Third Places and Neighborhood Entrepreneurship:
Evidence from Starbucks Cafés[1]

by

Jinkyong Choi
Columbia University

Jorge Guzman
Columbia University
NBER

Mario Small
Columbia University

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. When compared to census tracts that were scheduled to receive a Starbucks but did not get one, tracts that received a Starbucks saw an increase in the number of startups of 9.1% to 18% (or 2.9 to 5.7 firms) per year, over the subsequent 7 years. A partnership between Starbucks and Magic Johnson focused on underprivileged neighborhoods produced larger effects. Analyses suggest a networks mechanism is at play.

JEL: L26, R23, R32, Z13

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[1] We thank participants at the NBER Entrepreneurship Boot Camp, Duke Strategy Seminar, the University of Oregon Strategy Seminar, REER at Georgia Tech, the AIEA Virtual Seminar, and the Southern Economic Association meetings, as well as Pierre Azoulay, Vanessa Burbano, Bo Cowgill, Brandon Freiberg, Paul Ingram, Alex Oettl, David Robinson, Maria Roche, 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.

Contact. Choi: PhD student, Columbia Business School. Kravis Hall 9th Fl. Columbia University. JChoi27@gsb.columbia.edu. Guzman: Gantcher Associate Professor of Business. Columbia Business School. Kravis Hall 975. Columbia University. jag2367@gsb.columbia.edu. Small: Quetelet Professor of Social Science. Department of Sociology. Knox Hall, 5th floor, Columbia University. mario.small@columbia.edu

Sociologists have argued that local establishments such as restaurants, pubs, and cafés can improve neighborhood life (Oldenburg 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 can shape neighborhood social networks by making it less costly for people to meet with others, and by increasing the probability of unplanned contact with acquaintances or new connections. Networks have been repeatedly documented to be important for entrepreneurship (Sorenson and Audia 2000; Arzaghi and Henderson 2008; Sorenson 2018). 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 because in the 1980s, when many American 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 phases of a startup.

Starbucks cafés may also promote neighborhood entrepreneurship through other channels. The opening of a Starbucks is said to have a signaling effect. Entrepreneurs and investors considering a neighborhood seek evidence that it is poised for growth, and a Starbucks coffee shop may be a powerful signal (e.g., Florida 2002). In fact, real estate professionals have called the tendency for real estate prices to rise in a neighborhood after the opening of a Starbucks “The Starbucks Effect” (Anderson 2015; see Glaeser, Kim, and Luca, 2018a, 2018b for counterevidence). Other retailers may also expect the opening of a Starbucks to drive higher customer visits to their own establishments, or may believe Starbucks to be will informed about which locations are promising. In addition to these signaling effects, Starbucks cafés also provide a place for people to work independently on their new firm. By offering a space to linger and amenities such as free high-quality wireless internet, restrooms, and food, Starbucks may make it easier for entrepreneurs to start their firms.

Separate from such effects, there is the possibility of selection. Starbucks Corp. may select for their new coffee houses those neighborhoods where entrepreneurship was already poised to increase, even if a café had not opened. If the attributes that make a neighborhood attractive for Starbucks are also those that contribute to more startups, then the opening of a Starbucks coffee shop could be followed by higher entrepreneurship even if Starbucks were not the cause of this increase.

Using data on business registrations in the U.S. between 1990 and 2022 from the Startup Cartography Project (Andrews et al. 2022), we study whether the introduction of a Starbucks café into a neighborhood with no prior coffee shops increased 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), focusing on three distinct empirical analyses. 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 mobilization. These 'rejected' Starbucks are a natural control group because Starbucks Corporation also sought to open in those neighborhoods. However, this set of census tracts is small in number. Second, we consider a partnership between Starbucks Corporation and retired professional basketball player and entrepreneur Earvin "Magic" Johnson, initiated by Johnson, that aimed at improving under-resourced neighborhoods by introducing the cafés. Under the partnership, cafés were opened in low-income, minority neighborhoods, such as Harlem in New York City and Ladera Heights in Los Angeles. Examining the effect of these cafés is useful because the neighborhoods Johnson made a case for were not previously considered by Starbucks as potential sites for a café. However, while this effect would be interesting in its own right, it may combine the Starbucks effect with the benefits of endorsement and media attention that result from Magic Johnson's involvement. Third, we examine Starbucks' entry among all neighborhoods that did not previously have a coffee shop of any kind. The selection criteria for this third comparison set is less stringent, but its larger sample size allows higher statistical precision when estimating differences in entrepreneurship between treated and control tracts.

In all three approaches, we document a statistically significant increase in neighborhood entrepreneurship following the opening of a Starbucks café. We do not observe pre-trends in any of the three comparisons. In the sample of all tracts without coffee shops, we estimate that neighborhoods that receive a Starbucks as their first coffee shop see an increase in local entrepreneurship of 5.5% to 13.6%. This increase amounts to 1.1 to 2.9 additional new startups per year in the tract, with the effects persisting for at least seven 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 firms per year. When we compare the neighborhoods that had a Starbucks open to the neighborhoods that rejected Starbucks, the increase is 9.1% to 18%, or 2.9 to 5.7 firms. In addition, 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 fake 'entry' of a rejected Starbucks is insignificant and the coefficient is negative, suggesting our effect is driven not by site selection but by the physical opening of a Starbucks.

Across multiple analyses, we find evidence consistent with the idea that the role of Starbucks in promoting social networks is an important mechanism behind observed the increase in entrepreneurship. First, the benefit of a Starbucks café is larger precisely when it would offer new opportunities for neighborhood socialization. When, rather than focusing on neighborhoods without prior coffee shops, we study those that already have coffee shops, we do not observe higher entrepreneurship after a Starbucks opens. Neighborhoods with existing coffee shops may already have these kinds of socialization spaces. Second, the benefit of Starbucks coffee shops is similar to that of other community-oriented cafés and larger than that of coffee shops that do not function as "third places." As we noted, coffee shop companies differ. When we consider the entry of all coffee shops that are not Starbucks, the effect is small and fleeting. When we repeat our approach with neighborhoods that open a Dunkin' Donuts—which are typically not set up for extended seating—we do not see an increase in entrepreneurship. In contrast, when we repeat it on neighborhoods that open a Caribou Coffee—a chain in Minnesota and Wisconsin with a model similar to Starbucks'—we do see an increase in entrepreneurship. 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.

Third, when we probe in greater detail the selection process by which Starbucks decides where to establish, we find that the neighborhoods where we find an effect are not those that Starbucks Corp. tends to select. We estimate a machine learning model (gradient-boosted tree) that predicts whether a neighborhood opens a Starbucks from a large number of neighborhood observables obtained from the 2000 U.S. Census. The observables that best predict the opening of a Starbucks include those indicating young, high-income, and educated residents—a finding consistent with Starbucks' brand image as catering to the highly educated. But the selection process does not appear to explain our effects. One, we find that the number of pre-existing cafés in the neighborhood is positively correlated with the probability of getting a Starbucks. Two, when we use these observables to estimate individual neighborhood treatment effects (Wager and Athey, 2018), we find that a neighborhood's estimated effect is negatively correlated with the number of cafés and with the probability of getting a Starbucks. The strongest effects of Starbucks on entrepreneurship are among those neighborhoods least likely to see a new Starbucks.

Fourth, while we do not argue that signaling and remote work are playing no role in the Starbucks effect, the tests we perform surface little evidence that these mechanisms are salient in driving it. When we consider firms that most intuitively benefit from proximity to a Starbucks, such as retail and food establishments, we do not find that our effect is concentrated in these groups. Moreover, when we test for a change in the local real estate market by considering whether real estate startups, such as leasing offices and real estate agencies, increased in the neighborhood, we find no effect. Finally, when we consider the availability of wifi at Starbucks under the assumption that it would be necessary for most remote work, we find similar effects before 2010, when Starbucks did not offer free unlimited wifi (only two hours of wifi for Starbucks Rewards members); before 2008, when Starbucks offered only paid wifi; and before 2004, when Starbucks offered no wifi at all.

Fifth, we find that the decay of the effect as the distance from the neighborhood increases follows what would be expected of a network mechanism. While person-to-person interactions decline quickly with distance, the gradient for wages and real estate prices is typically less steep.[2] We find that the Starbucks effect deteriorates quickly with distance; it is one-fourth the original size for neighborhoods 1 to 2 kilometers away, and one-tenth for those 2 to 10 kilometers away.

Sixth, when we use geocoded data to study heterogeneity across locations, we see two additional indications of a network mechanism: the effect is larger for larger Starbucks cafés and for those with greater foot traffic. Finally, the effect is similar for another establishment that stimulates networks and 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 physical proximity to others is important for idea generation, creativity, and problem-solving (Marshall 1920; Allen 1970; Saxenian 1996; Sorenson and Audia 2000; Andrews 2019; Roche 2020; Kerr and Kerr 2021; Roche et al. 2024; Atkins et al, 2022), and for acquiring startup capital and resources (Stuart and Sorenson 2003; Arzaghi and Henderson 2008; Guzman and Stern 2015; Kerr and Kominers 2015; Agrawal et al. 2017; Leonardi and Moretti 2023). 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) study, which found that Prohibition reduced patenting, but only in counties that had a social structure that revolved around saloons, and with contemporaneous work by Andrews and Lensing (2024) relating the count of Starbucks cafés in a county to innovation.[3] Our results also bring new life to Saxenian's (1996) characterization of another third place, Walker's Wagon Wheel, as an anchor of social structure in Silicon Valley. Policy interventions to increase regional entrepreneurship

[2] The importance of proximity for knowledge spillovers 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) report that proximity benefits of firms dissipate within 10 miles, even for knowledge-based industries such as software (SIC 7371-73, 75).

[3] Besides our focus on a different geographic scale than Andrews and Lensing (2024) and a different outcome (entrepreneurship), our analysis is specifically targeting those neighborhoods that lack of socialization opportunities and its benefits to local firms, while they study the production of innovative ideas.

often underscore the benefits of third places, as they increase the ability of regional stakeholders to interact and work together.[4] Our work adds greater depth to the understanding of how these organizations contribute to entrepreneurship.

Second, our findings contribute to research on neighborhood effects and economic outcomes. Social scientists have shown that the economic outcomes of individuals are associated with the neighborhood in which they reside (Kain, 1968; Wilson 1987; Wilson 1996; Porter 1997; Glaeser and Sacerdote, 2000; Durlaf 2004; Sharkey and Faber 2014; Chyn and Katz 2021), and that this association is in part due to differences in neighborhood social environments (Wilson 1996; Glaeser 2000; Small 2004; Ivković and Weisbenner 2007; Brown et al 2008; Small and Adler 2019; Chetty et al 2022a, 2022b). However, randomized experiments that allow people to move out of disadvantaged neighborhoods have shown little effect from moving on adult employment (Kling et al. 2007; Chetty et al. 2016; Nakamura et al. 2022). The effects on children, in contrast, are significant (Bobonis and Finan, 2009; Chetty and Hendren 2018a, 2018b). One possible explanation is that adults will not be able to join the social dynamics and culture of a new neighborhood while children will. These facts have made neighborhood researchers argue that improving neighborhoods themselves is important (e.g. Sampson 2008, 2012), and place-based policies focused on neighborhoods have indeed seen some success (Busso et al. 2013). Startups account for 15% of gross job creation in the U.S. (Decker et al. 2014), and this job creation is disproportionately local (Samila and Sorenson 2011; Glaeser, Kerr, and Kerr 2015). Promoting local entrepreneurship may be a way to improve neighborhood conditions.

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 often credited to the introduction of a coffee shop concept to

[4] For example, after participating in MIT's Regional Innovation Entrepreneurship Program (REAP), aimed at helping local regions develop regional innovation and entrepreneurship ecosystems, the university Tec de Monterrey invested in a collaboration with the Cambridge Venture Café to open the Venture Café Monterrey to "[bring] bringing together entrepreneurs, investors, government, companies, universities, and civil society organizations" (Garcia, 2022).

the U.S. in which the expectation was not only to sell coffee, but also to give customers the opportunity to linger, socialize, and connect. The concept that a shared place can lead to neighborhood socializing and community action was formalized in Oldenburg's (1989) classic work on "third places" (see also Jacobs 1961; Putnam 2000; and Klinenberg 2018). 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.

