

The Evolution of Offline Retailing

Omni-channel and Experiential Marketing in Shopping Malls

by

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To Curiosity, the Seed of Every Human Insight

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Abstract

The offline retailing landscape has been dramatically changed due to the competition from e-commerce and shifts in consumer shopping habits. This dissertation adopts the perspective of shopping malls, a unique format of retail agglomeration, to study how they adapt to these changes. Motivated by a desire to bridge academic research and real-world marketing practices, this work consists of two essays that empirically focus on the embrace of omni-channel and experiential marketing strategies by shopping malls. Methodologically, the approaches represent advancements in causal inference, machine learning, and network analysis, with significant implications for managers and policymakers.

In the first essay of my dissertation, I examine the impacts of an emergent retail format introduced by shopping malls as part of an experiential channel: pop-up shops. Pop-up shops have emerged as an innovative retail strategy employed by shopping mall managers to counter the increasing competition from e-commerce and to revitalize foot traffic. While concerns persist about the potential competitive effects of pop-up shops on permanent tenants, this study empirically examines the impact of pop-up shops on host businesses by addressing two key questions: First, how do pop-up shops affect traffic and sales in host shopping malls and their permanent store tenants? Second, what are the underlying mechanisms driving these effects? Utilizing a unique data set from 100 shopping malls and 112 pop-up shops, this research reveals that pop-up shops increase daily mall traffic and store sales, with no significant change in store visits. These effects suggest the coexistence of spillover and competition mechanisms: pop-up shops attract additional traffic to the mall, benefiting permanent stores through spillover effects, while competing for consumers' mental shopping time and reducing exploratory shopping at permanent stores. Overall, the positive effects of pop-up shops distinguish them from traditional retail formats and highlight collaboration

opportunities for mall managers, permanent store owners, and policymakers.

In the second essay, I turn my attention to the existing channel members—permanent store tenants—and investigate the impacts and interconnections among them. As shopping malls increasingly rely on experiential anchor and social stores to attract traffic and enhance consumer engagement, mall managers often offer rent subsidies to these tenants under the assumption that their presence generates positive spillovers to surrounding retailers. However, little empirical evidence exists to validate whether, and under what conditions, such stores truly benefit the broader mall ecosystem. Leveraging a novel and large-scale dataset of individual-level shopping paths across six shopping malls in China, we develop a new method to quantify store externality—the extent to which a store contributes to foot traffic and sales at neighboring stores. Using a multivariate random forest framework and variable importance measures (VIMs), we estimate traffic and sales externality indices for each store. We find that contemporary anchor stores, on average, generate significantly greater spillover benefits than non-anchor stores, supporting their strategic role in the tenant mix design. In contrast, social stores—such as restaurants and entertainment venues—exhibit limited or even negative externalities, suggesting that their traffic tends to remain contained. Heterogeneity analyses reveal that anchor stores associated with mass-market and young brands drive stronger spillovers than their luxury or established counterparts. Furthermore, using Non-negative Matrix Factorization (NMF) to cluster shoppers by behavioral patterns, we identify three distinct segments: purpose-driven, leisure group, and experience-seeking shoppers. Store externalities vary substantially across these groups, with anchor stores being most effective for leisure and experience-oriented shoppers, and social stores generating positive spillovers only among leisure shoppers. We further identify two data-driven store groups—leisure and experiential stores—that closely align with the needs of different shopper segments. Our findings offer new insights into retail agglomeration dynamics and provide actionable guidance for mall managers in optimizing rent strategies and tenant placement based on both store characteristics and shopper heterogeneity.

Contents

Abstract	iv
Chapter 1.	1
1 Introduction	1
2 Institutional Background and Conceptual Framework	5
2.1 Institutional Background of Pop-up Shops	5
2.2 Conceptual Framework	7
3 Data	10
3.1 Mall traffic, store visits, and sales	10
3.2 Permanent Store and Mall Features	11
3.3 Pop-up Shop Features	12
3.4 Supplementary Data	13
4 Identification	13
4.1 Model-free evidence	16
4.2 Impacts of Pop-Up Shops on Malls	18
4.3 Robustness Check	19
5 Impacts on Permanent Store Tenants	22
5.1 Average Effect on Permanent Store Tenants	22
6 Comparison with New Store Entries	24
7 Mechanism	25
7.1 Spillover	27
7.2 Competition	30
7.3 Alternative Explanations	31

7.4	Heterogeneous Treatment Effect at Mall Level	34
8	Post Treatment Effect	35
9	Conclusions and Implications	36
	References	40
	Appendix	44
1A.1	More Details of Pop-up Shops	44
1A.2	Additional Details of Data and Matching Process	47
1A.3	Robustness Check	50
1A.4	Details of PSM With Time-Varying Features	54
1A.5	Estimation Results of Heterogenous Treatment Effects	55
Chapter 2.		56
1	Introduction	56
2	Related Literature	60
2.1	Shopping Malls and Hedonic Shopping Values	60
2.2	Retail Agglomeration and Externalities in Malls	61
2.3	E-commerce, Clickstream Data, and Offline Shopper Tracking	62
3	Data and Exploratory Analysis	63
3.1	Data Details	63
3.2	Traffic, Sales and Rents of Contemporary Anchor and Social Stores	64
4	Store Externality Index	68
4.1	Derive the Metric	68
4.2	Traffic and Sales Externality of Anchor Stores	71
4.3	Traffic and Sales Externality of Social Stores	72
4.4	Heterogeneous Externalities for Different Anchor Store Brand	75
5	Heterogeneous Store Externalities Across Shopper Segments	79
5.1	Shopper Segmentation Using Unsupervised Machine Learning	80
5.2	Store Externalities Within Shopper Clusters	83

5.3	Store Clusters Based on Shopping Patterns	89
6	Discussion	92
	References	96
	Appendix	101

List of Figures

1	Conceptual Framework	8
2	Model-Free Treatment Effects on Daily Mall Traffic	17
3	Summary of Main Effects	27
4	Model-Free Post-Treatment Effects on Daily Mall Traffic	35
1A.1	Average Mall Traffic After Matching	49
1A.2	Average Store Visits and Sales After Matching	49
1	Sales Externality Index versus Unit Rent	71
2	Marginal Effects of Mass Brand on Anchor Stores' Externality Index	78
3	Marginal Effects of Young Brand on Anchor Stores' Externality Index	79
4	Heatmap of Shopper Cluster Centroids by Feature Weights	83
5	Average Store Weights on Latent Features	85
6	Anchor Stores' Externality Index Across Shopper Cluster	87
7	Social Stores' Externality Index Across Shopper Cluster	89
8	Heatmap of Store Cluster Centroids by Feature Weights	91
9	Proportion of Visits to Experiential and Leisure Stores by Shopper Segment	92
2A.1	Explained Variance Improvement per Additional Latent Feature (K)	102
2A.2	Elbow Method for Determining Optimal Number of Clusters	102

List of Tables

1	Summary Statistics	14
2	Effects of Pop-Up Shops on Mall	19
3	Effects of Pop-Up Shops on Store Visits and Sales	23
4	Effects of New Store Entries on Malls	25
5	Heterogenous Treatment Effects on Store Visits	32
6	Heterogenous Treatment Effects on Store Sales	33
7	Post Effects of Pop-Up Shops on Mall	36
1A.1	Product Categories of Permanent Stores	47
1A.2	Summary Statistics for Pop-up Shop Features	47
1A.3	Proportion of Pop-Up Shops in Operation	48
1A.4	Matching Variables	48
1A.5	Full Sample Regression Without Matching	50
1A.6	Falsification Test	50
1A.7	Impacts of Pop-Up Shops on Mall with PSM	51
1A.8	Exclude day = -1	52
1A.9	Alternative Function Forms	52
1A.10	Weekend Pop-up Shops	53
1A.11	Heterogenous Treatment Effects at Mall Level	55
1	Summary Statistics	65
2	Comparison of Anchor and Non-Anchor Stores	67
3	Comparison of Social and Non-social Stores	67
4	Summary of Traffic and Sales Externality Index	70
5	Externality Indices of Anchor Stores	73

6	Externality Indices of Social Stores	74
7	Summary of Five Latent Features	82
8	Summary of Shopper Clusters	84
2A.1	Anchor Stores' Externality Index By Brand Features	101
2A.2	Shopper Cluster-Level Heterogeneity in Anchor Stores' Externality Index . . .	103
2A.3	Shopper Cluster-Level Heterogeneity in Social Stores' Externality Index . . .	104

Chapter 1.

From Threat to Opportunity: The Impacts of Pop-up Shops in Shopping Malls

1 Introduction

Given the rising cost of marketing and the increasing demand for memorable shopping experiences by consumers (Forbes, 2024), pop-up shops have emerged as a new retailing format in the recent decade. Unlike permanent stores, pop-up shops operate for a limited duration and are designed to create experiential and hedonic shopping environments, with the aim of engaging customers and generating buzz (Klein et al., 2016; Robertson et al., 2018; Warnaby and Shi, 2018; Zogaj et al., 2019; Rosenbaum et al., 2021). For example, since 2019, the global skincare brand SK-II has launched multiple pop-up shops worldwide, utilizing innovative technologies such as eye-tracking, robotic advisors, and augmented reality (AR) to offer non-contact, personalized skincare consultations and product recommendations (BeautyTech, 2022; Chaileedo, 2022).¹ Empirical studies highlight the effectiveness of pop-up shops for featured brands, demonstrating increased brand awareness (Klein et al., 2016; Rosenbaum et al., 2021), higher customer engagement (Rosenbaum et al., 2021; Henkel and Toporowski, 2023), and greater future purchase intention (Spitzkat and Fuentes, 2019; Zhang et al., 2019; Zogaj et al., 2019). At the same time, commercial landlords and mall managers have increasingly adopted pop-up shops to attract shoppers and boost their revenue in response to growing e-commerce competition and shifting consumer preferences (The

¹See Appendix 1A.1 for additional examples.

Wall Street Journal, 2016; Hughes, 2017). Reflecting this growing popularity, the global pop-up shop market was valued at 8.5 billion dollars in 2020 and is projected to reach 15.2 billion dollars by 2027 (Sarma, 2024).

Despite their growing adoption and government initiatives supporting pop-up shops to revitalize underutilized retail spaces (GOV.UK, 2012), concerns have emerged regarding the potential negative impacts of introducing these temporary retail formats. Permanent store tenants in shopping malls often perceive pop-up shops as competitive threats, fearing that they may cannibalize existing sales. Specific concerns include adverse effects on customer access, traffic flow, and visibility due to adjacency and line-of-sight issues (Cooper, 2017). Shopping mall owners also face challenges, including uncertainty in rental income from the unpredictable leasing needs of pop-up shops and the potential loss of permanent tenants (The Wall Street Journal, 2013). These concerns have prompted policymakers to take action. For instance, the Australian Retailers Association has argued that “the code governing pop-up shops in shopping centers is hurting permanent retailers and needs to change” (Cooper, 2017). In response, the Australian Competition and Consumer Commission issued a draft determination proposing that shopping center owners and managers grant casual licenses to pop-up shops only after evaluating their impact on permanent retailers (Bencic, 2017).

While existing research has primarily focused on the benefits of pop-up shops as a new offline channel from the perspective of featured brands (e.g., Zhang et al. 2019; Henkel and Toporowski 2023), limited attention has been given to their broader impact on their host environments. Specifically, it remains unclear whether pop-up shops pose a genuine threat to their host businesses, including shopping malls and the malls’ permanent store tenants. This study addresses this gap by investigating two key questions: First, how do pop-up shops influence traffic and sales within host shopping malls and their permanent tenants? Second, what underlying mechanisms drive these effects?

To address these questions, we propose a conceptual framework that captures the unique impacts of pop-up shops on neighboring businesses through two countervailing mechanisms—

spillover and competition. Empirically, we utilize a unique dataset of daily traffic and sales records of 28,595 stores across 100 shopping malls over two years. We observe 112 brand-initiated pop-up shops during this period. We assess the effects of pop-up shops on mall performance by evaluating mall-level traffic and on store performance by examining store-level traffic and sales data. Our design allows us to address the endogeneity issue due to potential non-random assignment of “treatment” (i.e., presence of pop-up shops) through a difference-in-difference (DiD) approach with coarsened exact matching (CEM) (Iacus et al., 2009). The findings show that on average, pop-up shops increase mall traffic by 3.05% (or 1,438 visits) and increase store sales by 3.56% (or 429.38 RMB), suggesting that pop-up shops generally have a positive impact on host environments, primarily driven by spillover effects. However, we do not find significant changes in store visits, indicating the presence of an opposing competition mechanism that offsets the potential increase in store visits generated by the spillover effect.

To assess the validity of the spillover and competition mechanisms, we conducted further investigations into the heterogeneous effects of pop-up shops on different types of permanent stores. The results of heterogeneity analyses show that permanent stores in closer product categories and physical proximity to pop-up shops experienced greater increases in visits, supporting the spillover mechanism. Our findings also reveal that permanent stores associated with independent brands, which are more reliant on exploratory shopping traffic, experienced more pronounced decreases in store visits compared to chain brands, despite no significant differences in sales reductions. This evidence support the existence of the competition mechanism, suggesting that pop-up shops primarily introduce competitive pressure on consumers’ shopping time budgets rather than monetary budgets. We also examine the effects of pop-up shops post treatment, and the analysis results show that the impacts diminish two weeks after the pop-up shops exits. Additionally, we compare the effects of pop-up shops with those of new store entrants, finding that while pop-up shops enhance mall performance, new store entrants significantly reduce store visits and sales. These results em-

pirically highlight the unique promotional advantages of pop-up shops and distinguish them from traditional store entrants.

Our research contributes to the literature and offers insightful managerial implications in several ways. First, we extend the existing literature on omnichannel marketing strategies, where retailers integrate offline and online channels to enhance overall business efficiency (e.g., Gao and Su 2017; Bell et al. 2018; Ailawadi and Farris 2020). Unlike prior studies that focus on the impact of offline channels on the featured firms themselves, we shift the perspective to their broader effects on host venues. Specifically, we not only document pop-up shops as an emergent and effective experiential channel, but also examine their external impacts on host malls and adjacent businesses. Our findings provide robust evidence that pop-up shops serve as a powerful promotional tool, driving increased mall traffic and store sales. These results counter concerns about their competitive threats and highlight their potential as a win-win strategy for both landlords and tenants. This perspective introduces a new angle to studying omnichannel retail strategies by emphasizing the collaborative role of venue partners, an underexplored aspect in extant research.

Second, our work extends the current literature on the effectiveness of marketing tools for offline retailers by providing a new lens for mall managers to understand the benefits and pitfalls of introducing pop-up shops as a potential strategy to improve retail performance. The retail environment has gone through profound changes in the past decade. The rise of online shopping has significantly impacted traditional brick-and-mortar stores, leading to decreased foot traffic in malls, which is further exacerbated by the COVID pandemic. It has become crucial for malls to adapt and meet the evolving preferences of consumers by offering unique, engaging experiences that cannot be replicated online (PQ Media, 2021; Shah et al., 2023; Mortimer et al., 2024). By empirically distinguishing pop-up shops from traditional store entrants, we highlight their role as an innovative marketing phenomenon that drives increased mall traffic and boosts store sales. Furthermore, our findings underscore the need for policymakers to support these emergent experiential temporary shops through potential

incentives, regulations, or guidelines.

Third, we demonstrate that the benefits of pop-up shops are not uniformly distributed across all permanent stores; instead, their impact varies depending on store characteristics. While pop-up shops generally increase mall traffic and store sales, they can also reduce exploratory shopping, potentially intensifying competition for certain tenants. We propose a dual-mechanism framework to illustrate the impact of pop-up shops on permanent stores, and further show both spillover and competition mechanisms are moderated by the characteristics of these stores. Specifically, the spillover mechanism is more pronounced in permanent stores that are either in the same product categories or located physically close to the pop-up shops. Meanwhile, the competition mechanism is more pronounced in permanent stores that are more reliant on exploratory shopping.

These findings highlight the importance for store owners in host malls to understand how pop-up shops may affect their businesses based on their brand, product category, and mall location. Store owners can then tailor collaboration strategies with incoming pop-up shops to maximize potential benefits while mitigating potential downsides.

2 Institutional Background and Conceptual Framework

2.1 Institutional Background of Pop-up Shops

Pop-up shops originated from traditional temporary stores, but the modern concept of the pop-up shop did not take shape until the late 2000s (Russo Spena et al., 2012). As defined by Warnaby and Shi (2018), pop-up shops are “an ephemeral retail-oriented setting that facilitates direct, experientially-oriented customer-brand interactions for a limited period”. More importantly, unlike conventional short-term kiosks or stalls in shopping malls, contemporary pop-up shops have evolved into a growing phenomenon that brands leverage to foster deeper connections with consumers through innovative and immersive retail experiences. While the implementation of pop-up shops varies across industries, from luxury goods to high-tech

products (De Lassus and Freire, 2014; The Wall Street Journal, 2021a), contemporary pop-up shops stand out from other offline retail formats due to three key distinguishing features: new retail entrants, ephemerality, and experiential value.

New Retail Entrants

To attract shoppers and boost revenue, shopping mall managers often allocate highly visible retail spaces to third-party pop-up brands at discounted rents (The Wall Street Journal, 2013). These locations are typically found in indoor atriums on the ground floor or outdoor plazas near the main entrance—areas that are not occupied by regular stores. These spaces often take the form of stands, stalls, or modular panel houses and are equipped with portable, easily assembled decor components (Warnaby and Shi, 2019). As a result, the setup costs for pop-up shops are considerably lower than those for traditional storefronts. By utilizing these spaces, pop-up shops enter shopping malls, offering new products and services to shoppers, potentially creating competition for existing permanent stores. However, pop-up shops differ from traditional new store entrants and temporary stores due to the following two features.

Ephemerality

Unlike traditional store entrants, pop-up shops occupy removable retail spaces that are designed to last only for a limited time, typically less than a week (Zhang et al., 2019). This temporariness can amplify their impact by creating a sense of urgency or scarcity (Zogaj et al., 2019; Henkel and Toporowski, 2023), while also ensuring that their effects on surrounding businesses are short-lived.

Experiential Values

One of the key features that differentiates pop-up shops from traditional temporary stores is the hedonic value they offer to consumers (Zogaj et al., 2019; Henkel et al., 2022). According to a survey conducted by Rosenbaum et al. (2021) with pop-up shop owners, the top managerial objectives include connecting with current and prospective customers, strengthening brand value and awareness, and introducing or testing new products. In other words, the primary goal of pop-up shops for the hosting brands is not focused on generating revenue but

rather on building relationships with consumers and accessing new target markets (Warnaby and Shi, 2019; Henkel and Toporowski, 2023). To achieve these goals, pop-up shops often utilize aesthetically appealing retail spaces designed to create exclusive, interactive, and experiential shopping environments (De Lassus and Freire, 2014). These spaces frequently feature interactive activities, unique services, and exclusive products unavailable through other channels, with less emphasis on price-driven sales promotions. For detailed examples and the setup process of pop-up shops, please refer to section Appendix 1A.1.

2.2 Conceptual Framework

While existing studies have demonstrated the usefulness of pop-up shops for their featured brands, particularly in enhancing brand identity and fostering consumer relationships (Klein et al., 2016; Spitzkat and Fuentes, 2019; Zhang et al., 2019), their unique characteristics leave their impact on neighboring businesses uncertain. From the perspective of host shopping malls, the introduction of pop-up shops presents both opportunities and challenges. On the one hand, mall managers expect these temporary stores to attract additional foot traffic; on the other hand, pop-up shops may merely capitalize on the existing customer base within the mall and introduce new competition for permanent store tenants. This dual nature creates ambiguity regarding their overall influence on the mall environment. To address this uncertainty, we propose a dual-mechanism framework (Figure 1) that illustrates two opposing forces—budget competition and traffic spillover—that shape changes in mall traffic, store visits, and sales.

Budget Competition Effects

According to mental accounting theory (Thaler, 1999), shoppers have pre-determined mental budgets for specific categories which influence how they allocate their money or time among stores in the mall. Acting as new entrants that provide unique products and services, pop-up shops can potentially compete with permanent stores for these limited budgets. Existing research has documented such competitive dynamics triggered by new permanent store entries

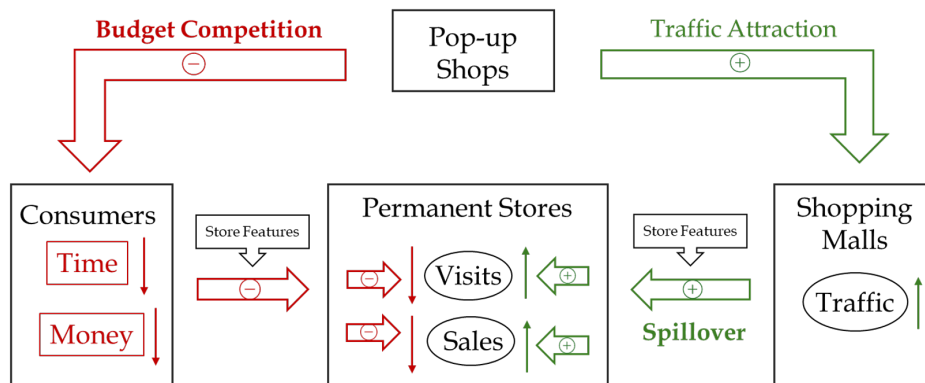


Figure 1: Conceptual Framework

(Pauwels and Srinivasan, 2004; Singh et al., 2006; Ailawadi et al., 2010; Vitorino, 2012). As illustrated on the left-hand side of Figure 1, this competition could result in declines in visits and sales for permanent stores.

