The Impact of Store Location on Customer Foot Traffic and Store Performances: Evidence from Shopping Malls

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Abstract

The significance of store location in retail success is widely recognized. In this study, we estimate the causal effect of store location on customer traffic and revenues, utilizing unique foot traffic data from a shopping mall conglomerate. To address endogeneity concerns, we leverage escalator maintenance as a natural source of variation in location quality. When escalators are closed for maintenance, previously prime locations become less desirable as customers need to travel longer distances to reach stores in affected areas. We find a 15% percent decline in foot traffic when location quality deteriorates due to the closure of escalators. To understand the mechanism behind our results, we cluster consumers according to their behavior within the mall. Our analysis reveals that stores that attract a larger share of impulse buyers experience a sharper decline in foot traffic. Using path-level data, we show that all consumer clusters are likely to use alternative paths during escalator maintenance, but only impulse buyers are significantly more likely to switch to other stores along these new paths. Our results offer guidance in optimizing store locations and inform the design of contracts between retailers and mall owners.

Keywords: Location value, natural experiment, foot-traffic, shopping mall

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1 Introduction

The retail sector has undergone a significant transformation in recent years, especially within the brick-and-mortar store domain. The surge in online shopping has put immense pressure on physical retail outlets. Despite the challenges, the sector is projected to grow by 4.8% in 2021, signifying resilience and adaptability. In 2021, in-store retail sales in the U.S. reached the $4.44 trillion mark, demonstrating the continuing scale and potential of offline retail (National Retail Federation report, 2021)[1]. One critical factor influencing this resilience is the strategic location of retail businesses. The age-old adage "location, location, location" emphasizes the critical role of location in attracting walk-in traffic and driving revenue (Bell, 2014). Retailers situated in areas with high footfall, easy accessibility, and proximity to key properties like anchor stores, enjoy a distinct advantage in capturing consumer attention.

In parallel, the role of such locational advantage is also well-recognized in academics. For example, Armstrong et al. (2009) emphasizes the role of prominence in consumer search models. The idea is that the mere fact that the firm is first visited provides extra advantages that the firm can extract from the search costs arising from consumers' search orders.[2] Location is clearly one of those factors in determining this prominence (Gerdeman, 2012; Florida and Adler, 2022). This insight is particularly relevant in offline retail environments, where prime locations near entrances or escalators are seen as valuable for increasing consumer traffic because they can easily capture the attention of potential customers and draw them in before any other competitors can appeal to them. Mall owners often reflect this value by charging premium prices for such locations (Sirmans and Guidry, 1993; Netzell, 2013).

However, the challenge for mall owners and developers lies in quantifying the value of location. This research seeks to measure the advantage arising from a retailer's physical location and quantify its effects on customer foot traffic and sales. We first document that stores located near high-accessibility points, such as escalators, experience measurable advantages in consumer traffic. Yet, establishing the causal relationship between location and store performance is challenging due to endogeneity concerns: stores located in premium locations may also possess stronger brand recognition, independently attracting higher consumer traffic. Therefore, it is crucial to separate the effects of intrinsic brand attractiveness from the locational advantage

[1] NRF, "Retail Sales to Now Exceed $4.44 Trillion in 2021, as NRF Revises Annual Forecast" https://nrf.com/media-center/press-releases/retail-sales-now-exceed-444-trillion-2021-nrf-revises-annual-forecast

[2] Recent research shows that prominence in retail can be achieved through various means, including targeted advertising, brand positioning, and strategic pricing promotions (Chan and Park, 2015; Mayzlin and Shin, 2011; Shin and Yu, 2021; Ke et al., 2022; Armstrong and Zhou, 2011; Zhou, 2011).

itself. Without addressing this distinction, estimates of location value could be biased upward, conflating genuine accessibility benefits with brand-driven consumer preferences. It is essential to distinguish between the effects of brand value and locational advantage on consumer behavior.

In online settings, studies have estimated the advantage of location through controlled experiments that randomize the rankings or positions (locations) of advertisers (Joo et al., 2024; Goli et al., 2023; Ursu, 2018). In offline retail, however, isolating locational advantage is more challenging since those experiments of changing store locations are not practically plausible. In addition, there exists a great degree of customer heterogeneity in their goal directness, which influences their shopping behaviors (Hui et al., 2009a). Some consumers may be goal-directed with specific goals in mind (e.g., to buy a specific brand of shoes or clothes), or at the other extreme, their trips can be purely driven by hedonic browsing experience (Moe, 2003). In the presence of such customer heterogeneity in their shopping patterns, detailed information on location and consumer path data within shopping environments (such as within the mall, clusters, or cities) that helps to identify customer heterogeneity has not been readily available, making it challenging to parse out the impact of location on their behavior. To address these challenges, our research utilizes a path-tracking dataset collected from four shopping malls in three different provinces in China. This dataset, compiled using advanced AI sensor technology, records detailed consumer paths within the malls, providing invaluable insights into shopping behavior. Our study proposes a novel measure of the value of a retailer's physical location and its impact on foot traffic and sales.

In offline retail, however, isolating locational advantage is more challenging since store locations cannot be experimentally manipulated. Moreover, consumer heterogeneity complicates matters: some shoppers are highly goal-directed (e.g., seeking a specific brand), while others engage in hedonic browsing (Hui et al., 2009a; Moe, 2003). Because detailed path-tracking data capturing such heterogeneity have rarely been available, prior studies have struggled to disentangle the impact of location on behavior. To address this gap, we use AI-enabled path-tracking data from four shopping malls in China to develop a novel measure of location value and its effect on foot traffic and sales.

A unique aspect of our approach is the use of exogenous shocks, such as escalator maintenance in the malls, as natural experiments. These maintenance activities, exogenous to store characteristics and consumer preferences, disrupt normal shopper traffic flow and alter the practical value of store locations, providing a credible source of variation in location quality. When escalators are under maintenance, stores previously in prime positions experience a decrease in accessibility. Locations that were once highly advantageous become less accessible, mirroring the effect of a virtual relocation in online environments. This change in accessibility requires customers to traverse longer distances, impacting their shopping behavior. By examining the variations in consumer pathways and store performance during these periods, we can identify the causal effect of location advantage. We also observe heterogeneous effects on different types of customers, with impulse buyers being most affected by these changes.

Additionally, we find substantial variation in the effect of store location across different retailers, suggesting the interaction effects of the store location and brand value on the prominence. These findings caution against overlooking the importance of location value and the endogeneity of brand value in driving consumer traffic, as this may lead to overstated estimates of location's impact on traffic and sales. By identifying how location effects differ across store types, we aim to provide valuable insights that assist mall owners in making informed decisions about fee structures, lease agreements, and store allocations.

More precisely, we begin our analysis by establishing a robust relationship between various traffic metrics and store performance. We observe that first visits and total visits are strongly associated with store sales, highlighting the importance of location quality in attracting consumer traffic and enhancing store performance. We then replicate classical hedonic regressions from the real estate literature to examine the impact of location characteristics on these traffic indicators. Our findings confirm the significance of accessibility, such as the presence of a nearby escalator, while also highlighting the importance of other factors such as store size and floor location.

To assess the causal impact of location quality, we utilize plausibly exogenous episodes of escalator maintenance, lasting for several days, as natural experiments. These escalator shutdowns effectively lead to a re-allocation of stores in terms of their prime locations, allowing us to observe changes in consumer behavior and store traffic in response to decreased location quality. We find that disruptions caused by escalator shutdowns lead to a significant decline in foot traffic for stores immediately adjacent to non-operational escalators. Interestingly, as the distance from these escalators increases, we observe diminishing negative impacts and eventual positive spillovers to stores located further away, suggesting a redistribution of traffic within the mall. These findings provide empirical support for the spatial competition models proposed by Hotelling (1929). However, we do not find a significant effect on sales, indicating that consumers with strong purchase intentions are less influenced by changes in location quality. We caution that our sales data may contain measurement errors, as it is self-reported at a weekly frequency, whereas our traffic data is recorded in real time on a daily basis. Furthermore, we find that well-established brand stores are less vulnerable to changes in location quality, suggesting that small retailers benefit most from prime locations and should pay a premium for them.

We then proceed to explore the mechanisms behind these results by examining detailed consumer path data. Through cluster analysis based on consumer shopping behaviors within the mall, we assess the differential impact of escalator maintenance on each consumer cluster. Our findings corroborate the aggregate results, revealing significant variations in consumer responses based on different clusters. Directed Buyers largely maintain their intended shopping paths despite some modest adjustments due to escalator disruptions, whereas Hedonic Explorers, characterized by more impulsive shopping behaviors, significantly alter their routes. This pattern suggests that different consumer types interact with the mall environment differently, driven by their specific motivations and the immediate shopping context. Our findings not only highlight the substantial impact of location quality on traffic but also suggest that small retailers and those appealing to impulsive buyers, such as accessories stores, stand to gain the most from prime locations. These insights are crucial for mall operators and retailers in strategizing store placements and optimizing lease agreements to enhance overall mall performance.

The remainder of the paper proceeds as follows: In Section 2, we briefly review the related literature. Section 3 describes our unique dataset and provides key descriptive statistics. Section 4 details our identification strategy and presents the main empirical results on the causal effects of store location. In Section 5, we further investigate heterogeneity in location value by analyzing consumer clusters and store characteristics. Section 6 concludes.

2 Related Literature

Our research is related to several research streams in economics and marketing. First, the significance of store location in retail success has been well-established by a substantial body of literature examining how location influences consumer behavior and store performance (Bell, 2014; Kumar et al., 2017). Traditional studies in real estate have demonstrated that factors such as proximity to anchor stores and accessibility significantly impact retail rents and store traffic (Carter, 2009; Sirmans and Guidry, 1993; Gatzlaff et al., 1994; Carter and Vandell, 2005). These studies commonly employ hedonic pricing models to quantify the premium attributed to strategic store placements within shopping centers. Also, research in urban economics has explored retail interdependence and agglomeration effects, which further emphasize the strategic value of location. Notably, Eppli and Benjamin (1994) identified that anchor tenants in shopping malls generate beneficial spillovers for smaller, non-anchor tenants, a phenomenon supported by subsequent studies using data on retail chain bankruptcies to estimate these effects causally (Shoag and Veuger, 2018; Benmelech et al., 2019; Knight, 2022).

Expanding on these themes of retail economics and location value, the literature also highlights the critical role of urban agglomeration and retail clustering on consumer behavior and store performance. Koster et al. (2019) examines the economic benefits of consumer footfall for retail stores, using spatial data to establish how pedestrian traffic influences rental income in Dutch shopping streets. This study not only emphasizes the economic importance of strategic store placement but also illustrates the substantial externalities present in retail configurations. Likewise, Vitorino (2012) applies an empirical entry game model to demonstrate how the presence of complementary retail offerings within shopping centers can bolster overall store performance, reinforcing theories of retail agglomeration and clustering. Also, the literature underscores the implications of urban agglomeration and retail clustering on consumer behavior and store performance. Leonardi and Moretti (2022) provides a compelling analysis of how regulatory changes in Milan affected the geographical concentration of restaurants, offering insights into the dynamics of urban retail agglomerations. This research complements the findings from Nakajima et al. (2018), who uses location lotteries at the Tokyo Tsukiji Fish Market to demonstrate how the diversity of neighboring stores can enhance the performance of specialized retailers. Our paper validate these concepts and further them by showing how unexpected changes in accessibility, such as escalator closures, can significantly reshape consumer movement and impact the economic value of retail locations.

