NBER WORKING PAPER SERIES

THIRD PLACES AND NEIGHBORHOOD ENTREPRENEURSHIP:
EVIDENCE FROM STARBUCKS CAFÉS

Jinkyong Choi
Jorge Guzman
Mario L. Small

Working Paper 32604
http://www.nber.org/papers/w32604

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024

We thank participants at the NBER Entrepreneurship Boot Camp, Duke Strategy Seminar, the University of Oregon Strategy Seminar, and Southern Economic Association meetings, as well as Vanessa Burbano, Bo Cowgill, Brandon Freiberg, Paul Ingram, David Robinson, Adina Sterling, Dan Wang, and Weilong Wang, for helpful comments. This work was generously supported by the Columbia Tamer Institute for Social Enterprise. The data from the Startup Cartography Project were partially funded by the Kauffman Foundation. Guzman has given occasional compensated talks where some of the results in this paper have been featured. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Third Places and Neighborhood Entrepreneurship: Evidence from Starbucks Cafés
Jinkyong Choi, Jorge Guzman, and Mario L. Small
NBER Working Paper No. 32604
June 2024
JEL No. L26,R23

ABSTRACT

Sociologists have shown that “third places” such as neighborhood cafés help people maintain and use their network ties. Do they help local entrepreneurs, for whom networks are important? We examine whether the introduction of Starbucks cafés into U.S. neighborhoods with no coffee shops increased entrepreneurship. We find that, when compared to census tracts that were scheduled to receive a Starbucks but did not do so, tracts that received a Starbucks saw an increase in the number of startups of 5.0%to 11.8% (or 1.1 to 3.5 firms) per year, over the subsequent 7 years. There was no effect on neighborhoods with prior cafés. A partnership between Starbucks and Magic Johnson focused on underprivileged neighborhoods produced larger effects. Starbucks locations with more square footage and those with a higher number of visits also produced larger effects.

Jinkyong Choi
Columbia University
1 Morningside Dr
unit 712
New York City, New 10025
jc5901@columbia.edu

Jorge Guzman
Columbia Business School
Kravis Hall, 975
655 W 130th St
New York, NY 10027
and NBER
jag2367@gsb.columbia.edu

Mario L. Small
Columbia University
mario.small@columbia.edu

Sociologists have argued that local establishments such as restaurants, pubs, and cafés can improve neighborhood life (Oldenberg 1989). These informal “third places” are said to provide the opportunity to talk to others outside of home (first place) and work (second), and to help people maintain friendships, exchange ideas, and build community. While the impact of third places on neighborhoods’ social networks and sense of community has been studied at length (Small 2009, Klinenberg 2018, Small and Alder 2019), their effect on economic activity has not (but see Andrews 2019). This paper examines the impact of a particular kind of third place on entrepreneurship in U.S. neighborhoods.

We consider Starbucks cafés. These cafés could contribute to entrepreneurship in a neighborhood through two mechanisms. First is networks. Networks have been repeatedly documented to be important to entrepreneurship (Sorenson 2018; Sorenson and Audia, 2000; Arzaghi and Henderson, 2008). When starting a company, entrepreneurs benefit from having others with whom to brainstorm and refine ideas, identify potential pitfalls, seek funders and other supporters, and navigate legal and logistical roadblocks. Starbucks Corporation, a Fortune 500 company, was distinct in this respect, because, in the 1980s, when many coffee shops primarily focused on selling food and drink, Starbucks invested in a model inspired by European cafés, wherein the coffee shop would provide a social setting for individuals to interact: “There wasn’t really a term for what [we were doing] until a few years later, in 1989, when sociologist Ray Oldenburg coined the term ‘third place’, describing a place beyond home and work where people could gather, relax and talk” (Pieper, 2022). As third places, Starbucks coffee shops may help entrepreneurs form and mobilize networks needed in the early phase of a startup.

Second is signaling. Entrepreneurs and investors considering a neighborhood seek evidence that it is poised for growth. The introduction of a Starbucks coffee shop may be a powerful signal (e.g., Florida, 2002; Glaeser et al, 2018). In fact, real estate professionals have called “The Starbucks Effect” (Anderson, 2015) the tendency for real estate prices to rise in a neighborhood after entry of a Starbucks coffee shop (see Glaeser, Luca, and Kim, 2018 for cross-sectional evidence). Other retailers may also find it more appealing to open an establishment if they expect

Starbucks to drive higher customer visits (demand pooling), or if Starbucks is more knowledgeable of locations with future opportunities.[2]

Using data on business registrations in the U.S. between 1990 and 2022 from the Startup Cartography Project (Andrews et al 2020), we study whether the introduction of a Starbucks café into a neighborhood with no coffee shops increases the number of new firms registered in that neighborhood. We use a staggered difference-in-differences approach that takes into account treatment heterogeneity and observable pre-trends (Callaway and Sant'Anna, 2021; Wooldridge, 2021), and focus on three distinct empirical comparisons. First, we compare census tracts that received a Starbucks to census tracts that expected a Starbucks but did not ultimately get one due to administrative issues such as city planning, zoning board rejection, architectural board rejection, or community organization. These 'rejected Starbucks' are a natural control group because Starbucks Corporation also sought to invest in those neighborhoods; however, this set of census tracts is small in size. Second, we consider a partnership between Starbucks and retired professional basketball player and entrepreneur Earvin "Magic" Johnson, initiated by Johnson, that aimed at improving under-resourced neighborhoods by introducing the cafés. These locations are in low-income, minority neighborhoods, such as Harlem in New York City and Ladera Heights in Los Angeles, which were previously not considered by Starbucks as potential sites for entry. However, the treatment could combine the Starbucks effect with the effect of Magic Johnson himself. Third, we examine Starbucks' entry to census tracks when compared to all census tracts that did not previously have a coffee shop. For this analysis, we find that there were no pre-trends in our estimates, at least for our outcome variable. This third comparison set is broader, but it provides a more precise estimate of our treatment effect.

In all three approaches, we document a significant effect of Starbucks' entry on neighborhood entrepreneurship. In our preferred specification, neighborhoods that receive a Starbucks as their first coffee shop see an increase in local entrepreneurship of 5.0% to 11.8%. This increase amounts to about 1.1 to 3.5 additional new startups per year in the tract, with the effects persisting for at least 7 years. The effects are significantly larger for a Magic Johnson Starbucks, which increases the number of expected startups by 29.7%, or 4.3 new registered

[2] Economics typically separates the information signal in Starbucks entry from demand pooling, an agglomeration externality. We consider them together because they imply a similar mechanism through which Starbucks makes other retailers change their preference for the neighborhood benefits.

firms per year. When we perform a placebo test by creating a fake treatment variable for the cases where a Starbucks opening plan was rejected, the estimated effect for the 'entry' of a rejected Starbucks is insignificant and the coefficient is negative, suggesting our effect is not driven simply by site selection but the entry of Starbucks itself.

Between the two possible mechanisms for the main effect, we find evidence consistent with networks. First, when there are already other coffee shops in the neighborhood, there is no Starbucks effect, which suggests it is less the Starbucks signal than its contribution to places for networking. Places with other coffee shops may have been saturated. However, coffee shops, we have said, differ among themselves. When we consider the entry of all coffee shops that are not Starbucks, the effect is small. Moreover, when we repeat our approach with other coffee chains with a lesser commitment to local network building, neighborhoods that receive a Dunkin Donuts (which is typically not set up for extended seating) or a Dutch Bros (which offers no seating, only drive-through coffee) do not see an increase in entrepreneurship. In contrast, neighborhoods that open a Caribou Coffee—a chain in Minnesota and Wisconsin with a model similar to Starbucks'—do see an increase. This result is also consistent with our finding that Magic Johnson Starbucks had much larger effects than other Starbucks, since the Magic Johnson establishments targeted neighborhoods lacking local community establishments. Second, we find little support for an effect of Starbucks on the kind of entrepreneurship that a signaling mechanism would suggest. When we examine new entrepreneurship across different industries, we find effects close to our main estimate on retail and food entrepreneurship, but no effect on real estate entrepreneurship (including leasing and agents). Third, the effect spills over to nearby neighborhoods, and deteriorates quickly with distance. The effect is one-fourth the original size for neighborhoods 1 to 2 kilometers away, and one-tenth from 2 to 10 kilometers. While person-to-person interactions decline quickly with distance, wages and real estate prices typically do not.[3] Fourth, when we look at heterogeneity across locations, we see several indications of a network mechanism. The effect is larger in larger Starbucks cafés and in those with greater foot traffic. Finally, the effect is similar for another establishment that stimulates networks and

[3] This has been shown in previous entrepreneurship work. Arzaghi and Henderson (2008) document that in Midtown Manhattan, the benefits of networking for entrepreneurship are non-existent after 1 km. Rosenthal and Strange (2005), also in Manhattan, show the effects reduce significantly after 1-5 miles. At the U.S. level, where most travel is by car rather than foot, Rosenthal and Strange (2003) show that there are still some effects of startups after 10 miles.

supports business—restaurants—but not for another that stimulates networks but not as often for business transactions—bars.

Together, these results provide new evidence of the importance of local establishments to neighborhood conditions, contributing to two research fields. First is research on entrepreneurship. As the examples of Kendall Square in Cambridge, Massachusetts and Sand Hill Road in Silicon Valley, California illustrate, entrepreneurship responds strongly to local spatial conditions, because of the importance of physical proximity to others for generating ideas, creativity, and problem solving (Marshall, 1920; Allen, 1970; Saxenian 1996; Sorenson and Audia, 2000; Kerr and Kerr, 2021; Oettl et al, 2022; Andrews, 2019; Roche, 2020), and for acquiring startup capital and resources (Sorenson and Stuart, 2003; Agrawal et al, 2017; Guzman and Stern, 2015; Kerr and Kominers, 2015; see also Moretti 2012, Leonardi and Moretti 2023; Arzaghi and Henderson, 2008). However, few studies on space and entrepreneurship have evaluated either the causal effects of introducing a new organizational form to a neighborhood or the specific effect of third places. Our results are consistent with Andrews's (2019), who finds that Prohibition reduced patenting, but only in counties that used to have a social structure that revolved around saloons, and bring new life to Saxenian's (1996) emphasis on another third place, Walker's Wagon Wheel, as an anchor of social structure in Silicon Valley. As knowledge spillovers continue to increase in their importance in the spatial economy (e.g., Davis and Dingel, 2019), understanding the way they are shaped by space is critical.

Second, the findings contribute to research on neighborhood effects and economic opportunity (Wilson 1987; Porter 1997). Recent research using randomized control trials or administrative tax data has shown that growing up in low-income neighborhoods affects future earnings, college attendance, and other outcomes (Kling et al. 2007; Chetty and Hendren 2018a, 2018b). While these findings have encouraged some to think of how to support people to move to better neighborhoods (Chetty and Hendren 2018a), they should also call for understanding how to improve neighborhoods themselves (Sampson 2012). Researchers who have argued for improving neighborhoods have focused on jobs (e.g. Wilson 1987, 1996**)**. Startups account for 15% of gross job creation in the U.S. (Decker et al, 2014) and this job creation is disproportionately local (Glaeser, Kerr, and Kerr, 2015; Samila and Sorenson, 2011), underlining the important relationship between our focus and employment.

1. Starbucks Corporation

Starbucks Corporation is a multinational chain of coffee shops with about 34,000 locations in 80 countries. It is the world's largest coffee chain, with three times as many locations, and thirteen times the market capitalization of the second largest, Dunkin' Donuts (Wikipedia, 2021; NYSE, 2023). Starbucks' success is sometimes credited to the introduction to the U.S. of a coffee shop concept where the expectation was not only selling coffee but also giving customers the opportunity to linger, socialize, and build community. The concept had been formalized in Oldenberg's (1989) classic work on "third places." Recognizing the similarities, Starbucks explicitly stated its value proposition as creating a "third place experience." For example, in 2004, CEO Howard Schultz described Starbucks' business strategy in its stockholder annual report (10K) as follows:

> The Company's retail goal is to become the leading retailer and brand of coffee in each of its target markets by selling the finest quality coffee and related products and by providing each customer a unique Starbucks Experience. This third-place experience, after home and work, is built upon superior customer service as well as clean and well-maintained Company-operated retail stores that reflect the personalities of the communities in which they operate, thereby building a high degree of customer loyalty. (Starbucks Corporation, 2004)

The coffee shops were expected to be friendly and accessible, encouraging conversation and lasting visits as part of a routine (see also Jacobs, 1961; Putnam, 2000; Klinenberg, 2018).

1.1 The Magic Johnson Partnership

In 1997, Earvin "Magic" Johnson established the Johnson Development Corporation "to identify opportunities to revitalize communities and pursue business development in under-served neighborhoods" (BusinessWire, 1998). As part of that endeavor, he convinced Schultz to create a partnership to bring Starbucks cafés to inner cities, which were then an untapped market. Schultz explained at the time: "We recognize that many urban cities do not have a wide variety of retail choices, and we have been looking into ways to bring the Starbucks Experience to these areas for some time. We weren't quite sure how to do this until we met Earvin 'Magic' Johnson, and now we're convinced that we have the right partner to make this happen" (BusinessWire, 1998). Johnson and Starbucks established "Urban Coffee Opportunities" (UCO) through a 50/50 partnership; the first UCO store opened in 1998 in Ladera Heights, California. A year later, Johnson boasted that the coffee shops created third places to build community: "The store is doing exactly what we had hoped—providing not only the best coffee, but also the best hangout spot in town—and it's one of the top new Starbucks stores opened in Southern California. We look forward to building on this great foundation as we go into more new communities" (BusinessWire, 1999). Johnson also argued that the locations would promote community development by signaling. During the opening of the Harlem location, he explained: "This will be the anchor to attract other businesses to Harlem […] Starbucks is being very courageous. Now, other business leaders will say, 'See? Starbucks did it. We can do it, too" (Kuntzman, 1999).

2. Data and Measures

We study the change in neighborhood entrepreneurship after the introduction of the first Starbucks café into a neighborhood. We focus on census tracts, geographic areas commonly used to designate neighborhoods in the U.S. (Krieger, 2006, Sperling, 2012). While census tracts are intended to be relatively stable over time, they are merged or split when a location's population changes significantly. We use the 2010 census tract geographic boundaries and harmonize data from previous censuses to those boundaries. We add data from three other datasets, incorporating the location of Starbucks coffee shops, the entry of other types of third places—including other coffee shops, restaurants, and bars—and the number and characteristics of new businesses established in the area. We describe each dataset in turn.

