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Does the Starbucks effect exist? Searching for a relationship between Starbucks and adjacent rents

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Abstract

Purpose – The purpose of this paper is to test the popular perception that the storefront location choices of premium brands are positively related to adjacent rents. Focusing on the case of Starbucks, a popular international coffee chain, the authors examine the association between Starbucks locations and rents in Manhattan, New York.

Design/methodology/approach – The authors use a multi-year data set for average rent per square foot for office and multifamily residential properties within 1/10th of a mile of several hundred coffee shop locations in Manhattan, controlling for vacancy, job density, overall amenity density (WalkScore), coffee shop density, transit accessibility, neighborhood and the Starbucks brand. The authors take two different methodological approaches to isolate potential statistical evidence for an association between Starbucks locations and adjacent rents: the authors run a pooled-cross-sectional model and apply propensity-score matching.

Findings – The authors find a statistically significant positive relationship between the presence of Starbucks and average office rents when applying the authors' pooled-cross-sectional model and applying propensity-score matching. This finding is consistent with several potential causal hypotheses: Starbucks may be attributed to higher rent office locations; the "Starbucks effect" may cause higher rents in adjacent locations; or there may be a mutual reinforcing of positive feedback between Starbucks locations and office rents. The authors find no strong association between Starbucks and residential rents (one model indicates an effect of 2.3 percent on residential rent at 10 percent level of significance), which challenges the direct linearity of the consumption theory of gentrification popularly called the "Starbucks effect."

Originality/value – In the literature, the existence, causality and directionality of a relationship between Starbucks locations and neighborhood change have been largely unstudied. In this paper, the authors test the hypothesis that there is a positive correlation between Starbucks locations and rents.

Keywords Rents, Market value, Starbucks, Coffee shop

Paper type Research paper

1. Introduction

It is a widespread perception that the presence of certain chain brands, such as a Starbucks coffee shop, is indicative of a "good" or "gentrifying" neighborhood (e.g. Carapetian, 2017; Iversen, 2015), also known as the "consumption-side explanation" or "consumption theory" of gentrification (Lees *et al.*, 2010). This follows the common belief that the demand for specific products indicates the presence of a higher income demographic that consumes, for example, relatively expensive coffee. Another similar example is the notion that it is a good time to buy property right before a Whole Foods opens, as a growing demand for organic groceries illustrates that the area is gentrifying or in an otherwise rising trajectory with income levels and property values.

The April 2018 arrest of two African–American men at a Starbucks location in the Rittenhouse Square neighborhood of Philadelphia, Penn. in the USA may further cement this unproven relationship in the popular imagination (e.g. Dias *et al.*, 2018; Mock, 2018;

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Butler, 2018). In the literature, the existence, causality and directionality of a relationship between Starbucks locations and neighborhood change have been largely unstudied. In this paper, we test the hypothesis that there is a positive correlation between Starbucks locations and rents by estimating the effect of Starbucks on adjacent rents in Manhattan, New York.

The remainder of this paper is structured as follows: we review the literature on the relationship between location characteristics, including retail amenities and the Starbucks brand specifically and rents. A description of the data is provided next. We then describe the methodological approach and the results. The paper closes with concluding remarks.

2. Literature review

We are not aware of any peer-reviewed study that has used a quantitative approach to explore the correlation or causal relationship between Starbucks, or any other major retail chain and rents. In the popular and gray literature, some evidence has been presented that this relationship might exist, though there is limited evidence distinguishing correlation from causation.

The real estate data provider Zillow found higher for-sale residential value appreciations for homes located within a quarter of a mile of Starbucks compared to US metropolitan area wide appreciation (Rascoff and Humphries, 2016). In an exploratory working paper, Glaeser *et al.* (2018) found a similar positive correlation between Starbucks proximity and for-sale home prices at the zip code level and also found that the number of Yelp reviews Starbucks received explained more variance and reduced the significance of Starbucks proximity. Using time-series data to explore causality, Rascoff and Humphries found that for grocery stores Whole Foods and Trader Joes, housing prices within a one mile radius began to increase more rapidly than the metropolitan area appreciation rate after such a store opens (Rascoff and Humphries, 2016). Real estate consultancy Gardner (2007) examined the valuation of various urban amenities, including coffee shops, located within 1.5 miles of a home. Coffee shops were not found to have a statistically significant impact. Consequently, there is limited initial basis to hypothesize that certain stores and local services are amenities for which there is a willingness to pay.

On the level of place, the findings of Tu and Eppli (1999, 2001) support that buyers of residential real estate pay a premium for mixed-use, denser urban environments that are walkable and connected. It is reasonable to believe that retail amenities are a component of such places. This study also relates to academic studies on real estate prices and rents, in general. We apply hedonic models as defined by Rosen (1974), which allows for the estimation of implicit prices of real estate attributes. As consumption of real estate consists of both property and locational characteristics, choices made by consumers reveal underlying preferences of characteristics and amenities (Taylor, 2008).

In large part because of data availability, previous research on the value of location characteristics has primarily focused on for-sale housing (Sirmans *et al.*, 2005). Both Rascoff and Humphries (2016) and Glaeser *et al.* (2018) examined the relationship between for-sale housing prices and Starbucks locations. However, the literature clearly indicates that testing any hypothesis about residential gentrification necessitates scrutiny of the housing costs paid by renting households, especially in New York City (Freeman and Braconi, 2004). Hedonic studies of residential rents are scarcer. Löchl and Axhausen (2010) modeled residential rents in Zurich with 14 spatial explanatory variables (in addition to building/unit variables): car travel time to central business district (CBD); regional car accessibility to employment; regional public transport accessibility to employment; distance to nearest rail station; a dummy variable for highway proximity; a dummy variable for noise; local job density; local residential density; local foreign-born population density; income tax level; slope; a dummy variable for lake views; a continuous variable measuring viewsheds of any natural environment terrain; and evening solar exposure. All variables were statistically significant in two alternative OLS regressions with R^2 over 0.8. Brunaer *et al.* (2010) explored a novel modeling technique but included only one location variable, a categorical variable for district/neighborhood. Baranzini and Ramirez (2005) examined four accessibility variables (distance to primary school, distance to a green zone, distance to public transport stop and distance to downtown) and four measures of environmental quality. The four accessibility variables were all significant in a mixed model combining public and private rentals with an R^2 of 0.61.

