-specific patterns from broader retail conditions. These data are obtained from the same Shinhan Card dataset as the dependent variables.¹

3.2. Empirical Strategy and Spatial Diagnostics

To identify sub-districts with structurally low offline food consumption, this study estimates a two-way panel fixed effects model with monthly card transaction data. The baseline specification is defined as follows.

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \mu_i + \lambda_t + \varepsilon_{it}$$

where y_{it} represents one of three log-transformed outcomes for sub-district i in month t , including log food expenditure, the log number of transactions, and log expenditure per transaction. The term μ_i represents the sub-district fixed effect reflecting all time-invariant unobserved characteristics, and λ_t includes additive year and calendar-month indicators to account for annual shifts and recurring seasonality. The vector $\mathbf{x}_{it}$ contains time-varying covariates, and ε_{it} is an idiosyncratic error term. All models are estimated separately for the Food and Retail channels, yielding six specifications in total.

³ Ministry of the Interior and Safety, Large-Scale Retail Establishment Registry, Public Data Portal: <https://www.data.go.kr/data/15154948/openapi.do>

⁴ Korea Federation of Small and Medium Business, Commercial Establishment Registry, Public Data Portal: <https://www.data.go.kr/data/15083033/fileData.do>

The covariate vector $\mathbf{x}_{it}$ includes counts of hypermarkets, mid-size marts, traditional markets, small supermarkets, convenience stores, and specialty grocery stores, along with the elderly rate, the proportion of elderly residents living alone, log visiting population, and log total population. Log total population is included as a covariate rather than used for normalization, which allows its elasticity to be estimated freely. Retail channel models additionally include log expenditure on living goods and log expenditure on clothing to capture co-moving general retail activity and distinguish food-specific patterns from general retail conditions.

HC3 heteroskedasticity-robust standard errors are reported. Because HC3 does not account for within-sub-district serial correlation, statistical significance is treated as model-based descriptive evidence. Time-varying confounding, reverse causation, and joint determination of supply and transactions preclude causal interpretation.

The estimated sub-district fixed effects μ_i summarize period-average place differences over 2023–2025 under the specified controls. They may also contain influences from centrality, inflow demand, unmeasured prices or quality, and persistent card-coverage differences. Therefore, they are not causal place effects or estimates of unmet food need. For screening purposes, sub-districts where μ_i falls below the 10th percentile of the cross-sectional distribution are classified as consumption-vulnerable. This procedure is applied separately for each channel and dimension. Places near the cutoff may change position under a different sample or specification, and the ranking does not propagate first-stage estimation uncertainty.

Sub-districts are then cross-tabulated into four mutually exclusive types, including Type A (Neither), which is not consumption-vulnerable in either channel; Type B (Retail-only), vulnerable only in the Retail channel; Type C (Food-only), vulnerable only in the Food channel; and Type D (Both), vulnerable in both channels. The three dimensions are analyzed separately rather than collapsed into a single index, because total expenditure, transaction frequency, and expenditure per transaction each reflect a distinct aspect of offline food consumption. These labels describe cross-category positions under the model, period, and cutoff rather than inferred classes or observed trajectories.

To examine whether offline food consumption vulnerability is spatially clustered, Global Moran's I is calculated for both model residuals and sub-district fixed effects using a row-standardized Queen contiguity matrix. Global Moran's I is defined as follows.

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where n is the number of sub-districts, x_i is the variable of interest for sub-district i , $\bar{x}$ is its mean, and w_{ij} is the spatial weight between sub-districts i and j . Spatial weights are defined using a row-standardized Queen contiguity matrix, where $w_{ij} = 1$ if sub-districts i and j share a boundary or vertex and $w_{ij} = 0$ otherwise.

Local Indicators of Spatial Association (LISA) identify statistically significant local clusters using the standardized fixed effects value and its spatial lag for each sub-district. LL clusters identify sub-districts with structurally low offline food consumption surrounded by similarly underperforming neighbors, which may signal early food desert conditions. LH clusters identify isolated sub-districts with low consumption located in active commercial areas, indicating a distinct formation mechanism. Statistical significance is assessed at the nominal 5% level using a permutation procedure. The local tests are exploratory and are not adjusted for multiple comparisons.

4. Results

4.1 Determinants of Sub-District Food Consumption

Table 1 reports the fixed effects estimates for log food expenditure, log transaction count, and log expenditure per transaction across the Food and Retail channels. Several patterns are consistent across all three dimensions.

[Table 1 about here]

Among supply variables, small supermarkets and specialty grocery stores show positive and significant associations in both channels across all three dimensions. This result suggests that small food outlets may complement rather than substitute overall consumption activity. Large stores, including hypermarkets and mid-size marts, show no consistent significant association. This indicates that attracting large retail stores may not be an effective policy option. However, mid-size marts show a positive association with Food expenditure per transaction, which may indicate larger purchases per visit in the Food channel. Convenience stores show a negative association in the Retail channel across multiple dimensions. This pattern is consistent with a substitution effect that reduces spending at other store types. Traditional markets are positively associated with all three Retail outcomes but show no significant Food channel associations.

Among population variables, the elderly rate is negatively associated with Food transaction count but positively associated with Food mean transaction value and all three Retail outcomes. This suggests that sub-districts with larger elderly populations show reduced food visit frequency but higher spending per visit and greater overall retail activity. The proportion of elderly residents living alone shows opposite signs across the two channels. The association is positive for Food total expenditure and Food expenditure per transaction, but is not statistically significant for Food transaction count. In the Retail channel, the association is negative across all three dimensions. This indicates that sub-districts with more elderly single-person households may focus their spending on food necessities, whereas discretionary retail purchases remain limited. Log total population is statistically significant in both channels but is less than one. This result shows that population normalization is misspecified and supports including total population as a covariate. The adjusted R^2 values are highest for the transaction dimension and lowest for the expenditure dimension. This suggests that transaction frequency is closely related to observed local characteristics, whereas total expenditure is influenced by additional unobserved factors.