This concept of location value extends into the digital realm, where controlled experiments in online settings allow researchers to randomize the rankings or positions of advertisers (Joo et al., 2024; Ursu, 2018). These experiments illustrate the direct correlation between visibility and increased consumer engagement and sales. In contrast, in offline brick-and-mortar settings, replicating such controlled experiments is challenging due to the impracticality of altering physical store locations. Additionally, the significant heterogeneity in consumer behavior — ranging from goal-directed to hedonic browsing (Hui et al., 2009a; Moe, 2003) — complicates the assessment of location value, as its impact can vary widely based on consumer intent and shopping style. Our paper is the first to utilize a similar type of variation that shifts positions of stores in the offline retail environment. By exploiting escalator closures as shifters of location quality, we aim to identify the value of location.[3]

[3]This approach is akin to the natural experiment strategy used in studies that exploit the creation and closure

Another strand of research closely related to ours explores the impact of geo-tracking and path-tracking technologies in retail environments. Technologies such as mobile applications and RFID tags provide firms with precise data on consumer locations and movements, greatly enhancing the accuracy of behavioral predictions (Narang and Luco, 2024; Ghose et al., 2019; Faber, 2014; Hui et al., 2009a,b; Seiler et al., 2017; Wang et al., 2021). Studies like Narang and Luco (2024) show that geo-tracking data can substantially improve prediction accuracy over traditional demographic-based models, enabling more effective marketing strategies that are responsive to consumer behavior patterns. This technology also plays an important role in physical retail settings, where path-tracking data reveal details of consumer interactions with their environment. For instance, Hui et al. (2009a) and Ghose et al. (2019) demonstrate how tracking consumer trajectories can lead to increased transaction amounts and faster redemption behaviors, thereby enhancing retail profitability. The utility of such data extends to optimizing store layouts and configurations; Seiler et al. (2017) found that longer consumer paths within stores correlate with higher expenditures, suggesting strategic layout designs can significantly boost sales. Similarly, Wang et al. (2021) leverages AI-enabled sensor technology to assess the impact of various marketing campaigns on overall mall traffic, suggesting that tailored marketing efforts can significantly boost consumer visits. Complementing these findings, Joo et al. (2023) show that anonymized GPS-based geotargeted ads increase both online and offline engagement for small businesses, with particularly strong effects for independent retailers during periods of reduced foot traffic such as the COVID-19 pandemic Building on these insights, our study utilizes escalator maintenance as a natural experiment to assess the causal impact of location quality. We explore how changes in accessibility influence consumer traffic, effectively isolating location effects from factors such as brand value and customer heterogeneity.

3 Data

In this section, we provide a comprehensive overview of our dataset and describe typical behaviors of average mall visitors. We then define the key traffic measures used in our analysis and present descriptive evidence of location value.

of transportation options (Faber, 2014; Redding and Daniel, 2016; Bernard et al., 2019) or policy changes affecting the availability of new transportation means such as Uber and Lyft (Zhang et al., 2022; Shin et al., 2023). Other research has utilized various policy changes (Chiou and E. Tucker, 2022; Chen et al., 2024) and natural events (Sim et al., 2022; Simonov et al., 2022) as quasi-natural experiments to study economic and marketing phenomena. For an extensive review of quasi-natural experiments in marketing, see Goldfarb et al. (2022).

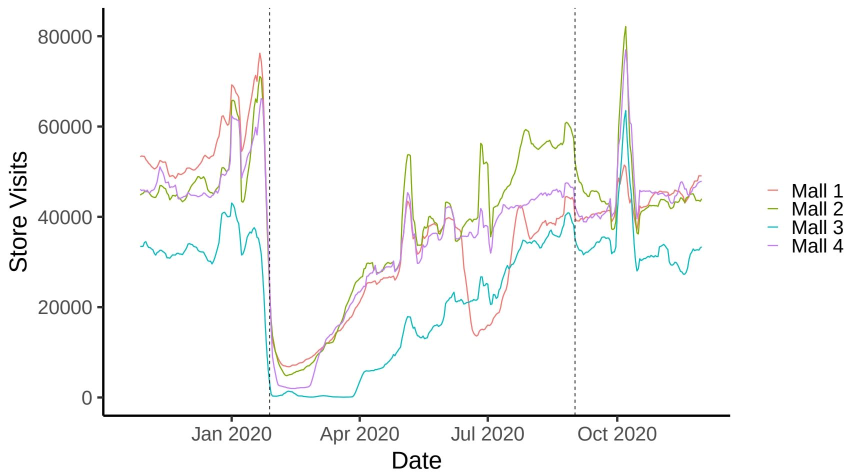


Figure 1: Store visits for malls in data

3.1 Mall Traffic Data

Our primary data source is derived from a consumer traffic dataset collected across four major shopping malls in three different provinces in China. These malls are equipped with advanced AI sensor systems that monitor consumer movement throughout the mall. Specifically, AI-enabled sensors are installed at all mall entrances, at the entrance of each store, and in key common areas within the mall, ensuring comprehensive tracking. With over 250 sensors per mall on average, this setup allows for continuous, high-resolution tracking of individual shopper paths—from entry to store visits and exits. The system employs image recognition algorithms to distinguish individuals based on their unique visual features, reconstructing each shopper's full trajectory and recording the time spent in each location. Importantly, the system distinguishes individuals based on non-facial visual features such as clothing and body dimensions (e.g., height, head size, shoulder width) to assign each visitor an anonymous identifier upon entry, enabling reconstruction of their trajectory and time spent at each location. For privacy reasons, the system does not store personal information and resets identifiers daily. Thus, if a consumer exits and returns the next day, they are treated as a new visitor. This technology is now widely deployed across hundreds of malls in China, offering rich, real-time behavioral data that is critical for analyzing consumer traffic patterns and in-mall shopping behavior.[4]

The dataset covers foot traffic at a consumer-day level from September 2019 to November 2020. To ensure data quality, we focus on a sub-sample of consumers with reliable location

[4]For a comprehensive explanation of the data collection technology, please refer to Martini et al. (2020).

tracking. Specifically, we consider consumers whose location in the mall is known for any 15 minute interval. Some tracking gaps may occur due to blind spots or errors in the image recognition algorithm. In Figure 1, we plot a moving average of store visits for each mall, clearly illustrating how Covid-19 lockdowns impacted mall activity. We also observe heterogeneity in the timing of full reopenings post-lockdown, attributable to the differing dates when provinces lifted restrictions. For our analysis, we exclude days during which the malls were partially closed due to Covid-19 lockdowns. After these steps, we are left with a substantial number of daily observations, with each mall recording an average of over 15,000 unique consumers per day.

To complement the foot traffic data from AI-enabled sensors, we also include comprehensive information about each store, such as its category, size, as well as self-reported weekly statistics including store traffic and sales. These statistics are provided by the individual stores as part of their contractual obligations with the mall owner. Table 4 in the Appendix A1.1 demonstrates that the correlation between self-reported store traffic and different traffic metrics from the sensor technology is in the range of 0.8-0.85, suggesting that the sensor technology effectively captures the mall visit patterns. Moreover, while the sensor data is available at a high-frequency (real-time daily), the self-reported data is recorded weekly and even monthly for certain stores. For these reasons, we rely primarily on the sensor-based traffic data in our main analysis to capture the dynamics of mall visits.

Table 1: Mall Summary Statistics

	Mall 1	Mall 2	Mall 3	Mall 4	Avg	Pre-Covid Avg	Post-Covid Avg	Difference (Post-Pre)
Visit Patterns:								
Mall Traffic	15,856	19,852	16,231	14,132	16,518	18,944	14,054	$-4,889^{***}$
Mall Visit Time	36.5	35.9	27.3	48.7	37.1	37.8	36.7	-1.1^{**}
Weekend Mall Traffic	18,651	30,681	23,089	20,027	23,112	26,565	19,819	$-6,746^{***}$
Weekend Mall Visit Time	40.6	38.3	28.0	51.8	39.7	40.5	39.3	-1.1
Mall Composition:								
Number of Stores	240	132	208	253	208.25			
Median Store Size (sq. m.)	138.45	129.08	143.82	154.86	141.55			
Max Store Size (sq. m.)	6,631	23,807	4,061	10,932	11,858			
Min Store Size (sq. m.)	55	124	65	78	80			
Number of Floors	6	4	5	4	4.75			
Number of Escalators	16	10	12	12	12			
Days in data	234	155	238	213	210			

Note: Mall traffic is computed at a daily level averaged over all days in the data; Visit time is in minutes per day and is computed as the sum of time inside the mall for every visitor. Days when the mall was partially open or closed due to Covid-19 are excluded from the data. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents: $p < 0.01$.

In Table 1, we provide an overview of key characteristics for the malls included in our study.

Overall, the malls demonstrate a high degree of similarity in terms of size, with the exception of *Mall 2*, which has fewer floors and stores but features a larger anchor store. Interestingly, *Mall 4* attracts less consumers on average than other malls but their activity in the mall as measured by visit time is significantly higher than for consumers of other malls. As anticipated, there is a noticeable increase in mall traffic during weekends, indicating the influence of leisure time and consumer preferences for shopping and recreational activities on these weekend days. Furthermore, we observe a significant decline in traffic in the post Covid period for some malls, indicating the impact of the pandemic on mall activities. Pre-pandemic, the average daily foot traffic across all malls was 18,944 visitors, while during the post-Covid period, it decreased to 14,054 visitors ($p = 0.000$). Similarly, the average visit time per day decreased from 37.8 minutes to 36.7 minutes ($p = 0.012$)[5]. Since our main analysis is based on comparisons of traffic patterns within a short window of time (before, during, and after the week of escalator maintenance), we do not expect that including post-Covid data will bias our results.

Table 2: Shopper Behavior Summary Statistics: Mall 4

	Weekday	Weekend	Pre COVID-19	Post COVID-19
Visit Statistics:				
Median Time Inside	64.57	74.02	69.08	66.72
Median Activity + Shopping Time	42.43	47.17	44.65	43.63
Median Shopping Time	6.67	11.88	9.40	7.43
Median Shopping Time | Shopping time > 0	42.72	48.92	45.94	44.13
Median Number of Visits	2	2	2	2
80-th Percentile of Number of Visits	5	6	5	5
Median Product Categories Visited	1	1	1	1
Consumers with 10 Minutes+ in Restaurants	39%	40%	38%	40%
Path Statistics:				
Median Time Walking	16.12	21.13	17.95	17.55
Median Floors Visited	3	3	3	3
Median Unique Zones PassedBy	20	24	21	20
Median Escalators Used	3	4	3	3

*For this table we remove consumers with maximum time in a single store over 200 minutes to filter out employees. We also only keep consumers whose first and last location are mall gates to ensure highest quality of tracking. Time related variables are in minutes.

Next, we describe behavior of an average mall visitor in Table 2. The table provides various attributes, including median shopping time, number of visits, product categories visited, the share of visitors interested in food, floors visited, escalator usage, and the 80-th percentile of the number of visits. The data highlights significant heterogeneity in consumer activity patterns

[5]Additional comparisons of pre- and post-pandemic data, such as distributions of traffic to product categories, are relegated to the Appendix A1.2.

within the mall. Notably, a considerable proportion of visitors are primarily drawn to the mall for dining experiences, as evidenced by the 38% of visitors that spent at least 10 minutes at one of the available restaurants in the mall. This indicates that the mall may serve as a popular destination for individuals seeking culinary options and social interactions, contributing to its vibrant atmosphere. On the other extreme, active shoppers, defined as those exceeding the 80-th percentile in terms of the number of store visits, exhibit distinctive characteristics compared to the average mall consumer. These active shoppers stand out by making an average of 5 store visits, in contrast to the median of 2 visits for all consumers. Moreover, we observe a persistent trend in consumer preferences for specific store visit patterns, as documented in Table 11 in the Appendix A1.3. When a consumer visits a particular store category, they are more likely to continue visiting other stores within the same category, suggesting that they enter the mall with a specific product category in mind. These findings highlight a distinct group of visitors who actively explore multiple stores, underscoring diverse trip purposes and a heightened interest in shopping. This observation aligns with previous research, such as Moe (2003), which has documented similar patterns among distinct groups of online shoppers. In Section 4, we will explore these patterns further for a comprehensive examination of consumer shopping behaviors to investigate the heterogeneous effects on various consumer subgroups.

