Location, Location, Experience Creation:

The Market Dynamics and Financial Impacts of Experiential Retail

A thesis presented

by

Austin B. Fields

to

Applied Mathematics

in partial fulfillment of the honors requirements

for the degree of

Bachelor of Arts

Harvard College

Cambridge, Massachusetts

April 3, 2020

Abstract

Over the past two decades, the U.S. retail sector has undergone an enormous transformation. While retail sales are increasingly moving online and traditional brick-and-mortar stores have closed on a massive scale, new "experiential retail" concepts are proliferating throughout major cities. This paper studies the effects of this transformation on real estate lease contracts. In the theoretical section, I extend the Grossman and Shapiro (1984) model of informative advertising to include experience amenities and online competition. In my model, as consumers' preferences shift to e-commerce, some brick-and-mortar retailers exit the market and the remaining firms offer more experience. Additionally, landlords' increasing rent discrimination in favor of experiential tenants causes firms to enter the market and experience creation to decline. In the empirical section, using detailed data from lease contracts executed in New York City in 2019, I analyze the effects of experience – measured by Yelp and Google Places ratings, and two self-created experiential retail rubrics – on effective rent, tenant improvement allowance, free rent, and lease term. I document that, conditional on tenant industry, landlords perceive experiential retailers as a substitute to non-experiential ones, with no statistically significant difference in effective rents. However, I also document some important differences in lease contracts: experiential retailers receive greater tenant improvement allowances and sign longer leases than non-experiential retailers. Overall, my results suggest that experience creation may play an important financial role in lease negotiations.

Acknowledgements

This paper would not have been possible without the generous support of my mentors, peers, and family. I would like to extend my sincere gratitude to my thesis advisor, Andrea Chegut, for being a tremendous source of inspiration and guidance throughout this project. I would also like to thank the economics thesis writing team, particularly Slavik Sheremirov, for all their direction and feedback. Furthermore, I am grateful to my brother, Hunter Fields, for his intellectual contributions and constructive skepticism. Lastly, I would like to thank all my real estate, economics, and mathematics teachers and mentors, who laid the foundation to make this work possible.

Contents

1 Introduction

Over the past two decades, U.S. retail has transformed enormously, as consumers continually choose online retailers over brick-and-mortar stores. Traditional stores, particularly in the apparel sector, are shutting down at record-high rates, with over 9,300 closures in 2019, a 59 percent increase from 2018.[1] Despite the abrupt rise in retail vacancies and a corresponding spike in bankruptcies – dubbed the "retail apocalypse" – a significant portion of apparel sales still occurs at brick-and-mortar establishments. To distinguish themselves from online sellers, physical stores rely more and more on "experiential retail" concepts, offering differentiated amenities that are not easily transferable to the internet. Hence, understanding the differences between experiential and traditional brick-and-mortar retail is increasingly important for real estate researchers and practitioners in today's challenging retail environment.

In this thesis, I study the factors contributing to increased attention to in-store experiences in the retail sector. I analyze the value of experiential retail from landlords' perspectives and examine evidence for rent discrimination. In particular, I address the following question: Do landlords perceive experiential retail as a substitute, benefit, or risk to non-experiential tenants? To my knowledge, this is the first paper examining the market dynamics and financial impact of experiential retail on landlord–tenant negotiations. I provide both theoretical and empirical evidence illustrating how experiential retail interacts in the marketplace.

In the theoretical section, I develop a framework to explore tenants' responses to the rise of e-commerce by extending the Grossman and Shapiro (1984) model of informative advertising to include online sellers. Following their approach, I study

[1] See more at https://www.bloomberg.com/news/articles/2019-10-14/store-closures-may-be-even-worse-next-year-credit-suisse-says and https://coresight.com/wp-content/uploads/2019/12/Weekly-US-and-UK-Store-Openings-and-Closures-Tracker-2019-Week-50-Dollar-General-Plans-To-Continue-Store-Expansion-in-Fiscal-Year-2020-Dec-13-2019.pdf.

oligopolistic and monopolistically competitive equilibria under differentiation in location and information availability. I then add two other sources of differentiation: experience amenity and resistance to online competition.

In my model, experience impacts consumer demand directly through three interconnected mechanisms. First, experience promotes brand awareness through electronic word-of-mouth – a modern form of advertising – with consumers sharing favorable experiences online via social media, thereby spurring demand. Second, I include experience in consumer surplus, so that firms that provide a better experience generate more surplus for consumers. This means that, everything else being equal, consumers prefer firms providing better experiences. Third, given consumers' preferences, experience enhances a firm's resistance to online competition.

Consistent with the recent trend, my model predicts that, as consumers' preferences shift from traditional retail to e-commerce, firms that invest sufficiently in the experience amenity survive, whereas firms that continue to rely on traditional channels exit the market. This result explains why increased e-commerce efficiency has led not only to brick-and-mortar retail bankruptcies, but also to increased attention to experience creation. Next, my model suggests that greater negative rent discrimination by experience – granting rent breaks to experiential tenants and charging premiums to non-experiential ones – results in new firms entering the market and incumbent firms providing less experience. In other words, I find that the more that landlords reward experience creation, the less that tenants create experiences.

In the empirical section, I examine the relationship between rent and experience, focusing on rent discrimination. Using a dataset of 166 retail lease contracts executed in New York City in 2019, I study rent and experience at the tenant level. Employing Rosen's (1974) hedonic pricing framework, I model rent as a function of lease conditions, building characteristics, and tenant characteristics. Despite "experiential retail" becoming a ubiquitous term among real estate practitioners, it still lacks a rigorous definition. Therefore, I develop two rubrics for "experiential retail" identification, adapting features of an experience from Pine and Gilmore (1998) and from "Beyond Buying" (2018), a consumer study conducted by JLL, a real estate services company.

Using Yelp and Google Places ratings, and my custom rubrics as proxies, I estimate the effect of experience on effective rent, tenant improvement (TI) allowance, free rent, and lease term.[2] Overall, I do not find evidence that, conditional on the sector, experiential tenants pay different effective rents than non-experiential tenants. However, experiential tenants receive disproportionately greater TI allowances and slightly longer lease terms. I document no statistically significant difference in free rent between the two groups. These findings suggest that experiential tenants receive greater cash benefits upfront in exchange for higher rent payments down the road – the two effects on average offsetting one another. Effectively, landlords are providing experiential tenants with zero-interest loans to incrementally improve their spaces, since the cash received upfront is amortized over the lease term with no additional borrowing cost. This benefit is material to tenants, as alternative sources of capital to finance such work in tenants' spaces would likely involve greater borrowing costs. Yet, these findings should be interpreted with caution, as my analysis is limited by a small and potentially biased sample of lease contracts. Still, this study takes the first and necessary steps to provide preliminary evidence of the role of experience in the complex landlord–tenant relationship.

The paper proceeds as follows. In Section 2, I provide background information regarding experiential retail in the United States. In Section 3, I review prior litera-

[2] Effective rent is total rent through all rent levels net of concessions, such as free rent and tenant improvement allowances. Tenant improvement (TI) allowances are one-time work value payments for tenants to use to apply idiosyncratic fittings and fixtures to their leased spaces.

ture. In Section 4, I present a theoretical framework to study brick-and-mortar retail firms when consumers' preferences shift to e-commerce, focusing on landlord–tenant interactions. In Section 5, I describe my empirical strategy and data, outlining the salient characteristics of experiential tenants. In Section 6, I report my empirical findings and discuss their implications. In Section 7, I summarize conclusions.

2 Background: The "Retail Apocalypse"

By and large, the growth of e-commerce has detrimentally affected historically successful brick-and-mortar establishments.[3] The liquidation of Toys "R" Us in 2018 helped drive the biggest quarterly decline in U.S. retail occupancy since 2009, according to real estate researcher Reis Inc.[4] That quarter, the national vacancy rate soared to just over 10 percent, the highest since 2014. Continual headlines regarding store closures at J.C. Penney, Sears, Payless ShoeSource, and of entire malls shutting down suggest that the United States faces a "retail apocalypse," as traditional in-store purchases continue to be redirected online. As illustrated in Figure 1, in 2019:Q1, over 10 percent of U.S. quarterly retail sales occurred through e-commerce, more than double the rate from 2010:Q1. Still, the story of brick-and-mortar retail's decline is more complicated than just sales shifting from brick-and-mortar to e-commerce. There are complementary interactive effects between the two channels that are not yet fully understood, and it is becoming increasingly difficult to differentiate between a strictly brick-and-mortar purchase and a strictly online purchase. Consumers are relying on both channels to shop and a sale's destination does not necessarily coincide with a sale's origin.

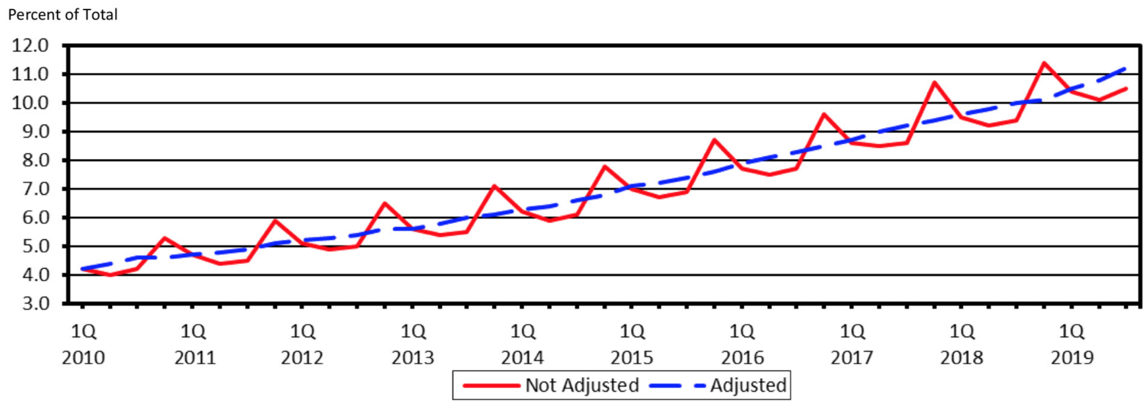
Moreover, not all brick-and-mortar retail has suffered equally from e-commerce disruption. Some prominent retail bankruptcies can be attributed to failed private equity buyouts, wherein the retailers' overwhelming debt burdens magnified e-commerce's disruptive effect. Despite online competition, a significant proportion of apparel sales still occurs at brick-and-mortar establishments,[5] and discount retailers

[3] See more at `https://www.nytimes.com/2019/04/12/business/retail-store-closings.html`.

[4] See more at `https://www.bloomberg.com/news/articles/2019-10-30/in-one-empty-store-retail-apocalypse-comes-with-zombies`.

[5] See more at `https://hbr.org/2018/06/5-surprising-findings-about-how-people-actually-buy-clothes-and-shoes`.

Figure 1: Estimated Quarterly U.S. Retail E-commerce Sales as a Percent of Total Quarterly Retail Sales



Notes: With much of e-commerce's growth coming from redirected purchases, the increased proportion of e-commerce sales challenges traditional brick-and-mortar retailers to remain relevant. (Source: US Census, Quarterly Retail E-commerce Sales 3rd Quarter 2019, November 2019)

such as Dollar General, Dollar Tree, and Family Dollar continue to expand rapidly.[6] Additionally, new types of brick-and-mortar "experiential retail" concepts are opening, such as experiential pop-up museums[7] and the American Dream mega-mall.[8] The former are "instagramable" and themed exhibits, while the latter is a 3 million square feet clustering of The Nickelodeon Universe amusement park, an aquarium, an ice rink, a ski slope, a water park, 350 stores, and over 100 restaurants.[9] Naturally, this brick-and-mortar retail success dichotomy raises the question as to why, under the same macroeconomic conditions, some brick-and-mortar retailers are systematically becoming obsolete and disappearing, while other brick-and-mortar retailers are expanding.

[6] See more at `https://coresight.com/wp-content/uploads/2019/12/Weekly-US-and-UK-Store-Openings-and-Closures-Tracker-2019-Week-50-Dollar-General-Plans-To-Continue-Store-Expansion-in-Fiscal-Year-2020-Dec-13-2019.pdf`.

[7] See more at `https://www.nytimes.com/2018/09/26/arts/color-factory-museum-of-ice-cream-rose-mansion-29rooms-candytopia.html`.

[8] See more at `https://www.nytimes.com/2019/12/27/arts/american-dream-mall-opening.html`.

[9] See more at `https://www.americandream.com`.

3 Literature Review

3.1 Defining Experience

Recently, consumer preferences have shifted more toward experiences and away from goods or services (Mcallister, 2019). Experiences differ from goods and services by providing more value for a consumer in the form of memorability (Pine & Gilmore, 1998). Whereas non-experiential offerings are external to the consumer and more objective in nature, experiences are personal, exist only at the individual level, and are rarely the same between individuals. Experiences are not exclusively forms of entertainment; whenever a firm engages with a consumer in a memorable and personal way, an experience is created. Pine and Gilmore place experiences on two axes – customer participation and connection – to categorize experiences into four realms: entertainment, educational, esthetic, and escapist. Pine and Gilmore also assert memorable experiences tend to exhibit the following characteristics: (1) experiences are themed in nature; (2) they harmonize impressions with positive cues and eliminate negative cues; (3) they mix in goods and memorabilia; and (4) experiences engage all five senses. Their set of economic distinctions between commodities, goods, services, and experiences is detailed in Table 1.

JLL's "Beyond Buying" (2018) breaks down experience into six dimensions after surveying 2,000 shoppers about their recent shopping experiences at twenty top retailers in ten retail sectors. These dimensions include:

1. *Intuitiveness.* It is simple and easy for shoppers to find what they are looking for, including quality products and new items.
2. *Human.* Shoppers have quality interactions with knowledgeable, reliable associates who treat them fairly.
3. *Meaningfulness.* The retailer makes a difference in the lives of shoppers, who

Table 1: Economic Distinctions: Commodities, Goods, Services, and Experiences

ATTRIBUTES	Commodities	Goods	Services	Experiences
Economy	Agrarian	Industrial	Service	Experience
Economic Function	Extract	Make	Deliver	Stage
Nature of Offering	Fungible	Tangible	Intangible	Memorable
Key Attribute	Natural	Standardized	Customized	Personal
Method of Supply	Bulk Store	Inventoried	On-demand	Revealed
Seller	Trader	Manufacturer	Provider	Stager
Buyer	Market	User	Client	Guest
Factors of Demand	Characteristics	Features	Benefits	Sensations
Competitive Position	Very Low	Low	Medium	High
Pricing Power	Very Low	Low	Medium	High

Notes: Pine and Gilmore's (1998) spectrum of commodities, goods, services, and experiences reveals how experiences differ from other products, ultimately resulting in greater product differentiation. Differentiation leads to greater pricing power (firms can price above their marginal cost) under a monopolistically competitive equilibrium.

feel a sense of pride when shopping there.

4. *Immersiveness.* The exterior and interior of the store are appealing and captivating. Shoppers enjoy spending time there.

5. *Accessibility.* Shoppers can shop where and when they want – store, mobile or website – and the retailer knows their preferences.

6. *Personalization.* The experience is how shoppers want it, with associates who: (1) understand shoppers' unique needs; (2) make recommendations based on shoppers' past behavior; and (3) reward shoppers based on loyalty.

Experience, of course, does not guarantee financial success. At value retailers, such as dollar stores, affordability ultimately supersedes experience ("Beyond Buying", 2018). Still, since shoppers have high expectations of what constitutes an ideal shopping experience, such criteria offer a useful framework for qualifying retail experiences and help distinguish different types of experiences.

Notwithstanding these guidelines, objective measures of experience that do not pose endogeneity concerns are still lacking in the literature. Consequently, as one of the various techniques utilized to proxy experience in my empirical analysis, from these authors, I adapt my own set of sufficient conditions for a tenant to be considered "experiential." These conditions are outlined in Table 2 in Section 5.

