How Efficient Are Firm Location Configurations? Empirical Evidence from the Food Service Industry

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Abstract

I study the welfare losses due to inefficient firm location configurations in the food service industry. Compared to the existing literature, my paper benefits from detailed data on roughly 400,000 US urban restaurants. I obtain restaurant locations and foot traffic from SafeGraph, collect their characteristics from Yelp and scrape local commercial real estate rental rates from major listing aggregators. Exploiting the assembled dataset, I estimate a structural model of consumer demand, firm entry and capacity optimization. I then develop an algorithmic approximation approach to analyzing the efficiency of firm location configurations and explore the welfare gains available through the spatial reconfiguration of firms. In the median market, reconfiguration can lead to an 8.51% increase in total industry profits with a simultaneous 7.73% improvement in the consumer welfare metric. Next, I find suggestive evidence that firms' incentives to spatially differentiate play an important role in shaping inefficient location configurations. Finally, I estimate that the fixed costs spent on redundant entry amount to more than $7 billion.

Keywords: Location configurations; Efficiency; Spatial demand; Spatial competition; Urban policy.

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1 Introduction

Markets with many small firms dispersed in space and catering to local consumers are prevalent in the service sector. Such markets rarely attract the attention of policy-makers: low barriers to entry and small market shares are traditionally associated with good consumer outcomes. However, economic theory points at multiple forces that can render firm location configurations inefficient in spatially differentiated markets: business-stealing incentives, local market power considerations, and suboptimal entry levels. These issues can lead to unrealized gains for both consumers and firms. How large are the resulting inefficiencies? What features of location configurations are responsible for welfare losses? Which source of inefficiency matters most? I address these questions empirically in the context of the food service industry.

I first collect granular data on characteristics and visitors of 403,588 restaurants in 387 urban markets across the US. Then I recover consumer preferences and firm profitability parameters and develop an algorithmic approach for exploring the welfare consequences of alternative firm location configurations. Finally, I use a perturbation method to shed light on the economic forces behind the losses of efficiency in the status quo market configurations. I find that sizeable welfare gains are available through location reconfiguration: in the median market, total industry profits can be increased by 8.51% with a simultaneous 7.73% improvement in the consumer welfare metric. Compared to the status quo, welfare-improving alternative configurations are associated with higher-quality restaurants made available to consumers with a relatively lower number of local options. Next, I find suggestive evidence that firms' incentives to spatially differentiate play an important role in shaping inefficient location configurations. Also, according to my estimates, more than $7 billion in fixed costs were spent on redundant entry into the industry. My paper contributes to the literature by providing first systematic evidence of welfare losses associated with firm location choices in the industry typically characterized by free entry and many small firms in each market area. Since this evidence suggests the need for policy intervention, I also provide a discussion of potentially welfare-improving regulatory measures.

The theoretical literature on spatial competition has long recognized the incentive issues associated with firm location decisions. The seminal contribution by Hotelling (1929) highlighted the incentives to steal business from competitors by locating closer to the average consumer when price competition is absent. Such incentives may lead to socially inefficient minimal differentiation. d'Aspremont et al. (1979) noted that when price competition is present, the outcome is the opposite: firms differentiate as much as possible to create local market power. Among others, Salop (1979) has shown that entry levels in spatially differentiated industries can be excessively high. Despite these well-known sources of inefficiency and the evidence that distance costs are important in a variety of retail contexts (see Thomadsen (2005) or Davis (2006b)), the spatially differentiated food service industry receives little attention from policymakers beyond hygiene standards enforcement.

According to Fischel (2015), zoning rules are primarily aimed at protecting residential areas from other economic activities and creating a pleasant local environment, while competition authorities monitoring activities rarely focus on the food service industry[1]. At the same time, restaurants take an increasingly central place in human life (see Davis et al. (2019)), and constitute a significant portion of economic activity. U.S. Census (2020) reported total industry sales of almost $770 billion in 2019, roughly 3.7% of the US GDP, while the U.S. Bureau of Labor Statistics (2020) estimated that the industry employed more than 9.7 million people. Therefore, determining if such a market suffers from welfare losses affecting millions of consumers and entrepreneurs can be of interest to policymakers.

Due to data limitations, it has previously been difficult to comprehensively analyze the location configuration efficiency in a market comprised of many small firms[2], such as the food service industry. Past industry investigations have either used data on a small subset of firms as in Thomadsen (2005), concentrated on small geographical areas as in Athey et al. (2018) and Davis et al. (2019), or lacked cost-side information as in Schiff (2015) and Couture (2016). This paper overcomes these challenges by combining multiple data sources: locations and foot traffic of US restaurants from SafeGraph, restaurant characteristics from Yelp, local commercial real estate rental rates from major listing aggregators, and consumer residency patterns from the US Census. Granular data on 403,588 restaurants and their visitors allows me to recover consumer preferences and firm profitability parameters, and to subsequently explore alternative spatial market configurations.

Specifically, exploiting the assembled dataset, I (i) estimate consumer demand, using a combination of aggregate- and micro-level information on consumer choices, (ii) recover markups, using the data on rental costs in the absence of detailed price information, (iii) back out the fixed costs, using an ex-ante zero-profit assumption and across-market variation in realized profits. The model estimates allow me to compute the profits of individual firms and a measure of consumer welfare for a given spatial configuration of firms.

To explore how profits and consumer welfare can be improved, I then develop an algorithmic approach to exploring alternative combinations of firm positions in the market space. The approach combines two combinatorial optimization heuristics, randomly shifting or switching firm locations, and only retaining the ones that improve welfare. This process proceeds in an iterative way, increasing the welfare metrics at every iteration. As a result of such gradual improvements, the best alternative market configuration is approximated. These approximations feature sizeable welfare

[1] For example, Simons and Delrahim (2019) report that none of the reported transactions in the Food Service and Drinking Places sector were investigated by either DOJ or FTC. The European Competition Network mentions the restaurant industry only in passing, does not list it as one of the "main markets subject to scrutiny [. . .] in the period 2004-2011" and does not describe any monitoring activities related to the food service.

[2] According to the NAICS Association there were roughly 650 thousand restaurants in the US in 2019, while National Restaurant Association reports that roughly 70% of restaurants are single-unit operations.

improvements associated with alternative firm location configurations, although the across-market variation of the estimates is substantial: total profits (the consumer welfare metric) increases range from 3.14% (3.58%) at the 0.1-quantile of the distribution to 19.63% (12.50%) at the 0.9-quantile. Areas with a lower number of local restaurant options are characterized by relatively higher-quality restaurants in the alternative location configurations compared to the status quo. Having established the presence of efficiency losses, I study the economic forces that result in suboptimal welfare through the lens of a simple perturbation method.