4.2 Distribution of Fixed Effects and Identification Rationale

Figure 1 shows the distribution of estimated sub-district fixed effects (μ_i) for the food and retail channels across the three dimensions. In both channels, the expenditure and transaction distributions show a left-skewed pattern with a lower tail. This pattern indicates that a subset of sub-districts has structurally depressed offline food consumption levels after controlling for time-varying covariates. Furthermore, this distribution suggests that structural food consumption vulnerability reflects a structural separation rather than a continuum, which supports the threshold-based classification.

[Figure 1 about here]

The three dimensions, including total expenditure, transaction frequency, and expenditure per transaction, reflect distinct behavioral aspects of offline food consumption. Total expenditure measures overall market activity at local establishments, transaction frequency captures visit behavior, and expenditure per transaction indicates purchase size per visit. Analyzing all three dimensions provides a clearer assessment of consumption vulnerability than a single composite index, because low total expenditure, infrequent purchasing, and low purchase value per visit may reflect different underlying mechanisms with distinct policy implications.

4.3. Cross-Category Lower-Tail Patterns and Descriptive Characteristics

Table 2 presents the food consumption vulnerability classification based on a 10th percentile threshold of estimated fixed effects. It reports the number of sub-districts in each type along with the average demographic and supply characteristics relative to the non-vulnerable benchmark, Type A (Neither).

[Table 2 about here]

Most sub-districts show no consumption vulnerability in either channel, which indicates that structural offline food consumption deficits are concentrated in a limited geographic area. A symmetric pattern emerges in the off-diagonal cells, with equal numbers of Food-only (Type C) and Retail-only (Type B) sub-districts under the expenditure and transaction dimensions. This equal count is a mathematical

consequence of applying the same threshold to both channels and does not imply symmetric formation processes. Sub-districts vulnerable in both channels simultaneously (Type D) number 11, 11, and 3 across the three dimensions. The lower count under the unit price dimension may reflect a more dispersed spatial distribution of unit price vulnerability. Figure 2 maps the spatial distribution of the four types across the three dimensions.

[Figure 2 about here]

Sub-districts in the old town are concentrated in Type D and Type C under the expenditure and transaction dimensions. In contrast, Type B sub-districts are located mainly outside the old town boundary. This pattern suggests that the formation mechanism may be driven by supply shortfalls in demographically stable areas rather than population decline.

Under the expenditure and transaction dimensions, Type D sub-districts are concentrated within the old town boundary. Type C sub-districts appear in adjacent inner-city areas and isolated peripheral locations, whereas Type B sub-districts are dispersed across outer ring areas. The unit price dimension shows a different spatial structure. Type D is confined to a few core old town sub-districts, whereas Type C and Type B extend across the city. This divergence suggests that unit price vulnerability operates along an independent spatial axis, which supports retaining all three dimensions in the typology.

Regarding demographic characteristics, population size declines consistently from Type A to Type B, Type C, and Type D. Type D sub-districts retain only 26–37% of the population of Type A. Type C retains 35–52%, and Type B retains 54–61%. In most cases, this population decline is greater than the corresponding supply shortfalls. This indicates that demographic contraction may be a main factor rather than a consequence of supply withdrawal alone. The rate of elderly residents living alone shows the opposite pattern and rises toward more vulnerable types. Type C records the highest rate under the unit price dimension (41.1%), which is consistent with small-volume purchasing behavior among elderly single-person households.

For Type D, the number of convenience stores and specialty grocery stores decreases to between 13% and 43% of the levels in Type A. This indicates a substantial reduction in small retail infrastructure along with demographic decline. For Type C, supply variables remain close to the levels of Type A, but the population decreases more sharply. This pattern indicates that consumption vulnerability is driven mainly by demand-side demographic factors rather than deficits in physical supply. For Type B, the population remains stable, but small retail supply shows large shortfalls. This suggests a supply-side gap in stable residential areas.

These patterns show three distinct pathways to structural food consumption vulnerability, including a simultaneous supply and demand decline for Type D, a demographic contraction pathway for Type C, and a supply infrastructure gap for Type B. Each pathway may represent a different stage in the progression toward food desert conditions. Section 5 discusses the implications of these pathways for policy design.

4.4. Global and Local Spatial Association

Table 3 reports the Global Moran's I statistics for the residuals and sub-district fixed effects across the two channels and three dimensions. The Global Moran's I for the residuals is statistically insignificant across all six specifications. This result indicates that the fixed effects structure captures unobserved spatial heterogeneity. In contrast, the Moran's I for the fixed effects is positive and significant across all specifications. The values range from 0.096 to 0.164, which confirms that structural offline food consumption levels are spatially clustered. The higher autocorrelation in the Food channel (0.131–0.164) compared to the Retail channel (0.096–0.124) suggests that offline food consumption vulnerability is more geographically concentrated than retail vulnerability.

[Table 3 about here]

Table 4 summarizes the LISA cluster counts across the two channels and three dimensions. In the Food channel, LL clusters are the most numerous under the expenditure and transaction dimensions (12 and 11 sub-districts, respectively), whereas HH clusters are fewer. In the Retail channel, this

pattern is reversed. HH clusters are more numerous, with a maximum of 14 sub-districts under the unit price dimension. In contrast, LL clusters decrease and disappear under the unit price dimension. This contrast shows the different spatial patterns of the two channels identified in Section 4.3.