3.2 Advertising Experience

Since experiences are more subjective in nature and less absolute than goods or services, they can be hard to quantify for consumers, real estate practitioners, and researchers alike. Consequently, novel experiences present relatively high search costs for consumers and often interact with advertising to reach consumers. For this reason, in Section 5, I propose employing measurements of voluntary consumer-to-consumer advertising as one of several techniques to proxy experience.

This paper will take the partial view of advertising, thus assuming advertisements provide information to consumers (announce the existence of a product, quote its price, inform consumers about retail locations, and describe the product's quality) to enable consumers to make rational choices (Tirole, 1988). Butters (1977) explores the effect of advertising under monopolistic competition and imperfect information. Assuming high consumer search costs, Butters shows lower equilibrium levels of advertising increases informational product differentiation, which allows firms to raise prices.

Advertising technology is not strictly restricted to business-to-consumer advertisement. Traditional word-of-mouth (WOM) advertising, which was originally defined as an oral form of interpersonal, non-commercial communication among acquaintances (Arndt, 1967), has evolved into a new form of communication, namely electronic word-of-mouth (eWOM) communication. The advent of the internet and social media has revolutionized communication technology, allowing consumers to share and exchange consumption-related content with each other quickly and conveniently. eWOM communication can take the form of consumers posting their photos, opinions, comments, and/or reviews of products and services anywhere online – from discussion forums, to retail websites, and to social media platforms.

Though the mechanism is not completely understood, positive eWOM activity – which boosts the popularity of establishments – is linked to customer satisfaction and experience quality (Zhang, Ye, Law, & Li, 2010; Kim, Jang, & Adler, 2015). However, positive experiences work in concert with a consumer's need for social interaction, desire for economic incentives, concern for other consumers, and the potential for self-enhancement to determine eWOM activity (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Cheung & Lee, 2012). eWOM is a superior form of advertising compared to traditional WOM, having greater scalability, speed of diffusion, permanency, accessibility, and measurability. As a result, many hospitality and tourism-related studies have investigated the impact of eWOM communication, exploring how eWOM influences hotel sales (Ye, Law, & Gu, 2009), destination choices (Di Pietro, Di Virgilio, & Pantano, 2012), and restaurant popularity (Zhang et al., 2010; Kim et al., 2015). These studies suggest complementary online reviews positively benefit a firm. While external marketing efforts (business-to-consumer advertising) are effective initially, beyond a relatively early stage of a new product's growth cycle, their efficacy quickly diminishes and eWOM becomes the main growth propellant (Goldenberg, Libai, & Muller, 2001). Information dissemination is dominated by eWOM, rather than by business-to-consumer advertising. Therefore, companies put substantial effort and investment into enhancing positive eWOM communications (Goldenberg et al., 2001).

eWOM activity and property rents have been studied in the context of professional and non-professional social media influencers. Sun (2019) suggests that online influencer behavior has a significant positive correlation with effective rents in New York City retail properties, both for spatial and non-spatial models. This implies firms are willing to pay a premium to locate around influencer "hot spots." Influencer studies partially motivate my experiential retail rent discrimination hypothesis, illustrating how eWOM activity can generate sufficiently positive spillover effects to warrant rent discrimination. However, influencer studies differ from my work, in that experiential retail concerns both the providers of traffic draw and beneficiaries of traffic draw, while influencer studies mainly analyze the beneficiaries of eWOM activity. I propose experiential retail may originate eWOM activity and non-experiential tenants may pay a premium to cluster around that activity.

3.3 Product Differentiation and Rent Discrimination

Compared to completely homogeneous goods, product differentiation softens price competition and increases firm profits. Product differentiation under spatial competition traces back to Hotelling's (1929) seminal duopoly linear city model. Under quadratic transportation costs, two firms producing homogeneous goods will maximize product differentiation (through locational choice) when they play a two-stage game. This makes the total set of goods heterogeneous, since goods are defined by both the product itself and where they are sold. Firms first simultaneously choose their location, and then simultaneously choose their prices (Aspremont & Gabszewicz, 1979). Salop's (1979) circular city model builds on this principle, exogenously imposing maximum differentiation to study a two-stage game where firms first simultaneously decide whether to enter a circular market and then compete in prices. This model makes predictions about both an oligopolistic equilibrium and monopolistically competitive equilibrium. Building on Butters's (1977) advertising analysis, Grossman and Shapiro's (1984) work studies product differentiation under the presence of a second form of differentiation: imperfect information. Assuming consumers only learn about firms through advertising technology, Grossman and Shapiro's (1984) work demonstrates that improved efficiency of advertising (a reduction in the cost per exposure) increases the competitiveness of the market and causes prices to fall. Later in this paper, I motivate my empirical analysis by expanding on Grossman and Shapiro's (1984) work to study two new axes of differentiation: experience amenity and resistance to e-commerce competition.

Price discrimination is commonplace in retail rent markets. Inter-center rent discrimination traces to a center's consumer drawing power, building design features, locational characteristics, and prevailing market characteristics (Sirmans & Guidry, 1993). Intra-center rent discrimination stems from landlords evaluating a tenant's traffic-generating potential and overall riskiness (default probability) when determining individual lease rents (Benjamin, Boyle, & Sirmans, 1992; Brueckner, 1993). Tenants that generate positive externalities for a center are compensated via rent substitution. In large shopping centers, low-order good retailers and smaller retailers receive demand externalities from the additional traffic that is generated by high-order anchor retailers (Ingene & Ghosh, 1990). In exchange, large anchors in shopping malls pay relatively lower rent per square foot for boosting sales of surrounding retailers (Gould, Pashigian, & Prendergast, 2005). Conversely, retailers that generate less traffic and take advantage of this externality subsidize the rent of anchors. Especially when consumers have imperfect information and face high search costs, retailers selling similar products tend to agglomerate together, making high traffic drawing tenants desirable (Wolinsky, 1983).

3.4 Rent Determination

Rosen's (1974) work on hedonic prices lays the foundation for many real estate pricing models. Rosen offers a model of product differentiation based on the hedonic hypothesis that goods are valued for their utility-bearing attributes. Observed prices of differentiated products and the specific amounts of various characteristics associated with these products reveal to market participants the implicit prices – the hedonic prices – of the product's attributes. Econometrically, hedonic prices are estimated by regressing product prices on the quantities of characteristics, where the set of coefficients for each characteristic composes the set of hedonic prices. This methodology is commonly employed in other commercial real estate studies of price discrimination and rent determinants (Benjamin et al., 1992; Sirmans & Guidry, 1993; Chegut & Langen, 2019; Sun, 2019).

4 Theoretical Framework

To help make sense of brick-and-mortar retail firm behavior under shifting consumer preferences, due to the rise of e-commerce, I explore a new theoretical framework that expands on Salop (1979) and on Grossman and Shapiro (1984). As detailed earlier, eWOM functions as a modern type of advertising technology that has a significant relationship with experience. Consequently, I study eWOM advertising and experience together, to fully understand how firms invest in experience as consumers' preferences change. I suggest experience can be understood as a new type of amenity, through which firms differentiate themselves. Moreover, given imperfect information, consumers learn about experience amenities through electronic word-of-mouth (eWOM) advertising.[10] I propose more experiential tenants are associated with greater positive eWOM activity, so investment in experience also influences brand awareness.[11] Better experience and consumer brand awareness ultimately lead to greater traffic draw.

I depart from Grossman and Shapiro in two main ways. First, I introduce a new variable, experience, in which firms invest to increase consumer surplus. I propose that experience is directly linked to eWOM activity, which determines consumers' brand awareness. Second, I introduce e-commerce, which detrimentally affects demand for shopping at brick-and-mortar stores. I propose that a firm's experience influences its resistance to e-commerce competition, given consumers' sensitivity to experience. In a later version of my model, landlords rent discriminate when signing individual leases, substituting rent for positive external effects, such as increased total

[10] This assumption is based on Goldenberg et al.'s (2001) work, which finds other forms of advertising lose efficacy beyond a relatively early stage of a new product's growth cycle.

[11] Anecdotally, since sharing one's enjoyable experiences is a popular way users engage on social media platforms, retail establishments that tend to go viral on social media are usually more experiential. A salient characteristic of being experiential is inviting consumers to share their positive experiences online with other consumers.

consumer traffic. I assume experience generates significantly positive spillover effects, compelling landlords to rent discriminate between experiential and non-experiential tenants.

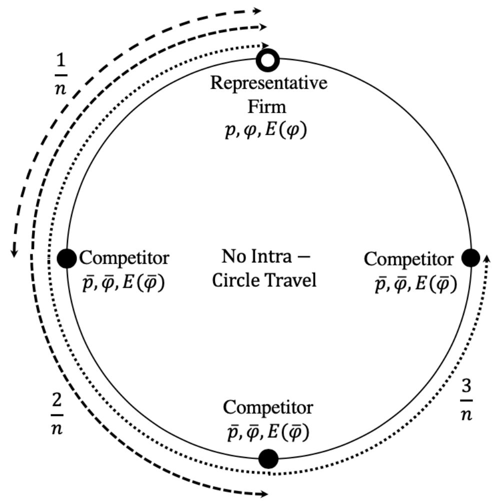
4.1 Model

Consumers are located uniformly around a circle of unit length. Population density is given by δ people per unit length. Firms are located around the circle's perimeter and all travel occurs along the circle's perimeter. Following Salop (1979), I assume that all firms are evenly spaced along the circle. No travel occurs within the circle, due to prohibitively high intra-circle travel costs. Consumers buy only one unit of the product sold and attach a gross dollar value of v to the good itself. A product located a distance z from a consumer provides benefit $v-tz$, where t is the transportation cost per unit distance. Each firm has some experience amenity with gross dollar value E, and the cost function $\omega(E)$ maps consumer experience dollar value to firm experience cost dollar value. Firms face a fixed cost F and a constant marginal production cost c. Therefore, firm i's profit is $(p_i - c)D_i - F - \omega(E_i)$ if it enters (where D_i is the demand it faces) and zero otherwise. Firms face no entry or capacity costs. Figure 2 provides an illustrative visualization of a city with four firms.

The surplus obtained by a consumer purchasing a product at distance z units from the consumer at price p is $v - tz - p + E$. Consumers purchase a unit of the good only if they are aware of the existence of at least one firm offering positive surplus for the good and select the firm that offers the greatest surplus if they know of several firms. Moreover, consumers only purchase from brick-and-mortar stores if they prefer brick-and-mortar establishments to e-commerce.

Focusing on the product-specific information, I employ information technology like in Butters (1977). Consumers rely on information garnered through eWOM posts to

Figure 2: Theoretical Model Overview



Notes: Consumers are located uniformly on a circle of unit length. Population density is given by δ people per unit length. n firms are evenly spaced around the circle's perimeter and all travel occurs along the circle's perimeter. A representative firm chooses price p and brand awareness ϕ (which determines E), conditional on observing their competitors' choices, $\bar{p}$ and $\bar{\phi}$, to maximize profits.

know what firms exist. A post reveals to the consumer the price, experience amenity, and distance to a given firm. Consumers remember all information from posts seen and the content of posts is accurate. Consumers only engage with firms whose prices they see.

A brand awareness ϕ for a representative firm measures the fraction of the whole population exposed to at least one of the firm's posts. Since posts are not targeted to specific consumers, this implies that each consumer learns about the representative firm with probability ϕ. Let $r > 0$ be the probability a consumer is exposed to a single specific post. The probability that a consumer sees a single post is independent of the probability that they see another single post. If there are m posts about a single firm, then the probability that a consumer sees *none* of the firm's posts is $(1-r)^m$. This implies the brand awareness for that firm is given by $\phi = 1 - (1-r)^m$. Solving for m, the number of posts about a firm is given by $m = \ln(1-\phi)/\ln(1-r)$.

I propose that a firm's experience directly determines its brand awareness. I assume greater brand awareness – through eWOM activity – results from consumers encountering brick-and-mortar experiences. Additionally, firms do not cheat by adopting alternative advertising channels, such as employing influencers (that is, paying influencers directly to promote the firm). Therefore, the number of posts m about a firm depends on the gross dollar amount of experience E each consumer receives, such that $m = f(E)$, where $f_E > 0$. I assume f is an injective function, so solving for E yields:

$$E(\phi) = f^{-1}\left(\frac{\ln(1-\phi)}{\ln(1-r)}\right) \tag{1}$$

Additionally, I assume all functional forms of f^{-1} produce $E_\phi > 0$ and $E_{\phi\phi} > 0$. Intuitively, this reflects how it becomes increasingly expensive, from an experience perspective, to reach higher brand awareness. This could be so because consumers are heterogeneous in their tendency to post on social media, so the experience has to be that much better to instigate less active users to post. Likewise, consumers could be heterogeneous in their tendency to look for posts. This implies consumers that search less for posts on their own will be increasingly difficult to reach.

4.2 Equilibrium

Similar to Grossman and Shapiro (1984), the following market equilibrium is the non-cooperative Nash equilibrium in prices p and brand awareness ϕ. In this equilibrium, each firm takes as a given the brand awareness $\bar{\phi}$ and price $\bar{p}$ chosen by all other firms and selects its own ϕ and p to maximize profits. In a symmetric equilibrium, all firms choose the same ϕ and p. The oligopoly equilibrium sets the number of firms exogenously (assumes no firms enter/exit), so firms can earn positive profits. Conversely, the monopolistic competition equilibrium sets the number of firms endogenously through the zero profit condition (assumes free entry/exit).

Consider the expected demand function for a representative firm D_i.[12] Departing from Grossman and Shapiro, it is now assumed consumers always have the additional option of purchasing goods online. It is assumed consumers are heterogeneous in their preferences to shop in-store versus online. The probability that consumers will choose to shop in-store is given by the firm's resistance to e-commerce factor β. I represent consumers' individual preferences by drawing i.i.d. random variables from the uniform distribution over $[0, 1]$. Consumers shop in-store only if their value is less than β. This implies that the probability of a consumer shopping at a brick-and-mortar store is β and the probability of a consumer shopping online is $1 - \beta$. I propose that greater levels of experience shift β according to an experience sensitivity parameter s, and use the following functional form:[13]

$$\beta(E) = 1 - e^{-sE} \tag{2}$$

Parameter s can be thought of as consumers' sensitivity to experience, determining a firm's resistance to e-commerce factor, given an amount of experience. Decreases in s represent consumers increasing their preferences for e-commerce relative to brick-and-mortar establishments when experience is held constant.

A representative firm's demand can be decomposed into two components, such that $D_i = \beta(E) \times x(p, \phi)$. One component of demand is the firm's resistance to e-commerce factor, $\beta(E)$, and the other component is very similar to what is proposed in Grossman and Shapiro (1984), $x(p, \phi)$. Since the derivation of $x(p, \phi)$ in this paper is very similar to what is proposed in Grossman and Shapiro (1984), with the only

[12] Henceforth, expected demand and demand are used interchangeably.
[13] Under this functional form, $E \in [0, \infty) \implies \beta \in [0, 1)$

modification being adding E to the consumer surplus equation, the derivation is omitted here, but it is included in Appendix A.

I now solve for the representative firm's optimal choice of p and ϕ, given its competitors' choices, $\bar{p}$, $\bar{\phi}$, and the total number of firms n. Using the derivation included in Appendix A that results in Equation (A.7), the representative firm's profits are given by:

$$\pi(p,\phi) = (p-c)\times\beta(E(\phi))\times\left(\frac{\delta\phi(\bar{p}-E(\bar{\phi})-p+E(\phi))}{t}+\frac{\delta\phi}{n\bar{\phi}}\right)-F-\omega(E(\phi)) \quad (3)$$

As was shown by Grossman and Shapiro, it is straightforward to show the elasticity of demand for symmetric equilibria is given by $\epsilon = pn\phi/t$. Therefore, a greater number of firms and/or less information asymmetry (greater brand awareness) increases elasticity. Conversely, increasing transportation costs increases differentiation, which decreases elasticity.

