E-commerce and the Changing Value of Retail Co-location in Cities

May 2025

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Abstract

With the growth of e-commerce, do retail tenants continue to co-locate so that consumers can benefit from reduced travel and comparison shopping? Do retail rents and property prices reflect changes in benefits from retail clustering due to e-commerce proliferation? In this project, we use parcel level data to create novel metrics of retail clustering, document changes in retail clustering over time and test whether retail property values have changed in response to changing demand for in-person retail services. Specifically, we hypothesize that the rise of e-commerce has caused an increase in clustering for stores with experiential goods and a decrease in clustering for all other retail store types. Further, we expect that these changes in clustering patterns impact retail rent and property values. Results indicate that retail clustering did get more concentrated between 2006 and 2022, although it was markedly more pronounced in New York City than Los Angeles. The number of new retail leases, the amount of retail space leased and average rents also declined and plateaued over this same time period, when e-commerce revenues were exploding. Retail properties proximate to bigger commercial clusters sold for higher prices in Los Angeles relative to other non-retail commercial properties. Clustering, however, imposed a relative price discount for retail properties in New York City. In New York City, any initial premium from nearby commercial clusters gets attenuated over time. On the other hand, there was not a significant change in the value of commercial clustering for retail properties in Los Angeles

Acknowledgments: We thank Chris Cahill for excellent research assistance and NYU's Furman Center for sharing their property transaction data.

1 Introduction

Without a doubt, the rise of e-commerce has changed the value of physical real estate assets devoted to retail uses. Over the last decade and a half, the square footage of the average new retail lease in most major markets has declined. In addition, and in notable contrast to ever-increasing residential prices, real retail rents have fallen (Brooks and Meltzer, 2024).

However, real estate investors know that not all locations are created equal, and that asset value depends critically on local determinants of value. One key determinant of value for real estate of all types is the type, quality, and mix of neighbors. When leasing a site, or evaluating the current leases on a site, investors need to be able to evaluate not just the value of current tenants and leases, but the value of tenant synergy – in economics terms, agglomeration.

For example, in the not-too-distant past, the sales draw of a mall's anchor tenant, usually a department store, created overall value by driving traffic to other retailers. The value of this draw was reflected in lower rents for such anchors, and higher rents for the surrounding stores (Pashigian and Gould, 1998; Gould et al., 2005). In recent decades, the value of these anchors has sunk precipitously. Yet new anchors have arisen. Apple stores now offer nearby tenants many of the same valuable spillovers – customers, and particularly affluent ones – formerly offered by department stores (Chung et al., 2019). Grocery stores also now serve as anchor tenants (Relihan, 2017).

In this paper, we investigate how patterns of retail co-location have changed over the last two decades and relate those changes to the value of retail real estate – a topic that has received scant attention in the academic literature. By "retail," we mean not just the typical set of retail goods like clothing or electronics stores, but all consumer-facing activities, including food away from home, hospitality, and personal services such as nails or haircuts. As we detail below, we employ novel measures of retail clustering with rich transaction and administrative data to help understand the relationship between co-location and value.

Some of the results reveal trends that are consistent across the two markets, New York City and Los Angeles. First, we document shifts in the clustering of retail over the nearly two decades between 2006 and 2022, when e-commerce was growing precipitously. Retail clusters become more concentrated over this time period, consistent with the expectation that in order to compete with online shopping, retail is increasingly concentrated in single locations instead of scattered across smaller clusters. However, this increase in retail concentration is more pronounced in New York City than Los Angeles.

Second, over this same time period the initiation of retail leases and the amount of retail square footage leased plateaued, coincident with the acceleration in the growth of e-commerce revenues. Retail rents decline for New York City (although less so since the early 2000s, when the CoStar data is more reliable) and are essentially flat for Los Angeles. Rents, however, are sticky for commercial spaces (often with terms of 10 years or longer) and it may be harder to tease out a systematic response to e-commerce competition.

When we use sales prices to test for changes in the capitalization of retail clustering into land values, the patterns are different across New York City and Los Angeles. We find that while properties proximate to bigger commercial clusters consistently sell for higher prices, the premium for retail properties depends on the market. In New York, there is a discount for retail properties near bigger commercial clusters, relative to other non-retail commercial uses. And this discount gets bigger over time. In Los Angeles, there is a modest retail premium, which attenuates slightly over time but still remains positive relative to other non-retail commercial uses.

2 How the Rise of E-commerce is Reflected in Retail Property Values

In this section, we lay out the fundamentals that drive retail location and rents, and then consider how e-commerce induced changes in those fundamentals, including the prevalence and mix of commercial neighbors, could affect the value of retail land.

2.1 Retail Market Fundamentals

The value of any parcel of land is determined by its "highest and best use." For commercially zoned land, this is typically determined by the potential income from economic activity that takes place on that parcel. And for retail land, the value, or potential income stream, is a function of the broader market for retail goods and services. Establishments stay operational when revenues meet or exceed business expenses. On the cost side, rent is usually the most significant budget item, especially for enterprises that are not capital intensive, such as retailers. Whereas a business can adjust labor costs to a point (by employing fewer people, for example), rent is usually fixed for the term of the lease. Moreover, rents and the supply of space vary across neighborhoods within the same city, presumably capturing variation in the costs and benefits of operating in those particular locations. This is in contrast to labor costs, which vary substantially less within the same city for comparable jobs.

The retail market is also affected by localized demand fundamentals. All else equal, retailers prefer to locate closer to a consumer base. The density and composition of this consumer-based can change for any number of reasons, and the viability of retail is affected by such shifts. We acknowledge that transit costs, such as distance to a freeway, major road, or public transit, mediate the cost of consumer access. For purposes of this framework, we consider these transit fundamentals fixed.

Finally, the presence of nearby establishments can bring agglomerative benefits. In the retail case, this means economies of scale in co-location due to shared customer bases or lower transportation and search costs. Therefore, the value of any individual retail parcel depends not only on the economic activity of that particular site, but the economic activity of nearby sites as well (Kickert and Vom Hofe, 2018; Dodds and Dubrovinsky, 2014). One implication of this is that if nearby retail spaces are unoccupied or not drawing customers, for example due to online substitution, the benefits of clustering could be attenuated and ultimately reflected in depreciated values at that location.

2.2 How E-commerce Disrupts Retail Market Fundamentals

In the absence of e-commerce, consumers incur costly transport costs to search for and purchase goods in person. Therefore, retail clustering that allows for search and multiple purchases in the same location is very valuable to consumers. After the arrival of e-commerce, consumer transit costs decline to near zero for online purchases, as do search costs, due to the technological capabilities of searching for products across many sellers and online comparison shopping.

Given this, we expect that e-commerce should change the value of the physical location, and co-location, of retail. This is in notable contrast to goods producers, for whom supply-side cost determinants, rather than demand-side customer costs, drive overall costs. Consumers no longer need to visit the establishment in person to discern across product quality or type. Brick-and-mortar stores for goods that can be easily purchased online – items such as books and movie rentals – should disappear almost entirely. We do not, however, expect in-person consumption to disappear as there are still goods and services that are either impossible to consume online or so costly to discern with respect to quality and use online that in-person shopping will still be preferred. Experiential retail, like dining or hair salons, are two examples of consumption that should persist in person. This implies a very different mix of retail establishments, and potentially a very different type of clustering to attract customers and therefore retail tenants. The spacing of clusters and their proximity to the consumers may also change, since the customers' willingness to travel has been eroded by the e-commerce alternative (Brynjolfsson et al. (2009). Zentner et al. (2013)).

The above framework motivates three predictions about retail clustering and land value in the context of e-commerce proliferation. First, we expect that the clustering of physical retail establishments should change substantially with the rise of e-commerce. We expect experiential retail, such as restaurants or beauty salons, to increasingly cluster near other establishments, both those that also rely on in-person patronage and those that are less experiential. We expect a decline in clustering for establishments that sell exclusively physical products such as clothing or shoes.

Second, we expect retail land to depreciate in value. We hypothesize that reduced demand for physical retail space drives this decline, and that the retail space margin (relative to other non-retail commercial uses) adjusts slowly over time due to the inability easily to convert uses.

Third, we hypothesize that land values adjust to reflect the benefits of retail clustering, but that clustering now benefits a more narrow range of retailer types. The dispersion of clustered locations may also change: there may be fewer and bigger clusters to maximize shopping spillovers or more dispersed and smaller cluster to minimize travel costs. Either way, we expect that physical retail clustering is associated with higher land values when it includes services and products that cannot themselves be easily replicated online or that benefit from nearby retail activity that cannot be substituted online. The value of retail clustering will also be higher in locations where the agglomeration benefits are the greatest—this could be small neighborhood scale clusters or the largest destination retail centers.

3 What We Know About the Land Value Capitalization of Commercial Clustering

The literature on retail agglomeration, and specifically the land value capitalization of those benefits, is thin. Most studies attempting to quantify the benefits from urban agglomeration measure them in terms of wage differentials or premia (Dekle and Eaton, 1999; Combes et al., 2010; Rosenthal and Strange, 2004, 2008). However, there are some studies that have documented how production-based agglomeration economies get translated into land values. Dekle and Eaton (1999) completed one of the earliest papers to quantify the magnitude and reach of agglomeration effects on land values. They focus on financial services and manufacturing and find that both generate small, but significant, land value responses (as measured by a residential rental index, which they assume moves with commercial rents). However, the effect decays much faster over space for the financial services than manufacturing, suggesting more localized benefits for the former type of activity.

Subsequent papers that leverage actual commercial, and specifically office, rents find similar localized agglomeration effects. Drennan and Kelly (2011) find that increases in rents are associated with higher concentrations of "producer service employment" (their measure of agglomeration economies) and that this association is the most pronounced in the central business core of MSAs. The rent effects from agglomeration economies are also most prevalent in the largest MSAs. Liu et al. (2022) incorporate both vertical and horizontal agglomeration economies in high-rise commercial buildings (as opposed to only the horizontal ones that had previously dominated the agglomeration literature). They find that increases in localized employment (e.g., in the same zip code) are associated with higher commercial rents, and that this relationship is even stronger for increases within the same building. Therefore, the rent capitalization of agglomeration benefits follows the same steep attenuation over space as those observed for wage premia in previous studies (Rosenthal and Strange, 2001, 2003, 2005, 2004; Arzaghi and Henderson, 2008).

Finally, related papers estimate the value of retail access, and especially how this value is mediated by the concentration and diversity of retail services. Proximity to a mix of retail, in both urban and mall settings, is reflected in higher residential land and house values (Meltzer and Ghorbani, 2017; Sirpal, 1994; Couture, 2016). The higher residential values documented in these studies should in theory translate into increased local demand for services—an economic benefit for the businesses that should also be reflected in the commercial rents. Furthermore, if either the degree or nature of clustering, or the perceived premium of having the clustering nearby, is disrupted by online alternatives, the valuation of the clustering should respond accordingly.

4 Data

This project relies on three major sources of data. The study areas include all five boroughs of New York City and all of Los Angeles County, both of which accurately track property classification and use codes.

First, we measure retail lease attributes with lease-level data purchased from CoStar. We observe all recorded retail leases by CoStar from the beginning of their collection in the mid-1990s through 2022 for the New York City and Los Angeles markets (we have determined that the leases are most trustworthy from 2005 and later; see Brooks and Meltzer (2024)). For each lease, we observe the square footage and location. For most leases, and with much greater likelihood after the mid-2000s, we also observe rent per square foot and the term of the lease. The leased spaces should include stores, restaurants, personal services, like nail salons or laundromats, and in some cases other medical or social services when they occupy storefront spaces. We geocoded all lease addresses using Google's location API. The number of recorded commercial leases becomes increasingly sparse at sub-municipal geographies, so we limit our CoStar analyses to the market level.

Second, we obtain land use and building data for both locations, including information on the size of the lot, the size of the structure, and the use classification of the lot and/or structure as determined by the local planning department and/or Assessor. We have records for the universe of parcels from New York City's PLUTO database for the years 2004 to 2022.[1] For Log Angeles, we use the Assessor's Secured Basic File for the years 2006 to 2022. This file is the County's most complete public property record.

Finally, we have real property prices dating back to the mid-1990s for New York City and Los Angeles. For New York City, transactions data are available from the city's finance department.[2]. For Los Angeles County, we have nearly complete sales data from the County Assessor.

While we have access to information for all property types, we restrict the analysis to only commercial uses. Furthermore, we categorize building and use classifications into four broader

[1]This dataset includes more than seventy fields derived from data maintained by multiple city agencies, including the planning and finance departments.

[2]We thank the Furman Center at NYU for sharing their archive of sales transaction data)

categories to capture predominantly (i) retail uses, (ii) office uses, (iii) theater and hotel uses and (iv) industrial commercial uses. The composition of each of these categories with respect to specific building classifications is listed in Table 1. While these categorizations do not reflect differences in the types of services or goods at each site, they should capture coarser differences with respect to consumer-facing, experiential and production-oriented activities. For example, industrial parcels should house more goods-producing activities, while hotels and theaters should represent more experiential retail. Office uses are still service-oriented, but not necessarily consumer-facing in the way that retail is; they are, however, often complementary to retail uses.[3]

5 Methodology

We test our three predictions using methods to take advantage of our fine-grained micro data. We develop a novel, parcel-level measure of clustering, document how retail clustering changes across time and space, and test whether or not those changes correspond with changes in commercial land values.

5.1 Measuring Point-level Clustering

Since retail clustering takes place at a very small scale – the scale at which customers achieve the benefits of lower search and transit costs – we need a metric that captures this very localized variation. Specifically, we leverage point pattern methods inspired by Buzard et al. (2017); see also Anselin (1995), Getis (1984) and Getis and Ord (1992).

This method has two key advantages over more prominent measures, such as the Ellison Glaeser index (Ellison and Glaeser, 1997). Rather than producing, as those indices do, one value per industry and geography, our measure produces a value unique to each establishment.

Our cluster metric takes advantage of the pairwise distances we observe in our parcel data, producing a fine-grained measurement at distances of our discretion. This is useful because the geographic scope of agglomeration should vary depending on the type of commercial activity and the distance over which the interactions take place (Kerr and Kominers, 2015; Brown and Rigby, 2013). The second key advantage of our method is to measure clustering at the individual parcel, allowing us to characterize clustering and its correlates beyond the mean.

We define

$$C_i(r) = \sum_{j \neq i} I(d_{ij} < r) \ .$$

The estimand $C_i(r)$ reports the count of all parcels within a distance r of parcel i. The numerator is the number of parcels $j \neq i$ within distance r of parcel i, denoted $\sum_{j \neq i} I(d_{ij} < r)$. The function

[3] We eliminate any repeat sales transactions for a single parcel within the same calendar year, which are likely not arms length. We also drop parcels with extremely low sales values or square footage in the bottom fifth percentile.

$I(x)$ is the indicator function and takes on the value 1 if the distance of parcel i to parcel j, d_{ij}, is less than radius r, and zero otherwise. We can consider clustering in particular type or use m by limiting to just type or use m parcels.

For the current analysis we start with a radius of 500 feet and we calculate the clustering along two dimensions: by total number of parcels and by gross square footage of the built structures on those parcels.[4]

5.2 Estimating Relationship Between Clustering and Retail Outcomes

We use this statistic to test our first prediction that clustering in the retail industry has changed alongside e-commerce proliferation. Using clustering in non-retail commercial uses (specifically the three non-retail categories constructed using the land use data: office, theater-hotel and industrial) as the counterfactuals, we compare the distributions of clustering over time for each locality. Because we do not observe plausibly random variation in clustering, we view this as a descriptive exercise.

We already see, in Tables 2 and 3, that there are differences across the types of properties and uses. For example, in both Los Angeles and New York City, retail properties are typically located in the biggest clusters (in terms of the number of parcels) compared to other property types. Theater and hotel properties have the highest recorded sales prices. In Los Angeles, retail properties tend to be the oldest and the smallest in size. In New York, however, they are not as old as industrial properties and tend to be smaller in size (except for industrial properties which are also the smallest among the property types).