Table 3: Summary Statistics of Store Traffic Metrics at Weekly Frequency

	Definition	Mean	20-th Percentile	80-th Percentile
Passerby's	Number of consumers seen near the store entrance	11,109.1	3,759.6	16,055.2
Visits	Number of consumers who went to the store	1,655.3	421.0	2,017.8
First Visits	Number of consumers who went to the store as their first visit	528.2	78.0	620.0
Long Visits	Number of consumers who were in a store for 10+ minutes	510.9	71.0	649.0
Time in Store	Average minutes spent in store per person	13.46	4.68	19.89
Revisits	Number of consumers who returned after a visit	161.4	28.0	180.0
Store Traffic Share	Share of mall traffic that the store gets	0.0063	0.0018	0.0084
Sales	Sales in RMB (self-reported by stores)	127,074.9	29,347.2	133,068.6
Sales per Visitor	Sales per visitor in RMB (self-reported by stores)	41.8	15.4	57.3

Throughout the paper, we use a variety of metrics that capture store performance. Table 3 provides a comprehensive description of those metrics. The "Passerby's" column represents the number of consumers captured by the AI sensor near the store entrance, indicating the traffic flows or passers-by who are potential exposed to the store. The "Visits" column represents the number of consumers who actually entered the store, as detected by the AI technology. The "First Visits" column indicates the number of consumers who visited the store before visiting any other store in the mall. The "Long Visits" column represents the number of consumers who spent 10 minutes or more inside the store. The "Time in Store" column shows the total minutes spent by consumers in the store. The "Revisits" column indicates the number of consumers who returned to the store after a previous visit. The "Sales" column represents the sales in RMB reported by the stores. We also report correlations between our traffic metrics in Table 4. The correlations exhibit an intuitive pattern: metrics more directly indicative of consumer purchases, such as "First Visits" or "Time in Store", show higher correlations with sales. Conversely, metrics less directly tied to purchase intent, such as "Pass-bys", demonstrate comparatively lower correlations with sales. To isolate the effects of fluctuations in the number of mall visitors, we convert traffic metrics into shares, representing the proportion of overall mall traffic that each store attracts.

Although our dataset includes self-reported sales figures, the data provider has advised us to interpret them with caution due to potential measurement error and inconsistent reporting frequencies—some stores report only monthly, while others report sporadically. As a result, we rely primarily on traffic-based metrics such as visits, passerbys, and first visits, which are measured consistently and frequently, and are widely used by retailers in this industry as proxies for store performance.

Table 4: Correlation Coefficients Among Traffic Metrics

Metrics from Sales Data	Passerby's	Visits	First Visits	Long Visits	Time in Store
Visits (Self-report)	0.54	0.80	0.85	0.79	0.84
Sales	0.47	0.66	0.76	0.67	0.67

3.2 Descriptive Evidence of Location Effects

Our next set of descriptive results adopts an approach commonly used in real estate literature. We regress store traffic on various attributes of store location to understand how these attributes influence consumer demand. Key location attributes in our analysis include store floor and proximity to escalators, serving as a measure for ease of access. We also consider store size, which may indicate the range of products a store can display, given its physical constraints. Having multiple malls allows us to control for brand fixed effects. The regression coefficients are identified since in the data we find that there is variation in location for the same brand across different malls.[6] We caution against interpreting these results causally since we do not know the sources behind this variation. The results are presented in Table 5.

The table reveals several insights into how location features influence traffic metrics such as the share of first visits, sales share, and the proportion of first visits. Notably, the presence of a nearby escalator, indicating a prominent mall location, is associated with an additional 0.45% of overall mall first visits, which is a significant effect in magnitude given that a typical mall in our sample has over 200 stores. We also find that stores with a nearby escalator have 5.1% more first visits among their total visits. Furthermore, an increase in store size by 100 square meters is associated with an additional 0.11% of overall mall first visits. This correlation is not surprising, as larger spaces are often occupied by well-known brands with high brand value. Moreover, our findings remain consistent across various traffic metrics and are robust to the inclusion of brand fixed effects, although some of the coefficients decrease in magnitude.[7]

Table 5: Descriptive Evidence of Location Value

	Mall 4			All Malls		
	First Visits Mall %	Sales Mall %	First Visits Among Visits %	First Visits Mall %	Sales Mall %	First Visits Among Visits %
Floor 2	-0.395*	-0.360**	-9.693***	-0.079	-0.220	-6.040***
	(0.202)	(0.142)	(1.701)	(0.093)	(0.144)	(1.360)
Floor 3	-0.278	-0.365**	-5.858***	-0.221	-0.357**	-9.643***
	(0.211)	(0.148)	(1.599)	(0.140)	(0.158)	(1.405)
Western Brand	0.283	0.287*	-1.501	–	–	–
	(0.216)	(0.157)	(1.468)	–	–	–
Store 100sqm	0.112***	0.151***	1.625***	0.082	0.066**	0.944***
	(0.012)	(0.017)	(0.312)	(0.066)	(0.029)	(0.265)
Next to Esc	0.453***	0.279***	5.157***	0.204**	0.077	2.757***
	(0.106)	(0.075)	(1.382)	(0.096)	(0.065)	(0.918)
Next to Esc*Store 100sqm	-0.079***	-0.114***	-1.484***	-0.197***	-0.013	-0.884***
	(0.018)	(0.019)	(0.317)	(0.037)	(0.018)	(0.182)
R-squared Adj.	0.202	0.291	0.159	0.884	0.876	0.776
No. Observations	2,017	2,017	2,011	6,706	6,706	6,670
Brand FE	No	No	No	Yes	Yes	Yes

Note: Store clustered standard errors in parentheses. We use the data from Oct 2019 to Jan 2020 for all malls in our data, aggregated at a weekly level excluding the food court and the underground floor. We multiple share of mall metrics by 100 to convert them to %. Brand FE are constructed based on store name. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents: $p < 0.01$.

Finally, we find that stores located on the first floor receive a higher percent of mall first

[6] We find very little temporal variation in store location within the same mall.

[7] Table 12 in the Appendix A1.4 presents results for additional traffic metrics such as visits, passerbys, and sales per square meter.

visits. This could be explained by their ease of access: consumers without a clear shopping intent are less likely to visit stores on higher floors due to higher travel costs. Note that the disadvantage of being on the second floor is less pronounced than that on the third floor. This can be partly explained by the spillover effect from food courts, which are usually located on the top floors of typical Chinese shopping malls. We expect consumers visiting the food court are more likely to stop by stores on the third floor with a higher propensity than the second floor stores. Since the food court is one of the most popular destinations in a shopping mall, its spillover effects could offset some of the travel costs incurred to reach higher floors. Although spillover effects are an important factor in quantifying the value of location, this paper focuses on location as a shifter of travel costs. We refer readers interested in the broader implications of spillover effects to the relevant literature in urban and real estate studies (Shoag and Veuger, 2018; Benmelech et al., 2019; Miyauchi et al., 2021; Knight, 2022; Oh and Seo, 2023), and in marketing, where cross-category spillovers in advertising have been documented as an important factor in ad-serving policies (Lu and Yang, 2017; Lu et al., 2025).[8]

4 Typology of Consumer Shopping Behaviors

Given the diverse consumer base of our shopping mall, it is crucial to evaluate the heterogeneous effects on each subgroup of consumers for our analysis. To achieve this, we employ a hierarchical clustering algorithm to define distinct subgroups based on their behaviors within the mall. We initially categorize consumers into three primary groups: *Hangout*, *Activity*, and *Shoppers*, each representing different shopping behavior patterns.

The *Hangout* group represents 16% of mall visitors and comprises consumers who do not visit any stores at the mall. These individuals might include teenagers using the common space for leisure activities, business people having meetings, or companions waiting for their loved ones to finish shopping.[9] The *Activity* group represents 35% of mall visitors and includes consumers who only visit service stores available in the mall, such as restaurants, beauty salons, and the cinema. Lastly, the *Shoppers* group represents 49% of mall visitors and consists of consumers who visit at least one store that sells products, indicating their engagement in shopping activities.

In our analysis, we specifically focus on the *Shoppers* group to examine the effect of store

[8]Suggestive evidence of the food court spillover effect using our path-level data is presented in Table 13 in the Appendix A1.5.

[9]Notably, approximately 62% of users in this group are identified as male by the AI sensors, which aligns with cultural norms where husbands wait in designated areas while their spouses shop.

location on consumer behavior, as this aspect is particularly relevant for them. Unlike the "Hangout" group, which does not visit any stores, and the "Activity" group, which is engaged in goal-oriented visits to service locations like cinemas where store location is less critical, the "Shoppers" directly interact with retail spaces, making the study of store location crucial. We further explore consumer heterogeneity within the "Shoppers" group, a core consumer group for mall retailers. For each shopper, we calculate a set of behavior variables that describe their behavioral patterns. These variables include cumulative measures of shopping activity, such as the number of visits and total time devoted to shopping. Additionally, we include measures that capture shopping trip characteristics, such as travel speed within the mall, the number of unique store categories visited, frequency of return visits to the same locations, and the breadth of the path (i.e., the number of unique mall areas passed by).

Using these variables, we employ a K-means clustering algorithm to segment shoppers into distinct consumer groups. The selection of the number of clusters is determined by a standard procedure that computes inertia (sum of squared distances of samples to their closest cluster center) and identifies an inflection point beyond which additional clusters do not significantly improve the separation of the samples (Chiang and Mirkin, 2010). Table 6 presents the identified clusters of Shoppers, their shares, and the defining behavioral characteristics.[10]

As the table shows, we have identified three distinct types of shoppers, each characterized by unique shopping patterns and behavior trajectories within the shopping mall. These shopper groups are: *Directed Buyers*, *Hedonic Explorers*, and *Food Enthusiasts*. *Directed Buyers* represent one extreme of the shopping behavior spectrum. These consumers exhibit purposeful and goal-directed shopping behaviors, focusing on efficiently achieving their shopping objectives. They spend the least amount of time inside the mall, approximately 46.95 minutes, but make targeted visits to specific stores, dedicating the largest amount of time per store visit (5.29 minutes). They only visit 2 stores on average and focus their shopping within stores of 1 product category. Their shopping patterns align closely with goal-oriented decision-making processes.

On the other end of the spectrum, we find the *Hedonic Explorers*. This group of shoppers displays a markedly different shopping pattern characterized by high curiosity and exploration, not necessarily specific product purchasing goal in mind. They engage in extensive wandering around the mall, spending the most time inside, approximately 94.31 minutes, visiting numerous areas and a diverse range of store categories (3 unique categories visited). For these shoppers,

[10] In the Appendix A2 we show that the clustering results are not sensitive to the choice of the number of clusters.

Table 6: Segmentation of Shoppers Using K-Means ($k = 3$)

Behavior Characteristics	Hedonic Explorers	Directed Buyers	Food Enthusiasts
Mean Shopping Visit Time	4.51	5.29	4.52
Median Shopping Visit Time	3.20	5.07	4.08
Shopping Visits	6.00	2.00	2.00
Activity Visits	1.00	0.00	3.00
Time Inside	94.31	46.95	148.15
Time in Restaurants	0.00	0.00	62.43
Time in Entertainment	0.00	0.00	0.00
Time in Services[11]	0.00	0.00	0.00
Unique Places per Minute Walking	1.30	1.13	1.02
Visits per Hour Walking	14.42	7.83	8.88
Unique Store Categories Visited	3.00	1.00	1.00
Unique Store Categories Passed-by	8.00	4.00	7.00
Max Passerby's of Same Zone	2.00	2.00	2.00
Elevators Used	1.00	0.00	1.00
Escalators Used	5.00	2.00	6.00
Share	0.21	0.54	0.26

*This table reports behavior characteristics for a median consumer within the cluster; Time is reported in minutes

the shopping experience seems to be more about hedonic exploration and browsing, driven by the desire to experience a wide range of products and store offerings.

Lastly, we have identified a unique group of shoppers known as *Food Enthusiasts*. This group comprises individuals who are avid food lovers and show a strong interest in the culinary offerings available at the mall. They dedicate a significant amount of their mall time to dining at restaurants, spending about 62.43 minutes on average, and exploring various food options, reflected in their high activity visits count (3.0) primarily at food-related venues. They visit shopping stores as well but their main goal in the mall seems to be dining.