To solve for the profit maximizing conditions,[14] I take the first order conditions with respect to p and ϕ. The former is given by:

$$\pi_p = \beta\left(\frac{\delta\phi(\bar{p}-E(\bar{\phi})-p+E(\phi))}{t}+\frac{\delta\phi}{n\bar{\phi}}\right)-(p-c)\beta\left(\frac{\delta\phi}{t}\right)=0$$

$$p = \frac{\bar{p}+c-E(\bar{\phi})+E(\phi)}{2}+\frac{t}{2n\bar{\phi}} \quad (4)$$

Under perfect information (ϕ and $\bar{\phi}=1$), the formula collapses to Salop's findings. Greater imperfect information about competitors (lower $\bar{\phi}$) raises p, while greater

[14] The second order conditions for a profit maximum are satisfied in the neighborhood of a symmetric equilibrium for my convex functional form of ω (the hessian matrix of profit is negative semi-definite). It is straightforward to confirm computationally that this condition is satisfied for reasonable parameters, such as those presented in Footnote 16.

imperfect information about the representative firm's product (lower ϕ) lowers p.

The other first order condition is given by:

$$\pi_\phi = \delta(p-c)\beta_E E_\phi(\phi)\left(\frac{\phi(\bar{p}-E(\bar{\phi})-p+E(\phi))}{t}+\frac{\phi}{n\bar{\phi}}\right)+$$
$$\beta\delta(p-c)\left(\frac{\bar{p}-E(\bar{\phi})-p+E(\phi)}{t}+\frac{\phi E_\phi(\phi)}{t}+\frac{1}{n\bar{\phi}}\right)-\omega_E E_\phi(\phi)=0$$

In the symmetric equilibrium $\bar{p}=p$ and $\bar{\phi}=\phi$. Cleaning up the notation:

$$\frac{\delta(p-c)\beta_E E_\phi(\phi)}{n}+\beta\delta(p-c)\left(\frac{\phi E_\phi(\phi)}{t}+\frac{1}{n\phi}\right)=\omega_E E_\phi(\phi) \tag{5}$$

From these two first order conditions, I obtain the two equations that describe the symmetric oligopoly equilibrium (exogenous n).

$$p-c=\frac{t}{n\phi} \tag{6a}$$
$$(p-c)\left(\frac{\delta\beta_E E_\phi}{n}+\frac{\delta\beta\phi E_\phi}{t}+\frac{\delta\beta}{n\phi}\right)=\omega_E E_\phi \tag{6b}$$

In the monopolistically competitive equilibrium, n is endogenously determined by the zero profit condition under free entry/exit. Since it is assumed in Equation (A.6) that $(1-\bar{\phi})^n \approx 0$ and above that $\bar{\phi}=\phi$, this implies nearly all consumers are reached in equilibrium (the probability an individual is reached by no firms is approximately zero). Since nearly all consumers are reached by at least one firm and fraction β of consumers buy one unit of the good in stores ($1-\beta$ consumers are lost to e-commerce), total market quantity demanded approximately equals $\beta\delta$. So, by symmetry, each firm faces approximately $\beta\delta/n$ in quantity demanded. Therefore, to make n endogenous, the following approximation must hold.[15]

$$\pi = (p-c)\frac{\beta\delta}{n} - F - \omega = 0$$

$$(p-c)\frac{\beta\delta}{n} = F + \omega \tag{6c}$$

4.3 Results

I use these equations to perform comparative statics analyses. Combining Equation (6a) with Equation (6b) and with Equation (6c) gives the two equations that govern the profit maximizing ϕ and n under monopolistic competition. Plugging their solutions into Equation (6a) gives the profit maximizing markup, $p - c$.

$$\frac{t}{n\phi}\left(\frac{\delta\beta_E E_\phi}{n} + \frac{\delta\beta\phi E_\phi}{t} + \frac{\delta\beta}{n\phi}\right) = \omega_E E_\phi \tag{7a}$$

$$\frac{t}{n\phi} = \frac{n(F+\omega)}{\beta\delta} \tag{7b}$$

Solving this system of two equations, using similar reasonable parameters to Grossman and Shapiro's (1984) base case,[16] allows me to study equilibrium behavior as specific exogenous parameters shift. I observe the following results.

[15] While n is assumed to be discrete in the demand derivation, it will be treated as continuous for the sake of the comparative statics analyses. However, valid values of n must be discrete.

[16] My parameters are: $r = 0.1$; $t = 250$; $F = 750$; $\delta = 1000$; $s = 0.5$; $\omega = 100E^2$; $E = 0.5\ln(1 - \phi)/\ln(1 - r)$.

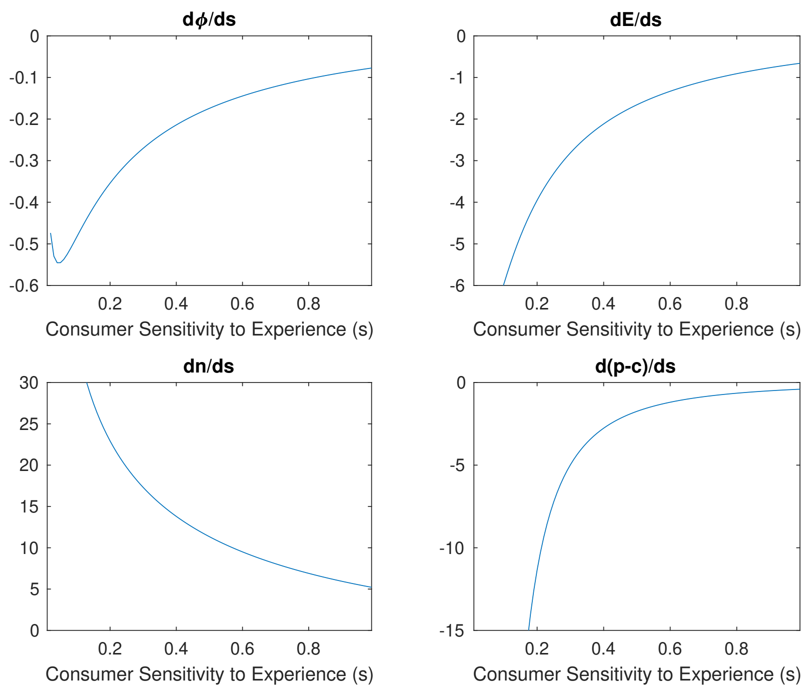
Proposition 1 *Under monopolistic competition, as consumers' preferences for e-commerce increase for a given experience, firms provide more experience, some firms exit, and firms gain pricing power.*

Consumers' preferences for e-commerce increasing for a given experience can be represented by consumers becoming less sensitive to experience (reduced s). This is to say that consumers increase their preference for e-commerce when experience is held constant. In Figure 3, I observe the comparative statics $\frac{d\phi}{ds} < 0$, $\frac{dE}{ds} < 0$, $\frac{dn}{ds} > 0$, and $\frac{d(p-c)}{ds} < 0$ within a range of reasonable parameters. This means as consumers' preferences change and they become less sensitive to experience, some firms exit and remaining firms choose a greater brand awareness ϕ. This implies that firms provide more experience, since $E_\phi > 0$. This could explain why providing experience has become more relevant over the past two decades as e-commerce has become a better substitute to brick-and-mortar establishments (lower inconvenience costs with expedited shipping, et cetera, have decreased s). With less sensitivity to experience, consumers require more experience to visit physical stores. Additionally, firms exiting, which softens competition, also increases firms' pricing power (markup over marginal unit good cost $p - c$).

Proposition 2 *Under monopolistic competition, as experience-to-eWOM conversion efficiency increases, firms provide less experience, some firms exit, and firms gain pricing power.*

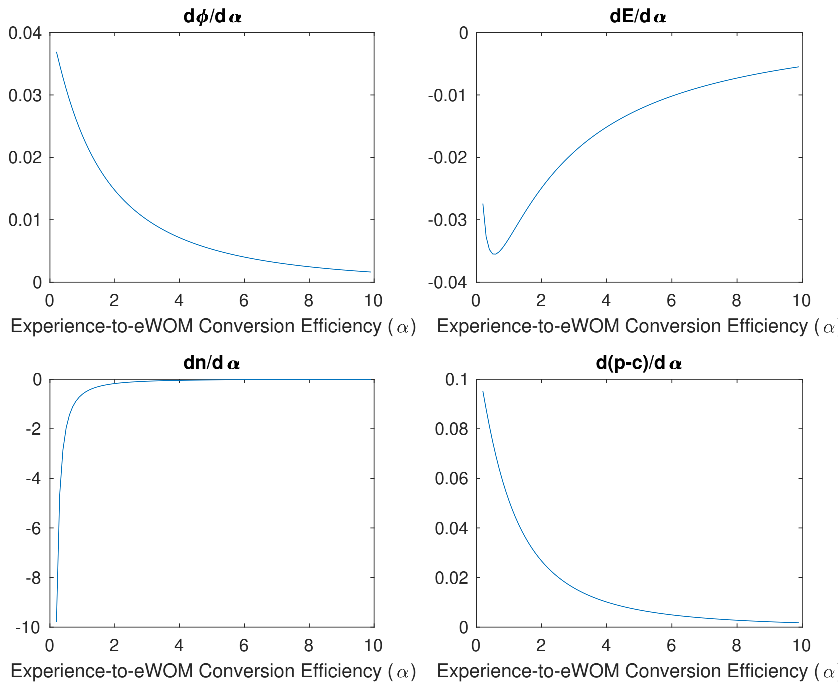
Using the functional form $E(\phi) = \frac{1}{\alpha}\left(\frac{\ln(1-\phi)}{\ln(1-r)}\right)$ for f^{-1} in Equation (1), I observe the comparative statics $\frac{d\phi}{d\alpha} > 0$, $\frac{dE}{d\alpha} < 0$, $\frac{dn}{d\alpha} < 0$, and $\frac{d(p-c)}{d\alpha} > 0$ within a range of reasonable parameters in Figure 4. Increases in experience-to-eWOM conversion efficiency intuitively represents greater eWOM activity for a given level of experience. This would be the case if social media users suddenly start posting more when experience is held constant. Increases in experience-to-eWOM conversion efficiency instigate some firms to exit, which decreases competition. Increased efficiency reduces the amount of experience provided. However, brand awareness is heightened due to the increased efficiency. Firms' pricing power (markup over marginal unit good cost $p-c$) increases under softened competition. For the zero profit condition to hold, these results imply a firm's demand decreases as experience-to-eWOM efficiency improves.

Figure 3: Comparative Statics: Consumer Sensitivity to Experience



Notes: Using similar reasonable parameters as proposed by Grossman and Shapiro (1984), decreasing s under monopolistic competition results in a greater brand awareness ϕ and a decrease in the number of firms n in equilibrium. Since $E_\phi > 0$, this causes firms to provide more experience E. Firms' pricing power (markup over marginal unit good cost $p-c$) increases under softened competition.

Figure 4: Comparative Statics: Experience-to-eWOM Conversion Efficiency

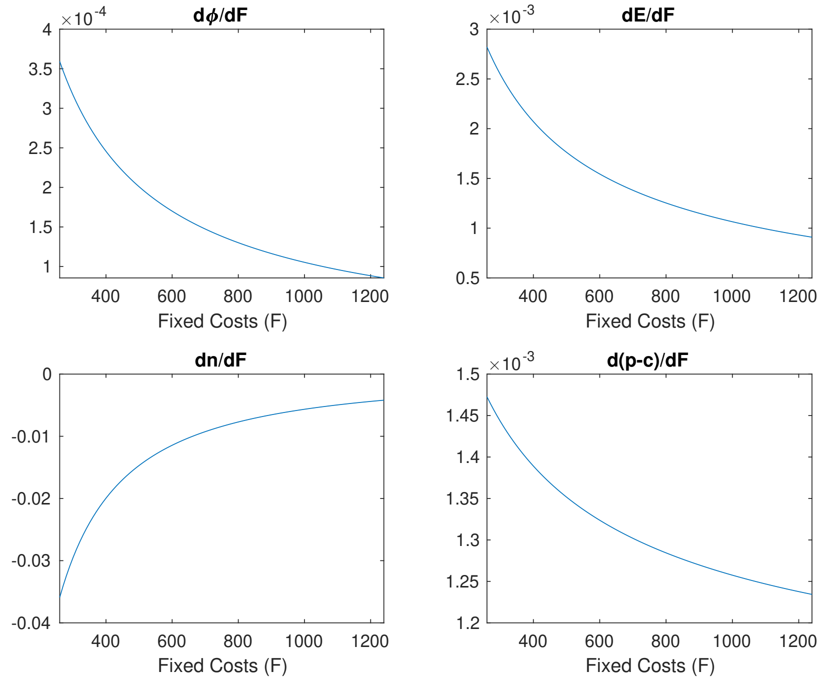


Notes: Using similar reasonable parameters as proposed by Grossman and Shapiro (1984), increasing experience-to-eWOM conversion efficiency α under monopolistic competition results in a higher brand awareness ϕ and a decrease in the number of firms n in equilibrium. Firms provide less experience E due to the heightened efficiency. Firms' pricing power (markup over marginal unit good cost $p - c$) increases under softened competition.

Proposition 3 *Under monopolistic competition, as fixed costs decrease, firms provide less experience, some firms enter, and firms lose pricing power.*

In Figure 5, I observe the comparative statics $\frac{d\phi}{dF} > 0$, $\frac{dE}{dF} > 0$, $\frac{dn}{dF} < 0$, and $\frac{d(p-c)}{dF} > 0$ within a range of reasonable parameters. Here, the intuition is that decreases in fixed costs instigate some firms to enter, which increases competition. Heightened competition reduces the amount of experience provided, which lowers brand awareness. Firms' pricing power (markup over marginal unit good cost $p - c$) decreases under heightened competition.

Figure 5: Comparative Statics: Fixed Costs

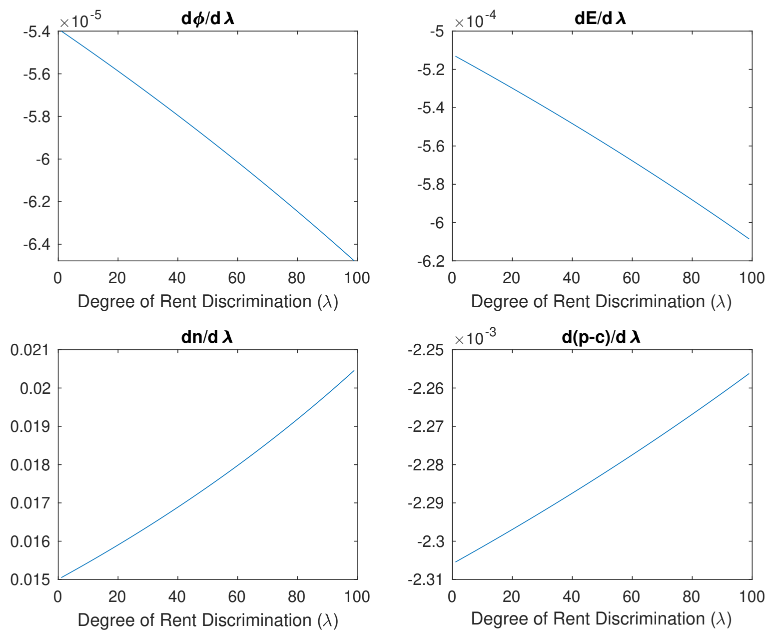


Notes: Using similar reasonable parameters as proposed by Grossman and Shapiro (1984), decreasing F under monopolistic competition results in a lower brand awareness ϕ and an increase in the number of firms n in equilibrium. Since $E_\phi > 0$, this causes firms to provide less experience E. Firms' pricing power (markup over marginal unit good cost $p - c$) decreases under heightened competition.