2.1 Starbucks and Other Third Place Locations

We identify Starbucks locations using Reference USA (Infogroup) annual snapshot files from 1997 to 2021. Reference USA is a business marketing database focused on tracking local establishments. It uses Yellow Pages and other local listings to track businesses, their industry code, their location, and contact information. To identify Starbucks Corporation locations, we searched for "Starbucks" as the business name and gathered geographic coordinates and address information. We coded as openings all cases in which an establishment did not exist in 1997 and appeared in Infogroup in either 1998 or a later year. Using North American Industry Classification System (NAICS) codes, we also identified other coffee shops (722515 *Snack and*

Nonalcoholic Beverage Bars),[4] bars (722410 *Drinking Places (Alcoholic Beverages)*), and restaurants (722511 *Full-Service Restaurants*).

We developed five measures. *Gets First Starbucks—No Prior Café*, our main treatment variable, records whether the year is the tract's first with a Starbucks and the tract had no prior coffee shops of any type. *Gets First Starbucks—Has Prior Café* is an indicator for whether the year is the tract's first with a Starbucks and the tract already had a coffee shop. *Gets First Café—No Prior Café* records whether the year is the tract's first year with a coffee shop of any kind. While in principle all coffee shops may create a third place for the community to interact, non-Starbucks coffee shops during our period were more likely to focus on volume and quick turnaround than on creating a community environment. *Gets First Restaurant—No Prior Restaurant* and *Gets First Bar—No Prior Bar* are equivalent variables for restaurants and bars.

Figure 1 plots the distribution of new Starbucks by year, for neighborhoods that did not have one and received one during our sample period. At its height, almost 600 neighborhoods received their first coffee shop thanks to the entry of Starbucks, leading to a total of 3,970 census tracts that had no coffee shops in 1997 but received a Starbucks during our sample period. The majority of this activity occurs between 2001 and the Great Recession in 2008 giving our data good coverage before and after this entry.

To obtain the location and establishment date of the Magic Johnson partnership, we used The Wayback Machine, a platform offered by the Internet Archive (archive.org) that stores historical versions of websites. We accessed earlier versions of the Magic Johnson Enterprises website and record the locations listed as part of Urban Coffee Opportunities (UCO; Appendix Figure A1 includes a screenshot). We triangulated using Yelp, directories of Starbucks location, and newspaper announcements of Starbucks openings. We identified 68 Magic-Starbucks locations (see Appendix Table A5).[5] We matched these locations with Reference USA to obtain their opening year. Three locations did not match with any establishment in Reference USA, leaving us with 65 in total.

---

[4] Coffee shops are by far the most common establishment type in NAICS code 722515, but it may also include others, such as candy stores and ice cream shops (a majority of which also sell coffee). We also ran our estimates with more stringent definitions that removed these, and our results are effectively unchanged.

[5] News reports covering the end of the partnership between Magic Johnson and Starbucks in 2010, when all locations were sold back to Starbucks, suggest there may have been between 105 and 125 locations. However, only 68 are listed in the historical versions of the UCO website.

This matching to UCO firms also helps increase our confidence in the coverage of Starbucks coffee shops by Reference USA. Ninety six percent of Starbucks in the UCO data are also in Reference USA (i.e., 65 out of 68). The high rate is particularly notable given that UCO targeted urban and minority neighborhoods—the ones least likely to be accurately covered by Reference USA. Furthermore, UCO is formed at a moment in history early in the development of the Reference USA sample (1998-2005), a period where the data company is most likely to have had unresolved measurement issues. We are thus reasonably confident that our whole sample closely approximate the universe of Starbucks establishments.

2.2 Startup Formation using Business Registration Records

We measure entrepreneurship using data from the Startup Cartography Project (SCP) (Andrews, Fazio, Guzman, Liu, and Stern, 2022). The SCP is a dataset built using business registration records to measure the quantity and quality of entrepreneurship at any level of geographic granularity within 49 states and Washington D.C. from 1988-2022. After 2016, not all states are included due to data collection drop-offs.[6]

Business registration represents the legal process through which a new legal firm is created. The process includes all corporations, limited partnerships, and limited liability companies created in a location.[7] Each business registration record includes the date of registration, name of the firm, the directors of the firm, the address, the corporate form, and the jurisdiction (i.e., Delaware or local). Some of these characteristics can be used to measure firm quality (see below).

We create four measures of entrepreneurial activity for each census tract and year. Summary statistics for these are presented in Table 1. *Number of Startups,* our main dependent variable, is the number of new firms registered in each census tract and year. The average census tract has 21 registrations, or 1.8 per month. The remaining three measures are indicators of quality. *Number of Corporations* is the number new corporations (as opposed to LLCs and partnerships). Corporations offer entrepreneurs a clear separation of corporate personhood between the firm and the owner. They also offer stronger minority shareholder rights, and stronger governance. If

[6] Three states (South Carolina, Illinois, and Michigan) are not included for 2016 to 2018. Only 8 states are included from 2018 to 2022, New York, Texas, California, Florida, Tennessee, Georgia, Kentucky, and Alaska (representing almost 40% of US GDP).
[7] General partnerships and sole proprietorships do not require a legal registration to be founded.

a company wishes to receive external equity investment or list in public markets, being a corporation is a practical necessity. Corporations, however, are inconvenient for a smaller business due to double taxation and additional governance complexity. Accordingly, entrepreneurs who are more interested in growth are more likely to register as corporations. Empirically, registering as a corporation predicts a doubling to tripling of the probability of achieving high value acquisitions, IPOs, or high employment (Guzman and Stern, 2020; Andrews et al, 2022). *Number under Delaware* represents the number of firms under Delaware jurisdiction, which is helpful for firms requiring a more complex regulatory environment (Guzman, 2023). The Delaware General Corporate Law is the best understood corporate law in the U.S., with a long cannon of decisions that are useful in creating predictable contracts even in cases of significant complexity. Delaware also has an advanced institutional setup to deal with corporate arbitration, including its highly reputed Court of the Chancery. Furthermore, Delaware's decisions and legal framework are generally regarded as pro-business. If the firms are raising institutional venture capital, then being in Delaware is typically a requirement of investors themselves. However, it also comes with additional costs: keeping a Delaware registration requires maintaining two different registrations (one in Delaware, one in the local state). Therefore, while Delaware registrations are only about 4% of all firms in the data, they are over 60% of all public firms. Empirically, entrepreneurs that select into Delaware are about 20 times more likely to achieve high value acquisitions, IPOs, or high employment (Guzman and Stern, 2020; Andrews et al, 2022). Finally, *Number High Tech* is the number of companies whose name uses words associated with the high-tech industry, using the list in Guzman and Stern (2015).[8] High tech companies are known to have particularly large local economic multipliers, leading to higher economic impact (Bartik, 2022).

2.3 Local Characteristics using Census Data

We add tract-level demographic information from various sources. We obtain estimates of total population and black, Hispanic, and Asian population from the 2000 Decennial U.S. Census. To estimate population density, we use land area data from the Tiger Line shapefile for

[8] The approach identifies all words that are over-represented in U.S. Cluster Mapping Project (Delgado et al, 2016) clusters: Aerospace Vehicles and Defense, Biopharmaceuticals, and Information Technology and Analytical Instruments. Examples include "semiconductors," "biotherapeutics," "circuit," and "molecular."

the 2010 ACS. We use the HUD 2012 Q1 ZIP Code to Tract Crosswalk Table[9] to obtain estimates of tract-level average wages from the U.S. Census ZIP Code Business Patterns.

2.4 Starbucks Rejected from Establishing in a Census Tract

We also document the tracts that rejected Starbucks for reasons extraneous to the choices and strategic planning of Starbucks Corporation. To do so, using a manual search in LexisNexis and Google News, we found news on all possible Starbucks that could have taken place but did not due to a local objection. These include city planning and zoning board issues, architectural board rejections, and community mobilizations against the opening of a Starbucks café. Appendix Table A3 includes the list of 13 rejected Starbucks cafés in our data and their date and location.

2.5 Analytical Samples

Based on these data, we developed three samples for analysis. The first, focused on census tracts that did not have coffee shops, compares tracts where Starbucks attempted to enter but was rejected to those where Starbucks successfully entered. The sample spans from 1997, the first year of Reference USA, to the last year for which we have data for each state.

The second sample is based on the Johnson-Starbucks partnership. The first coffee shop in this partnership was opened in 1998. We focus on the twenty-year period between 1990 and 2010, the year the partnership ended. Starting in 1990 allows us to examine the pre-treatment period for all observations in our sample, which we can do in this case even without Reference USA data because we know there where no Magic Johnson Starbucks before 1998. Because the census tracts targeted by the partnership may be idiosyncratic, we developed a matching procedure to draw a distribution of control tracts observably similar to the treated tracts.[10]

The third sample considers all tracts that did not have a coffee shop of any kind beginning in 1998. We provide summary statistics across neighborhood demographics for each treatment group in Table 2, as well as for neighborhoods that got a Starbucks but had prior coffee shops and neighborhoods that never got a Starbucks. A few patterns are notable. One, the

---

[9] We used 2012 Q1 Crosswalk table because HUDS reflected the 2010 Tract boundaries from then.

[10] Our matching procedure was as follows: First, we excluded all tracts in Alaska and Hawaii, and all tracts that had no residents at any point in our study period. Next, we split the sample into ventiles across three variables—population density, proportion of Black residents, and average wage—and estimated the relative incidence r_{vj} of the treated tracts across the ventiles of each variable. Finally, we estimated the weight of each census tract as the product of r_{vj} across the three variables and drew 5,000 control tracts using this product as sampling weights.

neighborhoods where Starbucks opened are slightly different from those in which it did not (column ‘All Other’). Starbucks neighborhoods have higher wages, density, and more startups. Two, however, there are no differences in demographic characteristics or wages between neighborhoods where Starbucks opens the first coffee shop and those that had prior coffee shops. The major observed difference is the number of startups. This difference is, in a sense, what motivates our analysis. Three, rejected Starbucks neighborhoods are more urban and have fewer black and Hispanic residents than Starbucks neighborhoods, even though wages are similar. Four, Magic Johnson neighborhoods have significantly higher population densities and on average four times the number of black residents, yet far fewer startups.

Empirically, each analytical sample provides distinct advantages and disadvantages. The sample including rejected Starbucks offers perhaps the cleanest control group, but it does so at the cost of precision in our estimates, since the number of rejected Starbucks is relatively small and more idiosyncratic. The Magic Johnson sample has a larger control group and allows studying the use of third places in neighborhoods that are highly disadvantaged, and are therefore likely to benefit from a third place. However, this sample has only a small number of Starbucks events, 65. There is also a risk that this treatment may overstate the benefits of third places, because the association with Magic Johnson additionally led to significant media attention and community buy-in. The full sample offers more precision and a larger set of both treatment and control tracts, covering the majority of the U.S., but it does so at the cost of being the sample at most risk of endogeneity. Starbucks Corporation naturally chooses locations through strategic planning so that, even in the absence of pre-trends, concerns over selection could linger.

3. Empirical Strategy

3.1 Two-Way Fixed Effects Estimators

We implement a staggered difference-in-differences estimator with two-way fixed-effects, taking advantage of recent advances in econometric methods that account for heterogeneity in treatment effects across cohorts and locations. We focus specifically on changes in the conditional mean of the number of startups, using a Poisson model. The typical two-way fixed effect model estimates, for each census tract i at time t, an equation of the form

$$Y_{it} = \beta \times D_{it} + \gamma_i + \lambda_t + \epsilon_{it}$$

Where Y_{it} represents the number of startups, γ_i is a tract fixed effect, λ_t a year fixed effect, D_{it} is a binary treatment representing the entry of a third place into a tract, and ϵ_{it} is a random error. The coefficient of interest is β, representing the average proportional increase in the number of firms between treated and non-treated neighborhoods.

We extend this model by building on Wooldridge (2021) and other work that seeks to account for treatment heterogeneity and to avoid "prohibited" comparisons that may create biased estimates (de Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021). In essence, the Woodridge extended two-way fixed effects incorporates cohort and time-specific coefficients. Specifically, for each census tract i, on year t, first treated on year τ, we implement the regression:

$$Y_{it} = \beta_{t\tau} \times \ g_{i\tau} \times \lambda_t + \gamma_i + \lambda_t + \epsilon_{it}$$

where $g_{i\tau}$ is a series of indicators representing the individual year in which tract i was treated (and 0 if never treated), and $\beta_{t\tau}$ are individual coefficients for each treatment cohort and year. We report the marginal effects (as Poisson elasticities) for our main estimate, and as individual coefficients before and after treatment in event study analyses. Standard errors are clustered at the county level.

One disadvantage of implementing the Wooldridge approach is that including a fully interacted set of indicators removes all variation in the pre-period, and hence does not allow estimating pre-trends in the level of entrepreneurship before the introduction of Starbucks into a neighborhood. Therefore, we complement the Wooldridge estimator with event study estimates using the approach by Callaway and Sant'Anna (2021). This approach uses linear regression and a doubly-robust estimator to account for selection into treatment and avoid issues with treatment heterogeneity. When we run this model, we prefer using the number of new firms as the dependent variable, instead of a transformation such as logarithm or the inverse hyperbolic, given recent concerns over the lack of validity of these estimators around zero (Cohn et al, 2022).

For the rejected Starbucks analysis, we compare treated to rejected tracts, which are the never-treated tracts. For the other analyses, we compare treated census tracts to not-yet-treated census tracts. Focusing on not-yet-treated neighborhoods in these cases allows us to partially account for selection issues. Given the possibility that neighborhoods that are a good candidate for a coffee shop are different from others in ways that are unobservable to us, the locations used as controls in the not-yet-treated specification were also appealing to Starbucks, but they simply introduced the café later.

4. Results

4.1 Event Study Estimates

Our first set of results, in Figure 2, presents the event study estimates of the impact of the first Starbucks on the number of firms in a census tract. We use the Callaway and Sant'Anna estimator with 95-percent confidence intervals of bootstrapped standard errors clustered at the county level. The coefficients are reported in the Appendix.

Panel A reports changes in the number of startups in tracts that had no prior coffee shops and in which Starbucks opened a coffee shop compared to those in which Starbucks attempted to open a coffee shop but was rejected. There are no pre-trends in the number of startups before Starbucks. After the entry of Starbucks, the coefficient shows minimal effect at year 0, and then increases and becomes positive and significant after year 2.

Panel B reports changes in the number of startups after the opening of Magic Johnson Starbucks coffee shops in neighborhoods with no prior coffee shops. MJ Starbucks coffee shops tended to open in locations that were previously not considered by Starbucks—particularly, predominantly African American urban neighborhoods. The neighborhoods often had high potential but were severely lacking local establishments. Panel B shows that the effect is substantially larger than that of a typical Starbucks. The MJ Starbucks increases the number of startups by 8.43 firms per year on average through year 7. Relative to the mean, this figure implies an effect of 44%.

Panel C expands our analysis to all census tracts without coffee shops. The estimates are smaller to those in Panel A and have more precise standard errors. The coefficients show flat pre-trends before the introduction of a Starbucks, and rise over time afterwards. By year 7, the neighborhood is producing 3.9 more startups, relative to a sample mean of 21 startups per year.