However, pop-up shops differ from classic new store tenants in two significant ways. First, their primary managerial goal is often to build customer-brand relationships rather than to maximize immediate sales or revenue like a traditional temporary storefront (Warnaby and Shi, 2018; Rosenbaum et al., 2021). Consequently, their marketing strategies tend to be less price-driven, meaning they do not directly compete with permanent stores for shoppers' monetary budgets. As a result, pop-up shops are more likely to compete for consumers' time or attention budgets rather than their financial budgets, leading to varying effects on store visits and sales at permanent stores. Second, the temporary nature of pop-up shops limits their operation to short periods, typically concentrating their effects during their presence. While these impacts may appear pronounced during this time, they are unlikely to persist once the pop-up shop concludes its run.

Additionally, the effects of budget competition can vary considerably across permanent stores, depending on specific store characteristics. Factors such as product assortment, store location, and reliance on distinct shopping behaviors all influence how a store is impacted by the competition introduced by pop-up shops. These variations underscore the moderating role that store features play in the budget competition mechanism, suggesting the potential

for heterogeneous treatment effects across different types of permanent stores.

Traffic Attraction and Spillover Effects

To showcase their brand image and increase consumer exposure, pop-up shops strategically design their retail spaces to feature inclusive services and interactive activities. By fulfilling the experiential and social needs of shoppers—needs that are not typically met by traditional permanent stores—mall managers allocate highly visible spaces to pop-up shops, anticipating that their introduction will provide consumers with an additional reason to visit the host mall (Kidder, 2019). In this sense, these aesthetically appealing, interaction-focused retail spaces function similarly to mall-initiated marketing campaigns, such as themed events, which have been shown to boost traffic and sales for offline retailers and shopping malls (Zhang and Wedel, 2009; Guyt and Gijbrecchts, 2020; Wang et al., 2022).

As shown on the right-hand side of Figure 1, pop-up shops can positively impact malls and their permanent tenants by acting as promotional tools that attract additional shoppers. Once inside, these new visitors may be inclined to explore other permanent stores within the mall, potentially leading to increased visits and sales for these tenants. This process suggests a spillover effect, where the introduction of pop-up shops can result in higher average visits and sales for permanent stores.

Additionally, much like the budget competition mechanism, the spillover effect is unlikely to be uniform across all stores. Its magnitude can vary based on store-specific characteristics, such as product offerings, location within the mall, or targeted customer demographics. As a result, some permanent stores may experience greater gains from the additional mall traffic drawn by pop-up shops, while others may see limited benefits. This variation highlights how permanent store features can moderate the spillover mechanism, creating heterogeneous outcomes among different types of stores within the mall.

Overall Effects

When considering both budget competition and traffic spillover mechanisms together, the increases in store visits and sales driven by spillover effects could, to some extent, offset the decline due to competitive effects. With the proposed framework, our research aims to examine the existence of spillover and budget competition mechanisms and explore how these two mechanisms jointly influence visits and sales of permanent stores in the host malls.

3 Data

To investigate the impacts of brand-initiated pop-up shops on host shopping malls and their permanent store tenants, we procured a comprehensive and unique data set of daily traffic and sales records from 28,595 stores across 100 shopping malls in China, spanning two years. In addition, we collected information on pop-up shops from online platforms.

3.1 Mall traffic, store visits, and sales

With the rise in offline digitalization technology, brick-and-mortar stores are increasingly adopting data-driven approaches for more informed management decisions (Shah and Murthi, 2021). For this study, we collaborated with a company that collects data using a standard format from 100 shopping malls located in 80 cities across China. All these malls belong to the same chain and are similar in terms of interior décor style and types of stores hosted. The dataset includes daily records for all permanent store tenants from January 2017 to December 2018. It also captures daily mall traffic and the number of daily visits to each permanent store, obtained with state-of-the-art customer monitoring systems. These systems employ AI chip-embedded sensors, positioned at mall and store entrances, to monitor customer traffic. As soon as a person enters through any entrance, the sensors record their presence. These data are analyzed in real-time by image processing algorithms embedded in the chips, which establish the number of person-visits with a high degree of accuracy (Wang et al., 2022). To protect customer privacy, the systems cannot identify individual customers,

remove duplicates, or monitor how long customers remain in the mall. These limitations don't affect the overall usefulness of the systems given that the systems are consistent across 100 malls and over the observation time window. Counting traffic is also a widely accepted, standard metric for mall operators and the most precise measure currently available. In addition, we also obtained the stores' daily sales amounts from mall managers, collected by point-of-sales machines in each permanent store, which is the most used payment method ².

3.2 Permanent Store and Mall Features

To examine the effects of pop-up shops on different types of permanent stores, we gathered data on a range of store characteristics, including their specific floor level within the mall, floor area (measured in square meters), and brand name. According to the brand name, each store is classified into six product categories, based on industry-standard criteria³: groceries, household essentials, anchor stores, fashion, restaurants, or entertainment (see Table 1A.1 in Appendix 1A.2 for detailed descriptions of these categories). In addition, we obtained information concerning the average price level of the products, the national branch network size, and the age of each brand to examine the pop-up shops' effects regarding the brand features of each store. Furthermore, to empirically compare the effects of new permanent store entries and pop-up shops, we also obtained the entry and exit date of each permanent store tenant. We also obtained mall features including total business area, cumulative operational days, locations, nearby population density, nearby bus stations, nearby universities and high schools, and city features involving city tier, gross domestic product (GDP) per capita to enable us to generate comparable control groups, which we will discuss more in detail later in the Identification Section.

²Mall managers have control over all the POS machines in each store for better rent design and related managerial purposes.

³It is a widely acceptable classification standard in the industry, and all the 100 shopping malls in our dataset use the same classification for management purposes.

3.3 Pop-up Shop Features

To collect information about pop-up shops, we searched three platforms using the keyword “pop-up”. These platforms included articles posted by the official WeChat accounts of the 100 malls, all posts on Weibo.com, and news articles published by a major news web portal—Sina.com. To promote such temporary events, all pop-up shops were announced by shopping malls through their official WeChat account. We analyzed text, images, and video in each post collected from the official WeChat accounts of 100 malls to obtain the names of malls, pop-up brands, and their operating periods. Besides the WeChat official account, some pop-up events were also promoted on social media platforms (Weibo.com) or news websites (Sina.com). We matched the information collected across platforms. In total, we identified 112 pop-up shops launched in 100 shopping malls during 2017–2018 ⁴.

Building on the 1) classification criteria proposed in the literature (e.g., Warnaby and Shi 2018; Rosenbaum et al. 2021), and 2) our specific sample, we further explored the characteristics of these 112 pop-up shops across seven dimensions. Summary statistics for these features are presented in Table 1A.2 in Appendix 1A.2. Among the 112 pop-up shops, 54% featured chain brands (versus independent brands). In terms of brand category, entertainment brands constituted the largest category (41%), followed by household essentials (28%) and fashion (14%). Approximately half (53%) of the shops were brand-centric (versus product-centric)⁵. Furthermore, 68% of the pop-up shops were located in the atriums of shopping malls, while 32% were located in the outdoor space near the main entrance. Only 8% of the pop-up shops primarily featured price deductions, while the rest (92%) focus on offering an experiential and exclusive shopping environment. Moreover, 70% of them also promoted on social media (Weibo) in addition to promoting in the official account in WeChat. In terms of their tim-

⁴This period marks the early stage of pop-up shops’ popularity in China. In recent years, this retail format has grown rapidly, with the number of shops increasing significantly each year.

⁵By examining texts, posters, photos, and video recordings regarding each pop-up shop, we identify a pop-up shop as brand-centric if the pop-up shop aims to promote the brand, such as by hosting exhibitions or artistic performances that can increase brand awareness, and identify a pop-up shop as product-centric if the goal is to promote specific products (or product lines).

ing, around half (46%) of the pop-up shops chose to start their operation on Saturdays or Sundays, whereas the rest start on weekdays.

3.4 Supplementary Data

In addition to the primary data sets, we obtained weather information from weather.com and holiday information from a Chinese government website to account for the potential impacts of weather and holidays on customers' shopping behaviors. We also gathered detailed information about in-mall marketing campaigns initiated by shopping malls during the same two-year period, including their timing, and themes.

Table 1 presents the summary statistics for key variables. Our data set includes 28,595 stores in 100 malls and a period of 730 days. Of the 100 malls, 50 operated a total of 112 pop-up shops during the two-year observation period. On average, 1.12 pop-up shops (SD = 1.83) appear in each mall. Among these 50 malls, 27 of them only hosted one pop-up shop. For the 23 malls hosting more than one pop-up shops, there is no overlap among pop-up shops. Most pop-up shops only operate for less than a week (with an average duration of 3.71 days).

4 Identification

A key empirical challenge in identifying the causal effect of pop-up shops is that malls that host pop-up shops could differ inherently from those that do not, in terms of mall area, location, population density, or managerial strategies. Thus, a simple comparison of traffic and sales between malls with and without pop-up shops may be misleading. To address this identification challenge, we leveraged our panel data set and employed a Difference-in-Difference (DiD) strategy to identify the impact of pop-up shops. Because pop-up shops operate during different time periods and in a subset of malls (for most cases just one mall), a DiD identification strategy can address the potential selection bias by comparing changes

Table 1: Summary Statistics

Variables	N	Mean	SD	Max	Min
Mall level variables					
Pop-up shops dummy (0/1)	100	.5	.50	1	0
Number of Pop-up shops	100	1.12	1.83	9	0
Average daily traffic	100	36,635.82	12,318.1	106,329.3	8,824.55
Average daily total sales (RMB)	100	1,995,070	1,049,888	7,515,868	322,926.2
Cumulative operational days	100	1,743.75	808.03	4,391	773
Total business area	100	61,763.64	13,771.48	138,119.2	34,260
Relative distance to CBD	100	.41	.34	2.44	.04
Nearby population densities	100	5,124.82	5,286.11	27,645.3	186.2
Number of nearby bus stations	100	13.82	5.19	20	0
Number of nearby high schools	100	2.17	2.42	15	0
Number of nearby universities	100	1.04	1.59	7	0
City GDP per capita (RMB)	100	135,998.9	59,588.85	317,242.5	33,548.33
City tier	6 level: towns; small cities; emerging cities; regional centers; major cities; global metropolises				
Mall–day level variables					
Daily traffic	72,951	36,589.01	17,003.02	287,302	400
Pop-up shops dummy (0/1)	73,000	.01	.07	1	0
In-mall campaign dummy (0/1)	73,000	.55	.50	1	0
Weather condition	3 levels: good; fair; bad				
Holiday	23 holidays, including 10 official holidays, 3 online shopping days, and 10 theme festivals				
Store–day level variables					
Daily store visits	11,203,293	546.51	1,210.12	164,155	0
Daily store sales (RMB)	12,067,899	12,068.39	56,793.47	13,000,000	0

Notes: The daily mall traffic varies both across malls and over time. There are some missing observations in traffic, visit and sales. An examination of these omissions revealed no discernible pattern related to store features, suggesting their absence does not bias our results.

in traffic and sales before and during the pop-up shops' presence in malls (i.e., treatment group) with a baseline of changes in traffic and sales in similar malls with no pop-up shops (i.e., control group) during the same period.

The DiD identification strategy can capture all time-invariant variations between treatment and control groups. However, one potential concern regarding the DiD estimation is that treatment malls and control malls may have different time-variant unobservables, which may violate the parallel assumption (Callaway and Sant'Anna, 2021). To mitigate this concern, following previous studies (Singh and Agrawal, 2011; Zervas et al., 2017; He et al., 2021), we conducted a matching approach before estimating the DiD model to make treatment malls and control malls as comparable as possible in terms of a comprehensive list of observable variables. Specifically, we applied coarsened exact matching (CEM) (Iacus et al., 2009) to stratify malls using the following observable characteristics: average mall traffic in the previous two years, average store sales in the previous two years, cumulative operational days, total business area, relative location to downtown, population density within a three-kilometer radius, number of bus stations within a three-quarter-kilometer radius, numbers of universities and high schools within a three-kilometer radius, city tier, and GDP per capita of the city⁶. The matching procedure produced nine strata. With stratified t-tests, we tested whether malls in the treatment and control groups were comparable in terms of matching features. None of these t-tests rejected the null hypothesis that the two groups had the same average (at a 5% significance level), suggesting that the malls in the treatment and control groups are comparable on key observed features (for a summary of the treatment and control group variables before and after matching, see Table 1A.4 in Appendix 1A.2). Therefore, variation in the treatment (i.e., presence of pop-up shops) across shopping malls in the same stratum enabled us to identify their effects on a mall's retail performance.

⁶Since all 100 shopping malls belong to the same chain, the brand categories, store layouts, and number of stores are largely similar across malls in the same city tiers. Additionally, since pop-up shops can only be located in either the central atriums on the ground floor or the outdoor space near the main entrance, the relative location of pop-up shops is usually not a factor that can influence the choice of mall for operating them.

The interventions, namely, the presence of pop-up shops, occur at different times throughout the observation period and for different malls, with a finite duration. Thus, the treatment is reversible —once the pop-up shops cease their operation, the intervention is no longer in effect (Acemoglu et al., 2019). Most importantly, the assignment of treatment, i.e. having a pop-up shop in a mall, is determined by the manager in each mall, which makes each pop-up shop an independent event. Accordingly, we constituted one experiment for each pop-up shop and identified control malls for each experiment, one after another. For each experiment, the malls in the same stratum as the treatment mall represent candidate control malls⁷. To avoid potential contamination by other treatments, we also required that no pop-up shop appear in control malls two months before and after the pop-up shop periods. To address the potential SUTVA violation (Rubin, 1986), wherein consumers might switch from untreated malls to treatment malls due to the presence of pop-up shops, we required that control malls not be located in the same town as each treatment mall. After dropping unmatched malls, we identified 89 malls with 70 unique experiments in 43 treatment malls, with a mean of 9.3 control malls in each experiment. For each experiment, we defined the pop-up shop operating window as the post-treatment period for both treatment and control malls⁸ and the two weeks before the start date of the pop-up shop as the pre-treatment period.

4.1 Model-free evidence

Before showing the formal estimation results, we use model-free evidence to demonstrate whether treatment and control malls are comparable in the pre-treatment periods and

⁷In our context, the treatment rollouts (i.e., pop-up shops) are not only staggered but also reversible. Traditional TWFE (Two-Way Fixed Effects) models with staggered rollouts utilize units after treatment as controls alongside units that have never been treated when estimating treatment effects. This approach may pose challenges, particularly when treatment effects vary over time (Goodman-Bacon, 2021). Therefore, we adopt a stricter approach to identify control malls. We ensure that no control mall can be treated during each specific pop-up shop window, sharing similar spirits with Callaway and Sant’Anna (2021) and Baker et al. (2022).

⁸Table 1A.3 in Appendix 1A.2 summarizes the proportion of pop-up shops in operation out of the total 70 pop-up shops on each day of operating window.

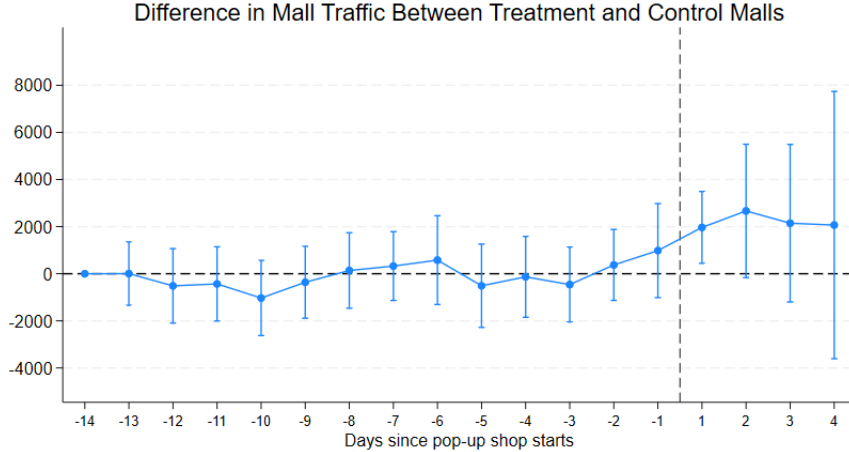


Figure 2: Model-Free Treatment Effects on Daily Mall Traffic

Notes: This figure illustrates the differences in average mall traffic between treatment and control malls during the two weeks prior to (days -14 to -1) and the period of (days 1 to 4) pop-up shop events. Observations from day four onwards, following the commencement of pop-up shops, are consolidated into a single node, represented as “4”. This approach is because only a few pop-up shops in our sample were operational for more than four days. The bars show the 90% confidence interval.

whether treatment malls experience a larger traffic increase during the presence of pop-up shops. Specifically, we first calculated the difference between treatment and control malls for each period. We then used such difference on the 14th day before the opening of pop-up shops (day=-14) as the benchmark and calculated the difference in differences between the focal day and the benchmark day. These metrics are demonstrated in Figure 2⁹. The bars in the figure are the confidence intervals. These raw data patterns show that 1) the traffic in treatment malls and control malls are largely parallel two weeks before pop-up shops (day -14 to day -1); 2) treatment malls experience a larger traffic increase during the period of pop-up shops (day 1 to day 4)¹⁰. We use econometric analyses to formalize these insights in the next subsection.

⁹We also visualize the raw traffic trends for treatment and control malls separately in Figure 1A.1 in Appendix 1A.2, which suggests a parallel trend in mall traffic between the two groups. Similarly, Figure 1A.2 in Appendix 1A.2 presents the average store visits and sales for stores in treatment and control malls, demonstrating that the trends are also parallel at the store level.

¹⁰We also observe that there is a slight increase one day before the opening of pop-up shops (day = -1). This may be attributed to the anticipation effect as the setup of pop-up shops is visible to customers, leading them to anticipate an upcoming event before it officially begins. We also conduct a robustness check by removing observations in day = -1 (Barreca et al., 2011) in Appendix 1A.3 to avoid this anticipation effect and find results are consistent.

4.2 Impacts of Pop-Up Shops on Malls

In this subsection, we formally estimate the average effect of pop-up shops on daily mall traffic. For each of the experiments (pop-up shop), a log-linear model is adopted to identify the effect on mall traffic as follows:

$$\log(\text{mall_traffic}_{mt}) = \alpha_m + \beta \text{Popup}_{mt} + \mu \text{Post}_t + \boldsymbol{\delta} \mathbf{T}_t + \boldsymbol{\theta} \mathbf{X}_{mt} + \epsilon_{mt} \quad (1)$$

where the dependent variable mall_traffic_{mt} is the amount of traffic of mall m at day t . The unit of analysis thus is at the day–mall level. The dummy variable Popup_{mt} equals 1 if there is a pop-up shop at mall m on the day t and 0 otherwise. Post_t is a dummy variable that equals 1 if day t is during a pop-up shop and 0 if it is in the pre-treatment period. μ accounts for trends between the pre- and during pop-up shop periods in each experiment. α_m are mall-fixed effects that capture all time-invariant characteristics of malls. We allowed parameters μ and α_m to vary across 70 experiments but keep β constant. Then β is the coefficient of interest that quantifies the average effect of the pop-up shops on daily mall traffic across experiments.

To control for the effects of contemporaneous changes within shopping malls on mall traffic, we 1) summarized a vector of seasonality variables in \mathbf{T}_t , including weekday dummies, week dummies, month dummies, year dummies and holiday name dummies, to rule out the impact of seasonality; 2) included an in-mall marketing campaign indicator in \mathbf{X}_{mt} , which captures the effects of mall-wide promotions (Guyt and Gijsbrechts, 2020; Wang et al., 2022); 3) included a new store entry indicator in \mathbf{X}_{mt} to capture the effects new permanent entrants; 4) included a three-level category variable of weather conditions in \mathbf{X}_{mt} to rule out the impacts of weather.

The estimation results in Column (1) of Table 2 reveal that the average impact of pop-up shops on mall traffic is significantly positive ($\hat{\beta} = .030$; $p = .008$). Our results remain consistent as we gradually relax the control variables and fixed effects, as shown in Columns

Table 2: Effects of Pop-Up Shops on Mall

	(1)	(2)	(3)	(4)
Dependent variable:	log(mall traffic)	log(mall traffic)	log(mall traffic)	log(mall traffic)
Pop-up shops	.030*** (.011)	.031*** (.011)	.031*** (.011)	.031*** (.011)
Time fixed effects	Yes	Yes	Yes	No
Mall fixed effects	Yes	Yes	No	No
Control variables	Yes	No	No	No
Observations	11,766	11,766	11,766	11,766
R-squared	.884	.883	.694	.416

Notes: Column (1) displays the results from Equation 1. In column (2) to column (4) we gradually remove the control variables, mall fixed effects and time fixed effects, and the main effects are robust across different functional forms. Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year, and holidays. Control variables include in-mall marketing campaigns, store entries, and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

(2) to (4), indicating that the observed effect is not influenced by them. On average, pop-up shops increase daily mall traffic by 3.05%¹¹. This result supports the existence of the traffic attraction effect, namely that pop-up shops can help attract additional traffic to the shopping mall through the carefully designed physical retailing spaces and experiential experiences they offer¹².