Specifically, I marginally perturb the status quo market configurations by shifting one firm at a time and interpret the consequences of such shifts using standard spatial competition models. In such models, if a market is dominated by business-stealing incentives that push firms to locate close to the average consumer, firm shifts should result in increased consumer welfare and profit losses. To the contrary, if a market is dominated by differentiation incentives that lead to local market power, firm shifts should result in consumer welfare and profit increases. Empirically, a sizeable portion of individual firm shifts that increase consumer welfare, also result in profit increases of these firms, which points to local market power considerations as the economic force that significantly contributes to the socially inefficient firm positions across the market space.

Additionally, I assess the resources firms spent on redundant entry. Across the sample markets, more than $7 billion of fixed costs could be saved without harm to consumers or remaining firms if the latter were positioned efficiently. More precisely, these resources would be saved if a subset of firms were removed from the industry, and the remaining firms were spatially reconfigured to achieve the same level of within-market welfare as before the removal.

My findings indicate a space for policy interventions by documenting the substantial magnitudes of welfare losses. Moreover, my results suggest that currently underserved areas can benefit from the introduction of local quality standards. Also, since differentiation incentives are found likely to play an important role in the emergence of inefficient firm location configurations, more restrictive zoning rules have the potential to improve market outcomes.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 provides an overview of the restaurant data I collected for this paper. Section 4 introduces the structural model of consumer choice and firm behavior. Section 5 outlines the estimation procedure and presents the structural estimates: consumer preferences parameters, firm markups, and entry fixed costs. Section 6 describes the algorithmic approach to search for welfare-improving alternative spatial configurations, the perturbation method of exploring economic forces behind efficiency losses, and reports the obtained findings. Section 7 concludes.

2 Contributions to the literature

By exploring the efficiency of food service firm location configurations across multiple US urban markets I make several contributions to the existing literature. First, I develop tools appropriate for inferring the magnitudes and sources of efficiency losses in a setting where the number of firms per market is large, contributing to the toolbox for analyzing the spatial competition. Second, I collect granular data on an industry that has previously been hard to study from the efficiency perspective of firm location configurations and thus contribute to the empirical literature on the restaurant industry. This section reviews previous research providing the reader with the relevant background, and outlines this paper's position in the literature.

Spatial markets Product differentiation decisions have long been recognized as important strategic choices that determine both firm profitability and consumer welfare. Theoretical literature beginning at least with the seminal contribution by Hotelling (1929) has modeled differentiation through the lens of spatial heterogeneity of firms and consumers. Multiple subsequent variations include Eaton and Lipsey (1975), Salop (1979), d'Aspremont et al. (1979), de Palma et al. (1985), Economides (1989), and Vogel (2008). Although the spatial component of these models has to some extent been used as a modeling device, the intuition stemming from this literature (significance of travel costs, business-stealing incentives, and local market power considerations) can be directly applied to contexts where differentiation is *actually* geographic. Relatedly, empirical research has recognized that markets, in which consumers have to travel to purchase the good, are inherently differentiated. Thus, multiple perspectives of spatial markets – including consumer preferences with regards to traveling and firm location decisions – have received attention in the industrial organization literature. While these contributions are outlined below, it should be noted that the efficiency of location configurations has been relatively out of focus in the empirical research, and this paper attempts to fill in this gap, and to reconnect empirical evidence with theoretical efficiency considerations.

Consumer preferences with regards to travel distance and product characteristics have been the focus of several papers. Smith (2004) estimates demand for supermarkets to quantify the market power in the supermarket industry in the UK. Thomadsen (2005) recovers the demand and supply parameters in a fast-food market in order to understand the impact of spatial differentiation and ownership structure on market prices. Davis (2006b) estimates a spatial demand system in the movie theater industry to analyze the impact of firm prices on competitors and to study market definition. Houde (2012) investigates the gasoline station industry, estimates consumer demand accounting for the information on consumers' commuting paths, and uses the estimated parameters to simulate the price effects of a merger. Athey et al. (2018) demonstrates the potential of machine-learning models to predict consumer demand in the food service industry using individual-level mobile device location data. In this paper, I make use of the estimation procedures developed by the previous research outlined above and incorporate the available micro-data on consumer choice in the spirit of Berry et al. (2004), extending the existing methodology on spatial demand estimation.

The second strand of literature has focused on firm entry and location choices that determine spatial product availability and differentiation. The seminal papers by Bresnahan and Reiss (1990, 1991) study the determinants and effects of spatial entry without modeling different degrees of competition across locations within a given market. Mazzeo (2002) extends the model in Bresnahan and Reiss (1991) to allow for endogenous product differentiation by the entering firms. Seim (2006) studies market entry decisions for the case where competition effects vary across locations within a market and illustrates firms' incentives for spatial differentiation. Orhun (2013) extends the Seim (2006) approach by allowing the private information on locations within the market to be correlated across firms. Thomadsen (2007) explores the equilibrium outcomes in a location choice games between two fast food retailers using an estimated demand system. Yang (2012) documents the existence of across-chain spatial spillover benefits. Datta and Sudhir (2013) study the effects of zoning laws on entry and differentiation. Zheng (2016) develops a model of dynamic oligopolistic spatial competition and quantifies preemptive incentives. Despite concentrating on firm location decisions, these papers pay only tangential attention to the efficiency of the resulting location configurations. Instead, in the present paper, I concentrate on analyzing the welfare implications of firm location configurations. To this end, I develop an algorithmic approach to exploring alternative spatial configurations and a perturbation method that suggests which of the economic sources of inefficiency (business-stealing or market power) is responsible for suboptimal configurations[3]. At the same time, to estimate the firm profitability parameters (entry fixed costs and markups), I use two elements of spatial entry literature, which complement my demand estimates determining competition for consumer visits. First, I use the post-entry interaction in the form of equilibrium capacity optimization (similarly to the standard equilibrium in prices as in e. g. Draganska et al. (2009)) to back out markups. Second, I employ a zero-profit analog of entry conditions in Bresnahan and Reiss (1990, 1991) to estimate the fixed costs of opening a restaurant. Additionally, recovering fixed costs also allows me to quantify the inefficiencies stemming from the suboptimal entry which has been explored in the theoretical literature (see Spence (1976), Mankiw and Whinston (1986) or Anderson et al. (1995)) and empirically studied by Berry and Waldfogel (1999) for the case of the radio industry.