Proposition 4 *Under monopolistic competition, as landlords increase the magnitude of experiential retail negative rent discrimination (experiential tenants are granted greater rent concessions), firms provide less experience, firms enter the market, and pricing power is reduced.*

I introduce a new term $-\lambda E$ to the cost of providing experience, ω, to study the effect of rent discrimination when experiential tenants receive rent concessions. This negative term represents giving experiential tenants a discount proportional to the experience they provide. Earlier analyses assumed $\lambda = 0$, meaning no positive or negative rent discrimination was present. In Figure 6, I observe the comparative statics $\frac{d\phi}{d\lambda} < 0$, $\frac{dE}{d\lambda} < 0$, $\frac{dn}{d\lambda} > 0$, and $\frac{d(p-c)}{d\lambda} < 0$ within a range of reasonable parameters. Here, the intuition is greater rent discrimination reduces costs, instigating some firms to enter, which increases competition. Heightened competition reduces experience provided and lowers brand awareness. Firms' pricing power (markup over marginal unit good cost $p - c$) decreases under heightened competition.

Figure 6: Comparative Statics: Rent Discrimination



Notes: Using similar reasonable parameters as proposed by Grossman and Shapiro (1984), increasing λ under monopolistic competition results in a lower brand awareness ϕ and an increase in the number of firms n in equilibrium. Since $E_\phi > 0$, this causes firms to provide less experience E. Firms' pricing power (markup over marginal unit good cost $p - c$) decreases under heightened competition.

4.4 Discussion

Combining these results with Sirmans and Guidry's (1993) rent discrimination theory helps make sense of how the emphasis on experience has changed with the rise in e-commerce. As my theory suggests, firms provide more experience when more consumers choose online retailers over brick-and-mortar, experience being held constant. This explains why firms have focused on experience creation over the past two decades. Additionally, my model suggests this trend should trigger a net decrease in the number of firms, potentially justifying the growth in reported vacancies and bankruptcies. Moreover, as presented in Sirmans and Guidry (1993), tenants often generate positive spillover effects on their neighbors, justifying rent concessions. If a landlord signs two neighboring tenants, and one tenant's heightened experience generates positive spillovers for the other, the first tenant can substitute experience for rent with landlords that rent discriminate by experience. However, as also suggested by my model, greater rent discrimination decreases the experience provided by a firm and causes other firms to enter the market. Though a decrease in s causes a decrease in the number of firms and an increase in E, if landlords rent discriminate in favor of experiential tenants, some firms, according to my model, will re-enter the market and the provided experience will fall, creating a buffering effect. This movement seems counter intuitive; the more that landlords reward experience creation, the less that tenants provide experience in equilibrium. These results are limited by my model not capturing tenants partially advertising through alternative channels, such as through social media influencers. These dynamics remain open for future research.

In the next section, I test for evidence of rent discrimination by experience, conditional on other relevant variables. However, I do not find a statistically significant negative or positive correlation, suggesting that landlords view experiential tenants and non-experiential tenants as direct substitutes, from a rent perspective.

5 Empirical Strategy

5.1 Methodology

I analyze empirically the relationship between the experiential features offered by tenants and the rent charged by landlords, with a focus on rent discrimination by experience. I use the hedonic pricing framework proposed by Rosen (1974), which is popular in commercial real estate literature (Benjamin et al., 1992; Sirmans & Guidry, 1993; Chegut, Eichholtz, & Rodrigues, 2015; Chegut & Langen, 2019; Sun, 2019). I model rent per square foot (PSF) as a function of hedonic lease characteristics, building characteristics, location, and time fixed effects.[17]

In the dataset used, the rent paid by tenants is not observed period by period. Instead, I have data only on starting rent and effective rent. Effective rent per month, defined in Equation (8), is the total rent through all L rent levels minus concessions, such as a free rent period and a one-time work value payment. Variable r_l denotes the monthly rent PSF at rent level l, and variable t_l denotes the number of months at rent level l. Variable t_{free} measures months of free rent, variable w is the total one-time work value payment PSF, and variable t_{total} is the total lease duration in months. While starting rent only captures the rent of the first period, effective rent captures the weighted average of all rent bumps and concessions. Therefore, I use effective rent to proxy for the total rent paid over the entire term of a lease.

$$r_{effective} = \frac{\sum_{l=1}^{L} r_l t_l - r_1 t_{free} - w}{t_{total}} \tag{8}$$

Ideally, I would like to define "experiential" tenants as the treatment group and "non-experiential" tenants as the control group. However, landlords' perceptions of

[17] Rent PSF and the logarithm of rent PSF are both commonly used in the literature. In this study, all rents are in U.S. Dollars.

tenant experience are not measurable at the time of lease execution. Therefore, I propose several strategies to proxy for landlords' perceptions of tenant experience. First, I use present-day eWOM consumer rating averages (post lease signing), since they are observable measures of consumer experience satisfaction. Later in this paper, I develop two rubrics to classify tenants as "experiential" according to a weak and a strong definition of experiential retail. For both the eWOM average rating and rubric classification strategies, I assume that within a reasonable time horizon,[18] present-day experiences reported by consumers and observed tenant qualities approximate landlords' expectations at lease execution – such that posterior observations can serve as a proxy for historical expectations. This limitation that could not be avoided with the available data.

Important determinants of effective rents include the following: (1) lease characteristics, such as transaction square footage and lease term; (2) building characteristics, such as whether the building was renovated; and (3) tenant incentives, such as tenant improvement (TI) allowances[19] and the free rent period offered at lease signing. Both TI and free rent are subtracted from the asking rent at the time of lease negotiation. To account for heterogeneity in effective rents due to lease and building characteristics, I control for factors such as the logarithm of transaction size, lease duration, free rent, TI, whether the building was renovated, and whether the lease is a sublease.[20]

Since property markets are heterogeneous, comparing effective rents over different

[18] In this study's case, the maximum time gap is no more than thirteen months past lease execution.

[19] Tenant improvement (TI) allowances are one-time work value payments for tenants to use to apply idiosyncratic fittings and fixtures to their leased spaces. They are negotiated in conjunction with rent and other lease concession agreements. Landlords typically view TI as a type of loan to the tenant, that will be amortized over the term of the lease through higher subsequent rent and/or decreases of other lease concessions. Since TI payments are typically not risk-free, landlords often embed a borrowing cost when issuing TI.

[20] A sublease is the renting of property by a tenant to a third party for a portion of the tenant's existing lease contract. Even if a tenant subleases a property, the original tenant is still liable for the obligations stated in the lease agreement, such as the payment of rent each month.

locations can lead to unobserved submarket effects. I therefore add submarket fixed effects.[21] Consistent with Chegut and Langen (2019), I cluster standard errors by submarket and execution year. I control for varied macroeconomic conditions at the time of lease commencement through the addition lease-commencement quarter dummies. Lastly, I control for heterogeneity in effective rents due to tenant industry, in order to ensure any experience rent differential is relative to tenants within the same industry.[22]

As specified in Equation (9), I model the logarithm of effective rent of tenant i, $\ln(r_i)$, as a function of an experience proxy, E_i, a vector of lease and building characteristics, X_i, a vector of lease location dummies, L_i, a vector of lease-commencement quarter dummies, T_i, and a vector of tenant industry dummies, I_i. My coefficient of interest is β, which measures the "experiential" value of effective rent.

$$\ln(r_i) = \alpha + \beta E_i + \gamma X_i + \delta L_i + \zeta T_i + \theta I_i + \epsilon_i \tag{9}$$

Since landlords might discriminate using tenant incentives instead of rent, I analyze for evidence of discrimination by experience with TI, free rent, and lease term. As specified in Equation (10), I model each tenant incentive of tenant i, τ_i, as a function of an experience proxy, E_i, an updated vector of lease and building characteristics, $\tilde{X}_i$, a vector of lease location dummies, L_i, a vector of lease-commencement quarter dummies, T_i, and a vector of tenant industry dummies, I_i. For each tenant incentive regression, the logarithm of effective rent is used instead of TI, free rent, or lease term in the prior lease characteristics vector, X_i, from the Equation 9 specification (whatever the new dependent variable is) to arrive at the updated lease characteris-

[21] The dataset defines 28 submarkets for NYC. See more at `https://property.compstak.com/New-York-City`.

[22] I use three-digit NAICS codes for business subsectors. See more at `https://www.census.gov/programs-surveys/economic-census/guidance/understanding-naics.html`.

tics vector, $\tilde{X}_i$. This controls for heterogeneity in tenant incentives due to variable effective rent. Standard errors are clustered by submarket and execution year. My coefficient of interest is $\tilde{\beta}$, which measures the "experiential" value of each tenant incentive.

$$\tau_i = \tilde{\alpha} + \tilde{\beta}E_i + \tilde{\gamma}\tilde{X}_i + \tilde{\delta}L_i + \tilde{\zeta}T_i + \tilde{\theta}I_i + \tilde{\epsilon}_i \tag{10}$$

5.2 Data

5.2.1 Sources and Sampling

I study retail leases executed across New York City boroughs in 2019, obtained from CompStak, a company specialized in gathering and quality checking lease and sales comparables from brokerage professionals.[23] The dataset contains information on individual leases, such as tenant name, address, square footage, starting rent, effective rent, free rent, TI, lease duration, execution date, lease expiration date, building characteristics, and brokerage information.[24] Using leases with execution dates spanning from January 2019 to November 2019, the underlying CompStak sample consists of 594 proposed leases in 499 buildings in New York City. I only consider leases for busi-

[23] See more at `https://compstak.com`. The underlying CompStak data is rather new and to my knowledge, this subset has never been studied before, though Sun (2019) looked at retail leases that CompStak collected from earlier years.

[24] Unassigned free rent and TI values are treated as zero. This is the case for 151 TI observations and 125 free rent observations. Due to the already limited size of my sample, dropping entries without data presented an intractable solution. I expect there may be some bias from this methodology. However, I believe the manufactured bias is less harmful than the bias created by dropping incomplete entries. Still, these findings should be interpreted cautiously.

nesses verifiable[25] on Yelp[26] and Google Places.[27] Where businesses are verifiable, I augment the data by manually collecting[28] proxies of experience such as the average online rating.[29] This procedure leaves 212 verifiable businesses in the truncated sample. Since I study the relationship between experience and rent over the entire term of a lease, I consider only tenants for which CompStak reports effective rent, thus cutting my final sample to 166 total lease contracts.[30]

Ratings are measured on a spectrum of one to five stars.[31] Google's rating guidelines are presented in Figure 7.

---

[25] I identify tenants by the CompStak reported tenant name and address. However, given that some leases are executed in a corporate name that differs from the respective business name in the dataset, some tenants are unidentifiable. Moreover, many proposed leases in the CompStak sample do not reflect actually opened businesses, so such leases are discarded from the sample. Given my analysis setup, I only consider tenants that (1) closely match both the CompStak supplied business address and name and (2) have at least a single observable rating on both Yelp and Google Places.

[26] Yelp is a business directory service and crowd-sourced review forum. See more at `https://www.yelp.com/about`.

[27] This is Google's listing for local business search results. See more at `https://cloud.google.com/maps-platform/places/`.

[28] Experience proxies are sampled from February 8, 2020 through February 11, 2020.

[29] Yelp uses a recommendation software, a review filter, to ensure review and rating credibility. See more at `https://blog.yelp.com/2010/03/yelp-review-filter-explained`. Suspected erroneous or fabricated reviews are not included in a business's rating. To my knowledge, Google Places ratings are not filtered. However, Google Places scores are calculated from user ratings and a variety of other signals to ensure that the overall score best reflects the quality of the establishment. See more at `https://support.google.com/business/answer/4801187?hl=en&ref_topic=6109351`.

[30] The data is biased toward national tenants, as many smaller tenants execute leases under unidentifiable names. Additionally, from looking at industry distributions in Figure 21 in Appendix B, the sample seems biased toward tenants in the Food Services and Drinking Places NAICS subsector.

[31] Yelp reports that restaurant reviews, a major category of the businesses they support, are not time-dependent. See more at `https://blog.yelp.com/2018/09/restaurant-ratings-on-yelp-are-remarkably-consistent-no-matter-whos-writing-them-when-and-where`.

Figure 7: Google Places Rating Guidance

1 Star	Hated it
2 Stars	Disliked it
3 Stars	It was okay
4 Stars	Liked it
5 Stars	Loved it

Lastly, in addition to Yelp and Google Places data, I record if tenants satisfy conditions associated with being "experiential." Adapted from "Beyond Buying" (2018) and Pine and Gilmore (1998), I propose that experiential retail can be identified and characterized by the following set of sufficient conditions.

1. *Artistic Installations*

   The tenant takes an extra effort to augment consumers' experiences by displaying some form of art installation. The installations are featured in the store (rather than hidden or understated), differentiated, memorable, typically displayed in a manner that invites consumers to pose in front of them for photos, and are non-core to the tenant's principal business model (meaning the installations are not necessary for the tenant to operate). The installation can be any form of visual art, including the manner in which a tenant artistically displays its merchandise, if done so in a captivating way. This condition does not include art galleries, since their primary business model is to display art. See Figure 9 in Appendix B for examples.

2. *Customization*

   The tenant customizes or personalizes products to consumers' specific tastes and preferences in-store. Online-only customization is excluded. Customization is broken down into four major categories, as follows: hair, nail, and skin;

food and beverage; apparel and accessories; and household goods. Hair, nail, and skin customization includes all hair salons, barber shops, nail salons, and tattoo parlors. Food and beverage customization includes eating establishments that offer build-your-own style items on their menus. Apparel and accessories customization includes establishments that offer tailoring, embroidery, and engraving. Household goods customization includes establishments that offer personalized furniture, furnishings, floral arrangements, and miscellaneous home items. See Figure 10 in Appendix B for examples.

3. *Entertainment*

   The tenant provides traditional forms of in-store entertainment for consumers. This includes bowling alleys, arcades, movie theaters, art galleries, painting and pottery studios, museums, libraries, and live music. The form of entertainment is core to the tenant's principal business model (meaning it is a primary traffic driver and is necessary for the tenant to operate). See Figure 11 in Appendix B for examples.

4. *Events*

   The tenant periodically runs events for consumers. The events are designed to be interactive, provide entertainment, and bring communities together. Examples include book signings, local artist meet-and-greet sessions, community social events, food and beverage tastings, et cetera. This does not pertain to privately organized corporate or personal events. The "Events" category differs from "Entertainment," in that events are transitory. See Figure 12 in Appendix B for examples.

5. *Experiential Grocer*

   The grocer creates an immersive environment, typically characterized by a mix of bright and aesthetic displays, food tastings or demonstrations, ready-to-eat food buffets, strong customer service, and greater accessibility and convenience (through in-store, delivery, and pick-up options). See Figure 13 in Appendix B for examples.

6. *Fitness Classes*

   The tenant's core business model is to provide recreational group fitness classes. Consumers report feeling a sense of camaraderie exercising alongside other members of their community, under the instruction of a fitness expert. See Figure 14 in Appendix B for examples.

7. *Memorabilia*

   The tenant sells branded memorabilia. The memorabilia encourages consumers to commemorate their in-store experiences. The memorabilia is distinctly different in product type from the tenant's principal business model. For example, a food and beverage service establishment is counted if their memorabilia is branded apparel, but not if their memorabilia is exclusively take-home food and beverages. See Figure 15 in Appendix B for examples.

8. *Mixed Program*

   The tenant provides at least two distinct business offerings. For example, this occurs when an apparel and accessories store, a museum, a gym, or a book store offers an in-store cafe or beverage bar; when a cycling store offers a full array of items for purchase in addition to a full maintenance shop; and when a restaurant offers popular live music performances. Though the degree of separability between the two business offerings may differ across examples, all tenants that fall into this category create a single memorable experience by combining two distinct experiences into one. See Figure 16 in Appendix B for examples.