Studies of office rent determinants have found that a combination of specific lease terms, building characteristics, and location almost completely explain rent variations, though some studies have found that vacancy rates are the single most important determinant (Hysom and Crawford, 1997). An important distinction between the residential and office hedonic literature is the use of vacancy as an independent variable in office models. Recent availability of private databases compiling commercial rent data has enabled US studies such as Bollinger *et al.* (1998), who examined regional and neighborhood location variables, as well as building characteristics, that are determinants of office rents. Their location variables included regional location, highway accessibility, transit accessibility, housing accessibility, neighborhood economic and racial demographics, retail accessibility and neighborhood workforce mix (industrial and professional services). Dunse and Jones (1998) studied office rents in Glasgow, Scotland but modeled only CBD proximity as a regional location attribute. Farooq *et al.* (2010) modeled the Toronto office market. Consistent with the theoretical framework and literature reviewed by Hysom and Crawford, Farooq *et al.* modeled office vacancy as an independent variable. Their model also included the size of total neighborhood office inventory, total employment, transit accessibility, CBD proximity, airport accessibility and neighborhood land use mix (residential and industrial).

3. Data

We obtained street address and opening date attributes for 266 Starbucks and non-Starbucks coffee shop locations in Manhattan from Hoover's business research database, a subsidiary of Dun & Bradstreet (www.hoovers.com/), for Standard Industrial Classification (SIC) codes 54,990,201 (food stores – coffee) and 58,120,304 (eating places – coffee). D&B Hoover's is a private commercial database of business records that includes location, business type by SIC code (a US government classification system) and date of opening. However, in this database, all of the Starbucks locations were missing opening date information. We obtained this sub-data set for Starbucks locations directly from David Firestein of SCG Retail, a full-service retail real estate advisory services company that provides exclusive tenant representation to Starbucks in New York City (www.theshoppingcentergroup.com/location/newyorkcity/). We then defined a buffer zone distance of 0.1 mile around each shop location and selected a sample of 177 shop locations with minimal overlap[1], shown in Figure 1. We selected a search distance of 0.1 mile to approximate one city block, as we expect the effect of Starbucks or coffee shop on office rents to be local. We overlaid these buffer zones on the coffee shop location data to calculate the total number of coffee shops within each zone (including the centroid coffee shop).

For each coffee shop buffer zone, we then obtained information on rents per square foot and overall vacancy rate spanning the third quarter of 2007 to the second quarter of 2017 for office and multifamily residential products from the American commercial real estate data provider CoStar (www.costar.com). CoStar is a commercial real estate research and online listing service that includes a large database of building-level data on asking rents obtained through surveys of property owners and managers and canvasses of properties. Unfortunately, data on covariates were missing from CoStar for some observations, most notably rent data. When estimating office rents, our original data set included 7,080 quarterly rent observations at 177 locations. This decreased to 4,970 observations at 157