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" (Business Wire 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" (Business Wire 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 about the socializing benefits the café created in the neighborhood: "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" (Business Wire 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 neighborhood entrepreneurship after the introduction of a Starbucks café. We focus on census tracts, geographic areas commonly used to designate neighborhoods in the U.S. (Krieger 2006; Sperling 2012). Census tracts are intended to be relatively stable over time, but 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, and the number and characteristics of new businesses established in that tract. We describe each dataset in turn.

2.1 Starbucks and Other Third Place Locations

We identify Starbucks locations using Reference USA (Infogroup). Reference USA is a business marketing database tracking local establishments. It uses Yellow Pages and other local listings to identify businesses, their industry code, their location, and contact information. We obtained annual snapshot files of Reference USA from 1997 to 2021 through the Wharton Research Data Service (WRDS). These annual snapshots include all local establishments as tracked by Reference USA in that year, including their latitude and longitude, allowing a retrospective picture of establishments in a neighborhood.

To identify Starbucks 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 Reference USA 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*),[5] 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, indicates whether a Starbucks has opened in an neighborhood and this neighborhood that did not have any coffee shops prior to the Starbucks. *Gets First Starbucks—Has Prior Café* indicates whether a Starbucks has opened in a neighborhood but this neighborhood had prior coffee shops. *Gets First Café—No Prior Café* records the opening of the first coffee shop in a neighborhood when the coffee shop is not a Starbucks. *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 years in which a Starbucks opens in a neighborhood, for those neighborhoods for which *Gets First Starbucks—No Prior Café* is equal to 1. At its height, almost 600 neighborhoods received their first coffee shop thanks to the entry of Starbucks. In total, we identify 3,970 census tracts that had no coffee shops in 1997 but received their first coffee shop as 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 the Starbucks opening dates.

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 recorded the Starbucks locations listed under Urban Coffee Opportunities in this website (Appendix Figure A1 includes a screenshot). We triangulated using Yelp, directories of Starbucks locations, and newspaper announcements of Starbucks openings. We identified 68 Magic Johnson Starbucks locations (see Appendix Table A5).[6] We matched these locations with Reference USA to obtain their opening year. Three locations did not match any establishment in Reference USA, leaving us with 65 in total.

[5] Coffee shops are by far the most common establishment type in NAICS code 722515; however, the code includes 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 what we believed to be candy stores and ice cream shops, and our results were effectively unchanged.

[6] 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.

The match rate between the firms listed on the UCO website and Reference USA also serves as a validation of how well our sample covers Starbucks locations. Ninety-six percent of Starbucks in the UCO data are also in Reference USA (i.e., 65 out of 68). It is notable that UCO targeted urban and minority neighborhoods—which may be less accurately covered by Reference USA. Furthermore, UCO was formed at a moment in history early in the development of the Reference USA sample (1998-2005), a period during which unresolved measurement problems, if the data had them, would be more likely to present themselves. We are therefore reasonably confident that our whole sample closely approximates 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 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.[7]

Business registration represents the legal process through which a new firm is created. In the U.S., filing a business registration is a requirement to create all corporations, limited partnerships, and limited liability companies. In fact, it is the filing itself that legally creates the firm.[8] 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).

We create four measures of entrepreneurial activity in 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 used to differentiate firms of higher economic potential following Guzman and Stern (2015, 2020). *Number of Corporations* is the number new corporations (as opposed to LLCs or limited partnerships).

[7] 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).

[8] General partnerships and sole proprietorships do not require a legal registration to be founded.

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 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[9] 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 a high value acquisition, IPO, or high employment (Guzman and Stern 2015, 2020; Andrews et al. 2022). *Number under Delaware* represents the number of firms under Delaware jurisdiction. This jurisdiction 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 foundation to deal with corporate arbitration, including a highly reputed Court of the Chancery. Furthermore, Delaware's decisions and legal framework are generally regarded as pro-business. If a startup is raising institutional venture capital, then being a Delaware corporation is typically required by the investors. However, such registration also comes with additional costs, as it requires maintaining two different registrations (one in Delaware, one in the local state).[10] Consistent with the benefits of Delaware accruing to more sophisticated firms, over 60% of all public firms are in Delaware jurisdiction, even though Delaware incorporated firms represent less than 4% of all business registrations. Empirically, entrepreneurs that select into Delaware are predicted to be 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

[9] Corporations are a separate legal entity independent of the founder. The corporation is required to pay corporate income taxes; the founder is required to pay taxes on dividends or salary income. Limited liability companies offer pass-through taxation, which means income is only recognized as personal income. If small, corporations can also file taxes as S-corps which also allow pass-through taxation.

[10] Based on informal conversations, we have learned that the double-registration amounts to an additional administrative burden of a few thousand dollars for the startup. While this amount is small for the prototypical high-growth startup, it may be significant for a local entrepreneur.

list in Guzman and Stern (2015).[11] 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 the total population and black, Hispanic, and Asian populations from the 2000 Decennial U.S. Census, retrieved at the ZIP code level. The data are aggregated and converted to 2010-vintage census tract-level values using the HUD 2012 Q1 ZIP Code to Tract Crosswalk Table to match our reporting unit of 2010-vintage census tracts.

To estimate population density, we use land area data from the Tiger Line shapefile for the 2010 ACS. We use the HUD 2012 Q1 ZIP Code to Tract Crosswalk Table[12] 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 locations that could have opened 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 multiple data sources, we developed three samples for analysis, focusing on census tracts that did not have coffee shops. The first sample is composed of those tracts where Starbucks successfully entered and those where Starbucks attempted to enter but was rejected.

[11] The approach identifies all words that are over-represented in the names of Reference USA firms that match to industries belonging to the following 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.”

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

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; it is composed of tracts where a Magic Johnson Starbucks opened and, based on a matching procedure we developed, a draw from a distribution of control tracts observably similar to those with a Magic Johnson Starbucks.[13] Tracts with a new Starbucks café that is not a Johnson-Starbucks one are not part of this sample. The first coffee shop in the Johnson-Starbucks 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 in this sample. Note that, in contrast to other analyses, we are not constrained by the fact that the Reference USA data starts in 1997 because we know there were no Magic Johnson Starbucks cafés before 1998.

The third sample consists of all tracts that did not have any coffee shop before 1998. We compare those that received their first coffee shop as Starbucks after 1998 to those that never got any kind of coffee shop.

Table 2 reports neighborhood demographics for each relevant group in our sample: neighborhoods that received their first Starbucks and had no prior cafés, neighborhoods that received their first Starbucks and had prior cafés, neighborhoods where a Magic Johnson Starbucks opened, neighborhoods where a Starbucks planned to open but was rejected, and other neighborhoods that had no coffee shops and never received a Starbucks. A few patterns are notable. One, neighborhoods where Starbucks was the first café and neighborhoods that already had prior cafés when Starbucks entered are highly similar across all demographic dimensions. They have similar incidences of minorities, population density, and wages. Two, in contrast, the neighborhoods with no coffee shops that did not receive a Starbucks (column v) have lower wages and a lower share of black, Hispanic, and Asian residents. Three, neighborhoods where Starbucks planned to open but was rejected also have similar wages to other Starbucks neighborhoods, but they are more urban (twice the population density) and have fewer black, Hispanic, and Asian residents. Four, Magic Johnson neighborhoods have significantly higher

[13] Our matching procedure seeks to find tracts that have similar proportion of black residents, wages, and population density to those that received a Magic Johnson Starbucks. To achieve this, we first split all census tracts in ventiles for each of these three variables and estimate, for each ventile j of measure v , the share $s_{j,v}$ of tracts that have a Magic Johnson Starbucks. Then, for each tract i, we estimate a sampling weight equal to the product of these shares $w_i = s_{i,j,black} * s_{i,j,wages} * s_{i,j,popden}$ and draw 5000 control tracts based on these weights. A comparison of the distribution of these observables for the Magic Johnson and control tracts is provided in Appendix Figure A2.

population density, four times that of a normal Starbucks tract, four times the number of black residents, and 30% more Hispanic residents. This pattern is consistent with UCO's focus on inner-city African American neighborhoods.

Each of these samples provides distinct advantages and disadvantages for our empirical analysis. The sample based on rejected Starbucks cafés 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 neighborhoods that are highly disadvantaged and therefore more 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 overstates the benefits of third places, because the association with Magic Johnson additionally led to significant media attention and community buy-in. Studying all tracts without coffee shops offers a larger set of both treatment and control tracts, allowing higher precision and 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 careful 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 following 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 avoid "prohibited" comparisons that may create biased estimates (de Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021). Similar to Callaway and Sant'Anna (2021), the Wooldridge approach accounts for this issue by incorporating cohort and time-specific coefficients. Specifically, in each year $t,$ for each census tract i that was 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 an indicator representing the individual year in which tract i was treated (and 0 if it is never treated), and $\beta_{t\tau}$ the individual coefficients for each treatment cohort and year. We report the average marginal effects (as Poisson elasticities) for our main estimate. Standard errors are clustered at the county level.

One disadvantage of implementing this extended two-way fixed effects model is that it requires including a fully interacted set of indicators by treatment cohort, which 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 control approach to account for selection into treatment. When we run this model, we prefer using the number of new firms as the dependent variable, instead of a transformation such as the logarithm or the inverse hyperbolic sine, given recent concerns over the lack of validity of these transformations around zero (Cohn et al. 2022).

For the rejected Starbucks analysis, we focus on a comparison between treated and never-treated tracts, since the tracts that reject a Starbucks are by definition never treated. For the other analyses, we compare treated tracts to not-yet-treated 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 good candidates for a coffee shop are different from others in ways that are unobservable to us, we see the locations used as controls in the not-yet-treated specification as also appealing to Starbucks, but simply receiving the café later.

4. Results

4.1 Event Study Estimates

Our first set of results, in Figure 2, presents event studies estimating, for each neighborhood, the difference in the number of new firms before and after the opening of the first Starbucks (coefficients are reported in the Appendix).

Panel A uses the tracts with a rejected Starbucks as controls. There are no pre-trends in the number of startups before Starbucks opens. Once the Starbucks opens, the coefficient shows minimal effect at year 0, and then increases and becomes positive and significant after year 2. In our appendix, we also present robustness tests varying the definition of a “rejected” Starbucks.[14]

Panel B considers the number of startups after the opening of Magic Johnson Starbucks cafés. The number of startups increases slightly in year 0, and plateaus at a higher level after two years from opening. The increase is significantly larger than the other analyses. This difference is consistent with Magic Johnson’s thesis that these neighborhoods were severely lacking local socialization establishments.

Panel C expands our analysis to all census tracts without coffee shops. The estimates have more precise standard errors than those in Panel A. The point estimate is slightly higher, though within the same confidence interval. The plot shows flat pre-trends before the opening of a Starbucks, and an increase over time after. By year 7, the neighborhood is experiencing 3.9 additional startups per year, compared to a sample mean of 21 startups per year.

These results document a positive increase in entrepreneurship for neighborhoods where a Starbucks opens and no 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 other businesses opening contemporaneously with Starbucks 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. However, if this type of bias was the predominant driver of our results, then we should have seen differences in registrations for such businesses at year 0 or even year -1, before the establishment opened.

[14] Four of the neighborhoods that rejected a Starbucks ultimately did get one years later. We report our event study removing all observations after the neighborhood’s future Starbucks opens (Figure A4) and removing these neighborhoods altogether (Figure A5). Our results remain similar to the main result.

4.2 Average Increase in Neighborhood Entrepreneurship

We next consider the average effect of receiving a new Starbucks on neighborhood entrepreneurship. Moving beyond event studies allows us to use count data regressions through Poisson specifications rather than linear models. Estimating both Poisson and linear models also allows us to evaluate the extent to which some outlier census tracts may be driving our results.

Table 3 column 1 reports a Poisson regression with rejected Starbucks. For this column, we use the traditional Poisson two-way fixed effects estimator to allow us to incorporate two treatments simultaneously: our main treatment—the opening of a Starbucks—and a placebo treatment which is equal to 1 for the years after the rejected Starbucks was expected to open and 0 otherwise. The coefficient for actual Starbucks entry is positive and significant with a value of 0.09, while the one for the rejected Starbucks is noisy with a negative value. While the entry of a Starbucks predicts more entrepreneurship, the mere expectation of entry does not.