[Table 4 about here]

Among LL clusters, sub-districts such as Dongdaesin 3-dong, Gamcheon 2-dong, Cheongnak 1-dong, and Ami-dong appear across multiple Food channel specifications. Additionally, the Retail transaction dimension includes peripheral sub-districts outside the old town, including Cheongnyongnopo-dong and Hwamyeong 2-dong. No sub-districts are identified as Retail unit price LL clusters. Among LH clusters, Mangmi 2-dong and Gwangan 2-dong appear as isolated pockets of structurally low food consumption within active commercial areas. The full lists of LL and LH sub-districts are provided in Supplementary Tables 9 and 10.

Figures 3 and 4 show the LISA cluster distributions for the Food and Retail channels. In the Food channel (Figure 3), LL clusters are concentrated within the old town boundary under the expenditure and transaction dimensions. These clusters of structurally low offline food consumption appear in areas with severe urban decline, which suggests that these sub-districts may be primary candidates for food desert formation. The unit price dimension shows a different pattern. LL clusters remain in the old town core, whereas an HH cluster appears in the northwestern periphery. This divergence supports the finding in Section 4.2 that unit price vulnerability operates along an independent spatial axis.

[Figure 3 and 4 about here]

The Retail channel (Figure 4) shows a different spatial structure. LL clusters extend beyond the old town into peripheral areas, and HH clusters appear in the northeastern part of the city. The Retail unit price dimension shows no LL clusters. Significant clusters include only HH and LH types concentrated in the northeast. This result reflects high unit price consumption in new, high-income residential areas that are separate from the old town.

5. Discussion

This study identifies sub-districts with structurally low offline food consumption in Busan using sub-district fixed effects from monthly card transaction panel data. This approach differs from traditional distance-based accessibility metrics and reflects structural differences in consumption behavior by excluding time-varying influences. The ability to identify vulnerable sub-districts without survey data or physical distance measures offers a methodological contribution. The fixed effects reflect persistent differences in offline food retail activity that are not explained by observable supply and demographic conditions. This framework can be applied to other regions where high-frequency transaction data are available at fine geographic scales.

The three-dimensional typology, including expenditure, transaction frequency, and expenditure per transaction, reflects distinct behavioral aspects of offline food consumption rather than redundant measures of the same phenomenon. Total expenditure measures overall market activity at local establishments, transaction frequency captures visit behavior, and expenditure per transaction indicates purchase size per visit. Low total expenditure, infrequent purchasing, and low purchase value per visit may reflect different mechanisms. For example, elderly single-person households may make frequent but small-volume purchases, resulting in low total expenditure despite regular visit behavior. Combining these three dimensions into a single composite index would obscure such distinctions and reduce the diagnostic precision of the typology.

The fixed effects estimates support this conclusion at a detailed level. The rate of elderly residents living alone shows opposite signs across the two channels, being positive in the Food channel and negative in the Retail channel. This pattern indicates that the same demographic change influences consumption through different mechanisms depending on the type of retail channel. This variation shows that food consumption vulnerability cannot be explained through a single demand-side factor, which supports the dual channel framework of this study. Among supply variables, only small supermarkets and specialty grocery stores show consistent significance across models. In contrast, hypermarkets and traditional markets provide low explanatory power. This result suggests that

attracting large retail stores may not be an effective policy option, whereas increasing the density of small retail outlets can be a more useful supply-side intervention. The estimated population elasticity is also less than one in both channels. This finding implies that population composition, such as age structure and household type, is more important than population scale in determining structural consumption levels.

The comparison of demographic and supply characteristics shows three distinct processes of structural food consumption vulnerability that have different policy implications. Type D sub-districts, which are vulnerable in both the Food and Retail channels, retain only 26–37% of the population of the non-vulnerable benchmark, Type A (Neither). These areas also experience a large reduction in small retail infrastructure, where the number of convenience stores and specialty grocery stores decreases to between 13% and 43% of the benchmark levels. The supply shortfall is more severe than the population decline, which indicates that commercial infrastructure decreases faster than the resident population in these areas. This pattern shows a simultaneous decline in both supply and demand. Therefore, these areas require a combination of supply-side incentives (such as subsidies for small grocery outlets) and welfare interventions for the population.

Type C sub-districts, which are vulnerable only in the Food channel, show a different pattern. Supply variables in these areas remain close to the benchmark levels, but the population has decreased sharply. The rate of elderly residents living alone in Type C sub-districts is higher than that in Type D under the unit price dimension. This finding suggests that the main constraint is not physical access to food stores but the consumption behavior of an aging and declining population. For these sub-districts, demand-side interventions for elderly single-person households (such as mobility support, delivery services, and welfare programs) may be more effective than increasing retail supply.

Type B sub-districts, which are vulnerable only in the Retail channel, show a different structure. Population levels remain relatively stable at 54–61% of the benchmark, but convenience stores and specialty grocery stores show large shortfalls relative to the population size. This difference is consistent with a supply-side mechanism where commercial infrastructure does not match stable

residential demand. Therefore, targeted supply-side policies, such as incentives for convenience stores or specialty grocery stores, may directly improve food access in Type B sub-districts. Figure 5 summarizes the factors, characteristics, and policy implications for each consumption vulnerability type. The diagram serves as an interpretation aid that identifies candidate explanations and evidence requirements for each pattern rather than a causal typology or validated risk classification. Policy action should therefore be preceded by field verification combining resident travel surveys, store entry and exit records, and food security measures.