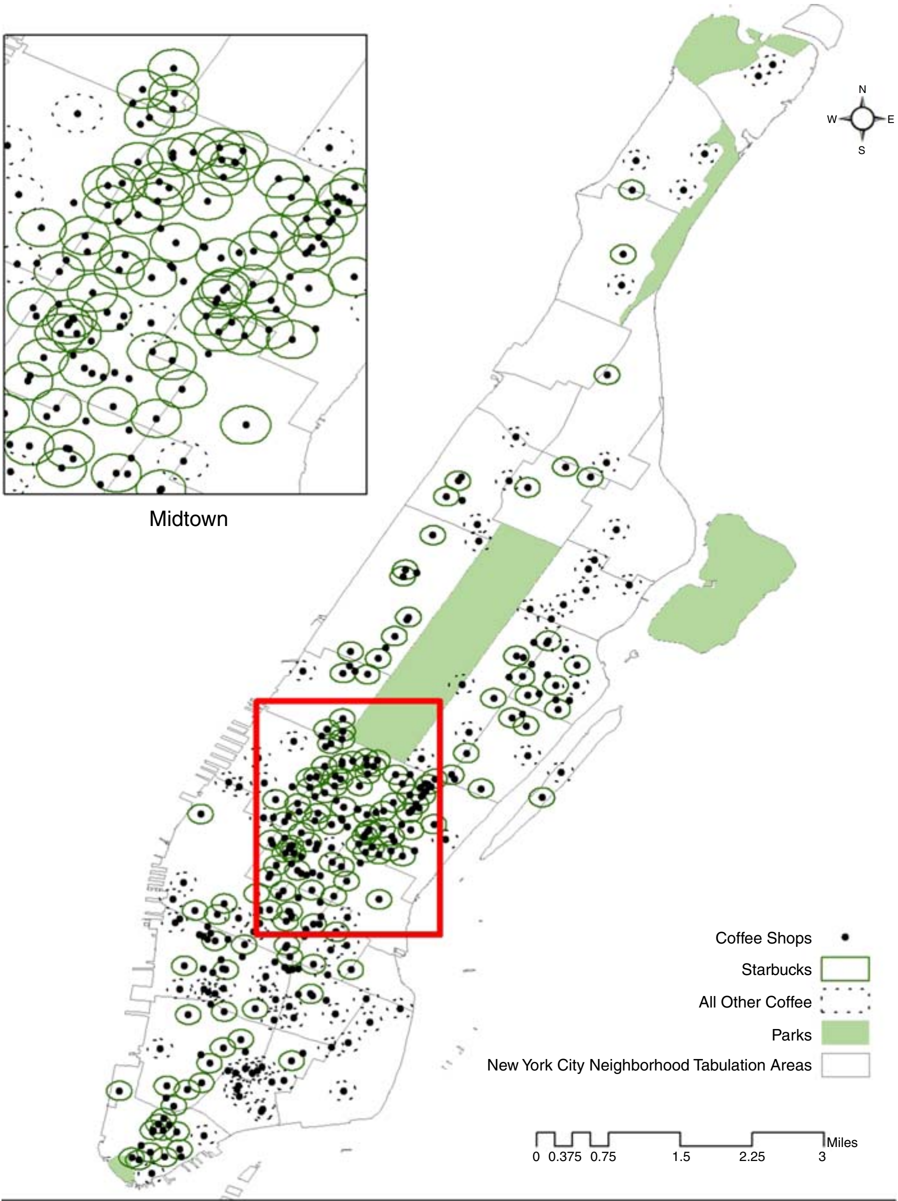

Figure 1. Manhattan coffee shop locations from Hoovers/Dunn & Bradstreet database (2/2017)

locations when removing observations lacking information on all variables and having a year of opening that is subsequent to the observed period (such as an observation in 2007 for a location were the coffee shop is indicated to have opened in 2010). Table I shows the descriptive statistics for the data set with office rents. For the residential data set, the initial number of quarterly rent observations was 7,080 at 177 locations, which decreased to a final sample of 5,385 observations at 154 locations when the data were treated as mentioned above. Table II shows the descriptive statistics for the data set with residential rents.

Table I. Descriptive statistics of Starbucks locations and other coffee shops by sample when estimating office rents

	Starbucks		Non-Starbucks	
	Mean	SD	Mean	SD
Avg. office rent (gross, observations quarterly, $/sq.ft.)	54.48	15.46	50.64	15.40
Average office building age (years)	87	15	89	16
Number of coffee shops	2.4	1.5	1.6	0.7
Subway entrance count	5.1	4.3	1.1	1.6
Number of jobs	109,627	98,966	32,765	47,910
Population	1,631	1,365	2,213	1,211
Subway distance from centroid (meters)	128.4	101.9	327.1	208.6
Office vacancy (%, quarterly)	7.4	6.7	5.0	5.6
Year of opening	2001	3.9	2002	11.5
WalkScore	99	0.86	99	1.23
Office inventory (sq.ft.)	4,856,506	3,264,170	1,363,968	2,016,315
Number of observations	4,052		918	

Table II. Descriptive statistics of Starbucks locations and other coffee shops by sample when estimating residential rents

	Starbucks		Non-Starbucks	
	Mean	SD	Mean	SD
Effective rent per square foot (quarterly, $/sq.ft.)	4.85	1.20	4.74	2.01
Number of coffee shops	2.1	1.3	1.4	0.7
Population	2,728	1,567	2,845	1,289
Subway entrance count	3.9	4.1	0.9	1.6
Subway distance from centroid (meters)	166	138	345	234
Residential vacancy (%, quarterly)	3.6	2.5	3.1	1.3
WalkScore	99	0.99	98	2.76
Year of opening	2001	3.8	2005	9.2
Residential inventory (units)	1823	1,241	1,061	965
Number of observations	3,824		1,561	

When analyzing office rents, our data included gross rent levels, whereas the analysis on residential rents was based on effective rents. This is due to data availability and is of lesser concern as the impact of Starbucks on rent should be the same, regardless of rent measure[2].

In keeping with previous studies of office and residential rents, we collected several neighborhood location attributes. We obtained the average age of office buildings for each 1/10 mile buffer zone from CoStar. Each zone was assigned to a neighborhood based on the centroid/coffeeshop location within a New York City Neighborhood Tabulation Area, the small area unit used for the city's PlaNYC, a similar approach to that of Brunaer *et al.* (2010) (www1.nyc.gov/site/planning/data-maps/open-data/dwn-nynta.page). This neighborhood variable is a proxy for many of the regional location variables examined in other studies (e.g. Löchl and Axhausen, 2010; Bollinger *et al.*, 1998), including distance to the CBD. As previous studies (Löchl and Axhausen, 2010; Farooq *et al.*, 2010) modeled both land use mix and residential accessibility, we calculated the total jobs within each zone using an area-weighted sum by intersecting the zones with US Census block-level job counts from the 2014 release of the Longitudinal Employer-Household Dynamics program's Origin-Destination Employment Statistics. We similarly estimated the total residential population of each zone using block-level data from the 2010 US Census. As a proxy for accessibility to different types of destinations, we used ESRI's ArcGIS Network Analyst extension to calculate the distance to the nearest Metropolitan Transit Authority subway station entrance from the centroid/coffeeshop. To model transit accessibility by both proximity and richness, we also calculated the total count of subway entrances within each zone. Finally, we used the centroid's WalkScore (www.walkscore.com/methodology.shtml) as a proxy for retail accessibility. WalkScore is an amenity proximity, density and diversity measure available at the address level for US, Canadian and Australian cities that places weights on certain types of retail destinations and has been independently validated (Carr *et al.*, 2011).