Moreover, we find that stores vary significantly in the types of shoppers they attract. Table 7 highlights the average shopper types across different product categories. For example, stores in the *Clothing* and *Accessories* categories are visited by *Hedonic Explorers* approximately 50% of the time, whereas *Beauty Products* stores attract a much higher proportion of *Directed Buyers*. Furthermore, even within the same product category, there are notable variations in shopper types. Among *Clothing* stores, for example, the 85th percentile store has 25% *Directed Buyers*, compared to only 5% for the 15th percentile store. These within-category differences in shopper types may reflect variations in brand value, as well-known brands are more likely to draw *Directed Buyers* who visit the mall specifically to purchase from that brand. We will use the characterization of stores by consumer type in our main analysis as a proxy for brand value.

Table 7: Visitor Share by Store Category

Store Category	*No. Stores*	Food Enthusiasts		Hedonic Explorers		Directed Buyers	
		Mean	P15-P85	Mean	P15-P85	Mean	P15-P85
Accessories	40	0.20	0.13-0.28	0.46	0.34-0.61	0.35	0.24-0.48
Beauty Salon	3	0.38	0.37-0.40	0.26	0.22-0.31	0.35	0.30-0.40
Children Related Business	21	0.59	0.53-0.67	0.21	0.14-0.27	0.19	0.15-0.24
Clothing	84	0.15	0.12-0.18	0.53	0.45-0.62	0.32	0.22-0.39
Digital Products and Electronics	14	0.21	0.17-0.23	0.37	0.33-0.40	0.41	0.33-0.47
Home Decoration	6	0.26	0.16-0.35	0.39	0.29-0.54	0.34	0.24-0.43
Professional Beauty and Care	9	0.24	0.19-0.28	0.38	0.26-0.44	0.38	0.32-0.44
Restaurants and Food	59	0.58	0.40-0.75	0.18	0.12-0.24	0.24	0.12-0.35
Theme Experience	9	0.53	0.35-0.68	0.19	0.11-0.26	0.28	0.20-0.41

Note: This table reports average share of each consumer cluster for each store category. Even though in Table 6 a median *Direct Buyer* and *Hedonic Explorer* does not spend time in restaurants, some of these consumers still visit restaurants.

5 Main Results

In this section, we examine the causal relationship between store location value and customer traffic and revenues, leveraging escalator closures as exogenous interventions. While our earlier analysis showed a strong correlation between location quality and store traffic, establishing causality is difficult due to the non-random nature of consumer choice and confounding factors like brand value. Since store location may be endogenous and correlated with brand value, the previous correlations could be spurious, making it essential to separate the effects of brand value from locational advantage.

To address this, we use escalator closures as a natural experiment. These disruptions reduce accessibility to previously prime locations, affecting consumer pathways and store performance, particularly for nearby stores. By analyzing traffic patterns during these periods, we aim to isolate the causal effect of location quality on consumer behavior and store performance.

5.1 Identifying Variation: Detection of Closed Escalators

For our analysis, identifying variations arising from escalator closures is critical. Since we do not have access to the escalator maintenance schedule, we directly infer maintenance episodes from the data. Our assumption is that during maintenance, traffic levels will be below historical averages. However, the absence of traffic in our AI sensor footage does not conclusively indicate escalator closure; it could also be due to sensor malfunction. Hence, we exercise caution and implement a heuristic anomaly detection approach. Specifically, we cross-verify foot traffic data from multiple sensors along the escalator's route. For instance, if both the entry sensor on 1F

Table 8: Heuristic Anomaly Detection

Step	Description
1	Define m_{jt} as maintenance of escalator j at t;
2	For all j: Compute average past hourly traffic $\overline{y}_j$;
	- FOR each escalator, compute average past hourly traffic $\overline{y}_j(t)$ for period t.
	- Only consider escalators with $\overline{y}_j(t) > N$. This step is to focus on popular escalators.
3	For all j, t such that $\overline{y}_j > N$:
	- IF current traffic $y_{jt} < k \cdot \overline{y}_j$ or $y_{jt} < n$ for both ends (entry and exit), mark escalator as closed ($m_{jt} \leftarrow 1$). This indicates that if only one area (either entry or exit) shows reduced traffic, it might be due to sensor malfunction rather than an escalator breakdown.
	- Else $m_{jt} \leftarrow 0$.
	- This criteria considers escalators with significantly lower than average or minimal traffic at both ends as undergoing maintenance.
4	IF at t there are more closed zones than M, remove t from the analysis.
	- This step removes some of the holidays by considering abnormal closures.
5	IF competing escalator traffic y_{-jt} did not increase by C, then $m_{jt} \leftarrow 0$.
	- For our tuning parameters, this keeps $0 - 2$ candidate episodes per mall.
	- This ensures only escalators with unaffected competing zones are considered.

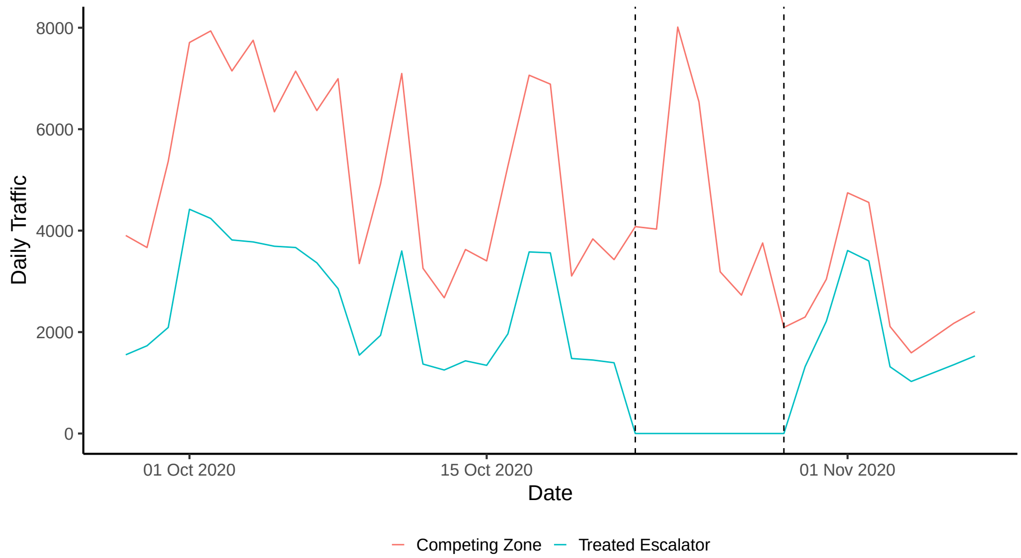
and the exit sensor on 2F show no traffic simultaneously, it is more likely the escalator is closed than both sensors malfunctioning at the same time. This cross-verification should improve the reliability of our detection method.

We also examine changes in traffic for "competing" escalators, those serving the same purpose, as one escalator undergoes maintenance. For example, if an escalator connecting floors 1F and 2F is under maintenance, we expect a sudden increase in traffic for all other escalators connecting the same floors. Candidate episodes violating this logic are removed. To avoid potential confounding effects, we remove data from the Covid-19 lockdown period in China (January 24 to August 1, 2020). This approach allows us to identify an average of one maintenance episode per mall, including episodes of varying duration.[12] Full details of the heuristic detection method are provided in Table 8.

Figure 2 illustrates an example of escalator maintenance episodes, displaying the daily traffic of an escalator from 1F to 2F during the maintenance period and control period before and after maintenance. The graph depicts a sharp decline in traffic to essentially zero over the course of a week, indicating the occurrence of maintenance. Concurrently, traffic to competing escalators increases, reflecting the diversion of foot traffic due to the closure. This escalator maintenance episode serves as our primary source of experimental variation.

[12] We do not filter out candidate episodes based on maintenance duration, as advised by industry experts. For instance, replacement of the NYC or Washington DC subway escalators is a notoriously lengthy process https://www.wmata.com/service/elevators-escalators/outage-types.cfm.

Figure 2: Example of Escalator on Maintenance



5.2 Estimating Value of Location

Our estimation design is captured in Equation (1). In this regression equation, y_{it} represents one of the traffic metrics at hourly frequence for store i at time t. These metrics include proportions of total mall store visits, time in store, first visits, and passbys. δ_i denotes store-weekday fixed effects, δ_t denotes time fixed effects. The variable "treated$_{it}$" serves as the treatment indicator, equal to 1 if the selected escalator is under maintenance.[13] The variable "dist$_i$" represents the path distance from store i to the treated escalator, derived from the store-escalator network constructed using a digitized mall map (see Appendix A3 for a detailed description of how we calculate distances between locations). We expect that the treatment effect will vary by distance from the escalator, with some stores getting positive spillovers during maintenance as consumer switch to alternative escalators. The treatment effect is mainly identified through temporal variation: comparing the traffic to the same store outside and during maintenance.[14]

$$y_{it} = \delta_i + \delta_t + \beta \cdot \text{treated}_{it} + \gamma \cdot \text{treated}_{it} \cdot \text{dist}_i + \varepsilon_{it} \tag{1}$$

Our main results for traffic, visits, and first visits are summarized in Table 9.[15] First, in

[13] We never observe more than one escalator under maintenance at the same time, which allows us to omit the escalator-specific subscript.

[14] Our key identifying assumption is that the escalator maintenance is mean independent of other events happening in the mall that could affect traffic to the affected stores.

[15] In the Appendix A5, we present estimates for alternative traffic metrics.

Table 9: Escalator Maintenance and Traffic: Main Results

	Passerby's Mall %			Visits Mall %			First Visits Mall %		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated	-0.11***	-0.13***	–	-0.10***	-0.11***	–	-0.09*	-0.10**	–
	(0.04)	(0.04)	–	(0.05)	(0.04)	–	(0.05)	(0.05)	–
treated*Dist	–	0.02***	–	–	0.02***	–	–	0.02***	–
	–	(0.00)	–	–	(0.00)	–	–	(0.00)	–
treated*{Dist = 0}	–	–	-0.17*	–	–	-0.16**	–	–	-0.14*
	–	–	(0.09)	–	–	(0.06)	–	–	(0.08)
treated*{Dist = 1}	–	–	-0.14**	–	–	-0.13*	–	–	-0.12
	–	–	(0.07)	–	–	(0.08)	–	–	(0.10)
treated*{Dist = 2}	–	–	-0.09	–	–	-0.07	–	–	-0.10
	–	–	(0.07)	–	–	(0.08)	–	–	(0.11)
treated*{Dist = 3}	–	–	-0.04	–	–	-0.04	–	–	-0.01
	–	–	(0.08)	–	–	(0.12)	–	–	(0.14)
treated*{Dist = 4}	–	–	-0.03	–	–	-0.01	–	–	-0.01
	–	–	(0.05)	–	–	(0.08)	–	–	(0.06)
treated*{Dist = 5}	–	–	-0.06	–	–	0.00	–	–	0.01
	–	–	(0.07)	–	–	(0.03)	–	–	(0.02)
treated*{Dist = 6}	–	–	0.03	–	–	0.01	–	–	0.03
	–	–	(0.04)	–	–	(0.04)	–	–	(0.04)
treated*{Dist = 7}	–	–	0.11***	–	–	0.10***	–	–	0.13***
	–	–	(0.03)	–	–	(0.03)	–	–	(0.03)
treated*{Dist ≥ 8}	–	–	0.10***	–	–	0.09***	–	–	0.08***
	–	–	(0.02)	–	–	(0.02)	–	–	(0.02)
Treated Stores	28	132	132	28	132	132	28	132	132
R-squared Adj.	0.642	0.747	0.748	0.5438	0.810	0.810	0.4645	0.810	0.824
No. Observations	9,072	43,092	43,092	9,072	43,092	43,092	9,072	43,092	43,092

Note: Clustered standard errors in parentheses. The data includes hourly store traffic for prime shopping period (13-20). We include 14 days before and after the maintenance episode as control periods. Results are based on maintenance of 1 escalator from 1F to 2F for 1 week. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$.

column (1), (4), (7) we estimate the baseline binary treatment model by only including stores that are near the escalator under maintenance in the treatment period. We find a significant decline in visits and traffic of 0.10% and 0.11%, respectively, as measured in percent of total mall visits and traffic. These effects are sizeable, given that there are about 250 stores in the mall and a typical store gets about 0.63% of mall traffic, our findings imply a decrease in visit share of 15.8% and a similar impact on traffic.