[Figure 5 about here]

The spatial analysis supports these findings. The Global Moran's I for sub-district fixed effects is positive and significant across all models. This result confirms that structural consumption vulnerability is spatially clustered rather than randomly distributed. The LISA results show that Low-Low clusters (sub-districts with low consumption surrounded by similar neighbors) are concentrated within the old town boundary of Busan under the Food expenditure and transaction dimensions. Sub-districts such as Dongdaesin 3-dong, Gamcheon 2-dong, and Ami-dong appear in multiple models. In contrast, Low-High clusters identify isolated areas of low consumption within active commercial areas. This pattern indicates a distinct group of vulnerable sub-districts where the formation mechanism differs from the contiguous old town cluster.

The concentration of offline food consumption vulnerability in the old town of Busan reflects the urban decline of the area. Busan shows the demographic and economic conditions associated with shrinking cities, including a continuous population outflow toward the capital region, a large loss of younger residents, a high proportion of elderly population, and the decline of the manufacturing base that was historically based on footwear, textiles, and shipbuilding industries. These conditions are severe in the old town districts of Jung-gu, Dong-gu, Seo-gu, and Yeongdo-gu. These districts correspond to the center of offline food consumption vulnerability identified in this study.

The vulnerability typology may reflect different stages of this decline process. This is consistent with the observation that urban shrinkage occurs in diverse forms rather than as a uniform process

(Grossmann et al., 2013; Häußermann & Siebel, 1988). Type B sub-districts, where the population remains stable but small retail stores begin to decrease, reflect an early stage of commercial disinvestment associated with supermarket redlining (Eisenhauer, 2001). Type C sub-districts represent an intermediate stage where demographic decline (including population aging, the outmigration of younger residents, and the mobility limitations of elderly single-person households) occurs faster than the reduction in physical supply (Iizaka et al., 2020; Yang & Kim, 2020). Type D sub-districts, where both population and supply have declined, represent an advanced stage of commercial and demographic decline.

These stages suggest that food consumption vulnerability in shrinking cities may signal early food desert conditions following a predictable pattern. This framework can be applied to other post-industrial cities where population aging and outmigration occur without corresponding economic growth.

Although this study does not directly measure food access deprivation, the structural patterns identified, particularly the spatial concentration of persistently low offline food consumption in sub-districts experiencing demographic decline and retail infrastructure withdrawal, may represent early warning signals of food desert formation. Sub-districts classified as Type D, where both supply and demand have declined, are primary candidates for further deterioration into food access deprivation, requiring prioritized monitoring and intervention. This diagnostic approach distinguishes this study from traditional food desert identification, which typically requires evidence of physical access constraints and unmet dietary needs that transaction data alone cannot provide.

Several limitations of this study should be noted. First, because transaction data are aggregated at the establishment level, expenditure metrics reflect both resident and non-resident consumption. Although this study controls for the visiting population, the analysis cannot fully separate the food purchasing behavior of registered residents from that of visitors and commuters. Second, channel classification introduces ambiguity, because food purchases at large retail outlets are recorded under the Retail channel rather than the Food channel. Third, lower-tail ranks do not propagate first-stage estimation

uncertainty, and results may be sensitive to the choice of cutoff, spatial weight matrix, and the boundary definition of the old urban core. Finally, the number of Type D sub-districts under the unit price criterion is small ($n = 3$), so patterns specific to this group should be interpreted with caution.

6. Conclusion

This study identifies sub-districts with structurally low offline food consumption in Busan, the second-largest city in South Korea, using sub-district fixed effects estimated from a monthly card transaction panel covering 205 sub-districts over 36 months. By using the structural component of consumption levels, which excludes time-varying influences through a two-way fixed effects framework, as the basis for identifying food consumption-vulnerable sub-districts, this study analyzes actual consumption behavior instead of physical proximity to food outlets. This study provides three main findings.

First, offline food consumption vulnerability in Busan is a multidimensional phenomenon that cannot be fully captured by a single composite index. Total expenditure, transaction frequency, and expenditure per transaction reflect distinct behavioral aspects of offline food consumption, including overall market activity, visit frequency, and purchase size per visit. These dimensions may function through different mechanisms within the same sub-district. For example, elderly single-person households often visit food outlets frequently but spend little per visit, a pattern that is not reflected in a single aggregate measure.

Second, vulnerability patterns differ across the food and retail channels. The same demographic characteristics act in opposite directions depending on the channel, which supports the usefulness of the dual channel framework.

Third, three distinct types of consumption-vulnerable sub-districts emerge, including Type D (Both), Type C (Food-only), and Type B (Retail-only). Each type is characterized by a different combination of demographic decline and retail supply shortfalls. These configurations may represent different

stages in the progression toward food desert conditions, where Type B reflects early commercial disinvestment, Type C reflects demographic decline, and Type D reflects simultaneous supply and demand decline.

These three types require different policy options. Type D sub-districts, concentrated in the old town of Busan, face a simultaneous collapse of both population and commercial infrastructure. This condition requires a combination of supply-side incentives for the entry of small grocery outlets and population-oriented welfare support. Type C sub-districts, where physical supply remains relatively intact but the resident population has aged and declined sharply, require demand-side interventions targeting elderly single-person households, such as mobility assistance and home delivery programs, instead of additional retail supply. Type B sub-districts, where the population is comparatively stable but small retail supply has not kept pace with residential demand, represent the clearest case for supply-side policies. In these areas, targeted incentives for the entry of convenience stores and specialty grocery stores can directly improve food access.