To test our second prediction – that retail land has depreciated with the rise of e-commerce, driven by a decline in demand for retail space – we analyze whether retail rents, the amount of leased square footage and retail sales prices have changed over time. Using data on leases (i) over time (t), we estimate

$$\text{lease sq ft}_{i,t} = \beta_0 + \beta_{1,t}\text{time}_t + \beta_2\text{zip FE}_i + \beta_3 X_{i,t} + \epsilon_{i,t}.$$

The coefficient $\beta_{1,t}$ measures whether the average retail lease square footage declines over time, conditional on location (zip code fixed effects) and property and lease characteristics ($X_{i,t}$). We use this same specification to examine changes in retail rents.

Finally, we use hedonic regression analyses to evaluate our third hypothesis, which states that changes in retail clustering should impact land value. Specifically, we estimate

[4] We replicate the analyses with other radii; those results are not shown here. We also drop extremely high cluster values in the top fifth percentile of the distribution for each locality

$$\begin{aligned} \text{value}_{i,t} &= \beta_0 + \beta_1 \text{clustering}_{i,t} + \beta_2 \text{year}_t + \beta_{3,t} \text{clustering}_{i,t} * \text{year}_t + \beta_4 \text{clustering}_{i,t} * \text{retail}_{i,t} \\ &+ \beta_5 \text{clustering}_{i,t} * \text{year}_t * \text{retail}_{i,t} + \beta_5 X_{i,t} + \epsilon_{i,t} \end{aligned}$$

where i is an individual property-transaction and t is time in years.[5] We are interested in the relationship between retail clustering and value, relative to other commercial land use types, as measured by β_4, and whether this relationship changes over time, as measured by $\beta_{5,t}$. In the baseline model, we estimate retail prices relative to any other non-retail commercial use (e.g., office, hotel/theater and industrial). We run alternate analyses where we restrict the sample to only retail and industrial uses, so that retail is estimate relative to a use that is less likely to be affected by e-commerce disruptions.[6]

We operationalize land values by using sales transaction price per lot square foot and regress the natural log of price-per-square-foot on measures of clustering, use classifications and parcel-level characteristics, such as lot area, gross building square footage, number of stories, year of alterations and year built. Note that for regressions on the New York City sample we can include county (or borough) fixed effects and for Los Angeles we include supervisorial distrct fixed effects (there are five of these districts in LA County). Standard errors are clustered at the sub-borough area (equivalent to the PUMA) in New York City and Mapbook codes in Los Angeles (which indicate a small geography, of which there are about 2,400, determined for planning purposes). All prices are adjusted to 2023 values.

6 Findings

6.1 Has Retail Clustering Changed Over Time?

For this first part of the analysis we leverage parcel-level land use data from New York City and Los Angeles to track the clustering of retail and, for comparison, other commercial uses over the two decades between 2006 and 2022.

We first document that e-commerce was indeed proliferating during the study period. Figure 1 illustrates the rapid growth of e-commerce since 1998, when the Economic Census started tracking its activity. The top panel shows e-commerce sales as a share of total retail sales. While e-commerce is still well below twenty percent of retail sales (around 16 percent as of 2024), the share more than doubled between 2006 and 2019. The bottom panel illustrates the rapid growth of e-commerce against the relatively flat change in retail sales more generally. Again, the increase in e-commerce

[5] We replicate the baseline regression with quarter-year controls. Those results are consistent with the regressions and are available from the authors upon request.

[6] We recognize that industrial uses may also respond to e-commerce proliferation since they can house the distribution centers. However, there is not a clear relationship between the growth of distribution centers and clustering of industrial uses. If anything, distribution centers benefit from being dispersed and don't generate any obvious positive spillovers from clustering.

sales is steepest since around 2008. Therefore, while e-commerce emerged before our earliest data point, we capture the main period of proliferation.

We recognize that, over the past few decades, e-commerce was not the only shock to the retail sector. We identify three other industry-wide transformations that could also relate to the changes in urban retail co-location that we observe. First, since the mid-1970s, there has been the rise, and fall, of the mall. Originally deisgned as an alternative to urban shopping experiences, the growth of these retail centers peaked by 2000 and has been declining ever since (see Appendix Figure 1). While malls could certainly be a credible substitute for urban retail clusters, the growth in this shopping format preceded that of e-commerce. Therefore, any changes in urban retail co-location since the mid-2000s is more likely associated with e-commerce than with mall-related drivers.

Second, retail firms have notoriously consolidated over this time period. Smith and Ocampo (2025) characterize changes in retail concentration between 1990 and 2012 and do find evidence of retail consolidation, although it is not uniform across a retail types. For example, they show that local consolidation of groceries was much weaker than changes in national concentration; the opposite is true for furniture stores. Clothing stores, on the other hand, became less consolidated over the same time period. Although the Smith and Ocampo (2025) analysis does not cover the full period of e-commerce expansion, some of the documented consolidation may have still been in response to the growth in online commerce. We acknowledge that in the current analysis we cannot entirely disentangle the retail consolidation phenomenon from the e-commerce one.[7]

Finally, Couture and Handbury (2020) have documented that between 2000 and 2010 urban centers experienced a ”revival” of young, professional households due to an increased preference for retail and cultural amenities disproportionately available in cities. Their evidence is particularly strong for the more experiential services, like restaurants. This shift in demand could certainly induce changes in the way retail co-locates in cities, but on net this increase in brick-and-mortar services should work in the opposite direction as the substitution forces imposed by e-commerce. Therefore, we need to continue to consider the differential impacts among more experiential retail, which is less likely to be replaced by online products.

Now we turn to our measure of retail and commercial clustering. Before assessing the change in clustering over time, we first use 2022 data to establish that our concentration measure captures variation in retail clustering across space. For illustration, we disaggregate NYC into into the five boroughs that comprise it—Manhattan, the Bronx, Brooklyn, Queens and Staten Island—and Los Angeles County into its five municipalities, and plot the distribution of retail clustering (see Appendix Figures 3 and 4). While the boroughs and cities all contain a diverse range of neighborhoods, they are also broadly characterized by different land use and retail landscapes. See Brooks and Meltzer (2024) for additional analyses using our concentration metric that confirm its

[7] In future analyses with more fine-grained information on the type or retail services, we can exploit the fact that retail consolidation has impacted different types of retail services and establishments in varied ways and at different geographic scales.

credibility in capturing variation in clustering across space.

We generate distributions of the clustering metric for both New York City and Los Angeles County, for two points in time, to test if retail concentration has changed over the two decades of our study period. Panel (a) of Figure 2 shows the distribution of commercial clustering in New York City in 2006 and 2022. Panel (a) uses all commercial parcels including retail and other non-retail uses. There is a meaningful shift down and out in the distribution, indicating that commercial clustering has become more concentrated over time into larger clusters, rather than disparate smaller clusters. Panel (b) shows a similar figure for retail-only clusters, or clusters of only retail parcels around a centroid retail parcel. The flattening of the curve over time is again evident and it is clear that much of the overall shift is due to an increasing concentration of retail-only clusters over time. Illustrated a different way, Figure 5 plots out the difference between the 2006 and 2022 distributions. For retail especially, the drop in the smaller cluster sizes and the increase in the bigger cluster sizes indicates a trend towards more concentration overtime. These patterns suggest that retail agglomeration economies are achieved in the context of more retail options in one place, to perhaps minimize travel costs and maximized search efficiencies. This is consistent with our hypothesis about how establishments shift to compete with the core benefits of online shopping.

For comparison, we generate similar distributions for office, theater and hotel, and industrial use parcels. These are displayed in panels (c), (d), and (e) of Figure 2. The shift in distributions for office and theater/hotel clusters looks similar to that for the retail parcels. Namely, office and theater/hotel clusters increase in concentration, although it is more dramatic for the theater/hotel uses (even though these presumably represent more experiential uses that cannot be easily replaced online). The change in distributions over time for industrial uses, however, is the opposite of what we observe for the other consumer-oriented or service-oriented clusters. The industrial-only clustering gets less concentrated over time. That is, the peak of the distribution gets higher indicating a higher frequency of smaller clusters over time.

We generate similar distributions for Los Angeles; these are displayed in Figure 3. Panel (a) shows an overall pattern of change similar to that in NYC: a shift to the right indicating an increase in the concentration of commercial clustering over time. This shift is slightly more pronounced for the retail-only clusters in panel (b). Again, for ease of interpretation, we also plot the change in clustering for each property classification in Figure 4. The biggest increase in concentration is among the industrial uses, or the least experiential classification of the property types. While there is a decline in smaller clusters for retail and theater/hotel uses (i.e., the classifications most likely to include experiential services) the growth in bigger clusters is not as pronounced. Unlike NYC, the clustering of office uses are relatively stable.

6.2 Has the Value of Retail Space Changed Over Time?

We now turn to evaluating whether these changes in clustering relate to changes in lease value, lease size and sales prices. We follow up with an analysis using parcel level information on the universe of property sales that supports a more fine grained analysis of the relationship between property values and retail clustering.

6.2.1 Documenting Changes in the Demand for Retail Space

We first turn to information from CoStar on retail rents and leased retail square footage. Since the data on leases are sparse and therefore estimates noisy at sub-city levels, we use these data only to examine citywide patterns.

First, we document the changes in lease initiations and the amount of square footage leased in those new contracts. Figure 6 shows that for both NYC and Los Angeles, the volume of new leases plateaued or declined in the past decade, after a precipitous rise in the early 2010s. We do not display the results here, but this trajectory is consistent across other large cities in the U.S., with varying degrees of intensity (see Brooks and Meltzer (2024) for results on additional cities).[8] In addition, while the total amount of retail square footage leased per year increased through the mid-2010s, it then started to decline and plateau, coinciding with the flattening of the number of new leases (see Figure 7).[9]

As a first attempt at testing if land values reflect the changing demand for retail space, in the context of changing retail clustering, we regress rent per square foot on year fixed effects and plot the trends over time (see Figure 8). While rents do decline over time for NYC, the change in rent is not statistically significant. And the trend for Los Angeles is essentially flat. Rents, however, are sticky for commercial spaces (often with terms of 10 years or longer) and it may be harder to tease out a systematic response to e-commerce competition.

To confirm that retail rents are not simply capturing broader economic fluctuations, we plot retail rents against several benchmarks. First, Appendix Figure 5 shows CoStar's retail rents alongside residential rents (accessed via Zillow). Although the trends (and the completeness of the data) vary, most markets show residential rents increasing while retail rents are flatter. Second, we compare CoStar rents to housing prices (also accessed via Zillow), which are more available and are a decent proxy for overall consumption and economic well-being over this time period (see Appendix Figure 6). There is again a divergence between housing prices and retail rents. Finally, we plot rents for industrial and office spaces relative to retail rents in our markets (using aggregate data obtained from CBRE; see Appendix Figure 7). Here retail rents decline relative to industrial and office rents. Altogether, these patterns suggest that the declines in retail rents over

[8]We consider the CoStar data the most reliable from around 2005 and later; but the rise in leases and square footage is still observable during the second half of the 2000s.

[9]We confirm that there is not much meaningful change in the typical size of the retail space leased. If anything, there is a slight decline in the size of the biggest leases over time (see Brooks and Meltzer (2024))

time (especially in recent years) are particular to that sector.

Altogether, the patterns of rents and leased square footage over the past decade indicate at best a flat valuation of retail space at a time when retail revenues are growing and residential property values are rising. These trends are consistent with growing online commerce, which has at best stunted the preceding growth of retail in cities.

6.2.2 Do Property Values Reflect Changes in Retail Clustering and Space Demand

The locational value of retail services and goods is largely driven by the positive consumption externalities generated by co-location and ease of one-stop-shopping. We documented changes in retail clustering over time in New York and Los Angeles that suggest it is becoming more concentrated. We now attempt to test the the degree to which retail clustering, and its increasing concentration over time, is capitalized into land values.

We establish that within each locality trends and distributions of sales transactions are quite similar across the four property type classifications. Figure 9 plots the median, top, and bottom quartiles of sales prices, by property type, for both markets. While prices trend up in L.A. over the course of the study period, the increase is evident for all property types (perhaps it is slightly steeper for the higher end of theater and hotels prices). Prices are relatively flat in New York City. Figure 10 shows the volume of sales over time for New York City and L.A. In both markets, the volume of sales for retail and industrial follow similar trends over time (although a 2015 peak and then drop in new York City is the most pronounced). The trends for office and theater/hotels uses are relatively flatter over time. Therefore there are not glaring differences across the property types to undermine the estimation strategy that follows. However, we do take advantage of the similarities between industrial and retail in their sales patterns when we use only industrial parcels as a counterfactual.

Next, we regress sales prices onto measures of commercial clustering and display the main results in Figure 11 for New York City and Figure 12 for Los Angeles County. The full set of estimates are presented in Appendix Table 1 and Table 2. Recall, we are interested in the coefficient on the interaction between *retail* and *cluster* and *year*, because it will tell us the association between the change in the price per lot square footage of a retail parcel (relative to parcels with non-retail commercial uses) and the change in nearby commercial clustering.

The results show different patterns for each location. In New York City, on average across the study period, bigger clusters have a price discount relative to other non-retail commercial parcels (see the first column of Appendix Table 1). However, this is off of a positive base, meaning that the net effect of nearby clusters is still positive. This is consistent with the expectation of locational premium for being near other commercial activities (although it appears weaker for retail uses).

When we allow the effect of the cluster to vary over time (see the second column of Appendix Table 1 and Figure 11), prices for retail parcels with more concentrated clustering decline relative to those located in non-retail commercial clusters. Specifically, by 2015, around the same time when we start to see a plateauing in demand for retail space, there is a significant and increasingly large discount for retail properties (relative to non-retail commercial properties) that are proximate to bigger commercial clusters. While COVID-19 may have contributed to some of the discount in later years, it is striking that the negative association intensified years before the pandemic hit.

Since some of the commercial activities taking place in theater, hotel and office parcels may be harder to distinguish from the consumer-facing retail activities we hope to isolate, we run an additional version of the regression retaining only retail and industrial uses. We can assume with more certainty that these classifications of properties likely host different kinds of activities and specifically consumer-facing versus production-oriented activities. The results of this regression are displayed in panel (b) of Figure 11 and the 3rd column of Appendix Table 1. The yearly estimates are estimated with more precision, and the overall pattern remains the same as that estimated using the full commercial sample.

Now we turn to results for Los Angeles. Like New York, nearby commercial clusters are associated with higher prices (see the first column of Appendix Table 2). However, unlike in New York City, there is no discount for retail properties relative to the other use types. The coefficient is actually positive and significant. Figure 12 plots the the interaction between retail and clustering over time, and while there is a slight trending downward of the price differential between retail and the other non-retail commercial prices, the price premium for retail remains intact (albeit marginally) until the very end of the study period when it becomes negative fort he final year in the series. We note again that any declining trend starts well before the years when COVID-19 would have impacted the retail markets.

We also run the regression on the restricted sample of retail and industrial parcels (see panel (b) of Figure 12), and again the results are consistent with those estimated off of the full commercial sample. If anything, the decline in the value of retail clustering is more pronounced and the "retail discount" shows up earlier.

As a final exercise, we exploit the full distribution of clusters to test if the price effects observed vary depending on the size of the retail clusters. We divide the sample based on whether the sale is near a cluster that is bigger or smaller than the median cluster size and re-run the baseline regression. The results for New York and Los Angeles are displayed in Figure 13 and Figure 14. While the declining prices are evident across the two strata, the dip is more pronounced for the transactions near smaller clusters, especially for New York City. This suggests that any attenuation in value of retail co-location is less severe for the bigger clusters, presumeably those with more retail options in one location. This is consistent with the expectation that physical retail co-location will remain valuable if it can compete with the advantages of online commerce, namely more choice and lower search costs in one retail node.