Second, we include all stores on the treated floor in all periods and allow the treatment effect to vary by distance: linearly in columns (2), (5), (8), and non-parametrically in columns (3), (6), (9). In the linear models, specified in columns (2) and (5), we quantify the treatment effect. We observe a negative impact on store visits (0.11%) and traffic (0.13%), measured as a percentage of total mall visits and traffic respectively, due to the escalator maintenance. Moreover, this negative effect diminishes with increasing distance from the treated escalator. This attenuation is demonstrated by a positive interaction between the treatment and distance, with increases of 0.02% for visits and traffic. These results suggest that while stores in close proximity to the non-operational escalator suffer significant traffic losses, the impact decreases for stores located further away.

To explore variations in the treatment effect across different distances, we employ a non-parametric approach by assuming that the treatment effect is specific to each distance band in columns (3), (6), (9). Our path distance metric is such that a score of 9 represents the distance between the treated escalator and the closest alternative on the same floor. We find that the treatment effect tends to decrease with each distance band, indicating that the negative impact of the escalator maintenance diminishes as the distance from the escalator increases. Furthermore, for distance bands beyond 5, the maintenance results in positive spillovers to more distant stores. Notably, stores in distance bands 7 and above experience significant positive spillovers, likely due to consumers rerouting to alternative escalators,[16] thereby increasing foot traffic and visits near those alternatives.[17] This type of redistribution effect is related to cross-media spillovers documented in advertising, where offline exposures trigger immediate reallocations of consumer attention online (Du et al., 2019).

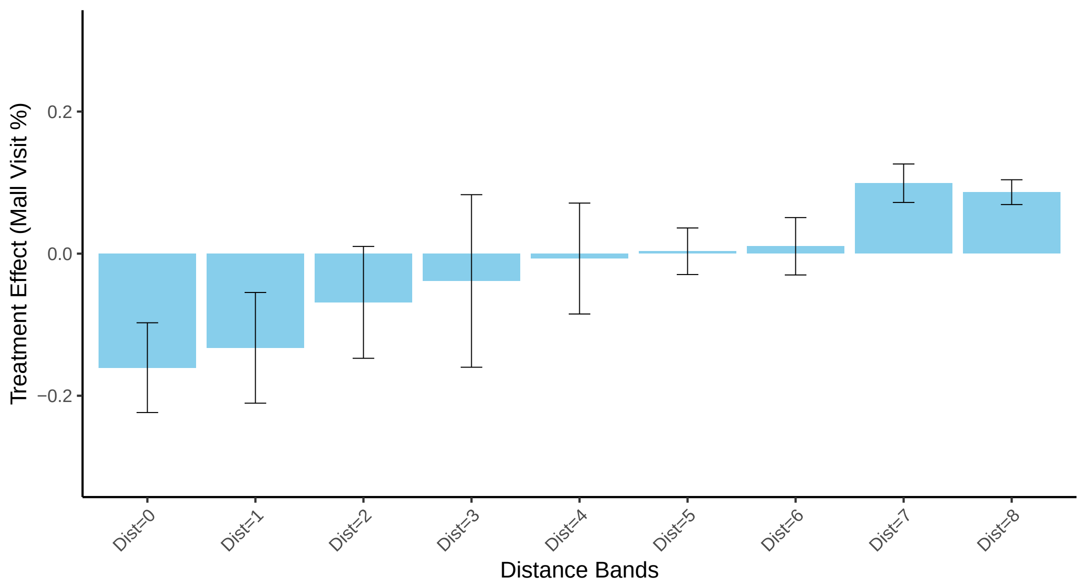
Figure 3 illustrates the heterogeneity of treatment effect across distance bands graphically. One could interpret this graph as empirical support for the location preference assumptions in the well-known Hotelling line. Escalator maintenance affects consumer paths within the mall in such a way that the shortest distance to stores near the affected escalator increases from certain mall entrances. For stores located further from the affected escalator, the change in effective distances is less pronounced. This variation prompts many consumers to avoid stores with increased travel costs due to the maintenance, opting instead for stores that are more accessible during this period.

While we find robust and significant impacts on consumer traffic, we do not find statistically significant effects on sales. This null result likely reflects measurement challenges: store sales data is self-reported at varying frequencies (weekly or monthly), unlike our daily, sensor-based traffic data. Additionally, short-term sales effects may be attenuated if consumers with strong purchase intent simply delay their purchases. Thus, we primarily rely on traffic metrics as a

[16] In Figure 9 of Appendix A3 we show that a typical mall in our data has a circular structure. In that case, being further away from one escalator is equivalent to being closer to an alternative one.

[17] The lack of significant treatment effects for distance bands 3 through 6 can be attributed to a balance of negative and positive impacts. Near the treated escalator, the negative effect is pronounced due to direct disruption. However, as the distance increases, this negative impact is offset by positive spillovers, resulting in a net effect of zero in these intermediate bands.

Figure 3: Value of Location: Treatment Effect by Distance Band



more precise indicator of consumer behavior.

Discussion

Given an average store visit share of 0.0063, our findings indicate a 15.8% (0.001/0.0063) reduction in store visit share resulting due to the nearby escalator closure. Back of the envelope calculation of the dollar value of this effect, disregarding selection biases, suggests a potential annual loss of approximately $31,912 per year ($\Delta$Visit Share $\times$ Mall Visits $\times$ Sales/Visitor $=$ $0.001 \times 15000 \times \$4.92 \times 365 = \$31,912/year$).[18]

We consider this number to be an upper bound on the true effect, as consumers with a higher purchase intent are more likely to visit the store even if the escalator is under maintenance. This implies that lost consumers are less valuable to the store than an average visitor. In the Appendix Table A5, we show that time per visit for those who reach treated store is significantly higher, reinforcing our assertion that the above estimate is an upper bound on the location effect, likely overstating the true economic effect. We also caution that this estimate should be interpreted as reflecting the short-term impact of the store's location. A prime location, if maintained over an extended period, may enhance brand visibility, thereby increasing the store's appeal

[18] Where we assumed that Sales/Visitor is equal to the average Sales/Visitor across all reported in Table 3 under the recent RMB to USD exchange rate set to 0.14.

and attracting more future consumers. However, our current analysis does not capture these potential long-term benefits associated with a prime location.

We also tried estimating the treatment effect on sales but with little success. First, not all stores report their sales to the mall owner. Second the reporting frequencies vary store to store as some stores report daily sales while other stores report sales only on the last day of each month. We estimate a regression (1) using weekly log sales as the dependent variable (y) , based on the subset of stores that consistently report sales. In the Appendix Table 16, we find that sales of treated stores went down by 7.4% on average but the effect is insignificant. This roughly supports the back of the envelope calculation drawn above.

Robustness: Consumer-Level Evidence

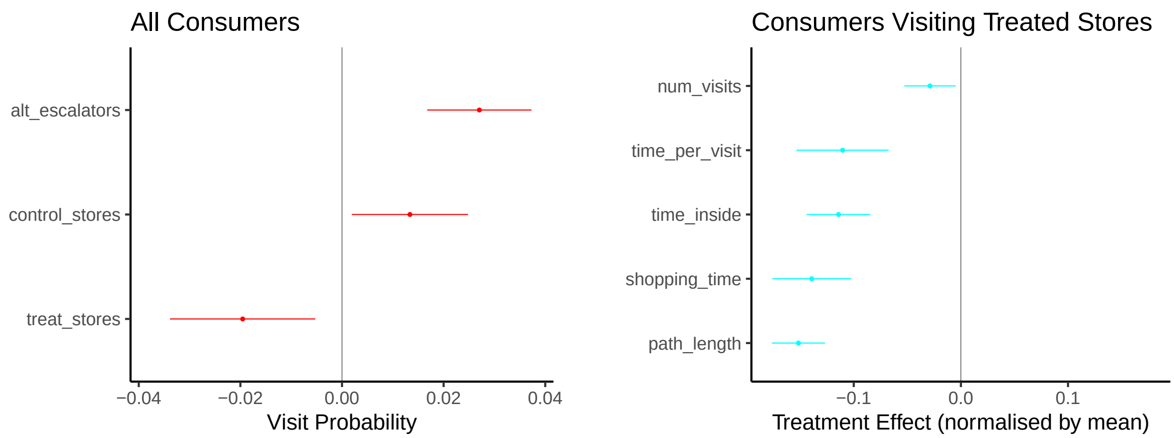
To verify the robustness of these results, we conduct the analysis using consumer-level data instead of aggregated store-level metrics. Figure 4 presents clear evidence of shifts in consumer behavior triggered by escalator maintenance. The left panel shows a decline in visit probability to stores near the malfunctioning escalator by 0.0198, while alternative paths involving other escalators and stores near these alternative escalators, which we defined as control, see an increase in visit probability. The right panel examines changes in broader shopping behavior, comparing consumers who typically visit the affected area during normal periods versus during maintenance periods. We find that these consumers spend approximately 10% less time in the mall and visit fewer stores when the escalator is closed, reinforcing our interpretation that increased travel costs deter exploratory shopping behavior. These consumer-level findings provide strong additional support for our main conclusions regarding the causal effect of location quality.

5.3 Heterogeneity in Location Value

Earlier we have identified that consumers differ significantly in their shopping behavior. In this subsection, we use individual consumer paths to understand if certain consumer types were more affected by the escalator disruption. We then use our findings and show that the share of impulsive consumers explains variation in location value beyond proxies of brand value, such as store popularity or size.

Our estimation design for path-level data is summarized in Equation (2). It is a simple fixed effects regression with heterogeneous treatment effects, which can vary with consumer cluster, denoted by $g(j)$. In this model, y_{jt} represents one of the metrics computed from the

Figure 4: Consumer-level Treatment Effect



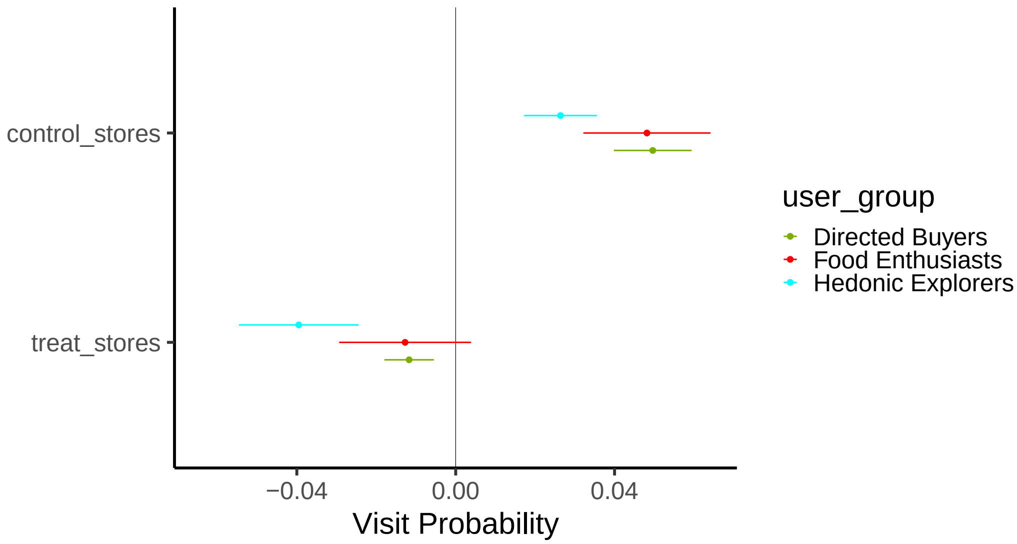
path of consumer j at time t. The variable $g(j)$ denotes the cluster group of the consumer as estimated in Section 3. Since we are unable to match consumers across different days, we treat each consumer*day as independent observation.[19] To ensure that clustering assignment was done during normal shopping periods, we exclude the treatment period (i.e., when the escalator is under maintenance) when we estimate the clustering model. Since we are interested in treatment effects conditional on unobserved consumer cluster, it is crucial that maintenance does not change consumer's cluster. For instance, if the same consumer is assigned to *Directed Buyer* pre-treatment but during treatment is assigned to *Hedonic Explorer*, then we cannot interpret our estimates as the treatment effect on a specific cluster. However, if the treatment is not strong enough to change the estimated consumer cluster, then this would not be a concern. In the Appendix A2.2, we show that the shares of identified clusters do not change significantly during the treatment period, which leads us to believe that it is safe to assume that clusters do not change with the treatment.

$$y_{jt} = \alpha_t + \beta_{g(j)} \cdot \text{treated}_{jt} + \varepsilon_{jt} \tag{2}$$

In Figure 5, we examine the treatment effects conditional on consumer clusters by estimating a regression (3) where the outcome variable (y) is the probability of visiting any store in the treatment or control areas. The results show significant heterogeneity in how different types

[19] The AI system does not maintain persistent customer identifiers across multiple days. While consumers can be tracked accurately during a single visit, including brief exits and re-entries on the same day, they are treated as new visitors if they return on a different day. This is because the system retains a moving window of a fixed number of recent visitor IDs and discards older ones as new consumers enter. As a result, we are unable to match individual consumers across different days.