A uniform policy approach applied across all three types may misallocate resources. It may direct resources toward increasing supply in areas where the main constraint is demographic, or toward welfare programs in areas where the primary deficit is commercial. The spatial concentration of the most vulnerable sub-districts in the old town of Busan, an area experiencing urban decline, suggests that without targeted intervention, these sub-districts face an elevated risk of progressing toward food desert conditions. By converting fine-grained merchant transactions into a transparent, cutoff-specific spatial screening framework, this study shows how applied spatial analysis can support local retail monitoring and prioritize field verification in shrinking cities without assigning a common cause or policy to observationally similar places.

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Tables

Table 1 Sub-District Fixed-Effects Estimates for Place-Based Offline Transaction Activity (N=7,380)

Variable	Recorded transaction value (N=7,380)		Recorded transaction count (N=7,380)		Mean transaction value (N=7,380)	
	Food	Retail	Food	Retail	Food	Retail
Food supply						
Large retail formats						
Hypermarket	0.008 (0.006)	-0.004 (0.005)	0.009 (0.007)	-0.001 (0.003)	-0.0005 (0.006)	-0.003 (0.004)
Mid-size mart	0.004 (0.003)	-0.003 (0.002)	-0.003 (0.003)	-0.002 (0.002)	0.007** (0.003)	-0.001 (0.002)
Traditional market	-0.004 (0.005)	0.013*** (0.004)	-0.001 (0.005)	0.006** (0.003)	-0.003 (0.005)	0.006** (0.003)
Small retail formats						
Small supermarket	0.005*** (0.001)	0.002* (0.001)	0.002 (0.001)	-0.0002 (0.001)	0.003** (0.001)	0.002*** (0.001)
Convenience store	0.001 (0.002)	-0.005*** (0.001)	0.001 (0.002)	-0.001 (0.001)	-0.0002 (0.001)	-0.004*** (0.001)
Specialty grocery store	0.004*** (0.001)	0.003*** (0.001)	0.001 (0.001)	0.001*** (0.001)	0.003*** (0.001)	0.001*** (0.004)
Population						
Elderly rate (%)	-0.002 (0.003)	0.021*** (0.003)	-0.007** (0.004)	0.007*** (0.002)	0.005* (0.003)	0.014*** (0.002)
Elderly living alone / elderly (%)	0.021*** (0.004)	-0.022*** (0.004)	-0.001 (0.004)	-0.014*** (0.002)	0.022*** (0.004)	-0.008*** (0.002)
Log(Visiting population)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Log(Total population)	0.234*** (0.072)	0.452*** (0.059)	0.380*** (0.074)	0.422*** (0.039)	-0.145** (0.069)	0.029 (0.041)
Other expenditure						
Log(living goods expenditure)		0.041*** (0.005)		0.013*** (0.003)		0.028*** (0.003)
Log(clothing expenditure)		0.001 (0.002)		-0.002* (0.001)		0.002 (0.001)
Adjusted R ²	0.282	0.057	0.404	0.190	0.257	0.155

Note. HC3 heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01. Year and calendar-month indicators are included in all models but not reported. Food is the focal merchant category; Retail is the general-retail comparator.

Table 2 Descriptive Characteristics by Cross-Category Lower-Tail Pattern and Accounting Margin (21 of 205 per category)

Variable	Lower-tail pattern	N	Population	Elderly rate	Elderly living-alone rate	Hypermarket	Mid-size mart	Traditional market	Small supermarket	Convenience store	Specialty grocery store
Recorded transaction value	A: Neither	174	17,538	25.7	29.8	0.3	1.0	0.2	18.9	15.4	22.7
	B: Retail-only	10	9812 (55.9%)	30.2 (117.5%)	26.9 (90.3%)	0.03 (9.4%)	0.53 (53.5%)	0.03 (12.5%)	9.07 (48%)	4.73 (30.7%)	8.2 (36.1%)
	C: Food-only	10	6115 (34.9%)	35.5 (138.1%)	39.4 (132.2%)	0 (0%)	0.03 (3%)	0.23 (95.8%)	10.3 (54.5%)	4.37 (28.4%)	6.2 (27.3%)
	D: Both	11	4655 (26.5%)	39.9 (155.3%)	41.3 (138.6%)	0 (0%)	0.06 (6.1%)	0.03 (12.5%)	8 (42.3%)	1.94 (12.6%)	3.73 (16.4%)
Recorded transaction count	A: Neither	174	17,474	25.8	29.9	0.3	1.0	0.2	18.8	15.5	22.6
	B: Retail-only	10	9474 (54.2%)	34.2 (132.6%)	34.3 (114.7%)	0 (0%)	0.4 (41.2%)	0.03 (12.5%)	10.2 (54.3%)	3.17 (20.5%)	10.5 (46.5%)
	C: Food-only	10	6726 (38.5%)	33.3 (129.1%)	35.3 (118.1%)	0.17 (54.8%)	0.4 (41.2%)	0.3 (125%)	10.8 (57.4%)	3.93 (25.4%)	6.03 (26.7%)
	D: Both	11	5418 (31%)	36.4 (141.1%)	36.7 (122.7%)	0 (0%)	0.06 (6.2%)	0.03 (12.5%)	8.52 (45.3%)	2.24 (14.5%)	3.85 (17%)
Mean transaction value	A: Neither	166	17,393	26.2	29.7	0.3	0.9	0.2	18.2	14.6	22.5
	B: Retail-only	18	10689 (61.5%)	28.9 (110.3%)	29.3 (98.7%)	0.04 (12.9%)	0.61 (64.9%)	0.2 (87%)	14.2 (78%)	11.1 (76%)	13 (57.8%)
	C: Food-only	18	9068 (52.1%)	33.6 (128.2%)	41.1 (138.4%)	0.22 (71%)	0.57 (60.6%)	0.11 (47.8%)	14.1 (77.5%)	8.48 (58.1%)	8.19 (36.4%)
	D: Both	3	6405 (36.8%)	31.4 (119.8%)	38.4 (129.3%)	0 (0%)	0.11 (11.7%)	0 (0%)	11.1 (61%)	5.67 (38.8%)	4.78 (21.2%)