Column 2 reports the extended Poisson two-way fixed effects. Here, and in all subsequent columns, we focus on the average change in startups during the first seven years. The coefficient is 0.11 and significant at the 1% level, which suggests an 11.8% increase in the number of new firms registered each year. Column 3 is the linear estimate. The coefficient estimates an additional 5.7 firms per tract, implying an increase of a 18% increase in new firms, relative to the mean.

Columns 4 and 5 exhibit estimates of the increase in startups following of the opening of a Magic Johnson Starbucks. As in the event study, the effect is much larger for the Magic Johnson cafés. We estimate an increase of 30% to 36% on average in the first seven years, or 4.3 to 5.9 firms, relative to the mean number of startups per tract, in this sample.

Columns 6 and 7 study all tracts without coffee shops. The effects are more precise. The estimate for our linear specification represents an increase of 13.6%, more than twice as large as the Poisson model (5.5%), suggesting that, while effects are positive on average, there are some outlier tracts.

The remaining sections focus on understanding the mechanism.

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

Tables 4 and 5 begin to investigate whether the effect of Starbucks is through a networks mechanism. Table 4 reports the change in entrepreneurship when Starbucks enters a neighborhood that already has cafés and when cafés other than Starbucks enter a neighborhood. We report both average effects and year-by-year effects. Column 1 presents coefficients for the effect of opening a Starbucks among neighborhoods with no prior cafés—i.e., the same treatment as in the prior section. Column 2 considers neighborhoods with prior cafés. The differences are stark. Starbucks does not increase neighborhood entrepreneurship among neighborhoods that had existing coffee shops. The difference between the two columns is consistent with the benefit of Starbucks being dependent on the local incidence of institutions and locals' ability to form and sustain social networks. By and large, the mode of entry for Starbucks is similar for the neighborhoods in either column, as are their demographic characteristics (see Table 2). However, the effect of Starbucks is different depending on whether local residents already have other locations that serve as substitute establishments to socialize. If the Starbucks effect were only due to signaling, we would not expect the presence of other coffee shops to matter.

Column 3 exhibits estimates for the change in new startups following the opening of 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 social interaction, its effect should be smaller, and potentially zero. Indeed, we observe only a small and fleeting effect for coffee shops that are not Starbucks.

It is useful to clarify the relationship between column 2 and column 3, since, because of differences in their samples, they are not the inverse of each other. Column 2 focuses on neighborhoods with one or more coffee shops. 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. Column 3 focuses on tracts with no coffee shops, where treated tracts receiving their first one. The effect in both columns is small or zero, which means that Starbucks has little effect when there are several other potential third places (2.5 coffee shops on average), but adding a single non-Starbucks coffee shop to a neighborhood with no coffee shops is not enough either.

In Table 5, we compare the effect of Starbucks cafés to that of other companies that operate on different models. The first column considers Dunkin' Donuts, the second largest coffee chain brand in the U.S. and one which, in contrast to Starbucks, does not expressly seek to create a third-place experience. Dunkin' sells coffee at 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 4 makes evident how different Dunkin' and Starbucks are. Using data from SafeGraph, a company offering geolocated data and visit information for U.S. points of interest, we estimate the average number of hours that visitors remained in each location for Dunkin' and Starbucks, excluding visits that remained in the shop longer than 4 hours, as those are likely employees. As the figure shows, people spend far more time at Starbucks than Dunkin' coffee shops. These differences motivate our empirical comparison. While Dunkin' also selects promising neighborhoods, they do not offer a third place. If a network mechanism is driving the result, then the effect of the opening of a Dunkin' Donuts should be close to zero. The first column of Table 5 shows that this is the case.

In column 2, we examine the effect of a different coffee chain, Caribou Coffee. Caribou offers a third place concept similar to Starbucks', mostly in Minnesota and Wisconsin. Figure 5 shows that the distribution of visit length across these two chains is similar. Table 5 shows that the estimated effect of the opening of a Caribou Coffee location is positive and significant, with a point estimate close to that of Starbucks' (2.3 for Caribou vs 2.7 for Starbucks). Altogether, these results suggest that our estimated increase in neighborhood entrepreneurship is associated with whether the new coffee shop offers opportunities for people to socialize.

4.4 Selection of Starbucks Locations and Machine Learning Analysis

The argument of the previous section was that the effect of Starbucks on neighborhood entrepreneurship is heterogeneous, depending on whether the neighborhood already has a space for socializing. We study this heterogeneity in more detail using machine learning. The previous event studies relied on a staggered treatment over time, but current machine learning methods are not developed for panel data. Therefore, we focus on a cross-sectional version of our question. We study whether, among those neighborhoods that did not have a Starbucks in the year 2000, there is a difference in the 2010 entrepreneurship between those that had received a Starbucks by 2010 and those that had not. We do not limit this sample based on whether there are other coffee shops in the neighborhood.

We obtained 4,512 neighborhood characteristics as recorded in the year 2000 by downloading from the IPUMS National Historical Geographic Information System (NGHIS) all tract-level measures reported from the 2000 Decennial Census's long-form survey. The long-form census was administered to one out of every six households and includes questions on income, occupation, home ownership, disability, and many others. Since our startup counts are for 2010 tract definitions, we use the 2000 tract to 2010 tract correspondence provided by the census and estimate values for each 2010 tract based on the percent area covered.[15] We randomly split the final set of census tracts into a 60% training sample and a 40% estimation sample.

We report two analyses. The first characterizes the selection process: which neighborhood characteristics predict a Starbucks will open? We estimate a gradient-boosted tree with cross-validated parameters where the outcome is an indicator of whether the neighborhood received a Starbucks by 2010 based on all 2000 census-based observables. The ROC score in the estimation sample is 0.75: for two random neighborhoods, one where a Starbucks opened and one where it did not, the model will predict a higher probability for the one with Starbucks 75% of the time.

Next, we predict, in our estimation sample, the probability of a Starbucks opening for each neighborhood. Tables A7 and A8 in the Appendix report the 50 features that have the most positive and most negative correlation to this propensity score.[16] Both tables highlight features consistent with media portrayals and common intuition on the neighborhoods Starbucks would believe are promising. The tract features that correlate positively include the number of residents in managerial and professional jobs, the number in computer-related jobs, multiple measures related to income (household income, aggregate income, income by gender), multiple measures related to being young and a high-income earner, and counts of those recently migrating from other MSAs. All of these are indicative of the bohemian bourgeois culture often associated with Starbucks (Brooks, 2001; Florida, 2002). They confirm Starbucks mainly focused on affluent, professional, middle, and upper-middle-class neighborhoods. The most negatively correlated features also support this conclusion. They include measures of low income, such as low mortgage payments and a higher share of residents below the poverty line, as well as having a higher share of senior residents, and having a high percentage of residents who live in rural areas.

[15] For example, if census tract C in 2010 is accounted for, by area, 70% by the 2000 tract A and 30% by tract B, each variable will take the value $x_{2010,C} = 0.7x_{2000,A} \times 0.3x_{2000,B}$.

[16] An alternative approach could use feature importance scores, but these scores are highly sensitive to which other features are included and our data has many highly overlapping variables (e.g., total income, and income by each gender and race groups), rendering them uninformative.

In Table 6 we report a regression of the number of local coffee shops in 2000 on the propensity score. The coefficient is positive both with and without county fixed effects. This is consistent with Starbucks seeking larger markets, as having cafés in the neighborhood would indicate it is a good market for coffee. But it is inconsistent with selection driving our results. While Starbucks is less likely to select neighborhoods without cafés, those are the neighborhoods where we find an effect of Starbucks on local entrepreneurship.

Our second analysis studies treatment heterogeneity. In our training sample, we estimate a causal forest (Wager and Athey, 2018) in which the dependent variable is the number of startups registered in 2010 in the tract, treatment is getting a Starbucks, and the controls all neighborhood features from the 2000 census. We then predict the treatment effect for each neighborhood in our estimation sample and divide each neighborhood's effect by the average of its 2000 and 2010 entrepreneurship to have an estimate of the proportional increase.[17] We would not claim these treatment effect estimates are valid point estimates that account for the endogeneity in selection, but we posit that their correlation to other variables is indicative of where the benefits of Starbucks for neighborhood entrepreneurship are higher. We document two relationships in Table 6. One, columns 3, 4, and 5 report a negative correlation between the number of cafés in the neighborhood and the estimated treatment effect: the more neighborhoods the café has, the lower the predicted effect of Starbucks. Two, columns 6 and 7 report a negative correlation between the propensity to be treated, which was estimated independently through the gradient-boosted tree, and the neighborhood's treatment effect: the neighborhoods in which Starbucks is likely to open are not those where it has the largest impact on entrepreneurship.

Bringing these results together, we find evidence that Starbucks opens exactly in those neighborhoods that have been associated with its image of high income, educated, young consumers. However, these neighborhoods are not the ones where we find Starbucks entry is followed by higher entrepreneurship; those are instead neighborhoods that have a low incidence of socialization spaces and where the addition of a Starbucks may create the most significant change on the local options available to residents.

[17] This approach is equivalent to the proportional growth measures used by Davis, Haltiwanger, Schuh (1993) and Decker et al (2014) for firm employment, and avoids biasing growth estimates toward smaller neighborhoods.

4.5 Additional Evidence for Social Networks Mechanisms Using Geolocated Data

In this section, we investigate heterogeneity across some features of Starbucks cafés to ask whether those Starbucks cafés that are set up to create more social interaction produce larger effects. To do so, we use the 2019 monthly patterns data from SafeGraph. These data use smartphone information to track the number of visitors from census block groups to specific point-of-interests, such as cafés, as long as SafeGraph observes see four visitors in a month. We develop two measures: 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 reflects the potential to form social networks. However, this measure runs the risk of bias because our SafeGraph data are for 2019, which is many years after the Starbucks openings occurred. It is possible that the high levels of socialization we observe 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 square footage of a Starbucks is a less direct measure of the opportunity to form social networks as compared to actual 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 can be measured independently in SafeGraph.[18] In spite of these differences, the measures are highly correlated, as shown in Appendix Figure A7.

Panel A of Figure 3 studies visitor foot traffic. We split the locations by the estimated visits received during 2019 into quartiles and run a Poisson regression. We use a traditional two-way fixed effects estimator because it allows us to consider all treatments simultaneously and use the same control group for all specifications, making the estimates agnostic to the size of each tract. Consistent with a network story, a higher level of traffic matters for our effects. Starbucks cafés

[18] In the SafeGraph dataset, the variable is polygon_class. 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.

with below-median traffic in 2019 have about a third of the effect as those with above-median traffic.

We next study establishment size. We divide Starbucks locations into four natural groups. Those that are very small (less than 50 m^2) and almost always exist in a physical structure with other shops (e.g., 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 in Panel B show an increasing relationship between the square footage of a Starbucks and 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 conducive to an effective third place, such as opportunities for a high level of local interaction and the open space to do so, paired with a large number of visitors, for which we see large increases in neighborhood entrepreneurship following their opening.

4.6 Differences in Startup Industry: Retail, Food, and Real Estate

We provide further evidence on the mechanism by studying the industry of the startups formed. As Magic Johnson noted, Starbucks could serve as "the anchor to attract other businesses" to a neighborhood. In this case, the presence of Starbucks would serve as a catalyst for the neighborhood's local economy. Then, the benefits we document would be economically important but less consistent with a networks mechanism and instead related to signaling effects from Starbucks' opening. These signaling effects are likely to be most relevant to three sectors, retail, food, and real estate.

We identify a startup's sector by following the approach of Engelberg et al. (2021) (see Appendix B); we use the name of firms to categorize startups as belonging to a NAICS industry sector if they have a word that is ten times 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 7 column 1, we report the effect for all startups for which we are able to categorize any industry, for comparability and completeness. Columns 2 to 4 focus on specific sectors. Columns 2 reports the effect for firms in retail, which we consider as any firm belonging to sectors 44-45 (Retail Trade), and 72 (Accommodations and Food). The retail sector could benefit from the presence of Starbucks due to additional foot traffic and because Starbucks offers an amenity for shoppers. However, the estimate, 0.045, is the same, and not larger, than column 1, suggesting our effect is not concentrated only on local retail but instead more generalized. Column 3 repeats the same analysis only for food establishments since coffee consumption may be particularly complementary to food; the estimate is noisier but unchanged.