Figure 5: Consumer-level Treatment Effect by Cluster



of consumers respond to escalator maintenance. We find that both *Hedonic Explorers* and *Directed Buyers* are significantly less likely to visit treated stores during maintenance periods, while *Food Enthusiasts* are largely unaffected. Although all three groups increase visits to control stores, suggesting a general shift toward alternative paths, the reduction in visits is most pronounced among *Hedonic Explorers*. The difference in treatment effects between *Hedonic Explorers* and *Directed Buyers* is itself statistically significant, underscoring the heightened sensitivity of impulsive shoppers to changes in accessibility. In contrast, the more goal-directed nature of *Directed Buyers* and *Food Enthusiasts* makes them less likely to deviate from their planned destinations when faced with travel disruptions.

This suggests that store's share of *Hedonic Explorers* could be an important predictor of location value, as different stores may derive varied benefits from the same location due to their vulnerability to changes in location quality. Because these consumers are especially sensitive to accessibility, stores that disproportionately attract them are more vulnerable to disruptions in location quality, such as escalator maintenance.[20] We test this using the following regression, which expands our earlier estimation design by allowing the treatment effect to vary based on

[20] Analogously, policy shocks in retail categories, such as the removal of menthol cigarettes from store shelves, have been shown to significantly reshape consumer purchase patterns (Goli et al., 2024).

characteristics (X_i) such as store rank, store size, and the share of *Hedonic Explorers*[21]:

$$y_{it} = \delta_i + \delta_t + \beta \cdot \text{treated}_{it} + \gamma \cdot \text{treated}_{it} \cdot \text{Dist}_i + \eta \cdot \text{treated}_{it} \cdot X_i + \varepsilon_{it} \quad (3)$$

One might expect that stores with high brand value would be less affected by changes in location quality, under the assumption that brand-loyal consumers are more likely to seek them out regardless of accessibility. However, this is not necessarily the case. If well-known brands also attract a disproportionate share of impulse shoppers, who are especially sensitive to location frictions, these stores may in fact be more susceptible to location-related disruptions despite their brand strength. Table 10 columns (2), (5), (), we find that popular stores experience smaller treatment effects, consistent with the idea that brand appeal can mitigate the loss in foot traffic. We also find that larger stores are less affected in columns (3), (6), (9). This is expected, since larger stores are more likely to be closer to alternative escalators which receive spillover traffic or are more likely to be anchor stores which attract traffic independently of their location within a mall (Eppli and Benjamin, 1994; Vitorino, 2012). Finally, and most importantly, we find that the treatment effect becomes significantly larger as the share of *Hedonic Explorers* increases, even after controlling for other store attributes. Using the average treatment effect on Passerby's from Table 9 as a reference, a 0.1 increase in the share of *Hedonic Explorers* increases the magnitude of the treatment effect by approximately $100 * 0.1 * \frac{0.15}{0.11} = 14\%$, based on the coefficient estimate in column (1).

These findings underscore the importance for mall operators to consider the behavioral profiles of store visitors when planning mall configurations and negotiating lease agreements. In particular, stores that attract a higher share of impulsive shoppers, such as clothing and accessory boutiques (see Table 7), derive disproportionately greater value from prime locations. While brand-driven, goal-oriented consumers may still be influenced by accessibility, the impact is especially pronounced for more exploratory shoppers who are sensitive to friction in store access. Mall owners should therefore take into account the composition of a store's customer base when assessing location value. Consequently, the additional revenue generated by these stores could be captured through lease agreements that incorporate a higher percentage of sales into the rent structure. Such arrangements can support more efficient store placement and help

[21] We chose the specification which includes distance in order to have a larger sample size. If we were to only include stores right next to the escalator, our projection of the treatment effect on observables would become noisy because the number of stores remaining would be too small.

Table 10: Value of Location and Hedonic Consumers

	Passerby's Mall %			Visits Mall %			First Visits Mall %		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated	-0.02	-0.10*	0.00	0.06	-0.06	0.00	0.15	0.02	0.16
	(0.05)	(0.05)	(0.13)	(0.07)	(0.06)	(0.09)	(0.09)	(0.08)	(0.15)
treated*Dist	0.02***	0.02***	0.02	0.01***	0.01***	0.01*	0.01**	0.01**	0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
treated*store rank(0-1)		0.17***			0.27***			0.29***	
		(0.03)			(0.01)			(0.03)	
treated*100sqm			0.01*			0.04***			0.04***
			(0.00)			(0.01)			(0.00)
treated*share hedonic	-0.15*	-0.15	-0.20	-0.16	-0.16	-0.14	-0.32*	-0.32**	-0.42
	(0.07)	(0.10)	(0.18)	(0.13)	(0.11)	(0.18)	(0.15)	(0.10)	(0.26)
Treated Stores	128	72	128	128	72	128	128	72	128
No. Observations	36,576	36,576	21,024	36,576	36,576	21,024	36,576	36,576	21,024
R-squared Adj.	0.774	0.777	0.788	0.865	0.867	0.885	0.867	0.869	0.887

Note: Clustered standard errors in parentheses. The data includes hourly store traffic for prime shopping period (13-20). Regressions with store size include fewer stores since it is not observed for some of the stores. We also removed stores that had a significant change in cluster visit shares during treatment period. We include 14 days before and after the maintenance episode as control periods. Results are based on maintenance of 1 escalator from 1F to 2F for 1 week. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$.

maximize overall mall foot traffic and revenue.

6 Conclusion

This paper aims to estimate the causal effects of store location on consumer traffic and store performance, utilizing escalator closures as a natural experiment to provide a clear source of variation in location quality. This approach addresses potential endogeneity concerns from consumer visit decisions and isolates the true value of location in a retail context.

We first document that escalator closures lead to a measurable decrease in traffic to nearby stores, emphasizing the critical role of location quality, especially accessibility. The noticeable decline in consumer visits to stores closest to the non-operational escalator highlights the sensitivity of retail foot traffic to disruptions in mall accessibility. Although we do not find statistically significant effects on store sales, likely due to the coarser, weekly nature of the sales data and potential measurement noise, the reduction in foot traffic is substantial enough to suggest meaningful consequences for retail performance.

Moreover, we find significant heterogeneity in consumer responses to location disruptions. In particular, impulsive consumers such as *Hedonic Explorers* are especially sensitive to location quality, altering their shopping behavior based on proximity and accessibility, avoiding areas impacted by the escalator closure. This behavioral response highlights the distinct ways different shopper segments interact with the mall environment, shaped by their specific shopping motivations and sensitivity to travel costs.

Our analysis also reveals meaningful variation in the impact of escalator closures based on physical distance. Stores immediately adjacent to the closed escalator experience the largest declines in traffic, but this negative effect diminishes gradually with increasing distance. Indeed, stores located in more distant areas, especially those near alternative escalators, experience positive spillovers as consumers reroute their paths, inadvertently boosting visits in these areas. This pattern of impact, increasing positive interaction with distance, underscores the spatial aspect of location value within the mall. It illustrates that the treatment effect from an escalator closure is not uniformly distributed but instead decreases as the physical distance from the disruption increases, offering empirical evidence for Hotelling model.

Finally, we document variability in treatment effects based on store characteristics. Small and specialty retailers, particularly those reliant on impulsive visits, experience greater negative impacts from location disruptions compared to larger, more established brands. This finding indicates that mall operators should strategically consider store characteristics, consumer segments, and spatial layout when making leasing decisions to optimize mall-wide foot traffic and tenant performance.

Our study highlights several promising directions for future research. While we demonstrate substantial short-term impacts of location-quality changes, further research should investigate potential long-term effects on brand equity, store loyalty, and consumer learning. Additionally, our findings suggest cross-store spillover effects significantly influence optimal mall layouts and lease agreements, an important consideration for strategic mall management. Although our study does not explicitly quantify spillover effects, future work could explore how store characteristics, such as brand strength or product category, shape these spillovers and inform differentiated lease structures. For instance, premiums for prime locations could be tailored according to a store's reliance on impulsive foot traffic or sensitivity to accessibility disruptions.[22] Such an approach would provide deeper insights into strategically aligning store placement with consumer dynamics, thereby optimizing tenant and mall-wide performance.

Overall, our research underscores the critical importance of store location quality, accessibility, and consumer heterogeneity in determining retail performance. Specifically, we show that

[22] To empirically validate these implications, future research could rigorously examine actual lease contracts alongside store performance data, provided that such information is available.

small and specialty retailers, especially those targeting impulsive consumers, benefit most significantly from prime locations, emphasizing the need for mall operators to strategically differentiate lease agreements and store placements. Furthermore, understanding impulsive shoppers' characteristics and behaviors offers actionable insights for retailers aiming to maximize their appeal and capitalize on this important consumer segment. Leveraging these insights, mall operators and retailers can better optimize layouts, tailor marketing efforts, and cultivate an engaging environment that encourages exploration and unplanned purchases.

References

Armstrong, M., Vickers, J., and Zhou, J. (2009). Prominence and consumer search. *The RAND Journal of Economics*, 40(2):209–233.

Armstrong, M. and Zhou, J. (2011). Paying for prominence. *The Economic Journal*, 121(556):F368–F395.

Bell, D. R. (2014). *Location is (still) everything: The surprising influence of the real world on how we search, shop, and sell in the virtual one*. Houghton Mifflin Harcourt.

Benmelech, E., Bergman, N., Milanez, A., and Mukharlyamov, V. (2019). The agglomeration of bankruptcy. *The Review of Financial Studies*, 32(7):2541–2586.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Carter, C. (2009). Review articles: What we know about shopping centers. *Journal of Real Estate Literature*, 17(2):163–180.

Carter, C. and Vandell, K. (2005). Store location in shopping centers: Theory and estimates. *Journal of Real Estate Research*, 27(3):237–266.

Chan, T. Y. and Park, Y.-H. (2015). Consumer search activities and the value of ad positions in sponsored search advertising. *Marketing Science*, 34(4):606–623.

Chen, Y., Cui, X., Li, A., Wu, B., and Yang, L. (2024). The value of sharing market data through data analytics on digital platforms: Empower small businesses on alibaba's taobao marketplace. *Available at SSRN 4878048*.

Chiang, M. and Mirkin, B. (2010). Intelligent choice of the number of clusters in k-means clustering: An experimental study with different cluster spreads. *Journal of Classification*, 27(1):3–40.

Chiou, L. and E. Tucker, C. (2022). How do restrictions on advertising affect consumer search? *Management Science*, 68(2):866–882.

Du, R. Y., Xu, L., and Wilbur, K. C. (2019). Immediate responses of online brand search and price search to tv ads. *Journal of Marketing*, 83(4):81–100.

Eppli, M. and Benjamin, J. (1994). The evolution of shopping center research: a review and analysis. *Journal of Real Estate Research*, 9(1):5–32.

Faber, B. (2014). Trade integration, market size, and industrialization: evidence from china's national trunk highway system. *Review of Economic Studies*, 81(3):1046–1070.