4.3 Robustness Check

In line with the recommendations made by Goldfarb et al. (2022), we undertook a series of robustness checks to enhance the causal interpretation of our findings including 1) falsification test; 2) alternative matching methods; and 3) alternative function forms.

Falsification Test

To test the parallel assumption of our DiD identification approach, we ran a falsification

¹¹The effect of pop-up shops on the percentage change in mall traffic is given by $exp(\hat{\beta}) - 1$.

¹²We also estimate the effects of pop-up shops on mall traffic using the full sample before matching, following the approach of De Chaisemartin and d'Haultfoeuille (2020). The results, as shown in Table 1A.5 in Appendix 1A.3, are largely consistent with our primary findings.

test for the pre-treatment period, in which we manually assign a “fake” pop-up indicator to treatment malls in each experiment and code the pop-up shops as if they started from day -12, day -10, day -8, day -6, day -4 and day -2 (the true starting period is always day 1). Then we estimated Equation 1 with the new (fake) pop-up shop indicators in the pre-treatment period. Table 1A.6 in Appendix 1A.3 contains the results; we found no significant effect with the fake pop-up shop indicators (p-values $> .1$), in support of our assumption that the treatment and control malls, matched by CEM, exhibit similar trends in the pre-treatment period.

Alternative Matching Method

Instead of employing Coarsened Exact Matching (CEM), we opted for Propensity Score Matching (PSM, Rosenbaum and Rubin 1983), which allows us to use time-variant variables as matching variables. In addition to the static mall characteristics utilized in CEM, we also incorporated time-variant variables that describe the retail performance and the scheduling of in-mall marketing campaigns before the pop-up dates. These variables included average mall traffic and sales amounts from seven days and two months preceding the pop-up dates, the number of days since the last in-mall marketing campaign, and the number of days until the next in-mall marketing campaign. Through this matching process, we ensured that treatment and control malls were comparable not only in static mall characteristics but also in recent retail performance and in-mall marketing campaign tendencies before the pop-up dates. This approach helps alleviate concerns related to the strategic selection of pop-up dates. For more details on our PSM approach, please refer to Appendix 1A.4. With the control groups in each experiment identified by PSM, we re-estimated the impact of pop-up shops on mall traffic by adopting DiD regression with Equation 1. The results are presented in Table 1A.7 in Appendix 1A.3, where the coefficients of $Popup_{mt}$ on mall traffic are significantly positive ($\hat{\beta} = .023$; $p = .013$), which is consistent with our main findings.

Alternative Function Forms

Linear regression model In addition to employing a log-linear regression to estimate the percentage change in daily mall traffic, we re-estimate the effect on the absolute change in mall traffic using a linear regression model. The results, presented in Column (1) of Table 1A.9 in Appendix 1A.3, show that pop-up shops increase daily mall traffic by an average of 1,438 people ($\hat{\beta} = 1,438.207$; $p = .016$). This result aligns with our previous findings.

Adjustment for Different Time Trends Pop-up shops may strategically choose holidays or weekends to capitalize on the increased traffic during these periods. A potential concern arises from the possibility that treatment and control malls may exhibit different trends around these specific periods. To address this concern, we modified Equation 1 as follows. We added an interaction term of weekday dummies and $treat_m$ to allow the weekday effects to vary between the control and treatment malls. The regression results, presented in Column (2) of Table 1A.9 in Appendix 1A.3 show that the coefficient of $Popup_{mt}$ on mall traffic is significantly positive ($\hat{\beta} = .028$; $p = .014$)

Potential Selection of Pop-Up Shops' Timing There could be a potential concern that the timing of pop-up shops is strategically determined by mall or pop-up brand managers to maximize their impacts, which may challenge the causality of our results. For example, brands may choose to establish pop-up shops during weekends to leverage increased traffic in the shopping mall (Ahlbom et al., 2023). To alleviate this concern, we implement the following two approaches.

First, we examined whether our effects are consistent across pop-up shops starting on weekends versus weekdays. We modified Equation 1 by including an additional interaction term between the pop-up indicator and a dummy variable indicating whether the pop-up shop started on weekends or not. The results presented in Table 1A.10 in Appendix 1A.3 show that the difference between weekend and weekday pop-up shops is not significant ($\hat{\beta} =$

.039; $p = .121$), suggesting that the timing of pop-up shops does not affect the overall effect. Second, to capture potential time-variant unobservables that may influence the decision of timing selection, we also incorporated time-variant features, such as average mall traffic and sales amounts before pop-up dates, in PSM in the subsection Alternative Matching Method. Furthermore, we relaxed our primary model to allow for different time effects between treatment and control malls in the subsection Adjustment for Different Time Trends. The results of these robustness checks are consistent with our primary results.

5 Impacts on Permanent Store Tenants

5.1 Average Effect on Permanent Store Tenants

The findings reported above indicate a significant traffic attraction effect of pop-up shops, highlighting their pivotal role in attracting more shoppers to shopping malls rather than merely competing for existing customers base. Nevertheless, it remains unclear whether this increased foot traffic ultimately benefits the permanent store tenants of shopping malls given the potential interplay of both spillover and budget competition mechanisms. As illustrated in our conceptual framework in Figure 1, the prevalence of the spillover mechanism is expected to increase store visits and sales, while the prevalence of budget competition is expected to decrease store visits and sales. In this subsection, we employ the following log-linear model to evaluate the impacts of pop-up shops on the retail performance of permanent store tenants:

$$\log(\mathbf{store_outcome}_{st}) = \alpha_s + \beta Popup_{st} + \mu Post_t + \delta \mathbf{T}_t + \theta \mathbf{X}_{st} + \epsilon_{st} \quad (2)$$

where the dependent variable $\mathbf{store_outcome}_{st}$ contains (1) daily store visits ($store_visits_{st}$) and (2) daily store sales ($store_sales_{st}$) in permanent store s on day t . To specify, $store_visits_{st}$ is calculated as the total number of shoppers enter store s on day t captured by the camera

at the store entrance, and store_sales_{st} is the total amount of sales (RMB) of store s on day t . The unit of analysis thus is at the day–store level. The dummy variable Popup_{st} equals 1 if there are pop-up shops in the mall where permanent store s located on day t . α_s captures the store-fixed effects. To control for the effects of store entrants, we included an indicator to denote new store entrants in the same mall with store s in control variables (\mathbf{X}_{st}). The post-treatment dummy (Post_t) and the seasonal dummies (\mathbf{T}_t) are the same as those for Equation 1.

We present the estimation results in Table 3. The coefficients of pop-up shops on permanent store sales are significantly positive ($\hat{\beta}_{\text{store_sales}} = .035$, $p = .076$), and are statistically insignificant on permanent store visits ($\hat{\beta}_{\text{store_visits}} = .009$, $p = .359$). These results indicate that, on average, pop-up shops increase store sales by 3.56% (or equivalently, 429.38 RMB) without increasing store visits significantly.

Table 3: Effects of Pop-Up Shops on Store Visits and Sales

	(1)	(2)
Dependent variable:	log(store visits)	log(store sales)
Pop-up shops	.009 (.009)	.035* (.020)
Time fixed effects	Yes	Yes
Store fixed effects	Yes	Yes
Control variables	Yes	Yes
Observations	1,704,144	1,704,144
R-squared	.847	.731

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year, and holidays. Control variables include in-mall marketing campaigns, store entries, and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Considering our earlier findings at the mall level, where pop-up shops significantly boost daily mall traffic by 3.05%, the disparity between their effects on mall traffic and store visits suggests the existence of two countervailing effects acting on permanent stores. As illustrated in Figure 1, on the positive side, the additional mall traffic due to traffic attraction effects

also enters certain permanent stores, thus boosting their visits and sales. On the negative side, some stores experience a decrease in visits due to competition from pop-up shops, offsetting the spillover effect on store visits and leaving the average store visits unchanged. On average, the spillover mechanism dominates the budget competition mechanism, leading to net positive impacts on both mall traffic and store sales. These findings highlight the advantages of introducing pop-up shops as a strategy to enhance mall vitality and drive spillover benefits for permanent stores, helping to alleviate concerns among store owners who may perceive them as a competitive threat.

6 Comparison with New Store Entries

It is worth noting that although both pop-up shops and new store entries introduce additional competition, they differ fundamentally. While traditional store openings may also include promotional activities, they still differ from pop-up shops in two key aspects: (1) their managerial objectives primarily focus on sales and transactions, and (2) they occupy a permanent storefront within the shopping mall, typically replacing the space of an exiting store. As a result, they are less prominently positioned compared to pop-up shops, which are often located in high-visibility areas such as hallways and atriums. Therefore, new store entries may demonstrate more pronounced competition compared to pop-up shops. To empirically examine the effects of store entries on mall traffic, as well as on store visits and sales, we collected data on the entry and exit dates of each permanent store in 100 malls over two years. To make it comparable with pop-up shops, we only focus on the entry of large stores with areas exceeding 300 square meters. In total, our sample includes 924 store entries. We use the full observations for all matched malls during the two-year window to capture the effects of such new store entrants on malls and their existing permanent store tenants.

The results, as shown in Table 4, reveal that, unlike pop-up shops, a large permanent

Table 4: Effects of New Store Entries on Malls

Dependent variable:	log(mall traffic)	log(store visits)	log(store sales)
Store Entries	.004 (.004)	-.002** (.001)	-.011*** (.003)
Mall fixed effects	Yes	-	-
Store fixed effects	-	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	72,951	4,819,253	4,819,253
R-squared	.648	.733	.568

Notes: Robust standard errors are reported in parentheses. Control variables include in-mall marketing campaigns, pop-up shops, and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

store entry does not significantly increase mall traffic ($\hat{\beta}_{\text{mall_traffic}} = .317, p = .317$). Moreover, such an entry can adversely affect other permanent store tenants, decreasing store visits by 0.20% ($\hat{\beta}_{\text{store_visits}} = -.002, p = .046$) and store sales by 1.09% ($\hat{\beta}_{\text{store_sales}} = -.011, p < .001$), on average. These findings support our earlier argument that entries of permanent stores pose more intense competition compared to pop-up shops. They act as substitutes and directly compete with other permanent stores for customers' time and monetary shopping budgets. The lack of a highly visible location and the absence of an interactive or experiential shopping environment also limit their ability to attract additional mall traffic.

These findings suggest that pop-up shops differ from traditional store entries because of their dual nature: spillover as well as competitive effects. In the following section, we will provide empirical evidence to support the coexistence of two forces.

7 Mechanism

Our results thus far demonstrate that while pop-up shops increase mall traffic by 3.05% and store sales by 3.56%, they do not significantly affect visits to permanent stores on average. These average effects suggest the coexistence of two countervailing forces on permanent stores as summarized in Figure 3 below. Importantly, this indicates that pop-up shops should not

be categorically perceived as threats to permanent stores. Rather, pop-up shops attract additional shoppers through their traffic attraction effects, as evidenced by the positive average impact on mall traffic. This increased traffic spills over to permanent stores, benefiting them through higher visits and sales.

At the same time, pop-up shops introduce some competitive pressure, primarily by competing for shoppers' time shopping budgets rather than directly reducing store sales.

By offering experiential shopping environments that prioritize customer engagement over transactions, pop-up shops consume shoppers' time and attention, reducing their capacity to visit additional permanent stores. As a result, shoppers reduce their exploratory shopping (i.e., browsing for pleasure or gathering product information for future purchases) (Moe, 2003; Yim et al., 2014; Streicher et al., 2021), while still engaging in purposeful shopping geared toward immediate purchases (Janiszewski, 1998; Hui et al., 2009). This competition diminishes store visits without significantly affecting sales. The reduction in exploratory visits offsets the increased visits generated by the spillover effect, resulting in no overall change in average store visits. Meanwhile, sales remain positive because the spillover benefits persist, and the competition's effect on sales is relatively mild.

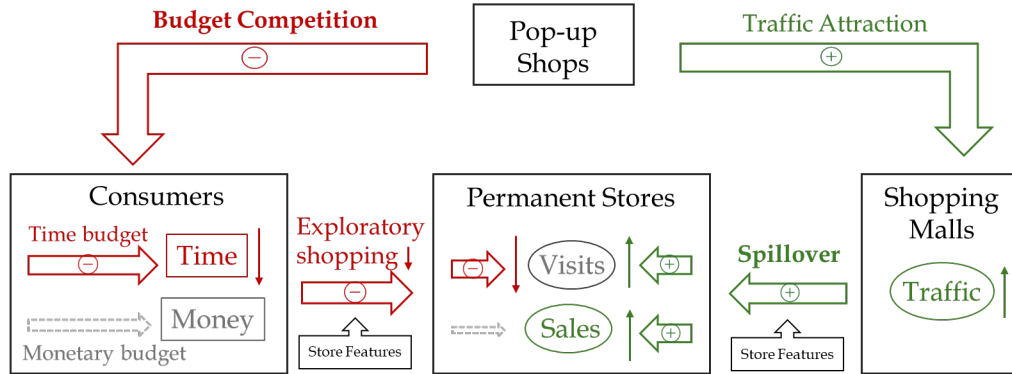


Figure 3: Summary of Main Effects

Notes: This figure illustrates the dual mechanisms supported by our data analysis on how pop-up shops impact host malls and their permanent store tenants. On the right, pop-up shops generate increased mall traffic (indicated in green), which spills over to permanent stores, leading to higher visits and sales. On the left, pop-up shops compete for consumers' time shopping budget (shown in red) but not their monetary budget (in gray), primarily reducing exploratory visits rather than purposeful shopping. As a result, the decline in exploratory visits offsets the increase in visits from the spillover effect, leaving overall store visits unchanged.

To further validate the proposed dual-mechanism framework, we investigated the spillover and competition effects separately through a series of heterogeneity analyses based on different characteristics of permanent stores. Specifically, if the spillover mechanism is at work, stores are more likely to benefit from additional mall traffic should experience a more pronounced increase in store visits. Conversely, if the mental competition mechanism is at work, permanent stores that rely more on exploratory shopping should experience a more negative effect on store visits. In the following subsections, we examine how the effects on permanent stores vary across different types of stores and use the findings to support the coexistence of two countervailing mechanisms.

7.1 Spillover

The spillover mechanism refers to the additional mall traffic attracted by pop-up shops, which subsequently increases visits to certain permanent stores. Stores in closer proximity to pop-

up shops are expected to benefit more from this traffic spillover. We examined two dimensions of proximity: product category proximity and physical distance proximity. For product category proximity, pop-up shops often provide interactive and hedonic shopping experiences, potentially raising awareness of their product categories and encouraging shoppers to visit similar stores for further exploration and comparison (Ma et al., 2024). Based on this conjecture, we classified the product category of each pop-up shop according to the same standard used for permanent store categories, as detailed in Section 3. We then generated an indicator to denote whether each permanent store belongs to the same product category as the pop-up shop. If the spillover mechanism is at work, we expected that permanent stores in the same product category as the pop-up shops would experience greater increases in store visits compared to those in different categories.

To test the spillover mechanism, we adopt the following model:

$$\begin{aligned} \log(\text{store_visits}_{st}) = & \alpha_s + \beta \text{Popup}_{st} + \mu \text{Post}_t + \lambda \text{Popup}_{st} \times \text{Same_cat}_{st} \\ & + \tau \text{Popup}_{st} \times \mathbf{W}_{st} + \delta \mathbf{T}_t + \boldsymbol{\theta} \mathbf{X}_{st} + \epsilon_{st} \end{aligned} \quad (3)$$

Same_cat_{st} is a binary variable indicating whether store s belongs to the same product category as the pop-up shop. We also interacted the pop-up shop dummy with the store’s product category and store size in \mathbf{W}_{st} to rule out alternative explanations by product category and store size. Other variables are defined the same as in Equation 2.

As the estimation results in column (1) of Table 5 show, permanent stores in the same product category as the pop-up shops experienced larger increases in store visits compared to those in different categories ($\hat{\lambda}_{\text{same.category}} = .064$, $p = .082$). These results indicate that the increased traffic from pop-up shops tends to have a greater positive impact on permanent stores that belong to the same category as the pop-up shops.

We also examined whether the spillover of store visits translates to the sales increase in permanent stores. To do this, we replaced the dependent variable in Equation 3 with store sales and presented the results in Table 6. As the result in column (1) shows, permanent

stores in the same product category as the pop-up shops experienced greater sales boost compared to those in different categories ($\hat{\lambda}_{\text{same_category}} = .149$, $p = .000$). This implies that pop-up shops not only prompt exploration and comparison within their product category but also effectively convert increased visits into sales. This phenomenon could be attributed to the experiential nature of pop-up shops, which typically prioritize offering an exclusive shopping environment over immediate transactions. As a result, pop-up shops raise awareness of permanent stores in the same category without introducing direct competition during the purchase stage.

Beyond category proximity, stores located in closer physical proximity to pop-up shops may also benefit more from the traffic spillover, as they are more easily noticed by shoppers entering the mall drawn by pop-up shops. We use the floor level on which permanent stores are located as a proxy for physical proximity to pop-up shops. Notably, all our pop-up shops are positioned on the first floor. Thus, if the spillover mechanism is effective, we anticipated that the effects of pop-up shops on store visits would be more salient for permanent stores located on lower floors compared to those located on higher floors. To formally test this conjecture, we included an additional interaction term between $Popup_{mt}$ and a categorical variable $Floor_{st}$ indicating store floors in Equation 3 to capture the heterogeneous effects on store visits across different floors.

As indicated by the estimation results in column (2) of Table 5, permanent stores located closer to pop-up shops (on lower levels) experienced greater increases in visits due to pop-up shops ($\hat{\lambda}_{1F} = .076$, $p = .003$; $\hat{\lambda}_B = .067$, $p = .048$; $\hat{\lambda}_{2F} = .070$, $p = .013$; $\hat{\lambda}_{3F} = .042$, $p = .084$) compared to those located above the third floor, which serves as the baseline. These results indicate that permanent stores in closer physical proximity to the pop-up shops benefit more from the additional traffic attracted by the pop-up shops.

We also examined the heterogeneous effects on store sales in terms of store floor levels. Results in column (2) in Table 6 indicate that stores located on lower floors tend to have a larger sales boost compared to those located above the third floor. However, such a

difference is not statistically significant. This could be due to the large sales variations among permanent stores within the same floor.

In sum, the findings from these two heterogeneity analyses reveal that permanent stores in closer proximity to pop-up shops tend to benefit more during the period of pop-up shops, which also provides empirical evidence to support the existence of the spillover mechanism.

On the other hand, we find that there is a negative impact of pop-up shops on store visits for the baseline store category, as shown by the significantly negative coefficient estimate for the pop-up shops. For example, $\hat{\beta}_{\text{visits}} = -0.115$ ($p < 0.001$) in column (2) of Table 5 shows that the baseline stores, i.e., those located on the fourth floor or higher and belonging to a different product category than the pop-up shops, experience a significant decline in visits due to the presence of pop-up shops. In contrast, the estimate of the corresponding coefficient for pop-up stores on store sales in Table 6 is not significant ($\hat{\beta}_{\text{sales}} = -0.030$, $p = 0.617$), indicating that the baseline stores do not experience a decrease in sales. These results suggest that an opposing competitive force from pop-up shops is at work: while it negatively impacts store visits for certain store groups, it does not necessarily result in a decline in sales. We will further elaborate on this mechanism in the next subsection.

7.2 Competition

Due to the experiential nature of pop-up shops, they tend to compete for consumers' time budgets rather than their monetary expenditures, thereby diminishing engagement in exploratory shopping. Consequently, the competition effect may be more influential in permanent stores that rely heavily on exploratory shopping. Independent brands, unlike more widely recognized chain brands, depend heavily on exploratory shopping to draw in traffic initially attracted by chain brands or anchor stores (Gould et al., 2005). This dependence is due to the lower awareness of these brands, which makes them less likely to be the primary destination for consumers planning their mall visits. To test the competition mechanism, we use independent vs. chain brands as a proxy to capture the variation in reliance on

exploratory shopping traffic. We gathered data on the total number of branches each brand has nationwide and create an independent brand indicator for those with branch numbers below the median within their product category. If the competition mechanism is at work, we expect that the effect on the visits to permanent stores associated with these independent brands will be more negative compared to stores associated with chain brands. Thus, we added an additional interaction term between the pop-up shop dummy and the independent brand indicator $Popup_{st} \times independent_brand_{st}$ into Equation 3.

The results are shown in column (3) of Table 5. As the results indicate, permanent stores with independent brands experienced a larger decline in store visits during pop-up shops compared to chain brands ($\hat{\lambda}_{independent_brands} = -.016$, $p = .092$). This finding provides evidence that pop-up shops also introduce competition to permanent stores. However, since they mostly compete for shoppers' time budgets, pop-up shops tend to have a larger impact on independent brand stores that heavily rely on exploratory shopping.

We also examined the heterogeneous effect on store sales between independent and chain brands, and the results are presented in column (3) of Table 6. The results show that the impact on store sales of independent brand shops is not significantly different from that of chain brands ($\hat{\lambda}_{independent_brands} = .008$, $p = .542$). This indicates that pop-up shops mainly compete for time budgets rather than monetary budgets, resulting in minimal heterogeneous effects on store sales between independent and chain brand stores.

Overall, these results suggest that pop-up shops create competitive pressure mainly on consumers' shopping time rather than their spending. Therefore, they do not directly impact purchase decisions or reduce the sales of permanent stores.