Across these analyses, the results document a positive increase in entrepreneurship for neighborhoods where a Starbucks opens without any previous trend. In each of the panels, the effect takes several years to emerge. The gradual increase of the effect provides comfort against the potential confounding role of Starbucks locations opening contemporaneously with other businesses as part of broader real-estate development efforts. For example, when a shopping mall opens, a Starbucks may open at the same time as other local stores. If so, then we would be attributing to Starbucks event that are merely contemporaneous. However, if this type of bias existed, then we should have seen differences in registrations for such businesses at year 0 or even year -1, before the establishment opened.

4.2 Average Effects

We next consider the average effect of receiving a new Starbucks on neighborhood entrepreneurship. Moving beyond event studies also allows us to use count data regressions through Poisson specifications rather than linear models. This ability is important because we can use these to estimators to evaluate the extent to which some outlier census tracts may be driving our results. Skewed outcomes across geography are a common feature of entrepreneurship research.

Table 3 column (1) reports the Poisson two-way fixed effects regression of the number of new startups on tracts without coffee shops that received a new Starbucks and on having rejected a new Starbucks. We use a Poisson TWFE estimator to incorporate two treatments simultaneously, our main treatment – receiving a Starbucks – and a placebo treatment which is equal to 1 when the rejected Starbucks was expected to open and 0 otherwise. The coefficient for actual Starbucks entry is positive and significant with 0.09, while the one for the rejected Starbucks is noisy with a negative value. While the entry of an actual Starbucks predicts more entrepreneurship the mere expectation of entry does not.

Column 2 is the Wooldridge extended Poisson TWFE and column 3 the linear Callaway and Sant'Anna estimator. The Poisson coefficient with never-treated controls is 0.112 and significant at the 1% level, which suggests an 11.8% increase in new firms (we report the not yet treated regression in the Appendix). The Callaway and Sant'Anna coefficient is 1.073, which suggests a 3.4% increase in new firms.

Columns 4 and 5 report the main estimates of the impact of the opening of an MJ Starbucks on neighborhood entrepreneurship. As in the event study, the effect is much larger for Magic Johnson than for the other Starbucks.

Columns 6 and 7 focus on the treatment effect of Starbucks among all neighborhoods in the data that did not have a coffee shop. The effects are more precise. The estimate for our linear specification is twice as large as the Poisson model, suggesting that, while effects are positive on average, there are significantly large effects in some outlier tracts.

Together, these results report a substantial average change in new business registrations in neighborhoods where a Starbucks coffee shop opens relative to control neighborhoods. There are many potential avenues through which this increase can take place. The next sections present evidence supporting a network mechanism, rather than forms of signaling.

4.3 Neighborhoods with Prior Coffee Shops and with Non-Starbucks Coffee Shops

In Tables 4 and 5, we begin testing the argument that when a Starbucks café enters a neighborhood without prior coffee shops, it creates a new space for socializing, which in turn promotes local entrepreneurship.

Table 4 exhibits the changes in entrepreneurship when Starbucks enters a neighborhood that already has cafés and when the new café is not a Starbucks. It also presents year-by-year effects to provide a richer picture. Column 1 presents coefficients for the effect of opening a Starbucks, among neighborhoods with no prior cafés; column 2, among neighborhoods with prior cafés. The differences are stark. Starbucks does not increase neighborhood entrepreneurship among neighborhoods that already had coffee shops. This finding is consistent with the idea that Starbucks has little impact among neighborhoods that already had coffee shops for people to build networks. Because the locations selected by Starbucks are unlikely to differ based on whether the neighborhood had prior coffee shops, strongly suggesting it is about the local incidence of institutions instead and the way the impact they have allow forming new social networks It is also less consistent with a signaling mechanism, such as the role of Starbucks in certifying the market potential of a neighborhood, attracting other businesses and customers, or changing real-estate prices. It also suggests that some intuitive omitted variables do not appear to be driving our effect, such as the entry of Starbucks contemporaneously with other types of establishments or a capacity by Starbucks to better predict future growth.

Column 3 exhibits coefficients for the effect of opening a coffee shop that is not a Starbucks, among neighborhoods with no prior cafés. Recall that during this period Starbucks was distinctively focused on creating a third-place experience for neighborhoods, while most other competing brands were not. Therefore, while the entry of a coffee shop may still create the opportunity for third places, the effect is likely smaller than the Starbucks effect, and potentially zero. Indeed, we observe only a small and fleeting effect for coffee shops that are not Starbucks.

It is important to emphasize that column 2 and column 3 are not the inverse of each other, due to differences in their sample. Column 2 focuses on neighborhoods with more than one coffee shop. The average number of coffee shops in a tract that Starbucks enters in this sample is 2.5, and 25% of tracts have 3 or more. These coffee shops have also likely been there for years. In contrast, column 3 is focused on tracts with zero coffee shops that get their first one. The effect in both columns is small or zero, meaning Starbucks has no effect when there are significant neighborhood institutions, but a single non-third place coffee shop is not enough to create these either.

We move to study the entry of specific brands more directly in Table 5. The first two columns consider two brands that offer coffee chains that, contrary to Starbucks, do not expressly seek to be third-places. Dutch Bros sells coffee only on drive-throughs; Dunkin Donuts sells coffee on sit-down coffee shops, but many of its stores do not offer seating, and those that do lack the lighting, amenities, and comfort level to encourage long stays.

Figure 3 bears out these facts. Based on data from SafeGraph, a company offering geolocated data and visit information for U.S. points of interest, it reports the average number of hours that tracked devices remained in the shop. We excluded devices that remained in the shop longer than 4 hours, as those are likely owned by employees. As the figure shows, people spend far more time at Starbucks than at either Dunkin Donuts. The differences with Dutch Bros, in Figure A4, are even more significant. If a network mechanism is driving the result, the effect of the opening of a Dunkin Donuts or a Dutch Bros should be statistically indistinguishable from zero. The first two columns of Table 5 show that they are. We also examine the effect of a different kind of coffee chain, Caribou Coffee, which seeks to offer a third place concept similar to Starbucks's. Caribou operates mostly in Minnesota and Wisconsin. Figure A5 shows that people spend about as much time in Caribou coffee shops as they do in Starbucks coffee shops. The third column of Table 5 shows that the estimated effect is positive and significant, with a point estimate close to that of Starbucks'. Altogether, these results suggest that coffee shops have an effect when they provide space for people to build their networks.

4.4 Additional Evidence for Social Networks Mechanisms Using Geolocated Data

Our analysis has been motivated by well-established sociological work on the benefits of third places to create social networks, and the way Starbucks enables their formation across neighborhoods. The evidence so far supports this conclusion. In this section, we investigate whether those Starbucks cafés that are set up to create more social interaction produce larger effects.

We use a different dataset from SafeGraph that focuses on location-tracking. The data tracks the number of visitors from census block groups to specific point-of-interests, such as cafés, for the top 1000 census blocks as long as they had more than 5 visitors in a month.

We consider two measures from this data, the number of visitors in 2019 (adjusted for differences in how well SafeGraph covers each state), and the size of the lot (in square meters) in which each Starbucks is located, which is estimated using satellite images. These two measures are imperfect proxies for the volume of social interactions produced by a given café, but each offers distinct advantages. The number of visitors a café receives over the course of a year directly measures the opportunity to form social networks. However, it runs the risk of being biased, because we have data for 2019, while the treatment effects we measure occur years earlier. In this case, a concern is that high levels of socialization in each café may be the result of previous success in the neighborhood brought along by earlier entrepreneurship.

The size of the lot, in contrast, is less likely to be biased, because the specific lot size does not typically change over time in most Starbucks locations. However, the size of a Starbucks is a less direct measure of the opportunity to form social networks than actual observed visits. In addition, because lots can be shared with other establishments (e.g., with hotels), the analysis must focus only on the subsample of lots that are not shared.[11] In spite of these differences, the measures are highly correlated, as shown in Appendix Figure A6.

Panel A of Figure 3 studies visitor foot traffic. We split the locations by the estimated visits received during 2019 into quartiles and ran a two-way fixed effects Poisson regression. we use this model (rather than the extended ones) to consider all treatments simultaneously and use the same control group for all specifications, while focusing on proportional effects, making the estimates agnostic to the size of each tract.

[11] This observed in the SafeGraph polygon_class variable. We limit our analysis only to the polygon being "OWNED_POLYGON" rather than "SHARED_POLYGON". 73% of Starbucks locations are owned polygon. SafeGraph also estimates the polygon size synthetically in some cases, but 97% of Starbucks locations are not synthetic.

A higher level of traffic matters for our effects. Starbucks cafés with below-median traffic in 2019 have about a third of the effect, when introduced previously, as those with above-median traffic.

Panel B reports effects across establishment size. We operationalize four natural groups of Starbucks size. Those that are very small (less than 50 m^2) and almost always exist within a broader establishment (e.g., Starbucks in malls, airports, or Target stores), small locations (between 50 and 200 m^2), medium locations (between 200 and 500 m^2), large locations (over 500 m^2). The results show an increasing relationship between Starbucks size and overall new firm formation. The null effect on small locations in malls also suggests that the co-opening of a Starbucks together with other establishments (e.g., other stores in a mall) is not a main determinant of our effect.

In short, it is precisely those establishments that offer the features of third places, such as opportunities for a high level of local interaction and the open space to do so, paired with a large number of visitors, that have the largest benefits.

4.5 Differences in Startup Industry

We next consider the industry of firms created by the introduction of a Starbucks café. As Magic Johnson noted, Starbucks could serve as "the anchor to attract other businesses." In this case, the presence of Starbucks would serve as a catalyst for the local and retail economy. Then, the benefits we document would be economically important, but less consistent with a networks mechanism and instead about signaling that changes the perceived value of the location to firms and the flow of customers to other local retail businesses (demand pooling).[12] If this is the case, we would expect the Starbucks benefits to be highly localized in these retail sectors.

We build on the approach pioneered in Engelberg et al (2021) (and reviewed in Appendix B), categorizing firms as belonging to a NAICS industry sector if they have a word that is ten times

[12] We considering a broader definition of signaling than simply information signaling. Information signaling focuses on the way the entry of Starbucks would help provide imperfect information to other retailers and customers about the promise of a location. We also include demand pooling, which is an agglomeration effect whereby, even in perfect information, the co-location of other retailers with Starbucks reduces the cost of attracting customers. Other agglomeration effects are theoretically possible (e.g., pooling of suppliers or workforce), but we consider those not first order at the neighborhood level.

more likely to be used by a firm in this sector than elsewhere, and if it is not one of the most common 300 words.

In Table 6, we report estimates for regressions predicting the number of new firms in three key sectors. Column 1 reports the effect for all startups for which we are able to categorize any industry, for comparability and completeness. Columns 2 reports the effect for firms in the retail sector, which we consider any firm in NAICS sectors 44-45 (Retail Trade), and 72 (Accommodations and Food). Our estimate of 0.045 is similar to our main effect, suggesting our effect is not focused only on local retail but instead more generalized. Column 3 repeats the same analysis only for food establishments (which have an important relationship to coffee) the estimate is noisier but unchanged.

We next consider a different group, the firms associated with sector 51 (Real Estate and Rental and Leasing). As emphasized in the real estate 'Starbucks Effect', the entry of Starbucks may both improve the amenities of a neighborhood and serve as a signal of its future growth potential. In Column 4, we look at the development of the local real estate sector and examine whether the Starbucks Effect in real estate (i.e., the signaling mechanism)—whereby the entry of a new Starbucks is a harbinger for gentrification and rising rents (which could also unlock capital for entrepreneurship)—is at play. If this were the case, we would see particularly large increases in new real estate firms. The coefficient is 0.005 and not significant – we do not observe an increase in new real estate firms.

We conclude that even though cross-sectional evidence shows coffee shops correlate with real estate prices (Glaeser et al 2023), we do not see a signaling impact in panel data.

4.6. The Effect of Starbucks on Nearby Neighborhoods

Our empirical design studies the impact of Starbucks on a census tract, but visitors to a Starbucks are likely to be also from other nearby tracts creating geographically localized spillovers. It is well established in economics that such proximity effects, when occurring through networks and in person interaction, dissipate quickly with distance. This also holds for entrepreneurship. For example, when considering Midtown Manhattan, Rosenthal and Strange (2005) and Arzaghi and Henderson (2008) show that most knowledge and networking impact is gone within one mile. Manhattan, however, is more urban than anywhere else in the U.S. When looking within the Bay Area, Kerr and Kominers (2015) show that innovative knowledge travels about a 15-minute drive, with a similar result for the whole U.S. in Rosenthal and Strange (2003). Other local effects that are not knowledge-based, such as employment and capital, dissipate more slowly (for example, according to the Census Bureau, the average commute time in New York is 35 minutes). In a network mechanism, we expect to see some geographic spillovers, but these also quickly decrease with distance.

We present, in Table 7, results on changes in neighborhood entrepreneurship for census tracts that also did not have coffee shops but had a Starbucks open in a close-by tract, based on the distance from the tract centroids. To avoid double-counting treatments, as in the case where a neighborhood has multiple Starbucks open nearby over time, we limit our analysis to the first Starbucks that opens within 10 km from the tract, so that each tract can be treated by a neighbor opening only once. We also limit this analysis to neighborhoods that never received a Starbucks themselves.

Ideally, we would want to consider distances below 1 km. However, the distance between centroids of most neighboring tracts is higher. We observe very few cases within 1 km and estimates are too noisy (column 1). Columns 2 through 4 focus on openings that are 1-2 km, 2-5 km, and 5-10 km, in distance. We observe a positive effect of Starbucks opening on these nearby neighborhoods. It is smaller in magnitude and decreases for further neighborhoods. Consistent with knowledge spillovers and networking benefits, the size of the effect for neighborhoods 1-2 km away is one-fourth of the main effect, and for neighborhoods beyond 2 km less than one-tenth.

4.7 Heterogeneous Effects Across Growth Orientation

While we have documented an average effect it is possible that the cafés mostly increase the number of those businesses that do not lend themselves to high local economic multipliers (Bartik and Sotherland, 2019) and economic growth. If so, then the effect we document may be less important. On the other hand, given the high importance that face-to-face interaction and social networks play in innovation and high-growth firms (Sorenson and Stuart, 2007; Catalini et al, 2022), it is also possible that the effect is larger for more innovative firms.