Table 3 Global Moran's I for Model Residuals and Estimated Sub-District Effects

Type		Food		Retail	
		Moran's I	p-value	Moran's I	p-value
Residual	Recorded transaction value	0.052	0.097	-0.051	0.850
	Recorded transaction count	0.046	0.125	-0.018	0.614
	Mean transaction value	-0.029	0.704	0.001	0.446
Estimated sub-district effect	Recorded transaction value	0.164	0.001	0.124	0.002
	Recorded transaction count	0.131	0.001	0.106	0.005
	Mean transaction value	0.155	0.001	0.096	0.010

Table 4 Local Spatial-Pattern Counts at the Nominal 5% Significance Level

		High-High	High-Low	Low-High	Low-Low	Not significant
Food	Recorded transaction value	1	5	2	12	185
	Recorded transaction count	2	5	1	11	186
	Mean transaction value	5	3	3	10	184
Retail	Recorded transaction value	9	3	3	7	183
	Recorded transaction count	8	8	0	10	179
	Mean transaction value	14	0	6	0	185

Figures

Fig. 1 Distributions of Estimated Sub-District Effects (μ_i) by Merchant Category and Accounting Margin

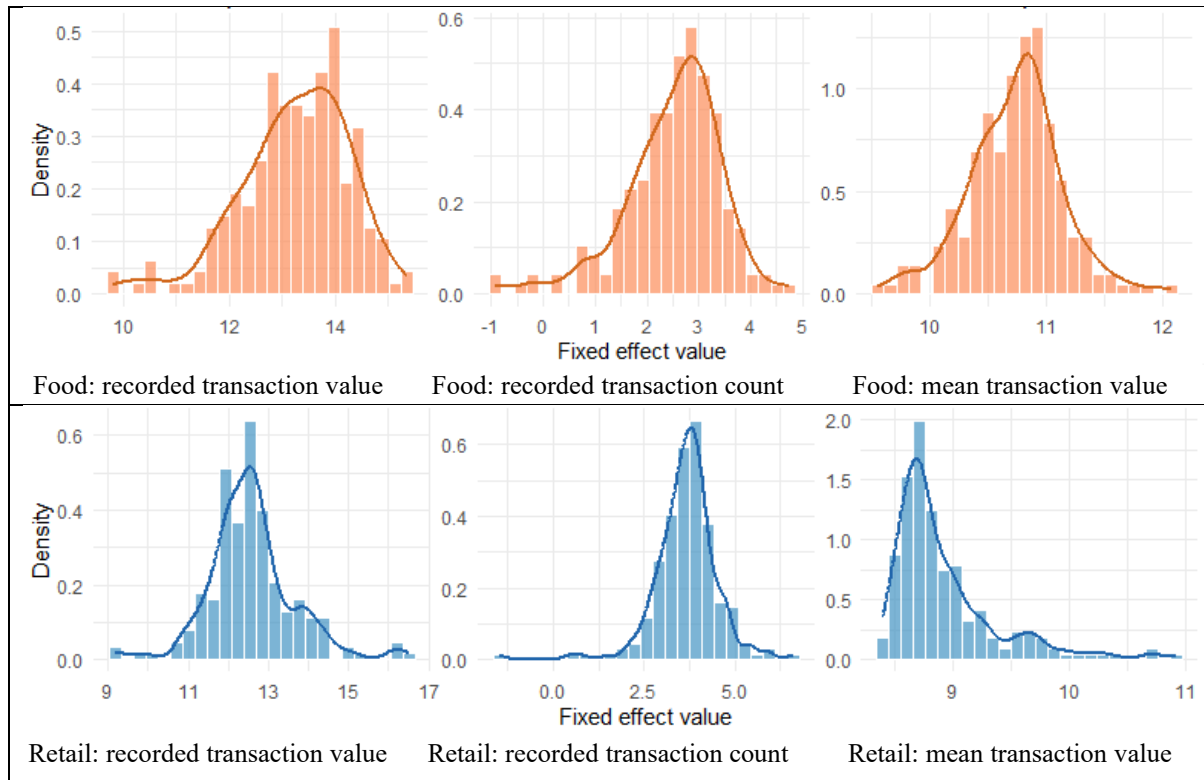


Fig. 2 Cross-Category Lower-Tail Patterns by Accounting Margin. Black outline: study-defined old urban core (Jung-gu, Dong-gu, Seo-gu, and Yeongdo-gu); the outline is contextual and not a model input