The risk of a confounding effect on office rent due to differences in building quality decreased somewhat by the fact that locational characteristics between zones with and without Starbucks are similar, with the average age of an office building in a Starbucks zone being 87 years and 89 years in non-Starbucks zones in the sample. Unfortunately, we lack information on the average age of residential buildings.

Availability of public transport diverges between Starbucks and other locations. The median network distance to a subway station entrance in Manhattan is 128 feet for Starbucks and 327 feet for other coffee shops in our pooled-cross-sectional sample when estimating office rents. Starbucks locations also have a higher number of subway entrances, at 5.1 on average compared to 1.1 for non-Starbucks coffee shop locations. In addition, Starbucks locations seem to be located where the number of jobs are greater, averaging 109,627 jobs within 1/10 of a mile, compared to 32,765 jobs for other coffee shops. Not surprisingly, given the higher number of jobs is that Starbucks locations have much larger office inventory, with an average of 4.3m square feet compared to 1.4m square feet in non-Starbucks locations. Following this, it is expected that non-Starbucks locations have higher residential populations, which is confirmed by the data. The population is on average 1,630 people near Starbucks locations compared to 2,213 at non-Starbucks locations. WalkScores are, however, very similar, at 99.5 and 99.0 for Starbucks and non-Starbucks office rent observations, respectively. This reflects the overall very high retail accessibility of all of Manhattan. Both groups have similar year of openings, with Starbucks locations having opened in 2001 on average and non-Starbucks locations in 2002.

In all, Manhattan should provide a setting for the testing a potential "Starbucks Effect" that mitigates many potential issues caused by omitted and spatially correlated rent determinants that could confound an effect of Starbucks on rents with unmeasured neighborhood characteristics compared to other US cities. Keeping the analysis confined to Manhattan, in addition to also controlling for neighborhood, removes much influence from variables that need controlling for in more heterogeneous data sets – an example being the inclusion of the level of property tax as a rent determinant in many other studies.

The descriptive statistics also provide some initial insight into the question of whether office rents are higher in locations with Starbucks compared to locations with a non-Starbucks coffee shop. Rents in Starbucks zones are slightly higher at \$60.10 per square foot and year for Starbucks zones and \$54.80 for non-Starbucks coffee shop zones. Average residential rents per square foot are also higher in Starbucks zones, with the premium ranging between 5 and 9 percent depending on the year.

It should be noted that because of coffee shops being both many and clustered on Manhattan, some locations of coffee shops and Starbucks overlap within and across the groups. Although this is good in the sense that it illustrates that our samples are geographically close (i.e. decreasing the likelihood of confounding relationship between Starbucks and rents with confounding characteristics that vary with geography), it makes estimation of the association difficult.

4. Methodology and results

We take two methodological approaches to estimate the relationship between rents (office and residential) and the presence of Starbucks. First, we apply a hedonic model using a pooled cross-section of quarterly rents spanning 2014 to the second quarter of 2017. We then apply propensity-score matching and three different matching schemes.

4.1 A pooled-cross-sectional model

We take advantage of the fact that we have quarterly data on rents over a longer period, allowing us to estimate rents on a pooled cross-section on the data. Estimating rents for each zone and quarter from the third quarter of 2007 to the second quarter of 2017 gives us a data set of 4,970 observations when estimating office rents and 5,385 observations when explaining residential rents. The ordinary least square model is as follows:

$$\ln(\text{rent})_i = X_i\beta + \text{Starbucks}_i\gamma + t + \varepsilon,$$

$$t = Q1\ 2014,\ \ldots,\ Q2\ 2017,$$

$$i = 1,\ \ldots,\ N. \tag{1}$$

Meaning that the natural logarithm of the average rent in quarter, *t,* in neighborhood, *i,* is regressed on *X,* a matrix of location characteristics and neighborhood. Given that the dependent variable is transformed to its natural logarithm, interpretation of binary variables, most notably the presence of Starbucks, is interpreted as suggested by Halvorsen and Palmquist (1980). This transformation is given by $g = 100[\text{Exp}(\beta i) - 1]$, where g is the percentage impact on the dependent variable.

4.1.1 Office rents. The results from the pooled-cross-sectional models are found in Table III. We run three different models, the first model including jobs and population, the second office inventory (sq.ft.) and the third all three of these explanatory variables. These variables should be proxy measures of the character of the area in terms of dominant land use and building size. variance inflation factors (VIF) do, however, not indicate any issue of multicollinearity[3]. All models have an explanatory power of 0.44 and show that Starbucks is associated with 9.2–11.1 percent increase in rent (coefficients of 0.104, 0.0878 and 0.0920), significant at the 1 percent level. An additional coffee shop of any type is found to increase rents by 1.1 percent and is significant at the 1 percent level. Surprisingly, the number of subway entrances is significant and shows a negative impact on rents. The variable indicating distance to subway is not significant.