9. *Spa Program*

   The tenant provides traditional spa relaxation treatments, such as facial treatments, massages, saunas, or steam rooms. This does not apply to hair removal services, hair salons and barber shops, nor to hair styling services – though a tenant would be counted if these services are offered in addition to relaxation treatments. See Figure 17 in Appendix B for examples.

10. *Technology Integration*

   The tenant augments consumers' experiences by using in-store integrated technology. Examples of this include salons providing consumers with iPads for entertainment while consumers wait, and apparel and accessories stores providing digital fitting rooms.[32] See Figure 18 in Appendix B for examples.

These conditions are used to define two different rubrics for experiential retail identification: a weak and strong one. Both rubrics are summarized in Table 2.

The weak definition includes all factors above, as each of them reasonably creates a differentiated and memorable experience. The strong definition excludes food and beverage customization and household good customization. Since these forms of customization typically do not contribute to a consumer's sense of identity as closely as other forms – such as consumers' clothes, accessories, hair styles, nails, and tattoos – they are less important for consumers. Moreover, experiential grocers are excluded since consumers typically do not garner strong emotional attachments with produce selections. Lastly, technology integration is excluded since it augments a consumer's experience, but it is rarely a defining feature that creates the experience.

[32] Digital fitting rooms allow shoppers to scan the tags of items brought into the fitting room to identify additional pieces that may "complete the look," as well as to request alternative sizes and colors for items being tried on. Sales associates are alerted via a digital watch.

Table 2: Experiential Retail Identification Rubrics

SUFFICIENT CONDITIONS	Weak	Strong
Artistic Installations	YES	YES
Customization (Apparel/Accessories)	YES	YES
Customization (Food/Beverage)	YES	NO
Customization (Hair/Nails/Skin)	YES	YES
Customization (Household goods)	YES	NO
Entertainment	YES	YES
Events	YES	YES
Experiential Grocer	YES	NO
Fitness Classes	YES	YES
Memorabilia	YES	YES
Mixed Program	YES	YES
Spa Program	YES	YES
Technology Integration	YES	NO
Leases	76	62
Buildings	71	58

Notes: Adapted from "Beyond Buying" (2018) and Pine and Gilmore (1998), I develop two sets of sufficient conditions for tenants to be considered "experiential," according to a weak and a strong definition. The definitions vary by the conditions that most closely affect experience memorability and differentiation.

5.2.2 Descriptive Statistics

My sample consists of 166 leases distributed across 150 buildings. According to my weak (strong) definition of experiential retail, there are 76 (62) experiential leases used as a treatment group and 90 (104) non-experiential leases used as controls.

Figure 19 in Appendix B maps both the distribution of the sample across the entire CompStak dataset and the distributions of groups within the sample. The majority of the buildings in my sample are located in Manhattan. The distribution of sample leases is similar to the distribution of the entire CompStak dataset.

Table 3 shows descriptive statistics by Yelp and Google Places rating. On average, the highest rated tenants pay the least in effective and starting rent, occupy the smallest spaces, and have the greatest proportion of experiential tenants according to both definitions.[33] Table 4 shows descriptive statistics for the full sample and by group. For the weak (strong) definition, on average, experiential tenants pay $24 ($11) less in effective rent PSF and starting rent PSF, lease 1,000 (1,100) square feet more, have half (half) a year longer term, and receive a quarter (quarter) star higher rating on Yelp and Google Places. Figure 20 in Appendix B show the distributions of TI PSF, free rent, lease term, and the logarithm of transaction size by group. On average, experiential tenants receive more TI PSF and free rent than non-experiential tenants. Figure 21 in Appendix B shows tenant industry distributions by group.

[33] This ignores the Yelp 1-2 rated tenants and the Google Places 1-3 rated tenants because of the small sample size for these categories.

Table 3: Descriptive Statistics: Average Yelp & Google Places Rating

	Yelp				Google Places			
	(1) 1.0-2.0	(2) 2.1-3.0	(3) 3.1-4.0	(4) 4.1-5.0	(5) 1.0-2.0	(6) 2.1-3.0	(7) 3.1-4.0	(8) 4.1-5.0
Effective Rent ($ PSF)	273.30	215.34	159.03	132.46	97.50	128.17	179.50	157.90
	(355.88)	(190.44)	(176.51)	(113.07)	(.)	(100.05)	(189.16)	(161.45)
Starting Rent ($ PSF)	275.67	211.94	153.01	131.23	100.00	129.11	177.63	154.88
	(356.73)	(189.78)	(168.83)	(114.77)	(.)	(100.26)	(189.33)	(159.51)
Transaction Size (SF)	2734.00	5529.47	3028.82	2001.56	1142.00	3632.00	5453.14	2142.18
	(2199.32)	(8106.69)	(4496.24)	(2692.32)	(.)	(1198.64)	(8188.62)	(2568.01)
Lease Term (Months)	89.88	110.26	116.05	107.74	124.00	71.67	112.43	109.09
	(47.91)	(62.61)	(44.05)	(58.40)	(.)	(48.95)	(63.07)	(53.29)
Free Rent (Months)	0.00	1.18	0.67	1.09	3.00	2.00	0.19	1.18
	(0.00)	(2.19)	(1.80)	(1.99)	(.)	(3.46)	(0.89)	(2.12)
TI Received (1=YES)	0.25	0.09	0.05	0.06	0.00	0.00	0.10	0.07
	(0.46)	(0.29)	(0.22)	(0.24)	(.)	(0.00)	(0.30)	(0.25)
TI ($ PSF)	43.05	10.55	3.85	4.64	0.00	0.00	15.82	4.86
	(81.50)	(39.74)	(17.71)	(21.94)	(.)	(0.00)	(50.66)	(21.19)
Building Renovated (1=YES)	0.00	0.35	0.15	0.09	0.00	0.00	0.26	0.12
	(0.00)	(0.49)	(0.37)	(0.29)	(.)	(0.00)	(0.45)	(0.33)
Sublease (1=YES)	0.00	0.00	0.03	0.00	0.00	0.00	0.02	0.00
	(0.00)	(0.00)	(0.16)	(0.00)	(.)	(0.00)	(0.15)	(0.00)
Experiential (Weak; 1=YES)	0.38	0.35	0.46	0.51	0.00	0.00	0.33	0.52
	(0.52)	(0.49)	(0.51)	(0.50)	(.)	(0.00)	(0.48)	(0.50)
Experiential (Strong; 1=YES)	0.38	0.29	0.36	0.41	0.00	0.00	0.26	0.42
	(0.52)	(0.46)	(0.49)	(0.50)	(.)	(0.00)	(0.45)	(0.50)
Observations	8	34	39	85	1	3	42	120

Notes: This table reports mean and standard deviations in parentheses of lease characteristics for Yelp and Google Places 1.0-2.0 star rated tenants, 2.1-3.0 star rated tenants, 3.1-4.0 star rated tenants, and 4.1-5.0 star rated tenants.

Table 4: Descriptive Statistics: Experiential Retail Rubrics

		Weak Definition		Strong Definition	
	(1)	(2)	(3)	(4)	(5)
	All	Non-Experiential	Experiential	Non-Experiential	Experiential
Effective Rent ($ PSF)	162.47	173.50	149.41	166.69	155.38
	(167.18)	(178.27)	(153.15)	(169.85)	(163.72)
Starting Rent ($ PSF)	159.84	170.77	146.90	163.89	153.04
	(165.88)	(178.87)	(149.17)	(170.66)	(158.66)
Transaction Size (SF)	3000.79	2525.97	3563.08	2588.95	3691.61
	(4850.83)	(3104.55)	(6303.87)	(3134.55)	(6803.19)
Lease Term (Months)	109.35	106.06	113.25	107.42	112.58
	(55.63)	(52.34)	(59.41)	(58.38)	(51.00)
Free Rent (Months)	0.96	0.84	1.10	0.84	1.15
	(1.95)	(1.74)	(2.18)	(1.75)	(2.26)
TI Received (1=YES)	0.07	0.04	0.11	0.04	0.13
	(0.26)	(0.21)	(0.31)	(0.19)	(0.34)
TI ($ PSF)	7.51	4.08	11.59	3.53	14.20
	(31.39)	(25.00)	(37.36)	(23.28)	(40.96)
Building Renovated (1=YES)	0.16	0.16	0.16	0.16	0.15
	(0.36)	(0.36)	(0.37)	(0.37)	(0.36)
Sublease (1=YES)	0.01	0.00	0.01	0.01	0.00
	(0.08)	(0.00)	(0.11)	(0.10)	(0.00)
Yelp Rating	3.87	3.74	4.02	3.79	3.99
	(1.01)	(1.06)	(0.91)	(1.06)	(0.91)
Google Places Rating	4.37	4.25	4.50	4.28	4.51
	(0.55)	(0.60)	(0.45)	(0.59)	(0.44)
Observations	166	90	76	104	62

Notes: This table reports mean and standard deviations in parentheses of lease characteristics for all tenants, non-experiential tenants according to the weak definition, experiential tenants according to the weak definition, non-experiential tenants according to the strong definition, and experiential tenants according to the strong definition. These definitions are outlined in Table 2.

6 Empirical Results

6.1 Effective Rent

Table 5 presents the results of the hedonic rent model specified in Equation 9 using Yelp ratings for the experience proxy. Column (1) documents the results for an estimation without any temporal, spatial, or industry fixed effects. Holding all else equal in this model, an extra star on Yelp is associated with an effective rent discount of 18 percent. In column (2), I control for location fixed effects by submarket. Holding all else equal in this model, an extra Yelp rating has a statistically significant predictive effect of an 11 percent effective rent discount. In column (3), I control for time fixed effects by lease-commencement quarter. Holding all else equal in this model, an extra star on Yelp still has a statistically significant predictive effect of a 10 percent effective rent discount. Finally, in column (4), I control for tenant industry fixed effects by three-digit NAICS code subsectors. However, I do not find any statistically significant predictive power from Yelp ratings in this specification. In all specifications of the model, I document significantly negative size effects, showing that effective rent PSF decreases with lease size. In contrast, in the last three specifications, I document significantly positive TI effects, showing effective rent PSF increases with the amount of the one-time work value payment.

I find similar results when using Google Places ratings for the experience proxy. Similarly, the full model specification in column (4) does not have any statistically significant predictive power from Google Places ratings. The full set of results from this analysis is documented in Table 9, included in Appendix C.

Table 6 presents the results of the hedonic rent model specified in Equation 9 using the weak definition of experiential retail from Table 2 for the experience proxy. Column (1) documents the results for an estimation without any temporal, spatial,

Table 5: Rent Discrimination by Yelp Ratings

Dependent Variable: Logarithm of Effective Rent

VARIABLES	(1) Lease Cond.	(2) +Loc. FE	(3) +Time FE	(4) +Ind. FE
Yelp Rating	-0.181**	-0.107*	-0.096*	-0.035
	(0.066)	(0.057)	(0.054)	(0.080)
ln(Transaction Size)	-0.245**	-0.227***	-0.216***	-0.167**
	(0.089)	(0.064)	(0.057)	(0.071)
Lease Term (Months)	-0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Free Rent (Months)	0.071	0.009	-0.005	-0.024
	(0.042)	(0.024)	(0.022)	(0.024)
TI ($ PSF)	0.003	0.004***	0.004***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Sublease (1=YES)	0.420***	0.210*	0.150	0.177
	(0.133)	(0.104)	(0.106)	(0.191)
Building Renovated (1=YES)	0.543**	0.249*	0.252*	0.145
	(0.201)	(0.131)	(0.129)	(0.120)
Location FE	NO	YES	YES	YES
Time FE	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES
Constant	7.192***	5.850***	5.688***	4.760***
	(0.631)	(0.380)	(0.319)	(0.494)
Observations	166	166	166	166
R-squared	0.192	0.662	0.671	0.733
F Adj R2	0.156	0.584	0.583	0.617

Notes: This table documents the effect of building and lease characteristics on effective rent per square foot. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** p<0.01, ** p<0.05, * p<0.1.

or industry fixed effects. I do not document a statistically significant predictive effect of being experiential on effective rent. In column (2), I control for location fixed effects by submarket. Holding all else equal in this model, being experiential is associated with a 21 percent effective rent discount. In column (3), I control for time fixed effects by lease-commencement quarter. Similarly, holding all else equal in this model, being experiential is associated with a 22 percent effective rent discount. Finally, in column (4), I control for tenant industry fixed effects by three-digit NAICS code subsectors. However, I do not find any statistically significant predictive power from being experiential in this specification. Like before, in all specifications of the model, I document significantly negative size effects, showing that effective rent PSF decreases with lease size. In contrast, in the last three specifications, I document significantly positive TI effects, showing effective rent PSF increases with the amount of the one-time work value payment. Additionally, in the first three specifications, I observe significantly positive sublease effects, showing that effective rent PSF is greater for subleases, not conditional on tenant industry.

I find similar results, though less statistically significant, by using the strong definition of experiential retail for the experience proxy. Similarly, the full model specification in column (4) does not find any statistically significant predictive power from being experiential. This analysis is documented in Table 10 in Appendix C.

Table 6: Rent Discrimination by the Weak Definition

Dependent Variable: Logarithm of Effective Rent				
	(1)	(2)	(3)	(4)
VARIABLES	Lease Cond.	+Loc. FE	+Time FE	+Ind. FE
Experiential (Weak)	-0.179	-0.206**	-0.224**	-0.173
	(0.120)	(0.084)	(0.086)	(0.125)
ln(Transaction Size)	-0.184*	-0.196**	-0.181***	-0.168*
	(0.097)	(0.071)	(0.065)	(0.085)
Lease Term (Months)	-0.001	0.001	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Free Rent (Months)	0.061	0.001	-0.015	-0.030*
	(0.045)	(0.020)	(0.018)	(0.018)
TI ($ PSF)	0.004	0.005***	0.005***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Sublease (1=YES)	0.583***	0.370**	0.285**	0.318
	(0.171)	(0.135)	(0.118)	(0.224)
Building Renovated (1=YES)	0.563**	0.242*	0.241*	0.156
	(0.209)	(0.134)	(0.140)	(0.119)
Location FE	NO	YES	YES	YES
Time FE	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES
Constant	6.138***	5.112***	4.996***	4.564***
	(0.585)	(0.414)	(0.376)	(0.659)
Observations	166	166	166	166
R-squared	0.156	0.665	0.679	0.740
F Adj R2	0.119	0.587	0.592	0.626

Notes: This table documents the effect of building and lease characteristics on effective rent per square foot. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a non-experiential tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** p<0.01, ** p<0.05, * p<0.1.

6.2 Tenant Incentives and Lease Term

Table 7 presents the results of the tenant incentive model specified in Equation 10 using my weak and strong definitions of experiential retail from Table 2 for the experience proxies. Column (1) documents the results of an estimation of TI using my weak definition with temporal, spatial, and industry fixed effects. Holding all else equal in this model, being experiential is associated with a $12 PSF TI premium. In column (2), I document the results of an estimation of TI using my strong definition with temporal, spatial, and industry fixed effects. Holding all else equal in this model, being experiential is associated with a $13 PSF TI premium. I document that free rent has a significantly positive TI effect, showing that TI and free rent often go hand-in-hand. Additionally, effective rent has a significantly positive TI effect, showing that greater TI is associated with greater rent net of concessions.

In column (3), I document the results of an estimation of free rent using my weak definition with temporal, spatial, and industry fixed effects. I do not document a statistically significant predictive effect of being experiential on free rent. In column (4), I document the results of an estimation of free rent using my strong definition with temporal, spatial, and industry fixed effects. Similarly, I do not document a statistically significant predictive effect of being experiential on free rent. I document that TI has a significantly positive free rent effect, illustrating that TI and free rent often coincide. I also find that lease term has a significantly positive free rent effect, supporting that lease term and free rent are correlated. Lastly, I find that being a sublease has a significantly negative free rent effect, showing that subtenants often receive less free rent.