7.3 Alternative Explanations

So far, we have presented evidence supporting our dual-mechanism framework regarding the effects of pop-up shops, as illustrated in Figure 3. Beyond our proposed mechanisms, an alternative explanation could be that pop-up shops tend to attract more impulse shoppers

Table 5: Heterogenous Treatment Effects on Store Visits

	(1)	(2)	(3)
	log(store visit)	log(store visit)	log(store visit)
Pop-up shops	-.058** (.023)	-.115*** (.031)	-.099*** (.031)
Same category \times pop-up	.064* (.037)	.064* (.037)	.063* (.037)
Basement \times pop-up		.067** (.034)	.065* (.034)
1st floor \times pop-up		.076*** (.026)	.071*** (.025)
2nd floor \times pop-up		.070** (.028)	.066** (.027)
3rd floor \times pop-up		.042* (.024)	.040* (.024)
Independent brands \times pop-up			-.016* (.009)
Time fixed effects	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes
Control interactions	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	1,704,144	1,704,144	1,704,144
R-squared	.847	.847	.847

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control interactions include interaction terms between the pop-up shop dummy and \mathbf{W}_{st} which includes product categories and store size. Control variables include in-mall marketing campaigns, new store entries, and weather conditions of malls.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 6: Heterogenous Treatment Effects on Store Sales

	(1)	(2)	(3)
	log(store sales)	log(store sales)	log(store sales)
Pop-up shops	-.008 (.049)	-.030 (.060)	-.038 (.058)
Same category \times pop-up	.149*** (.041)	.149*** (.041)	.149*** (.041)
Basement \times pop-up		.032 (.080)	.033 (.080)
1st floor \times pop-up		-.007 (.051)	-.004 (.052)
2nd floor \times pop-up		.030 (.054)	.032 (.055)
3rd floor \times pop-up		.035 (.053)	.036 (.053)
Independent brands \times pop-up			.008 (.013)
Time fixed effects	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes
Control interactions	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	1,704,144	1,704,144	1,704,144
R-squared	.731	.731	.731

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control interactions include interaction terms between the pop-up shop dummy and \mathbf{W}_{st} which includes product categories and store size. Control variables include in-mall marketing campaigns, new store entries and weather conditions of malls.

*** $p < .01$, ** $p < .05$, * $p < .1$.

compared to the regular customer base of shopping malls, leading to increased purchases. This explanation is consistent with the observed increases in mall traffic and store sales. However, it fails to account for why the average number of visits to permanent stores does not increase during the presence of pop-up shops. If additional impulse shoppers were drawn to the mall by pop-up shops, we would expect to see an increase in both store visits and sales. Instead, our findings show no significant change in store visits, accompanied by an increase in sales. This observation suggests that the shopping behavior of the existing customer base also changes in response to the presence of pop-up shops. By analyzing the “average” customer base’s shopping patterns, our empirical results indicate two key insights: 1) the total number of shoppers increases, while 2) exploratory visits to permanent stores decrease, making shopping behavior more purposeful.

7.4 Heterogeneous Treatment Effect at Mall Level

To investigate the boundaries of the positive impacts of pop-up shops on mall traffic, we conducted the heterogeneity analysis in terms of pop-up shop features by including interaction terms of pop-up shop features listed in Table 1A.2 with pop-up indicator in Equation 1. The estimation results are in Table 1A.11 in Appendix 1A.5. We gradually added pop-up shop features into the model and the results remain largely consistent.

Our findings indicate that pop-up shops promoted on social media platforms generate significantly more traffic to shopping malls than those that are not. Additionally, pop-up shops offering exclusive and interactive shopping experiences are more effective in attracting mall visitors compared to those focusing mainly on price promotions. We found no significant variation in the treatment effect on mall traffic concerning other features, such as whether the pop-up shop features a chain or independent brand, its location in an outdoor square versus an indoor atrium, or its product category.

8 Post Treatment Effect

The existing literature highlights the effectiveness of pop-up shops in enhancing brand awareness (Rosenbaum et al., 2021) and fostering customer engagement (Klein et al., 2016), which can benefit the long-term goals of the pop-up brand itself. However, given that pop-up shops are typically present for only a short duration and most do not establish permanent storefronts in shopping malls, their impact on mall traffic may not be long-lasting. In Figure 4 we present the model-free difference in mall traffic between treatment mall and control malls after CEM during the two-week pre-treatment, during treatment, and four-week post-treatment period. As it shows, the impact of pop-up shops on mall traffic gradually diminishes after the treatment period.

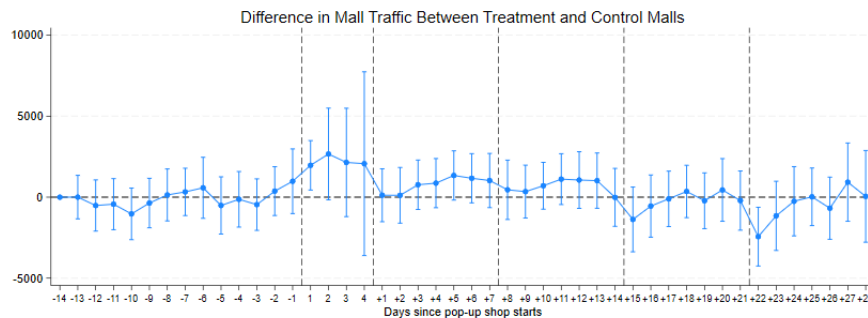


Figure 4: Model-Free Post-Treatment Effects on Daily Mall Traffic

Notes: This figure illustrates the differences in average mall traffic between treatment and control malls during the two weeks prior to (days -14 to -1), the period of (days 1 to 4), and four weeks post (days +1 to +28) pop-up shop events. Observations from day four onwards following the commencement of pop-up shops, are consolidated into a single node, represented as “4”. This approach is because only a few pop-up shops in our sample were operational for more than four days. The bars show the 90% confidence interval.

Next, we estimated the post-treatment effect based on Equation 1, where we also included observations from four weeks after the treatment period of each experiment. As the results in Table 7 show, in general, the impact of pop-up shops decreases after the treatment period and becomes insignificant in the third week of post-pop-up shops. This residual effect may be attributed to the possibility that the additional shoppers drawn by the pop-up shops return to explore the host malls after the pop-up shops have concluded. However, these visitors do not transition into loyal customers ultimately. These results indicate that the

positive impact on mall traffic is not long-lasting, which provides additional evidence of the promotional nature of pop-up shops.

Table 7: Post Effects of Pop-Up Shops on Mall

	log(mall traffic)
During pop-up shops	.040*** (.011)
First week after pop-up shops	.018** (.007)
Second week after pop-up shops	.026*** (.008)
Third week after pop-up shops	.014 (.011)
Fourth week after pop-up shops	.009 (.014)
Time fixed effects	Yes
Mall fixed effects	Yes
Control variables	Yes
Observations	30,768
R-squared	.867

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekday, week, month, year, and holiday dummies. Control variables include in-mall marketing campaigns, new store entries, and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

9 Conclusions and Implications

As pop-up stores have gained popularity worldwide due to their ability to offer personalized and interactive shopping experiences while building customer relationships in short-term retail formats, research into their impacts has also grown. Mall managers increasingly utilize this innovative retail strategy to revitalize foot traffic. However, concerns have been raised by permanent store owners and policymakers that pop-up shops may introduce unfair

competition, benefiting from the traffic of existing permanent stores without contributing sustainably to the mall ecosystem. While prior research has largely focused on the featured pop-up brands themselves, their broader impacts on neighboring businesses remain underexplored. Our study shifts the focus to host venues, investigating whether pop-up shops negatively affect shopping malls and their permanent store tenants by introducing new competitive pressures. The findings from our research offer valuable insights for mall managers, permanent store owners, and policymakers seeking to navigate the opportunities and challenges posed by this emerging retail format.

First, pop-up shops should not be categorically perceived as threats that merely take advantage of pre-existing foot traffic in malls. Instead, they have the potential to significantly increase overall mall traffic and boost store sales. Pop-up shops create exclusive, experiential retail spaces that fulfill shoppers' social and emotional needs, which in turn attracts more visitors to the mall. This increased traffic can then spill over to permanent stores, benefiting them by driving higher sales. Although pop-up shops are sometimes seen as competitive threats, particularly by permanent tenants, their primary objective is to build customer relationships and enhance brand identity, rather than to generate immediate revenue. As a result, they do not directly compete with permanent stores for consumers' monetary spending. These findings underscore the opportunity of pop-up shops as an innovative promotional tool that can help bring back mall traffic. Our results also offer important insights for policymakers regarding the adoption of pop-up shops. Policymakers should consider establishing clear guidelines and incentives for mall owners to integrate pop-up shops into their retail strategies, ensuring that both pop-up and permanent tenants can coexist harmoniously. Additionally, they should work to address concerns from permanent store owners, fostering a more open and dynamic offline retail environment that encourages innovation and embraces new retail formats.

Second, despite their overall promotional and spillover effect, pop-up shops are not flawless amplifiers. They do cannibalize customers' scarce resources with regard to time and

attention, thereby hurting exploratory shopping. This competition may negatively affect store visits, though it does not directly undercut sales at permanent stores. Consequently, it is essential for mall owners to recognize the potential negative impact on their permanent store tenants when opting to host pop-up shops. Particularly noteworthy is the scenario wherein a substantial proportion of permanent stores within the mall are associated with brands that rely heavily on exploratory shopping. In such cases, the decision to accommodate a pop-up shop may inadvertently outweigh its favorable impact, resulting in a decrease in store visits and sales on average. Moreover, as exploratory shopping is often associated with gaining brand and product knowledge for future purchase (Moe, 2003; Streicher et al., 2021), in instances where the host mall is in a nascent stage of development and predicated upon the cultivation of exploratory shopping patterns to expand its customer base, the cooperation with a pop-up shop may cannibalize such exploratory shopping, thereby limiting the potential for long-term growth.

Third, the impact of pop-up shops on permanent stores depends on store features. In general, stores with closer physical and category proximity to the pop-up shops benefit more from spillover effects, while stores associated with independent brands suffer more from the competition due to the reduction of consumers' exploratory shopping. A quick calculation indicates that some permanent stores could experience a sales increase of up to 2,365 RMB (19.6%), while others may face losses of up to 714 RMB (5.9%). These results help store owners understand the potential impacts on their stores. For those who may suffer more from pop-up shops, it is essential to develop appropriate strategies and prepare in advance. Furthermore, our findings also suggest that increased awareness of the product category could strengthen the spillover effects as permanent stores in the same product category as pop-up shops experienced a more pronounced increase in store visits and sales. Therefore, stores in different product categories may consider collaborating with pop-up shops, for instance through joint sales promotion, to increase the awareness of their stores and products and benefit from the traffic spillover.

Finally, this paper offers valuable insights for mall owners when making collaborative decisions with pop-up shops. Our findings suggest that pop-up shops serve as effective tools, not only boosting mall traffic but also benefiting permanent stores by increasing their average sales. At the same time, however, we also see adverse effects on the permanent stores that rely on exploratory shopping. Therefore, the overall impact on a particular shopping mall depends on the composition of its permanent store tenants. The higher the proportion of stores reliant on exploratory shopping, the less effective a pop-up shop may be. As a mall manager, the composition of its stores should be explicitly considered when negotiating renting retail space with pop-up brands. For example, most shopping malls apply flat rent schemes to pop-up shops currently, depending mostly on the duration of the pop-up shop. However, our heterogeneity analyses suggest that managers might practice effective floating rents, according to the layout of their permanent stores. In this sense, pop-up shops represent an opportunity not only for temporary rental incomes but also might contribute to broader management strategies and help optimize overall profits.

In addition to highlighting the appeal of pop-up shops as an emerging offline experiential marketing practice, our study provides a novel perspective on their external impacts on host venues. By shifting the focus from the featured brands to the broader retail ecosystem, this research contributes to the growing body of literature on the integration of offline channels within omnichannel retail strategies and the role of different offline marketing tools. As the first study to explore these broader effects, it lays a foundation for future research on the dynamics of pop-up retailing and its implications for host venues and permanent store tenants.

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Appendix

1A.1 More Details of Pop-up Shops

Concrete examples From March 2nd to 4th, 2018, Tmall collaborated with seven cosmetics brands, including Vichy, La Roche-Posay, Bai Cao Ji, Yunnan Baiyao, NIVEA, Shiseido, and Missha, to open a 3-day pop-up store at Wanda Plaza in Baiyun, Guangzhou. The pop-up store offered users a comprehensive experience combining interaction, beauty, photography, flash sales, and surprises through various experiences with different beauty products. Users could interact with their favorite cosmetic brands while experiencing the products. At the venue, online brand products were displayed on cloud shelves, and actual products were simultaneously displayed in the pop-up store. Users could easily access detailed information about the products by simply picking up the display screen using Bluetooth technology. The pop-up store also featured black technology devices such as AR makeup mirrors, allowing users to experience products listed on the beauty charts. Particularly, there was an Oscar-style makeup mirror where users could enter the makeup area to enjoy skin care and product usage demonstrations by professional makeup artists. After the transformation, users could leave their star-like photos on the "Oscar BLINGBLING photo wall" as a commemoration, instantly becoming a party queen. The photos were edited in real-time and uploaded, allowing users to obtain Oscar-worthy pictures anytime.



Source: <https://www.sohu.com>

Schwarzkopf, a German hair and cosmetics brand, opened a “Got2b” vintage pop-up store at Wanda Plaza in Wujiaochang, Shanghai from June 22nd to 24th, 2018. Inside the pop-up store, Schwarzkopf provided top stylists to offer customers free image consultations and hairstyle creations. Additionally, there was an interactive mirror in the store that utilized AI technology. Customers could freely choose makeup styles and hair colors to change their appearance, thereby selecting the hairstyle and hair color that best suited them.



Source: <https://www.sohu.com>

Sectors and features The success of pop-up shops reverberates across diverse sectors, spanning high fashion, culinary delights, cosmetics, and cutting-edge technology (The New York Times, 2013; The Wall Street Journal, 2019, 2021b). For example, clothing and accessories retailers might give customers a means to try on products virtually; shampoo brands provide free hairdressing services, including hair washing and maintenance; beverage retailers offer free samples; and fashion designers host customizing and sewing services, allowing customers to bring in their own clothes to be redesigned. Pop-up shops also often feature exhibits that present the brand’s development and culture or interactive games that allow customers to win branded gifts. Nordstrom’s Pop-In@Nordstrom initiative ¹³ includes themed pop-up shops that transition every four to six weeks.

Process The typical process for establishing a pop-up shop consists of three key steps. First, the pop-up brand decides to initiate a pop-up shop during certain periods, aligning with some primary marketing objectives. Second, the brand approaches potential shopping malls

¹³<https://press.nordstrom.com/news-releases/news-release-details/nordstrom-launches-pop-in-nordstrom-x-hanes>

that might accommodate temporary spaces for its pop-up shop, which leads to negotiations over rents, duration, and venue details. In this step, the pop-up brand chooses which mall to locate its pop-up shops. Third, the focal brand operates the pop-up shop, typically situated on the first floor or in the outdoor area of the shopping mall, in accordance with the terms agreed upon in the second step. It is important to note that both the pop-up brand and the mall management may promote the pop-up shops before or during the operational period. Promotional efforts can include activities on their official social media accounts or collaborations with influencers. Additionally, reports or articles about the pop-up shops may appear on news portals or the websites of the brands or shopping malls, either during or after the event, providing a summary of the activities.

1A.2 Additional Details of Data and Matching Process

Table 1A.1: Product Categories of Permanent Stores

Category	Description	Examples
Groceries	Large retailers that sell groceries and general merchandise	Walmart, T-Mall, Carrefour
Household essentials	Retailers or manufacturers of home goods and personal care products	Watsons, L’Oreal Paris, Tupperware
Anchor stores	Large, flagship stores with the broadest customer base and affordable goods	HM, Zara, Wanda Cinema, MINISO
Fashion	Retailers or manufacturers of apparel, shoes, accessories, and cosmetics	Tommy Hilfiger, Levi’s, Swarovski
Restaurants	Retailers or manufacturers of food, snacks, and beverages	Papa John’s, Burger King, Starbucks
Entertainment	Entertainment, recreation, service, and training providers	MZDance Studio, D-House Gym, Tam KTV

Table 1A.2: Summary Statistics for Pop-up Shop Features

Feature	Proportion
Brand	Chain brand: 54%; independent brand: 46%
Brand category	Groceries: 10%; household essentials: 28%; fashion: 14%; restaurants: 7%; entertainment: 41%
Type	Brand-centric: 53%; product-centric: 47%
Location	Atriums: 68%; outdoor: 32%
Feature	Price deduction: 8%; experiential and interactive environment: 92%
Promotion on social media	With: 70%; without: 30%
Starts from	Weekend: 45.5%; weekdays: 54.5%

Table 1A.3: Proportion of Pop-Up Shops in Operation

Days of Operation	1	2	3	4	5	6	7	7+
Proportion of Shops Still in Operation	70/70	31/70	24/70	12/70	10/70	7/70	7/70	4/70

Notes: "7+" summarizes the number of pop-up shops last for more than 7 days.

Table 1A.4: Matching Variables

Variable	Before Matching			After Matching		
	Treatment Mean(SD)	Nontreatment Mean(SD)	Difference (t-value)	Treatment Mean (SE)	Control Mean (SE)	Difference (t-value)
Average mall traffic	40,948.412 (14,274.078)	32,169.443 (8,177.987)	8,778.969*** (3.754)	38,496.67 (1,139.80)	35,477.85 (1,215.81)	3,018.82 (1.54)
Average total sales	2,365,629 (1,167,256.5)	1,619,242 (777,927.2)	746,386.7*** (3.739)	2,167,316 (90,775.39)	1,879,195 (153,352.1)	288,121 (1.33)
Cumulative operational days	1,968.22 (860.863)	1,516.688 (688.34)	451.533*** (2.873)	1,902.84 (115.06)	1,545.93 (154.73)	356.91* (1.81)
Total business area	66,107.952 (15080.884)	57,205.05 (10756.923)	8,902.90*** (3.375)	63,673.45 (1,404.84)	59,681.04 (2,216.48)	3,992.41 (1.33)
Relative distance to CBD	.363 (.239)	.452 (.42)	-.089 (-1.28)	.359 (.034)	.516 (.100)	-.157 (-1.503)
Population densities	6,367.488 (5,822.123)	3,892.899 (4,460.271)	2,474.588*** (2.368)	6,182.408 (788.57)	5,129.305 (2,293.81)	1,053.103 (.663)
Number of nearby bus stations	14.38 (5.03)	13.062 (5.341)	1.317 (1.256)	14.137 (.711)	13.038 (1.062)	1.098 (.837)
Number of nearby high schools	2.12 (2.219)	2.188 (2.679)	-.067 (-1.36)	2.045 (.327)	2.541 (.903)	-.496 (-1.510)
Number of nearby universities	1.18 (1.837)	.917 (1.334)	.263 (.814)	1.068 (.238)	1.117 (.338)	-.048 (-.1)
City tier	4.06 (1.077)	3.354 (1.36)	.706*** (2.841)	3.932 (.126)	4.153 (.262)	-.221 (-1.671)
City GDP per capita	132,335.14 (58,318.19)	140,056.39 (60,820.83)	-7,721.25 (-1.641)	134,224.6 (7,683.70)	132,235.5 (10,589.00)	1,989.1 (.141)

Notes: *** $p < .01$, ** $p < .05$, * $p < .1$.

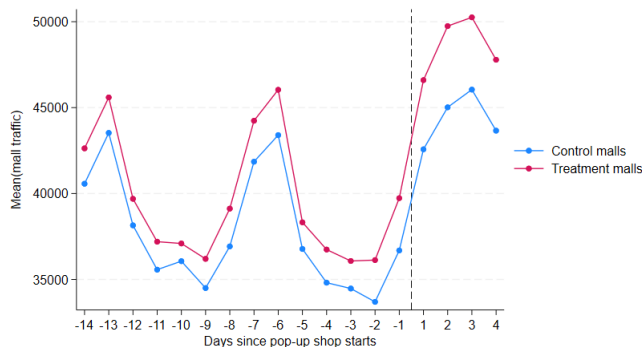


Figure 1A.1: Average Mall Traffic After Matching

Notes: This figure demonstrate average mall traffic in treatment and control malls two weeks before (day -14 to day -1) and during (day 1 to day 4) pop-up shops. Observations from day four onwards, following the commencement of pop-up shops, are consolidated into a single node, represented as “4”. This approach is because only a few pop-up shops in our sample were operational for more than four days.