As expected, the average building age is found to negatively impact rents and is significant at the 1 percent level for the above-mentioned period of rents. Residential

	(1)		(2)		(3)	
Model	ln(rent)	*t*-statistics	ln(rent)	*t*-statistics	ln(rent)	*t*-statistics
Starbucks	0.104***	(8.10)	0.0878***	(6.70)	0.0920***	(7.02)
Avg. office building age	−0.00758***	(−23.13)	−0.00721***	(−22.11)	−0.00722***	(−21.55)
Number of coffee shops	0.0108***	(4.53)	0.0131***	(5.61)	0.0122***	(4.98)
Number of subway entrances	−0.00295**	(−3.05)	−0.00271**	(−2.78)	−0.00271**	(−2.75)
Number of jobs	0.000000143***	(3.72)			0.000000110**	(3.00)
Population	−0.0000235***	(−7.66)			−0.0000135***	(−3.85)
Distance to subway	0.0000822*	(2.29)	0.000103**	(2.89)	0.000102**	(2.85)
Office vacancy (%, Quarterly)	0.00246***	(4.27)	0.00263***	(4.56)	0.00255***	(4.43)
WalkScore	0.0189***	(4.57)	0.00486	(1.21)	0.0116*	(2.56)
Office inventory (sq.ft.)			1.30e-08***	(8.58)	8.58e-09***	(4.93)
Constant	2.877***	(7.13)	4.118***	(10.43)	3.522***	(8.09)
R^2	0.4400		0.4404		0.4425	
N	4,970		4,970		4,970	

Notes: *t*-statistics in parentheses. Dependent variables are the natural logarithm of office gross rents. Heteroscedasticity robust standard errors are estimated. Binary variables that indicate neighborhood are included in all models but are suppressed from the output to save space (see footnote 6). The pooled cross-sectional model that estimates quarterly rents includes binary variables that indicate the quarter of observed rent that are suppressed from the output to save space. $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Table III.
Regression results

population is found to be negative and significant, whereas total jobs are positive and significant, as is the square footage of office inventory (all at 1 percent).

There is a possibility that the presence of Starbucks is endogenously related to other characteristics that positively impact rents but are not included in our model. This would cause an upward omitted-variable bias if Starbucks coffee shops are in more attractive locations. However, keeping in mind that we control for many variables that influence rent such as neighborhood, overall amenity density richness (through WalkScore), and property age, in addition to also isolating the effect of an additional coffee shop, the results provide support for the hypothesis that Starbucks is positively associated with office rents.

As described in our review of studies on rent determinants, vacancy is typically included in models that explain office rents and is assumed to be under some control of the landlord. As a robustness check, we run a model like model 3 without vacancy. Reassuringly, the variable indicating Starbucks hardly changes, to an effect of 9.8 percent (from 9.2 percent) and is still significant at the 1 percent level.

4.1.2 Residential rents. Two models explaining residential rents are shown in Table IV, with model 5 including inventory of residential units (not included in model 4). Although this variable is found to significantly impact rent (negatively, at 1 percent), it had no impact on the overall results, most notably the estimated relationship between Starbucks and rent. We found no significant effect from Starbucks proximity on residential rents in either model. The model specification includes the same explanatory variables as when explaining office rents, with two exceptions. The CoStar interface does not calculate average building age for custom surveys of residential properties, so this variable is absent from our model. Also, the number of jobs is also not included in the model, given that this explanatory variable is most likely to impact office rents[4]. Surprisingly, the number of coffee shops is found to have a negative effect on rents (−1.5 and −1.6 percent, significant at the 1 percent level). This might be a consequence of coffee shops being endogenously related to some measure of "busyness" such as freight traffic that negatively impacts residential attractiveness[5]. The explanatory power is 0.49 for both models. WalkScore, the number of MTA subway entrances and vacancy rates are found to positively impact residential rents and are statistically significant at the 1 percent level. Distance to subway has a positive coefficient although it is only significant at 10 percent in model 1.

Model	(4) ln(rent)	(4) *t*-statistics	(5) ln(rent)	(5) *t*-statistics	(6) ln(rent)	(6) *t*-statistics
Starbucks	−0.0162	(−1.59)	0.0201	(1.56)	0.0226*	(1.85)
Number of coffee shops	−0.0146***	(−5.12)	−0.0160***	(−5.40)	−0.0192***	(−6.95)
Population	−0.0000116**	(−2.89)	0.0000141**	(2.76)	0.0000144***	(2.80)
Number of subway entrances	0.00603***	(5.57)	0.00468***	(4.08)	0.00539***	(4.86)
Distance to subway	0.0000623	(1.76)	0.0000407	(1.12)	0.0000348	(0.95)
Residential vacancy (%, quarterly)	0.0103***	(6.48)	0.0102***	(6.36)		
WalkScore	0.0137***	(4.24)	0.0140***	(4.45)	0.013011***	(4.10)
Residential inventory (units)			−0.0000553***	(−7.39)	−0.0000532***	(−7.11)
Constant	−0.467	(−1.49)	0.417	(1.24)	0.522	(1.56)
R^2	0.4902		0.4973		0.4911	
N	5,385		5,385		5,523	

Notes: *t*-statistics in parentheses. Dependent variables are the natural logarithms of effective residential rents. Heteroscedasticity robust standard errors are estimated. Binary variables that indicate neighborhood are included in all models but are suppressed from the output to save space (see footnote 6). The pooled-cross-sectional model that estimates quarterly rents includes binary variables that indicate the quarter of observed rent that are suppressed from the output to save space. *,***Significant at the 10, 5 and 1 percent levels, respectively

Table IV. Regression results

As with office rents, we run models without vacancy as a robustness check. This is shown in model 6. Little happens with the Starbucks variable, it does, however, become significant at the 10 percent level, indicating a 2.3 percent effect on residential rent. This model also includes a slightly larger number of observations as some observations lacked information on vacancy.