Table 8 presents the results of the tenant incentive model for lease term. Column (1) documents the results of an estimation using my weak definition with temporal, spatial, and industry fixed effects. Holding all else equal in this model, being experi-

Table 7: TI and Free Rent Discrimination by Experience

Dependent Variables: TI and Free Rent

VARIABLES	(1) TI	(2) TI	(3) Free Rent	(4) Free Rent
Experiential (Weak)	11.839**		-0.190	
	(5.475)		(0.232)	
Experiential (Strong)		13.161**		-0.100
		(5.534)		(0.262)
ln(Effective Rent)	15.040***	13.976**	-0.400	-0.377
	(5.307)	(5.271)	(0.248)	(0.260)
ln(Transaction Size)	3.703	3.701	-0.163	-0.152
	(2.900)	(3.136)	(0.134)	(0.136)
Lease Term (Months)	-0.051	-0.040	0.011**	0.010**
	(0.071)	(0.070)	(0.005)	(0.005)
Free Rent (Months)	5.946***	5.840**		
	(2.120)	(2.118)		
TI ($ PSF)			0.023**	0.022**
			(0.008)	(0.008)
Sublease (1=YES)	10.433	23.878	-2.896***	-3.103***
	(16.084)	(15.421)	(0.841)	(0.869)
Building Renovated (1=YES)	5.608	6.248	0.096	0.081
	(11.381)	(11.432)	(0.475)	(0.473)
Location FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Constant	-104.798**	-100.598*	4.701**	4.576**
	(47.666)	(49.205)	(1.875)	(1.918)
Observations	166	166	166	166
R-squared	0.463	0.466	0.469	0.468
F Adj R2	0.230	0.234	0.239	0.237

Notes: This table documents the effect of building and lease characteristics on TI per square foot and free rent in months. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a non-experiential tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

ential is associated with 17 additional months of term. In column (2), I document the results of an estimation using my strong definition with temporal, spatial, and industry fixed effects. Conversely, I do not document a statistically significant predictive effect of being experiential on lease term in this specification. In both specifications, I document that transaction size has a significantly positive lease term effect, showing that larger tenants often execute longer leases. Moreover, I document that free rent has a significantly positive effect on lease term, showing that lease term and free rent are correlated.

Table 8: Lease Term Discrimination by Experience

Dependent Variable: Lease Term

VARIABLES	(1) Lease Term	(2) Lease Term
Experiential (Weak)	17.070**	
	(6.934)	
Experiential (Strong)		9.475
		(8.231)
ln(Effective Rent)	16.812	15.039
	(13.022)	(14.343)
ln(Transaction Size)	21.731**	21.204**
	(8.707)	(8.992)
Free Rent (Months)	6.864**	6.854**
	(2.935)	(2.943)
TI ($ PSF)	-0.125	-0.103
	(0.197)	(0.195)
Sublease (1=YES)	-8.657	9.618
	(25.755)	(30.352)
Building Renovated (1=YES)	-7.615	-6.448
	(17.268)	(17.348)
Location FE	YES	YES
Time FE	YES	YES
Industry FE	YES	YES
Constant	-97.319	-87.639
	(110.609)	(116.153)
Observations	166	166
R-squared	0.578	0.567
F Adj R2	0.394	0.379

Notes: This table documents the effect of building and lease characteristics on lease term in months. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a non-experiential tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

6.3 Discussion

My study presents early evidence that experiential retail does not contribute to effective rent differentials in New York City. However, I do find that experiential retail receives larger tenant improvement (TI) allowances and sometimes longer lease terms than non-experiential retail.[34] This result is fascinating and, to my knowledge, has not been documented in the literature. Landlords, per my interpretation, effectively provide experiential tenants a zero-interest loan to incrementally improve their spaces. This is a material benefit, as alternative sources of capital are likely more expensive. I conjecture that experiences on the margin are financed through TI (τ) and tenant equity (E).[35] If experience investments produce some marginal return on invested capital ($ROIC$) for tenants, and landlords charge tenants interest (i) on TI allowance concessions, then tenants earn a return on equity (ROE) from marginal experience investments as follows:

$$ROE = (E + \tau) \times ROIC - \tau i \approx (E + \tau) \times ROIC$$

Depending on an experiential tenant's marginal ROIC from improving their space, this effectively free loan from landlords could be an enticing leasing incentive to attract tenants that generate sufficiently positive spillovers for neighboring tenants. It is not clear why landlords prefer to provide experiential retail with this tenant incentive instead of reducing their effective rent. I conjecture that this could be a function of bargaining power. However, as I cannot address this issue with the data available, it remains open for future research. Moreover, these results should be interpreted as a

[34] I performed several robustness checks, each yielding no statistically significant predictive power from the experience proxy on effective rent. These alternative specifications included: using two-digit and six-digit NAICS code sectors for industry fixed effects and using lease-commencement year time dummies for time fixed effects.

[35] Tenants could partially finance improvements through other sources of capital, but I assume this is not the case for the sake of simplicity.

first step in studying these complicated tenant-landlord interactions. Additional data must be collected and curated to fully address the rent and lease concession tradeoffs occurring during lease negotiations.

This study's findings are limited by a small sample size with potentially biased TI and free rent distributions. Since unassigned free rent and TI values are treated as zero, these findings should be interpreted cautiously. Due to the already limited size of my sample, dropping entries without data presented an intractable solution. I expect there may be some bias from this methodology. However, I believe the manufactured bias is less harmful than the bias created by dropping incomplete entries. Additionally, the distribution of tenants is skewed heavily toward Food Services and Drinking Places, and high ratings. It is unclear if the distribution of tenant industries and tenant ratings is representative of the entire market. Comprehensive analyses of cross-city and cross-time data are needed to confirm these early findings. Future research with richer datasets should also consider exploring the interactive effects of experience and tenant industry to better understand the varying predictive effect of experience across industries.

Furthermore, my estimates may suffer from endogeneity bias. Though this analysis attempts to overcome this problem by creating and applying an experiential retail rubric, presently there is no universally accepted method for identifying or quantifying experience. Consequently, the proxies presented in this study may be insufficient. To address this concern, future research could employ an instrumental variable approach, using social media adoption at an urban scale as an instrument. I suspect that my estimates for the experiential effective rent differential may be inflated somewhat, as my model does not capture micro-locational value differences, but I have no means to verify this. Since experience may be positively correlated with a space's relative value within a submarket (that is, being located on a heavily trafficked corner, on the ground floor, et cetera), I suspect removing this omitted-variable bias might provide evidence of rent discrimination by experience. Unfortunately, I could not obtain the data necessary to conduct such analyses. As researchers and practitioners continue to develop an understanding of experiential retail, future research should explore alternative proxies of experience for experiential retail identification.

Given the relative novelty of the concept of experiential retail, it may still be too early to detect if landlords believe that experiential tenants generate sufficiently positive spillovers to warrant long-term rent concessions. Still, this study offers preliminary evidence that landlords view experiential and non-experiential tenants as exact substitutes, from an effective rent perspective, but provide experiential retail tenants additional concessions in the form of TI and sometimes a longer lease term.

7 Conclusion

Despite the rise of e-commerce, experiential brick-and-mortar retail has continued to proliferate across the United States. At a time when many traditional retailers are going bankrupt, experiential retail's continued growth has caught the attention of real estate researchers and practitioners alike. In this study, I shed light on (1) the potential economic mechanisms that could have led to the current market dynamics and (2) the financial impacts of experiential retail on landlord–tenant interactions.

To this end, I first propose a theoretical model describing the mechanism through which e-commerce's improvement – similar to the one that has taken place over the past few decades – shifts consumers' preferences away from brick-and-mortar establishments toward e-commerce shopping. That is, if retailers had not adjusted their in-store experiences, all else constant, demand would be redirected online. My model suggests that this preference shift results in some traditional retailers exiting the market, while remaining brick-and-mortar stores providing better experiences. I then theoretically consider tenants' behavior after several types of exogenous shocks, including shocks to experience-to-eWOM conversion efficiency, fixed costs, and the degree of experiential-retail rent discrimination by landlords.

In the second part, I analyze evidence of price discrimination empirically, using a sample of New York City retail leases executed in 2019. I proxy experience through Yelp and Google Places ratings, and through two rubrics of experiential retail developed in this paper. While I find no statistically significant evidence of rent discrimination, I document other salient facts about experiential tenants. Namely, experiential retail leases reflect different leasing contract characteristics, receiving additional tenant improvement (TI) allowances and longer lease terms than non-experiential tenants. This suggests that negotiations between experiential tenants and landlords lean toward a calculation of short-term versus long-term benefits, such that experiential tenants receive more cash benefits upfront in exchange for more rent later. On the margin, landlords are effectively granting experiential tenants a zero-interest loan to improve their spaces. This may be a powerful leasing incentive, depending on a tenant's return on invested capital from improving their space.

Data limitations prevent me from observing why experiential tenants receive greater tenant incentives than non-experiential tenants. Landlords may perceive experiential tenants as less susceptible to e-commerce disruption, so landlords are more willing to take risks with heftier TI payments upfront in exchange for greater rent payments and/or lease terms down the road. There may also be profit sharing agreements between landlords and experiential tenants that are not fully captured in my dataset.

Though this study is limited in scope, it takes some of the first and necessary steps to address the market dynamics and financial impacts of experiential retail. More data is needed, especially across geographies and time, to enhance these results. Additionally, integrating tenant sales into the analysis would provide greater insight into the relationship between experiences and tenants' financial performances. Lastly, alternative proxies for tenant experience expectations should be developed and studied. Nonetheless, this paper presents early evidence on the economic effects of experiential real estate, helping us better understand this nascent and expanding sector of the U.S. economy.

Appendices

Appendix A Demand Function Derivation

Consider the demand function for a representative firm $D_i = \beta(E) \times x(p, \phi)$. $\beta(E)$ is presented in Equation (2). $x(p, \phi)$ is derived below. Figure 8 at the end of the derivation provides an illustrative visualization of a city with four firms, decomposing demand into the various individual components.

Holding the number of firms constant, consumers can be partitioned into n groups, $k = 1, ..., n$, where, assuming full information and no e-commerce, the kth group is the set of consumers to whom the representative firm would offer their kth highest surplus of the n firms. The representative firm has $n-1$ rivals. Computing (1) the size N_k of each group, combined with (2) calculating the probability that each group sees a post for the representative firm and no posts for other firms that would yield higher consumer surplus, will produce this component of the demand function.

A consumer at a distance z from the representative firm can achieve surplus $v - tz - p + E(\phi)$ by purchasing from that firm. For $0 \leq z \leq 1/n$ consumers between the representative firm and the firm's nearest neighbor, they achieve surplus $v - t(1/n - z) - \bar{p} + E(\bar{\phi})$ by purchasing from the firm's nearest neighbor. Therefore, if z_1 is the location of the consumer indifferent between the two firms, assuming the consumer knows of both firms' existences, z_1 is given by:

$$v - tz_1 - p + E(\phi) = v - t(1/n - z_1) - \bar{p} + E(\bar{\phi})$$

$$z_1 = \frac{\bar{p} - E(\bar{\phi}) - p + E(\phi)}{2t} + \frac{1}{2n}$$

All consumers $z \leq z_1$ will, if fully informed, purchase from the representative firm if they prefer brick-and-mortar. Counting consumers on either side of the representative firm, the number of people in this partition (before the fraction of demand lost to e-commerce is introduced) is given by:

$$N_1 = 2\delta z_1 = \frac{\delta(\bar{p} - E(\bar{\phi}) - p + E(\phi))}{t} + \frac{\delta}{n} \tag{A.1}$$

Next, consider the consumer who would be indifferent between purchasing from the representative firm and the firm that is its second closest neighbor ($2/n$ distance away from the firm). Using the same logic as before, this consumer is located at z_2, given by:

$$v - tz_2 - p + E(\phi) = v - t(2/n - z_2) - \bar{p} + E(\bar{\phi})$$

$$z_2 = \frac{\bar{p} - E(\bar{\phi}) - p + E(\phi)}{2t} + \frac{1}{n}$$

Consumers who prefer brick-and-mortar between z_1 and z_2 find the representative firm second most-preferred if they have full information (they most prefer the firm that is closest to the representative firm). The number of consumers in the second group (before the fraction of demand lost to e-commerce is introduced) is $N_2 = 2\delta(z_2 - z_1)$. Substituting for $z_2 - z_1$ from above, $N_2 = \delta/n$. This result can be generalized as:[36]

$$z_k = \frac{\bar{p} - E(\bar{\phi}) - p + E(\phi)}{2t} + \frac{k}{2n} \qquad k = 1, 2, ..., n-1$$

$$N_k = \frac{\delta}{n} \qquad k = 2, ..., n-1 \tag{A.2}$$

The nth group comprises all those consumers not in the $(n-1)$ groups. That is,

[36] The difference between N_1 and N_k ($k \neq 1$) stems from allowing the representative firm to select a different p and ϕ from all other competitors, who select $\bar{p}$ and $\bar{\phi}$. Assuming a symmetrical equilibrium results in $N_1 = N_k, \forall k \neq 1$.

$N_n = \delta - \sum_{k=1}^{n-1} N_k$, or:

$$N_n = \frac{\delta}{n} - \frac{\delta(\bar{p} - E(\bar{\phi}) - p + E(\phi))}{t} \tag{A.3}$$

This gives all the necessary pieces to calculate the $x(p, \phi)$ component of the demand curve for the representative firm. If the probability of making a sale to the kth group is given by ϕ_k, then this component is:

$$x(p, \phi) = N_1\phi_1 + N_2\phi_2 + ... + N_n\phi_n$$

Consumers who prefer brick-and-mortar in the first group always purchase if they see a post because this is their most preferred firm. Therefore, $\phi_1 = \phi$. A sale results for the people in the second group if they see a post for the representative firm, but not for the representative firm's nearest neighbor (the neighbor that is preferable under full information). This occurs with probability $\phi_2 = \phi(1 - \bar{\phi})$. Assuming the value derived from v and $E(\phi)$ is sufficiently large, such that consumer surplus is non-negative and non-binding for any group, the probability a sale occurs to a consumer in the kth group is given by:

$$\phi_k = \phi(1 - \bar{\phi})^{k-1} \qquad k = 1, 2, ..., n \tag{A.4}$$

Substituting N_k from Equation (A.1), Equation (A.2), and Equation (A.3) and ϕ_k from Equation (A.4) into the demand function produces:

$$x(p, \phi) = N_1\phi_1 + \sum_{k=2}^{n-1} N_k\phi_k + N_n\phi_n$$

$$x(p,\phi) = \frac{\delta\phi(\bar{p} - E(\bar{\phi}) - p + E(\phi))}{t}[1 - (1-\bar{\phi})^{n-1}] + \frac{\delta\phi}{n\bar{\phi}}[1-(1-\bar{\phi})^n] \tag{A.5}$$

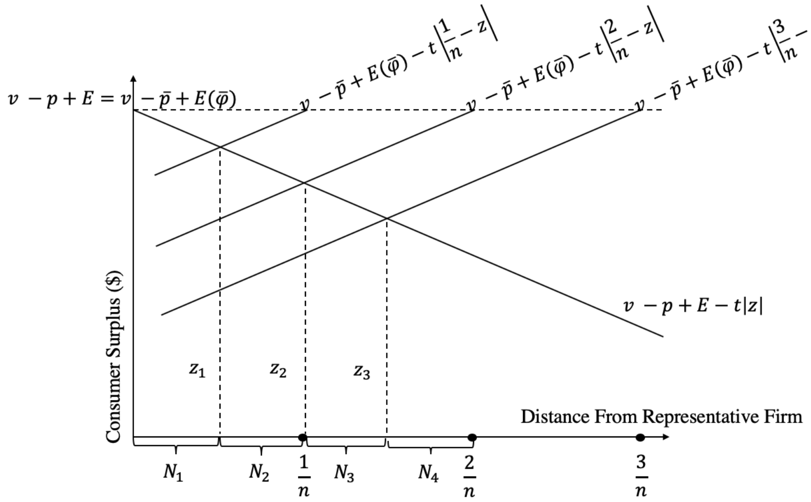
As is argued by Grossman and Shapiro, for reasonable parameter values such that $(1-\bar{\phi})^n$ is approximately zero, one can approximate Equation (A.5) as:

$$x(p,\phi) \approx \frac{\delta\phi(\bar{p} - E(\bar{\phi}) - p + E(\phi))}{t} + \frac{\delta\phi}{n\bar{\phi}} \tag{A.6}$$