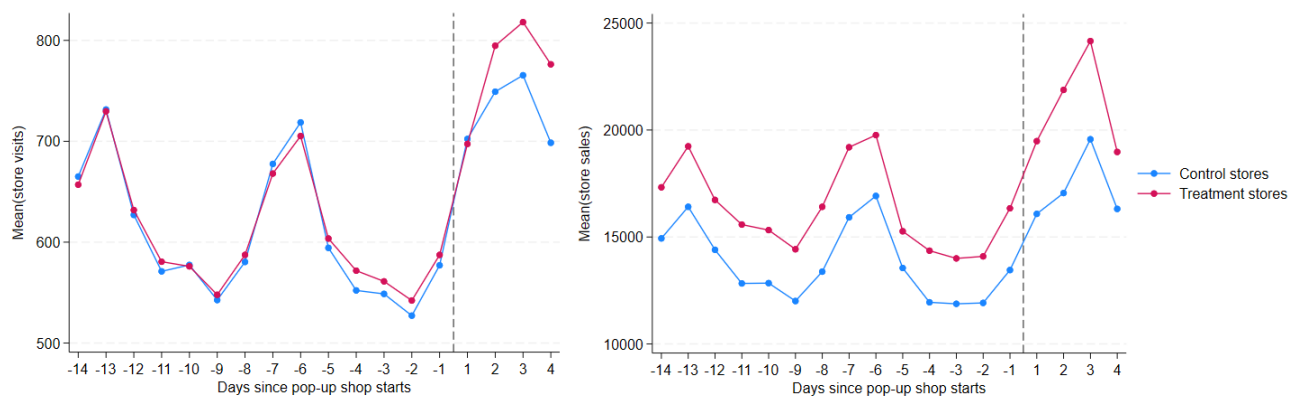


Figure 1A.2: Average Store Visits and Sales After Matching

Notes: This figure illustrates the average store visits and sales in treatment and control malls two weeks before (day -14 to day -1) and during (day 1 to day 4) pop-up shops. Observations from day four onwards, following the commencement of pop-up shops, are consolidated into a single node, represented as “4”. The results support the parallel trends assumption at the store level after matching the shopping malls.

1A.3 Robustness Check

Table 1A.5: Full Sample Regression Without Matching

	(1)
Dependent variable:	log(mall traffic)
Pop-up shops	.045**
	(.021)
Time fixed effect	Yes
Mall fixed effect	Yes
Control variables	Yes
Observations	72,951
R-squared	.851

Notes: In this table, we examine the impacts of pop-up shops on mall traffic using the full sample without matching. Standard errors are clustered at mall level in each experiment. The time fixed effects include coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 1A.6: Falsification Test

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	starts 12	starts 10	starts 8	starts 6	starts 4	starts 2
log(mall traffic)	days prior	days prior	days prior	days prior	days prior	days prior
Pop-up shops (fake)	-.007	.003	.012	.004	.003	.020
	(.013)	(.010)	(.009)	(.009)	(.010)	(.012)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mall fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,136	10,136	10,136	10,136	10,136	10,136
R-squared	.895	.897	.900	.895	.896	.896

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 1A.7: Impacts of Pop-Up Shops on Mall with PSM

	log(mall traffic)
Pop-up shops	.023** (.009)
Time fixed effect	Yes
Mall fixed effect	Yes
Control variables	Yes
Observations	15,030
R-squared	.888

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Restricted pre-treatment period Before the commencement of a pop-up shop, both mall and pop-up brand managers often engage in promotional activities on various social media platforms. These promotions may be conducted through their official accounts or by enlisting the assistance of influencers. Consequently, it is plausible that such advertising efforts begin to generate foot traffic to the mall even before the pop-up shop officially opens its doors. Figure 2 also shows the sign of this pattern. To mitigate any potential concerns arising from this proactive phenomenon, we have opted to exclude observations from the day prior to each experiential event (i.e., day -1) and proceed with estimating Equation 1 using the remaining observations. The outcomes are presented in Table 1A.8 below, revealing a statistically significant result ($\hat{\beta} = .032, p < .01$), which broadly aligns with our prior findings.

Table 1A.8: Exclude day = -1

	log(mall traffic)
Pop-up shops	.032*** (.012)
Time fixed effect	Yes
Mall fixed effect	Yes
Control variables	Yes
Observations	11,042
R-squared	.886

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 1A.9: Alternative Function Forms

	(1) log(traffic)	(2) log(mall traffic)
Dependent variable		
Pop-up shops	1,438.207** (597.594)	.028** (.011)
Weekday-treat dummies	No	Yes
Weekday fixed effects	Yes	No
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	11,766	11,766
R-squared	.840	.905

Notes: Column (1) shows the estimated effect on mall traffic using a linear regression. In column (2), we control for the different weekday effect between treatment and control malls by adding the interactions of weekday dummies and treatment indicator. Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 1A.10: Weekend Pop-up Shops

Dependent variable	(1) log(mall traffic)
Pop-up shops	.017 (.013)
Non-first pop-up shops	-
Weekend pop-up shops	.039 (.025)
Time fixed effects	Yes
Mall fixed effect	Yes
Control variables	Yes
Observations	11,766
R-squared	.884

Notes: In this table, we examine the different effects between pop-up shops starting on weekends versus weekdays. Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

1A.4 Details of PSM With Time-Varying Features

To address the potential endogeneity related to the timing of pop-up shops, we employ propensity score matching (PSM, Rosenbaum and Rubin 1983) and match the first day of each treatment mall with non-treatment day-mall level observations using a set of features that vary both across shopping malls and over time. To specify, the treatment group comprises the first treatment day of each experiment¹⁴. And the observations in the control group must meet two criteria: (1) No pop-up shop should have existed either two months before or after the selected day, and (2) both the observation day and the shopping mall should be comparable to the treatment mall on the first treatment day, as identified through the following PSM procedure. For each of the experiments, at the first stage of PSM where we estimate the propensity score of each day-mall level observation to be treated with logistic regression, we include not only all the mall features we use in CEM, but also additional time-varying variables such as holiday, days after the last holiday, days until the next holiday, year, month, interactions of city ID and weekdays, as well as average mall traffic and sales amount from the two months preceding the day. We identify the top 10 nearest neighbors for each of the treatment observations as control observations. Similar to CEM, we then construct a data frame that includes one week preceding the first treatment day as the pre-treatment period, and all observations during pop-up shops as the post-treatment period for both treatment and control malls. After removing the control malls with a smaller number of observations than the treatment mall in each experiment, we find an average of 7.5 control malls identified in each experiment ¹⁵.

¹⁴Similar to CEM, we remove treatments that have other treatments either two weeks before or after their operating windows to eliminate potential carryover effects. As a result, 88 treatments remain for matching.

¹⁵We impose the constraint that control observations should not have any treatment within two months. Consequently, it's possible that starting from the third day of a pop-up shop, for example, a matched mall no longer qualifies as a valid control observation because there is treatment within 60 days. Therefore, we remove such cases from the data frame.

1A.5 Estimation Results of Heterogenous Treatment Effects

Table 1A.11: Heterogenous Treatment Effects at Mall Level

DV: log(mall traffic)	(1)	(2)	(3)	(4)	(5)
Pop-up shops	.046*	.036*	.005	-.027	-.038
	(.027)	(.019)	(.019)	(.025)	(.057)
Chain brand pop-up shops	-.027				-.025
	(.024)				(.032)
Pop-up shops located in atriums	.000				-.005
	(.024)				(.027)
Groceries brand pop-up shops		.008			.032
		(.030)			(.028)
Household essentials brand pop-up shops		-.009			-.005
		(.031)			(.034)
Fashion brand pop-up shops		-.027			-.018
		(.036)			(.043)
Restaurant pop-up shops		-.011			-.013
		(.040)			(.042)
Non-first Pop-up shops			-.006		.001
			(.024)		(.029)
Pop-up shops promoted on social media			.039		.041*
			(.025)		(.025)
Pop-up shops featured interactive experience				.064**	.073***
				(.029)	(.024)
Brand-centric pop-up shops				.003	-.015
				(.024)	(.033)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Mall fixed effect	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	11,766	11,766	11,766	11,766	11,766
R-squared	.884	.884	.884	.884	.884

Notes: Standard errors are clustered at mall level in each experiment. The time fixed effects include (1) experiment-specific coefficients for post-treatment dummies and (2) experiment-invariant coefficients for weekdays, week, month, year and holidays. Control variables include in-mall marketing campaigns, new store entries and weather conditions.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Chapter 2.

Unveiling Store Externalities: A Novel Approach Using Consumer Shopping Path Data in Malls

1 Introduction

Shopping malls have long been a prominent retail format, providing physical spaces where various brick-and-mortar stores are located in close proximity, thereby facilitating convenient, multipurpose shopping trips for consumers (Ingene and Ghosh, 1990; Arentze et al., 2005). Due to their unique role in fostering retail agglomerations, shopping malls have historically achieved greater sales productivity per square foot compared to other retail formats, generating nearly \$819 billion in retail sales in 2022 (Coresight Research, 2023). However, the rise of e-commerce, coupled with shifting consumer preferences—particularly in the wake of the COVID-19 pandemic—has diminished the appeal of shopping malls, especially among younger generations (The Wall Street Journal, 2023). This trend has been further exacerbated by the widespread closure of traditional department stores that once served as cornerstones of these retail hubs (The Wall Street Journal, 2024).

To combat declining foot traffic and restore their attractiveness, mall managers are increasingly focusing on enhancing the hedonic shopping values (Hirschman and Holbrook, 1982; Bloch et al., 1994) that cannot be replicated online. These values are realized through a holistic environment featuring a diverse mix of store tenants (Gilboa et al., 2016). A key strategy has been leveraging specific stores to drive shopper traffic and generate spillover benefits for neighboring tenants. Anchor stores, for example, often specialize in diverse

product categories and attract significant foot traffic due to their strong brand reputation (Konishi and Sandfort, 2003). As consumer preferences evolve, the definition of anchor stores has shifted from traditional department stores, which were effective in providing utilitarian shopping values through one-stop shopping environments (Finn and Louviere, 1996), to contemporary anchor stores that specialize in specific product categories and offer epistemic and experiential shopping environments, satisfying consumers’ needs for fashion trends, exploration, and curiosity (Szocs et al., 2023). Additionally, to meet the social and recreational needs of younger shoppers (CNN, 2023; Forbes, 2024), mall managers have increasingly embraced social stores, such as restaurants, food and beverage outlets, and entertainment venues, as complementary strategies that enhance the social shopping value of malls (Babin et al., 1994; Keng et al., 2007). To attract and incentivize anchor and social stores to join their malls, developers often offer rent subsidies, offsetting these costs by charging rent premiums to other tenants (Gatzlaff et al., 1994; Pashigian and Gould, 1998; Gould et al., 2005; Teller and Reutterer, 2008; Koster et al., 2019). In essence, anchor and experiential stores function as “loss leaders” (Hess and Gerstner, 1987), designed to drive foot traffic and increase the overall value of the mall ecosystem.

Despite widespread assumptions in the literature and industry practice that anchor and social stores benefit neighboring retailers through traffic spillovers (Gould et al., 2005; Clapp et al., 2019), there remains little empirical evidence on whether, how, and for whom these spillovers occur. This gap leaves unresolved questions about the effectiveness of commonly used rent subsidy strategies, and limits mall managers’ ability to optimize tenant mix and pricing based on actual inter-store dynamics. Existing studies either rely on theoretical models or aggregate store-level metrics, lacking granular insights into how individual stores influence mall-wide traffic and sales through the pathways of shopper behavior.

To address this gap, we propose and implement a novel framework for empirically measuring store externality—defined as the extent to which a store’s traffic contributes to the foot traffic and sales of surrounding stores. Specifically, we seek to answer three key ques-

tions: First, how can a reliable method be developed to measure store externality? Second, based on this externality metric, do contemporary anchor and social stores positively impact shopping malls by benefiting neighboring stores? Third, How do store externalities vary by store characteristics and by the type of shoppers they serve?

To address these questions, we are collaborating with a data company that supports six shopping malls in China. The company collects individual-level shopping path data using advanced AI-embedded technology over a one-year period. Leveraging this unique dataset in offline retail environment, we compute daily shared traffic between store pairs based on the number of shoppers who visited both stores in the same trip.

We then apply a multivariate random forest (MRF) model (Ishwaran et al., 2021) to capture nonlinear relationships and correlations between store-level traffic and sales, using variable importance measures (VIMPs) to derive each store’s externality index. Based on the externality measure we derived, we show that contemporary anchor stores—such as Zara, H&M, and Starbucks—consistently generate greater traffic and sales externalities compared to non-anchor stores, justifying their strategic role in malls. However, social stores—including restaurants and entertainment venues—do not produce meaningful externalities on average, and in some cases may reduce the likelihood of shopper spillovers due to their absorptive nature.

In addition, we explore heterogeneity in externalities based on store characteristics. We find that the positive externalities attributed to anchor stores are primarily driven by those associated with mass-market and young brands, which appeal to a broader and trend-conscious customer base. In contrast, anchor stores affiliated with luxury or established brands show limited spillover impact, suggesting that not all anchor stores are equally beneficial from a mall-wide perspective.

We then introduce a novel, unsupervised machine learning approach—Non-negative Matrix Factorization (NMF)—to segment shoppers into behavioral clusters based on their observed store visit patterns. We identify three types of shoppers: purpose-driven, leisure

group, and experience-seeking. Re-evaluating store externalities within each segment reveals striking differences: anchor stores are most influential for leisure group and experience-seeking shoppers, but not for purpose-driven ones. Conversely, social stores generate positive externalities only for leisure shoppers, and even exert negative effects for experience-seeking shoppers, likely because they monopolize time and attention without stimulating further store visits. To better align store offerings with shopper needs, we further identify two new store clusters—leisure stores and experiential stores—that naturally match the behavioral preferences of leisure group and experience-seeking shoppers, respectively.

Our study contributes to the literature on retail agglomeration, experiential marketing, and shopper journey analytics in several important ways. First, we introduce an empirically grounded and interpretable method to quantify inter-store externalities, which can be used by mall operators, developers, and urban planners to assess store value beyond standalone performance. Second, we offer new evidence on which types of anchor and social stores actually deliver on their promised spillovers—highlighting the importance of considering brand type and consumer appeal in tenant selection and rent subsidy policies. Third, by incorporating consumer heterogeneity through behavioral segmentation based on granular behavioral data, we demonstrate that store effectiveness is not uniform and that aligning tenant strategies with specific shopper segments can significantly enhance overall mall performance.

For practitioners, our findings carry clear implications. Mall managers should move beyond generalized assumptions and instead adopt a data-driven approach to evaluating store contributions. Rent subsidies and placement strategies should prioritize anchor stores with mass-market and trend-sensitive appeal while revisiting the subsidization of social stores that may not deliver meaningful externalities. Moreover, managers can identify new store groupings based on the specific shopping needs they fulfill for different shopper segments, allowing for more targeted tenant mix and marketing strategies. Store owners, too, can benefit from understanding their externality profiles—those in high-externality locations may capitalize on neighboring traffic, while low-externality stores may need stronger positioning

or renegotiated lease terms.

2 Related Literature

2.1 Shopping Malls and Hedonic Shopping Values

The role of shopping malls has evolved significantly in response to rising competition from e-commerce and changing consumer expectations—particularly among younger generations. As functional, utilitarian needs (e.g., convenience, price comparison, breadth of selection) become increasingly well-served by online channels, offline retailers are repositioning themselves to emphasize hedonic shopping values—those related to sensory enjoyment, novelty, and social experience—that cannot be easily replicated in digital environments.

Babin et al. (1994) distinguish between utilitarian and hedonic shopping values, highlighting that while traditional department store anchors (e.g., Sears, Macy’s) were historically effective in fulfilling utilitarian needs (Bloch and Bruce, 1984), such as efficient one-stop shopping, these values are now more easily met through online channels. In contrast, hedonic values—such as multisensory stimulation (Holbrook and Hirschman, 1982), epistemic exploration and trend discovery (Bloch et al., 1989), and social interaction (Jarboe and McDaniel, 1987)—have become a key differentiator for physical retail environments (Forbes, 2024).

In response, shopping mall managers have increasingly prioritized the inclusion of contemporary anchor stores (e.g., Zara, H&M, Starbucks) and social stores (e.g., restaurants, entertainment venues) that are better equipped to deliver these hedonic experiences. These stores are not only expected to draw higher levels of foot traffic, but also to enhance the mall’s experiential value proposition. As a result, mall managers often provide substantial rent subsidies to these stores. However, what ultimately matters for overall mall performance is not only whether these stores attract visitors, but also whether the traffic they draw spills over into visits and purchases at neighboring stores—a question that remains empirically

underexplored.

2.2 Retail Agglomeration and Externalities in Malls

Shopping malls represent a unique retail format characterized by co-located, multi-purpose retailing. The agglomeration of diverse stores in a shared physical space reduces consumers' marginal transportation and search costs, facilitating one-stop shopping experiences and enhancing the mall's overall value to consumers (Ingene and Ghosh, 1990; Arentze et al., 2005). This format naturally gives rise to inter-store externalities, where some stores benefit from the traffic initially attracted by others (Eppli and Benjamin, 1994; Bell et al., 1998; Clapp et al., 2019).

The concept of externality is well-established in economics, yet empirical research on retail externalities within malls has primarily focused on effects at the mall or district level. For example, Koster et al. (2014) and Koster et al. (2019) examine the external effects of retail agglomeration on commercial property values and nearby businesses in shopping streets or districts. At the mall level, studies have explored the strategic use of anchor tenants—typically large, recognizable brands that receive preferential leasing terms—to attract traffic and indirectly support smaller retailers (Gatzlaff et al., 1994; Pashigian and Gould, 1998; Gould et al., 2005). Clapp et al. (2019) discuss how the entrance of anchor stores can have competitive as well as complementary effects on surrounding tenants, but empirical quantification of such effects remains limited.

Critically, existing studies have not directly measured the store-level externality—that is, the degree to which an individual store generates positive spillovers to others within the same mall. This is largely due to data limitations: quantifying inter-store influence requires granular, individual-level data capturing shoppers' in-mall paths—a type of data that, until recently, was rarely available in offline retail settings. While store-level influence has been studied extensively in online contexts using clickstream data, few studies have been able to replicate such analyses in the offline world due to the lack of comparable behavioral data.

2.3 E-commerce, Clickstream Data, and Offline Shopper Tracking

In contrast to offline retail, e-commerce platforms have long had access to clickstream data, which records users' browsing, clicking, and purchasing behaviors in real time. These data have enabled a rich body of work on consumer path analysis, product recommendation systems, and inter-product relationships (see Bucklin and Sismeiro (2003); Moe and Fader (2004); Montgomery et al. (2004); Ringel and Skiera (2016) for examples). Such analyses provide foundational insights and methodological tools—particularly in terms of user-item matrices and path modeling—that are increasingly transferable to physical retail environments as tracking technologies improve.

To better compete with online channels and make more informed decisions, offline retailers have begun to adopt a variety of digital tracking technologies. These include eye-tracking devices (Grewal et al., 2018; Chen et al., 2021), RFID tags (Hui et al., 2009a,b), Wi-Fi tracking (Ghose et al., 2019), and wearable video devices (Hui et al., 2013; Zhang et al., 2014). These technologies enable retailers to monitor in-store behavior, optimize layouts, and understand how shoppers navigate physical spaces.

Our study builds on this digitalization trend by leveraging a particularly advanced form of offline tracking: AI-powered re-identification (Re-ID) technology (Wang et al., 2022), which allows for highly accurate and privacy-compliant tracking of individual shoppers across stores and over time. This technology enables us to observe actual foot traffic patterns at scale and derive a new measure of store-level externality based on shared visits between store pairs.

By integrating insights from online shopping path analysis with emerging offline tracking capabilities, our work brings a novel, data-driven lens to the study of retail externalities. In doing so, we not only contribute to the literature on mall dynamics and tenant strategy but also advance methodological tools for measuring in-mall influence using real-world behavioral data.

3 Data and Exploratory Analysis

3.1 Data Details

We collaborate with a company that collects individual shopping path data across six shopping malls in China, covering the period from October 2019 to November 2020. This dataset provides detailed observations of shopper movements at key locations within the malls, including entrances, escalators, staircases, and central atrium areas. The data were collected using Person Re-Identification (ReID) technology, implemented through an advanced customer monitoring system equipped with AI chip-embedded sensors (Wang et al., 2022). This state-of-the-art technology detects individuals’ presence by utilizing real-time image processing algorithms to calculate person-visit metrics, uniquely identifying individuals based on physical characteristics and gait patterns.

For cameras located at store entrances, the system detects an individual’s presence as soon as they appear within the camera’s coverage area. The AI algorithm then classifies each detected movement into three categories: entry, exit, or pass-by, logging these interactions in real time. This technology enables us to reconstruct complete shopping paths for individual shoppers. Altogether, our dataset captures over 612 million person-visit records from approximately 29 million shoppers ¹.

In addition to shopping path information, we obtain daily store-level sales data (in RMB) from mall managers to measure retail performance. Furthermore, we collect detailed store attributes, including each store’s location within the mall (specific floor level), total area, brand name, product category, and unit rent (RMB per month per square meter). This comprehensive dataset enables a nuanced analysis of store performance. Additionally, we incorporate data on mall-initiated marketing campaigns, holidays, and weather conditions to account for their potential impact on retail performance.

Table 1 presents summary statistics for key variables. After excluding data from the

¹To protect privacy, the system does not retain information that allows tracking the same individuals across different days.

COVID-19 pandemic period (January 23, 2020 – July 31, 2020), our final dataset covers 1,158 stores over approximately six months. On average across all stores and dates in the observation period, each store receives 557 daily visits and generates RMB 21,015 in daily sales across the observation period.² The data also reveal that each shopper, on average, visits around 16 distinct stores per shopping trip, which accounts for approximately 8.3% of all stores within a given mall.³

3.2 Traffic, Sales and Rents of Contemporary Anchor and Social Stores

With shifting consumer preferences—particularly among younger generations—toward experiential in-store shopping, combined with the rapid rise of e-commerce and the impact of the recent pandemic, traditional anchor stores like department stores have become less effective at generating foot traffic and positive spillover effects for other tenants (CNN, 2023; The Wall Street Journal, 2024). Consequently, the concept and role of anchor stores have significantly evolved in recent decades. Unlike traditional anchors, which specialized in convenient one-stop shopping venues (Finn and Louviere, 1996), contemporary anchor stores such as Zara, H&M, Sephora, and Starbucks are specialized retailers strongly associated with reputable brands. Rather than merely offering convenience, these modern anchors attract shoppers through experiential and epistemic hedonic values, providing immersive, multisensory environments where consumers can explore new trends and enjoy novel shopping experiences (Holbrook and Hirschman, 1982; Bloch et al., 1989).