7 Synthesis and Conclusion

E-commerce has transformed the retail sector over the past two decades. It comes as no surprise that urban commerce, a phenomenon that relies on the physical proximity of consumers and retail providers, would be uniquely affected by the proliferation of a virtual substitute like online shopping and services. We test two propositions related to this paradigm shift and its impact on urban spaces. First, do we observe a shift in the physical co-location of retail activities over time, and specifically does retail clustering become more or less concentrated over the time period of e-commerce proliferation? Second, do changes in the physical clustering of retail get capitalized into land values?

We find evidence of increasing retail concentration over time for New York and Los Angeles, although it is more pronounced for the former. The distribution of retail clusters skews towards bigger clusters between 2006 and 2022, when growth of e-commerce revenues was accelerating. This pattern is consistent with the expectation that in order to compete with online shopping, retail is increasingly concentrated in single locations instead of scattered across smaller clusters.

We also see that this change in retail concentration corresponds with a flattening of new retail leases and retail rents. Retail rents simultaneously decline for New York City (although less so since the early 2000s, when the CoStar data is more reliable) and are essentially flat for Los Angeles.

Finally, there is evidence of a retail concentration price premium being attenuated since 2015 relative to other commercial uses, especially in New York City. In New York, there is always a discount for retail properties near bigger commercial clusters, relative to other non-retail commercial uses. And this discount gets bigger over time. In Los Angeles County, there is a modest retail premium, which attenuates slightly over time but still remains positive relative to other non-retail commercial uses.

Our results suggest that the shift of consumption online may indeed be having an affect on the physical features of cities, even attenuating some of the long-held benefits of urban density and commercial agglomeration. It is unclear, however, whether this is a net loss for cities as it all depends how the land is repurposed: if formerly retail uses are converted to more productive ones, such as housing, the economic and fiscal impacts may be net positive. Furthermore, while our study does not fully distinguish across specific compositions or locations of commercial clusters, it may be the case that there is heterogeneity in how retail clusters are valued. The direction and degree of land value capitalization will likely be a function of the degree of retail activity that is more or less substitutable online.

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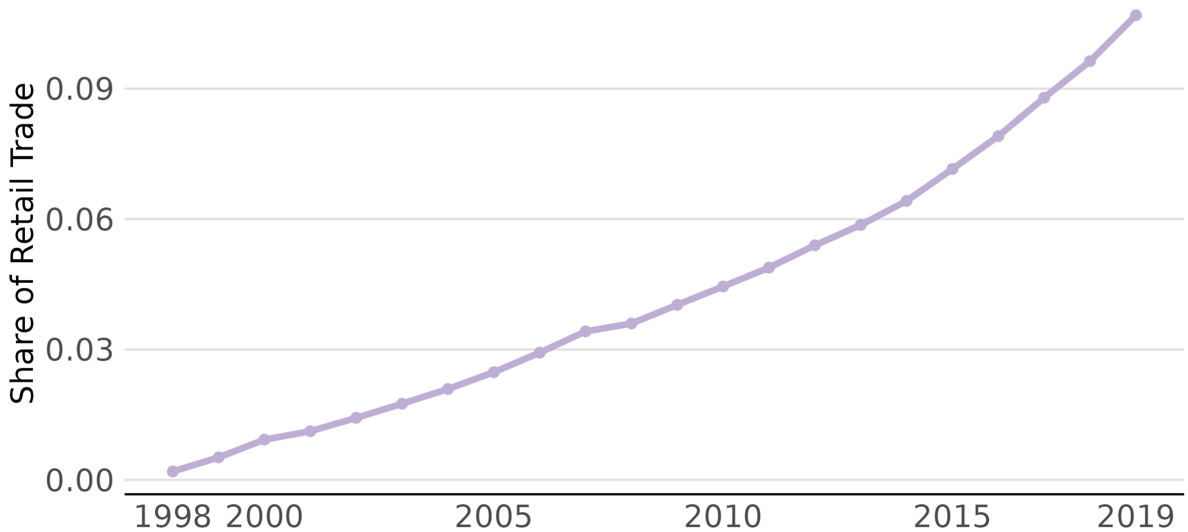
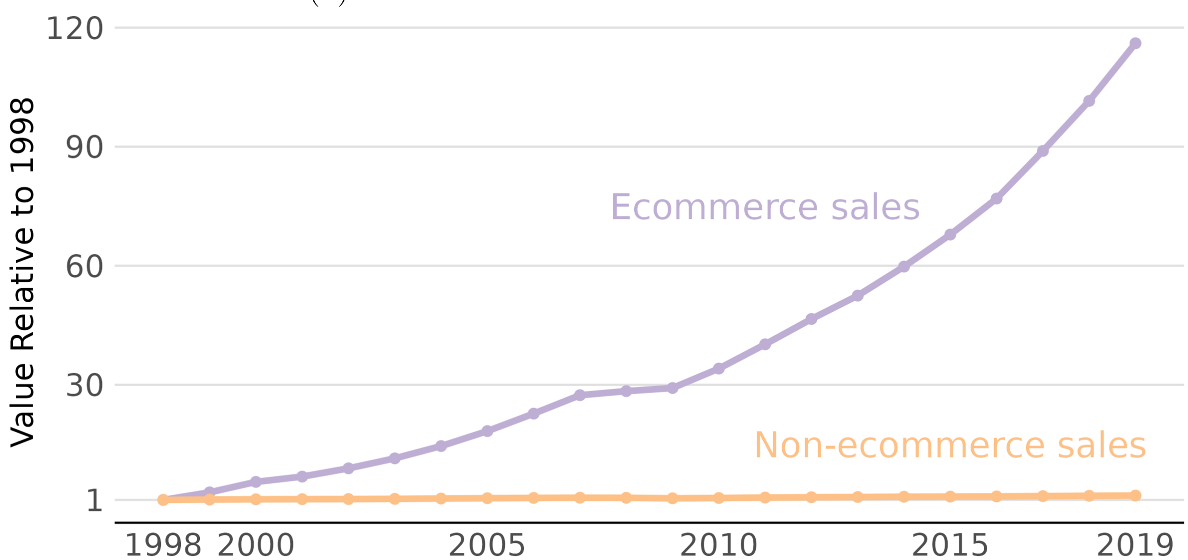
Figure 1: Change in Ecommerce Over Time

(a) Ecommerce Share of Retail Trade



(b) Ecommerce Retail Trade Growth Rate



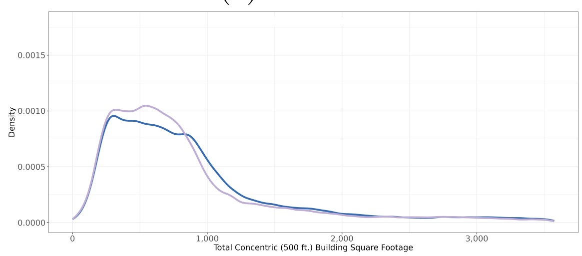
Note: Panel (a) reports the ecommerce share of all US retail trade. Panel (b) reports changes in the volume of retail trade, normalized to 1 in 1998. Thus, a value of 30 in panel (b) indicates that the value is 30 times higher than the 1998 value. Thus, while ecommerce remains well under one-quarter of US retail sales, growth in ecommerce far outstrips growth at physical retail establishments.

Sources: Data are Census tabulations from the Annual Survey of Retail Trade. We use Table 4 from https://www.census.gov/data/tables/2019/econ/e-stats/2019-e-stats.html. Data include only retail trade, NAICS 44-45. Data are available 1998 to 2019.

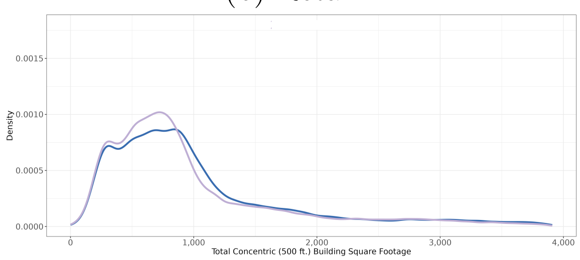
Figure 2: New York City: Distribution of Lot-Level Concentration

Year 2006 in purple and 2022 in blue

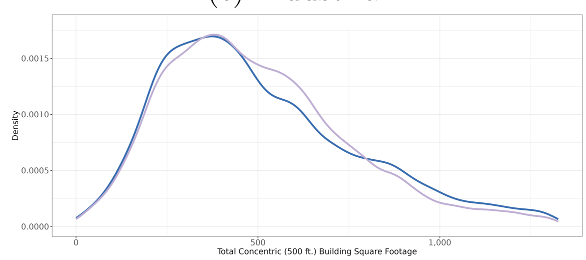
(a) Overall



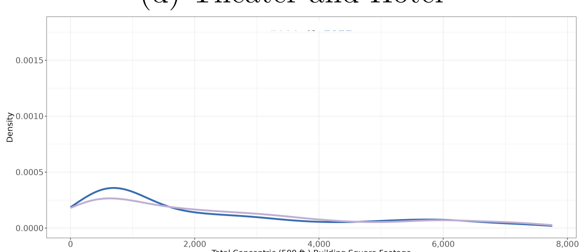
(b) Retail



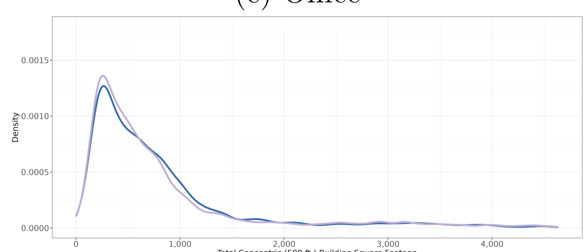
(c) Industrial



(d) Theater and Hotel



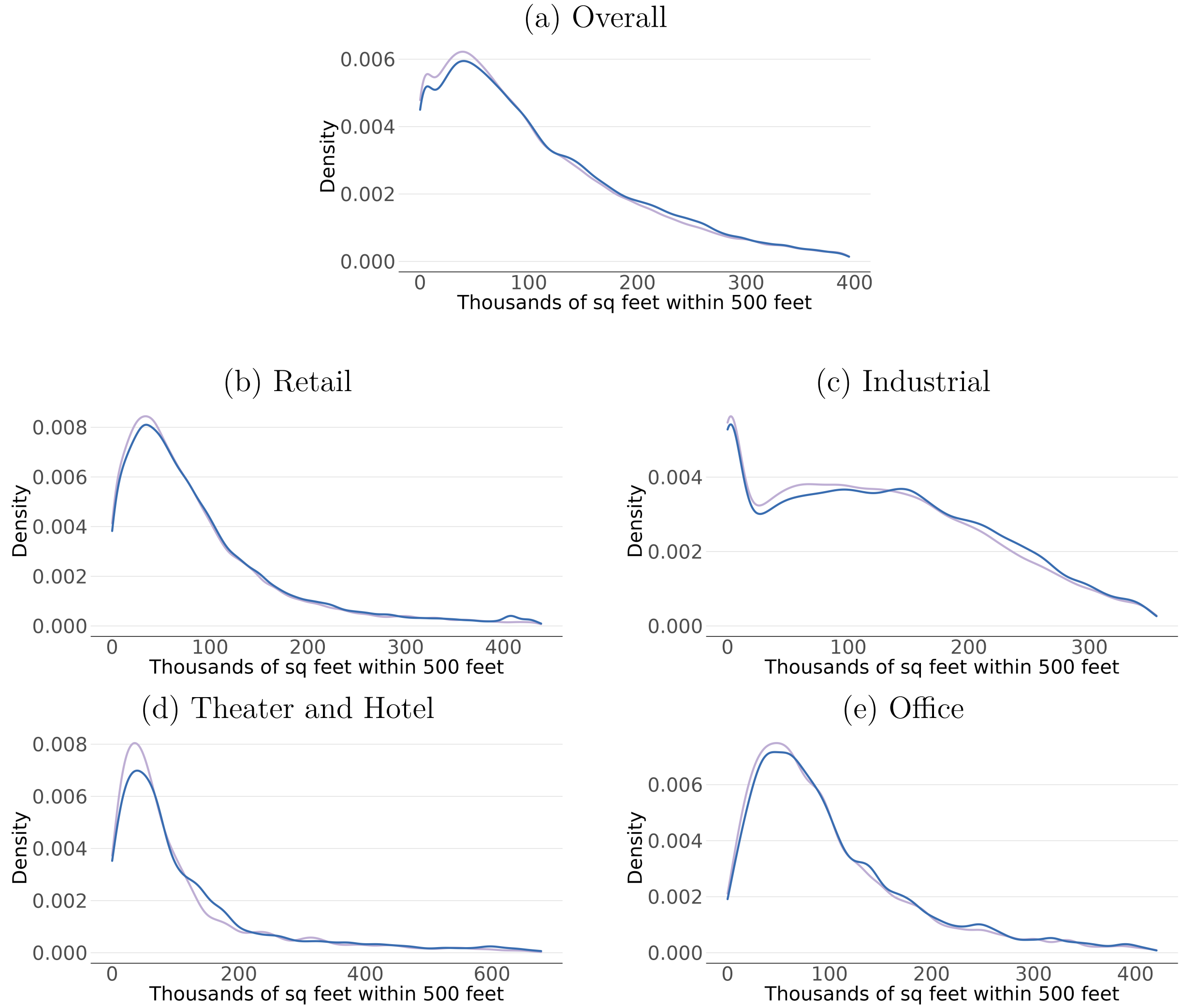
(e) Office



Note: New York: Land use data are from NYC's PLUTO. This figure shows the distribution of our parcel-level concentration measure. Specifically, for any given parcel, we measure total building square footage within 500 feet, for 2006 and 2022. We measure both total nearby building square footage and square footage of specific property types. For specific property types, we limit analysis to other properties of that type. For example, industrial concentration measures, for each industrial property, the total square footage of other industrial properties nearby. The purple line is 2006 the and blue line is 2022. For clarity, we omit concentration measures above the 95th percentile of each distribution.