4.2 Propensity-score matching

As previously mentioned, our main methodological challenge is that of endogeneity potentially introducing omitted-variable bias, namely that the presence of Starbucks is correlated with omitted locational characteristics that influence rents. When comparing sub-groups with observational data – a natural experiment of randomly assigning Starbucks coffee shops to various locations would be the ideal way of analysis, something that is infeasible – such omitted characteristics will bias results if impacting both selection (the presence of Starbucks) and outcome (rent). Propensity-score matching, as proposed by Rosenbaum and Rubin (1983), offers a way to control for such omitted and confounding variables. This is accomplished by estimating each observation's conditional probability of assignment to the treated sub-group, i.e. a location's probability of having Starbucks, given locational characteristics. Formally, this is stated as follows:

$$(X) \equiv Pr(D = 1|X) = E(D|X), \tag{2}$$

where $D =$ (0,1) refers to a location having Starbucks and X a multidimensional vector of locational characteristics. This estimated propensity score is given by probit regression (the output from our models that estimate propensity scores are shown in Tables V and VI and are not interpreted[6]). When propensity scores have been estimated for all observations, the so-called unconfoundedness is assumed. This means that assignment to the group of locations having Starbucks is independent of rents, given locational characteristics. Formally, this is stated as follows:

$$Y(0), Y(1) \perp D|X, \tag{3}$$

where Y (0,1) denotes the rent for non-Starbucks and Starbucks locations, respectively. $\perp$ signifies independence. For propensity-score matching to be a good way to estimate the relationship between Starbucks and adjacent rents, there must be a significant overlap

Table V.
Probit regression for estimation of propensity scores on office rent observations

Dependent variable	Presence of Starbucks	
Variable	Coefficient	*z*-values
Number of coffee shops	0.078***	(2.69)
Average office building age	0.007	(3.33)
Population	2.256e-4	(7.87)
Number of jobs	2.52e-06	(2.96)
Number of subway entrances	0.070	(5.13)
Distance to subway	−0.003	(−9.03)
Vacancy %	0.017	(3.66)
WalkScore	−0.042	(−1.36)
Office inventory (sq.)	1.99e-07	(8.43)
Year	−0.049	(−5.04)
Constant	101.114	(5.13)
Number of observations	3,337	
LR χ^2 (10)	1039.53	
Pseudo R^2	0.2648	

Notes: *Z*-values are shown in parentheses. *,**,***Significant at the 10, 5 and 1 percent levels, respectively

Dependent variable	Presence of Starbucks	
Variable	Coefficient	z-values
Number of coffee shops	0.187***	(6.78)
Population	−3.156e-4***	(−14.20)
Number of subway entrances	0.130***	(10.76)
Distance to subway	−0.002***	(−9.01)
Vacancy %	0.134***	(7.27)
WalkScore	0.089***	(4.82)
Inventory (units)	0.001***	(26.27)
Year	−0.079***	(−9.32)
Constant	150.240***	(8.63)
Number of observations	5,323	
LR χ^2 (8)	2431.92	
Pseudo R^2	0.3776	

Notes: Z-values are shown in parenthesis below the coefficient estimates. *,**,***Significant at the 10, 5 and 1 percent levels, respectively

Table VI. Probit regression for estimation of propensity scores on residential rent observations

between the sub-groups of observations so that the estimated propensity scores do not perfectly predict if a location has Starbucks or not. This is formally stated as follows:

$$0 < Pr(D = 1|X) < 1, \tag{4}$$

so that all propensity scores are within the interval of 0 and 1. When (3) and (4) hold, Rosenbaum and Rubin state that assignment to either category is strongly ignorable. This allows for the estimation of the average treatment effect on the treated (ATT) that is the estimated effect of Starbucks on adjacent rents. Formally, this is stated as follows:

$$\text{ATT} = (\tau|D = 1) = E\big[Y(1)\big|D = 1\big] - E\big[Y(0)\big|D = 1\big], \tag{5}$$

with τ denoting a location having Starbucks. We apply three different matching schemes to estimate the ATT. We match each Starbucks location with its closest non-Starbucks match on propensity scores, the four nearest matches, and apply kernel matching that implies that each Starbucks location is matched with the full sample of non-Starbucks locations that are weighted on their inverse propensity scores. Each matching scheme has specific benefits and drawbacks. Matching on nearest matches is straightforward and yields close matches while using a limited amount of data. Kernel matching uses more data, although some of the information is from less good matches on propensity scores (Caliendo and Kopeinig, 2008). When matching on the nearest and four nearest matches, matching is done with replacement, meaning that a non-Starbucks observation can be matched with several Starbucks observations if it is the closest match on propensity scores.

When choosing variables to include when estimating propensity scores, all variables that impact the outcome should be included (Brookhart *et al.*, 2006). We, therefore, include the same explanatory variables as when estimating the pooled-cross-sectional models with the exception of controlling for neighborhood, as we deem it more important to achieve good matches on the more fine-grain spatial location charateristics[7]. The effect of time on rent is captured by a variable for the year of the observations when matching Starbucks locations with non-Starbucks coffee shops[8].

As the commonly used approach of boostrapped standard errors is not valid for matching on nearest matches (Abadie and Imbens, 2006, 2008), standard errors as suggested by Abadie and Imbens (2006) are estimated for matching on the nearest and four nearest matches. Boostrapping with 250 replications is applied for the kernel estimate.

4.2.1 Office rents. The results from matching each Starbucks location with its nearest (1:1) and four nearest (1:4) non-Starbucks location matches on propensity scores, in addition to matching on all non-Starbucks that are weighted on their inverse propensity score, are shown in Table VII. The number of observations is 3,337, after exclusion of observations outside the range of common support (i.e. propensity scores that perfectly predict if a location has Starbucks). All matching schemes show a statistically significant (1 percent) difference in rents, with Starbucks locations having $7 per year and square foot higher rents (6.96, 6.80 and 7.10 for 1:1, 1:4 and kernel matching, respectively) (Table VIII).