In addition to contemporary anchor stores, mall managers have increasingly incorporated socially-oriented establishments—such as restaurants, cafés, and entertainment venues—to

²Some smaller stores do not have observations recorded for every day in the dataset, which is why the average daily traffic and sales calculated at the store-day level are slightly higher than those computed at the store level.

³We exclude shoppers who visited the same store more than 18 times in a single day—the top 0.5% quantile of visit frequency—from our dataset, as these individuals are likely to be store employees rather than genuine customers.

Table 1: Summary Statistics

Variables	N	Mean	SD	Max	Min
Mall level variables					
Num. of stores	6	193	50.2	252	131
Store level variables					
Average daily traffic	1,158	470.8	1,162	19,121	23.18
Average sales amount (RMB)	1,158	17,509	68,047	1,158,824	167.7
Area (sq-meters)	1,158	380.1	1,643	26,952	10.08
Anchor store dummy (0/1)	1,158	.07	.26	1	0
Social store dummy (0/1)	1,158	.27	.44	1	0
Nation brand dummy (0/1)	1,158	.30	.46	1	0
Mass brand dummy (0/1)	1,158	.26	.44	1	0
Young brand dummy (0/1)	1,158	.19	.39	1	0
Floor	5 levels: basement, 1F, 2F, 3F, 4F+				
Product category	5 levels: clothes and accessories, restaurants, entertainment, specialty store, others				
Store-day level variables					
Daily traffic	171,074	557	1,448	57,792	0
Daily sales amount (RMB)	171,074	21,015	91,574	5,846,397	0
Mall campaign dummy (0/1)	171,074	.35	.47	1	0
Store campaign dummy (0/1)	171,074	.06	.24	1	0
Weather condition	3 levels: good; fair; bad				
Holiday	23 holidays, including 10 official holidays, 3 online shopping days, and 10 theme festivals				
Shopper-day level variables					
Num. of distinct store visit	28,948,210	15.96	15.44	228	1

address shoppers' social hedonic needs. These "social stores" serve as popular destinations for gatherings, dining, and recreation, fostering interpersonal interactions among shoppers and appealing particularly to younger consumers (Jarboe and McDaniel, 1987; Szocs et al., 2023; Forbes, 2024).

Recognizing these dynamics, mall managers typically assume that contemporary anchor and social stores generate substantial benefits for surrounding retailers, primarily due to their strong ability to attract foot traffic and enhance shoppers' overall hedonic experiences (Keng et al., 2007). Accordingly, managers strategically offer rent discounts to encourage these stores to become permanent tenants, anticipating that their presence will attract visitors and indirectly drive increased sales for neighboring retailers (Gatzlaff et al., 1994; Gould et al., 2005; Koster et al., 2019).

To empirically evaluate these managerial assumptions, we first examine whether contemporary anchor and social stores indeed generate higher foot traffic, achieve greater sales, and benefit from reduced rents relative to other tenants. Table 2 indicates that contemporary anchor stores attract significantly higher daily foot traffic (2,205.42 visitors on average) and generate substantially higher daily sales (91,147.84 RMB) compared to non-anchor stores.⁴ Additionally, these contemporary anchor stores enjoy significantly lower monthly rent per unit area (183.37 RMB per square meter), with all observed differences statistically significant at the 0.01 level.⁵

Similarly, we investigate whether social stores exhibit comparable patterns. As shown in Table 3, social stores also attract significantly higher daily foot traffic (618.34 visitors) and achieve higher daily sales (20,704.48 RMB) compared to other retailers. Consistent with their intended role and the mall managers' strategic objectives, social stores likewise benefit from significantly lower monthly rents (360.46 RMB per square meter), reflecting deliberate discounting practices aimed at leveraging their potential to draw shopper traffic.

⁴Most contemporary anchor stores are categorized as apparel and specialty retailers by mall managers, with few belonging to food or entertainment (i.e., social) store categories.

⁵Some stores are excluded from this summary table due to missing rent information; however, no systematic pattern related to store category or size is found in the missing data.

Table 2: Comparison of Anchor and Non-Anchor Stores

	Anchor stores	Non-anchor stores	Diff.	T-value
Num. of stores	85	857		
Daily traffic	2,205.42 (3,521.16)	330.93 (328.60)	1,874.49*** (382.09)	4.91
Daily sales (RMB)	91,147.84 (220,022.90)	12,348.08 (23,116.51)	78,799.76*** (23,877.99)	3.30
Unit rent (RMB/month/ m^2)	183.37 (170.39)	512.82 (249.31)	-329.45*** (22.83)	-14.43

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 3: Comparison of Social and Non-social Stores

	Social stores	Non-social stores	Diff.	T-value
Num. of stores	309	633		
Daily traffic	618.34 (694.43)	452.45 (1,414.49)	165.89** (69.65)	2.38
Daily sales (RMB)	20,704.48 (33,826.40)	16,905.94 (21,785.06)	3,798.54* (2,110.23)	1.80
Unit rent (RMB/month/ m^2)	360.46 (239.55)	535.05 (256.28)	-174.59*** (20.99)	-8.32

*** $p < .01$, ** $p < .05$, * $p < .1$.

4 Store Externality Index

4.1 Derive the Metric

Despite these rent concessions, approximately 90% of mall rental revenue originates from smaller retailers (Gould et al., 2005). Therefore, mall managers provide discounted rents to anchor and social stores with the strategic expectation that these focal stores will generate traffic spillovers benefiting smaller neighboring retailers. Consequently, small retailers typically pay a premium to compensate for the discounted rents of anchor and social stores due to anticipated traffic agglomeration effects. Thus, it is crucial to empirically verify whether anchor and social stores genuinely enhance the performance of neighboring retailers through traffic spillovers.

To rigorously evaluate this question, we introduce a scientifically robust measure to quantify the extent to which traffic generated by a focal store benefits surrounding retailers in terms of foot traffic and sales. This concept aligns with the well-established economic notion of externalities. Previous literature in fields such as urban economics has similarly explored externalities within business districts, focusing on how a business area impacts the surrounding environment (e.g., Clapp et al. 2019; Koster et al. 2019). Leveraging individual-level shopper trajectory data and daily store sales information, we propose a novel metric termed the *store externality index*. This metric captures the extent to which variations in a store’s foot traffic influence the retail performance of neighboring stores, which aligns conceptually with the Variable Importance Measure (VIM) used in empirical modeling (Strobl et al., 2007).

Specifically, we derive this store externality index through the following steps: First, we quantify the traffic flow between every pair of stores. Using individual shopping path data, we calculate the shared daily traffic between stores i and j within mall m on day t , denoted as $a_{i,j}^{m,t}$, representing the number of shoppers visiting both stores within a single shopping trip. Then, the externality index of a focal store i is derived using the VIMs of $a_{i,j}^{m,t}$ from the

following model:

$$y_j^{m,t} = f(a_{i,j}^{m,t}, X_j^{m,t}, T^t), \quad i = 1, 2, \dots, j-1, j+1, \dots, n_m \quad (1)$$

where $y_j^{m,t} = (\text{traffic}_j^{m,t}, \text{sales}_j^{m,t})$ captures the traffic and sales of store j in mall m on day t . $X_j^{m,t}$ includes (1) store features such as product category, location (floor level), area, and brand category, and (2) time- and mall-specific control variables, like weather conditions and promotional campaigns. With T^t we account for seasonality such as weekends, weekdays, months, and holidays.

Across all stores j , the Variable Importance Measures (VIMs) of $a_{i,j}^{m,t}$ indicate their predictive strength for $y_j^{m,t}$ after controlling for other factors. Specifically, when store j 's traffic serves as the dependent variable, we derive the *traffic externality* for each focal store i . This measure quantifies the proportion of total traffic across all stores j attributable to the focal store i on average, effectively capturing the magnitude of its traffic spillover effect. Similarly, when store j 's sales amount is the dependent variable, we derive the *sales externality* for each focal store i . This measure reflects the extent to which the sales performance of other stores can be attributed to the focal store's traffic on average. Essentially, it represents the conversion efficiency or monetized value of the focal store's visitor traffic by indicating how significantly these visitors contribute to neighboring stores' sales.

To better capture non-linear relationships and complex interactions, we employ random forests (Breiman, 2001) to estimate the predictive model $f(\cdot)$. Tree-based methods widely adopt VIMs to quantify a predictor's contribution to the overall predictive accuracy (Ishwaran et al., 2008; Sikdar et al., 2022; Wallace et al., 2023).⁶ Additionally, considering the possible correlation between the two dependent variables—traffic and sales—we utilize a multivariate random forest approach (Segal and Xiao, 2011). Consequently, we simultaneously calculate both traffic and sales externality indices for each store i as the VIM derived

⁶We also use an XGBoost model to fit $f(\cdot)$ as a robustness check and derive the VIMs there. The results from XGBoost were broadly consistent with those reported here.

from the bivariate random forest model $f(\cdot)$. Specifically, we employ permutation importance, also known as Breiman–Cutler importance or Mean Decrease in Accuracy (MDA), which relies on out-of-bag (OOB) predictions to evaluate the predictive performance (Ishwaran et al., 2021). To account for correlations between multivariate dependent variables and further enhance the robustness of our VIMs, we adopt the Mahalanobis splitting rule (Ishwaran, 2015; Gregorutti et al., 2017).

Table 4 summarizes the traffic and sales externality indices for 1,158 stores across six shopping malls derived from the procedure described above.⁷

Table 4: Summary of Traffic and Sales Externality Index

Variables	N	Mean	SD	Max	Min
Traffic externality index	1158	.00139	.00497	.10521	0
Sales externality index	1158	.00365	.01478	.29935	0

Given that the sales externality index quantifies the monetary value of a focal store’s foot traffic by capturing its influence on neighboring stores’ sales, a higher sales externality generally indicates greater benefits to the mall, thus providing a justification for offering rent discounts. To assess this relationship visually, Figure 1 presents a scatter plot depicting each store’s sales externality against its monthly unit rent. The figure illustrates a clear negative correlation between stores’ sales externality and their charged unit rent. This result indicates that mall managers generally follow a logical pricing rationale based on perceived store benefits, thereby supporting the face validity of our externality metric.

Additionally, we observe from this descriptive analysis that anchor stores, despite paying lower rents, exhibit higher sales externalities than non-anchor stores. To formally examine this pattern, we conduct a more rigorous analysis in the subsequent subsection.

⁷For improved interpretability and comparability across datasets and varying store counts among different malls, we standardize the VIMs (Ishwaran et al., 2021). We also validate our results using VIM ranks as a robustness check, and findings from these analyses remain consistent with those based on raw VIM values.

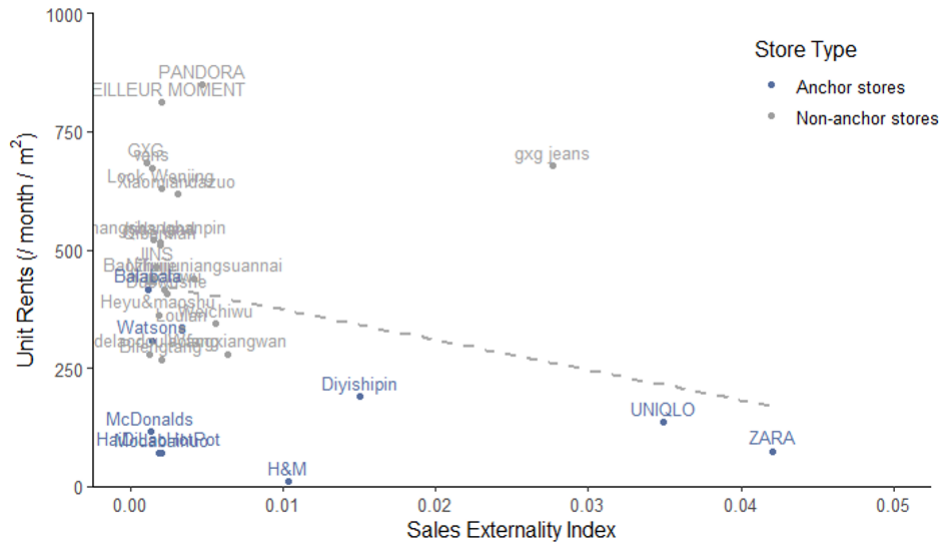


Figure 1: Sales Externality Index versus Unit Rent

Notes: This figure illustrates the negative correlation between a store’s sales externality index and the unit monthly rent charged by the mall. The dashed gray line represents the fitted linear average line of unit rent on sales externality.

4.2 Traffic and Sales Externality of Anchor Stores

The summary statistics presented in Table 2 indicate that anchor stores are typically charged lower rents, reflecting substantial discounts provided by mall managers who anticipate these stores’ ability to attract higher foot traffic and generate positive spillover effects for smaller retailers. Visualization results from Figure 1 further illustrate that anchor stores indeed tend to exhibit a stronger ability to drive sales at neighboring stores. To rigorously investigate whether anchor stores are genuinely more effective than non-anchor stores in generating externalities, we formally test whether significant differences exist in traffic and sales externality indices between these two store types, controlling for other relevant store characteristics. Specifically, we estimate the following linear model:

$$Index_{i,m} = \alpha_m + \beta Anchor_i + \gamma X_i + \varepsilon_i \quad (2)$$

Where the dependent variable $Index_{i,m}$ represents the traffic and sales externality indices

for store i in mall m . The term α_m denotes mall fixed effects, which control for baseline differences in externality across shopping malls. $Anchor_i$ is a binary indicator variable that equals 1 if store i is designated as an anchor store by mall management, and 0 otherwise. Thus, the coefficient β captures the difference in externality between anchor and non-anchor stores. With X_i we summarize a set of store features to control for other factors that may affect store externalities. Specifically, X_i includes the store’s floor level, product category, store area, and whether it is associated with a national brand.⁸

Table 5 presents the estimation results from equation 2⁹. Column (1) indicates that anchor stores exhibit significantly higher traffic externality compared to non-anchor stores after controlling for other store characteristics ($\hat{\beta} = .0026$, $p < .01$). This finding suggests that anchor stores, on average, contribute a larger share of the total traffic flow across stores within the same shopping mall than their non-anchor counterparts. Moreover, column (2) demonstrates that anchor stores also have significantly greater sales externality ($\hat{\beta} = .0098$, $p < .01$), indicating that store sales are more likely to be derived from visitor traffic originating from anchor stores rather than from non-anchor stores. Taken together, these results provide empirical evidence that anchor stores indeed exert a stronger influence on the traffic and sales performance of surrounding retailers. Consequently, offering rent subsidies to anchor stores appears to be a justified and effective strategy for mall managers.

4.3 Traffic and Sales Externality of Social Stores

In addition to anchor stores, mall managers increasingly seek to enhance the experiential value of offline shopping by introducing entertainment, food, and beverage venues, collectively termed “social stores.” These establishments act as destinations for social gatherings, dining, and recreational activities, effectively encouraging shopper interactions, particularly among younger generations (Szocs et al., 2023). As shown in Table 3, social stores indeed

⁸We define national brands based on the number of branches each brand operates nationwide. Brands whose branch count exceeds the upper tertile (top one-third) within each product category are classified as national brands.

⁹Stores without brand or product category information are excluded from the regression analysis.

Table 5: Externality Indices of Anchor Stores

	(1)	(2)
Dependent variable:	Traffic externality	Sales externality
Anchor store dummy	.0026*** (.00064)	.0098*** (.0020)
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	942	942
R-squared	.069	.080

Control variables include store floor, area, and a national brand indicator.
 *** $p < .01$, ** $p < .05$, * $p < .1$.

generate higher levels of foot traffic and sales, prompting mall managers to offer substantial rent discounts similar to those provided to anchor stores.

To determine whether the traffic from social stores translates into increased foot traffic and sales for other retailers within the same mall, we rigorously test for significant differences in store externality indices between social and non-social stores while controlling for other relevant store features. Similar to Equation 2, we employ the following linear model:

$$Index_{i,m} = \alpha_m + \beta Social_i + \gamma X_i + \varepsilon_i \quad (3)$$

Where, $Social_i$ is a binary indicator variable equal to 1 if store i is classified as a social store and 0 otherwise. Therefore, the coefficient β captures the externality difference between social stores and other stores. All other terms are defined consistently with those in Equation 2.

Table 6 presents the estimation results from Equation 3.¹⁰ In contrast to anchor stores, which exhibit significantly higher traffic and sales externalities, social stores show no significant difference in traffic externality compared to non-social stores (Column 1: $\hat{\beta} = -.00073$, $p > .1$). This indicates that, despite attracting greater traffic themselves, so-

¹⁰Stores lacking brand or product category information are excluded from the regression analysis.

cial stores do not significantly contribute to increasing foot traffic in other stores within the same mall. Furthermore, Column (2) of Table 6 reveals that social stores actually exhibit marginally lower sales externality compared to non-social stores ($\hat{\beta} = -.0025$, $p = .093$). This finding suggests that shopper traffic originating from social stores is less effective in generating sales at neighboring stores than traffic from non-social stores.

Taken together, these results indicate that although social stores effectively attract visitors to the shopping mall, the traffic they generate does not substantially benefit other stores and may even have a weaker conversion effect. A plausible explanation is that social stores typically encourage shoppers to spend more time and energy within their premises through the emotional state of pleasure they provided (Morrison et al., 2011; Elmashhara and Soares, 2020), thereby reducing the likelihood of visiting other retailers. Thus, despite mall managers' expectations that social stores could bolster overall mall traffic and generate positive spillovers, these stores may not provide the anticipated external benefits. Consequently, offering substantial rent subsidies to social stores could potentially undermine overall mall profitability.

Table 6: Externality Indices of Social Stores

	(1)	(2)
Dependent variable:	Traffic externality	Sales externality
Social store dummy	-.00073 (.00047)	-.00250* (.00149)
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	942	942
R-squared	.055	.058

Control variables include store floor, area, and a national brand indicator.

*** $p < .01$, ** $p < .05$, * $p < .1$.

4.4 Heterogeneous Externalities for Different Anchor Store Brand

Up to this point, we have demonstrated that contemporary anchor and social stores, due to the hedonic shopping experiences they offer, attract higher levels of foot traffic and sales compared to other retailers. Mall managers therefore provide substantial rent subsidies to these stores, intending to leverage them as experiential elements within the holistic shopping environment and expecting their foot traffic to spill over and benefit neighboring retailers. Specifically, contemporary anchor stores generally show greater effectiveness in contributing to surrounding stores' foot traffic and sales amount through their spillover effects. However, as illustrated in Figure 1, contemporary anchor stores differ considerably in their effectiveness in driving benefits to neighboring businesses. Hence, in this subsection, we empirically examine the factors contributing to this heterogeneity—particularly, the types of anchor stores most effective in generating traffic and sales spillovers.

Store externalities primarily vary due to the heterogeneity of their customer bases. Consequently, we focus our analysis on how characteristics associated with anchor-store brands affect their externality indices. According to prior literature, mass and luxury brands represent two fundamental categories distinguished by their operational philosophies and target markets. Mass brands typically appeal broadly, aiming to satisfy the needs of a large and diverse consumer base through affordability and accessibility (Silverstein and Fiske, 2003). In contrast, luxury brands distinguish themselves through exclusivity, superior quality, and premium pricing, thereby attracting a narrower, more niche market segment (Rosendo-Rios and Shukla, 2023). Additionally, compared to established brands, younger and emerging brands tend to appeal more strongly to younger consumers, who often seek novelty, innovation, and alignment with contemporary trends such as sustainability (Anderson and Sharp, 2010; Xi et al., 2022).

Guided by this rationale, we investigate whether contemporary anchor stores associated with mass or young brands differ systematically in their traffic and sales externalities compared to anchor stores associated with luxury or established brands. To operationalize these

distinctions, we collected data on each brand’s founding year and median product price, classifying brands as “mass” or “young” if they fall below the average product price or brand age within their respective product categories. We then interact these newly defined binary indicators with the anchor-store dummy variable and incorporate them into our main Equation 2, resulting in the following extended linear model:

$$Index_{i,m} = \alpha_m + \beta Anchor_i + \mu_1 Anchor_i \times Mass_brand_i + \mu_2 Anchor_i \times Young_brand_i + \gamma X_i + \varepsilon_i \quad (4)$$

Where, dummy variable $Mass_brand_i$ equals 1 if store i is associated with a mass brand, and 0 otherwise; similarly, $Young_brand_i$ equals 1 if store i is associated with a young brand, and 0 otherwise. Thus, the coefficient μ_1 captures the difference in externality indices between anchor stores associated with mass versus luxury brands, while the coefficient μ_2 captures the difference between anchor stores associated with young versus established brands. We also include the main effects $Mass_brand_i$ and $Young_brand_i$ in X_i to control for baseline differences between mass-market and luxury brands as well as between younger and established brands. All other variables are defined consistently with those specified in Equation 2.