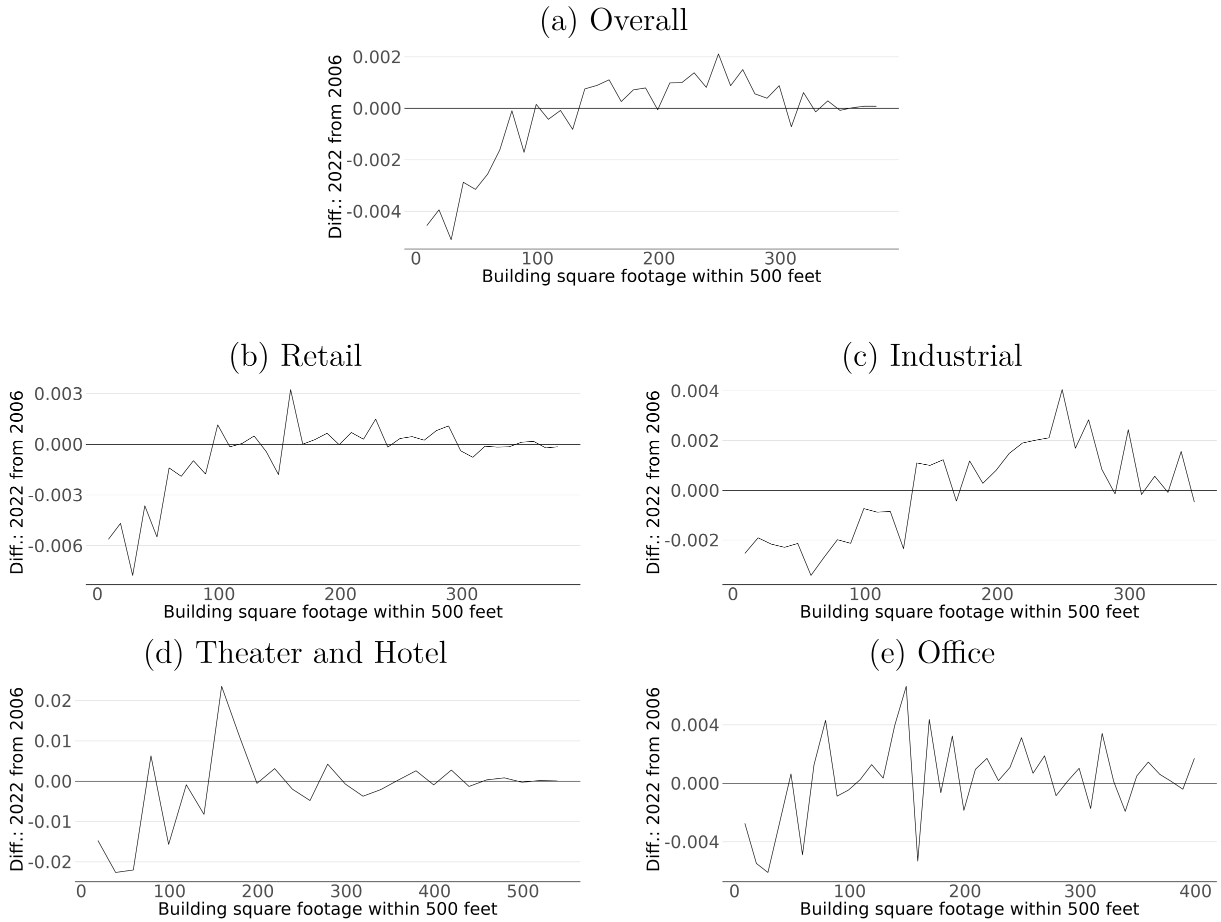
Figure 3: Los Angeles County: Distribution of Lot-Level Concentration

Year 2006 in purple and 2022 in blue



Note and Sources: Land use data are from the Los Angeles County Assessor. This figure shows the distribution of our parcel-level concentration measure. Specifically, for any given parcel, we measure total building square footage within 500 feet, for 2006 and 2022. We measure both total nearby building square footage and square footage of specific property types. For specific property types, we limit analysis to other properties of that type. For example, industrial concentration measures, for each industrial property, the total square footage of other industrial properties nearby. The purple line is 2006 the and blue line is 2022. For clarity, we omit concentration measures above the 95th percentile of each distribution.

Figure 4: Los Angeles County: Change in Distribution of Lot-Level Concentration



Sources: Land use data are from the Los Angeles County Assessor.

Notes: This figure shows the change in the distribution of our parcel-level concentration measure from 2006 to 2022. Specifically, for binned values of the amount of nearby building square feet, we calculate the share of all parcels in a given year that are in that bin. We report the difference in these bin-specific shares between 2022 and 2006. Positive values mean that that the 2022 value is higher than the 2006 value; negative values mean it is smaller. We measure total nearby building square footage as described in the note to Figure 3. For specific property types, we limit analysis to other properties of that type, as in 3.

Figure 5: New York City: Change in Distribution of Lot-Level Concentration

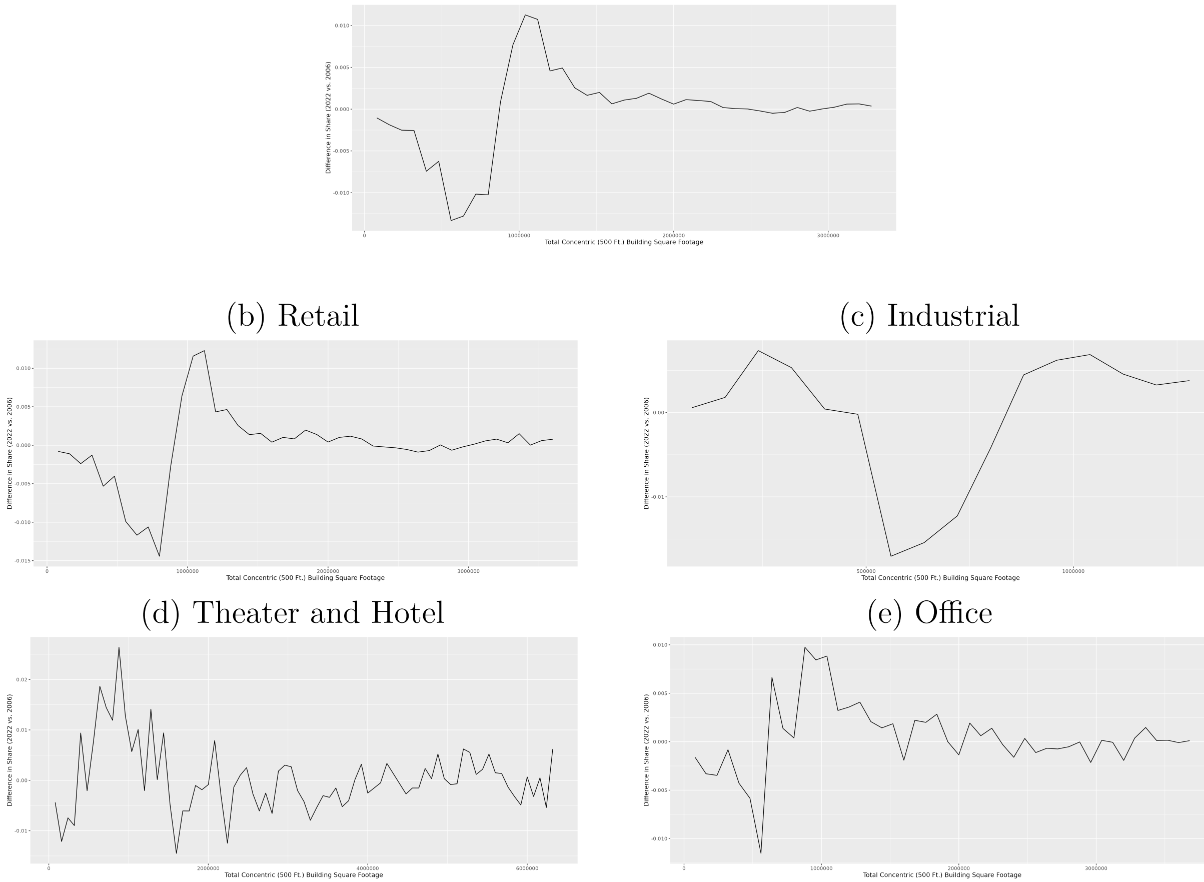
(a) Overall

(b) Retail

(c) Industrial

(d) Theater and Hotel

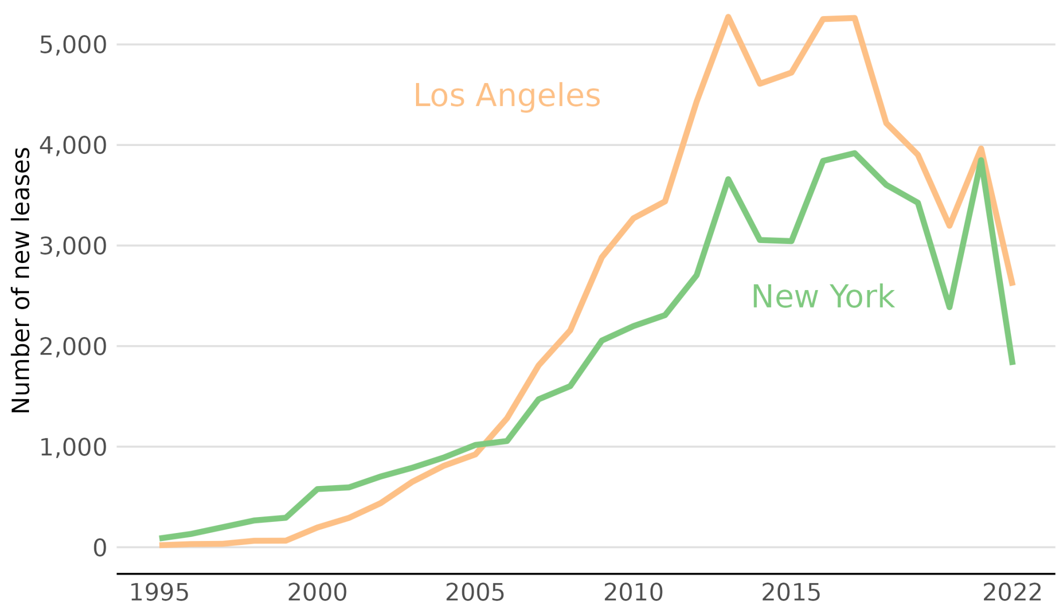
(e) Office



Sources: Land use data are from NYC's PLUTO.

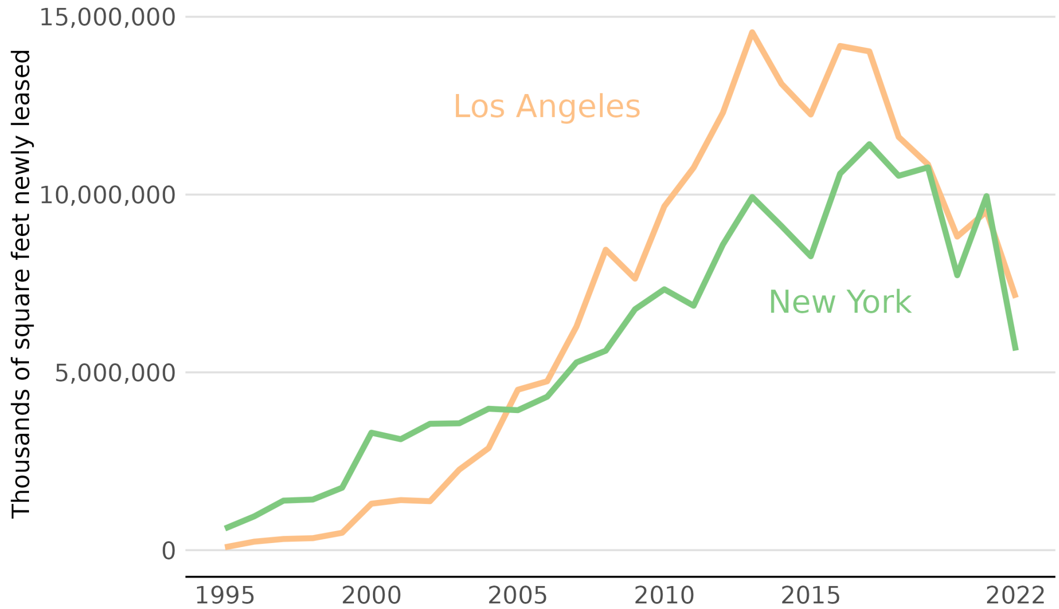
Notes: This figure shows the change in the distribution of our parcel-level concentration measure from 2006 to 2022. Specifically, for binned values of the amount of nearby building square feet, we calculate the share of all parcels in a given year that are in that bin. We report the difference in these bin-specific shares between 2022 and 2006. Positive values mean that that the 2022 value is higher than the 2006 value; negative values mean it is smaller. We measure total nearby building square footage as described in the note to Figure **??**. For specific property types, we limit analysis to other properties of that type, as in **??**.

Figure 6: Total Number of New Leases by Market and Year



Note: This figure uses CoStar lease data and reports the total number of new leases by market and year. Based on supplementary analyses (not shown here) we have determined that the reported data are mot reliable from around 2005 and later. Data for 2022 are incomplete and may not accurately represent the full year.

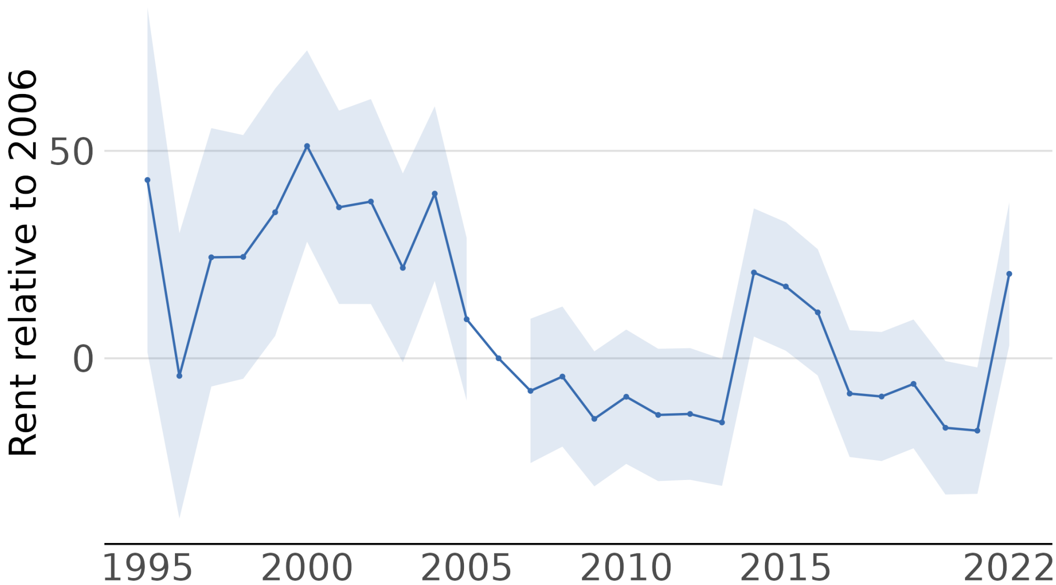
Figure 7: Total New Leased Square Footage by Market and Year



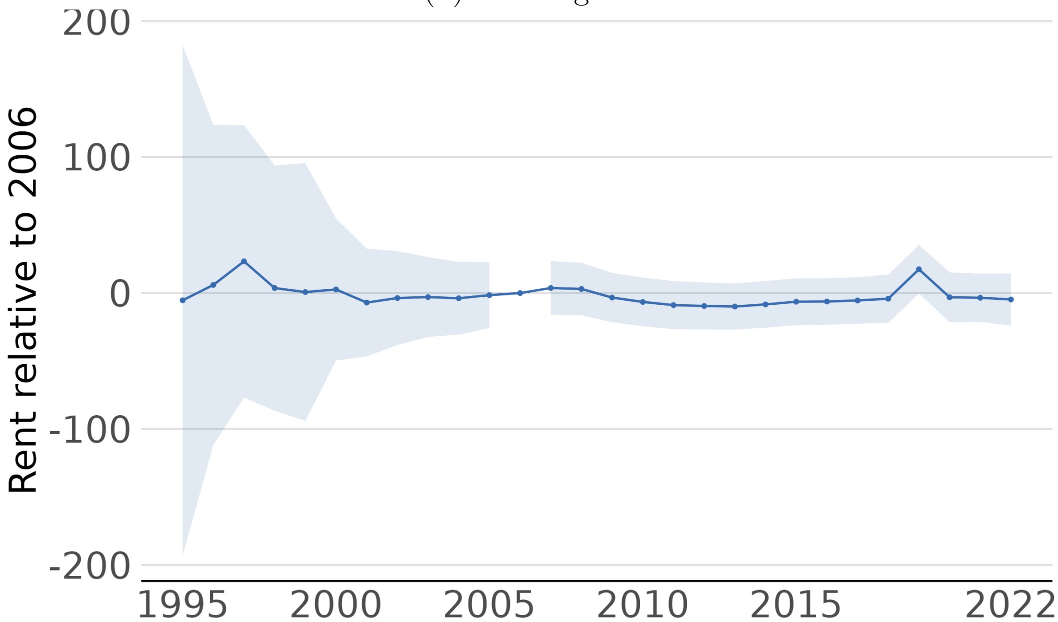
Note: This figure uses CoStar lease data and reports the total amount of square footage newly leased by market and year. Based on supplementary analyses (not shown here) we have determined that the reported data are mot reliable from around 2005 and later. Data for 2022 are incomplete and not accurately report an annual total.