In a work closely related to my paper, Seim and Waldfogel (2013) study the entry patterns by the government-controlled liquor monopoly in Pennsylvania. Specifically, Seim and Waldfogel (2013) explore the reasons behind the monopoly's store location choices and compare the outcomes to the profit- and welfare-maximizing locations. They find that the monopoly's behavior can be described as profit-maximizing with profit-sharing and uncover losses due to the suboptimal locations. In contrast to the case of Seim and Waldfogel (2013), I focus on investigating the welfare consequences

[3] For a reduced-form investigation of business stealing and cannibalization incentives see, e.g. Davis (2006a).

of firm location configurations in a free-entry many-firms industry[4]. Additionally, when searching for welfare-improving location configurations in this paper, I am able to algorithmically optimize firm locations without relying on the restrictive assumption that each consumer chooses to visit the nearest store made by Seim and Waldfogel (2013).

Restaurants I study the efficiency of firm location configurations in the context of the food service industry, which can be viewed both as a spatially differentiated market and as a provider of a desirable urban amenity. It has thus attracted attention not only of industrial organization scholars (see the already mentioned papers by Thomadsen (2005, 2007), Athey et al. (2018)) but also of researchers in urban economics. Schiff (2015) estimates the relationship between urban population, density and the variety of in the restaurant industry, finding that larger and denser areas also tend to be richer in terms of the number of cuisines present on the restaurant scene. Couture (2016) studies consumption benefits of density in urban areas by estimating a model of demand for restaurant trips. The data collected by Couture (2016) does not permit to analyze the firms' profits and does not allow for an efficiency analysis of spatial market configurations. Davis et al. (2019) study the social frictions in restaurant choices and find out that consumption segregation is approximately twice as low as their estimate of residential segregation. I contribute to the literature on restaurants as urban amenities in two ways. First, I collect, to the best of my knowledge, the most comprehensive dataset on the restaurant industry in the US, which includes restaurant characteristics, visit counts and origins of visitors, and the local real estate rental rates faced by the firms. Second, the resulting dataset allows me to add the supply-side perspective to the evaluation of restaurant location configurations in urban markets, and, consequently, to analyze the efficiency of spatial configurations, taking into account both consumer preferences and firms' technological parameters.

Overall, this paper (i) contributes to the literature on spatial entry by concentrating on the welfare implications of firm location configurations in a free-entry many-firms context, and (ii) widens the research on the restaurant industry, a provider of an important urban amenity, by collecting a granular dataset and analyzing both the consumer- and firm- sides of the location configurations issue.

3 Data description

Detailed information on both consumers and firms is required to estimate and interpret the efficiency losses due to firm location configurations. One needs data on consumer choices to infer preferences and data on firm behavior to determine the firms' profitability parameters. In order to systematically collect such information across multiple markets with many small firms, I combine data from

[4] Seim and Waldfogel (2013) are only looking at the free-entry case indirectly through a lens of a model with myopic entrepreneurs and under the prices fixed at the regulated level.

four sources: the location data company SafeGraph, the business review publisher Yelp, the American Community Survey by the U.S. Census, and several online commercial real estate listing aggregators.

The combined dataset enables me to study 387 urban markets across the US with granular information on the total of 403,588 restaurants. For each restaurant, I observe its precise geographic location, business name and important characteristics: geometric shape, price category, review score, cuisine, open hours. Thanks to the SafeGraph data I also observe the visit counts (measured using mobile device location information) for every restaurant for the month of July 2019, and the breakdown of the foot traffic by the visitors' home neighborhoods. Observing the population residency patterns recorded in ACS allows me to extrapolate the mobile device foot traffic counts to the general population and through that to determine the market demand conditions faced by each restaurant in the sample. Finally, I also observe an important component location-specific component of the restaurant costs – the commercial real estate rent – on the ZIP code level.

These data provide an empirical basis for understanding consumer preferences and firm profitability. SafeGraph and Yelp data are crucial for estimating the demand system. ACS and rental costs allow determining each restaurant's profitability in the absence of the firm-level price information. The rest of this section provides a detailed description of the assembled datasets.

3.1 Restaurant locations and foot traffic

I partnered with SafeGraph, a company specializing in location data, to obtain a dataset on locations, basic features and foot traffic counts of establishments across a variety of industries, including the food service industry. SafeGraph has assembled a continuously updated dataset on points of interest (POIs) – places where people spend time outside of home and work – covering 50 US states and the DC[5]. The subset of SafeGraph data in my disposal was exported in late August 2019 and includes information on 4,354,960 establishments. For the purposes of this paper, I concentrate on 594,374 restaurants (establishments with NAICS codes 711511 and 711513) included in the SafeGraph dataset.

The dataset is split into three parts: *Core Places*, *Geometry* and *Patterns*. *Core Places* provides a snapshot of points of interest current as of August 2019 and includes basic information such as location name, geographic coordinates, address, industry, phone number and opening hours. *Geometry* contains data on the precise geometric shape of each establishment (which allows one to compute the total area of the establishment). *Patterns* include the place foot traffic count and demographic aggregations that allow establishing where the visitors came from.

SafeGraph collects the foot traffic counts in the *Patterns* dataset with the help of third-party data

[5]SafeGraph also has a similar dataset on Canadian points of interest.

Home CBG	Visitors
391290211004	11
391290204002	10
391290217002	9
391290214022	5

(a) Example point of interest, CBG-breakdown of visitors.

Home CBG	Device count
391290211004	192
391290204002	998
391290217002	160
391290214022	246

(b) Mobile device count by home CBG (example).

Table 1: Extract of data illustrating the Safegraph data on and point of interest visitor breakdown by home neighborhood, and mobile devices count by home neighborhood

partners such as mobile application developers. These application developers share anonymized information on their users (mobile ad identifiers, geographic location of a device at a certain time) with SafeGraph, which further aggregated the data, merging it to locations and geometric shapes of points of interest level, and computing the POI visit counts. *Patterns* contains POI visit counts on the monthly level[6]. The data on foot traffic counts in my disposal dates from June 2017 to July 2019, however, I only use the July 2019 subsample for this project. The reasons for such sample selection are the following: (i) the set of restaurants present in the available data most accurately reflects the actual population of restaurants as of late summer 2019, (ii) the computational and memory burden of the estimation procedure.

Next, for select points of interest, *Patterns* contains the breakdown of visitors by their home neighborhood, defined as a Census Block Group (CBG)[7]. SafeGraph determines the home neighborhood of a given participating app user is determined using the "common nighttime location" strategy (see Place Manual for algorithmic details). Table 2a illustrates the breakdown of visitors by home neighborhoods for an example point of interest. The first column specifies the identifier of a given CBG (defined by the US Census), the second column lists the count of visitors, for whom that CBG is the home neighborhood. Note that, for this type of breakdown, visitors refers to *unique* visitors. Thus to determine the number of *visits* to a POI from a given CBG, I renormalize visitors by the ratio of total visitors to total visits.