Table 2A.1 in the Appendix presents the estimation results for equation 4. Similar to the approaches used in Lewis et al. (2006) and Johnson et al. (2020), we focus on understanding the marginal effects rather than detailing each coefficient estimate individually. Specifically, Figures 2 and 3 depict the marginal effects of anchor-store brand characteristics—mass-market versus luxury brands and young versus established brands—on stores’ traffic and sales externality indices, derived from the estimates in Table 2A.1.

Mass-Brand Anchor Stores Figure 2 shows the marginal effect of a store’s association with a mass brand (relative to luxury brands) on traffic and sales externality indices, separately for contemporary anchor stores and non-anchor stores, after controlling for other relevant store features.

As illustrated in the left panel, contemporary anchor stores associated with mass brands exhibit significantly higher traffic externalities compared to anchor stores associated with luxury brands. This difference, however, does not emerge for non-anchor stores. The finding suggests that mass-market anchor stores, on average, contribute a larger share of the total foot traffic flowing to other stores within the same mall, likely because mass brands generally attract broader and more diverse consumer segments compared to luxury brands, which target narrower niche markets (Rosendo-Rios and Shukla, 2023). Additionally, the results indicate that luxury-brand anchor stores do not differ significantly from non-anchor stores in traffic externality. Consequently, the higher externalities of anchor stores observed previously (in equation 2) primarily reflect the impact of mass-market anchor stores rather than luxury-brand anchor stores.

The sales externality index, illustrated in the right panel of Figure 2, displays a consistent pattern. While there is no significant difference in sales externality between mass-market and luxury brands among non-anchor stores, contemporary anchor stores affiliated with mass brands exhibit significantly greater sales externalities compared to all other store groups. This result underscores that mall-wide sales are more effectively converted from foot traffic originating from mass-market anchor stores than from luxury-brand anchor stores or any non-anchor stores.

Taken together, our findings indicate that contemporary anchor stores associated with mass brands not only drive greater proportions of overall foot traffic but also facilitate more effective conversions of shopper visits into purchases at other stores. Conversely, luxury-brand anchor stores offer no greater benefits than typical non-anchor retailers in terms of traffic or sales spillovers. These results provide crucial insights for shopping mall managers regarding rent-setting practices: luxury-brand anchor stores should not be offered rent discounts comparable to mass-brand anchors, as their presence does not generate comparable benefits for mall-wide traffic and sales performance.

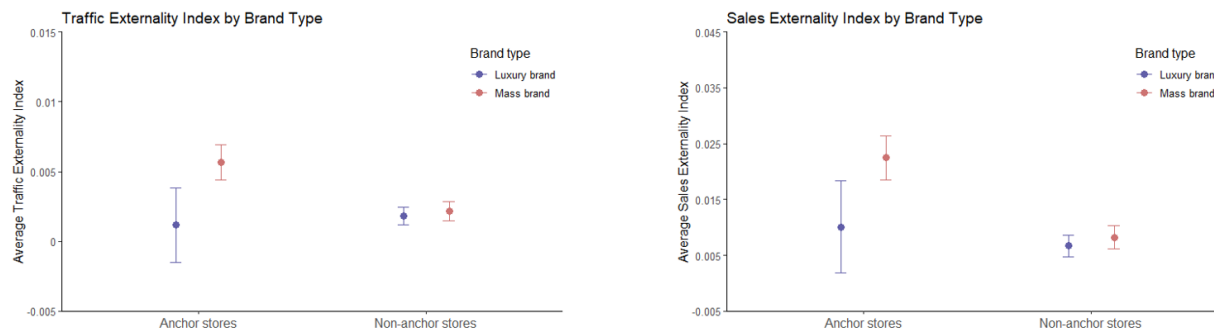


Figure 2: Marginal Effects of Mass Brand on Anchor Stores' Externality Index

Notes: The bars show the 95% confidence interval for each marginal effect

Young-Brand Anchor Stores Figure 3 illustrates the marginal effects of a store's association with a young brand (relative to established brands) on traffic and sales externality indices, separately for contemporary anchor stores and non-anchor stores.

As shown in the left panel, there is no statistically significant difference in traffic externality between young and established brands for either anchor or non-anchor stores. This suggests that, on average, foot traffic originating from young-brand anchor stores does not contribute more to other stores' traffic compared to that from established-brand anchor stores or non-anchor stores.

However, the pattern for sales externality reveals a noteworthy contrast. While anchor stores associated with established brands do not exhibit significantly higher sales externality than non-anchor stores, anchor stores affiliated with young brands generate significantly higher sales externality than all other groups. This indicates that, although young-brand anchor stores do not necessarily attract more traffic spillover, the traffic they do generate is more likely to result in purchases at neighboring stores.

This finding suggests a stronger "conversion power" of foot traffic from young-brand anchor stores. A possible explanation is that these stores tend to employ more arousing, immersive, and trend-driven experiential marketing strategies that resonate with younger customer segments (Anderson and Sharp, 2010). Such environments can elevate emotional engagement and purchase intention (Holbrook and Hirschman, 1982).

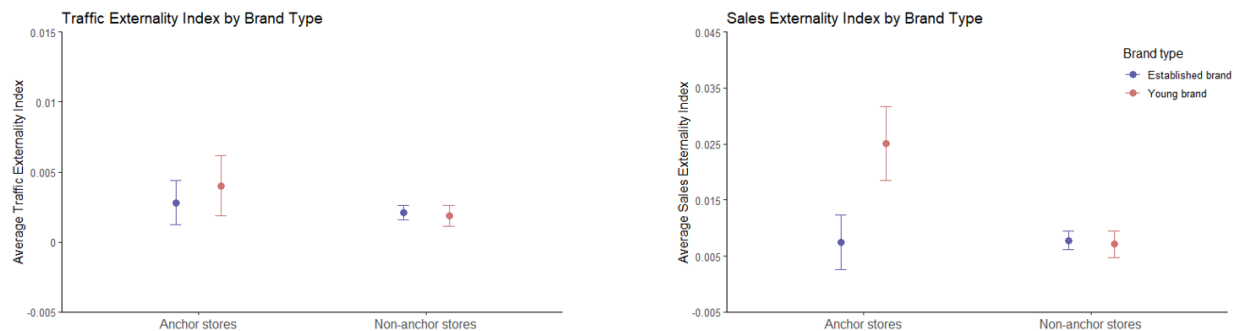


Figure 3: Marginal Effects of Young Brand on Anchor Stores' Externality Index
Notes: The bars show the 95% confidence interval for each marginal effect

From a managerial perspective, these results highlight the strategic value of young-brand anchor stores within the mall ecosystem. While their raw traffic volume may not exceed that of more established brands, the quality and impact of that traffic—especially in terms of converting visits into purchases at other stores—can be highly valuable. As such, mall managers should recognize and support the unique role young-brand anchors play in driving mall-wide sales performance.

5 Heterogeneous Store Externalities Across Shopper Segments

Thus far, we have derived each store's traffic and sales externality indices based on the complete sample of shopper foot traffic for each day. A higher externality index implies a more influential role in directing the traffic flow across the broader customer base. This also explains why contemporary anchor stores affiliated with mass-market brands tend to outperform others—they serve the widest range of shoppers.

However, relying solely on externality indices derived from the full shopper sample may obscure the specialized value that some stores provide to niche markets or specific customer segments. Given the inherent heterogeneity in shoppers' motivations, preferences, and shopping purposes, a single, aggregate externality measure could overlook the influence of certain

stores that are particularly valuable for targeted segments. From a managerial perspective, understanding this nuance is critical—mall managers often need to identify and leverage key stores that attract specific types of shoppers.

To address this, we explore the heterogeneity in store externalities across different shopper segments. Specifically, we first identify shopper clusters using an unsupervised machine learning approach based on their observed foot traffic patterns. We then re-estimate the traffic and sales externality indices for each store within each shopper group. This approach enables us to assess how the impact of stores varies across consumer types and helps identify which stores are most influential for distinct shopping needs.

5.1 Shopper Segmentation Using Unsupervised Machine Learning

Shopping malls provide a comprehensive offline shopping environment by integrating a variety of retailers with strategic layout design to fulfill diverse consumer needs (Jones et al., 2006). However, consumers differ significantly in their motivations, preferences, and perceived shopping value based on demographic and psychographic factors (Ruiz et al., 2004; Jackson et al., 2011). With our detailed individual-level shopper trajectory data, we are able to identify distinct shopper segments based on their store visit patterns.

Formally, we construct a daily shopper-store visit matrix with dimensions $N_t \times M_t$ for each day t :

$$V_t = \{v_{n,m,t}\}, \quad n = 1, 2, \dots, N_t; \quad m = 1, 2, \dots, M_t$$

where $v_{n,m,t}$ is an indicator equal to 1 if shopper n visited store m on day t , and 0 otherwise. Here, N_t is the number of shoppers and M_t is the number of stores in the mall on day t .¹¹

To reduce dimensionality and uncover latent shopping patterns, we apply Non-negative Matrix Factorization (NMF), a powerful and interpretable technique widely used in computer vision, image processing, and text analysis (Lee and Seung, 2000; Wang and Zhang, 2012).

¹¹A small number of stores enter or exit during the observation period. To ensure consistency, when we concatenate matrices V_t over time, we use a fixed column dimension $M = \max M_t$.

NMF approximates the original matrix V_t as the product of two low-rank non-negative matrices:

$$V_t \approx W_t \times H_t \quad (5)$$

Here, $W_t = (\mathbf{w}'_{n,t})$ is an $N_t \times k$ shopper-feature matrix, and $H_t = (\mathbf{h}_{m,t})$ is a $k \times M_t$ feature-store matrix, where $k \ll N_t, M_t$ is the number of latent features. Each row vector $\mathbf{w}'_{n,t}$ represents shopper n 's weights across the k latent features, and each column vector $\mathbf{h}_{m,t}$ denotes store m 's contributions to those features.

This decomposition allows us to represent each shopper by their distribution over k latent features. In our context, these latent features reflect distinct types of shopping needs that shoppers seek to fulfill, and that can be differentially provided by various stores within the mall. We then apply K-means clustering on these $\mathbf{w}'_{n,t}$ vectors to segment shoppers, following the approach in Zheng et al. 2023. This method offers two major advantages over clustering directly on the high-dimensional V_t matrix: (1) it is computationally efficient and robust over time due to the reduced dimensionality, and (2) it provides interpretable clustering results, as each cluster is defined by a set of latent features rather than hundreds of individual stores.

Moreover, because each $\mathbf{h}_{m,t}$ vector reflects a store's contribution to each latent feature, we can interpret each shopper cluster based on the top-weighted stores associated with the corresponding latent features. This structure also naturally enables us to cluster stores based on their roles in the shopper-path space.

To determine the optimal number of latent features for Non-negative Matrix Factorization (NMF), we calculate the proportion of variance in V_t explained by the NMF approximation for each value of k . Figure 2A.1 in the Appendix illustrates the marginal gain in explained variance from adding each additional latent feature. Based on the diminishing returns observed, we select five latent features ($k = 5$), resulting in a shopper-feature matrix W_t and a feature-store matrix H_t .

To interpret the five latent features, we extract each store's weights on the five features from the feature-store matrix H_t . By examining the top-weighted stores associated with

each feature, we infer the underlying themes of the five latent features in Table 7 below:

Table 7: Summary of Five Latent Features

Latent Feature	Characteristics	Example Stores
1	Sensory Retail	Sephora, VR Arcade, Apple Stores
2	Community Hub	Restarants, Cafes
3	Trend Curation	Zara, Levi’s, Li-Ning, Nike Kids
4	Personlized Offering	Beauty Nail Salons, Personal Skincare Studios/Clinics
5	Novelty Showcase	Gift Shops, Antique Stores, Specialty Toy Stores

Next, we use these five latent features to segment shoppers by applying K-means clustering to the shopper–feature matrix W_t . Using the elbow method again (left panel of Figure 2A.2), we determine that three shopper clusters offer the best solution. Figure 4 presents the centroid heatmap for each shopper cluster across the five latent features.

Our results reveal distinct behavioral patterns across the three shopper clusters. Shopper Cluster 1 exhibits uniformly low weights across all five latent features, suggesting that these shoppers are likely “purpose-driven”—they tend to visit specific stores with pre-determined goals and do not engage in exploratory shopping. Because their destinations vary individually, there is no dominant latent feature associated with this group.

In contrast, Shopper Cluster 2 shows the highest weights on the “trend curation” feature, followed by substantial weights on the “community hub” dimension. This cluster likely represents “leisure group shoppers” who tend to visit fashion retailers, such as apparel, accessories, and footwear stores for men, women, and children, as well as communal spaces. These shoppers likely shop with family or friends, reflecting diverse preferences and a greater need for social interaction.

Shopper Cluster 3 is characterized by high weights on “sensory retail”, “personalized offerings”, and “novelty showcase” features. These shoppers appear to seek immersive and experiential retail experiences, suggesting they are “experience-seeking” consumers who visit the mall for its hedonic and exploratory value.

To further profile these clusters, we summarize demographic characteristics derived from

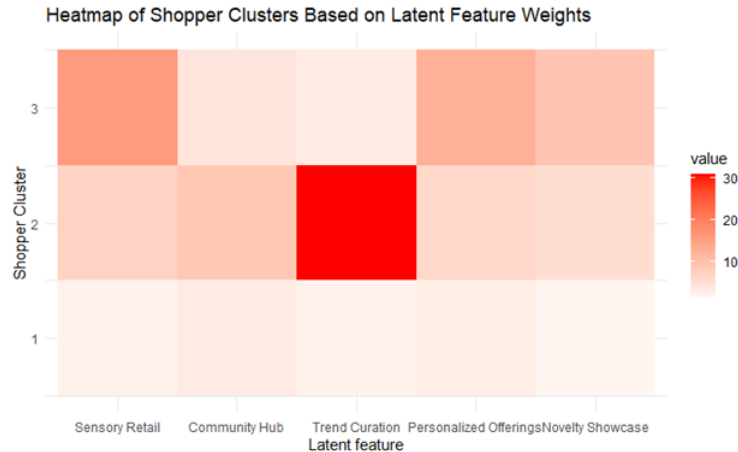


Figure 4: Heatmap of Shopper Cluster Centroids by Feature Weights

Notes: This figure illustrates the heatmap of the centroid for each shopper cluster on five latent features.

AI-enhanced video analytics, which estimate gender and age groups based on clothing and movement patterns. Table 8 reports the proportion of female shoppers, the distribution across three age groups (teens/kids: younger than 18; young adults: 18–30; adults: older than 30), and the average number of distinct stores visited per shopper within each cluster.

Consistent with our behavioral segmentation, Cluster 1 (purpose shoppers) visits the fewest stores on average (11.82) and has the lowest proportion of female shoppers (0.52). Cluster 2 (leisure group shoppers) visits the most stores on average (62.4) and has the highest proportion of teens and kids (0.061). Cluster 3 (experience seeking shoppers) has a moderate number of stores visited but the highest share of young female shoppers (0.60 and 0.606 for young adults and females, respectively).

With these three shopper clusters identified based on foot traffic patterns, we are now equipped to re-evaluate each store’s influence—i.e., its externality—within specific shopper segments, uncovering heterogeneity in store-level spillover effects across consumer groups.

5.2 Store Externalities Within Shopper Clusters

Our previous results in Section 4 show that, on average, contemporary anchor stores are more effective than other stores in driving both foot traffic and sales to neighboring retailers, while

Table 8: Summary of Shopper Clusters

Shopper Cluster	Avg. num. store visited	Prop. female	Prop. Teens/Kids	Prop. Young Adults	Prop. Adults
1. Purpose shopper	11.82	.52	.046	.551	.403
2. Leisure group shopper	62.40	.54	.061	.547	.391
3. Experience-seeking shopper	25.43	.60	.037	.606	.358

social stores exhibit weaker spillover effects. However, these average effects are based on the full sample of shoppers and may obscure important heterogeneity across different shopper groups. As identified in our analysis, shoppers fall into three distinct clusters: purpose-driven, leisure group, and experience-seeking shoppers. The effectiveness of contemporary anchor stores in generating externalities likely depends on the specific shopping needs they fulfill for each segment.

Figure 5 displays the average feature weights by store type across the five latent features. The left panel shows the differences in feature weights between contemporary anchor stores and non-anchor stores. The results indicate that anchor stores tend to have higher weights on the “community hub” and “trend curation” features compared to non-anchor stores, aligning well with the preferences of leisure group shoppers who value social interaction and exposure to current trends. In addition, contemporary anchor stores exhibit relatively higher weights on the “sensory retail” feature, suggesting that they may also better satisfy the experiential needs of experience-seeking shoppers.

The right panel of Figure 5 shows the average feature weights of social versus other stores across the five latent features. The results indicate that social stores have much higher weights on the “community hub” feature compared to non-social stores, which is intuitive given their function as destinations for dining, entertainment, and group activities. This suggests that social stores may also serve the needs of the leisure group shopper segment more effectively. They also show slightly, but not significantly, higher weights on the “personalized offering” feature, while exhibiting much lower weights on “sensory retail” and

“novelty showcase” features. Therefore, it remains unclear whether social stores are effective in fulfilling the preferences of experience-seeking shoppers.

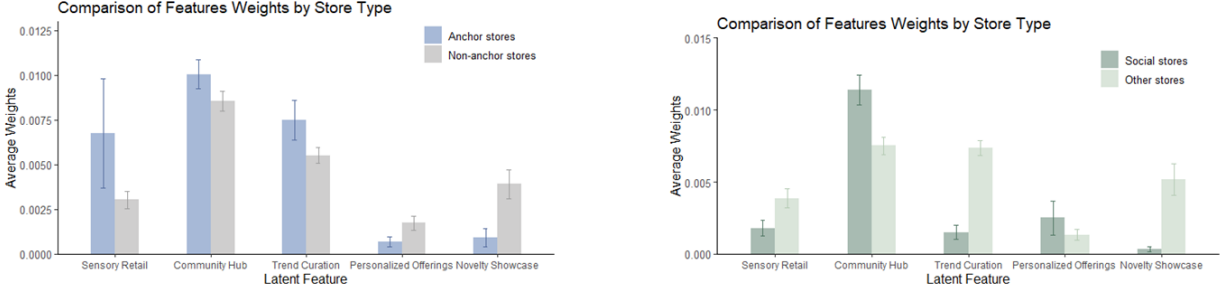


Figure 5: Average Store Weights on Latent Features

Notes: This figure shows the average weights across the five latent features by store type, reflecting how different types of stores contribute to various shopper needs. The left panel presents feature weights for contemporary anchor versus non-anchor stores, while the right panel presents feature weights for social versus other stores. The error bars present the 95% confidence intervals.

To explore this heterogeneity, we re-estimate the traffic and sales externality indices separately for each shopper cluster. Instead of assigning a single traffic and sales externality index to each store, we now derive three pairs of indices per store (one pair per shopper cluster), allowing us to compare how store influence differs across consumer types based on their distinct shopping patterns.

Contemporary Anchor Stores To formally test whether anchor stores exhibit different externalities across shopper clusters, we extend the model from Equation 3 by interacting the anchor store indicator with the shopper cluster indicators. Specifically, we estimate the following linear model:

$$\begin{aligned}
 Index_{i,m} = & \alpha_m + \beta Anchor_i + \theta_1 Anchor_i \times Leisure_shopper_i \\
 & + \theta_2 Anchor_i \times Experience_shopper_i + \gamma X_i + \varepsilon_i
 \end{aligned} \tag{6}$$

Where, the indicator variable $Leisure_shopper_i$ equals 1 if $Index_{i,m}$ for store i is derived using traffic from the leisure group shopper cluster, and 0 otherwise. Likewise, $Experience_shopper_i$ equals 1 if $Index_{i,m}$ is based on traffic from the experience-seeking shopper cluster. The coef-

efficient θ_1 thus captures the difference in the externality index of anchor stores between leisure group shoppers and the baseline group—purpose-driven shoppers. Likewise, θ_2 captures the difference in the externality index between experience-seeking shoppers and purpose-driven shoppers. To account for baseline differences in externality across shopper clusters, we also include *Leisure_shopper_i* and *Experience_shopper_i* as control variables in X_i .

The estimation results from Equation 6 are reported in Table 2A.2 in the Appendix. Figure 6 visualizes the estimated externality indices of anchor and non-anchor stores across shopper clusters, after controlling for other store-level covariates. These are computed using linear projections based on the estimates in Table 2A.2.

As shown in the left panel of Figure 6, anchor stores no longer exhibit significantly higher traffic externality than non-anchor stores within the purpose-driven shopper cluster. This is consistent with the behavioral characteristics of this group: these shoppers typically visit the mall with a predetermined objective and limited intention to browse, so visiting an anchor store does not significantly influence their likelihood of visiting other stores.

For the leisure group shopper cluster, anchor stores show significantly higher traffic externality compared to non-anchor stores. This may be because these shoppers often visit malls in groups or with family, and are more open to exploration and trend-seeking. Anchor stores—especially fashion-oriented ones—serve as focal points that inspire subsequent visits to other stores that satisfy various group members’ needs as showed in figure 5. Their broader appeal and visibility make them effective in directing traffic within the mall.

A similar pattern is observed in the experience-seeking shopper cluster: anchor stores exhibit significantly greater traffic externality than non-anchor stores. This may be attributed to the experiential environments that contemporary anchor stores often provide—immersive displays, personalized service, and curated product presentations—which align well with the hedonic motivations of experience-seeking shoppers as showed in figure 5. These sensory-rich experiences are more likely to engage shoppers and encourage extended visits, increasing the likelihood of entering additional stores.