After 1:1 matching, the samples of Starbucks and non-Starbucks coffee shop locations show no statistically significant differences in means for the average office building age, the number of jobs and distance to subway. Although other locational characteristics show statistically significant differences in characteristics, the economic meaning of these differences are minimal. The average population is 1,906 for Starbucks locations and 1,979 for non-Starbucks locations. Similarly, the number of subway entrances is 3.2 for Starbucks and 2.8 for non-Starbucks locations, respectively (significant at 1 percent). The same goes for WalkScore, the square footage of office inventory and the year of the observation, which exhibit minimal but statistically significant differences (1 percent). Worth mention is that the vacancy rate is almost 1 percent-point higher in non-Starbucks locations for 1:1 matching. Overall, 1:4, and kernel matching yields similar but slightly less balanced samples compared to 1:1 matching, although a very similar estimate of the ATT. It is very reassuring that the ATT is not sensitive to the matching scheme. In all, these results show a strong indication that Starbucks is positively associated with office rents, even after controlling for locational characteristics that impact rent.

4.2.2 Residential rents. After exclusion of observations outside the range of common support, the number of observations is 5,323 for estimation of propensity scores to examine the impact on residential rent. Our matching scheme on propensity scores results in estimates that indicate that the presence of Starbucks has no relationship with residential rents. Although differences in rents are statistically significant, they are very small ($0.13, $0.19 and $0.03 higher rent per year and square foot when applying 1:1 matching, 1:4 matching and kernel matching, respectively). Unfortunately, the samples do exhibit statistically significant differences in characteristics, with Starbucks locations having a greater number of coffee shops, a shorter distance to subway and a slightly lower inventory of residential units.

4.2.3 Rosenbaum-bounds robustness check. As a robustness check, we test the so-called Rosenbaum-bounds as proposed by Rosenbaum (2002). This tells us how sensitive our results are for hidden bias, meaning that the assumption of unconfoundedness is violated. This works so that if π_i is the probability of location i having Starbucks, the odds ratio is equal to:

$$\pi_i/(1-\pi_i). \tag{6}$$

For location i and j, an odds ratio can be defined as Γ:

$$\frac{\pi_i/(1-\pi_i)}{\pi_j/\left(1-\pi_j\right)} \equiv \Gamma. \tag{7}$$

Meaning that two locations with equal locational characteristics have odds of having Starbucks that diverge by Γ that can be seen as a multiplier of the degree of departure from random assignment caused by a confounding factor. Consequently, $\Gamma = 1$ means that there

Table VII. Estimated ATT (effect of Starbucks) on average gross office rent

	Starbucks locations	N:N 1 Controls (non-Starbucks)	N:N 1 Diff. (ATT)	N:N 1 SE (AI robust)	N:N 4 Controls (non-Starbucks)	N:N 4 Diff. (ATT)	N:N 4 SE (AI robust)	Kernel Controls (non-Starbucks)	Kernel Diff. (ATT)	Kernel SE (bootstrapped)
Avg. office rent 2014–2017 (gross)	55.053	48.090	6.964***	0.609	48.256	6.800***	0.527	47.960	7.093***	0.662
Number of coffee shops	2.054	1.482	0.572***		1.445	0.609***		1.489	0.565***	
Average office building age	90.839	90.415	0.424		90.250	0.589		91.932	−1.092***	
Population	1906.058	1979.363	−73.305*		2016.412	−110.355***		2085.293	−179.235***	
Number of jobs	73098.090	72637.441	460.650		73115.730	−17.639		70224.632	2873.458	
Number of subway entrances	3.291	2.786	0.506***		2.837	0.454***		2.530	0.761***	
Distance to subway	165.411	168.361	−2.950		170.686	−5.275*		174.744	−9.333***	
Vacancy %	6.146	7.088	−0.942***		6.953	−0.807***		6.290	−0.143	
WalkScore	99.395	98.931	0.465***		98.908	0.487***		99.100	0.295***	
Avg. office inventory (sq. ft.) 2014–2017	3231681.5	3475001.3	−243319.812***		3457568.53	−225887.023**		3123711.81	107969.694	
Year	2012.356	2012.550	−0.195**		2012.495	−0.139*		2012.049	0.307***	
Number of observations	3,337									

Notes: Standard errors are estimated as suggested by Abadie and Imbens (2006, 2008) for matching on the nearest and four nearest matches. Bootstrapping with 250 replications is done for the Kernel estimate. *,**,***Significant at the 10, 5 and 1 percent level (two-sample t-test of difference in means), respectively

Table VIII.
Estimated ATT (effect of Starbucks) on 2014–2017 average effective residential rent

		N:N 1			N:N 4			Kernel		
	Starbucks locations	Controls (non-Starbucks)	Diff. (ATT)	SE (AI robust)	Controls (non-Starbucks)	Diff. (ATT)	SE (AI robust)	Controls (non-Starbucks)	Diff. (ATT)	SE (bootstrapped)
Avg. residential rent 2014–2017 (effective)	4.852	4.987	−0.135***	0.080887318	5.037	−0.185***	0.0500	4.825	0.0271***	0.0620
Number of coffee shops	2.066	1.448	0.619***		1.383	0.683014354***		1.437	0.629***	
Population	2725.509	2742.397	−16.887		2890.377	−164.867366***		2881.799	−156.290***	
Number of subway entrances	3.901	1.890	2.011***		2.418	1.48298777***		2.058	1.842***	
Distance to subway	166.104	249.980	−83.876***		210.381	−44.2774792***		202.934	−36.830***	
Vacancy %	3.502	6.968	−3.466***		4.701	−1.19904306***		3.490	0.0118	
WalkScore	99.242	98.668	0.574***		98.917	0.324998388***		99.036	0.206***	
Inventory (units)	1744.042	2032.256	−288.214***		2083.143	−339.101376***		2005.457	−261.415***	
Year	2012.014	2012.547	−0.533***		2012.549	−0.534356725***		2012.342	−0.327***	
Number of observations	5,323									