Finally, through *Patterns*, I observe the count of mobile device users who have participating applications installed by home CBG. Table 2b provides an illustrative extract from the resulting home panel dataset. The first column specifies the identifier of a given CBG, the second column lists the count of devices for which the respective CBG was marked as home neighborhood.

Three features of the SafeGraph dataset are especially valuable for my purposes. First, total visit counts are informative of the overall attractiveness of restaurants. Second, the visitor breakdown by home neighborhood provides additional guidance into how far people are willing to travel to

[6]The daily visit counts are also available for POIs with a substantial amount of foot traffic.
[7]A CBG is a small geographical unit defined by the US Census with a typical population between 600 and 3,000 people.

visit a given place. Third, the availability of the restaurant area is essential for computing the rental costs faced by the business owners, which, given the lack of detailed pricing information, I use to recover the markups on the restaurant level via the capacity optimality conditions (see Section 4.2). Additionally, the basic restaurant characteristics in *Core Places* are essential for matching SafeGraph data to Yelp data, the subject of the next subsection.

3.2 Restaurant characteristics

To complement the SafeGraph dataset with more detailed information about the food service places' characteristics, I use the Yelp Fusion API. This API allows searching for and retrieve restaurants' information by making two types of HTTP requests. First, one can use a search query (such as the restaurant name) and geographical coordinates to look up a restaurant around a specific location. This API point returns all results that match the input search query. Second, one can find a restaurant by supplying its telephone number, provided that this number is present in Yelp's database. Due to a 5,000 daily limit on Yelp API requests, three distinct rounds of data collection were done using these API endpoints. First, the umbrella "food" search term was used to gather information on the restaurants located around a grid of points across the US[8]. Next, a daily `cron` job[9] was set up to look up individual restaurants from SafeGraph sample by their name and coordinates. Finally, a similar `cron` job was set up to look up restaurants by the phone number from the SafeGraph database. The data collection occurred between October 2019 and January 2020.[10]

I then match the restaurant characteristics data collected through Yelp Fusion API to the SafeGraph sample of 594,374 food service places. Specifically, I used geographical proximity, name similarity (as measured by the Levenshtein distance between the name-strings) and phone number equality as matching criteria. As a result, 89% of the restaurants in the SafeGraph database were matched to Yelp-originating restaurant characteristics. The matched dataset was stored in a PostgreSQL+PostGIS database that facilitates data retrieval and fast geography-related operations such as spatial joins and distance computations.

The characteristics obtained through Yelp include information on restaurant price category, restaurant rating and cuisine categories. Price category is a label ranging from one $ sign to four $ signs[11]. In absence of other information about the prices on the restaurant level, I used these categories to capture how expensive a given restaurant is. It should, however, be noted that there is also a quality-component to the price categories: restaurants in a two-$ category are more likely to be fancier in terms of the food and service than those in a one-$ category even conditional on

[8] Specifically, I used the centroids of all CBGs containing at least one restaurant from SafeGraph.
[9] `cron` is a unix utility that allows scheduling jobs to run periodically.
[10] As a result, the Yelp API responses potentially contain different amounts of information (such as the number of review counts) for different restaurants in the sample, a complication, from which I have to abstract in the rest of the paper.
[11] In my empirical specifications I treat all price categories starting with $$ and above as a single group.

	Q10	Q25	Med	Q75	Q90	Mean	SD
Urban	0.00	1.00	1.00	1.00	1.00	0.86	0.34
Area (sq. m.)	143.20	226.22	405.24	935.74	2658.76	1792.73	7596.66
Price	1.00	1.00	1.00	2.00	2.00	1.49	0.56
Rating	2.00	3.00	3.50	4.00	4.50	3.42	0.91
Visits	54.00	120.00	247.00	470.00	822.00	385.75	557.74

Note: Subset of data for July 2019.

Table 3: Restaurants sample summary statistics.

other observable restaurant features. Rating scores (averages of trusted Yelp restaurant reviews) potentially provide another measure of restaurant quality and attractiveness. A single review score can range from 1 to 5 stars, and Yelp ratings round the average score to the nearest half-star. A potential complication related to the aggregated ratings is that extreme ratings are likely to be associated with less-visited places and thus less reliable. Finally, cuisine categories capture some variation in food taste across restaurants.

Table 3 displays summary statistics for the restaurants sample. The median restaurant has an area of 405 square meters (4360 square feet), a $ price category (there is roughly the same number of $$ restaurants since the "mean" price category is 1.49$) and a 3.5-star rating. On average, around 386 visits to a restaurant were recorded in the SafeGraph *Patterns* data during July 2019. About 86% of restaurants are located in urban areas. The next subsection explains how urban areas are defined, and how I use the Census ACS to extrapolate the SafeGraph visits to visits by the entire consumer population.

3.3 Geography and population

The US Census data is essential to this paper as it allows understanding the geography of the sample (i.e. defining market areas and distance between consumers and restaurants). Also, it permits using the residency patterns of the entire consumer population to determine the total demand restaurants face by extrapolating the visit counts information from SafeGraph.

First, I used the American Community Survey geography files to establish the geographic location of each Census Block Group and to pin down the CBG population count. Figure 8 in Appendix A depicts the distribution of population counts across Census Block Groups, showing that most CBGs have between 500 and 2,500 residents. Figure 8 also shows a strong correlation between the CBG population and the number of mobile device users for whom that CBG is a home neighborhood according to SafeGraph data. On average, the SafeGraph sample includes 10.3% of the CBG population. Once the CBG populations and locations are known, I can (i) compute the distances between consumer home locations and restaurants, which facilitates demand estimation and (ii) extrapolate the restaurant demand observed in the SafeGraph data to the general population.

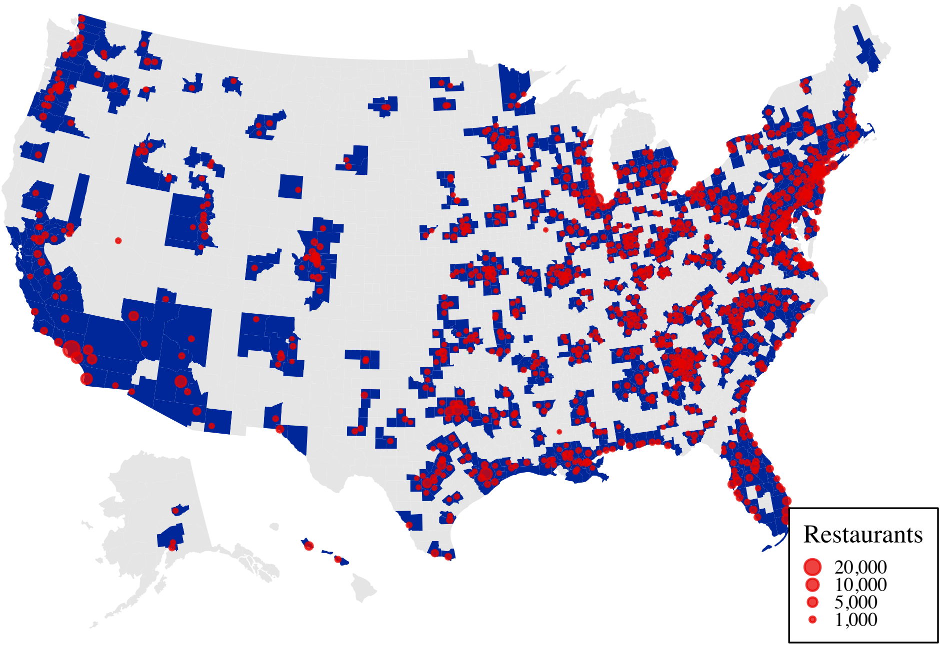


Figure 1: Counties containing urban areas (CBSAs) are highlighted in blue. Red circles indicate restaurant count at the county level.