The entrepreneurship literature often differentiates between two types of firms. One group, representing the majority of firms, are small businesses that, even if important for neighborhoods or their owners, very often remain at a small scale and are unlikely to experience significant employment growth or productivity growth. The other group, representing a small minority of firms, has been called high growth entrepreneurship (Guzman and Stern, 2020), innovation-driven entrepreneurship (Botello et al, 2023), or transformational entrepreneurship (Schoar, 2010), and represents those firms that introduce innovative ideas into the market, create traded goods across regions, and have skewed outcomes that drive economic growth.[13]

Recent work has emphasized that a firm's potential for high growth outcomes is partially predictable based on business registration information. For example, firms that are likely to grow register as Delaware corporations, since Delaware's jurisdiction and legal form allow complex financing contracts and appropriate governance (Guzman and Stern, 2020). In this section, we take advantage of these registration characteristics to evaluate whether our estimates also translate to increases in high growth entrepreneurship. We report our results in Table 8, focusing our analysis on Poisson estimates so that we can compare relative elasticities that are not sensitive to how different the overall incidence of each group is across neighborhoods.

Column 1 replicates our estimate for all firms, for comparability. Column 2 focuses instead on corporations and excludes LLCs. Corporations are more growth-oriented and lend themselves to better corporate governance. The effect is larger than our main effect, implying an increase of 8% in firms. Column 3 focuses instead on firms under Delaware jurisdiction, and the effect stays at 8%. In both cases, it appears that the impact of third places on more growth-oriented firms is, if anything, larger. Column 4 focuses on firms whose name is associated with high tech. Because the lexicon used in their names was the main classification mechanism, these firms are not necessarily growth-oriented, and can also include many small businesses, such as local tech consulting or home-based web development firms. The effect is positive but smaller, at 3.5%.

We conclude that the effects we document also benefit high growth entrepreneurship, and that we observe similar relative increases in new firm formation from third places. Even if the majority of firms founded will be local (due to these representing most firms in general), the percentage increase in each type of firm appears similar.

[13] The precise definition of high growth entrepreneurs and incidence depends on the measure, but using traditional ones including patenting, venture capital financing, other forms of equity financing, or predicted 'quality' estimates place the number below 5% (author's calculations, also Guzman and Stern, 2020).

4.8 Other Types of Third Places

Finally, we expand our approach to consider other types of third places, to provide further insight into the nature of our effect relative to other potential social institutions. We present in Table 10 the same three panels as Table 3 but consider instead the introduction of two other types of food establishments, bars and restaurants. We do not see an impact of bars on local entrepreneurship. This effect is different from the historical work in Andrews (2019), which was based on entrepreneurship during Prohibition. We hypothesize that one possibility is that the social structure of the U.S.—and the use of third places—has changed in a few ways in between the two periods. In particular, whereas in the past bars in the U.S. used to be a place for highly organized social activity where multiple social movements and civil rights actions began, American bars today appear to mostly cater to late-night outings amongst young people looking to drink. They may lack the continued social significance that, say, British pubs appear to continue having. The effect of restaurants, in contrast, is positive. This finding is also consistent with our mechanism, as sharing meals over business activities is a common practice.

5. Conclusion

Networks are important for economic activity, including entrepreneurship. Yet, the ability to form networks is mediated by space. We present evidence that the introduction of a new Starbucks café, intended to create a "third place" for community interaction, increased entrepreneurship in U.S. neighborhoods. The Starbucks effect is limited to neighborhoods that previously did not have coffee shops. The effects are consistent with a network mechanism, with physical larger and more visited Starbucks having larger effects, as do Magic Johnson Starbucks focused on underprivileged neighborhoods. The effects decrease quickly with distance, and are present for other coffee chains that copied that Starbucks concept.

Our estimates incorporate the full "causal pathway" of the impact of Starbucks on local activity—they estimate the change in startup formation after a Starbucks opens. However, there are several reasonable ways through which new third spaces promote networks and subsequent entrepreneurship. For example, a Starbucks café can both influence the behavior of current residents and attract new ones to the neighborhood, simultaneously strengthening and diversifying its social fabric. These interactions can promote entrepreneurship directly, but also increase the local incidence of supporting organizations such as banks, credit unions, and community development organizations. These institutions, in turn, may additionally evaluate prospective loans differently based on the perceived evolution of the neighborhood. Therefore, a clear understanding of how space shapes local business activity, including its potential to improve underserved neighborhoods, requires far more investigation. The advent of large datasets using geolocation and individual mobility flows promises to make this an important area of future economic inquiry.

References

Allen, T.J., 1970. Communication networks in R & D laboratories. *R&D Management*, *1*(1), pp.14-21.

Agrawal, A., Galasso, A. and Oettl, A., 2017. Roads and innovation. *Review of Economics and Statistics*, *99*(3), pp.417-434.

Anderson, Jamie. 2015. "Starbucks: Inspiring and Nurturing the Human Spirit… by Caffeinating Home Values". Zillow Research. Url: https://www.zillow.com/research/starbucks-home-value-appreciation-8912/

Andrews, R.J., Fazio, C., Guzman, J., Liu, Y. and Stern, S., 2022. Reprint of "The startup cartography project: measuring and mapping entrepreneurial ecosystems". *Research Policy*, *51*(9), p.104581.

Andrews, M., 2019. Bar talk: Informal social interactions, alcohol prohibition, and invention. *Alcohol Prohibition, and Invention (November 18, 2019)*.

Angrist, J.D. and Pischke, J.S., 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arzaghi, M. and Henderson, J.V., 2008. Networking off Madison avenue. *The Review of Economic Studies*, *75*(4), pp.1011-1038.

Bartik, T. and Sotherland, N., 2019. *Local job multipliers in the United States: Variation with local characteristics and with high-tech shocks.*

BusinessWire. 1998. . Starbucks Coffee Company and Earvin Johnson Team Up To Create "Magic" in Under-Served Communities. *Business Wire.* (February 5, 1998, Thursday) Url: https://advance-lexis-com.ezproxy.cul.columbia.edu/api/document?collection=news&id=urn:contentItem:3RYG-BM30-007D-M197-00000-00&context=1516831.

Callaway, B. and Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. *Journal of econometrics*, *225*(2), pp.200-230.

Chetty, R. and Hendren, N., 2018. The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics*, *133*(3), pp.1107-1162.

Chetty, R. and Hendren, N., 2018. The impacts of neighborhoods on intergenerational mobility II: County-level estimates. *The Quarterly Journal of Economics*, *133*(3), pp.1163-1228.

De Chaisemartin, C. and d'Haultfoeuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), pp.2964-2996.

Decker, R., Haltiwanger, J., Jarmin, R. and Miranda, J., 2014. The role of entrepreneurship in US job creation and economic dynamism. *Journal of Economic Perspectives*, *28*(3), pp.3-24.

Delgado, Mercedes, Michael E. Porter, and Scott Stern. Defining clusters of related industries. *Journal of Economic Geography* 16, no. 1 (2016): 1-38.

Duneier, M., 2015. *Slim's table: Race, respectability, and masculinity*. University of Chicago Press.

Florida, R., 2002. Bohemia and economic geography. *Journal of economic geography*, *2*(1), pp.55-71.

Glaeser, E.L., Kim, H. and Luca, M., 2018, May. Nowcasting gentrification: using yelp data to quantify neighborhood change. In *AEA Papers and Proceedings* (Vol. 108, pp. 77-82).

Guzman, J. and Stern, S., 2015. Where is Silicon Valley?. *Science*, *347*(6222), pp.606-609.

Guzman, J. and Stern, S., 2020. The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US States, 1988–2014. *American Economic Journal: Economic Policy*, *12*(4), pp.212-243.

Guzman, J., 2023. The Direct Effect of Corporate Law on Entrepreneurship. *Journal of Law, Economics, and Organizations.* forthcoming

Haltiwanger, J., Jarmin, R.S. and Miranda, J., 2013. Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, *95*(2), pp.347-361.

Hurst, E. and Pugsley, B.W., 2011. What Do Small Businesses Do?. *Brookings Papers on Economic Activity*.

Jacobs, Jane. 1961. *The Life and Death of Great American Cities.*

Kerr, W.R. and Kominers, S.D., 2015. Agglomerative forces and cluster shapes. *Review of Economics and Statistics*, *97*(4), pp.877-899.

Kerr, W.R., Nanda, R. and Rhodes-Kropf, M., 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives*, *28*(3), pp.25-48.

Klinenberg, E., 2018. *Palaces for the people: How social infrastructure can help fight inequality, polarization, and the decline of civic life*. Crown.

Kling, J.R., Liebman, J.B. and Katz, L.F., 2007. Experimental analysis of neighborhood effects. *Econometrica*, *75*(1), pp.83-119.

Krieger, N., 2006. A century of census tracts: health & the body politic (1906–2006). *Journal of urban health*, *83*, pp.355-361.

Kuntzman, G. 1999. Starbucks Goes Uptown – Grand Opening for First Harlem Store. *New York Post.* (May 6, 1999) https://nypost.com/1999/05/06/starbucks-goes-uptown-grand-opening-for-first-harlem-store/

Manson, S., Schroeder, J., Van Riper, D., Kugler, T., and Ruggles, S., 2022. IPUMS National Historical Geographic Information System: Version 17.0 [dataset]. Minneapolis, MN: IPUMS.

Marshall, Alfred. 1920. *Principles of Economics.* Palgrave.

Moretti, E., 2012. *The new geography of jobs*. Houghton Mifflin Harcourt.

Leonardi, M. and Moretti, E., 2023. The agglomeration of urban amenities: Evidence from Milan restaurants. *American Economic Review: Insights*, *5*(2), pp.141-157.

Oldenburg, R. 1989. *The great good place: Cafés, coffee shops, community centers, beauty parlors, general stores, bars, hangouts, and how they get you through the day.* Marlowe & Company; 3rd edition

Pieper, Heidi. 2022. *Reimagining the Third Place: How Starbucks is evolving its store experience.* Starbucks. Sept 13, 2022. Url: https://stories.starbucks.com/stories/2022/reimagining-the-third-place-how-starbucks-is-evolving-its-store-experience/ Accessed: July, 2023.

Porter, M.E., 1997. New strategies for inner-city economic development. *Economic development quarterly*, *11*(1), pp.11-27.

Roche, M.P., 2020. Taking innovation to the streets: microgeography, physical structure, and innovation. *Review of Economics and Statistics*, *102*(5), pp.912-928.

Roche, M.P., Oettl, A. and Catalini, C., 2022. *(Co-) Working in Close Proximity: Knowledge Spillovers and Social Interactions* (No. w30120). National Bureau of Economic Research.

Rosenthal, S.S. and Strange, W.C., 2003. Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, 85(2), pp.377-393.

Rosenthal, S.S. and Strange, W.C., 2005. The geography of entrepreneurship in the New York metropolitan area. *Federal Reserve Bank of New York Economic Policy Review*, 11(2), pp.29-54.

Sampson, R.J., 2012. *Great American city: Chicago and the enduring neighborhood effect*. University of Chicago Press.

Saxenian, A., 1996. *Regional advantage: Culture and competition in silicon valley and route 128, with a new preface by the author*. Harvard University Press.

Schoar, A., 2010. The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy*, *10*(1), pp.57-81.

Small, M.L., 2009. *Unanticipated gains: Origins of network inequality in everyday life*. Oxford University Press.

Small, M.L. and Adler, L., 2019. The role of space in the formation of social ties. *Annual Review of Sociology*, *45*, pp.111-132.

Small, M.L. and Gose, L.E., 2020. How do low-income people form survival networks? Routine organizations as brokers. *The ANNALS of the American Academy of Political and Social Science*, *689*(1), pp.89-109.

Sorenson, O. and Audia, P.G., 2000. The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940–1989. *American Journal of Sociology*, *106*(2), pp.424-462.

Stuart, T. and Sorenson, O., 2003. The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research policy,* 32(2), pp.229-253.

Sorenson, O., 2018. Social networks and the geography of entrepreneurship. *Small Business Economics*, *51*, pp.527-537.

Sperling, J., 2012. The tyranny of census geography: Small-area data and neighborhood statistics. *Cityscape*, pp.219-223

Stuart, T.E. and Sorenson, O., 2007. Strategic networks and entrepreneurial ventures. *Strategic Entrepreneurship Journal*, *1*(3-4), pp.211-227.

Starbucks Corporation. 2004. *Starbucks Corporation Annual report. 2004.*

Wooldridge, J.M., 2021. Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

Wilson, W.J., 1996. *When Work Disappears: The World of the New Urban Poor*. Vintage.

Wilson, WJ. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy, Second Edition.* University of Chicago Press; Second edition

Table 1: Summary Statistics (by tract-years)

Statistic	N	Mean	Median	St. Dev.
Third Places				
Gets First Starbucks—No Prior Café	1,357,664	0.026	0	0.158
Gets First Starbucks—Has Prior Café	1,357,664	0.078	0	0.267
Gets First Café—No Prior Café	1,357,664	0.280	0	0.449
Gets First Bar—No Prior Bar	1,357,664	0.154	0	0.361
Gets First Restaurant—No Prior Restaurant	1,357,664	0.116	0	0.320
Neighborhood Entrepreneurship				
Number of Startups	1,353,598	20.942	12	33.612
Number of Corporations	1,353,321	7.945	4	14.972
Number of Delaware Companies	1,353,321	0.341	0	3.141
Number of High Tech Companies	1,353,321	0.654	0	1.400
Neighborhood Characteristics				
Population	1,357,664	3,905.756	3,713.243	1,818.201
Population Density (per sq. km)	1,357,626	1,992.738	749.966	4,888.116

Note: This table reports summary statistics for census tract-year observations spanning from 1997 to 2016. There are 1,357,664 such pairs in our dataset. This sample size is reduced in our analysis due to our focus only on tracts without prior third places (which change depending on kind), and the use of an estimator focused on not-yet-treated comparisons. Detailed definitions of each measure are presented in Section II. The rows under "Third Places" report the number of tract-years that have various types of third places. The rows under "Neighborhood Entrepreneurship" highlight the number of businesses with different categories, sourced from the Startup Cartography Project. The rows under "Neighborhood Characteristics" present population data from the IPUMS NHGIS and the population density. Population density is calculated by dividing the population by the land area of the respective tract.

Table 2: Summary Statistics across Analytical Samples and Treatment Groups

	i) First Starbucks – No Prior Cafe		ii) First Starbucks – Prior Cafe		iv) Magic Johnson Starbucks		iii) Rejected Starbucks		v) All Other	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Number of Startups	32.41	46.55	44.47	73.20	21.72	34.09	84.63	156.28	19.92	33.11
Population Black	330.33	546.13	324.87	538.67	1308.71	1279.82	210.35	170.95	429.23	746.95
Population Hispanic	635.84	971.42	562.43	955.55	827.10	1092.94	361.43	456.40	441.79	854.64
Population Asian	224.50	386.98	207.24	335.56	204.93	366.58	130.43	104.64	113.68	257.28
Population	4048.41	2021.48	4579.90	2099.67	4000.94	1869.61	4266.76	1701.37	3795.79	1732.92
Population Density	1781.34	3978.45	1698.47	4171.42	6902.49	10 323.90	3293.61	3750.38	1589.84	3908.15
Average Wages	43 599.32	428 039.90	42 231.78	631 803.93	38 878.19	93 678.80	43 782.00	25 196.67	36 338.80	361 114.38

Note: This table presents detailed summary statistics for five analytical samples used in this study. We provide statistics for our various potential treatment samples, including differences between tracts that received a Starbucks, those that rejected one, and others. The unit of analysis is the census tract-year observations spanning from 1997 to 2016. However, for the analysis of rejected Starbucks, the observations extend from 1997 to 2020.