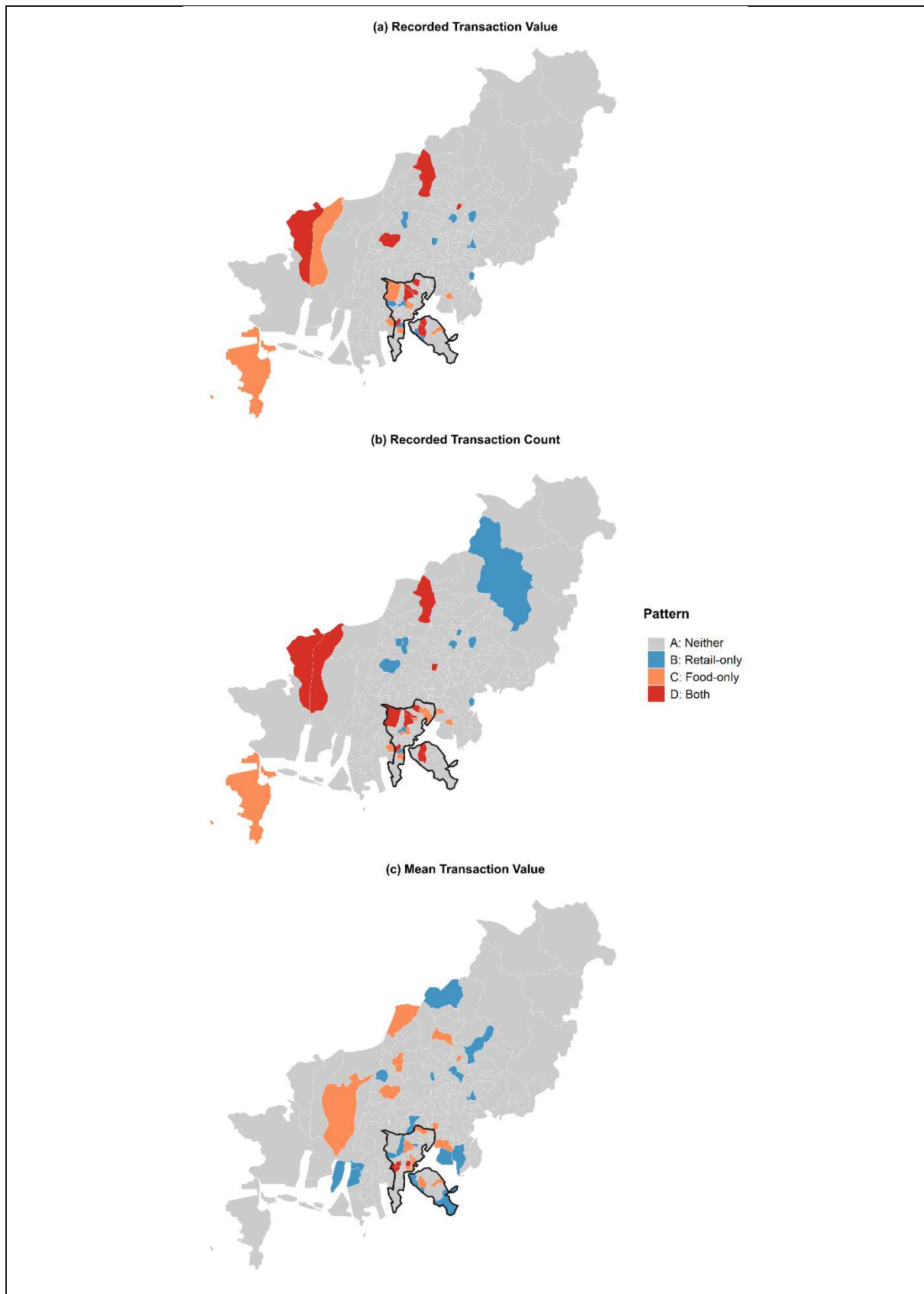


Fig. 3 Local Spatial-Pattern Maps for Estimated Food Sub-District Effects (μ_i). Patterns are permutation-significant at the nominal 5% level and are not adjusted for multiple local tests. Black outline: study-defined old urban core