The right panel of Figure 6 shows consistent patterns for sales externality. Among purpose-driven shoppers, anchor stores do not lead to greater purchase conversions in other stores. However, for both leisure and experience-seeking shoppers, traffic originating from anchor stores is significantly more likely to convert into purchases at neighboring stores. This reinforces the idea that anchor stores play a more critical role in driving sales spillovers for shopper groups who value discovery, trend engagement, and experiential retail.

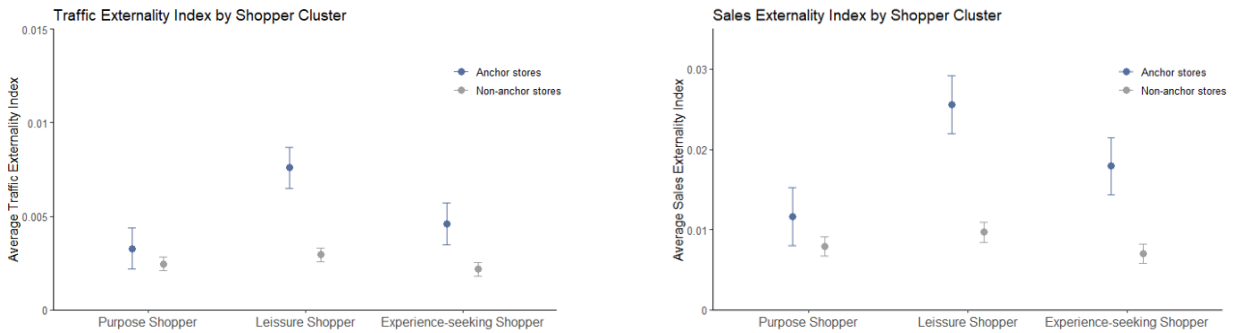


Figure 6: Anchor Stores' Externality Index Across Shopper Cluster

Notes: The bars show the 95% confidence interval for each marginal effect

Social Stores Following the same approach used to examine heterogeneity in anchor store externalities, we now test whether the influence of social stores varies across shopper clusters. Specifically, we estimate the following linear model:

$$\begin{aligned}
 Index_{i,m} = & \alpha_m + \beta Social_i + \theta_1 Social_i \times Leisure_shopper_i \\
 & + \theta_2 Social_i \times Experience_shopper_i + \gamma X_i + \varepsilon_i
 \end{aligned} \tag{7}$$

All variables are defined in the same manner as in Equation 6.

The estimation results from Equation 7 are presented in Table 2A.3 in the Appendix. Figure 7 visualizes the estimated externality indices of social versus other stores across the three shopper clusters, after controlling for store-level covariates.

Starting with traffic externality, we observe distinct patterns across shopper groups. For the purpose-driven shoppers, social stores exhibit slightly lower—but statistically insignifi-

cant—traffic externality compared to non-social stores. This is consistent with our earlier findings (Table 6), where social stores did not significantly contribute to broader mall traffic. Purpose-driven shoppers typically visit malls with clear goals and limited browsing intentions, so visiting a social store (e.g., restaurant or entertainment venue) is unlikely to alter their path through the mall or influence their decision to visit other stores.

For the leisure group shopper cluster, however, social stores demonstrate significantly higher traffic externality compared to non-social stores. This result suggests that social stores play a key role in shaping the mall experience for these shoppers, who often visit in groups or with family. Group-based shopping is typically more exploratory and socially oriented, with dining and entertainment acting as focal points that anchor group members in shared activities. These social settings may serve as a central meeting point, from which group members subsequently explore other stores based on varied individual preferences—leading to greater spillover traffic. These results are also consistent with our earlier finding that social stores are more strongly associated with the “community hub” feature that characterizes the preferences of leisure group shoppers, as shown in Figure 5.

In contrast, among experience-seeking shoppers, social stores exhibit significantly lower traffic externality relative to non-social stores. This group is characterized by a desire for immersive, personalized, and novel experiences, often driven by individual rather than group motivations. As shown in Figure 5, social stores are less effective at providing “sensory retail” and “novelty showcase” features, which are central to the preferences of this shopper group. While social stores may still attract experience-seeking shoppers due to their “personalized offering” attributes, they tend to function more as destinations than as transitional spaces. The time and attention shoppers devote to food, beverage, or entertainment venues may reduce their likelihood of continuing on to other stores. In this sense, social stores absorb rather than redirect experiential engagement, leading to weaker spillover effects within this segment.

Sales externality patterns closely mirror those observed for traffic. Among purpose-driven

shoppers, social stores do not significantly enhance sales conversions in other stores. For leisure group shoppers, social stores generate significantly higher sales externality—further reinforcing the notion that these stores stimulate broader shopping activity within social groups. Conversely, among experience-seeking shoppers, social stores again exhibit significantly lower sales externality. The deep engagement these shoppers have with social venues may limit their commercial interactions elsewhere in the mall, dampening the potential for cross-store purchases.

Together, these findings highlight the nuanced role of social stores in influencing shopper behavior. While they may not be broadly effective in driving externalities across all shopper types, they are particularly valuable in attracting and activating leisure-oriented, group-based traffic—suggesting that their rent subsidies may be best justified in malls or areas targeting such segments.

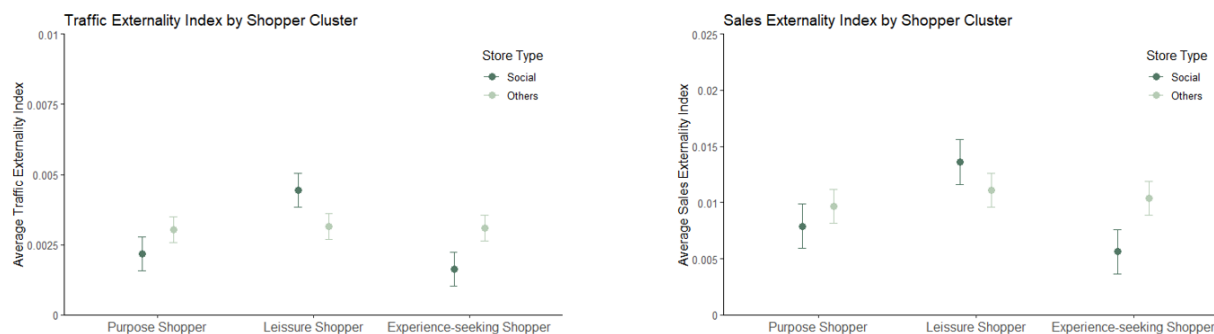


Figure 7: Social Stores' Externality Index Across Shopper Cluster

Notes: The bars show the 95% confidence interval for each marginal effect

5.3 Store Clusters Based on Shopping Patterns

Thus far, our findings show that both contemporary anchor stores and social stores exhibit higher traffic and sales externalities within the leisure group shopper segment. This aligns with their higher contributions to the “community hub” and “trend curation” features, which are particularly valued by this group. However, we also find that neither store category is especially serving the experience-seeking shopper segment, which prioritizes “personalized

offerings” and “novelty seeking”. This suggests a potential mismatch between the shopping needs of experience-seeking consumers and the value propositions offered by the current mix of prominent stores.

To identify stores that better align with the needs of each shopper segment, we move beyond traditional store classifications based on product categories and adopt an unsupervised approach. Specifically, we cluster stores based on their contributions to the five latent shopping features. We apply K-means clustering to the feature–store matrix H_t , where each vector $\mathbf{h}_{m,t}$ captures the weight of store m on each latent feature. Using the elbow method (displayed in the right panel of Figure 2A.2 in the Appendix), we determine that four store clusters ($k = 4$) provide the best fit. Figure 8 visualizes the centroids of these clusters as a heatmap, highlighting their feature composition.

The results indicate that Store Cluster 2 exhibits the highest weights on the “novelty showcase” feature, followed by “personalized offering” and “sensory retail.” Similarly, Store Cluster 4 shows the highest weights on “personalized offering,” with secondary emphasis on “sensory retail” and “novelty showcase.” These two clusters are well aligned with the shopping values prioritized by experience-seeking shoppers, making them strong candidates for serving this segment. We refer to these as experiential stores, as they fulfill the hedonic needs associated with novelty, personalization, and immersive experiences.

In contrast, Store Clusters 1 and 3 show high weights on “community hub” and “trend curation” features. These characteristics closely match the preferences of leisure group shoppers, who are more likely to shop in groups and explore trending or socially-oriented retail environments. We therefore refer to these clusters as “leisure stores”, as they are best suited to meet the social and epistemic needs of the leisure group shopper segment.¹²

To assess whether there is a potential alignment between store groups and shopper segments identified through our clustering approaches, we calculate the average proportion of leisure and experiential stores visited by each shopper segment during a single shopping trip.

¹²Leisure stores account for approximately 71.2% of all stores across the six malls.

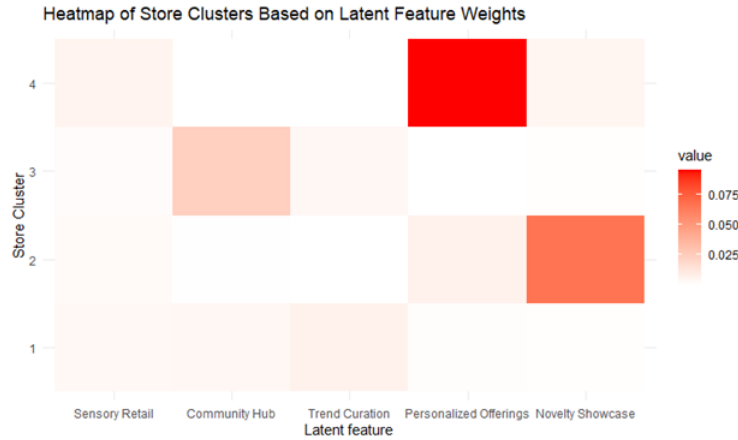


Figure 8: Heatmap of Store Cluster Centroids by Feature Weights

Notes: This figure illustrates the heatmap of the centroid for each stores cluster on five latent features.

As shown in Figure 9, leisure stores constitute the overwhelming majority of store visits for leisure group shoppers, accounting for 87.17% of their visits. In contrast, only 12.83% of their visits are to experiential stores. This pattern suggests that leisure group shoppers are highly concentrated in stores that offer strong “community hub” and “trend curation” features, which are central to their shopping motivations.

Conversely, experience-seeking shoppers demonstrate a clear preference for experiential stores, which account for 57.73% of their store visits. Leisure stores make up the remaining 42.27%. This result is consistent with our earlier findings and confirms that experiential stores—characterized by high contributions to “personalized offerings”, “novelty showcase” and “sensory retail”—are well matched to the preferences of experience-seeking shoppers.

Purpose-driven shoppers display a visitation pattern that closely mirrors the overall distribution of store types within the malls, with 69.06% of their visits occurring in leisure stores and 30.94% in experiential stores. This is in line with our earlier observations that purpose shoppers tend to follow individual, pre-defined shopping goals. As such, their visited stores vary considerably and are less systematically tied to specific shopping features.

Together, these results provide a new perspective on how malls can more effectively match store types to the needs of different shopper segments. Rather than relying on pre-defined classifications based on product categories or tenant labels, our approach demonstrates that

shopper visitation patterns can be used to empirically identify store groups that are particularly effective in serving specific consumer segments. This opens up new possibilities for tailoring tenant mix, marketing strategies, and rent policies based on behavioral alignment between stores and shoppers.



Figure 9: Proportion of Visits to Experiential and Leisure Stores by Shopper Segment

6 Discussion

In this study, we leverage a unique and large-scale dataset of shopper trajectories—an exceptionally rare resource in the context of offline retail—to develop and implement a novel approach for quantifying the effectiveness of store-level traffic spillovers. Specifically, we introduce the concept of a store externality index, which captures the extent to which the foot traffic of a focal store contributes to the traffic and sales performance of neighboring stores. Methodologically, this index is derived from a multivariate random forest model using variable importance measures (VIMs), enabling us to capture complex, nonlinear interactions between stores while accounting for both traffic and sales as outcomes.

Building on this framework, we evaluate whether contemporary anchor stores and social stores—both of which typically receive rent subsidies from mall managers due to their perceived hedonic appeal and ability to attract traffic—actually deliver positive externalities to surrounding businesses. We find that while contemporary anchor stores do, on average, gen-

erate meaningful traffic and sales spillovers, social stores are less effective in contributing to broader mall performance. This challenges the common managerial assumption that social stores are equally beneficial and deserving of subsidized rents.

To further explore the mechanisms behind these aggregate effects, we conduct heterogeneity analyses at two levels: store characteristics and shopper segments. On the store side, we distinguish between contemporary anchor stores based on brand type—specifically, whether they are associated with mass-market versus luxury brands and young versus established brands. We find that the observed benefits of anchor stores are largely driven by those associated with mass-market and young brands. These stores attract broader customer bases and demonstrate stronger conversion power, leading to greater spillover traffic and sales to other tenants.

On the consumer side, we propose a novel, unsupervised machine learning framework to segment shoppers into behavioral groups based on their foot traffic patterns. Using Non-negative Matrix Factorization (NMF) and unsupervised clustering approach, we identify three distinct shopper clusters: purpose-driven shoppers, leisure group shoppers, and experience-seeking shoppers. Re-estimating store externalities within each of these segments reveals nuanced differences in store performance. Anchor stores are particularly influential for leisure and experience-seeking shoppers, while they offer little benefit to purpose-driven shoppers, who tend to follow pre-planned and isolated shopping paths. Social stores, in contrast, perform well only for leisure shoppers—likely due to their group- and interaction-oriented nature—but underperform for both purpose-driven and experience-seeking shoppers.

To better match store types with shopper needs, we further apply clustering to group stores based on the latent shopping values they offer. This approach yields two distinct store types: leisure stores, which emphasize social interaction and trend-oriented experiences, and experiential stores, which cater to personalized, immersive, and novelty-driven preferences. These store groupings demonstrate strong alignment with the behavioral profiles of leisure and experience-seeking shoppers, respectively, providing a more meaningful alternative to

conventional product-based store classifications.

Together, these findings offer several important contributions and implications for both researchers and practitioners. First, we introduce a scalable, interpretable, and empirically grounded method to evaluate the external impact of individual stores—something that has long been assumed in theory but rarely measured in practice. This method can be readily adopted by shopping mall managers to inform strategic decisions around tenant mix, rent pricing, and space allocation.

Second, our findings provide actionable insights for mall managers regarding rent subsidy policies. Rather than providing blanket subsidies to all anchor or social stores, a more targeted approach is warranted. Contemporary anchor stores affiliated with mass and young brands generate substantial positive externalities and thus justify their rent discounts. In contrast, luxury-brand anchor stores and most social stores may not deliver sufficient spillovers to warrant the same treatment. Mall managers should also consider shopper heterogeneity when planning tenant mixes—selecting stores not only based on overall traffic generation but also based on their effectiveness in converting different shopper types into mall-wide value.

Furthermore, our results underscore the importance of incorporating shopper heterogeneity into tenant planning. Rather than relying solely on product categories or traditional store labels, mall managers can adopt data-driven methods to identify new store groupings based on the specific shopping needs they fulfill. This approach enables more precise alignment between store offerings and shopper preferences, enhancing the overall effectiveness of the retail environment and maximizing the value of strategic tenant placement.

Finally, store owners themselves can benefit from understanding their position within the broader ecosystem of a shopping mall. For those located near high-externality anchors, proximity may translate into meaningful boosts in foot traffic and sales. Conversely, stores with low externality contributions may need to invest more heavily in their own traffic acquisition or renegotiate rent terms that better reflect their role in the mall's value chain.

In summary, this research contributes to both the academic literature on retail agglomeration and the practical management of shopping malls by offering new tools, empirical evidence, and strategic recommendations that align store-level decisions with shopper behaviors and mall-wide performance.

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Appendix

Table 2A.1: Anchor Stores' Externality Index By Brand Features

Dependent variable:	(1) Traffic externality	(2) Sales externality
Anchor store \times mass brand	.00415*** (.00151)	.01089** (.00464)
Anchor store \times young brand	.00141 (.00123)	.018369*** (.00380)
Anchor store dummy	-.00134 (.00137)	-.00583 (.00421)
Mass brand dummy	.00032 (.00046)	.00152 (.00141)
Young brand dummy	-.00022 (.00045)	-.00068 (.00140)
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	942	942
R-squared	.081	.116

Control variables include store floor, area, and a national brand indicator.

*** $p < .01$, ** $p < .05$, * $p < .1$.

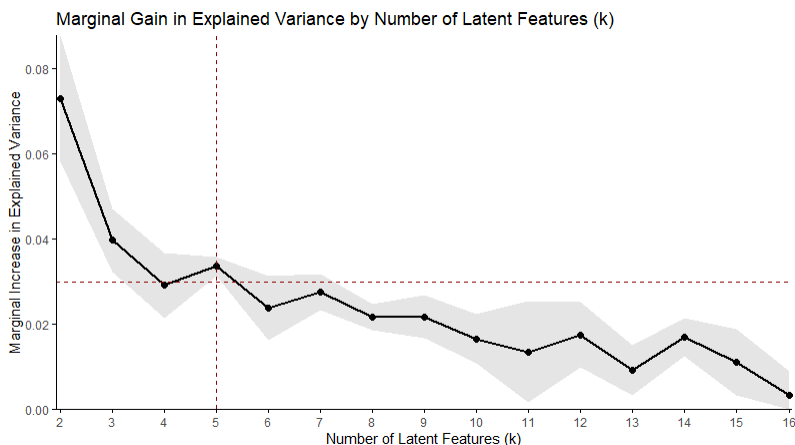


Figure 2A.1: Explained Variance Improvement per Additional Latent Feature (K)

Notes: This figure illustrates the average marginal gain in explained variance as additional latent features are added in the Non-negative Matrix Factorization (NMF) of the shopper-store visit matrix across six shopping malls. Marginal gains are computed as the first-order differences in explained variance for each value of k . The shaded area represents the range of these marginal gains across the malls.

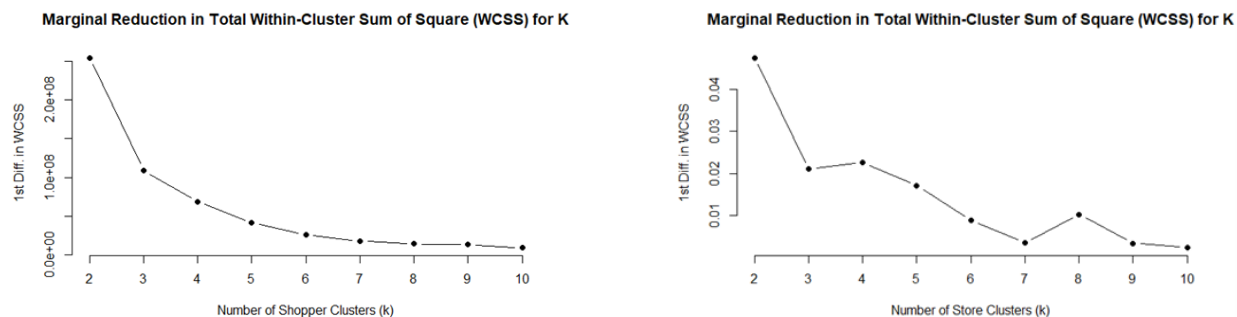


Figure 2A.2: Elbow Method for Determining Optimal Number of Clusters

Notes: This figure presents the marginal reduction in Total Within-Cluster Sum of Squares (WCSS) for different values of k (number of clusters), calculated as the absolute first-order difference in WCSS. The left panel shows the average marginal decrease in WCSS from K-means clustering on the shopper-feature matrix H_t across malls. The right panel shows the corresponding results from clustering on the feature-store matrix W_t .

Table 2A.2: Shopper Cluster-Level Heterogeneity in Anchor Stores' Externality Index

Dependent variable:	(1) Traffic externality	(2) Sales externality
Anchor store dummy	.00080 (.00060)	.00376* (.00198)
Leisure group shopper	.00048** (.00024)	.00176** (.00094)
Experience-seeking shopper	-.00029 (.00018)	-.00089 (.00081)
Anchor store × leisure group shopper	.00384*** (.00069)	.01209*** (.00266)
Anchor store × experience-seeking shopper	.00161** (.00081)	.00711*** (.00257)
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	2826	2826
R-squared	.070	.062

Control variables include store floor, area, and a national brand indicator.

*** $p < .01$, ** $p < .05$, * $p < .1$.

Table 2A.3: Shopper Cluster-Level Heterogeneity in Social Stores' Externality Index

Dependent variable:	(1) Traffic externality	(2) Sales externality
Social store dummy	-.00084** (.00040)	-.00175 (.00132)
Leisure group shopper	.00013 (.00023)	.00146 (.00089)
Experience-seeking shopper	.00006 (.00030)	.00073 (.00093)
Social store \times leisure group shopper	.00214*** (.00062)	.00425*** (.00166)
Social store \times experience-seeking shopper	-.00062 (.00051)	-.00299* (.00158)
Mall fixed effect	Yes	Yes
Control variables	Yes	Yes
Observations	2826	2826
R-squared	.055	.040

Control variables include store floor, area, and a national brand indicator.

*** $p < .01$, ** $p < .05$, * $p < .1$.