Table 3: Effect of Introducing a Starbucks Coffee Shop on Entrepreneurship, by Types of Panels

	Rejected vs. Accepted Tracts			Magic Johnson Tracts		All Tracts	
	(1) Poisson TWFE	(2) Extended TWFE (Never Treated)	(3) Callaway & Sant'Anna (Never Treated)	(4) Extended TWFE	(5) Callaway & Sant'Anna	(6) Extended TWFE	(7) Callaway & Sant'Anna
Gets First Starbucks - No Prior Café	0.087***	0.112***	1.073+	0.260***	5.927***	0.053***	2.853***
	(0.014)	(0.021)	(0.569)	(0.045)	(1.356)	(0.015)	(0.135)
Rejects Starbucks	−0.077						
	(0.054)						
Percent Increase	9.1%	11.8%	3.4%	29.7%	36%	5.5%	13.6%
Sample Mean	31.8	31.8	31.8	16.5	16.5	20.9	20.9
Additional Startups	5.9	3.5	5.9	4.3	5.9	1.1	2.9

Note: This table presents results from difference-in-differences regressions, organized into three panels that each employ distinct estimation techniques to assess the effect of various types of 'third places' on local entrepreneurial activity. Column 1 uses a conventional Poisson Two-Way Fixed Effects estimator. Column 2, 3, 5 and 7 reports the extended two-way fixed effect estimator reporting average marginal effect comparing to not-yet-treated, except for column 3 where it compares to never-treated. Column 4, 6, and 8 reports average treatment effect with estimator suggested by Callaway and Sant'Anna. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: The Effect of Other Third Places on Neighborhood Entrepreneurship.

	(1) Gets First Starbucks —No Prior Café	(2) Gets First Starbucks —Has Prior Café	(3) Gets First Café —No Prior Café
A. Extended TWFE Model			
Post Third Place	0.053***	-0.017+	0.003
	(0.015)	(0.010)	(0.006)
B. Year-by-Year Marginal Effects from Extended TWFE			
Post 0 Years	0.058***	-0.003	0.035***
	(0.012)	(0.007)	(0.007)
Post 1 Years	0.069***	-0.009	0.023***
	(0.014)	(0.008)	(0.006)
Post 2 Years	0.050***	-0.011	0.008
	(0.015)	(0.010)	(0.006)
Post 3 Years	0.057***	-0.016	0.005
	(0.017)	(0.010)	(0.006)
Post 4 Years	0.055***	-0.021+	-0.002
	(0.016)	(0.012)	(0.006)
Post 5 Years	0.045*	-0.027*	-0.001
	(0.018)	(0.013)	(0.007)
Post 6 Years	0.048**	-0.026+	-0.006
	(0.018)	(0.013)	(0.007)
Post 7 Years	0.044*	-0.028+	-0.009
	(0.019)	(0.015)	(0.008)
Num.Obs.	984533	343438	960414

Note: This table presents results from difference-in-differences regressions, organized into three panels that each employ distinct estimation techniques to assess the effect of various types of 'third places' on local entrepreneurial activity. Panel A, reports the extended two-way fixed effect estimator reporting average marginal effect comparing to not-yet-treated. Panel B reports independent marginal effects by year of treatment for the Extended TWFE model. Column (1) examines the effect of the first Starbucks in neighborhoods previously devoid of cafés, while Column (2) assesses the effect of first Starbucks location for the neighborhoods that already had cafés in the area. Columns (3) analyze the effects of the first instances of a café in the neighborhood. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: The Effect of Other Coffee Shop Brands on Neighborhood Entrepreneurship (Callaway -Sant'Anna Estimates)

	Not Third Place		Third Place
	Dutch Bros	Dunkin Donuts	Caribou Coffee
Coffee Shop Entry	−0.476	−0.741	2.977+
	(4.888)	(0.299)	(1.794)
Num.Obs.	56 434	55 985	56 397

Note: The unit of analysis is the tract-year. The table presents difference-in-differences estimates following Callaway and Sant'Anna estimator of the effect of specific brands of coffee shops that are not Starbuck on entrepreneurship. Dutch Bros is a coffee brand that only sells drive through. Dunkin Donuts is the largest coffee retailer after Starbucks, focused on volume instead of a third place experience. Caribou Coffee is a coffee shop that copied and also implemented the third place experience. Standard errors clustered by county. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Effect of Introducing a Starbucks Coffee Shop on Entrepreneurship, by industry of firms

	(1) Number of Startups	(2) Number of Retail Startups	(3) Number of Food Startups	(4) Number of Realty Startups
Gets First Starbucks—No Prior Café	0.045*	0.045+	0.042	0.005
	(0.022)	(0.027)	(0.027)	(0.023)
Percent Increase	4.7%	4.6%	4.3%	0.5%
Num.Obs.	848 383	832 644	819 952	803 097

Note: The unit of analysis is the tract-year. The table presents difference-in-differences estimates of the effect of introducing a Starbucks coffee shop on the formation startups in various industries. All columns display estimates from Poisson regression models with two-way fixed effects for both census tract and year, by different types of industries classified by the North American Industry Classification System two-digit sector codes. Retail refers to NAICS code 44, 45, and 72. Food refers to code 72. Realty refers to code 53. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: The Effect of Starbucks Opening in Nearby Neighborhoods Entrepreneurship (Callaway -Sant'Anna Estimates)

	(1)	(2)	(3)	(4)
Starbucks Entry in Nearby Neighborhood (< 1 km)	0.475			
	(0.381)			
Starbucks Entry in Nearby Neighborhood (1-2 km)		0.725+		
		(0.409)		
Starbucks Entry in Nearby Neighborhood (2-5 km)			0.219*	
			(0.098)	
Starbucks Entry in Nearby Neighborhood (5-10 km)				0.263**
				(0.092)
Num. Treated Neighborhoods	162	1266	6888	14118
Num.Obs.	1 096 140	1 096 140	1 096 140	1 096 140

Note: The unit of analysis is the tract-year. The table presents difference-in-differences estimates following Callaway and Sant'Anna estimator of the effect of specific brands of coffee shops that are not Starbuck on entrepreneurship. Dutch Bros is a coffee brand that only sells drive through. Dunkin Donuts is the largest coffee retailer after Starbucks, focused on volume instead of a third place experience. Caribou Coffee is a coffee shop that copied and also implemented the third place experience. Standard errors clustered by county. Significance levels are indicated as follows: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 8: Effect of Introducing a Starbucks Coffee Shop on Entrepreneurship, by Type of Firm

	(1) Number of Startups	(2) Number of Corporations	(3) Number under Delaware	(4) Number High Tech
Gets First Starbucks—No Prior Café	0.053***	0.079***	0.079*	0.034+
	(0.015)	(0.020)	(0.031)	(0.019)
Percent Increase	5.5%	8.2%	8.3%	3.5%
Census Tract F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Num.Obs.	984 533	984 359	984 341	984 359

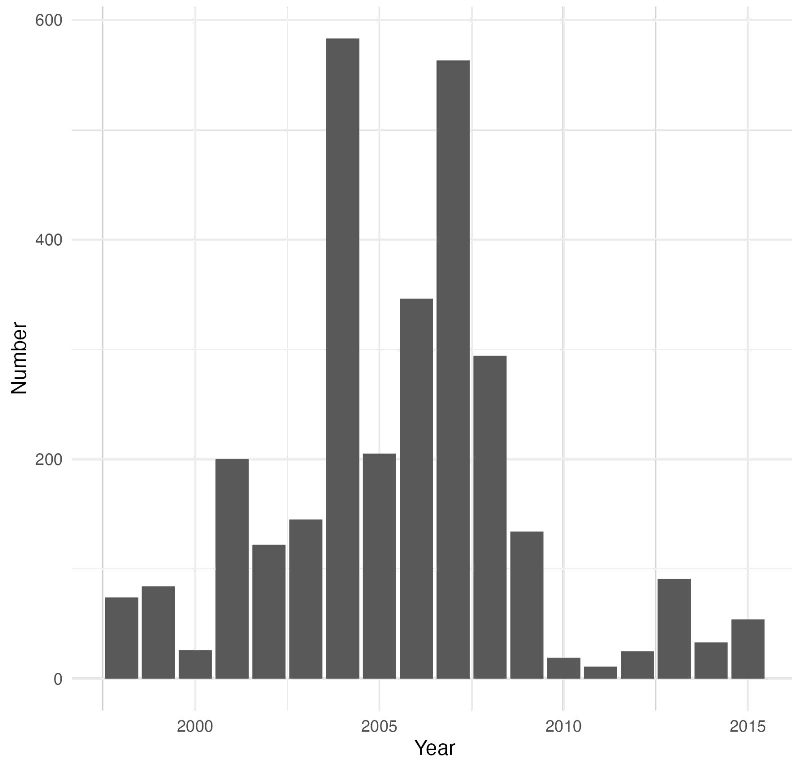
Note: The unit of analysis is the tract-year. This table presents difference-in-difference estimates of the effect of introducing an establishment on entrepreneurship in subsequent years, with two-way fixed effects for county and year. Column (1) reproduces results from the preferred model from Table 1. Columns (2) to (4) report the effects on the establishments of corporations, Delaware-registered firms, and technology companies, respectively. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 9: The Effect of Other Third Places on Neighborhood Entrepreneurship.

	Gets First Bar	Gets First Restaurant
A. Extended TWFE Model		
Post Third Place	-0.023**	0.060***
	(0.007)	(0.009)
B. Year-by-Year Marginal Effects from Extended TWFE		
Post 0 Years	0.002	0.034***
	(0.005)	(0.006)
Post 1 Years	-0.007	0.053***
	(0.006)	(0.007)
Post 2 Years	-0.013*	0.052***
	(0.006)	(0.009)
Post 3 Years	-0.022**	0.059***
	(0.007)	(0.009)
Post 4 Years	-0.031***	0.068***
	(0.008)	(0.010)
Post 5 Years	-0.037***	0.074***
	(0.009)	(0.012)
Post 6 Years	-0.041***	0.074***
	(0.011)	(0.013)
Post 7 Years	-0.045***	0.069***
	(0.012)	(0.014)
Num.Obs.	888180	268077

Note: This table presents results from difference-in-differences regressions, organized into three panels that each employ distinct estimation techniques to assess the effect of various types of 'third places' on local entrepreneurial activity. Panel A uses a conventional Poisson Two-Way Fixed Effects estimator. Panel B, reports the extended two-way fixed effect estimator reporting average marginal effect comparing to not-yet-treated. Panel C reports independent marginal effects by year of treatment for the Extended TWFE model. Column (1) examines the effect of the first bar in neighborhoods previously devoid of bars, and column (2) assesses the effect of first restaurant for the neighborhoods that did not have restaurant in the area. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

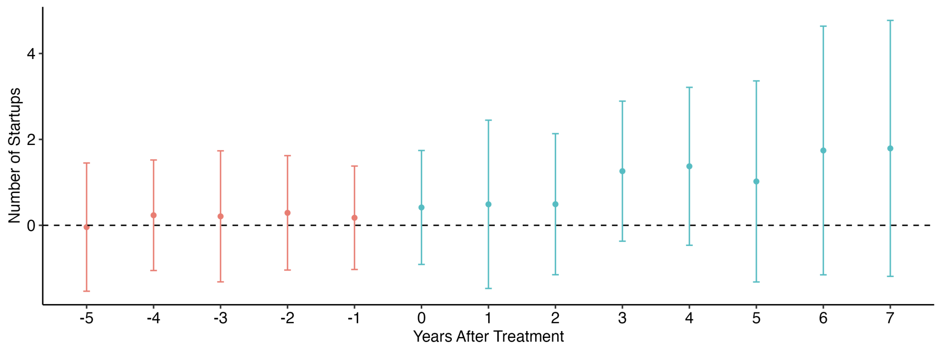
Figure 1: New Starbucks that are First Coffee Shop in Census Tract by Year



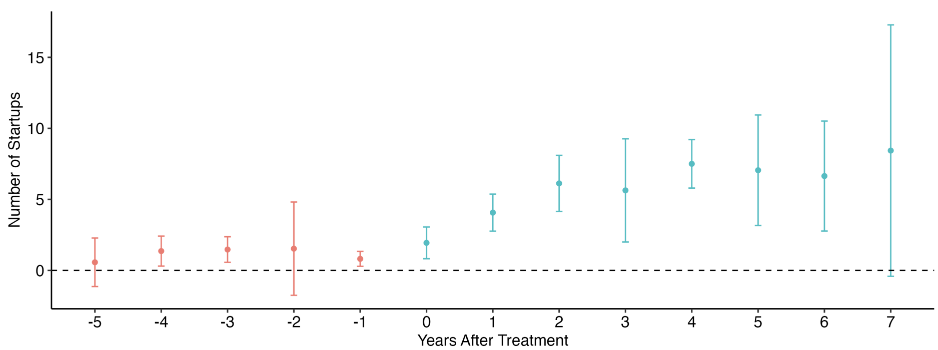
Note : This figure presents a histogram illustrating the annual count of new Starbucks establishments within a given census tract from 1998 to 2016. The Y-axis represents the number of new Starbucks, while the X-axis indicates the year.