Figure 8: Rent per Square Foot Over Time

(a) New York



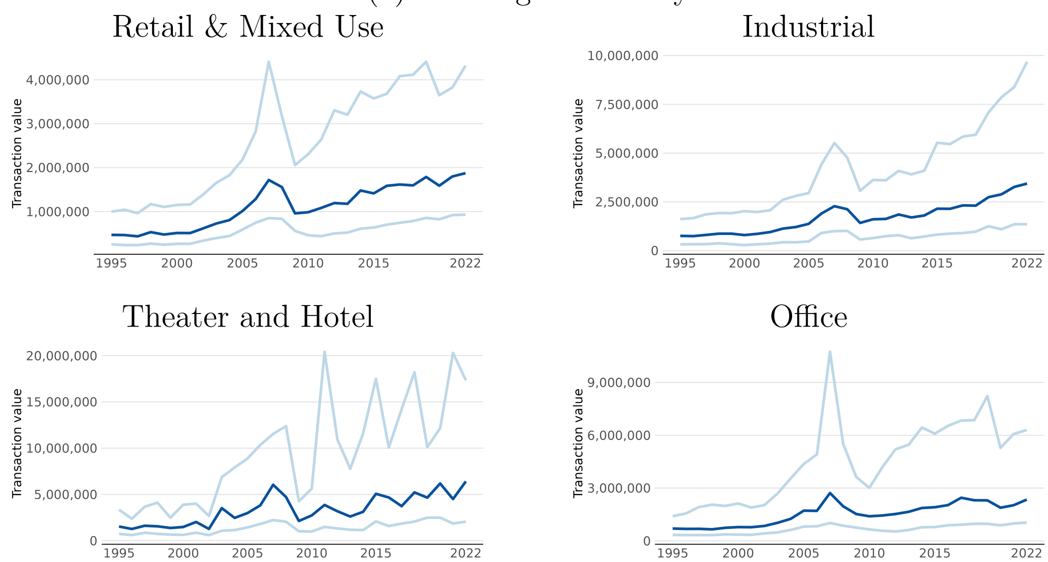
(b) Los Angeles



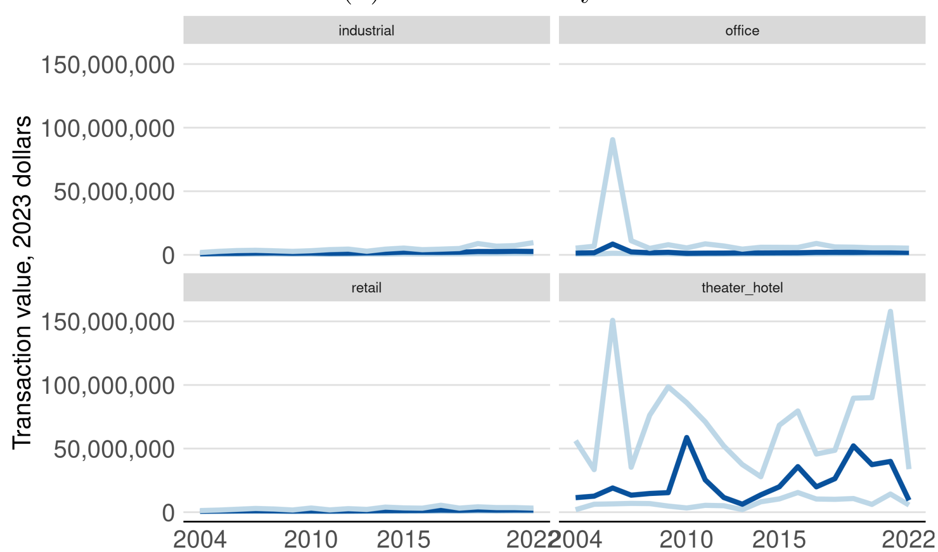
Note: This figure uses CoStar lease data and reports coefficients on year fixed effects from a regression of real lease value per building square foot on a set of year indicators. Shaded area shows the 95% confidence interval. Based on supplementary analyses (not shown here) we have determined that the reported data are mot reliable from around 2005 and later. Data for 2022 are incomplete.

Figure 9: Distribution of Transaction Value by Commercial Property Type

(a) Los Angeles County



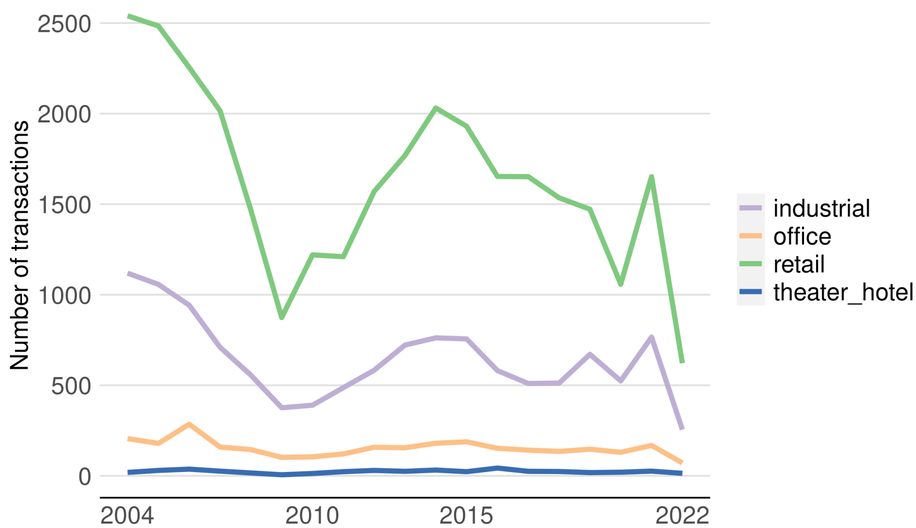
(b) New York City



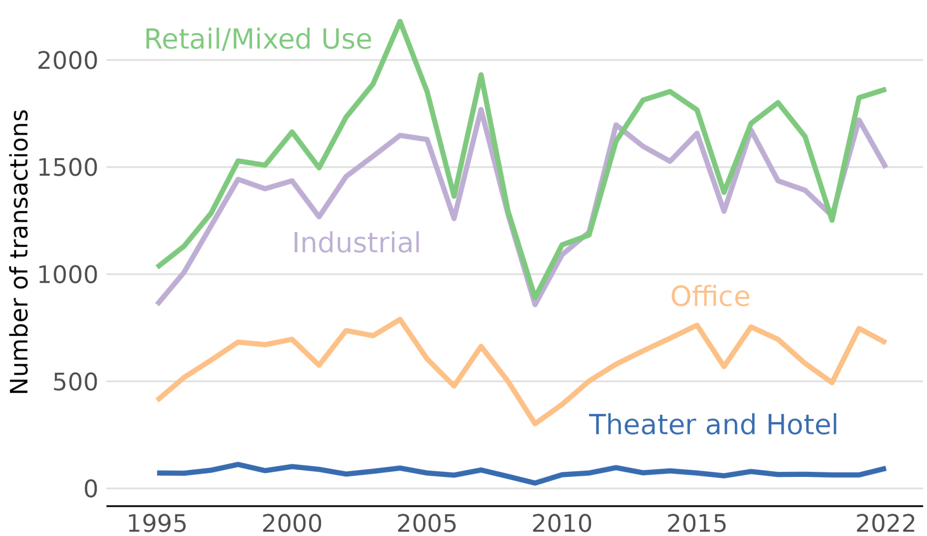
Note: This figure uses Los Angeles County Assessor and New York City Dept. of Finance data and reports the median (dark blue), 25th percentile and 75th percentile (both in light blue) of transaction value in 2023 dollars by commercial property type and year.

Figure 10: Number of Commercial Property Transactions by Year

(a) New York City



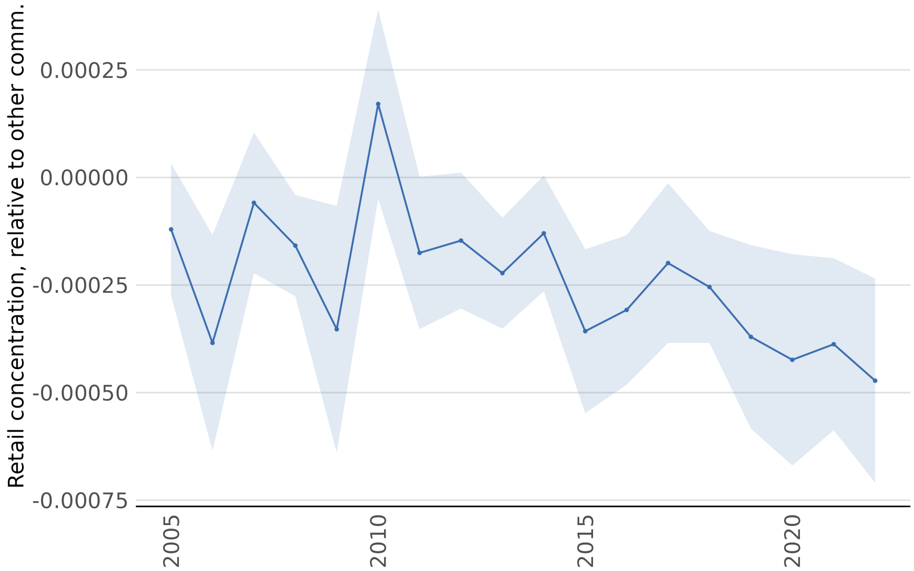
(b) Los Angeles County



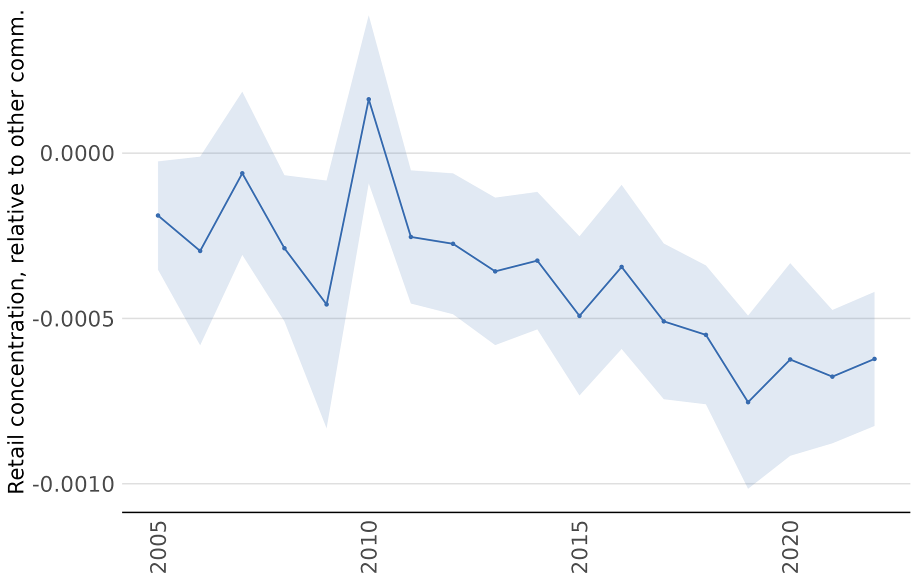
Note: This figure uses Los Angeles County Assessor and New York City Dept. of Finance data and reports the number of sales transactions by commercial property type and year.

Figure 11: New York City: Relationship Between Retail Concentration and Price Over Time

(a) Full commercial sample

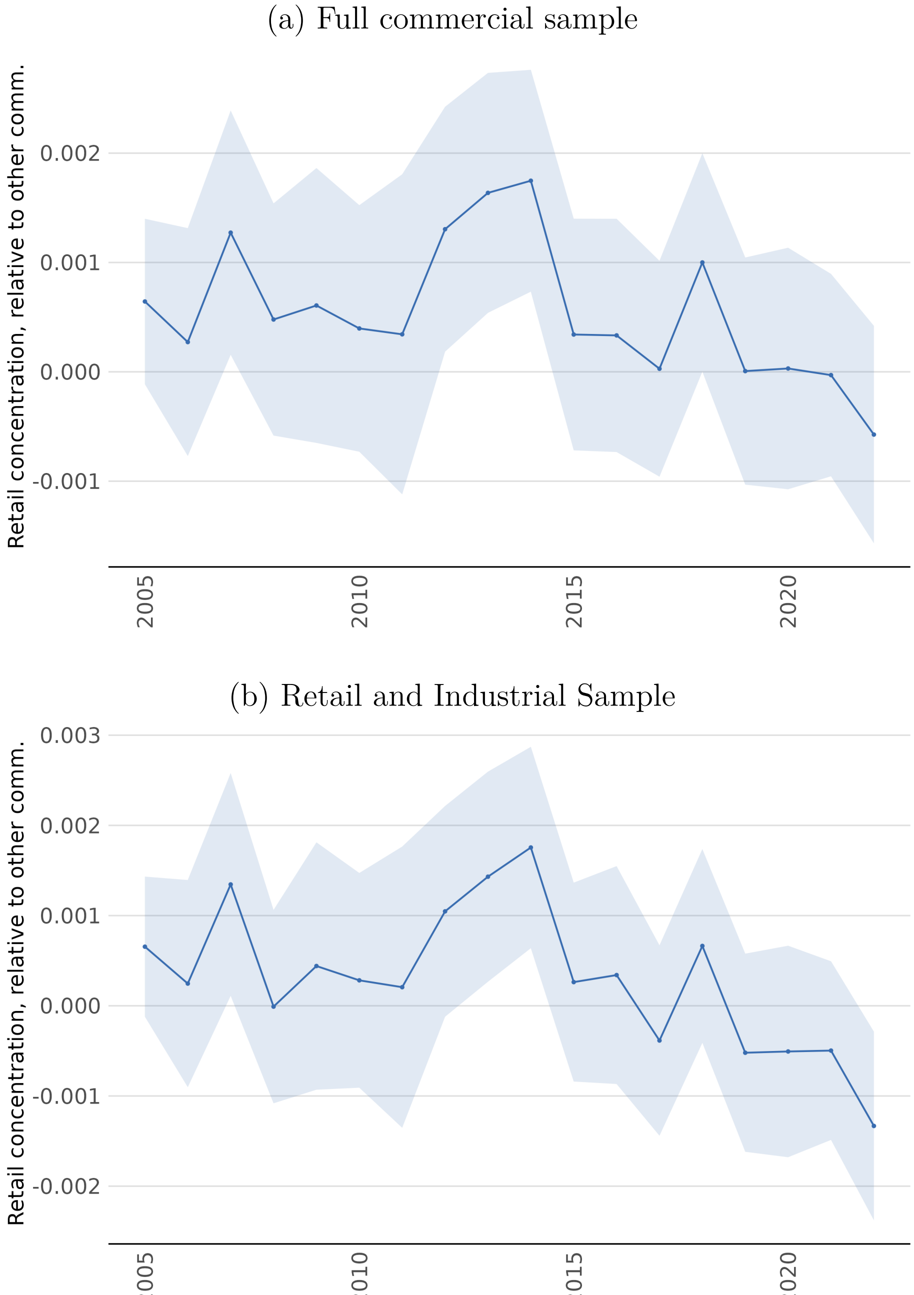


(b) Retail and Industrial Sample



Note: These figures plot the coefficients and 95% confidence intervals from the regression of log(real price per lot sq. ft.) on *clustering*year*retail*, controlling for property-level characteristics and borough fixed effects (full results displayed in Appendix Table **??**). Y-axis displays percentage change in real price of retail sales relative to non-retail commercial sales in the full sample panel and relative to industrial sales in the reduced sample panel.