Florida, R. and Adler, P. (2022). Locational strategy: Understanding location in economic geography and corporate strategy. *Global Strategy Journal*, 12(3):472–487.

Gatzlaff, D., Sirmans, S., and Diskin, B. (1994). The effect of anchor tenant loss on shopping center rents. *Journal of Real Estate Research*, 9(1):99–110.

Gerdeman, D. (2012). *Location, Location, Location: The Strategy of Place*. Harvard Business School Working Knowledge.

Ghose, A., Li, B., and Liu, S. (2019). Mobile targeting using customer trajectory patterns. *Management Science*, 65(11):5027–5049.

Goldfarb, A., Tucker, C., and Wang, Y. (2022). Conducting research in marketing with quasi-experiments. *Journal of Marketing*, 86(3):1–20.

Goli, A., Lambrecht, A., and Yoganarasimhan, H. (2023). A bias correction approach for interference in ranking experiments. *Marketing Science*.

Goli, A., Mummalaneni, S., and Chintagunta, P. (2024). Making a smooth exit? menthol bans and cigarette sales in massachusetts. *Marketing Science*, 43(3):564–589.

Hui, S. K., Fader, P. S., and Bradlow, E. T. (2009a). Path data in marketing: An integrative framework and prospectus for model building. *Marketing Science*, 28(2):320–335.

Hui, S. K., Fader, P. S., and Bradlow, E. T. (2009b). Research note—the traveling salesman goes shopping: The systematic deviations of grocery paths from tsp optimality. *Marketing science*, 28(3):566–572.

Joo, M., Chae, I., and Kim, A. J. (2023). Geotargeted mobile advertising for small businesses. *working paper*.

Joo, M., Shi, J., and Abhishek, V. (2024). Do sellers benefit from sponsored product listings? evidence from an online marketplace. *Marketing Science*, 43(4):817–839.

Ke, T. T., Shin, J., and Yu, J. (2022). A model of product portfolio design: Guiding consumer search through brand positioning. *Marketing Science*.

Knight, S. (2022). Retail demand interdependence and chain store closures. *working paper*.

Koster, H. R., Pasidis, I., and van Ommeren, J. (2019). Shopping externalities and retail concentration: Evidence from dutch shopping streets. *Journal of Urban Economics*.

Kumar, V., Anand, A., and Song, H. (2017). Future of retailer profitability: An organizing framework. *Journal of Retailing*, 93(1):96–119.

Leonardi, M. and Moretti, E. (2022). The agglomeration of urban amenities: Evidence from milan restaurants. *Social Science Research Network*.

Lu, S. and Yang, S. (2017). Investigating the spillover effect of keyword market entry in sponsored search advertising. *Marketing Science*, 36(6):976–998.

Lu, S., Yang, S., and Yao, Y. (2025). Within-category satiation and cross-category spillover in multiproduct advertising. *Journal of Marketing*, 89(2):119–140.

Martini, M., Paolanti, M., and Frontoni, E. (2020). Open-world person re-identification with rgbd camera in top-view configuration for retail applications. *IEEE Access*, 8:67756–67765.

Mayzlin, D. and Shin, J. (2011). Uninformative advertising as an invitation to search. *Marketing Science*, 30(4):666–685.

Miyauchi, Y., Nakajima, K., and Redding, S. J. (2021). The economics of spatial mobility: Theory and evidence using smartphone data. *National Bureau of Economic Research*.

Moe, W. W. (2003). Buying, searching, or browsing: Differentiating between online shoppers using in-store navigational clickstream. *Journal of consumer psychology*, 13(1-2):29–39.

Nakajima, K., Nakajima, K., and Teshima, K. (2018). Identifying neighborhood effects among firms: Evidence from location lotteries of the tokyo tsukiji fish market. *null*.

Narang, U. and Luco, F. (2024). Geo-tracking consumers and its privacy trade-offs. *working paper*.

Netzell, O. (2013). The effect of accessibility on retail rents: testing integration value as a measure of geographic location. *Journal of Property Research*, 30(1):1–23.

Oh, R. and Seo, J. (2023). What causes agglomeration of services? theory and evidence from seoul. *Working Paper*.

Redding, S. J. and Daniel, D. M. (2016). Estimating neighborhood effects: evidence from wartime destruction in london. Technical report.

Seiler, S., , and Pinna, F. (2017). Estimating search benefits from path-tracking data: Measurement and determinants. *Marketing Science*.

Shin, J. and Yu, J. (2021). Targeted advertising and consumer inference. *Marketing Science*, 40(5):900–922.

Shin, M., Shin, J., Ghili, S., and Kim, J. (2023). The impact of the gig economy on product quality through the labor market: Evidence from ridesharing and restaurant quality. *Management Science*, 69(5):2620–2638.

Shoag, D. and Veuger, S. (2018). Shops and the city: Evidence on local externalities and local government policy from big-box bankruptcies. *Review of Economics and Statistics*, 100(3):440–453.

Sim, J., Cho, D., Hwang, Y., and Telang, R. (2022). Frontiers: virus shook the streaming star: estimating the covid-19 impact on music consumption. *Marketing Science*, 41(1):19–32.

Simonov, A., Sacher, S., Dubé, J.-P., and Biswas, S. (2022). Frontiers: the persuasive effect of fox news: noncompliance with social distancing during the covid-19 pandemic. *Marketing Science*, 41(2):230–242.

Sirmans, C. and Guidry, K. (1993). The determinants of shopping center rents. *Journal of Real Estate Research*, 8(1):107–115.

Ursu, R. M. (2018). The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions. *Marketing Science*, 37(4):530–552.

Vitorino, M. A. (2012). Empirical entry games with complementarities: An application to the shopping center industry. *Journal of Marketing Research*.

Wang, T., He, C., Jin, F., and Hu, Y. J. (2021). Evaluating the effectiveness of marketing campaigns for malls using a novel interpretable machine learning model. *Information Systems Research*.

Zhang, S., Lee, D., Singh, P., and Mukhopadhyay, T. (2022). Demand interactions in sharing economies: Evidence from a natural experiment involving airbnb and uber/lyft. *Journal of Marketing Research*, 59(2):374–391.

Zhou, J. (2011). Ordered search in differentiated markets. *International Journal of Industrial Organization*, 29(2):253–262.

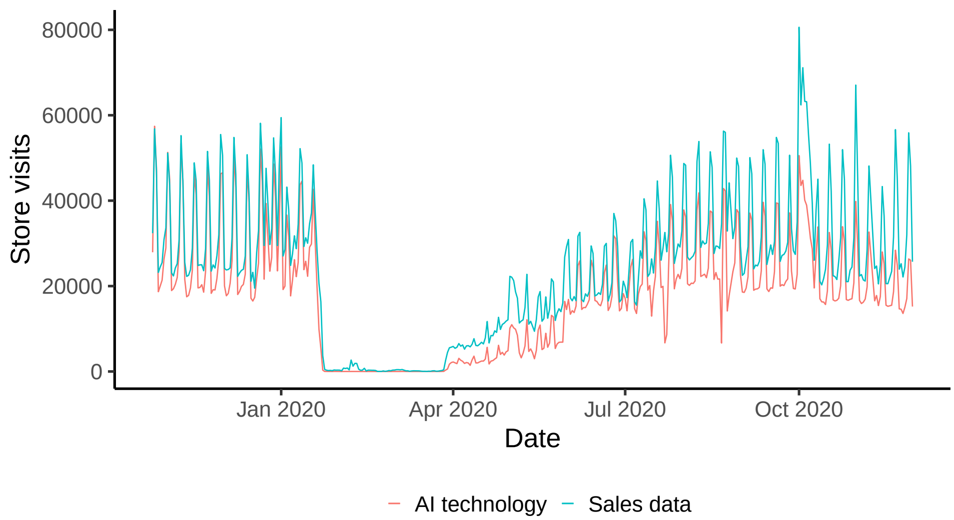
Appendix

A1 Supplementary Descriptives

A1.1 Comparing AI technology and self-reported data

Here we assess how traffic captured by the AI technology compares with the self-reported traffic from sales data. In Table 4 we report correlations between metrics from self-reported data and the AI technology. We find that metrics from AI technology are highly correlated with both visits and sales from the self reported data. In Figure 6, we assess how those two sources of traffic data compare for a specific mall. As can be seen, the AI traffic data tends to show lower values on average compared to the self-reported data. This is expected given that (a) the technology can miss some consumers; (b) we removed a large share of users from the AI data if their path was imperfectly tracked (for main analysis, at worst every 15 minutes). On average, this filtering eliminates approximately 40% of the consumers. One can also notice that there was a slight deterioration in performance after Covid-19, which could be due to an increase in the use of masks. In general, we observe that the AI-technology does a good job at capturing periods of peak demand. We conclude that the evidence above suggests that the sensor technology works reasonable well in capturing the dynamics of mall visits.

Figure 6: Traffic from Sales and AI data for Mall 3



A1.2 Effects of Covid on Category Mix

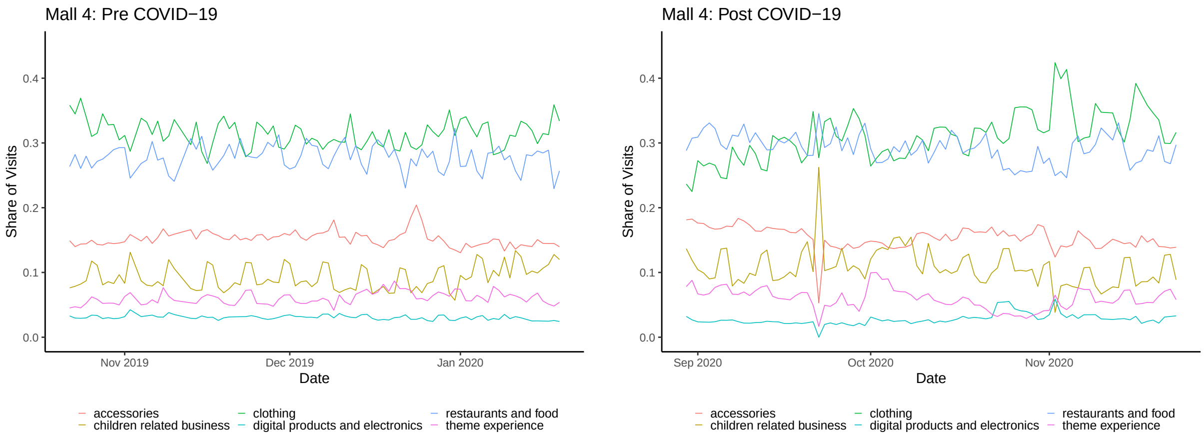


Figure 7: Share of Visits to Store Categories before/after Covid-19

A1.3 Persistence in Category Mix

The next table demonstrates the persistence in consumer preferences for store visit patterns.

Table 11: Conditional Distribution of Second Visits

First Visit To	Clothing	Large-scale Retail	Restaurants	Boutique	Children Stores	Theme Experience
Clothing	0.27	0.04	0.02	0.04	0.01	0.04
Large-scale Retail	0.11	0.36	0.11	0.14	0.20	0.08
Restaurants	0.15	0.20	0.51	0.18	0.16	0.40
Boutique	0.20	0.20	0.17	0.45	0.13	0.18
Children Stores	0.00	0.06	0.02	0.02	0.35	0.01
Theme Experience	0.02	0.01	0.02	0.02	0.01	0.10

A1.4 Descriptive Evidence of Location Value: Visits, Passerbys, Sales per Sqm

Table 12: Descriptive Evidence of Location Value: Additional Metrics

	Mall 4			All Malls		
	Visits Mall %	Passerby's Mall %	Sales per Sq	Visits Mall %	Passerby's Mall %	Sales per Sq
Floor 2	-0.217	-0.166**	-226.611**	0.028	-0.025	-414.797**
	(0.157)	(0.083)	(102.409)	(0.099)	(0.111)	(168.579)
Floor 3	-0.041	-0.139*	-154.940	-0.071	-0.174	-691.294***
	(0.176)	(0.083)	(120.610)	(0.139)	(0.113)	(169.841)
Western Brand	0.257	0.052	23.311	–	–	–
	(0.171)	(0.082)	(109.407)	–	–	–
Store 100sqm	0.098***	0.022	-52.793	0.055	0.077***	-54.721*
	(0.021)	(0.019)	(32.479)	(0.071)	(0.023)	(28.106)
Next to Esc	0.414***	0.262***	-45.226	0.128	0.316***	-72.926
	(0.107)	(0.061)	(86.046)	(0.094)	(0.071)	(104.679)
Next to Esc*Store 100sqm	-0.071***	-0.013	46.580	-0.135***	-0.058***	12.598
	(0.025)	(0.020)	(32.582)	(0.039)	(0.013)	(17.657)
R-squared Adj.	0.184	0.167	0.061	0.871	0.758	0.675
No. Observations	2,017	2,017	2,011	6,706	6,706	6,670
Brand FE	No	No	No	Yes	Yes	Yes

Note: Store clustered standard errors in parentheses. We use the data from Oct 2019 to Jan 2020 for all malls in our data, aggregated at a weekly level excluding the food court and the underground floor. We multiple share of mall metrics by 100 to convert them to %. Brand FE are constructed based on store name. .* represents $p < 0.1$, ** represents $p < 0.05$, and *** represents: $p < 0.01$.