Figure 1: Event Studies on the Effect of Starbucks Entry on the Number of Startups Founded by Neighborhood

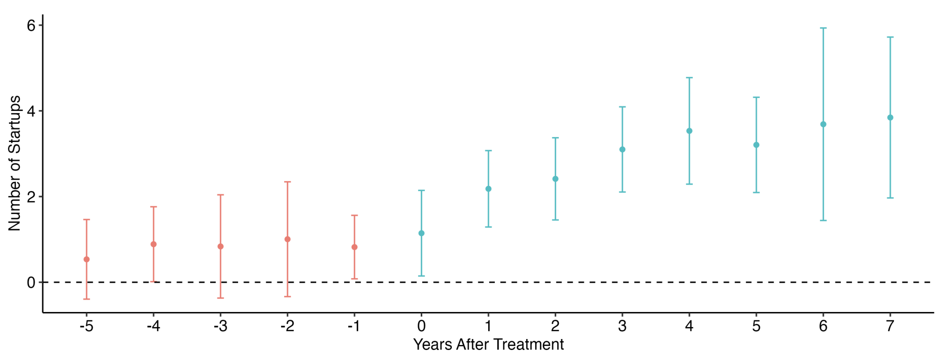
A. *Treated and Rejected Starbucks.*



B. *Magic Johnson Starbucks.*



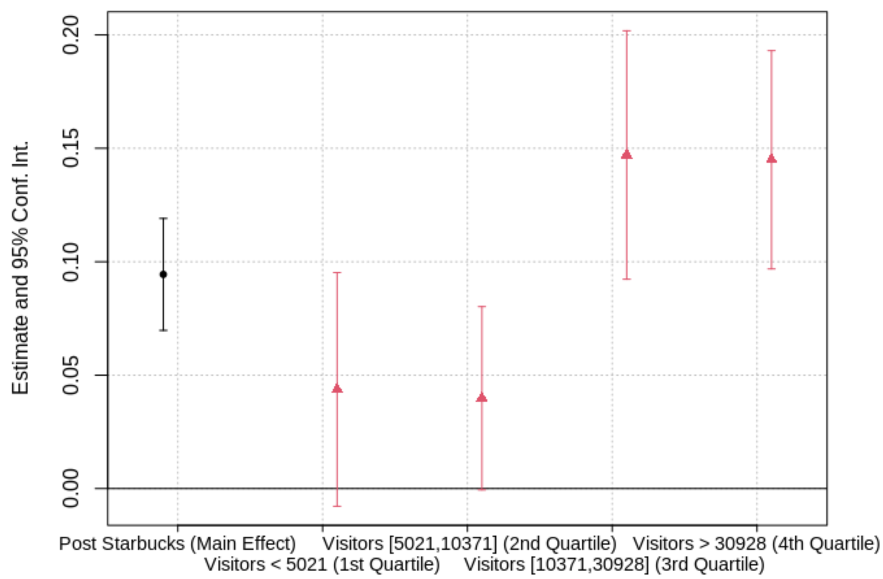
B. *All First Starbucks*



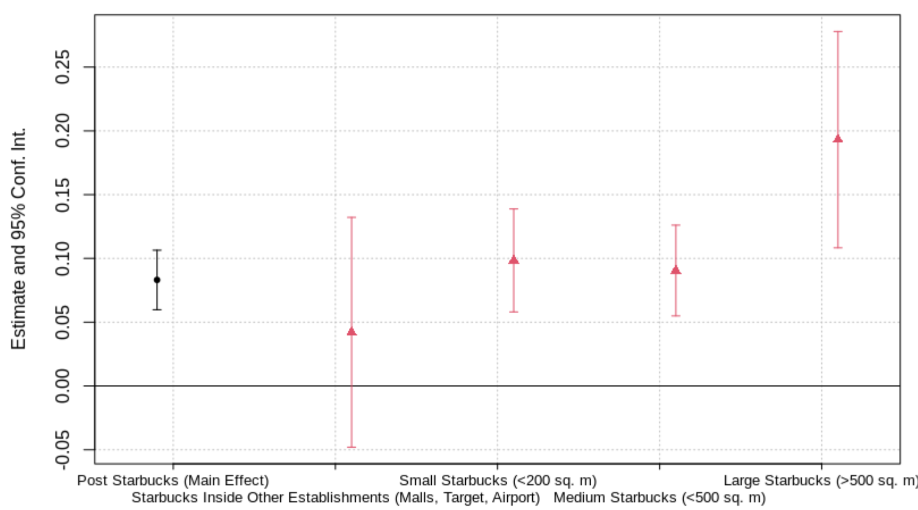
Notes: This figure shows the dynamic impacts following the entry of the first Starbucks for neighborhoods that had no prior coffee shops, utilizing various panel sets for analysis. Figure A compares census tracts that received their first Starbucks with those initially targeted by Starbucks for entry but ultimately rejected due to external reasons. Figure B compares census tracts that obtained a Magic Johnson Starbucks with those matched to resemble the distribution treated tracts closely through a matching procedure. Figure C compares census tracts that received their first Starbucks against all other tracts that remained without a Starbucks throughout our study period. Each figure reports the marginal effects employing the difference-in-differences methodology as per Callaway and Sant'Anna (2021), using the tracts that were not yet treated as the control group.

Figure 2: Heterogeneous Effects Depending on Visit Patterns and Square Footage

A. *Differences in Establishment Traffic*

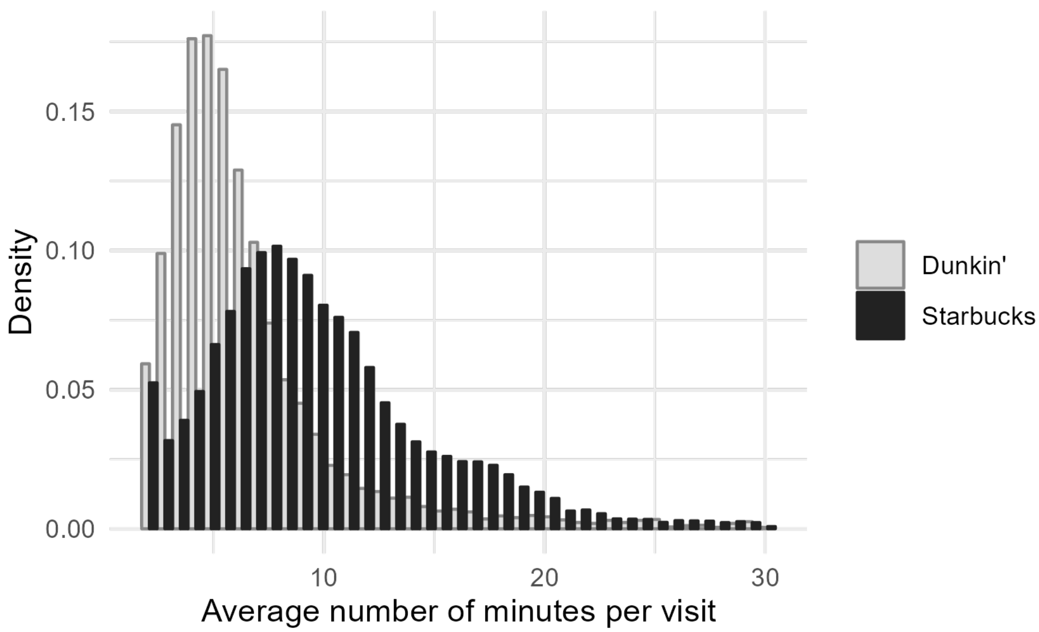


B. *Differences in Establishment Size*



Notes: These figures show the differential treatment effects of the first Starbucks entry on neighborhood entrepreneurship, segmented by the establishment's foot traffic and size. In Figure a, the analysis is based on the differentiation in foot traffic at Starbucks locations, whereas Figure b focuses on variations in store square footage. We classify both traffic volume and store dimensions by quantile values.

Figure 3: Average Length of Visit for Starbucks Establishments versus Dunkin'



Note : We use Safegraph data for the month of March 2019 to estimate the average duration of visits to each Starbucks location compared to Dunkin' (also known as Dunkin' Donuts), and plot the density of this duration. Safegraph provides count of visits for five groups: $<$ 5 mins, 5-20 mins, 21-60 mins, 60-240 mins, and $>$ 240 mins. We remove all visits that are longer than 240 minutes since they are mist likely to be workers rather than clients. For each bin, we assume the duration follows a Poisson distribution and estimate the expected time using the geometric mean of the range. We then estimate the average visit length per establishment as the mean expected time weighted by the number of visits per group.

Appendix

Table A1: Summary Statistics of a Panel of Neighborhoods that Accepted or Rejected Starbucks Entry

Panel A: Census Tracts that Rejected Starbucks Entry

Statistic	N	Mean	Median	St. Dev.
Third Places				
Gets First Starbucks—No Prior Café	418	0.043	0	0.203
Gets Starbucks Rejection	418	0.232	0	0.423
Neighborhood Entrepreneurship				
Number of Startups	418	61.067	26	114.105
Neighborhood Characteristics				
Population	418	4,039.776	4,179.354	1,513.026
Population Density (per sq. km)	418	2,502.866	1,212.397	3,125.355

Panel B: Treated Census Tracts

Statistic	N	Mean	Median	St. Dev.
Third Places				
Gets First Starbucks—No Prior Café	67,738	0.612	1	0.487
Neighborhood Entrepreneurship				
Number of Startups	67,738	34.525	23	45.092
Neighborhood Characteristics				
Population	67,738	4,064.390	3,892.293	2,020.255
Population Density (per sq. km)	67,738	2,104.284	970.054	4,755.367

Note: This table reports metrics from tract-years spanning 2002 to 2020, with 71,496 pairs in our dataset. Detailed metric definitions are in Section II. Number of Startups is sourced from the Startup Cartography Project. Rows under "Neighborhood Characteristics" presents population characteristics of the neighborhoods. The population data is from the IPUMS NHGIS. Population density is calculated by dividing the population by the land area of the respective tract.

Table A2: Summary Statistics of Neighborhoods by Magic Johnson Starbucks Introduction

Panel A: Magic Johnson Starbucks Census Tracts

Statistic	N	Mean	Median	St. Dev.
Third Places				
Gets Magic Johnson Starbucks	1,428	0.398	0	0.490
Neighborhood Entrepreneurship				
Number of Startups	1,428	24.749	10	40.024
Neighborhood Characteristics				
Population	1,407	4,388.113	4,089.021	1,725.067
Population Density (per sq. km)	1,407	5,600.762	4,155.287	5,670.808
Percent Black	1,407	0.317	0.212	0.295

Panel B: Control Census Tracts

Statistic	N	Mean	Median	St. Dev.
Neighborhood Entrepreneurship				
Number of Startups	104,517	16.347	7	31.632
Neighborhood Characteristics				
Population	104,517	3,995.729	3,706.250	1,870.941
Population Density (per sq. km)	104,517	6,920.009	4,087.361	10,371.210
Percent Black	104,517	0.352	0.246	0.293

Note: This table reports metrics from tract-years spanning 1990 to 2010, with 105,945 pairs in our dataset. Detailed metric definitions are in Section II. Number of Startups is sourced from the Startup Cartography Project. Rows under "Neighborhood Characteristics" presents population characteristics of the neighborhoods. The population data is from the IPUMS NHGIS, including 1991-1999 linear projections. Population density is calculated by dividing the population by the land area of the respective tract. Percent Black reports ratio of black residents in the tract, sourced from the 1994-2018 ZIP Codes Business Patterns (ZBP) and the HUD 2012 Q3 Crosswalk File.

Table A3: A List of Planned but Rejected Starbucks Locations

State	City	Census Tract	Full Address of the Proposed Location	Rejection Year
MT	Missoula	MT_063_000800	US-93 & S Reserve StMissoula, MT 59801	2005
IL	Normal	IL_113_000301	816 Osage St, Normal, IL 61761	2007
PA	Langhorne	PA_017_106100	E Maple Ave & S Pine St, Langhorne, PA 19047	2007
CT	Hartford	CT_003_504200	495 Farmington Ave, Hartford, CT 06105	2008
OH	Fairborn	OH_057_200900	675 E Dayton Yellow Springs Rd, Fairborn, OH 45324	2008
WA	Yakima	WA_077_000100	202 E Yakima AveYakima, WA 98901	2012
IL	Palatine	IL_031_803701	231 W Northwest Hwy, Palatine, IL 60067	2012
CA	San Francisco	CA_075_020300	2201 Market StSan Francisco, CA 94114	2013
MI	Grand Rapids	MI_081_002100	421 Michigan St NEGrand Rapids, MI 49503	2013
ID	Boise	ID_001_000100	215 S Broadway Ave, Boise, ID 83712	2013
CA	Berkeley	CA_001_423902	3001 Telegraph AveBerkeley, CA 94705	2014
TX	Longview	TX_183_000502	W Marshall Ave & N Spur 63, Longview, TX 75601	2019
TX	San Antonio	TX_029_130700	2607 I-35 Frontage Rd, San Antonio, TX 78208	2020

Table A4: The Effect of Magic Johnson Starbucks introduction on Yearly Census Tract Level Startup Formation

	Poisson TWFE		Ext. TWFE (Preferred)	Callaway & Sant'Anna
	(1)	(2)	(3)	(4)
Gets Magic Johnson Starbucks	0.249***	0.076	0.260***	5.927***
	(0.069)	(0.064)	(0.045)	(1.403)
Percent Increase	28.3%	7.9%	29.7%	36%
Census Tract F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes		Yes	Yes
Year x County F.E.		Yes		
Num.Obs.	105 378	104 901	105 945	105 945

Note: This table reports the effect of a Magic Johnson Starbucks on entrepreneurship within a Census tract using various difference-in-differences methods. Column (1) uses a Poisson model with fixed effects for Census tract and year; Column (2) adds log(pop density) as a control. Column (3) features the same Poisson regression but with two-way fixed effects for Census tract and a combination of county-by-year fixed effects. Column (4) implements the Wooldrige (2022) estimator for consistent TWFE Poisson with bootstrapped standard errors. Column (5) implements the Callaway and Sant'Anna estimator. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: A list of All Magic Johnson Starbucks Locations