Next, we consider whether the opening of Starbucks might have increased real estate prices. While real estate professionals have found a positive association between the presence of a Starbucks and real estate prices (e.g., Anderson 2015; Humphries and Rascoff, 2015), evidence in economics is more measured. In their systematic analysis of U.S. neighborhood amenities and real estate prices, Glaeser, Kim, and Luca (2018a, 2018b) find that the presence of Starbucks only minimally explains differences in real estate prices: "[the Starbucks effect is a] large effect, both economically and statistically, but the added explanatory power created by the Starbucks control is modest. […] The r-squared added by controlling for Starbucks, over and above the year dummies, is only .002 […]" (Glaeser, Kim, and Luca 2018b: p. 7). In addition, they find that "the presence of Starbucks is associated with price growth, but Starbucks presence is hardly a great predictor of which areas will grow" (Glaeser, Kim, and Luca 2018b: p. 7). Instead, in results that are parallel to what we find in Section 4.5, they find the activity of a Starbucks (in their case, visits proxied by Yelp reviews) is what predicts an increase in real estate prices.

To study the effect of Starbucks on real estate in our data, we consider in column 4 the startups associated with sector 53 (Real Estate and Rental and Leasing) under the assumption that a growing real estate market should also experience an increase in local real estate startups, such as leasing offices and real estate agents. The coefficient is very small, 0.005, and not significant. Consistent with Glaeser, Kim, and Luca, we do not find the opening of Starbucks has a large effect in local real estate markets.

While our goal is not to rule out the signaling mechanism, nor do we argue that we definitively do so, we believe this evidence supports our argument that a networks mechanism plays an important role behind the benefits we observe from the opening of Starbucks café on neighborhood entrepreneurship.

4.7 The Effect of Free Wifi at Starbucks

Next, we consider the role of Starbucks in providing a convenient place to do remote independent work. By having food, wifi, bathrooms, and comfortable seating, Starbucks can make it easier for some entrepreneurs to work on their firms. We focus our analysis on differences in the quality of wifi at Starbucks under the assumption that good wifi is critical for most remote work. The quality of wifi available at Starbucks evolved over time. Before 2002, the company did not offer any wifi. From 2002 to 2008, it offered paid wifi. From 2008 to 2010, it offered two hours of free wifi only to Starbucks Rewards members. After 2010, unlimited wifi began (see Starbucks, 2024). Table 8 repeats our analysis of all neighborhoods, but limits to the subsample of years before the adoption of unlimited wifi.[19] Column (1) reports a statistically significant effect of 1.2 new startups per year, on average, before 2002. Column (2) reports an effect of 4.3 when considering all years before 2008. Column (3) reports all years before 2010, with an effect of 3.5. None of these estimates are markedly different from the main effect of 2.7 startups, even though unlimited wifi was not available during their sample years. In fact, columns (2) and (3) are statistically larger.[20] Whether they are larger because these years represent the height of popularity of Starbucks as a social hub, or for another reason, may be a question to study in future work.

4.8 The Effect of Starbucks on Nearby Neighborhoods

We now consider a different type of evidence of a network effect. So far, we have studied the impact of Starbucks on the number of new startups in the census tract where that café opens. But visitors to a Starbucks are also likely to be from other nearby tracts, creating geographically localized spillovers. It is well established that such proximity effects, when occurring through networks and in-person interaction, dissipate quickly with distance. This pattern also holds for entrepreneurship. For example, when considering Midtown Manhattan, Rosenthal and Strange (2005) and Arzaghi and Henderson (2008) show that these networking benefits are non-existent above a distance of one mile. Manhattan, however, is more urban than anywhere else in the U.S.

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[19] We report the linear estimates because the Poisson estimator, which uses maximum likelihood, will not allow us to have a comparable sample across regressions as it will drop different census tracts depending on the years.

[20] We test this by following Paternoster et al (1998) and estimating a z-score as $Z = \frac{b_1 - b_2}{\sqrt{(SE_1)^2 + (SE_2)^2}}$ (see also Cohen et al, 2003, pgs. 46-47).

After examining the Bay Area, Kerr and Kominers (2015) show that citations between patents fall quickly beyond a 15-minute drive. Across the whole U.S., Rosenthal and Strange (2003) see proximity benefits dissipate within 10 miles. In contrast, local effects on entrepreneurship that are not knowledge-based, such as the ability to access employment and capital, dissipate more slowly (for example, according to the Census Bureau, the average commute time in New York is 35 minutes). If the Starbucks effect is due to networks, then we would expect to see geographic spillovers that decrease rapidly with distance.

Table 9 exhibits changes in neighborhood entrepreneurship for census tracts that also did not have coffee shops but had a Starbucks open in a nearby tract, based on the distance between the tracts' centroids (geographic center). 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 the centroid of most neighboring tracts is higher than that. Because there are few neighboring centroids less than 1 km apart, estimates based on that threshold are too noisy (column 1). Columns 2 through 4 exhibit the results for neighborhoods that have a Starbucks opening within 1-2 km, 2-5 km, and 5-10 km. We observe a positive effect of Starbucks opening on these nearby neighborhoods. This effect is smaller in magnitude, and it decays with distance, as expected. Consistent with a knowledge-based process, the decay is rapid: for neighborhoods just 1-2 km away, the effect is one-fourth of the main effect, and for neighborhoods beyond 2 km less than one-tenth.[21]

[21] As a robustness test, we report in Figure A8 a continuous difference-in-differences estimate (Callaway et al. 2024). We study, for all neighborhoods without coffee shops that also never get a Starbucks, a treatment that varies on its 'intensity' based on the distance between the centroid of a neighborhood and the first Starbucks that opened in the county. This sample is different from Table 8, since Table 8 focuses only on tracts within 10 kilometers, whereas counties typically cover areas of thousands of square kilometers. The approach also imposes additional assumptions to allow for a continuous estimate. Yet, even after these differences, the estimate is consistent with Table 8 – the effect of a Starbucks opening on neighborhood entrepreneurship is positive and decreases with distance.

4.9 Heterogeneous Effects Across Growth Orientation

We now assess the type of entrepreneurship stimulated and its potential for economic impact. It is possible that the Starbucks cafés mostly increase low-tech businesses, which have lower economic multipliers (i.e., additional jobs created).[22] On the other hand, given the high importance that face-to-face interaction and social networks play in innovation and high-growth firms (Stuart and Sorenson 2007; Catalini et al. 2022), it is also possible that the effect is larger for more innovative firms.

Our starting point is a distinction in the entrepreneurship literature between two types of firms. One, the majority of firms, is those small businesses that, even if important for neighborhoods or their owners, tend to remain small and are unlikely to create significant employment or productivity growth. The other has been called high-growth (Guzman and Stern 2020), innovation-driven (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 outsize outcomes that drive economic growth.[23] Recent work has shown that a firm's potential for high growth is partly predictable from its business registration information. For example, firms that are likely to grow will 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 Starbucks cafés contribute to high-growth entrepreneurship.

Column 1 of Table 10 reproduces our estimate for all firms, for ease of comparison. Column 2 focuses on corporations, excluding LLCs and limited partnerships. 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 the number of new corporations per year in the tract. Column 3 focuses on firms under Delaware jurisdiction, and the effect remains at 8%. 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 technology. Because the lexicon used in their names was the main classification mechanism, these firms are not necessarily growth-

[22] Bartik (2020) estimates that while the average U.S. job has an economic employment multiplier between 1.3 and 1.7, high-tech jobs can have as high as 2.5 or 3.

[23] While the precise definition of high-growth entrepreneurs and incidence depends on the measure, estimates in Guzman and Stern (2020) place the number below 5% of firm registrations.

oriented, and can also include many small businesses, such as local-technology 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.

4.10 Other Types of Third Places

As a final analysis, we expand our approach to consider the coffee shop effect relative to that of other potential social establishments. Table 11 has the same format as Table 3 but considers the opening 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 speculate that one possibility is that the social structure of the U.S.—and the use of third places—has changed in a few ways between the two periods. In particular, whereas historically bars in the U.S. used to be venues for highly-organized social activity where multiple social movements and civil rights actions began, today those activities may be less common in U.S. bars relative to purely social drink. In this respect, they may lack the continued social significance that, say, British pubs appear to maintain. The effect of restaurants, in contrast, is positive. This finding is also consistent with a network benefit 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. These effects are consistent with a network mechanism. They are limited to neighborhoods without prior coffee shops, and do not occur with other large coffee chains that do not offer a third place experience. The effects are larger for Starbucks with more visits and with a higher square footage. They decrease quickly with distance.

It is important to recognize that 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 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, or the way artistic activities take place in a neighborhood (e.g., see Jeong 2023). A clear understanding of how space shapes local business activity, including improving underserved neighborhoods, requires far more investigation.

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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: We report summary statistics for census tract-year observations spanning from 1997 to 2016. There are 1,357,664 observations in our data. The sample size in our analysis is smaller than the number of observations reported in this summary statistics, due to our focus only on tracts without prior coffee shops. Detailed definitions of each measure are presented in section 2.

Table 2: Summary Statistics across Analytical Samples

	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
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: We report summary statistics for census tract-year observations in five specific analytical samples used in our study, including tracts that received a Starbucks, those that rejected one, and others. Variables and each sample definition are explained in section 2. Column v) refers to the census tracts that did not have a prior coffee shop but also did not receive a Starbucks.

Table 3: Increase in Neighborhood Entrepreneurship after the Opening of a Starbucks Café for Census Tracts Without Coffee Shops

	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***	5.740***	0.260***	5.927***	0.053***	2.853***
	(0.014)	(0.021)	(1.467)	(0.045)	(1.444)	(0.015)	(0.150)
Rejects Starbucks	−0.077						
	(0.054)						
Percent Increase	9.1%	11.8%	18%	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	2.9	3.5	5.7	4.3	5.9	1.1	2.9
Num.Obs.	76 230	59 453	74 802	105 945	105 945	984 533	1 325 611

Note: We report estimates from difference-in-differences regressions estimating the increase in neighborhood entrepreneurship after the opening of a Starbucks. The sample is neighborhoods that had no coffee shops before the year Starbucks opened one. In columns 1-3 we study all openings and use rejected Starbucks as the control group. For columns 4 and 5, we study the Magic Johnson Starbucks openings and their matched controls. For columns 6 and 7, we include all tract-years with no coffee shops as control. The dependent variable is the number of firms registered in the census tract and year. Poisson TWFE refers to a Poisson regression with year and tract fixed effects. Extended TWFE refers to the Wooldridge (2021) Poisson estimator that uses cohort-specific estimates to account for potential estimation issues. Callaway & Sant'Anna refers to the linear estimator developed by Callaway & Sant'Anna (2021). For Extended TWFE and Callaway & Sant'Anna we report marginal effect average for the first seven years after treatment. Poisson estimates are reported as proportional increase, while linear models as the increase in the number of firms. Columns 2 and 3 use the never treated as a control group. Columns 4-7 use not-yet-treated. 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: Increase in Neighborhood Entrepreneurship after the Opening of a Starbucks Café for Other Types of Tracts

	(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: We report estimates from Poisson extended two-way fixed effects regressions on neighborhood entrepreneurship after the opening of a Starbucks. Panel A, reports the average marginal effect comparing to not-yet-treated over the first seven years after treatment. Panel B reports independent marginal effects by year since treatment. Column (1) presents the effect of the first Starbucks in neighborhoods previously devoid of cafés; Column (2), the effect in neighborhoods that already had cafés. Column (3) exhibits 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

	Not Third Place	Third Place
	(1)	(2)
	Dunkin' Donuts	Caribou Coffee
Coffee Shop Entry	−0.001	2.292***
	(0.221)	(0.552)
Num.Obs.	635 073	172 855