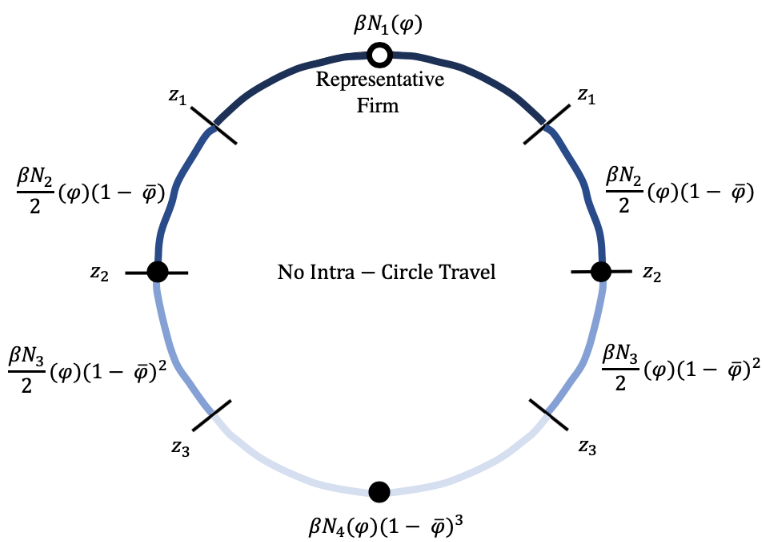
Therefore, total demand, accounting for demand lost due to e-commerce, for firm i is approximately given by:

$$D_i \approx \beta(E(\phi))\left(\frac{\delta\phi(\bar{p} - E(\bar{\phi}) - p + E(\phi))}{t} + \frac{\delta\phi}{n\bar{\phi}}\right) \tag{A.7}$$

Figure 8: Demand Derivation Visualization



(a) Linear Representation



(b) Circular Representation

Notes: Consider the demand function for a representative firm $D_i = \beta(E) \times x(p, \phi)$. $\beta(E)$ is presented in Equation (2), so all that remains to be solved for is $x(p, \phi)$. Holding the number of firms constant, consumers can be partitioned into n groups, $k = 1, ..., n$, where, assuming full information and no e-commerce, the kth group is the set of consumers to whom the representative firm would offer their kth highest surplus of the n firms. Computing (1) the size N_k of each group, combined with (2) calculating the probability that each group sees a post for the representative firm and no posts for other firms that would yield higher consumer surplus, will produce $x(p, \phi)$.

Appendix B Figures

Figure 9: Examples of *Artistic Installations*

(a) Taco Dumbo, Midtown West

(b) Herschel Supply Co., SoHo

Notes: Taco Dumbo, a taqueria and margarita bar located in Midtown West, offers "beach-side" seating alongside an artistic branded neon sign. Herschel Supply Co., a hipster luggage company located in SoHo, draws consumers in with an artistic rainbow wall display showcasing their iconic backpacks. These are examples of memorable and differentiated artistic installations that immerse consumers in the retail environment.

Figure 10: Examples of *Customization*

(a) Sweetgreen, Penn Station

(b) Trek, Upper West Side

Notes: Sweetgreen, a fast-casual salad restaurant located at Penn Station, offers a build-your-own salad option, where consumers choose each ingredient. Trek, a cycling shop located on the Upper West Side, offers their "Project One" program, allowing consumers to fully customize their bikes. These examples of customization allow consumers to tailor purchases to their precise tastes and preferences.

Figure 11: Examples of *Entertainment*

(a) AR Workshop, Gramercy Park

(b) Museum of Ice Cream, SoHo

Notes: AR Workshop, a boutique "Do it yourself" ("DIY") studio located in Gramercy Park, offers hands-on classes for creating custom home decor. The Museum of Ice Cream, an interactive art exhibit located in SoHo, showcases ice cream and candy themed exhibits in a maze of rooms containing a rock-candy cave, a unicorn, and a swimming pool of rainbow sprinkles. These examples of entertainment draw in consumers for the principal purpose of being entertained.

Figure 12: Examples of *Events*

(a) Lululemon, Fifth Avenue

(b) Huckberry, Hudson Square

Notes: Lululemon, an athletic apparel retailer located on Fifth Avenue, runs community events, ranging from workshops to workout classes with local ambassadors. Huckberry, an outdoors gear and apparel brand located in Hudson Square, runs events, ranging from surfboard waxing demonstrations to bourbon tastings. These examples of events both encourage consumers to engage with their local community and emphasize the tenants' missions.

Figure 13: Examples of *Experiential Grocer*

(a) Lincoln Market, Brooklyn

(b) Met Fresh, Queens

Notes: Lincoln Market, a grocer located in Brooklyn, showcases "farmers' market" style produce displays. Met Fresh, a grocer located in Queens, offers ready-to-eat food and a "beer cave." These experiential grocers exhibit ways in which grocers create differentiated consumer experiences.

Figure 14: Examples of *Fitness Classes*

(a) Row House, Murray Hill

(b) CorePower Yoga, Penn Station

Notes: Row House, a boutique fitness rowing studio located in Murray Hill, guides participants through a high intensity rowing workout. CorePower Yoga, a yoga studio located at Penn Station, combines traditional yoga with strength training and cardio. These fitness classes attract consumers by promoting a sense of camaraderie amongst participants, as participants exercise alongside other members of their community.

Figure 15: Examples of *Memorabilia*

(a) Shake Shack, Columbus Circle

(b) Blue Bottle Coffee, City Hall

Notes: Shake Shack, a fast casual restaurant chain located at Columbus Circle, sells branded apparel, accessories, and toys. Blue Bottle Coffee, a coffee shop located at City Hall, sells branded accessories, brewing equipment, and coffee beans. These examples of memorabilia remind consumers of their in-store experience with branded take-home keepsakes.

Figure 16: Examples of *Mixed Program*

(a) Book Club, NoHo

(b) GRIT BXNG, Union Square

Notes: Book Club, an independent book store in NoHo, features an in-store coffee, beer, and wine bar. GRIT BXNG, a boxing studio located in Union Square, offers a full-service liquor bar where consumers can socialize. These examples of a mixed program showcase tenants combining two distinct business offerings into one, to create a more memorable experience.

Figure 17: Examples of *Spa Program*

(a) Equinox, FiDi

(b) COMPLETE, Union Square

Notes: Equinox, a fitness club located in FiDi, offers a variety of facials, massages, body treatments, waxing services, saunas, steam rooms, and whirlpools. COMPLETE by CompleteBody, a fitness club located in Union Square, offers massages, facials, cryotherapy, saunas, and a Himalayan salt lounge. These spa programs showcase tenants providing relaxing memorable experiences for consumers.

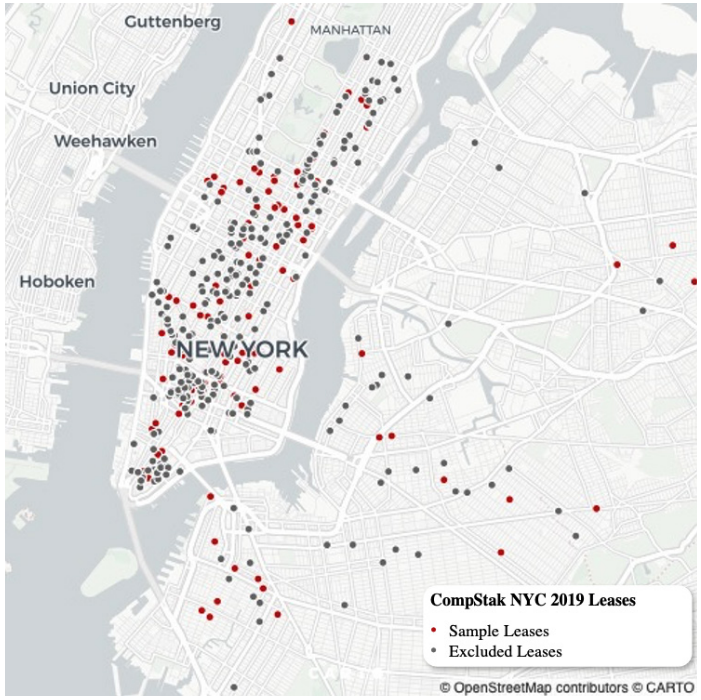
Figure 18: Examples of *Technology Integration*

(a) Mango, SoHo

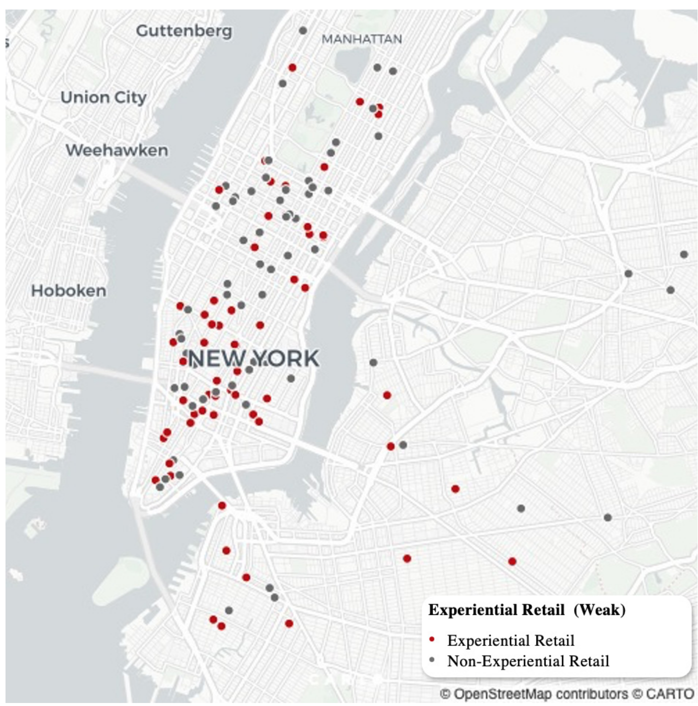
(b) Dreamdry, Columbus Circle

Notes: Mango, an apparel and accessories store located in SoHo, offers digital fitting rooms, where shoppers scan the tags of items brought into the fitting room to identify additional pieces that may “complete the look,” as well as to request alternative sizes and colors for items being tried on. Sales associates are alerted via a digital watch. Dreamdry, a hair salon located in Columbus Circle, provides clients with iPads for entertainment while they wait. These examples of technology integration showcase technology being used to enhance consumers’ experiences.

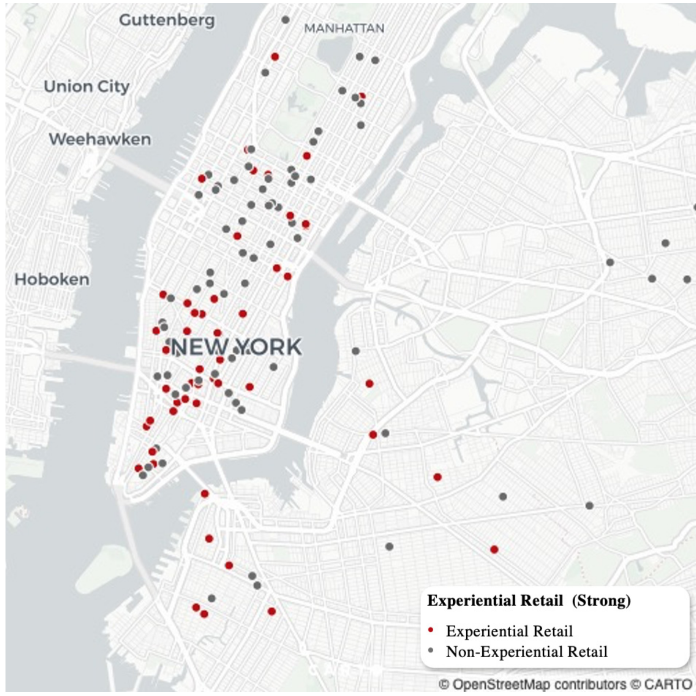
Figure 19: Sample Location Distributions



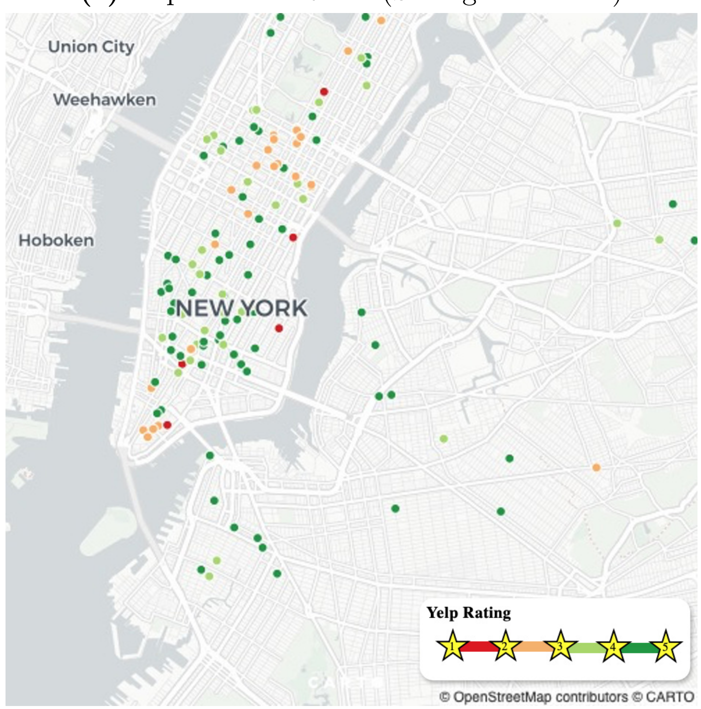
(a) Sample Leases



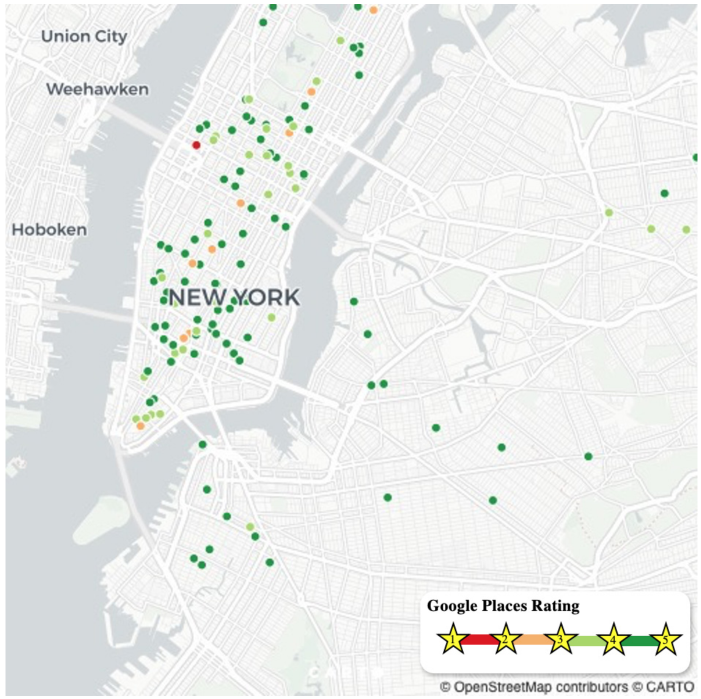
(b) Experiential Retail (Weak Definition)



(c) Experiential Retail (Strong Definition)



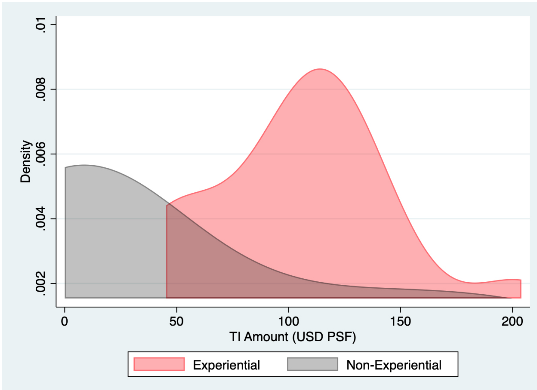
(d) Yelp Rating



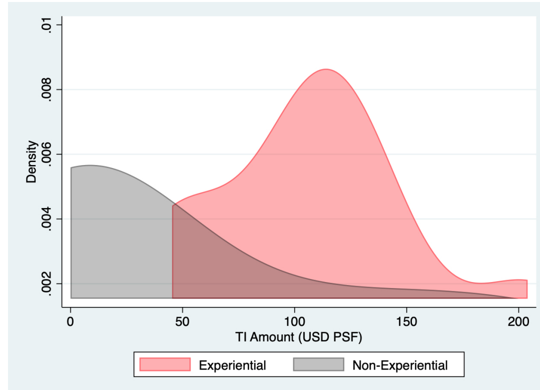
(e) Google Places Rating

Notes: These maps show the locations of all leases included in the sample, the locations of experiential retail leases within the sample (for both my weak and strong definitions), and the locations of differently rated leases within the sample (by Yelp and Google Places). In each map's case, a few observations lie outside of the map's frame.