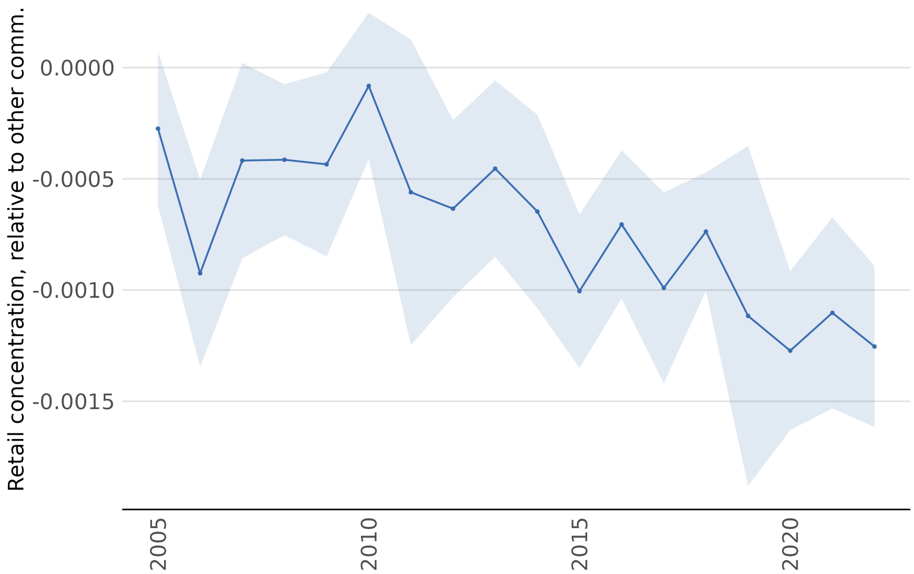
Figure 12: Los Angeles County: Relationship Between Retail Concentration and Price Over Time



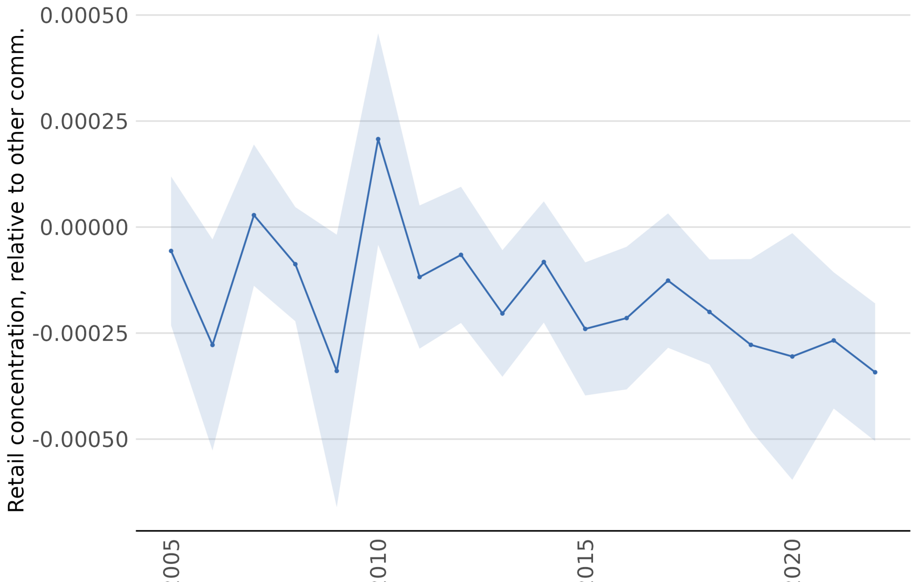
Note: This figure plots the coefficients and 95% confidence intervals from the regression of log(real price per lot sq. ft.) on *clustering*year*retail*, controlling for property-level characteristics and borough fixed effects (full results displayed in Appendix Table **??**). Y-axis displays percentage change in price of retail sales relative to non-retail commercial sales.

Figure 13: New York City: Relationship Between Retail Concentration and Price Over Time, by Cluster Size

(a) Small clusters (below the median size)



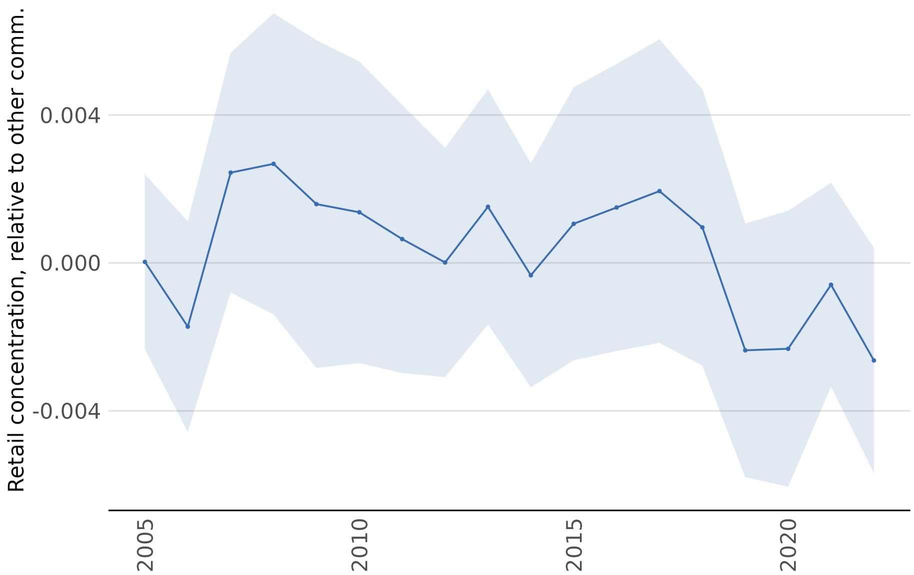
(b) Large clusters (above the median size)



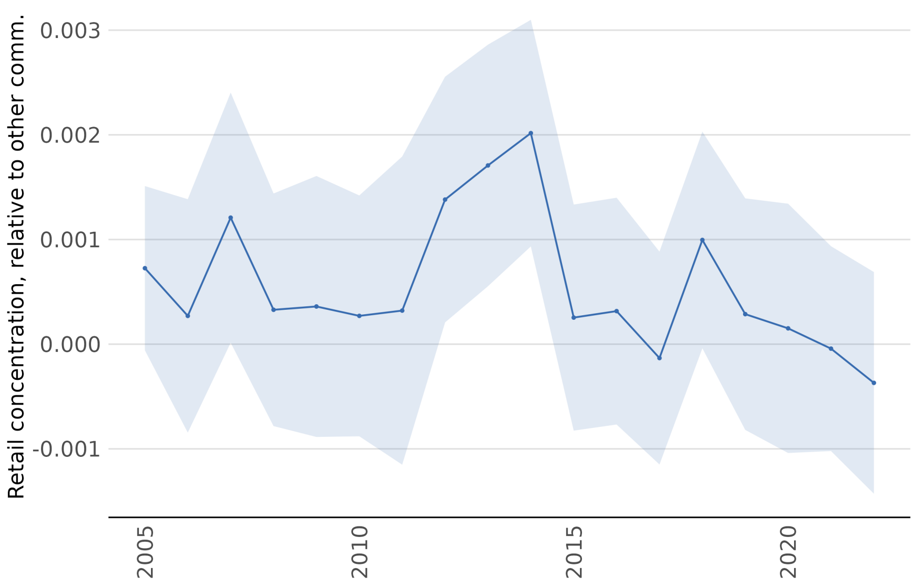
Note: These figures plot the coefficients and 95% confidence intervals from the regression of log(real price per lot sq. ft.) on *clustering*year*retail*, controlling for property-level characteristics and borough fixed effects, stratified by median cluster size. Y-axis displays percentage change in real price of retail sales relative to non-retail commercial sales in the full sample panel and relative to industrial sales in the reduced sample panel.

Figure 14: Los Angeles County: Relationship Between Retail Concentration and Price Over Time, by Cluster Size

(a) Small clusters (below the median size)



(b) Large clusters (above the median size)



Note: These figures plot the coefficients and 95% confidence intervals from the regression of log(real price per lot sq. ft.) on *clustering*year*retail*, controlling for property-level characteristics and borough fixed effects, stratified by median cluster size. Y-axis displays percentage change in real price of retail sales relative to non-retail commercial sales in the full sample panel and relative to industrial sales in the reduced sample panel.

Table 1: Use Code Definitions for Los Angeles County and New York City

Category	Use Classification: **Los Angeles County, based on use code**	Use Classification: **City of New York, based on building class**
Retail mixed use	First two digits of `use code` is either 10, 11, 12, 13, 14, 15, 16, or First two digits of `use code` is either 21, 22, 23, 24, or First three digits of `use code` is either 651, 653, 655	Store buildings: K1, K2, K3, K4, K5, K6, K7, K8, K9 Residential mixed-use: S0, S1, S2, S3, S4, S5, S9 Retail condo: RK Commercial units of condos: R7, R8
Office	First two digits of `use code` is either 17 or 19	Office buildings: O1, O2, O3, O4, O5, O6, O7, O8, O9 Office condo: RB
Theater and hotel	First two digits of `use code` is either 18 or 61 or First three digits of `use code` is either 650, 654	Hotels: H1, H2, H3, H4, H5, H6, H7, H8, H9, HB, HH, HR, HS Theatres: J1, J2, J3, J4, J5, J6, J7, J8, J9
Industrial	First two digits of `use code` is either 30, 31, 32, 33, 34, 35, 36, 37, 38, 39	Warehouses, industrial: E1, E2, E3, E4, E7, E9, F1, F2, F4, F5, F8, F9 Garages: G0, G1, G2, G3, G4, G5, G6, G7, G8, G9, GU, GW Industrial condo: RW

Sources: New York City codes are available here: https://www.nyc.gov/assets/finance/jump/hlpbldgcode.html. Los Angeles codes are available upon request from the Los Angeles County Assessor.

Table 2: New York City: Property Characteristics

	Commercial property type			
	Office	Retail/Mixed Use	Theater and Hotel	Industrial
Number of lots within 500 ft				
mean	106.2	136.8	77.4	97.7
sd	51.6	56.3	42.9	53.6
count	3,105	33,297	500	13,120
Total structure sqft within 500 ft				
mean	1,354,131	1,196,596	3,015,065	655,158
sd	2,031,422	1,642,056	2,580,731	673,117
count	3,105	33,297	500	13,120
Log(Real sale value)				
mean	14.9	14.3	16.8	14.4
sd	1.7	1.4	1.7	1.6
count	3,105	33,297	500	13,120
Lot area, square feet				
mean	11	7	21	15
sd	32	53	69	95
count	3,105	33,297	500	13,120
Building square footage, 1000s of feet				
mean	48	27	89	13
sd	179	167	152	41
count	3,105	33,297	500	13,120
Year built				
mean	1912.5	1914.1	1948.3	1533.4
sd	251.3	185.3	157.2	795
count	3,105	33,297	500	13,120
Total units				
mean	4.6	5.4	24.9	1.9
sd	17.2	21.3	82.1	46
count	3,105	33,297	500	13,120
Stories				
mean	4	3.5	11.2	1.3
sd	6.7	5.3	10.7	1.5
count	3,105	33,297	500	13,120

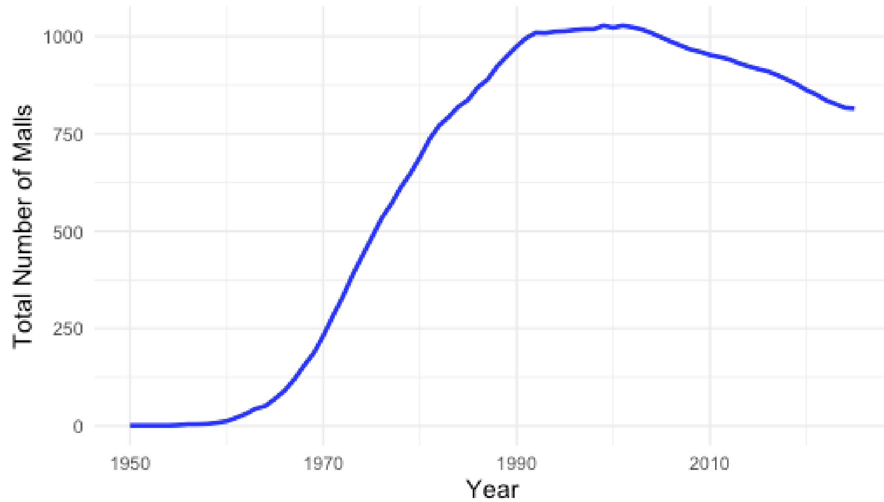
Table 3: Los Angeles County: Property Characteristics

	Commercial property type			
	Office	Retail/Mixed Use	Industrial	Theater and Hotel
Number of lots within 500 ft				
mean	17.3	19.3	17.5	15.4
sd	17.3	30.6	16.4	18.5
count	28,525	77,013	68,136	3,662
Total structure sqft within 500 ft				
mean	141,542	110,384	145,203	153,143
sd	291,016	184,149	126,083	286,471
count	28,097	75,767	67,094	3,580
Log(Real sale value)				
mean	13.9	13.5	13.7	14.5
sd	1.6	1.5	1.7	1.6
count	28,525	77,013	68,136	3,662
Lot area, square feet				
mean	30,689	20,851	66,946	42,467
sd	71,201	67,804	207,632	166,860
count	28,525	77,013	68,136	3,662
Building square footage				
mean	17,425	5,763	14,785	23,663
sd	56,217	17,337	35,331	51,798
count	28,457	76,328	67,798	3,654
Year built				
mean	1963.9	1953.2	1967.4	1960.5
sd	22.2	24.6	20.3	24.7
count	27,689	65,410	53,111	3,534

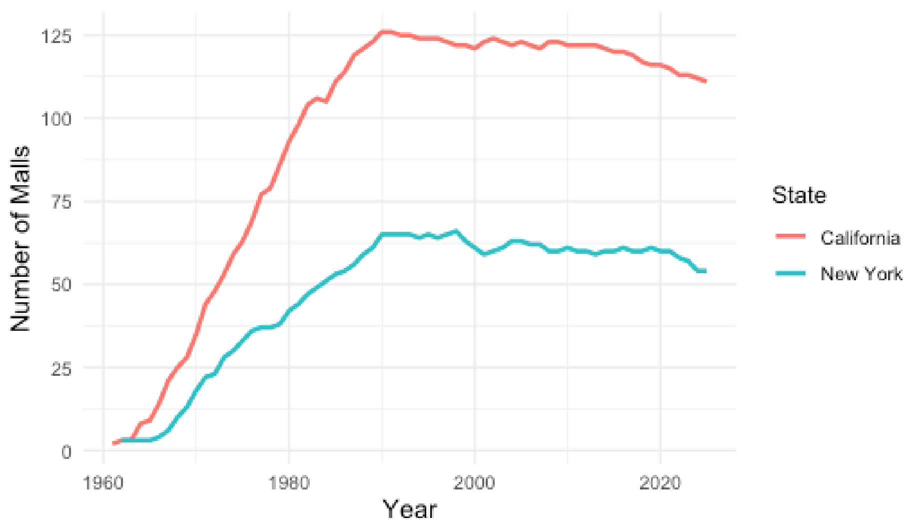
Appendix: Additional Figures and Tables

Appendix Figure 1: Change in the Prevalence of Malls Over Time

(a) National, Number of Malls Over Time



(b) New York and California, Number of Malls Over Time



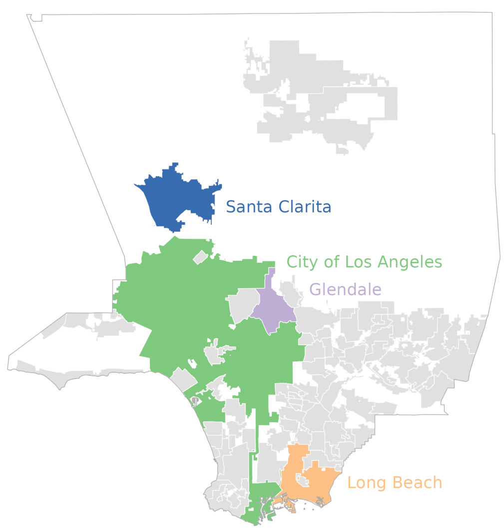
Note: Panel (a) reports the cumulative number of malls across the U.S. Panel (b) reports the cumulative number of malls for New York and California, the states where New York City and Los Angeles are located, respectively

Sources: Data are pulled from a list of active and dead malls documented by Wikipedia: https://en.wikipedia.org/wiki/List_of_shopping_malls_in_the_United_States.