Notes: Standard errors are estimated as suggested by Abadie and Imbens (2006, 2008) for matching on the nearest and four nearest matches. Bootstrapping with 250 replications is done for the Kernel estimate. *,**,***Significant at the 10, 5 and 1 percent level (two-sample *t*-test of difference in means), respectively is no hidden bias, whereas $\Gamma = 2$ means that two observations with the same observed characteristics, one might be twice as likely to be have Starbucks. With an estimate of Γ, the upper and lower confidence bounds of p-values of significance of the estimated effect tell us how much bias that makes the analysis uninformative. For office rents, Γ corresponds to 2.2, 2.1 and 2.2 for 1:1, 1:4 and kernel matching, respectively. This indicates that locations would need to have a 2.2 times higher true probability of having Starbucks given the same observed locational characteristics for the analysis to be uninformative. When estimating the effect on residential rents, Rosenbaum bounds are 1.2, 1.3 and 1.2 for 1:1, 1:4 and Kernel matching, respectively. This indicates a very high sensitivity to hidden bias when estimating effect on residential rents, which is to be expected given that the impact of Starbucks is very small (if any).

5. Conclusion

We examine the relationship between rents and an adjacent Starbucks. Our data set consists of zones of 0.1 mile surrounding Starbucks coffee shops and equivalent zones surrounding non-Starbucks coffee shops. We limit our analysis to Manhattan in New York City, and control for neighborhood, building age, WalkScore, vacancy rates and transport accessibility to address concerns a possibility that the presence of Starbucks is endogenously related to locational characteristics that impact rents.

To test if Starbucks proximity is positively associated with office rents, we run models predicting average rents within zones of 0.1 mile surrounding both Starbucks and non-Starbucks coffee shops. The models control for neighborhood, WalkScore, building age, working- and living population, access to public transport, and the number of coffee shops. Consequently, we isolate Starbucks variable from the variance potentially explained by coffee shops in general. When controlling for the above-mentioned variables, we find that Starbucks is significantly and positively correlated with office rents when running a pooled cross-section of quarterly rents spanning 2014–2017. In this model, Starbucks is associated with a 9.2–11.1 percent increase in office rent within 0.1 mile of the Starbucks location. We also find that an additional coffee shop, irrespective of brand, is associated with a 1.1 percent higher average office rent within a 0.1-mile zone (from the pooled-cross-sectional model on quarterly office rent). Further robustness to our analysis is given by propensity-score matching. The results from three different matching schemes are consistent with the hypothesis that Starbucks proximity is positively associated with office rents, with results indicating \$7 higher rent per year and square foot.

These results provide the first estimate of the relationship between office rents and a major retail brand-name, Starbucks. This finding is consistent with several potential causal hypotheses: Starbucks may be atributed to higher rent office locations; the "Starbucks effect" may cause higher rents in adjacent locations; or there may be a mutually reinforcing positive feedback between Starbucks locations and office rents. Future research can build on the exploratory models in this paper to test these hypotheses.

When we apply similar models to data on residential rents, we find that the Starbucks variable is not significant in two models and significant at the 10 percent level when we exclude vacancy. It then indicates that Starbucks has a positive effect of 2.3 percent on residential rent. In other words, we did not find strong evidence for the direct linearity of the consumption theory of gentrification, also known as the "Starbucks effect." Our models have only moderate explanatory power, so it is possible that there is a relationship that we are unable to detect with this sample. Alternatively, our findings may imply that coffee shops are an amenity that is valued on the market for office properties while not being valued among residential renters. Alternatively, it could be that Starbucks location selection criteria gravitate to more expensive office locations. The significance of the Starbucks variable in the office model, and not in the residential model, provides some modest support for the notion that the presence of Starbucks has a causal positive effect on office rents (in contrast to simply being in more attractive locations), as a proxy-effect would be likely to produce a positive impact on residential rents as well.

Notes

1. Some observations slightly overlap between the groups (between 1 and 17 percent of the total zone area). It should be noted that greater overlap within each group is present, in other words, the sample includes Starbucks locations that are closer than 0.2 miles to other Starbucks locations. The same is true within the non-Starbucks location sample.
2. The office data set only includes base and gross (total) rent, while the residential data set does not include gross rent.
3. For Model 3, office inventory has the highest VIF value (besides neighborhood dummies that are not interpreted), at 4.2 which is below what is typically considered problematic (4).
4. We did, however, run models explaining residential rents that included the number of jobs. This variable was not statistically significant and did not change the overall results.
5. The neighborhood control variables are as follows: Chinatown, Clinton, Gramercy, Hudson Yards/Chelsea/Flatiron, Midtown/Midtown South, Murray Hill/Kipps Bay, SoHo/Tribeca/Civic Center/Litt, Turtle Bay/East Midtown, Upper East Side/Carnegie Hill, and West Village.
6. This output is not discussed, as the only purpose of the probit regression is to estimate propensity scores to match on. A measure of success is how well this matching results in balanced samples without statistically significant differences in covariates (shown in Tables III and VII).
7. We did run models that did include neighborhood variables as a robustness check. Several of these had to be excluded (12 out of 22) due to violating the common support assumption, as location perfectly predicted the presence of a Starbucks. This model gives results similar to those presented, indicating that a Starbucks locations having higher rents, although explanatory variables exhibiting statistically significant differences in characteristics.
8. In the econometric models time is captured through binary variables indicating the quarter of transaction. This would not be appropriate for estimating propensity scores, as each variable is given equal weight and that quarter is less important compared to achieving good matches on locational characteristics.

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