Note: The unit of analysis is the tract-year. The table presents difference-in-differences estimates of the effect of specific brands of coffee shops that are not Starbucks on entrepreneurship, following Callaway and Sant'Anna (2021). Dunkin' 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 in the Midwest. Because Caribou is a regional player, we limit the regression to states where we observe at least 5 treated census tracts. 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: Heterogeneous Effects on the Benefit of Starbucks on Entrepreneurship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	P(Starbucks Opens)		Estimated Neighborhood Benefit of Starbucks (Causal Forest)				
Number of Cafés in 2000	0.021***	0.021***	−0.417***	−0.472***			
	(0.003)	(0.002)	(0.048)	(0.050)			
Indicators of Number of Cafés in 2000							
1 Café					−0.599***		
					(0.073)		
2 Cafés					−0.865***		
					(0.128)		
More than 2 Cafés					−0.917***		
					(0.218)		
Propensity Score							
P(Starbucks Opens)						−2.517***	
						(0.254)	
Quintiles of Propensity Score							
20-40th Percentile							−0.707***
							(0.091)
40-60th Percentile							−1.102***
							(0.149)
60-80th Percentile							−1.430***
							(0.149)
80-100th Percentile							−1.628***
							(0.133)
County Fixed Effects	No	Yes	No	Yes	No	No	No
Num.Obs.	25 580	25 580	25 580	25 580	25 580	25 580	25 580
R^2	0.006	0.237	0.004	0.288	0.004	0.009	0.022

Note: OLS regression. This table uses predictions from machine learning methods to learn about treatment heterogeneity. The sample is all census tracts that did not have a Starbucks in 2000, which we divide into a random 60% training sample and 40% estimation sample. Reported regressions are all in the estimation sample. Columns 1 and 2 use the probability of getting a Starbucks by 2010 as the dependent variable. We estimate this probability by running, in the training sample, a gradient-boosted tree that uses 4512 census tract characteristics available from the 2000 long form Decennial census and then predicting this value in the estimation sample. Columns 3 through 7 are estimates of individual benefits of Starbucks, which we obtain by running, in our training sample, a causal forest model (Wager and Athey, 2018) with the number of startups in 2010 as the dependent variable, getting a Starbucks as treatment, and tract observables as controls. We do not claim the estimates from the causal forest are valid point estimates of the effect; our goal is only to study how they correlate to other observables to elucidate our mechanism. Standard errors, clustered at the county level, in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: The Effect of Introducing a Starbucks Coffee Shop on Entrepreneurship, by Industry of Firm

	(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. 'Food' is categorized under NAICS code 72. 'Retail' encompasses NAICS codes 44, 45, and 72, with the inclusion of code 72 for food businesses, which are typically regarded as local small businesses. 'Realty' corresponds to NAICS 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 8: Increase in Neighborhood Entrepreneurship Before Free Unlimited Wifi

	(1) Before 2002	(2) Before 2008	(3) Before 2010
Gets First Starbucks - No Prior Café	1.152***	4.277***	3.487***
	(0.100)	(0.138)	(0.129)
Num.Obs.	282 900	707 250	848 700

The table reports the estimates during the period before Starbucks offered unlimited free wifi. The quality of wifi available at Starbucks evolved over time. Before 2002, they did not offer any wifi. From 2002 to 2008, they offered paid wifi. From 2008 to 2010, it was two hours of free wifi only to Starbucks Rewards members. After 2010, unlimited wifi began. Standard errors clustered at the county level in parenthesis. Callaway and Sant'Anna estimator in sample of all tracts. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: The Effect of Starbucks Opening on Entrepreneurship in Nearby Neighborhoods

	(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. This table provides difference-in-differences estimates using the Callaway and Sant'Anna estimator to assess the impact of Starbucks openings on entrepreneurship in nearby neighborhoods. The analysis reports four estimates for different proximity sets: within 1 km, between 1-2 km, 2-5 km, and 5-10 km. Standard errors are clustered by county. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: The 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

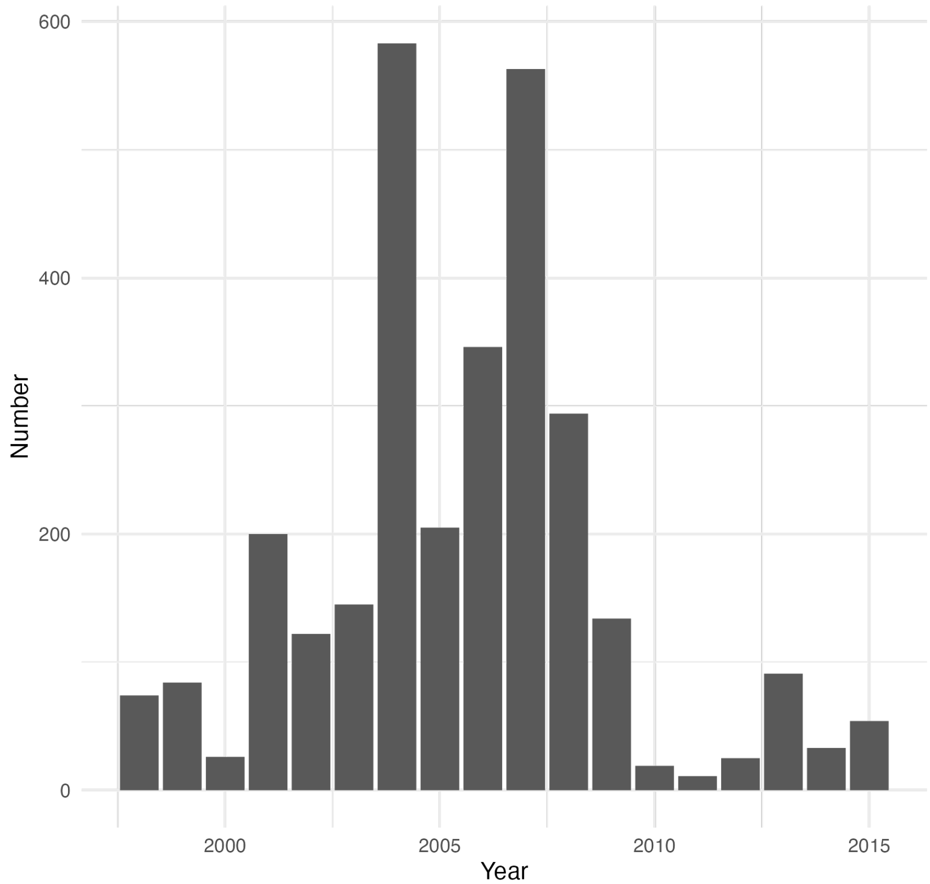
Note: The unit of analysis is the tract-year. This table presents difference-in-difference estimates of the effect of introducing an establishment on entrepreneurship in subsequent years, with two-way fixed effects for county and year. Column (1) reproduces results from the preferred model from Table 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 11: 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 replicating Table 4. Panel A reports the extended two-way fixed effect estimator, reporting the average marginal effect compared to not-yet-treated tracts. Panel B 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; column (2), of a first restaurant in neighborhoods previously lacking restaurants. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

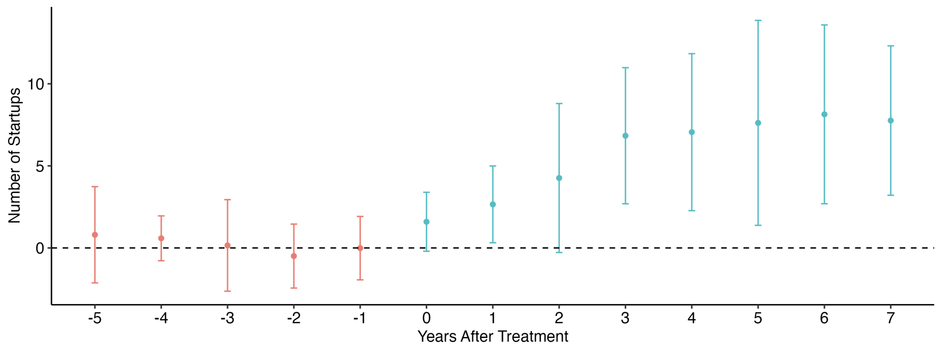
Figure 1: New Starbucks that are First Coffee Shop in Census Tract by Year



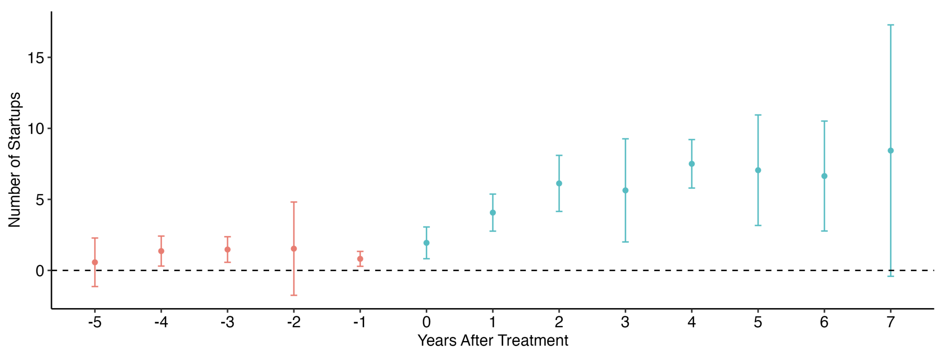
Note: The figure reports the number of census tracts that received their first coffee shop that was also a Starbucks by year.

Figure 2: Event Studies of the Effect of Starbucks Entry on the Number of Startups Founded by Neighborhood