Section 5 contains details on how (i) assists in demand estimation and (ii) permits backing up markups on the restaurant level.

Next, I performed a spatial join to establish the membership of each Census Block Group and each sample restaurant in a Core-based statistical area (CBSA), or to establish a lack of such membership. CBSAs are defined by the Office of Management and Budget as geographic areas tied by commuting to an urban center with a population of at least 10,000 people. For the purposes of this paper, I use CBSAs as market areas. To illustrate the geographical distribution of urban areas, Figure 1 highlights the counties containing CBSAs, and also reports the corresponding county-level restaurant count. While one can expect defining markets as CBSA may lead to more options in the consumers' choice sets, there are several advantages to this definition. First, CBSAs span large geographic areas and thus are unlikely to restrict consumer choice sets in a detrimental way. Second, market definition is not the primary goal of this paper, and CBSAs, as standard well-defined geographical units, provide a convenient default option.

In the remainder of the paper, I concentrate on restaurants located in CBSAs, excluding the areas surrounding New York City and Los Angeles to reduce the computational burden of the estimation procedure. Table 12 in Appendix A reports summary statistics for the remaining 387 markets used in estimation.

	N		Means		Rent quantiles		
Source	Listings	ZIP codes	Listings per ZIP	Sq. footage	Q25	Q50	Q75
Loopnet	47023	9690	4.853	5968.348	1.030	1.500	2.125
Crexi	20903	6678	3.130	5641.394	1.000	1.330	1.960
CommercialExchange	10519	3376	3.116	6489.963	0.975	1.250	1.792
All	78445	10841	7.236	5963.897	1.000	1.417	2.080

Table 4: Commercial real estate listings summary statistics.

3.4 Commercial real estate rent

Lastly, I collected local information on commercial real estate rental rates, an important cost factor for most retail industries including the food service industry. In the absence of detailed price data, I use rental rates to recover the profitability of a given restaurant by modeling the firms' tradeoff between additional rent payments and increased consumer visits.

I scraped three online platforms that list commercial real estate offerings to collect rental rates: Loopnet, Crexi and CommercialExchange. Loopnet and Crexi are some of the most prominent commercial real estate listings platforms: both are on the first page of Google results for the search query "commercial real estate search" and regularly mentioned on industry guides like Reonomy (2019). CommercialExchange is slightly less prominent and supplements the first two sources.

The data was scraped off the platform websites in March 2020 and filtered only to contain offers on spaces labeled as "retail"[12]. Listings typically provide information on the rental rate per square foot, area of the offered lot (either total area or a range) and the location of the offering (up to a ZIP code in case of Loopnet).

The resulting dataset contains listings in 10,841 ZIP codes, which constitutes roughly one-fourth of all US ZIP codes. I observe around 7 listings in an average ZIP code with typical rental rates ranging from 1 to 2 dollars per square foot[13]. I estimate the rental rate faced by a given restaurant by the mean rate on listings observed in the respective ZIP code, since more accurate location matching is not possible for the richest data source, Loopnet. Table 4 provides detailed summary statistics on the commercial real estate listings dataset.

It should be noted, that while the commercial rent data was gathered during the early signs of the COVID-19 outbreak in the US, I do not expect the lower value of rental space to be reflected in the rental rates of the observed listings.

[12]Crexi and CommercialExchange have hidden APIs that allow filtering for retail-type listings, while Loopnet has similarly-formatted URLs that lead to webpages only containing retail listings in a specific ZIP code.

[13]For compatibility with restaurant area computation, the square foot units were later translated into square meters.

3.5 Resulting sample

To summarize, the resulting sample consists of 403,588 restaurants in 387 urban markets around the US. I observe restaurant characteristics, SafeGraph visit counts for July 2019, visitor breakdown by home neighborhood, restaurant area and the rental rate it faces. Table 13 in Appendix A shows an example restaurant record. Also, Table 14 illustrates the matched by Census Block Group data on population according to Census and the SafeGraph sample size.

The next section outlines the structural model of consumer and firm behavior, which I use in conjunction with the constructed sample to estimate consumer preferences and firm profitability parameters (markups and fixed costs), which are essential for determining the scale and economic sources of firm location configuration (in)efficiency.

4 Model

In order to build a framework for investigating the efficiency of firm location configurations, I specify an empirical model of consumer and firm behavior suitable for analyzing the available data. In the model, spatially heterogeneous consumers choose the restaurant to visit, taking into account restaurant attractiveness (determined by its characteristics) and the distance costs associated with traveling. Firms make binary market entry decisions, then choose the location and the capacity, and finally compete in the market for consumer visits.

Conditional on the structural parameters, the model implies several key quantities and relationships. First, the model predicts restaurant market shares on both aggregate and location-specific level. Next, the optimality of the firm capacity choice reflects the tradeoff between additional consumer and higher rental costs. Moreover, the ex-ante zero-profit assumption connects the realized firm profits with the entry fixed costs. These model implications are instrumental for recovering the structural parameters from the available data. Section 4.1 provides details on the consumer choice, Section 4.2 specifies the firm behavior model.

4.1 Consumer choice

Specification I model consumer demand using a multinomial logit choice specification with spatial heterogeneity. Each consumer is characterized by the home location (home CBG) and makes a decision on which restaurant to visit (if any) on a given day, taking into account the restaurant proximity and its characteristics. Jointly these characteristics determine the restaurant's quality that all consumers agree on, while differentiation is along the spatial dimension. I assume the restaurant choice set to consist of all restaurants in the same market (CBSA) as the consumer's home location.