A1.5 Food Court Spillover Effects

Here we compare visit probabilities of third floor stores for consumers that visited food court (on fourth floor) and those that did not. We find that food court visitors are significantly more likely to also shop in stores on the third floor suggesting a food court spillover effect on nearby stores. Note that this effect decays with distance, as the same effect does hold for second floor stores.

Table 13: Suggestive Evidence of Food Court Spillover on Nearby Floor

Metrics from Sales Data	Food Court	Others
$\mathbb{P}$[Visited store on 3F|Type]	0.252	0.184
$\mathbb{P}$[Visited store on 2F|Type]	0.167	0.171

A2 Clustering Results

A2.1 Alternative Clustering Algorithms

In this section, we assess how the results of our clustering change qualitatively when we use other algorithms. First, we re-run a K-means with a different number of clusters ($k = 4$). In Table 14 we describe the recovered clusters. We find that the first three clusters are similar in observables to the ones we have identified in the manuscript. We assign them the previously defined labels: *Hedonic Explorers Directed Buyers*, *Hedonic Explorers*, and *Food Enthusiasts.* The final cluster includes only 3% of consumers that seem to primarily visit entertainment areas, such as the cinema. Thus, we do not think that expanding the number of clusters in our main analysis would add much value.

Table 14: K-means clustering with $k = 4$

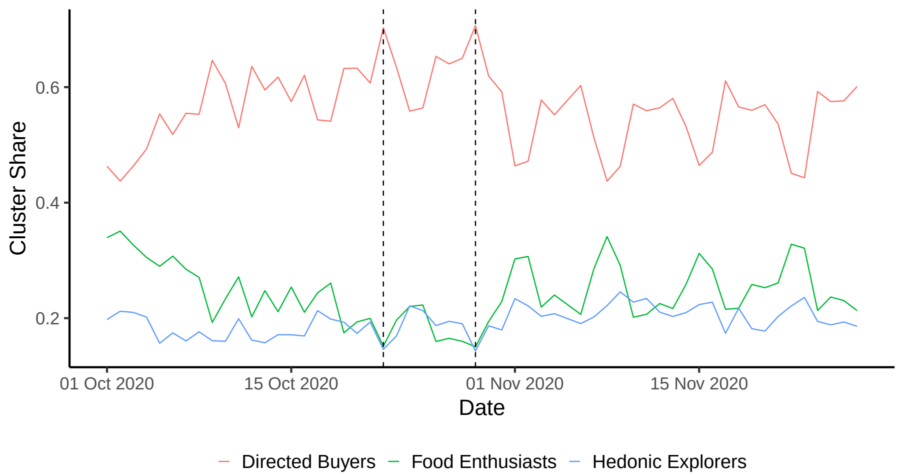
Behavior Characteristics	Hedonic Explorers	Directed Buyers	Food Enthusiasts	Cluster 4
Mean Shopping Visit Time	4.52	5.35	4.57	3.93
Median Shopping Visit Time	3.20	5.12	4.13	3.48
Shopping Visits	7.00	2.00	2.00	2.00
Activity Visits	1.00	0.00	3.00	3.00
Time Inside	93.92	44.97	136.44	200.98
Time in Restaurants	0.00	0.00	64.35	7.00
Time in Entertainment	0.00	0.00	0.00	123.55
Time in Services[23]	0.00	0.00	0.00	0.00
Unique Places per Minute Walking	1.29	1.14	1.01	1.19
Visits per Hour Walking	14.44	7.86	8.65	10.24
Unique Store Categories Visited	3.00	1.00	1.00	1.00
Unique Store Categories Passed-by	8.00	4.00	6.00	7.00
Max Passerby's of Same Zone	2.00	2.00	2.00	2.00
Elevators Used	1.00	0.00	1.00	1.00
Escalators Used	5.00	2.00	6.00	5.00
Share	0.19	0.51	0.25	0.03

*This table reports behavior characteristics for a median consumer within the cluster; Time is reported in minutes

A2.2 Cluster Shares over Time

One concern with our analysis was that the treatment was so disruptive that it potentially switched clusters of certain clusters causing bias in our cluster-level treatment effects. In Figure 8, we show that the shares of recovered clusters were unaffected by the treatment which supports the validity of our estimates.

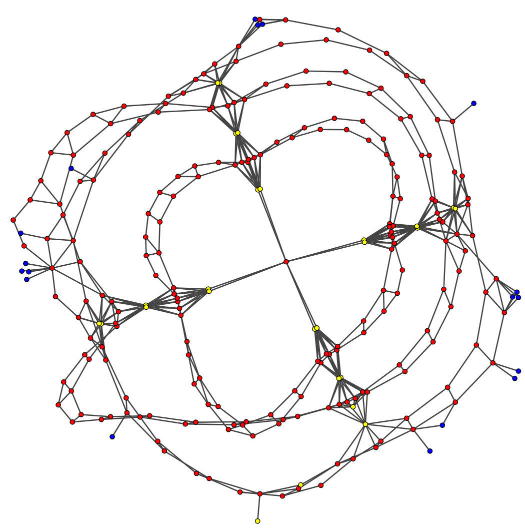
Figure 8: Share of Shopper Types over Time in Treated Mall



A3 Data Processing

Measuring Distances Within a Mall

Figure 9: Example Mall Map



In Figure 9, we present a network representation of 3 floors and a food court, from an example mall. The network is constructed by considering neighboring stores as connected nodes. Stores are depicted in red, exits in blue, and escalators in yellow. We use network representations of malls to compute a proxy for physical distance between locations using path distance. As can be seen, the mall has a circular layout that is a typical characteristic of the malls of our data provider. Although technically there are narrow walkways that allow consumers to travel from non-neighboring stores in the mall, such routes are uncommon, and we exclude them from the analysis. Food-court is placed on the highest floor of the mall and serves as an anchor area that stimulates consumers to traverse the entire mall in order to reach it. Parking is not displayed on this map but it is located underground.

Our definition of distance is based on the path distance in the network representation. For any pair of stores (i, j), $\text{dist}(i, j) \equiv |P(i, j)|$, where $P(i, j)$ is the shortest path between i, j in the mall network. If the path involves escalators, we add additional 5 units of distance since the average time it takes to travel on an escalator is approximately equal to the average walking time for a path of length 5. Elevator use to change floors is less common in our sample: 65% of consumers use escalators and only 35% travel by elevator. For simplicity, we do not incorporate elevators in the distance calculation.

A4 Heuristic Detection of Closed Escalators

Since we were not provided with the specific escalator maintenance schedule, we developed a rule-based anomaly detection technique to infer escalator maintenance episodes directly from the traffic data.

Our approach involved searching for episodes that satisfied the following criteria: Hourly escalator traffic fell below a threshold value K and was also lower than $\sigma\overline{T}i$, where $\overline{T}i$ represents the mean traffic for escalator i estimated using past and future realizations within a 21-day window. Additionally, the hour of the day was within the interval $[13, 20]$, which corresponds to normal operating hours. This interval was chosen to ensure that a zone had sufficient hourly traffic, avoiding anomalies from periods of low visitor activity during the morning hours. We excluded days with more than M zones closed in the mall, and we also excluded data from underground floors to focus on the main shopping areas. Furthermore, we removed data during the active period of Covid-19 with severe lockdowns in China (January 24, 2020, to August 1, 2020) to eliminate potential confounding effects from pandemic-related restrictions.

Following the application of our anomaly detection technique and additional manual filtering, we identified a total of 7 episodes of varying duration as escalator maintenance periods. These episodes ranged from short maintenance durations, lasting about an hour, to longer maintenance periods that spanned several days. For additional validation, we examined changes in traffic for ”competing” escalators—those serving the same purpose—as one of the escalators underwent maintenance. For example, if an escalator connecting floors 2F and 3F was under maintenance, we anticipated a sudden increase in traffic for all other escalators connecting the same floors. The results of this robustness check can be found in the appendix. Figure **??** displays the escalator traffic over time for two exemplary escalators that were identified as undergoing maintenance according to our anomaly detection algorithm.

A5 Additional Main Results

Table 15: Escalator Maintenance and Traffic: Other Traffic Metrics

	Time in Store Mall %			First Visits Among Visits %			Time p Visit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
treated	-0.08*	-0.08**	-0.06*	-3.62*	-3.70*	-4.66	1.29***	1.07***	1.50***
	(0.04)	(0.04)	(0.03)	(2.10)	(1.91)	(4.46)	(0.44)	(0.40)	(0.38)
treated*Dist	–	0.01***	–	–	0.69***	–	–	-0.05	–
	–	(0.00)	–	–	(0.19)	–	–	(0.05)	–
treated*{Dist = 0}	–	–	-0.06*	–	–	-4.66	–	–	1.50***
	–	–	(0.03)	–	–	(4.46)	–	–	(0.38)
treated*{Dist = 1}	–	–	-0.14	–	–	-4.77	–	–	0.43
	–	–	(0.10)	–	–	(3.83)	–	–	(0.96)
treated*{Dist = 2}	–	–	-0.08	–	–	-4.80	–	–	2.64***
	–	–	(0.11)	–	–	(4.43)	–	–	(0.98)
treated*{Dist = 3}	–	–	-0.04	–	–	-0.55	–	–	0.54
	–	–	(0.09)	–	–	(3.62)	–	–	(0.57)
treated*{Dist = 4}	–	–	0.00	–	–	-0.45	–	–	1.19*
	–	–	(0.05)	–	–	(3.27)	–	–	(0.64)
treated*{Dist = 5}	–	–	-0.01	–	–	-0.36	–	–	-0.14
	–	–	(0.02)	–	–	(2.90)	–	–	(0.53)
treated*{Dist = 6}	–	–	0.01	–	–	2.39	–	–	0.51
	–	–	(0.02)	–	–	(1.59)	–	–	(0.55)
treated*{Dist = 7}	–	–	0.08***	–	–	6.25***	–	–	-0.45
	–	–	(0.03)	–	–	(1.03)	–	–	(0.69)
treated*{Dist = 8}	–	–	0.08***	–	–	3.66***	–	–	0.90**
	–	–	(0.03)	–	–	(0.89)	–	–	(0.42)
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treated Stores	38	133	133	38	133	133	38	133	133
R-squared Adj.	0.323	0.698	0.698	0.160	0.130	0.131	0.213	0.216	0.217
No. Observations	9,072	43,092	43,092	9,072	43,092	43,092	9,072	43,092	43,092

Note: Clustered standard errors in parentheses. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$.

Table 16: Escalator Maintenance and Sales

	log Sales	
	(1)	(2)
treated	-0.074	-0.062
	(0.091)	(0.127)
treated*Dist	–	0.019
	–	(0.021)
Treated Stores	17	46
R-squared Adj.	0.909	0.908
No. Observations	68	184

Note: Clustered standard errors in parentheses. The data includes weeekly sales from stores that consistently report sales throughout the sample period. We exclude stores that report 0 sales for more than 3 consecutive days. * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$.