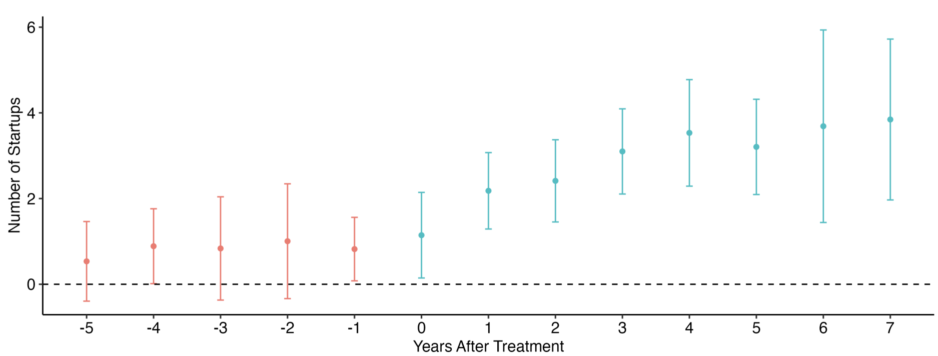
A. *Treated and Rejected Starbucks.*



B. *Magic Johnson Starbucks.*



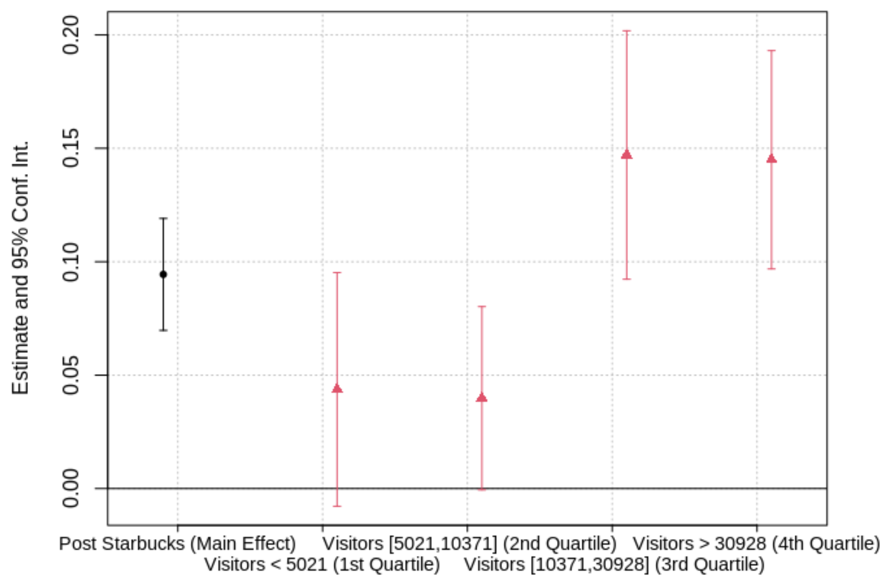
C. *All First Starbucks*



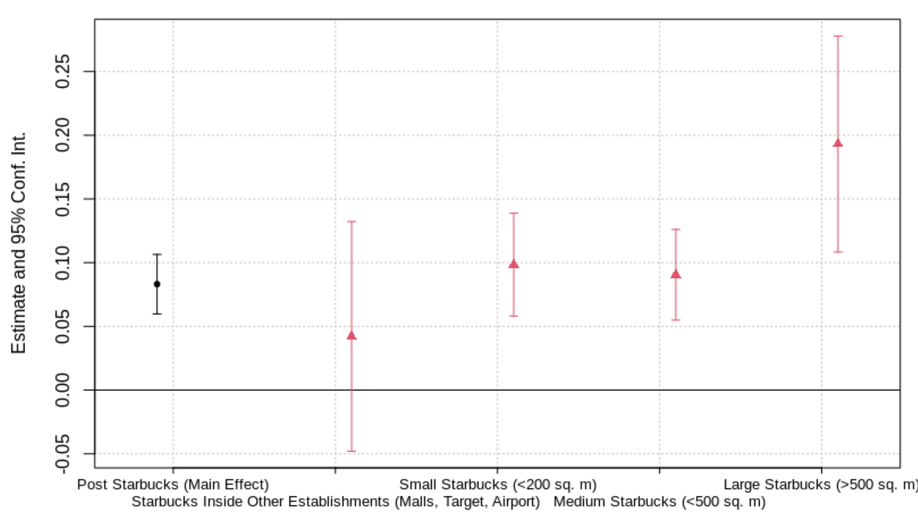
Note: This figure shows the impact over time of the entry of the first Starbucks into census tracts that previously did not have coffee shops, using each of analytical samples defined in section 2. 95 percent confidence intervals are reported. Panel A compares census tracts that received a Starbucks café to those initially targeted by Starbucks for entry but ultimately rejected for reasons external to the company. Panel B compares tracts that received a Magic Johnson Starbucks café to those that did not but that where matched to resemble the distribution of treated tract closely through a matching procedure. Panel C compares tracts that received their first Starbucks café to all tracts that remained without a Starbucks café for our study period. Each figure reports the marginal effects employing the difference-in-differences methodology as per Callaway and Sant'Anna (2021).

Figure 3: Heterogeneous Effects Depending on Visit Patterns and Square Footage

A. *Differences in Establishment Traffic*

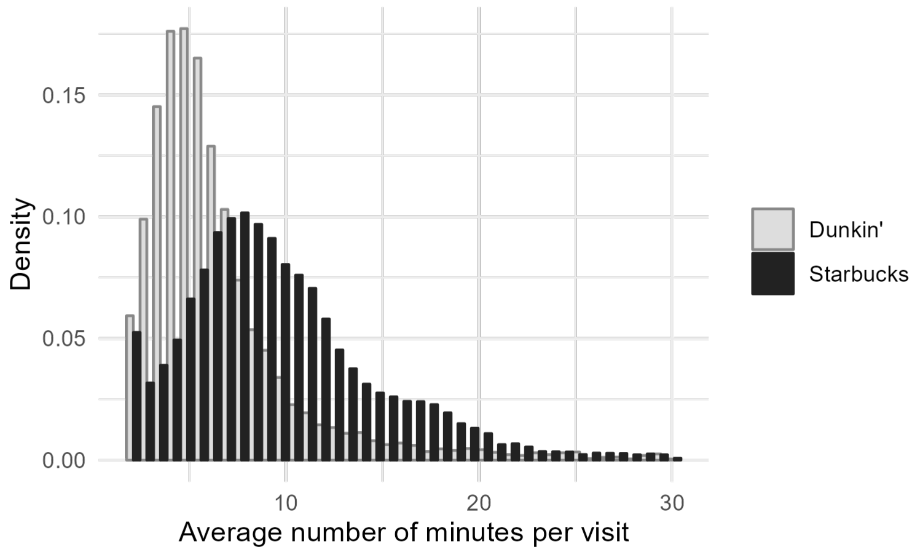


B. *Differences in Establishment Size*



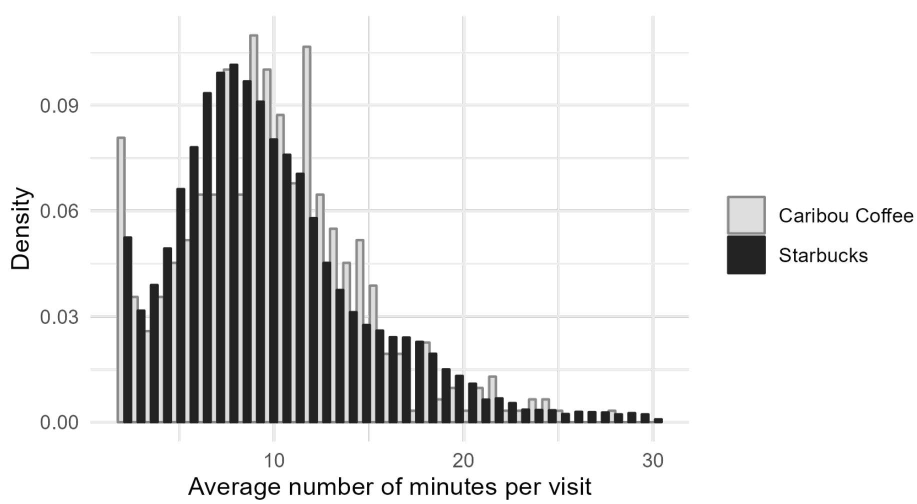
Note: These figures show the differential treatment effects of the first Starbucks entry on neighborhood entrepreneurship, segmented by the establishment's foot traffic and size. In Panel A, the analysis is based on the differentiation in foot traffic at Starbucks locations, whereas Panel B focuses on variations in store square footage.

Figure 4: 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 most 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 5: 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 most 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 measures from tract-years spanning 1998 to 2020. Detailed variable definitions are presented in section 2. 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 2. 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	Planned Address	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

Note: This table lists Starbucks locations that were proposed but ultimately rejected due to non-economic factors such as denials by local architectural boards, zoning board rejections, and community resistance. * in the "Rejection Year" column indicates neighborhoods that initially rejected Starbucks but did eventually receive a Starbucks, albeit at varying intervals. For instance, Berkeley, Boise, Palatine, and Yakima opened locations soon after their initial rejections, whereas Grand Rapids and Fairborn opened locations more than five years later. Recognizing these variations, we employ different sample specifications: (1) using the rejection year for all neighborhoods, (2) excluding all neighborhoods that eventually received a Starbucks, and (3) excluding neighborhoods only after they have actually opened a Starbucks (thus accounting for the period between rejection and store opening).

Table A4: 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 A4: 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 A5: Not-Yet-Treated Poisson Estimate for Rejected Startbucks

	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 A6: Coefficients for Event Study Estimates

	Rejected Sample	Magic Johnson Sample	All Census Tracts Sample
Time to Starbucks Entry(-5)	0.803	0.573	0.688***
	(1.157)	(0.766)	(0.107)
Time to Starbucks Entry(-4)	0.588	1.362**	0.989***
	(0.539)	(0.499)	(0.141)
Time to Starbucks Entry(-3)	0.154	1.471***	0.942***
	(1.101)	(0.400)	(0.130)
Time to Starbucks Entry(-2)	−0.494	1.532	1.058***
	(0.769)	(1.560)	(0.121)
Time to Starbucks Entry(-1)	−0.012	0.814**	0.858***
	(0.762)	(0.253)	(0.152)
Time to Starbucks Entry(0)	1.595*	1.941***	1.207***
	(0.709)	(0.522)	(0.110)
Time to Starbucks Entry(1)	2.656**	4.070***	2.266***
	(0.923)	(0.621)	(0.153)
Time to Starbucks Entry(2)	4.260*	6.126***	2.186***
	(1.792)	(0.926)	(0.154)
Time to Starbucks Entry(3)	6.836***	5.635**	3.051***
	(1.636)	(1.755)	(0.178)
Time to Starbucks Entry(4)	7.053***	7.505***	3.317***
	(1.888)	(0.953)	(0.160)
Time to Starbucks Entry(5)	7.618**	7.054***	3.199***
	(2.464)	(1.911)	(0.173)
Time to Starbucks Entry(6)	8.140***	6.645***	3.728***
	(2.150)	(1.846)	(0.221)
Time to Starbucks Entry(7)	7.761***	8.436*	3.869***
	(1.797)	(4.089)	(0.231)
Num.Obs.	3562	5045	69 769
Std.Errors	by: county	by: county	by: county

Note: The table reports the coefficients corresponding to Figure 1, detailing dynamic group-time average treatment effects employing the method proposed by Callaway & Sant'Anna (2021). Column (1) considers the 'never treated' as the control group, whereas Columns (2) and (3) uses the 'not yet treated' as the control group. Standard errors clustered at the county level in parenthesis. Significance levels are indicated as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

N	VariableTable	VariableUniverse	VariableDescription	Corr.
1	Sex by Occupation Type	Persons	Male >> Management, professional, and related occupations	0.376
2	Upper Contract Rent Quartile	Persons	Upper contract rent quartile	0.372
3	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units Paying Cash Rent	Lower contract rent quartile	0.367
4	Sex by Industry Type	Persons	Male >> Professional, scientific, management, administrative, and waste management services	0.361
5	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units Paying Cash Rent with a Householder Who Is White Alone, Not Hispanic or Latino	Aggregate gross rent	0.356
6	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units with Cash Rent	3 or more bedrooms >> $1,000 or more	0.355
7	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Civilian Noninstitutionalized Persons 18 to 34 Years of Age Not Enrolled in School	Male >> No disability >> Not high school graduate	0.354
8	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Nonfamily Households	$60,000 to $74,999	0.353
9	Sex by Detailed Selected Management, Professional, and Related Occupation Type	Persons	Female >> Management, business, and financial operations occupations: Management occupations, except farmers and farm managers	0.353
10	Sex by Detailed Selected Management, Professional, and Related Occupation Type	Persons	Male >> Management, business, and financial operations occupations: Business and financial operations occupations	0.352
11	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Civilian Noninstitutionalized Persons 18 to 34 Years of Age Not Enrolled in School	Female >> No disability >> Bachelor's degree	0.350
12	Sex by Detailed Selected Management, Professional, and Related Occupation Type	Persons	Male >> Professional and related occupations: Computer and mathematical occupations	0.348
13	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units Paying Cash Rent with a Householder Who Is White Alone, Not Hispanic or Latino	Median gross rent	0.343
14	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Persons 15 Years and Over with Income in 1999	Median income in 1999 >> Female	0.342
15	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Persons 16 Years and Over with Earnings in 1999	Median earnings in 1999 >> Worked full-time, year-round in 1999 >> Female	0.341
16	Sex by Industry Type	Persons	Female >> Professional, scientific, management, administrative, and waste management services	0.340
17	Sex by Industry Type	Persons	Male >> Finance, insurance, real estate and rental and leasing	0.340
18	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Nonfamily Households	$75,000 to $99,999	0.339
19	Sex by Detailed Selected Management, Professional, and Related Occupation Type	Persons	Male >> Management, business, and financial operations occupations: Management occupations, except farmers and farm managers	0.337
20	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units with Cash Rent with Householder Who Is White Alone, Not Hispanic or Latino	$1,000 to $1,249	0.337
21	Time Leaving Home to Go to Work	Persons	9:00 a.m. to 9:59 a.m.	0.337
22	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Female >> $55,000 to $64,999	0.335
23	Total Aggregate Nonfamily Household Income in 1999	Persons	Aggregate income in 1999	0.335
24	Sex by Occupation Type	Persons	Female >> Management, professional, and related occupations	0.335
25	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Female >> $50,000 to $54,999	0.334
26	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Nonfamily Households	$50,000 to $59,999	0.332
27	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Median household income in 1999 >> Owner-occupied	0.331
28	Sex by Detailed Selected Management, Professional, and Related Occupation Type	Persons	Female >> Management, business, and financial operations occupations: Business and financial operations occupations	0.331