Formally, consider consumer i residing in home-CBG h of market m choosing the restaurant on day d. The utility from visiting restaurant r in market m is assumed to take the following form:

$$\begin{aligned} u_{i(h)rd} &= -\rho_m d(h,r) + \underbrace{\alpha_m + x_r'\beta + \gamma_r^B + \gamma_r^C + l_{CBG(r)}'\lambda + \xi_r}_{\delta_r} + \varepsilon_{i(h)rd} \\ &= -\rho_m d(h,r) + \delta_r + \varepsilon_{i(h)rd}, \end{aligned} \tag{1}$$

while the mean utility of not visiting the restaurant is normalized to zero: $u_{i(h)0d^*} = \varepsilon_{i(h)0d}$. In this specification x_r are observed characteristics of the restaurant that include the price category dummies, rating, total area in square meters; $d(h,r)$ is the distance in kilometers between the centroid of CBG h and restaurant r; γ_r^B is a brand fixed effect; γ_r^C is a cuisine category fixed effect; $l_{CBG(r)}$ are characteristics of r's neighborhood (CBG) in terms of non-restaurants establishments count; ξ_r is the unobserved characteristic of restaurant r common to all consumers; and $\varepsilon_{i(h)rd}$ is the consumer-option-specific shock with a type-I extreme value distribution.

This model allows me to focus on the consumer tastes heterogeneity with regards to restaurant locations, which is the focus of this paper. At the same time, I do not model unobserved variation in consumer preferences beyond the logit errors. This reduces the computational burden and renders feasible both estimation and exploration of alternative market configurations, given that the choice sets are option-rich: typical market areas contain several hundred food service options[14].

Model implications The specified model implies two sets of moments used for estimation. First, the aggregate share of restaurant r in market m is predicted to be

$$\begin{aligned} s_{r(m)} &= \int \mathbb{1}\left\{u_{i(h)r(m)} > u_{i(h)r'(m)} \,\forall r'(m) \neq r(m)\right\} \mathrm{d}P(\varepsilon)\mathrm{d}F_m(h) \\ &= \int \frac{\exp\left[-\rho_m d(h,r) + \delta_r\right]}{1 + \sum_{r' \in R(h)} \exp\left[-\rho_m d(h,r') + \delta_r'\right]} \mathrm{d}F_m(h), \end{aligned} \tag{2}$$

where $F_m(\cdot)$ denotes the distribution of consumers across home-CBGs and is directly observed in the data, and $R(h) = \{r : r \in m(h)\}$ is the choice set of consumer residing consisting in CBG h.

Second, the model predicts an additional set of moments taking the form of choice probabilities of consumer i residing in home-CBG h conditional on i's choice belonging to a given subset of restaurants:

$$\mathbb{E}\left[s_{h,r|R}\right] = \mathbb{E}\left[\mathbb{1}\left\{i(h) \text{ choice } = r\right\} | \mathbb{1}\left\{i(h) \text{ choice } \in R\right\}\right] = \frac{\exp\left[-\rho_m d(h,r) + \delta_r\right]}{\sum_{r' \in R} \exp\left[-\rho_m d(h,r') + \delta_{r'}\right]} \tag{3}$$

In eq. (3) R is any set of food service options containing restaurant r. These moments are useful

[14] Moreover, characteristics data is missing for roughly 11% of the restaurant sample, complicating the standard implementation of random coefficients estimation.

since neighborhood-level conditional shares are observed in the data for restaurants with high enough visit counts and are used for estimation.

4.2 Firm behavior

Specification I model the interaction between firms using an entry and price-and-capacity choice game followed by market competition (consumers visiting restaurants and profits being realized). First, potential entrants make binary entry decisions in each market and the set of market participants is determined. Second, the firms that entered choose the desired location to operate in. Once locations are set, firms choose prices, and then capacity (area of the restaurant), which affects consumer demand. After that, the market operates and firms earn profits discounted on the monthly level. Essentially, the market is modeled as static once the entrants' locations, prices and capacities are determined, which I view as an approximation of the long-run steady state of the industry.

While the sequence of moves in my firm behavior model is fairly standard, the choice of capacity in a given location requires a few comments. On the one hand, capacity choice conditional on location can be interpreted literally: in the commercial real estate data I collected it is not uncommon that area ranges are offered at a given address, rather than a fixed area. On the other hand, this model part can be viewed as an approximation of decision-making of a restaurant owner, who first chooses a suitable neighborhood, then gets informed of the local demand conditions, and finally optimizes price and then the capacity for these conditions. I interpret capacity as a reduced-form way of capturing the idea that consumers may prefer more spacious places and/or that larger restaurants can fit more visitors.

Entry and location choice Consider firm r contemplating entering market m. I assume that r is informed of its type $\theta_r \in \Theta$, which corresponds to its price category, and decides whether to pay the type-specific fixed cost $FC(\theta_r)$ and take part in the market interaction. Each firm knows that this interaction will consist of (i) the location choice game; (ii) the price and capacity optimization game conditional on entry locations; (3) a flow of discounted monthly profits, corresponding to consumer visits. For this part of the model, I assume that firm decisions constitute a rational-expectations zero-profit equilibrium. That is, the entering firm r is informed of the competitor count by price category $\{n(\theta)\}_{\theta\in\Theta}$ and expects that the profits earned in the market interaction, given the competitor count, will exactly outweigh the fixed cost of entry:

$$
\begin{aligned}
\mathbb{E}\left[\Pi_r \mid \theta_r, \{n(\theta)\}_{\theta\in\Theta}\right] &= \mathbb{E}\left[\sum_{t=0}^{\infty} \varphi^t \pi_r^* \mid \theta_r, \{n(\theta)\}_{\theta\in\Theta}\right] - FC(\theta_r) && (4)\\
&= \mathbb{E}\left[\sum_{t=0}^{\infty} \varphi^t \left((p^* - mc)_r q_r^* - \text{Rent}_r \times a_r^*\right) \mid \theta_r, \{n(\theta)\}_{\theta\in\Theta}\right] - FC(\theta_r) && (5)\\
&= 0,
\end{aligned}
$$

In eq. (4), φ is the monthly discount factor and π_r^* is the equilibrium monthly profit realization. In eq. (5), $(p^* - mc)_r$ is the realization of r's equilibrium markup, q_r^* is the equilibrium monthly visit count to r, a_r^* is r capacity (the area of the restaurant), and Rent_r is the commercial rent rate in the area of firm r's equilibrium location. The expectation is taken with respect to the type-specific outcomes in the location choice and price-capacity-optimization continuation game. That is, firm r's type θ_r maps into the probability distribution of outcomes in the continuation game, and for each firm type, the expected present value of the profit flow just covers the fixed costs required for entry.