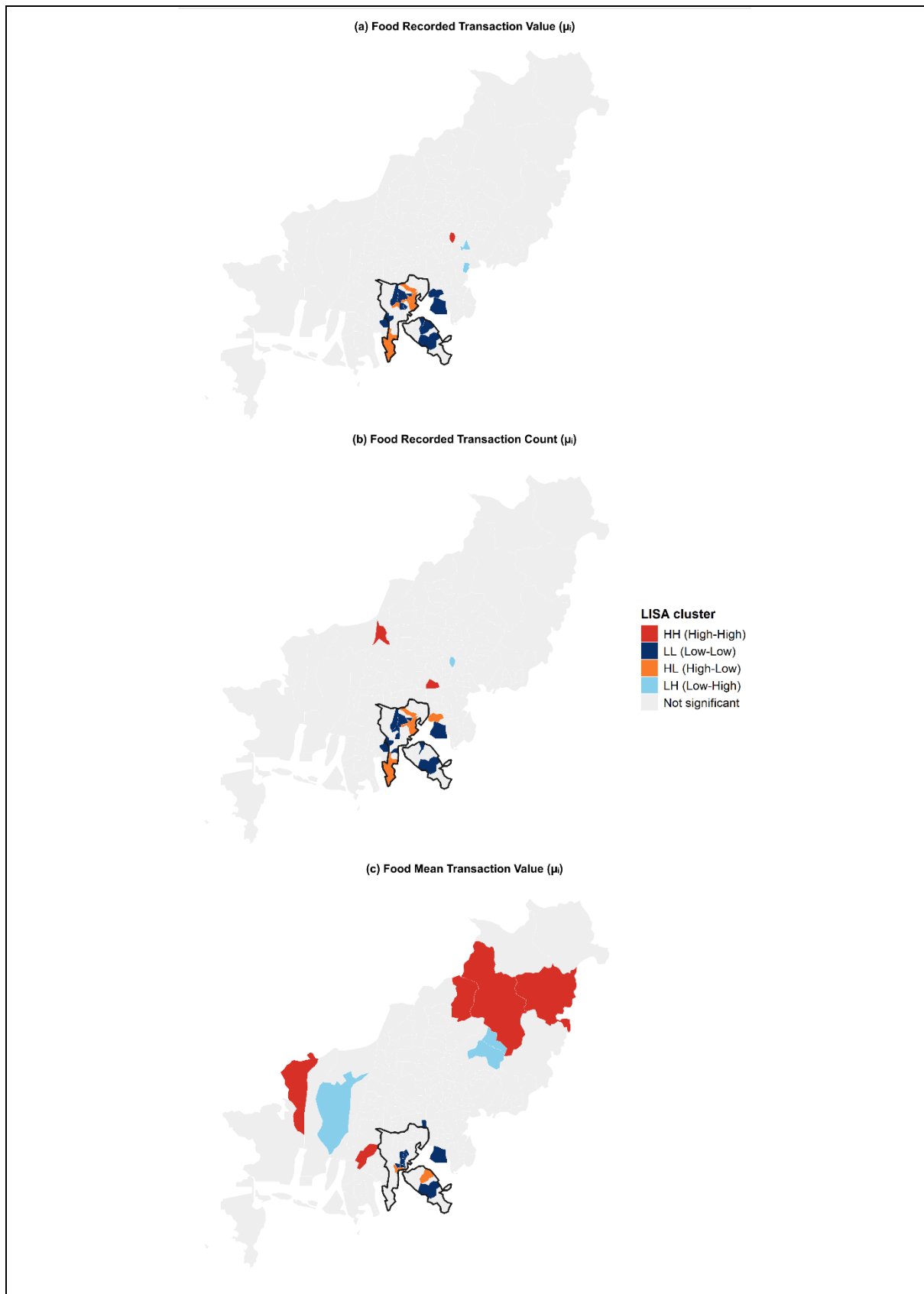


Fig. 4 Local Spatial-Pattern Maps for Estimated Retail Sub-District Effects (μ_i). Patterns are permutation-significant at the nominal 5% level and are not adjusted for multiple local tests. Black outline: study-defined old urban core

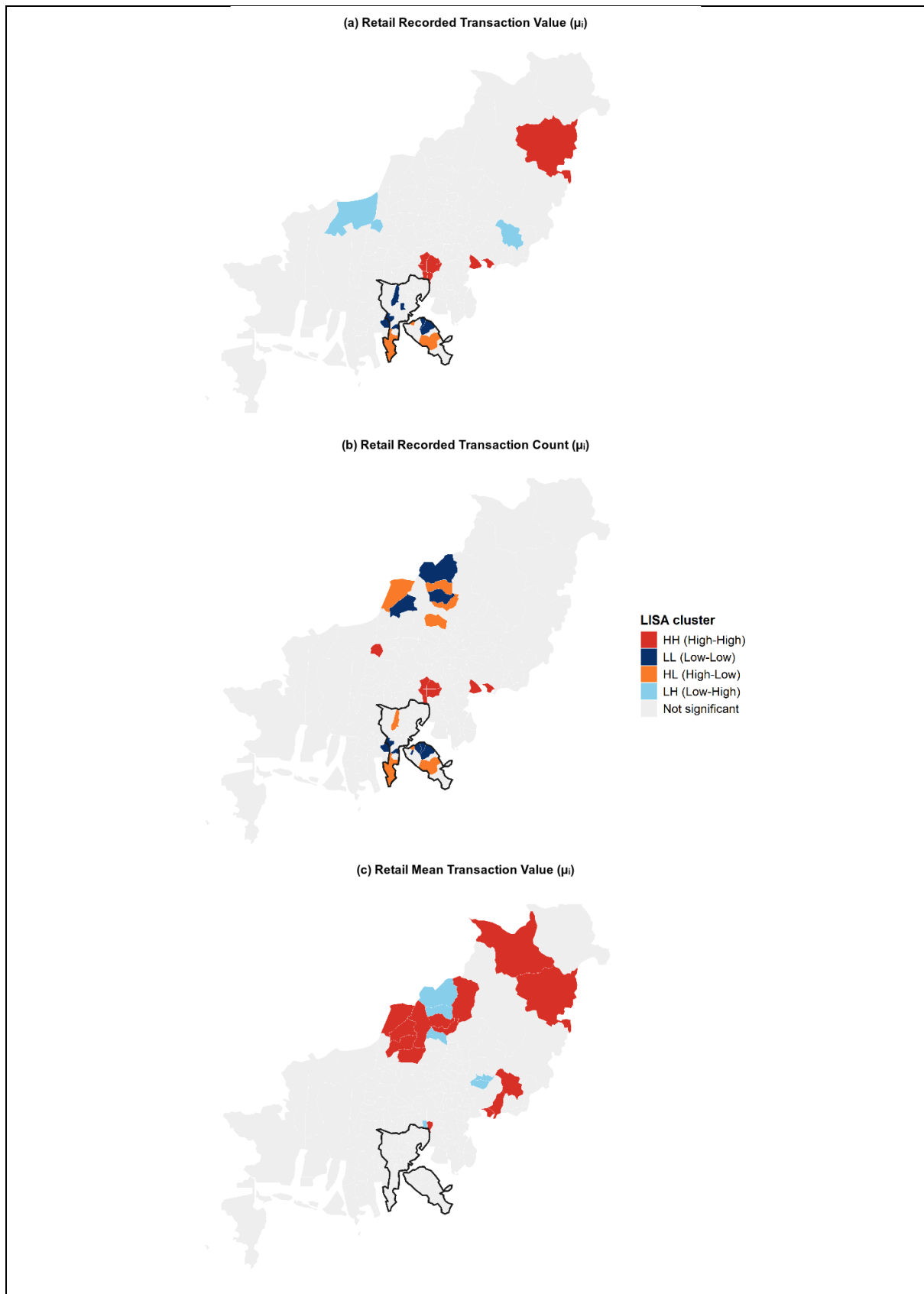


Fig. 5 A Two-Stage Screening Framework for Low Offline Transaction Activity