Appendix Figure 2: Maps of New York City and Los Angeles County Analysis Areas

(a) New York City

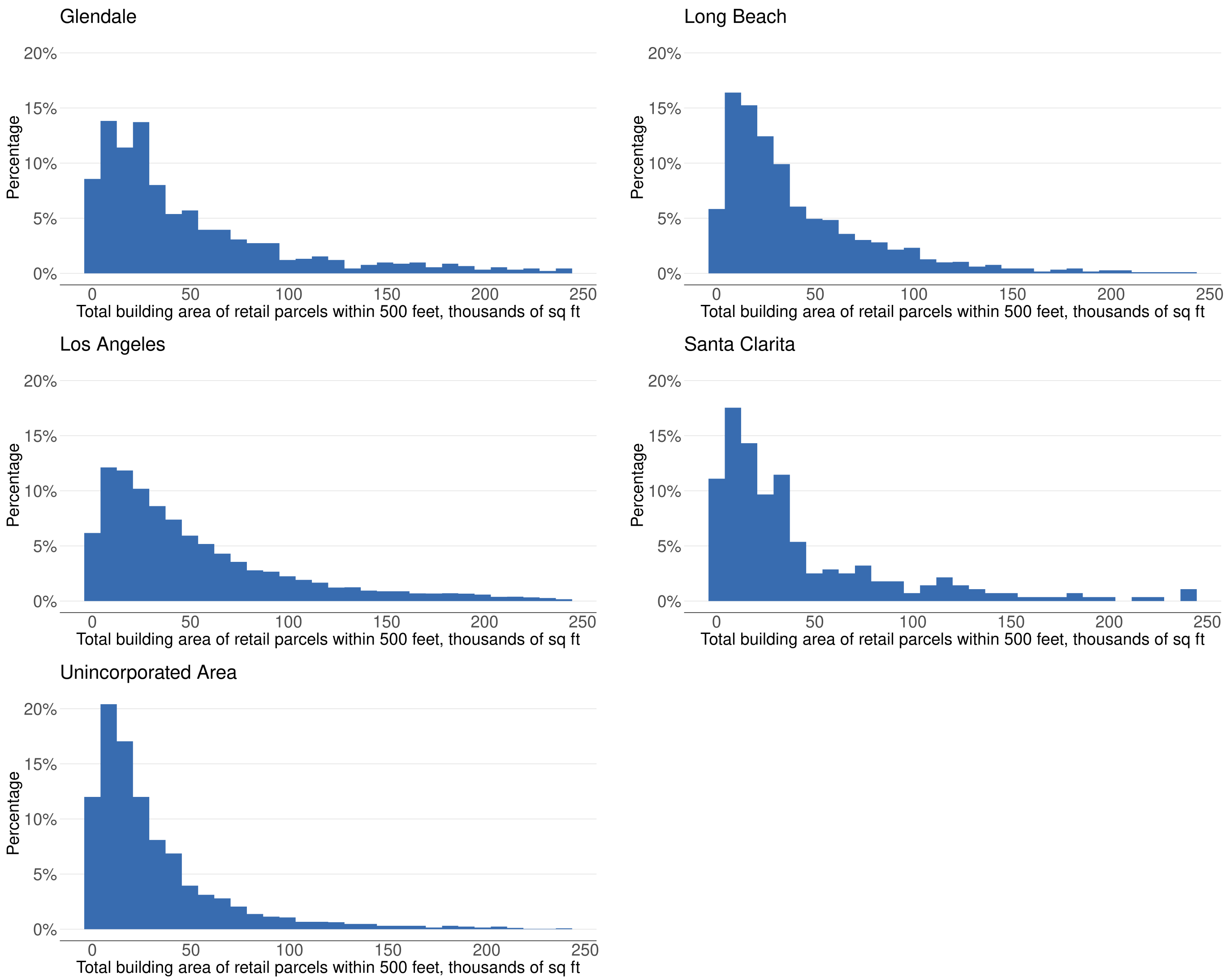
(b) Los Angeles County



Note: The top figure shows the five boroughs of the city of New York in blue. The bottom figure shows the County of Los Angeles (omitting the offshore islands). Other incorporated places are shown in light blue.

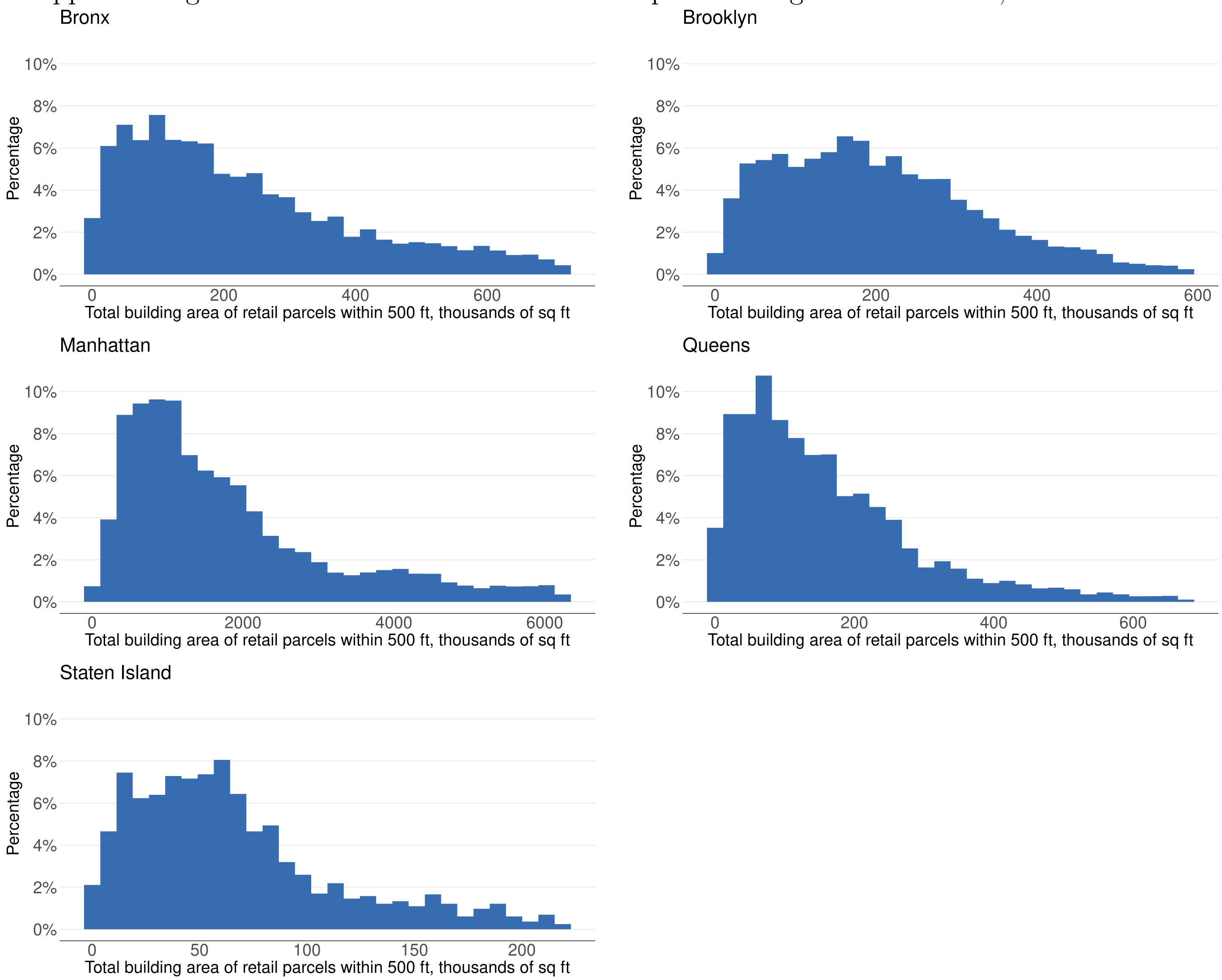
Sources: City outlines from US Census Bureau place shapefiles, downloaded from NHGIS (Manson et al., 2022). County outline for Los Angeles from Los Angeles City GIS website (City of Los Angeles, 2022).

Appendix Figure 3: Distribution of Total Retail Square Footage Concentration, Los Angeles



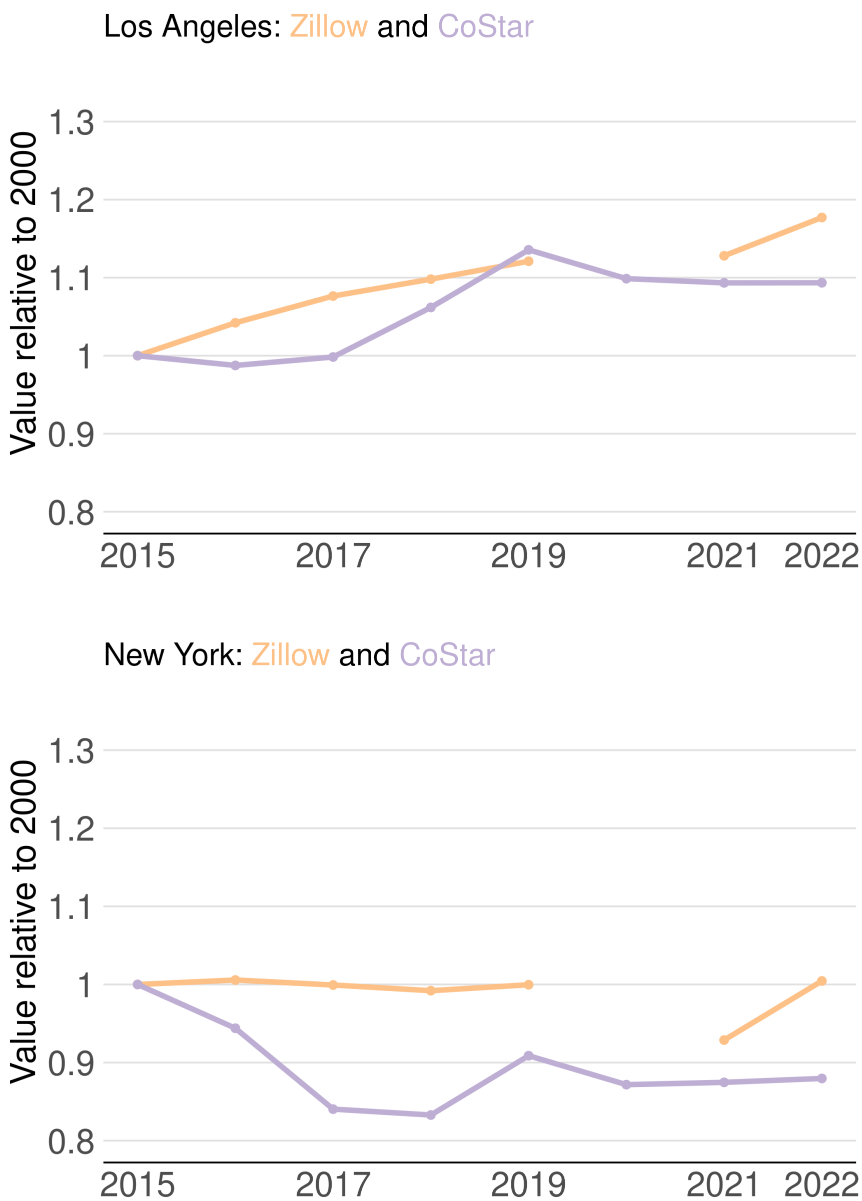
Note: We use only lots in the city of Los Angeles, the unincorporated area of Los Angeles County, the incorporated municipalities of Glendale, Long Beach and Santa Clarita. For Los Angeles parcels, ”retail” is identified by commercially zoned properties in retail use. Retail concentration is measured as the total amount of square footage zoned retail within 500 ft. of a retail-zoned parcel. The figure shows concentration of total square footage of parcels zoned for retail in four municipalities and the unincorporated area in 2022. For visibility, we omit the top 5th percentile of values. The distributions are relatively consistent across the cities, with the highest peaks in Long Beach and part of the unincorporated areas (where there are higher concentrations of smaller retail clusters). The City of Los Angeles has the thickest distribution, indicating a wider range of retail clusters and its diversity in land use patterns within the municipality.

Appendix Figure 4: Distribution of Total Retail Square Footage Concentration, New York



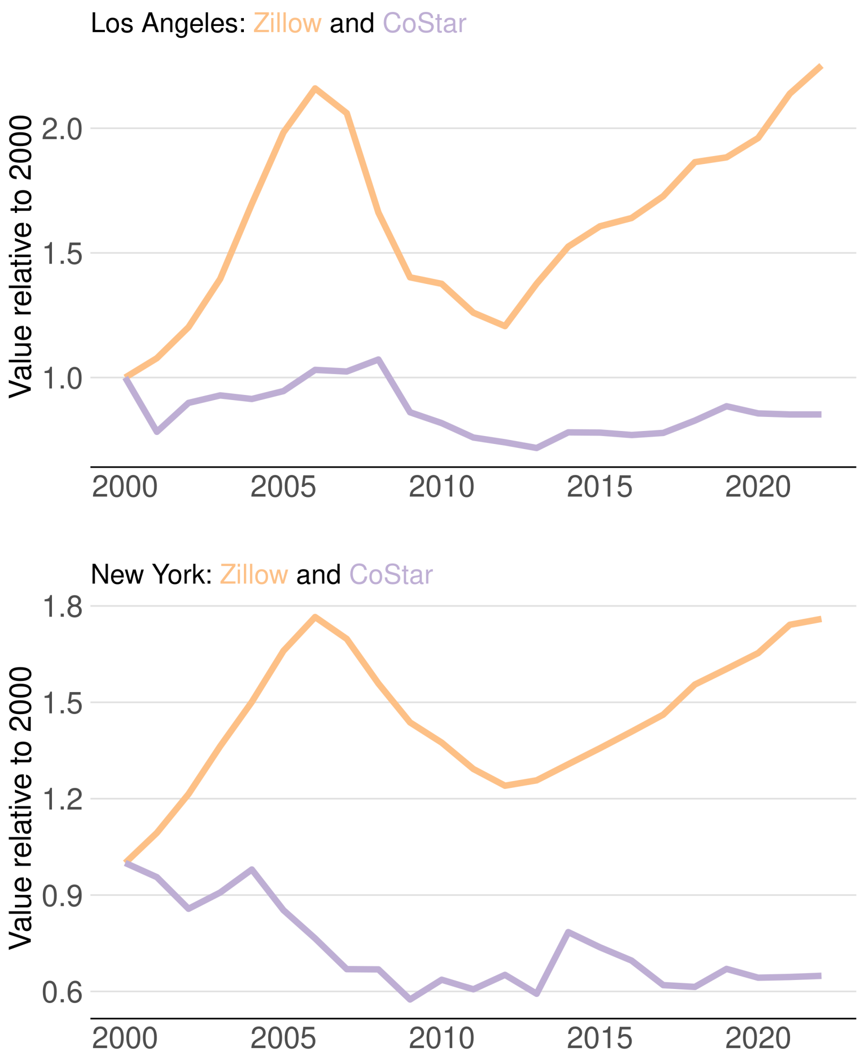
Note: Land use data are from NYC's PLUTO. Retail concentration is measured as the total amount of square footage zoned retail within 500 ft. of a retail-zoned parcel. The figure shows concentration of total square footage of parcels zoned for retail in all five boroughs in 2022. For visibility, we omit the top 5th percentile in each borough. Note that the horizontal axes for Manhattan and Staten Island differ from the other boroughs.