After the set of market m participants is determined, each firms privately observes its mean quality (excluding the price- and capacity- components) $\delta_r^{-p,a}$, and all competitors play a location choice stage game. On this stage, the set of actions coincides with the set of locations in the market $\{l : l \in m\}$[15], and strategies map firm r's type $\delta_r^{-p,a}$, and location l into choice probabilities $P(\delta_r^{-p,a}, l)$ such that $\sum_{l \in m} P(\delta_r^{-p,a}, l) = 1$.

Price and capacity choice Once locations are realized, each firm r observes its marginal cost draw mc_r, the locations of competitors and chooses its price p_r^*, resulting in the markup $(p^* - mc)_r$. That is, firms price based on their location, mean quality, and local competition information.

Next, firms observe market conditions and, endowed with the knowledge of their mean quality up to the capacity component δ_r^{-a}, choose the operational area (capacity) under the following tradeoff. On the one hand, a greater area leads to more consumer visits; on the other hand, firms pay extra rent for the additional unit of area.

Formally, consider market m with the realized vector of firm locations $\{l(r)\}_{r \in m}$, realized markups $\{(p^* - mc)_r\}_{r \in m}$ and vector of mean utilities excluding the capacity component $\left\{\delta_r^{-a}\right\}_{r \in m}$, where $\delta_r^{-a} = \delta_r - \beta_a a_r^*$, with a_r^* being the equilibrium area or firm r. On the last stage of the market interaction game, each firm decides on its capacity. Equilibrium area of firm r satisfies

$$a_r^* = \arg\max_{a_r} \left[(p^* - mc)_r q_r \left(a_r, a_{-r}^*, \{l(r)\}_{r \in m}, \left\{\delta_r^{-a}\right\}_{r \in m} \right) - \text{Rent}_{l(r)} \times a_r \right], \tag{6}$$

That is, firms act as price-takers in the commercial real estate rental market, and equilibrium capacity choices are optimal given market conditions (demand, rental costs, competitors' locations and properties) and competitors' capacity choices.

The specified model of firm behavior allows me to estimate markups on the firm level using the area-rent tradeoff and the fixed costs using the zero-profit assumption.

[15] With some abuse of notation, m refers to the set of restaurants, home locations and restaurant locations.

5 Estimation

To estimate the structural parameters that govern consumer preferences and firm profitability, I combine model implications with the variation in the data. The observed aggregate and location-specific market shares provide guidance into consumer preferences; the capacity optimality permits backing up the per-visit markups on the firm level with the help of the observed rental costs and the estimated demand system; the ex-ante zero-profit condition allows me to recover the fixed costs of entry using the across-market variation in firm profits.

The estimation consists of several steps. In the first step, I estimate restaurant attractiveness and distance costs market-by-market, combining the spatial demand estimation approach by Davis (2006b) with the Berry et al. (2004) way of utilizing micro-moments for preference parameter estimation. Second, I decompose restaurant attractiveness into characteristics, taking into account the endogeneity of capacity as measured by the restaurant area. Third, I use the recovered demand system and the observed rental costs to compute the markups charged by the restaurants. Finally, I use the across-market variation in the realized average profits (which are observable once the markups are known) to estimate the fixed costs in a regression framework.

The estimation results indicate that (i) distance costs are important determinants of consumer choice, and (ii) there is substantial heterogeneity in markups charged by different restaurants. Thus, alternative firm location configurations can substantially affect both consumer welfare and industry profits.

The rest of this section provides details of the estimation procedure and the parameter estimates, which pave the way towards analyzing the location configuration efficiency.

5.1 Consumer side

5.1.1 Estimation procedure

There are two sets of demand system parameters to be estimated. The first parameter set contains distance costs and alternative-specific constants for every studied market $m \in M : \{(\rho_m, \boldsymbol{\delta}_m)\}_{m \in M}$. The second parameter set $(\alpha_m, \beta, \lambda, \gamma^B, \gamma^C)$ consists of characteristics-related coefficients β, market dummies α_m, location-related coefficients λ, as well as brand and cuisine dummies γ^B and γ^C. Since SafeGraph data allows to [partially] observe restaurant shares conditional on the home location of consumers and to construct sample moments as in (3), I follow Berry et al. (2004) who use a two-step step approach in a setting where micro-moments are available. Specifically, I estimate $\{(\rho_m, \boldsymbol{\delta}_m)\}$ market-by-market by matching predicted aggregate shares in (2) to the observed shares, and minimizing the discrepancy between the sample micro-moments and the model predictions in (3). Subsequently, I estimate the second set of parameter $(\alpha_m, \beta, \lambda, \gamma^B, \gamma^C)$ in an IV-regression of the full vector $\delta = \{\delta_m\}_{m \in M}$ on the observed restaurant characteristics, accounting for the modeled endogeneity of the restaurant area. Such a two-step approach allows me to estimate distance costs in a way that is robust to the relationship between consumer residency patterns and the unobserved restaurant characteristics ξ_r.

Estimation of distance costs and alternative-specific constants To recover the distance costs and mean utilities of visiting restaurants in each market I use the GMM estimation procedure developed in Berry et al. (2004) and incorporate the observed spatial consumer heterogeneity similarly to Davis (2006b). Specifically, the estimation proceeds as follows. For a given market m a value of the ρ_m parameter is picked. Then, the vector of product mean utilities $\boldsymbol{\delta}_m$ is iterated until convergence similarly to the BLP inner loop and Davis (2006b): $\delta'_r = \delta_r + \ln(\hat{s}_{r(m)}) - \ln\left(s_{r(m)}\left(\boldsymbol{\delta}_m, \rho_m, F_m\right)\right)$, where $\hat{s}_{r(m)}$ are observed market shares and $s_{r(m)}\left(\boldsymbol{\delta}_m, \rho, F_m\right)$ are computed according to eq. (2). Next, I evaluate the sample analog of moments in eq. (3) using the current value of ρ_m and the vector of mean utilities $\boldsymbol{\delta}_m$ obtained through the aggregate share matching. The value of ρ_m is updated until the distance between the model predictions in eq. (3) and the sample micro-moments is minimized. As in Berry et al. (2004), this procedure avoids search over $\boldsymbol{\delta}_m$ directly, which eases the computational burden in markets with the number of alternatives in the order of several hundreds or even thousands.