Magic Johnson Starbucks Location	State	City	Open Year	address
Camp Wisdom & Highway 67	TX	Dallas	2001	3431 West Camp Wisdom Road in Oak Cliff
Loop 610 & I-45	TX	Houston	2005	1450 GULFGATE CENTER MALL
Rainier & Edmonds	WA	Seattle	1999	4824 Rainier Ave. S.
Martin Luther King Way	WA	Seattle	2000	2921 Martin Luther King Way
Atlantic & Florence	CA	Bell	2004	7121 Atlantic Ave
Western & Slauson	CA	Los Angeles	2002	1850 W. Slauson Avenue. Los Angeles, CA. 90047
Avalon & Dominguez	CA	Carson	2003	20810 Avalon Boulevard. Carson, CA. 90746
Wilmington & 119th	CA	Los Angeles	2004	11864 Wilmington Ave, Los Angeles, CA 90059
Atlantic & Washington	CA	Commerce	2003	5201 E. Washington Blvd. Commerce, CA. 90040
Wilshire & Union	CA	Los Angeles	2003	1601 Wilshire Blvd. Los Angeles, CA. 90010
Donohue & East Bay Shore	CA	East Palo Alto	2003	1745 East Bayshore Blvd. palo Alto CA
Atlantic & Imperial	CA	Lynwood	2003	10925 Atlantic Avenue. Lynwood, CA.
Artesia & Western	CA	Gardena	2007	1759 W Aretsia
Broadway & 8th Street	CA	Oakland	2004	801 BROADWAY
Gardena Valley Center	CA	Gardena	2003	1258 W REDONDO
Fruitvale Station	CA	Oakland	1999	3060A E 9th StFruitvale Station
Hawthorne & El Segundo Blvd	CA	Hawthorne	2002	12770 Hawthorne Blvd
Fair Oaks & Orange Grove	CA	Pasadena	2002	671 N. Fair Oaks Avenue Fair Oaks Renaissance Plaza Pasadena, CA 91103.
Pacific & Belgrave	CA	Huntington Park	2004	6021 Pacific Blvd.Huntington Park, CA 90255
Richmond & San Pablo	CA	Richmond	2004	15521 San Pablo Avenue Vista Del Mar Center Richmond, CA 94806
Hollywood Park Marketplace	CA	Inglewood	2004	3351 W Century BLVD
Euclid & Federal	CA	San Diego	2004	1722 Euclid Ave
La Brea & Centinela	CA	Inglewood	2004	941 N. La Brea Avenue La Brea Plaza Inglewood, CA 90302
Fairmount and University	CA	San Diego	2001	3895 Fairmount Avenue City Heights Village Shopping Center San Diego, CA 92105
Baseline & Riverside	CA	Inland Empire	2004	120 W Base Line Rd
Sweetwater and the 805	CA	San Diego	2001	1860 Sweetwater Road A-1 National City, CA 919507660
Plaza & Grove	CA	San Diego	2003	2230 E Plaza Blvd, National City, CA 91950
Long Beach and Willow	CA	Long Beach	2001	141 E WILLOW ST
Fillmore & O'Farrell	CA	San Francisco	2004	1501 Fillmore Street The Fillmore Center San Francisco, CA 94115
Compton & Alameda	CA	Los Angeles	2004	101 E Compton Blvd, Compton, CA 90220
Sony Metreon	CA	San Francisco	1997	120 4th St
Crenshaw & Coliseum	CA	Los Angeles	2006	3722 Crenshaw Blvd.The Coliseum Center Los Angeles, CA 90016
San Pablo Dam & San Pablo	CA	San Pablo	2010	2415 San Pablo Dam Rd # 108, San Pablo, CA 94806
Eastern & Florence	CA	Los Angeles	2004	7000 Eastern Ave # F
Hoover & Jefferson	CA	Los Angeles	2000	3303 S. Hoover Street. A-2. Los Angeles, California 90007
Firestone & Garfield	CA	Southgate	2002	8622 Garfield Ave
Ladera Center	CA	Los Angeles	1998	5301 W Centinela Blvd. Ladera Center. Los Angeles, CA 90189
Firestone & Long Beach	CA	Southgate	2004	8924 Long Beach Blvd.South Gate, CA 90280
LaBrea & San Vicente	CA	Los Angeles	1999	1250 S La Brea Ave, Los Angeles, CA 90019
Tweedy & Otis	CA	Southgate	2004	4181 Tweedy Blvd. Southgate, California 90280
Slauson & I-5	CA	Los Angeles	2005	7724 Telegraph Road Los Angeles, CA 90040
Sherman Way & Sepulveda	CA	Van Nuys	2004	15355 Sherman Way, Van Nuys, CA 91406
29th & Quebec	CO	Denver	2003	7304 E. 29th Ave Denver, CO 80238
Colfax & Kalamath	CO	Denver	2003	1050 W Colfax Ave in Denver, Colorado 802042072
Colfax & Chambers	CO	Denver	2003	15290 E Colfax Ave, Aurora, CO 80011
Midtown Center (56th & Capitol)	WI	Milwaukee	2004	5610 W Capitol Dr, Milwaukee, WI 53216
47th and Cicero	IL	Chicago	2000	4701 South Cicero Avenue Chicago, IL 60632.
71st & Stony Island	IL	Chicago	2004	7101 S Stony Island Ave Chicago, IL 60649
Hyde Park - 55th & Woodlawn	IL	Chicago	2004	1174 E 55th St, Chicago, IL 60615
Madison & Morgan	IL	Chicago	2002	1001 W MADISON ST
Wilson and Magnolia	IL	Chicago	2000	4600 North Magnolia in Illinois 60640-5083
Fairlane Towne Center	MI	Dearborn	2004	18900 Michigan Ave, Dearborn, MI 48126
Eastpointe	MI	Eastpointe	2002	22511 Gratiot Ave. Eastpointe, MI 48021.

Table A5: A list of All Magic Johnson Starbucks Locations *(continued)*

Magic Johnson Starbucks Location	State	City	Open Year	address
Jefferson and East Grand	MI	Detroit	2007	7201 E Jefferson, Detroit, MI 48214
Telegraph & 9 mile	MI	Southfield	2001	22506 Telegraph Road. Southfield, MI 48033
East Lansing	MI	East Lansing	1999	E Lansing, Grand River & Charles, East Lansing, Michigan
Mayfield and Lee	OH	Cleveland	2002	3093 Mayfield Road Heights Rockefeller Building Cleveland Heights, OH 44118
Shoppes at Metro	MD	Hyattsville	2000	3601 East-West Highway, Hyattsville, Md.
Largo Plaza	MD	Largo	2003	10586 Campus Way South Largo, MD 20774.
Capital Centre	MD	Prince George's County	2004	861 CAPITAL CENTRE BLVD # A
Rivertown Commons	MD	Prince George's County	2005	6171-A Oxon Hill Road. Oxon Hill, Maryland 20745
125th and Lennox Ave.	NY	New York City	1999	83 West 125th Street, New York, NY.
1385 Metropolitan Avenue	NY	New York City	2002	1385 Metropolitan Avenue, New York, NY
Atlantic Center	NY	New York City	2004	139 Flatbush Ave, Brooklyn, NY 11217
Cascade Road	GA	Atlanta	1999	3660 Cascade Road SW Atlanta, GA 30331.
Hairston & Covington	GA	Atlanta	2002	2071-A South Hairston Rd. Decatur, Georgia 30035
Lauderdale Lakes	FL	Lauderdale Lakes	2001	3399 N. State Road 7/Highway 441 at W. Oakland Park Blvd.
Biscayne & 69th Street	FL	Miami	2004	6825 BISCAYNE BLVD

Table A6: The Effects of Magic Johnson Starbucks on Neighborhood Entrepreneurship, by Neighborhood Characteristics

	(1)	(2)
Gets Magic Johnson Starbucks	0.273***	0.252***
	(0.059)	(0.055)
Gets Magic Johnson Starbucks:Log(Percent Black)	0.087***	
	(0.016)	
Gets Magic Johnson Starbucks:Log(Population Density)		0.035
		(0.072)
Num.Obs.	105420	105504

Note: This table reports the effect of the introduction of a Magic Johnson Starbucks on entrepreneurship outcomes in consideration of several characteristics of a Census tract. Column (1) report the Magic Johnson Starbucks' treatment effect and its interaction effect with the percentage of Black residents. Column (2) report the Magic Johnson Starbucks' treatment effect and its interaction effect with population density of a Census tract. Standard errors clustered at the county level in parenthesis" and remove line skip before significance levels. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7: Not-Yet-Treated Poisson Estimate for Rejected Startbucks

	(1) Extended TWFE
Gets First Starbucks - No Prior Café	0.023*
	(0.011)
Precent Increase	2.3%
Sample Mean	31.7
Additional Startups	0.7
Num.Obs.	59 453

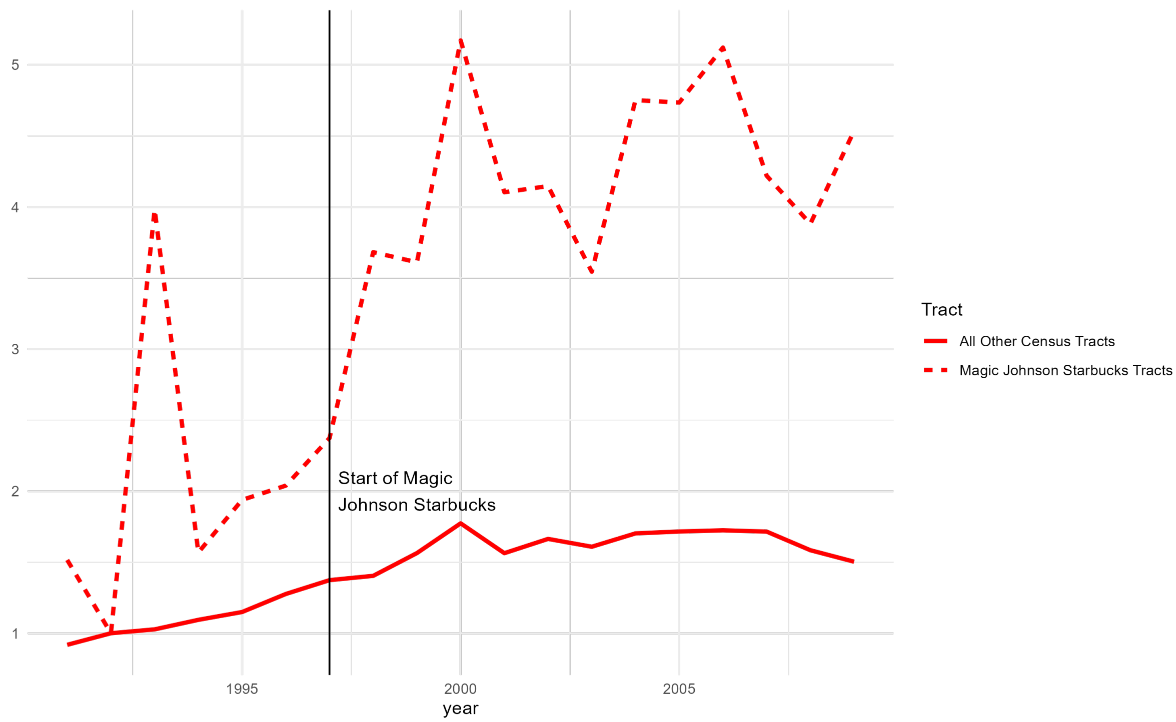
Note: This table presents for our Poisson estimator using not yet treated group in the rejected Starbucks analysis. We do not focus on the not yet treated for our rejected Starbucks analysis because the empirical comparison is with those neighborhoods that did not get Starbucks (due to being rejected).We report it here only for completeness. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A8: Coefficients for Event Study Estimates

	Rejected Sample	Magic Johnson Sample	All Census Tracts Sample
Time to Starbucks Entry(-5)	−0.042	0.573	0.688
	(0.525)	(0.766)	(0.113)
Time to Starbucks Entry(-4)	0.234	1.362	0.989
	(0.490)	(0.499)	(0.131)
Time to Starbucks Entry(-3)	0.209	1.471	0.942
	(0.571)	(0.430)	(0.125)
Time to Starbucks Entry(-2)	0.290	1.532	1.058
	(0.490)	(1.546)	(0.113)
Time to Starbucks Entry(-1)	0.176	0.814	0.858
	(0.462)	(0.253)	(0.147)
Time to Starbucks Entry(0)	0.416	1.941	1.207
	(0.464)	(0.527)	(0.109)
Time to Starbucks Entry(1)	0.489	4.070	2.266
	(0.726)	(0.600)	(0.155)
Time to Starbucks Entry(2)	0.492	6.126	2.186
	(0.566)	(0.947)	(0.138)
Time to Starbucks Entry(3)	1.261	5.635	3.051
	(0.609)	(1.733)	(0.173)
Time to Starbucks Entry(4)	1.374	7.505	3.317
	(0.672)	(0.909)	(0.159)
Time to Starbucks Entry(5)	1.022	7.054	3.199
	(0.893)	(1.933)	(0.181)
Time to Starbucks Entry(6)	1.742	6.645	3.728
	(1.051)	(1.860)	(0.212)
Time to Starbucks Entry(7)	1.791	8.436	3.869
	(1.107)	(4.039)	(0.222)

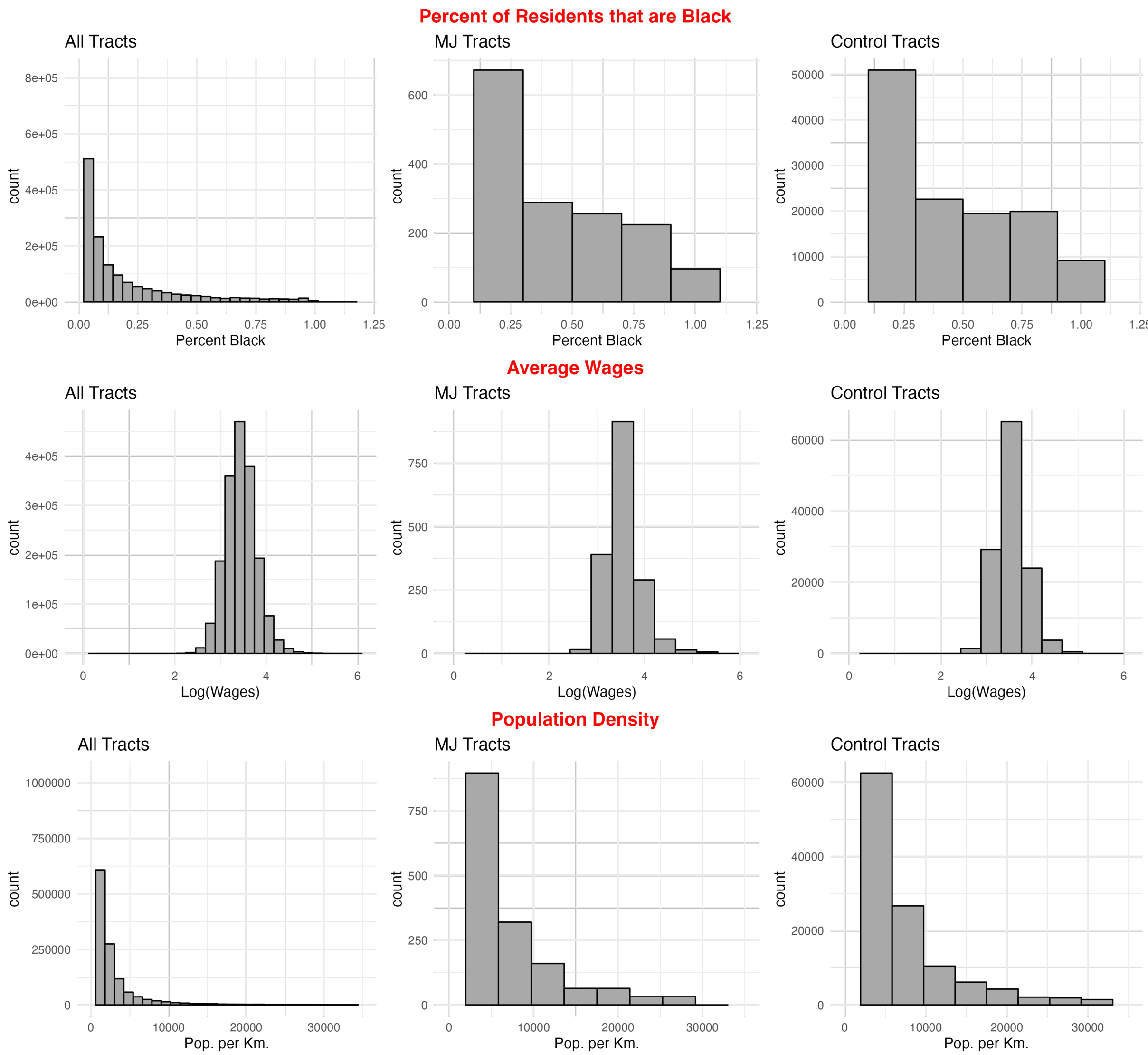
Note: The table reports the coefficients for Figure 2, event study estimates. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A1: Estimated Startup Quality Over Time