Appendix Figure 5: CoStar Retail and Zillow Residential Rent per Sq. Foot, 2022 Dollars



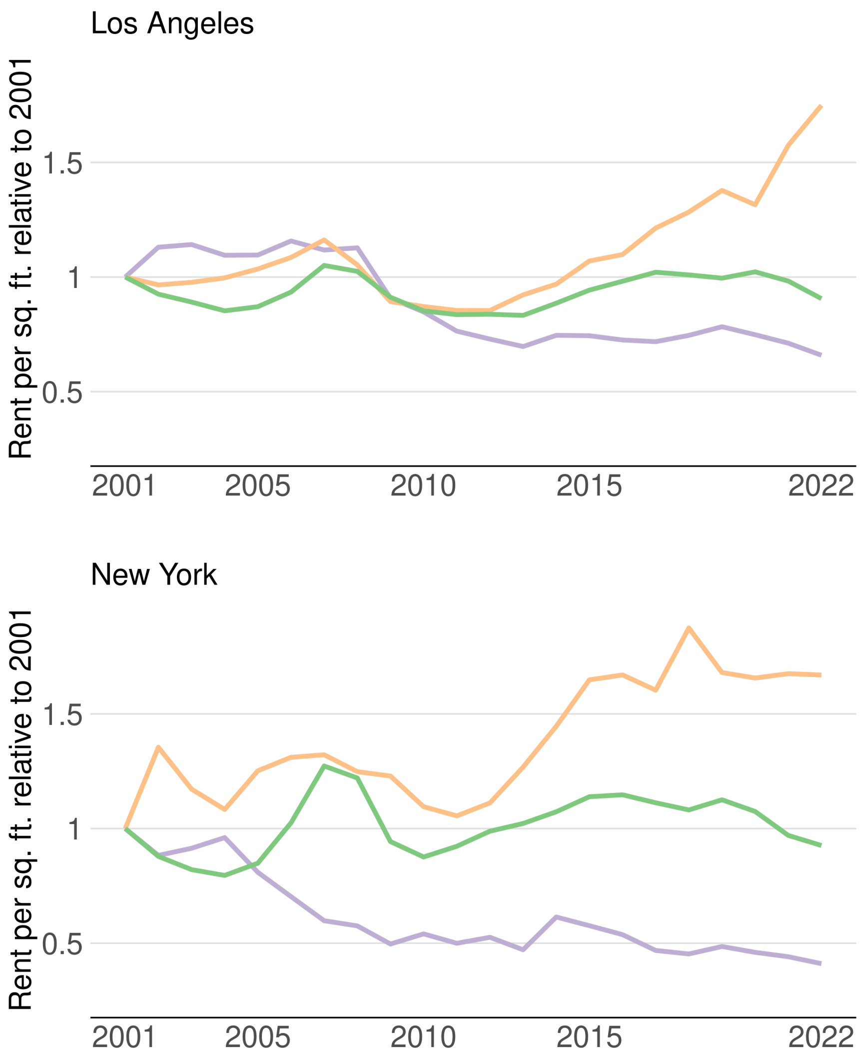
Note: This figure compares CoStar median retail rent per square foot in 2022 dollars (purple) to a Zillow residential rental price index (orange), also in 2022 terms. We normalize both indices to 1 in 2015. Because Zillow does not report a rental index for all markets and years, there are gaps in the orange series.

Appendix Figure 6: Real Home Prices vs. CoStar Rents, Relative to 2000



Note: This figure shows the median CoStar retail rent per square foot by market and the mean Zillow home price index. We adjust both series for inflation to 2022 dollars, and normalize both series to 1 in 2000.

Appendix Figure 7: CoStar Rents versus CBRE Office and Industrial Rents, Relative to 2001



Note: This figure shows median CoStar retail rent per square foot (purple), and mean CBRE gross asking rent for office (green) and industrial properties (orange), all by market and year. We adjust both series for inflation, and normalize all values to one in 2001 when our data series are complete for all metro areas.

Appendix Table 1: New York Regression Results

Dependent Variable:	Log(Price per Lot SF)		
Model:	(1)	(2)	(3)
Cluster Measure	0.0008^{***}	0.0005^{***}	0.0005^{***}
	(8.82×10^{-5})	(0.0001)	(0.0001)
Retail/MU	0.4215^{***}	0.4151^{***}	0.4704^{***}
	(0.0435)	(0.0428)	(0.0475)
Office/Commercial	0.4758^{***}	0.4600^{***}	
	(0.0513)	(0.0512)	
Theater/Hotel	0.7409^{***}	0.7195^{***}	
	(0.1394)	(0.1292)	
Building Sq. Footage (Adj.)	-0.0008	-0.0009	-0.0004
	(0.0006)	(0.0006)	(0.0005)
Lot Area (Adj.)	-0.0018^{***}	-0.0017^{***}	-0.0018^{***}
	(0.0006)	(0.0005)	(0.0006)
Units	-0.0002	-0.0002	2.57×10^{-5}
	(0.0002)	(0.0002)	(0.0003)
Stories	-0.0254	-0.0200	-0.0293^{*}
	(0.0242)	(0.0203)	(0.0147)
Year Built	-0.0005	-0.0004	-0.0021^{***}
	(0.0009)	(0.0009)	(0.0008)
Condo Ind.	-1.546^{***}	-1.548^{***}	
	(0.2479)	(0.2367)	
Cluster Measure $\times$Retail/MU	-0.0001^{***}	$9.4 \times 10^{-5*}$	7.91×10^{-5}
	(3.23×10^{-5})	(5.3×10^{-5})	(9.23×10^{-5})
Cluster Measure $\times$ 2005		0.0002	0.0002^{***}
		(0.0001)	(8.74×10^{-5})
Cluster Measure $\times$ 2006		0.0004^{***}	0.0004^{**}
		(0.0001)	(0.0002)
Cluster Measure $\times$ 2007		0.0002^{**}	0.0002
		(7.48×10^{-5})	(0.0001)
Cluster Measure $\times$ 2008		0.0003^{***}	0.0005^{***}
		(8.48×10^{-5})	(0.0001)
Cluster Measure $\times$ 2009		0.0004^{**}	0.0005^{***}
		(0.0001)	(0.0002)
Cluster Measure $\times$ 2010		7.15×10^{-5}	6.4×10^{-5}
		(0.0001)	(0.0002)
Cluster Measure $\times$ 2011		0.0004^{***}	0.0004^{***}
		(0.0001)	(0.0001)
Cluster Measure $\times$ 2012		0.0003^{***}	0.0004^{***}
		(0.0001)	(0.0001)
Cluster Measure $\times$ 2013		0.0004^{***}	0.0004^{***}
		(8.56×10^{-5})	(0.0001)

Dependent Variable:	Log(Price per Lot SF)		
Model:	(1)	(2)	(3)
Cluster Measure × 2014		0.0003^{***}	0.0005^{***}
		(6.93×10^{-5})	(0.0001)
Cluster Measure × 2015		0.0006^{***}	0.0006^{***}
		(0.0001)	(0.0001)
Cluster Measure × 2016		0.0005^{***}	0.0004^{**}
		(0.0002)	(0.0002)
Cluster Measure × 2017		0.0004^{***}	0.0007^{***}
		(0.0001)	(0.0002)
Cluster Measure × 2018		0.0004^{***}	0.0006^{***}
		(0.0001)	(0.0001)
Cluster Measure × 2019		0.0004^{***}	0.0007^{***}
		(0.0001)	(0.0002)
Cluster Measure × 2020		0.0004^{**}	0.0005^{**}
		(0.0001)	(0.0002)
Cluster Measure × 2021		0.0002	0.0005^{***}
		(0.0001)	(0.0001)
Cluster Measure × 2022		0.0004^{***}	0.0005^{***}
		(0.0001)	(0.0001)
Cluster Measure × 2005 ×Retail/MU		-0.0001	-0.0002^{**}
		(7.81×10^{-5})	(8.35×10^{-5})
Cluster Measure × 2006 ×Retail/MU		-0.0004^{***}	-0.0003^{**}
		(0.0001)	(0.0001)
Cluster Measure × 2007 ×Retail/MU		-5.89×10^{-5}	-6.08×10^{-5}
		(8.33×10^{-5})	(0.0001)
Cluster Measure × 2008 ×Retail/MU		-0.0002^{**}	-0.0003^{**}
		(6.01×10^{-5})	(0.0001)
Cluster Measure × 2009 ×Retail/MU		-0.0004^{**}	-0.0005^{**}
		(0.0001)	(0.0002)

Dependent Variable:	Log(Price per Lot SF)		
Model:	(1)	(2)	(3)
Cluster Measure × 2010 ×Retail/MU		0.0002	0.0002
		(0.0001)	(0.0001)
Cluster Measure × 2011 ×Retail/MU		-0.0002*	-0.0003**
		(9.02×10^{-5})	(0.0001)
Cluster Measure × 2012 ×Retail/MU		-0.0001*	-0.0003**
		(8.05×10^{-5})	(0.0001)
Cluster Measure × 2013 ×Retail/MU		-0.0002***	-0.0004***
		(6.57×10^{-5})	(0.0001)
Cluster Measure × 2014 ×Retail/MU		-0.0001*	-0.0003***
		(6.86×10^{-5})	(0.0001)
Cluster Measure × 2015 ×Retail/MU		-0.0004***	-0.0005***
		(9.71×10^{-5})	(0.0001)
Cluster Measure × 2016 ×Retail/MU		-0.0003***	-0.0003***
		(8.86×10^{-5})	(0.0001)
Cluster Measure × 2017 ×Retail/MU		-0.0002**	-0.0005***
		(9.47×10^{-5})	(0.0001)
Cluster Measure × 2018 ×Retail/MU		-0.0003***	-0.0005***
		(6.63×10^{-5})	(0.0001)
Cluster Measure × 2019 ×Retail/MU		-0.0004***	-0.0008***
		(0.0001)	(0.0001)
Cluster Measure × 2020 ×Retail/MU		-0.0004***	-0.0006***
		(0.0001)	(0.0001)
Cluster Measure × 2021 ×Retail/MU		-0.0004***	-0.0007***
		(0.0001)	(0.0001)
Cluster Measure × 2022 ×Retail/MU		-0.0005***	-0.0006***
		(0.0001)	(0.0001)
Fixed-effects			
Year	Yes	Yes	Yes
Borough	Yes	Yes	Yes
Fit statistics			
Observations	41,940	41,940	38,982
R^2	0.36229	0.36768	0.34728
Within R^2	0.13213	0.13945	0.11504

Clustered (sba) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Appendix Table 2: Los Angeles Regression Results

Dependent Variable:	Log(Price per Lot SF)		
Model:	(1)	(2)	(3)
Cluster Measure	0.0015***	0.0013***	0.0008***
	(0.0002)	(0.0003)	(0.0003)
Retail/MU	0.2305***	0.2307***	0.1710***
	(0.0430)	(0.0430)	(0.0457)
Office/Commercial	0.2336***	0.2329***	
	(0.0563)	(0.0563)	
Theater/Hotel	0.5403***	0.5410***	
	(0.0993)	(0.0990)	
Building Sq. Footage (Adj.)	0.0104***	0.0104***	0.0086***
	(0.0012)	(0.0012)	(0.0016)
Lot Area (Adj.)	-0.0058***	-0.0058***	-0.0051***
	(0.0008)	(0.0008)	(0.0009)
Year Built	-0.0068***	-0.0068***	-0.0062***
	(0.0008)	(0.0008)	(0.0008)
Cluster Measure× Retail/MU	0.0019***	0.0013***	0.0022***
	(0.0003)	(0.0004)	(0.0004)
Cluster Measure× 2005		-0.0006**	-0.0006**
		(0.0003)	(0.0003)
Cluster Measure× 2006		-0.0002	-7.09×10^{-5}
		(0.0004)	(0.0005)
Cluster Measure× 2007		-0.0001	-0.0002
		(0.0004)	(0.0005)
Cluster Measure× 2008		0.0005	0.0006
		(0.0004)	(0.0004)
Cluster Measure× 2009		0.0003	0.0005
		(0.0005)	(0.0005)
Cluster Measure× 2010		-0.0003	-0.0004
		(0.0004)	(0.0004)
Cluster Measure× 2011		7.15×10^{-5}	-0.0003
		(0.0004)	(0.0005)
Cluster Measure× 2012		0.0004	0.0004
		(0.0004)	(0.0004)
Cluster Measure× 2013		2.27×10^{-5}	0.0001
		(0.0004)	(0.0004)

Dependent Variable:		Log(Price per Lot SF)	
Model:	(1)	(2)	(3)
Cluster Measure× 2014		-9.1×10^{-5}	-0.0002
		(0.0004)	(0.0005)
Cluster Measure× 2015		0.0009**	0.0006*
		(0.0004)	(0.0004)
Cluster Measure× 2016		0.0002	-0.0001
		(0.0004)	(0.0005)
Cluster Measure× 2017		0.0001	-5.5×10^{-5}
		(0.0004)	(0.0004)
Cluster Measure× 2018		0.0003	0.0001
		(0.0004)	(0.0004)
Cluster Measure× 2019		0.0009**	0.0010**
		(0.0004)	(0.0005)
Cluster Measure× 2020		0.0005	0.0006
		(0.0004)	(0.0004)
Cluster Measure× 2021		0.0005	0.0004
		(0.0003)	(0.0004)
Cluster Measure× 2022		0.0004	0.0007*
		(0.0004)	(0.0004)
Cluster Measure× 2005 × Retail/MU		0.0006*	0.0007*
		(0.0004)	(0.0004)
Cluster Measure× 2006 × Retail/MU		0.0003	0.0002
		(0.0005)	(0.0006)
Cluster Measure× 2007 × Retail/MU		0.0013**	0.0013**
		(0.0006)	(0.0006)
Cluster Measure× 2008 × Retail/MU		0.0005	-9.2×10^{-6}
		(0.0005)	(0.0005)
Cluster Measure× 2009 × Retail/MU		0.0006	0.0004
		(0.0006)	(0.0007)
Cluster Measure× 2010 × Retail/MU		0.0004	0.0003
		(0.0006)	(0.0006)
Cluster Measure× 2011 × Retail/MU		0.0003	0.0002
		(0.0007)	(0.0008)
Cluster Measure× 2012 × Retail/MU		0.0013**	0.0010*
		(0.0006)	(0.0006)

Dependent Variable:	Log(Price per Lot SF)		
Model:	(1)	(2)	(3)
Cluster Measure× 2013 × Retail/MU		0.0016***	0.0014**
		(0.0006)	(0.0006)
Cluster Measure× 2014 × Retail/MU		0.0017***	0.0018***
		(0.0005)	(0.0006)
Cluster Measure× 2015 × Retail/MU		0.0003	0.0003
		(0.0005)	(0.0006)
Cluster Measure× 2016 × Retail/MU		0.0003	0.0003
		(0.0005)	(0.0006)
Cluster Measure× 2017 × Retail/MU		2.81×10^{-5}	-0.0004
		(0.0005)	(0.0005)
Cluster Measure× 2018 × Retail/MU		0.0010**	0.0007
		(0.0005)	(0.0005)
Cluster Measure× 2019 × Retail/MU		6.77×10^{-6}	-0.0005
		(0.0005)	(0.0006)
Cluster Measure× 2020 × Retail/MU		3.04×10^{-5}	-0.0005
		(0.0006)	(0.0006)
Cluster Measure× 2021 × Retail/MU		-2.99×10^{-5}	-0.0005
		(0.0005)	(0.0005)
Cluster Measure× 2022 × Retail/MU		-0.0006	-0.0013**
		(0.0005)	(0.0005)
Fixed-effects			
Year	Yes	Yes	Yes
DISTRICT	Yes	Yes	Yes
Fit statistics			
Observations	54,199	54,199	42,869
R^2	0.31497	0.31653	0.30220
Within R^2	0.24787	0.24958	0.23203

Clustered (map_book) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1