29	Unrelated Individuals for Whom Poverty Status Is Determined by Poverty Status in 1999 by Living Arrangement by Educational Attainment	Persons	Income in 1999 at or above poverty level >> Non-family Householder: Not living alone >> High school graduate	0.330
30	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Households	25 to 34 years >> $75,000 to $99,999	0.329
31	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Nonfamily Households	Median income in 1999 >> Female	0.329
32	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Nonfamily Households	Aggregate income in 1999 >> Male	0.328
33	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Persons 16 Years and Over with Earnings	Aggregate earnings in 1999 >> Female	0.328
34	Population Not in Families for Whom Poverty Status Is Determined by Poverty Status in 1999 by Imputation of Income in 1999 (Percent of Income Imputed)	Persons	Income in 1999 at or above poverty level >> No income imputed	0.328
35	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units with Cash Rent with Householder Who Is White Alone, Not Hispanic or Latino	$900 to $999	0.327
36	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Female >> $65,000 to $74,999	0.327
37	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Male >> $75,000 to $99,999	0.327
38	Population 16 Years and Over with Earnings in 1999 by Sex by Work Experience in 1999 by Earnings in 1999	Persons	Female >> Worked full-time, year-round in 1999 >> $55,000 to $64,999	0.327
39	Population 5 Years and Over Living in MSA/PMSA in 2000 that Lived in the U.S. or Puerto Rico in Different House in 1995 by Selected Residence in 1995 by Residence in 1995 - MSA/PMSA Level	Persons	In United States in 1995 >> Different MSA/PMSA in 1995	0.326
40	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Households	25 to 34 years >> $100,000 to $124,999	0.326
41	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Full-Time, Year-Round Workers 16 Years and Over with Earnings in 1999	Aggregate earnings in 1999	0.324
42	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Male >> $65,000 to $74,999	0.324
43	Sex by Industry Type	Persons	Male >> Information	0.324
44	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Households with Householder Who Is White Alone, Not Hispanic or Latino	$100,000 to $124,999	0.323
45	Population 16 Years and Over with Earnings by Sex by Earnings in 1999	Persons	Female >> $45,000 to $49,999	0.322
46	Population 16 Years and Over with Earnings in 1999 by Sex by Work Experience in 1999 by Earnings in 1999	Persons	Female >> Worked full-time, year-round in 1999 >> $65,000 to $74,999	0.322
47	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Civilian Noninstitutionalized Persons 18 to 34 Years of Age Not Enrolled in School	Male >> No disability >> High school graduate (includes equivalency)	0.322
48	Population 16 Years and Over with Earnings in 1999 by Sex by Work Experience in 1999 by Earnings in 1999	Persons	Male >> Worked full-time, year-round in 1999 >> $75,000 to $99,999	0.321
49	Population 5 Years and Over Living in Different House in 1995 by Residence in 2000 - MSA/PMSA Level by Residence in 1995	Persons	Living in an MSA/PMSA in 2000 >> In United States in 1995	0.321
50	Sex by Occupation Type	Persons	Male >> Sales and office occupations	0.320

Note: This table reports the 50 features that are most positively correlated to the probability of the neighborhood obtaining a Starbucks by the year 2000, based on the long-form information from the 2000 U.S. Census (SF3 tables) among all neighborhoods without a Starbucks in 2000. The total number of features is 4,512. We split our census tracts at random in to a 60% training sample, and a 40% estimation sample. We train a gradient-boosted tree with cross-validated parameters in the training sample. Then, we predict the probability of receiving a Starbucks in the estimation sample. Finally, we consider the correlation of each feature with this prediction, in the estimation sample.

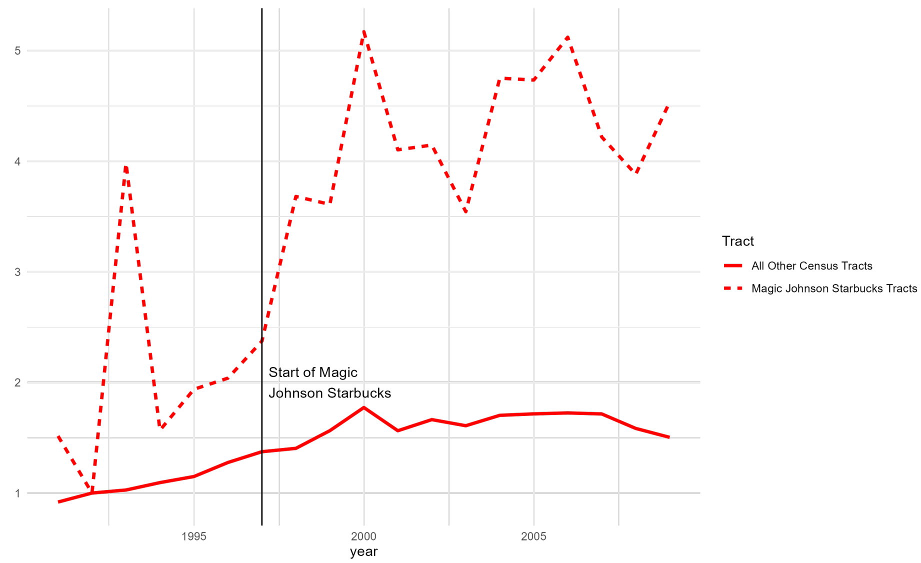
Table A8: 50 Data Features Most Negatively Correlated with P(Starbucks Opening)

N	VariableTable	VariableUniverse	VariableDescription	Corr.
1	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Owner-Occupied Housing Units with a Mortgage	$400 to $499	-0.246
2	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$40,000 to $49,999	-0.246
3	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Owner-occupied >> 65 to 74 years >> Built 1939 or earlier	-0.239
4	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Renter-Occupied Housing Units with Cash Rent	3 or more bedrooms >> $300 to $499	-0.235
5	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$20,000 to $34,999 >> $40,000 to $49,999	-0.233
6	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Owner-Occupied Housing Units with a Mortgage	$500 to $599	-0.232
7	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$10,000 to $19,999 >> $40,000 to $49,999	-0.231
8	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$50,000 to $59,999	-0.231
9	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$20,000 to $34,999 >> $30,000 to $39,999	-0.231
10	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$35,000 to $39,999	-0.230
11	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Owner-Occupied Housing Units with a Mortgage	$300 to $399	-0.230
12	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Owner-occupied >> 75 years and over >> Built 1939 or earlier	-0.229
13	Urban and Rural Population	Persons	Rural: Nonfarm	-0.226
14	Percent of the Population in Sample	Persons	Total	-0.226
15	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$30,000 to $34,999	-0.225
16	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$35,000 to $49,999 >> $40,000 to $49,999	-0.225
17	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Owner-occupied >> Income in 1999 below poverty level >> With Social Security income	-0.224
18	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$10,000 to $19,999 >> $30,000 to $39,999	-0.221
19	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$20,000 to $34,999 >> $50,000 to $59,999	-0.221
20	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$35,000 to $49,999 >> $50,000 to $59,999	-0.217
21	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$35,000 to $49,999 >> $30,000 to $39,999	-0.217
22	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$50,000 to $74,999 >> $40,000 to $49,999	-0.213
23	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$10,000 to $19,999 >> $50,000 to $59,999	-0.213
24	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$60,000 to $69,999	-0.211
25	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$25,000 to $29,999	-0.210
26	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units without a Mortgage	$150 to $199	-0.209
27	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$50,000 to $74,999 >> $50,000 to $59,999	-0.209

28	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Owner-occupied >> Income in 1999 below poverty level >> Complete plumbing facilities	-0.208
29	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	Less than $10,000 >> $40,000 to $49,999	-0.207
30	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$20,000 to $34,999 >> $20,000 to $29,999	-0.206
31	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with a Mortgage	White alone >> $400 to $499	-0.205
32	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$10,000 to $19,999 >> $20,000 to $29,999	-0.204
33	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	Less than $10,000 >> $30,000 to $39,999	-0.203
34	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$20,000 to $34,999 >> $60,000 to $69,999	-0.201
35	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with a Mortgage with Householder Who Is White Alone, Not Hispanic or Latino	$400 to $499	-0.201
36	Population 5 Years and Over by Residence in 2000 - MSA/PMSA Level by Residence in 1995 - House Level	Persons	Not living in an MSA/PMSA in 2000 >> Same house in 1995	-0.200
37	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with Householder Who Is White Alone, Not Hispanic or Latino	$20,000 to $24,999	-0.200
38	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Owner-occupied >> 55 to 64 years >> Built 1939 or earlier	-0.200
39	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$10,000 to $19,999 >> $60,000 to $69,999	-0.199
40	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units without a Mortgage	$100 to $149	-0.197
41	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$50,000 to $74,999 >> $30,000 to $39,999	-0.196
42	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$35,000 to $49,999 >> $60,000 to $69,999	-0.196
43	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	Less than $10,000 >> $50,000 to $59,999	-0.195
44	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with a Mortgage	White alone >> $300 to $399	-0.194
45	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Occupied Housing Units	Bottled, tank, or LP gas	-0.194
46	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units	$50,000 to $74,999 >> $60,000 to $69,999	-0.192
47	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with a Mortgage	White alone >> $500 to $599	-0.191
48	Urban and Rural Population	Persons	Rural: Farm	-0.189
49	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Specified Owner-Occupied Housing Units with a Mortgage with Householder Who Is White Alone, Not Hispanic or Latino	$300 to $399	-0.188
50	Population 5 Years and Over Who Speak Languages Other than English at Home by Race by Age Groups by Ability to Speak English	Owner-Occupied Housing Units with a Mortgage	$200 to $299	-0.188

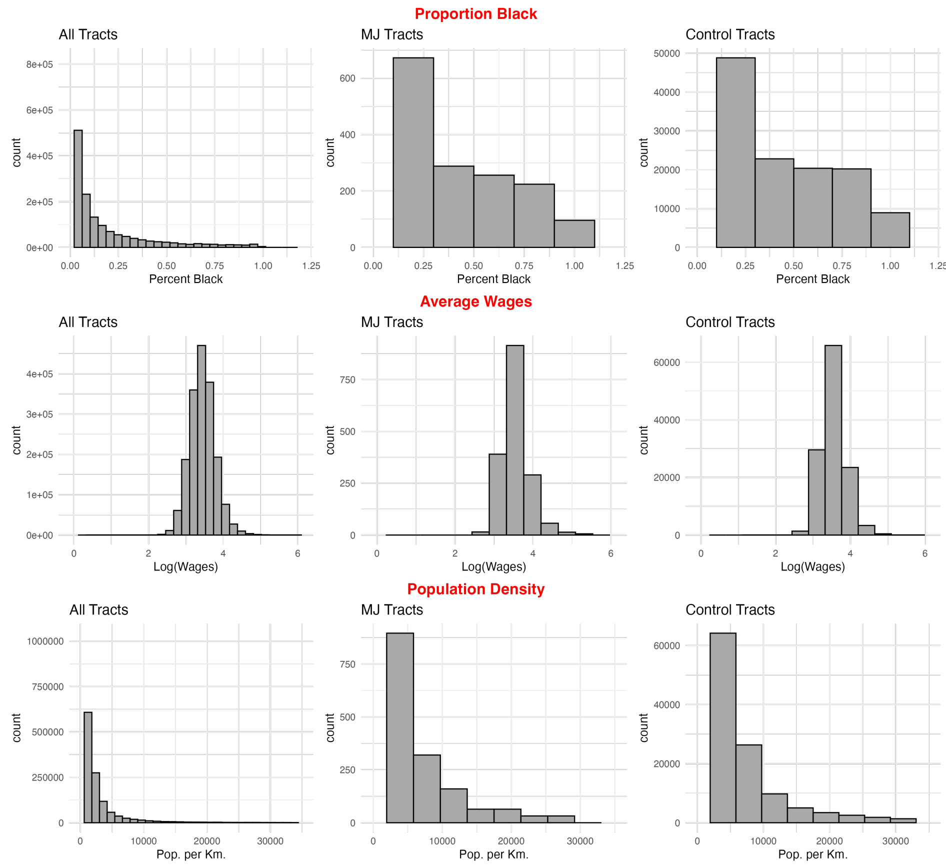
Note: This table reports the 50 features that are most negatively correlated to the probability of the neighborhood obtaining a Starbucks by the year 2000, based on the long-form information from the 2000 U.S. Census (SF3 tables) among all neighborhoods without a Starbucks in 2000. The total number of features is 4,512. We split our census tracts at random in to a 60% training sample, and a 40% estimation sample. We train a gradient-boosted tree with cross-validated parameters in the training sample. Then, we predict the probability of receiving a Starbucks in the estimation sample. Finally, we consider the correlation of each feature with this prediction, in the estimation sample.