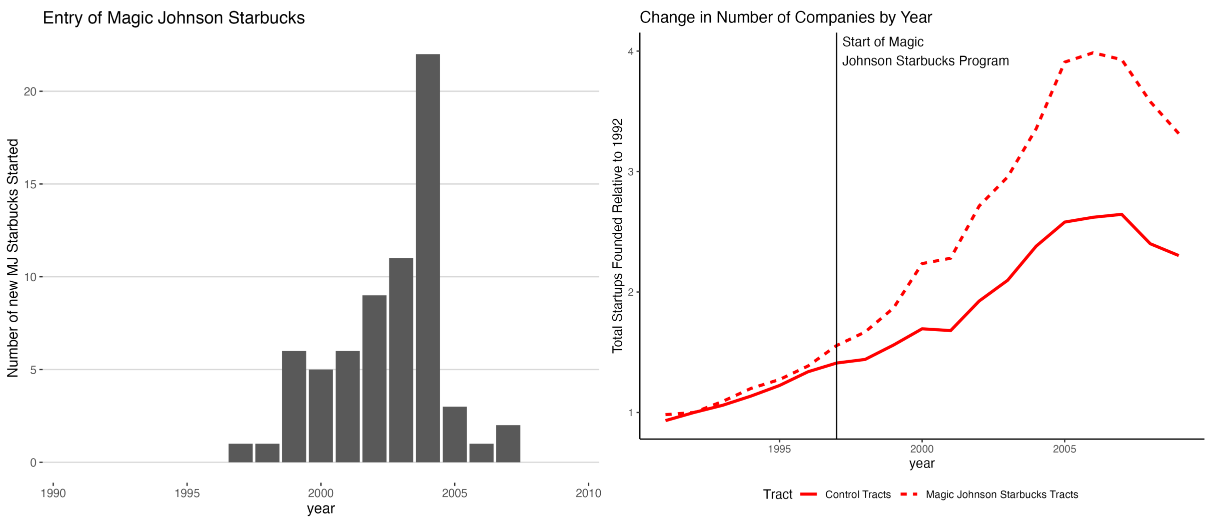
Note : The figure displays the quality-adjusted count of startups, computed by multiplying the number of startups by the quality of startups for each tract-year pair. Our data, ranging from 1994 to 2010, is sourced from the Startup Cartography Project, using the methodology set out by Guzman and Stern (2020). The red line marking 1998 signifies the commencement of the Magic Johnson Starbucks initiative.

Figure A2: Comparative Distribution of Key Metrics: Tracts with Magic Johnson Starbucks vs. Matched Controls



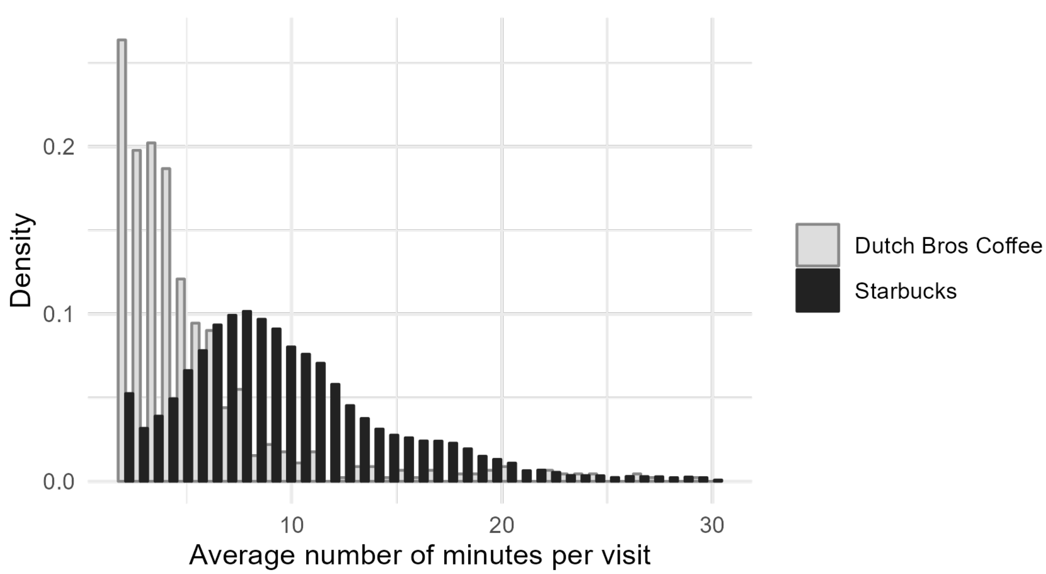
Note: This figure compares key statistics between tracts receiving a Magic Johnson Starbucks and matched control tracts. Displayed metrics include the percentage of black residents, average wages, and population density. The X-axis enumerates the tracts. The Y-axis, in successive rows, measures the percentage of black residents, average wages, and population density, respectively.

Figure A3: Entry of Magic Johnson Starbucks Over Time



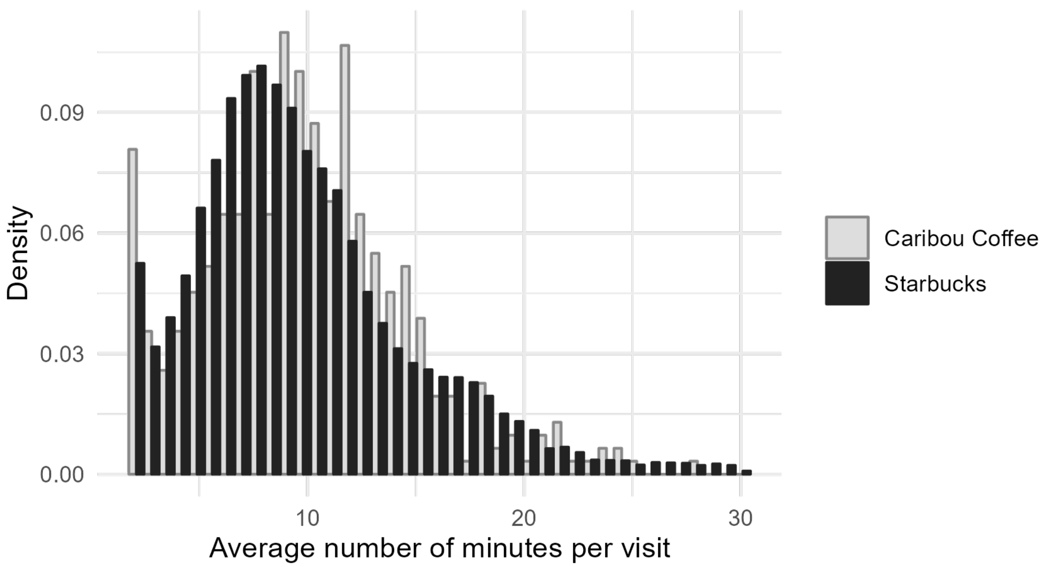
Note: This figure juxtaposes the establishment timeline of Magic Johnson Starbucks from 1997 to 2007 with the trajectory of startup quantity in treated versus control tracts. The left panel displays the distribution of the years in which Magic Johnson Starbucks establishments were introduced. The right panel contrasts the progression of average startups per tract between treated and control tracts, with annual counts referenced against the 1992 average.

Figure A4: Average Length of Visit for Starbucks Establishments versus Dutch Bros



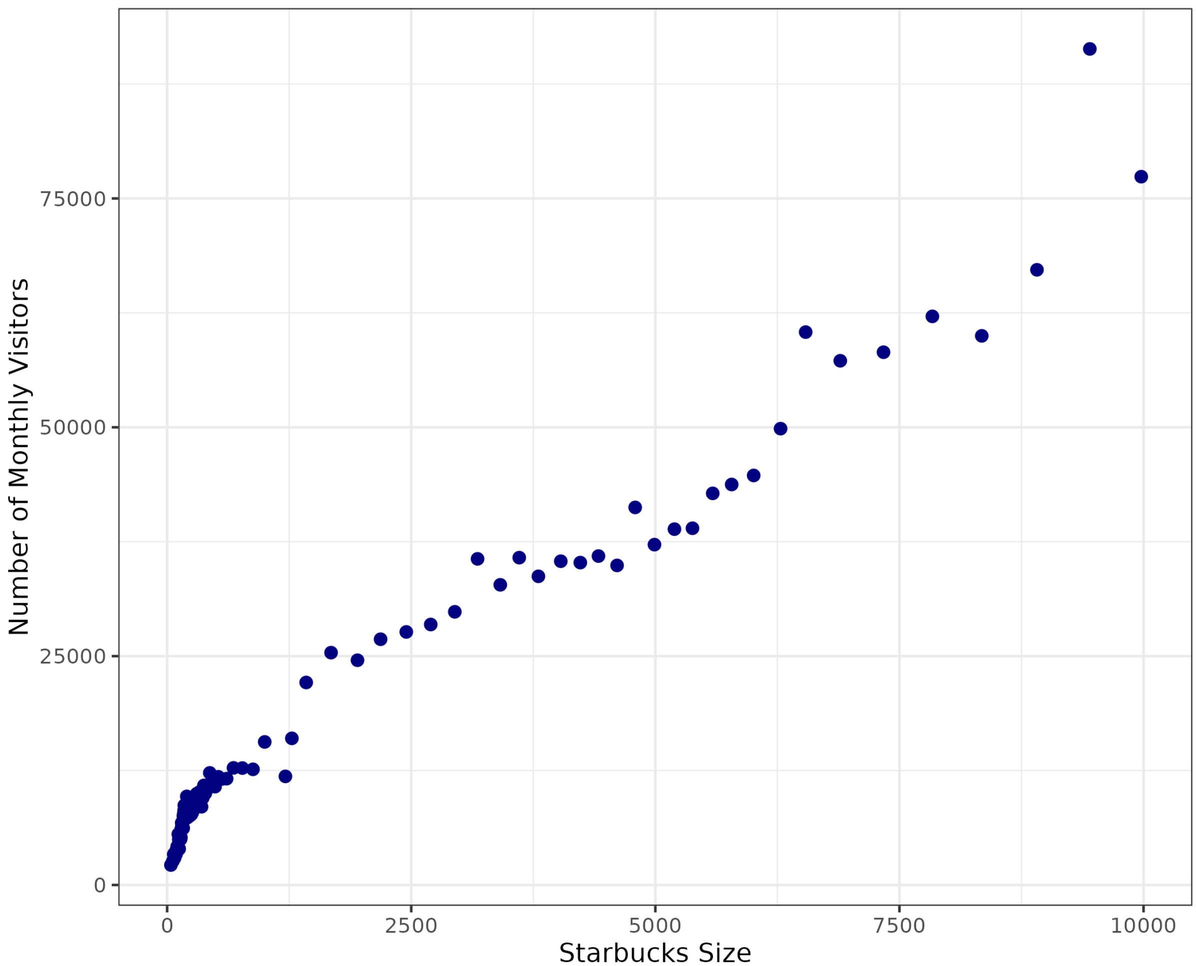
Note : We use Safegraph data for the month of March 2019 to estimate the average duration of visits to each Starbucks location compared to Dutch Bros, and plot the density of this duration. Safegraph provides count of visits for five groups: $<$ 5 mins, 5-20 mins, 21-60 mins, 60-240 mins, and $>$ 240 mins. We remove all visits that are longer than 240 minutes since they are mist likely to be workers rather than clients. For each bin, we assume the duration follows a Poisson distribution and estimate the expected time using the geometric mean of the range. We then estimate the average visit length per establishment as the mean expected time weighted by the number of visits per group.

Figure A5: Average Length of Visit for Starbucks Establishments versus Caribou Coffee



Note : We use Safegraph data for the month of March 2019 to estimate the average duration of visits to each Starbucks location compared to Caribou Coffee, and plot the density of this duration. Safegraph provides count of visits for five groups: $<$ 5 mins, 5-20 mins, 21-60 mins, 60-240 mins, and $>$ 240 mins. We remove all visits that are longer than 240 minutes since they are mist likely to be workers rather than clients. For each bin, we assume the duration follows a Poisson distribution and estimate the expected time using the geometric mean of the range. We then estimate the average visit length per establishment as the mean expected time weighted by the number of visits per group.

Figure A6: Relationship Between Square Footage of Starbucks and Foot Traffic



Note: This graph displays the binned scatterplot relating the number of monthly visitors in 2019 to a Starbucks versus the size of the Starbucks in square meters. Both data are provided by Safegraph, a company providing geolocated information into point of interests and commerce.

Appendix B. Industry Tagging Algorithm

Our firm registration data does not include industry codes. To assign firms to industries we develop an industry tagging algorithm based on the words in firm names. Our approach proceeds in three steps.

First, we consider all firms with a primary NAICS code assigned in a large firm dataset provided by Infogroup USA.[1] We count the number of times a word appears in firm names for each NAICS two-digit industry. Second, we define *word quotient* as the number of times a word appears in an industry divided by the number of firms in an industry - we scale the word frequency to avoid industries with many firms dominating the classification. For example, words like "mining" or "biotechnology" are highly relevant to industries with relatively few firms. Third, we assign each word to an industry if (i) it has the highest word quotient and (ii) the quotient is at least twice as high as the next highest one (quotient ratio ≥ 2). Firms are then linked to industries if the words in their names are assigned to a specific industry.

Words with the highest quotient ratio (i.e., those that are most closely associated with specific industries), include "wharehousing" (NAICS 49), "mining" and "quarry" (NAICS 21), and "winery" and "panaderia" (NAICS 31). The median value of the quotient ratio is 8.5. Words around this value include "attorneys" (NAICS 52), "volkswagen" (NAICS 44), "key" (NAICS 56), "powerwashing" (NAICS 23), "abstract" (NAICS 54), and "cooling" (NAICS 23).

In total, we have 5,507 words which tag about 54.6% of companies in our regression sample. We exclude N55 and N99. Within these tagged companies, 81% are assigned to exactly one industry, 17.2% to two, and 1.8% to three or more. Many of the companies tagged in two industries are those that span multiple sectors, such as "Commercial Properties Magazine, Inc", which is tagged as NAICS 51 (Information) and 53 (Real Estate), or "Stella Kids Yoga" which is tagged as NAICS 61 (Educational Services) and 62 (Health Care and Social Assistance).

In our main analysis, we assign a firm an industry as long as it is tagged to that industry, i.e., a firm can be tagged to multiple industries. In untabulated results, our findings are robust to assigning a firm an industry when the firm is tagged to only one industry.

[1] Infogroup USA dataset includes firms covering the majority of the U.S. economy (similar to Dunn & Brandstreet).