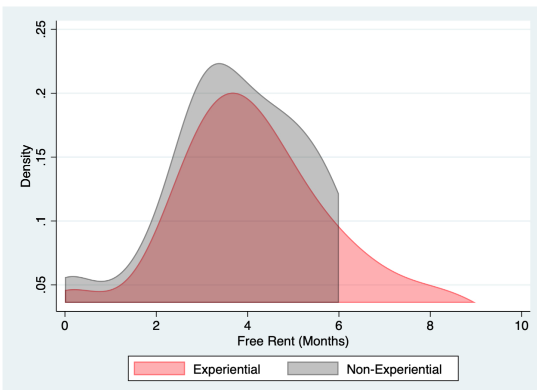
Figure 20: Lease Characteristics: Densities by Experience



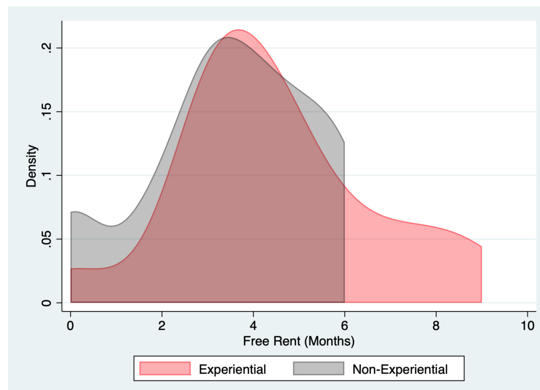
(a) TI by Weak Definition



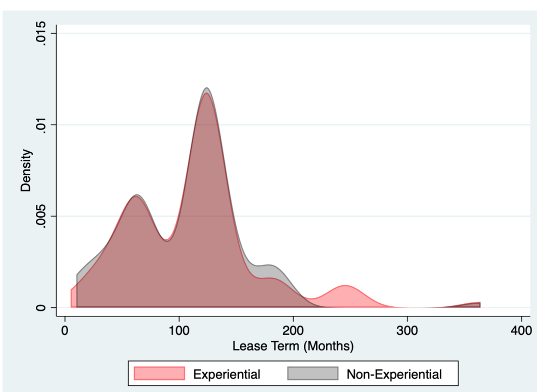
(b) TI by Strong Definition



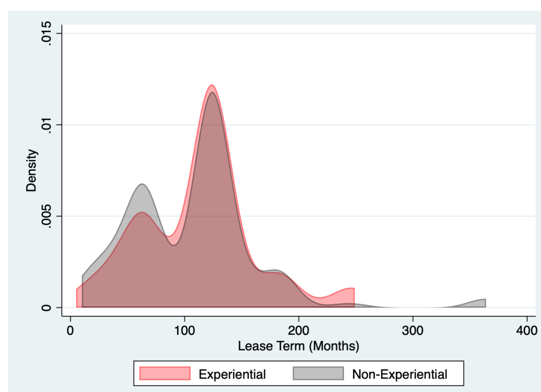
(c) Free Rent by Weak Definition



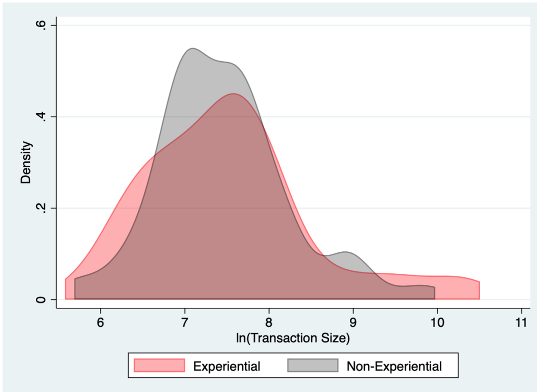
(d) Free Rent by Strong Definition



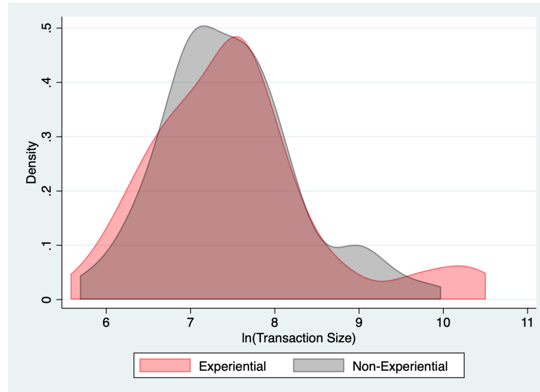
(e) Lease Term by Weak Definition



(f) Lease Term by Strong Definition



(g) ln(SF) by Weak Definition



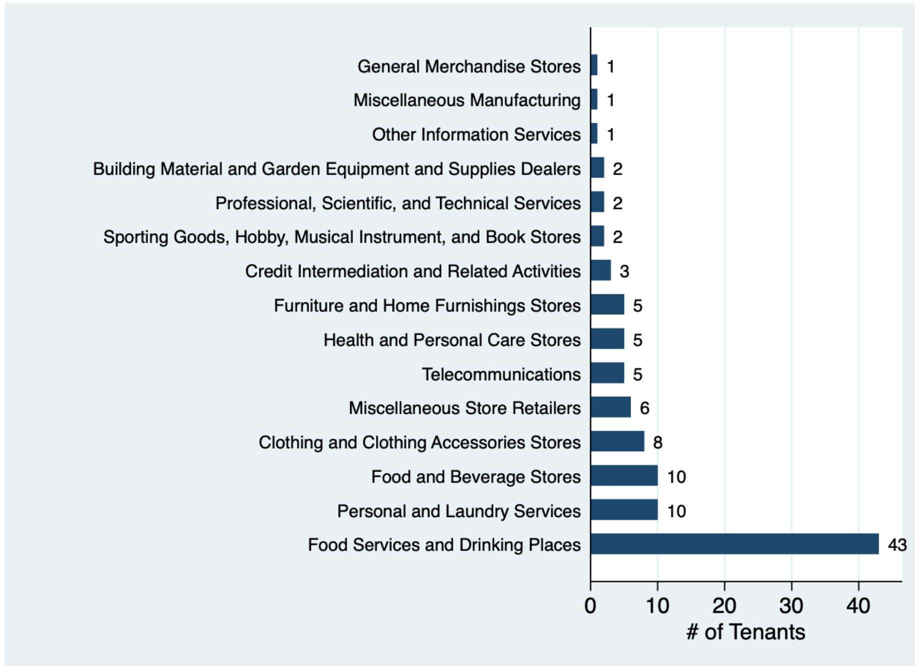
(h) ln(SF) by Strong Definition

Notes: These figures depict density distributions of TI PSF, free rent, lease term, and the logarithm of transaction size using kernel density estimates with a Gaussian kernel. TI and free rent distributions do not include tenants with unassigned values.

Figure 21: Tenant Industry Distribution by Experience

(a) Non-Experiential (Weak)

(b) Experiential (Weak)



(c) Non-Experiential (Strong)

(d) Experiential (Strong)

Notes: These figures breakdown three-digit NAICS code industry subsectors by my weak and strong definitions of experience.

Appendix C Tables

Table 9: Rent Discrimination by Google Places Ratings

Dependent Variable: Logarithm of Effective Rent

VARIABLES	(1) Lease Cond.	(2) +Loc. FE	(3) +Time FE	(4) +Ind. FE
Google Places Rating	-0.148	-0.233	-0.220	-0.076
	(0.141)	(0.143)	(0.138)	(0.131)
ln(Transaction Size)	-0.211*	-0.233***	-0.221***	-0.171**
	(0.116)	(0.073)	(0.068)	(0.077)
Lease Term (Months)	-0.001	0.001	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Free Rent (Months)	0.064	0.006	-0.007	-0.026
	(0.041)	(0.023)	(0.021)	(0.019)
TI ($ PSF)	0.003	0.004***	0.004***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Sublease (1=YES)	0.390***	0.100	0.035	0.137
	(0.134)	(0.096)	(0.105)	(0.232)
Building Renovated (1=YES)	0.569**	0.237*	0.240*	0.146
	(0.209)	(0.136)	(0.136)	(0.119)
Location FE	NO	YES	YES	YES
Time FE	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES
Constant	6.898***	6.519***	6.355***	5.018***
	(1.207)	(0.910)	(0.806)	(0.824)
Observations	166	166	166	166
R-squared	0.153	0.667	0.677	0.733
F Adj R2	0.115	0.590	0.590	0.617

Notes: This table documents the effect of building and lease characteristics on effective rent per square foot. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Rent Discrimination by the Strong Definition

Dependent Variable: Logarithm of Effective Rent

VARIABLES	(1) Lease Cond.	(2) +Loc. FE	(3) +Time FE	(4) +Ind. FE
Experiential (Strong)	-0.107	-0.133	-0.159*	-0.085
	(0.122)	(0.086)	(0.092)	(0.118)
ln(Transaction Size)	-0.184*	-0.193**	-0.179**	-0.160*
	(0.099)	(0.076)	(0.068)	(0.091)
Lease Term (Months)	-0.001	0.001	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Free Rent (Months)	0.061	-0.000	-0.016	-0.029
	(0.045)	(0.020)	(0.018)	(0.018)
TI ($ PSF)	0.003	0.005***	0.005***	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Sublease (1=YES)	0.443***	0.177*	0.073	0.140
	(0.147)	(0.087)	(0.096)	(0.206)
Building Renovated (1=YES)	0.565**	0.246*	0.246*	0.145
	(0.206)	(0.125)	(0.129)	(0.119)
Location FE	NO	YES	YES	YES
Time FE	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES
Constant	6.102***	5.107***	4.997***	4.539***
	(0.596)	(0.448)	(0.396)	(0.690)
Observations	166	166	166	166
R-squared	0.147	0.655	0.669	0.734
F Adj R2	0.110	0.576	0.580	0.618

Notes: This table documents the effect of building and lease characteristics on effective rent per square foot. Location fixed effects are measured at the submarket level. Time fixed effects are measured by lease-commencement quarter dummies. Industry fixed effects are at the NAICS three-digit level. The base case is a non-experiential tenant that is located on Park Avenue, commences in 2019:Q1, and is in the Food Services and Drinking Places subsector. Standard errors are clustered by submarket and execution year. *** p<0.01, ** p<0.05, * p<0.1.

References

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, *4*(3), 291. Retrieved from `http://search.proquest.com/docview/1297342536/`

Aspremont, C., & Gabszewicz, J. (1979). On hotelling's "stability in competition". *Econometrica*, *47*(5), 1145. Retrieved from `http://search.proquest.com/docview/1296438965/`

Benjamin, J. D., Boyle, G. W., & Sirmans, C. (1992). Price discrimination in shopping center leases. *Journal of Urban Economics*, *32*(3), 299–317.

Beyond buying. (2018). *Jones Lang LaSalle*.

Brueckner, J. (1993). Inter-store externalities and space allocation in shopping centers. *The Journal of Real Estate Finance and Economics*, *7*(1), 5–16.

Butters, G. (1977). Equilibrium distributions of sales and advertising prices. *The Review of Economic Studies*, *44*(3), 465. Retrieved from `http://search.proquest.com/docview/1294382909/`

Chegut, A., Eichholtz, P., & Rodrigues, P. (2015). Spatial dependence in international office markets. *The Journal of Real Estate Finance and Economics*, *51*(2), 317–350.

Chegut, A., & Langen, M. (2019). The financial impacts of coworking: Rental prices and market dynamics in the commercial office market.

Cheung, C. M., & Lee, M. K. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems*, *53*(1), 218–225.

Di Pietro, L., Di Virgilio, F., & Pantano, E. (2012). Social network for the choice of tourist destination: attitude and behavioural intention. *Journal of Hospitality and Tourism Technology*, *3*(1), 60–76.

Goldenberg, J., Libai, B., & Muller, E. (2001). Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing Letters*, *12*(3), 211–223.

Gould, E., Pashigian, B., & Prendergast, C. (2005). Contracts, externalities, and incentives in shopping malls. *The Review of Economics and Statistics*, 411–422. Retrieved from `http://search.proquest.com/docview/194685288/`

Grossman, G., & Shapiro, C. (1984). Informative advertising with differentiated products. *Review of Economic Studies*, *51*(1), 63–81. Retrieved from `http://search.proquest.com/docview/839186387/`

Hennig-Thurau, T., Gwinner, K., Walsh, G., & Gremler, D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 38. Retrieved from `http://search.proquest.com/docview/229636468/`

Hotelling, H. (1929). Stability in competition. *Economic Journal*, *39*, 41–56. Retrieved from `http://search.proquest.com/docview/58142891/`

Ingene, C. A., & Ghosh, A. (1990). Consumer and producer behavior in a multipurpose shopping environment. *Geographical Analysis*, *22*(1), 70–93.

Kim, D., Jang, S., & Adler, H. (2015). What drives café customers to spread ewom? *International Journal of Contemporary Hospitality Management*, *27*(2), 261–282.

Mcallister, K. (2019). What's an experience worth? the math is tricky; increasingly, people are valuing experiences over things. but the hard part is knowing how to compare the two. *Wall Street Journal (Online)*. Retrieved from `http://search.proquest.com/docview/2307030630/`

Pine, B. J., & Gilmore, J. H. (1998). Welcome to the experience economy. *Harvard business review*, *76*(4), 97–105. Retrieved from `http://search.proquest`

.com/docview/80041459/

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55.

Salop, S. (1979). Monopolistic competition with outside goods. *Bell Journal of Economics*, 141. Retrieved from http://search.proquest.com/docview/236471744/

Sirmans, C., & Guidry, K. (1993). The determinants of shopping center rents. *Journal of real estate research*, *8*(1), 107–116. Retrieved from http://search.proquest.com/docview/38578840/

Sun, X. (2019). Evaluating the impact of online influencers on retail property rent - a case study in new york city.

Tirole, J. (1988). *The theory of industrial organization*. Cambridge, Mass.: MIT Press.

Wolinsky, A. (1983). Retail trade concentration due to consumers' imperfect information. *The Bell Journal of Economics*, *14*(1), 275–282.

Ye, Q., Law, R., & Gu, B. (2009). The impact of online user reviews on hotel room sales. *International Journal of Hospitality Management*, *28*(1), 180–182.

Zhang, Z., Ye, Q., Law, R., & Li, Y. (2010). The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, *29*(4), 694–700.