Figure A1: Estimated Startup Quality Over Time



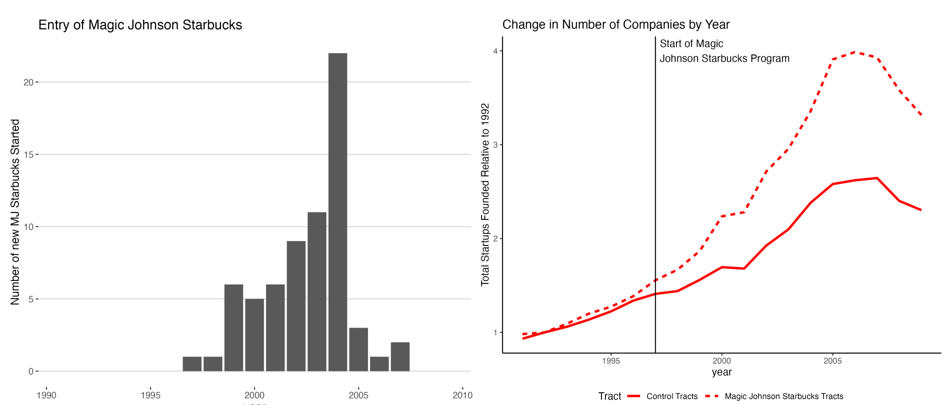
Note : The figure displays the quality-adjusted count of startups, computed by multiplying the number of startups by the quality of startups for each tract-year pair. Our data, ranging from 1994 to 2010, is sourced from the Startup Cartography Project, using the methodology set out by Guzman and Stern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

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



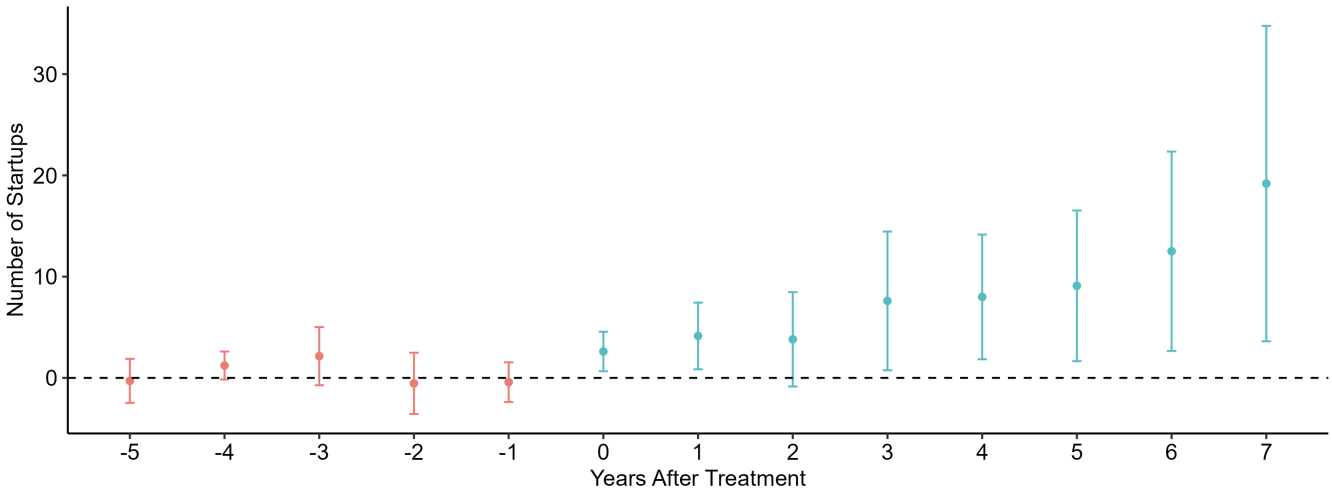
Note: We report the observables for the tracts that receive a Magic Johnson Starbucks compared to controls. Our matching procedure seeks to find tracts that have similar proportion of black residents, wages, and population density to those that received a Magic Johnson Starbucks. To achieve this, we first split all census tracts in ventiles for each of these three variables and estimate, for each ventile j of measure v, the share $s_{j,v}$ of tracts that have a Magic Johnson Starbucks. Then, for each tract i, we estimate a sampling weight equal to the product of these shares $w_i = s_{i,j,black} * s_{i,j,wages} * s_{i,j,popden}$ and draw 5000 control tracts based on these weights.

Figure A3: Entry of Magic Johnson Starbucks Over Time



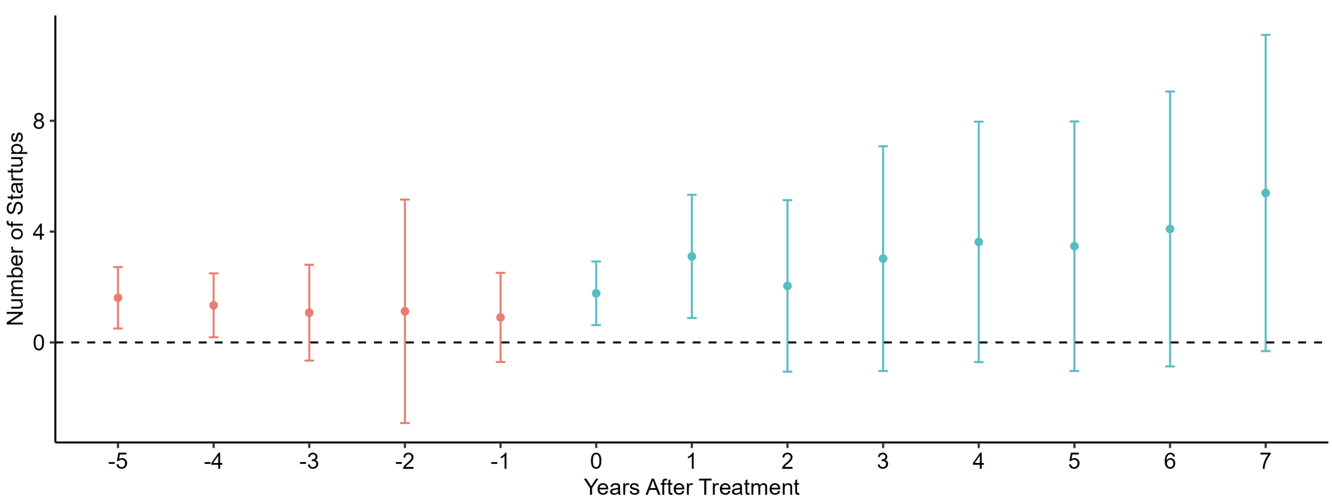
Note: This figure juxtaposes the establishment timeline of Magic Johnson Starbucks from 1997 to 2007 with the trajectory of startup quantity in treated versus control tracts. The left panel displays the distribution of the years in which Magic Johnson Starbucks establishments were introduced. The right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

Figure A4: Event Study Comparing Treated Neighborhoods to Neighborhoods Scheduled to Receive a Starbucks but Did Not Get One; Alternative Specification #1



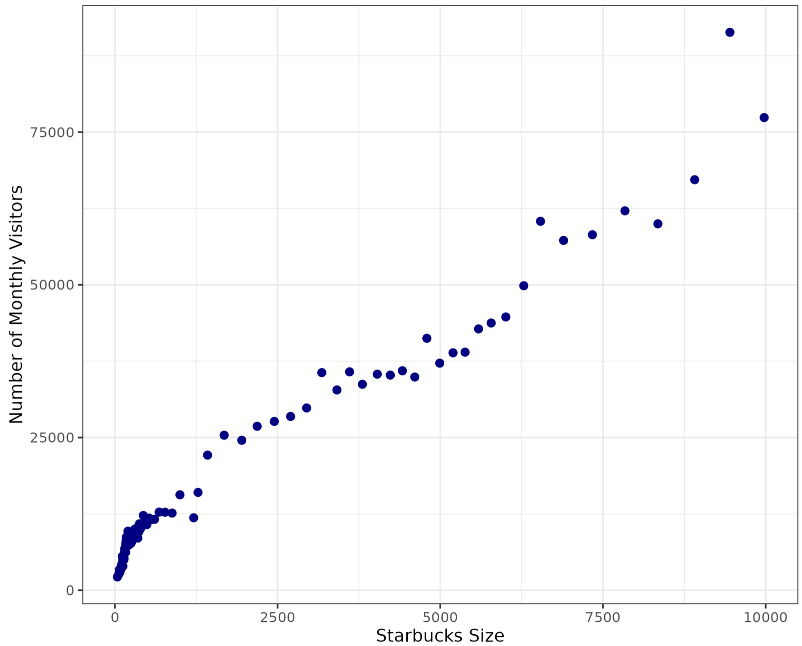
Note: This figure shows the impact over time of the entry of the first Starbucks into census tracts that previously did not have coffee shops, using an alternative analytical sample for "rejected" Starbucks neighborhoods (Panel A in Figure 2). Under this specification, neighborhoods that initially rejected Starbucks remain in the "rejected" group only until they actually open a Starbucks, thus capturing the interim period between rejection and eventual store opening. The figure reports marginal effects estimated via the difference-in-differences methodology of Callaway and Sant'Anna (2021), with 95 percent confidence intervals.

Figure A5: Event Study Comparing Treated Neighborhoods to Neighborhoods Scheduled to Receive a Starbucks but Did Not Get One; Alternative Specification #2



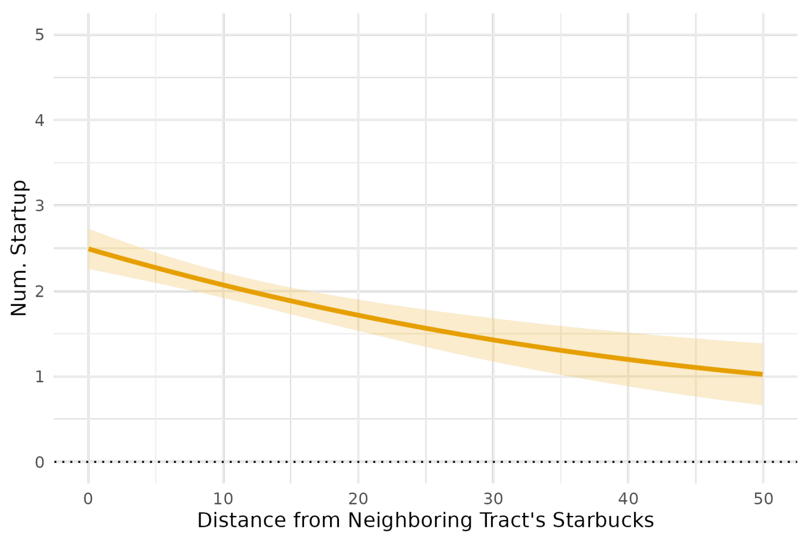
Note: This figure shows the impact over time of the entry of the first Starbucks into census tracts that previously did not have coffee shops, using an alternative analytical sample for "rejected" Starbucks neighborhoods (Panel A in Figure 2). This alternative specification excludes neighborhoods from the "rejected" group if they eventually received a Starbucks, even if they initially rejected one. Thus, the "rejected" group here comprises solely neighborhoods that never received any Starbucks throughout the study period. The figure reports marginal effects estimated via the difference-in-differences methodology of Callaway and Sant'Anna (2021), with 95 percent confidence intervals.

Figure A6: Relationship Between Establishment Size and Number of Visitors to a Starbucks in SafeGraph Data



Note: This figure plots a binned scatterplot between the size of a Starbucks and the number of monthly visitors it receives, as tracked in SafeGraph data.

Figure A7: Continuous Difference-in-Differences Treatment Effects



Note: This figure plots estimates of the number of startups based on distance for continuous difference in differences treatment effects following the approach by Callaway et al (2024). We consider, for all tracts that never received a Starbucks, the proximity to the first Starbucks that opens in the same county. Relative to Table 6, they estimate different effects since Table 6 considers instead tables at a specific distance.

Appendix B. Industry Tagging Algorithm

This section is based on the methodology developed by Engelberg et al. (2024), which we quote as below:

"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 & Bradstreet).