Estimation of characteristics-related coefficients After the first step of estimation is completed, the distance cost parameter ρ_m and the vector of alternative-specific constants $\boldsymbol{\delta}_m$ is recovered for every market m. Next, I use cross-sectional variation in restaurant characteristics and in the recovered δ-s to estimate coefficients on the characteristics $(\alpha_m, \beta, \lambda, \gamma^B, \gamma^C)$. The main coefficient of interest is β_a, the coefficient that determines the impact of the measure of restaurant capacity[16] on the restaurant attractiveness to consumers. β_a determines the tradeoff between additional visits and additional rent faced by the firm on the capacity optimization stage. This tradeoff is essential for estimating markups on the restaurant level, at the same time, given the timing in my firm behavior model, the restaurant capacity is endogenous to the unobserved restaurant characteristics. Thus to estimate β_a, I instrument restaurant capacity with the characteristics of neighbor-firms, BLP-like instruments similar to those used in Davis (2006b). That is, I assume that restaurant r's quality δ_r is related to the characteristics of neighbor-firms are only through the choice of capacity. In the empirical specification, I define neighbor-restaurants as those located within a 1-km radius (10-15 minutes of walking distance), which can be perceived as immediate competitors. I use the averages of rating and cuisine categories counts as well as the share of same-category food places among neighbor-restaurants as characteristics of these immediate competitors. Thanks to the instrumental variable approach, I subsequently use the estimated β_a to recover restaurant markups.

[16] In my empirical specification, I use the log of the restaurant area as the capacity measure. The log-specification ensures that firm capacity optimization problem is concave.

Statistic	*N*	*Mean*	*SD*	*Min*	*Q25*	*Median*	*Q75*	*Max*
δ_r	403,471	−7.11	1.40	−12.80	−8.01	−7.10	−6.20	−0.02
$-\rho_m$	387	−0.11	0.06	−0.40	−0.13	−0.09	−0.06	−0.01

Table 5: Summary statistics on ρ_m and δ_r

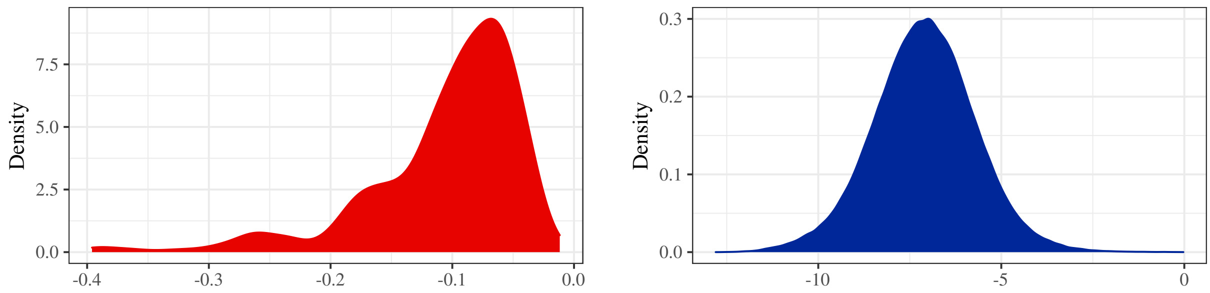
Details As outlined above, markets are defined as Core-based statistical areas (CBSAs). Aggregate market shares on the CBSA level are assumed to be measured perfectly by

$$\hat{s}_r(m) = \frac{\text{Visits}_r}{\text{Days} \times \sum_{h \in m} \text{Devices}_h}$$
$$\hat{s}_0(m) = 1 - \sum_{r \in m} \hat{s}_r(m),$$

where Days is the number of days in the month of data used for estimation; Visits_r and Devices_h are directly observed in the data. Location-specific market shares (conditional on the set of restaurants for which the location-specific visit count is observed) are defined analogously.

Algorithm 1 in Appendix B summarizes the estimation procedure. I use the Nelder-Mead algorithm on the optimization step of the algorithm. Also, for this iteration of the estimation procedure, I use the identity matrix as the weighting matrix $\boldsymbol{W}$ in Algorithm 1.

Discussion and identification intuition In the spatial demand estimation setting, several papers (e.g. Davis (2006b) or Thomadsen (2005)) rely on the aggregate market shares in order to estimate the spatial demand system, including the distance costs. To identify distance costs, an assumption of orthogonality between the unobserved product characteristic ξ and the product location close to or far away from consumers is commonly required[17]. Instead, in this paper, due to the availability of micro-moments, I identify the distance costs parameter in a given market using the across-home-CBG variation in conditional restaurant shares. As a result, similarly to Berry et al. (2004), the distance cost estimate is robust to the assumptions on the relationship between the unobserved restaurant characteristic and restaurant location or characteristics. The decomposition of mean restaurant quality δ_r into restaurant characteristic is analogous to Berry et al. (2004). In contrast to the papers mentioned above, I do not model or estimate the unobserved variation in consumer tastes, concentrating on spatial heterogeneity of consumers. This decision allows me to specifically concentrate on the spatial dimension of the market and avoid the extra computational burden associated with the random coefficients approach. Incorporating richer heterogeneity is further limited by the missing data on characteristics, and is left as a possible direction for future research.



(a) Distribution of ρ_m across markets

(b) Distribution of δ_r across restaurants

Figure 2: Estimates of ρ_m and δ_r

5.1.2 Estimation results

Distance costs and alternative-specific constants Figure 2 presents the output of the first step of the estimation procedure in Algorithm 1 which recovers the market-level distance cost parameter. Figure 2a displays the distribution of distance costs across sample markets (CBSAs), and Figure 2b displays the distribution of restaurant mean utilities. Table 5 presents the corresponding summary statistics. Line 2 of the summary statistics table shows that the distance cost parameter is estimated to be negative in all sample CBSAs. The maximum of $-\rho_m$ across markets is equal to -0.01, strictly below zero, reflecting that the estimation procedure resulted in the distance negatively affecting the value of restaurant to consumers in all markets. Moreover, distance costs are an important determinant of consumer choice: in an average market, a 10-kilometer consumer-restaurant distance increase is equivalent to a 0.75-standard deviation decrease in restaurant quality. At the same time, there is a substantial amount of heterogeneity in distance costs across markets: the 25-percentile distance coefficient is about two times higher in magnitude than the 75-percentile coefficient. Moreover, as Figure 2a shows, the distribution of the distance costs exhibits a relatively heavy left tail. In contrast, the distribution of mean utilities is symmetric around its mean of -7.108, as one can observe in line 1 of the summary statistics table. Table 15 in Appendix B reports the relationship between the estimated distance costs and the observed market characteristics (area, firm count and market population), showing that distance costs are estimated to be lower in larger markets, potentially due to the better transportation system in such larger markets. Population size and firm count are relatively unimportant predictors of the estimated distance costs.

Characteristics coefficients Table 6 presents the output of the second part of Algorithm 1, the estimates of the parameters vector β that determines the impact of restaurant characteristics on its quality index δ_r. Columns (1) and (2) show the main coefficients of interest estimates in the OLS regression of the recovered δ_r vector on the price dummies, rating, number of cuisine categories associated with the restaurant and log of the restaurant area in square meters. Column (1) only includes the market fixed effects, column (2) additionally includes the restaurant brand and category

[17] In a setting with richer data, Houde (2012) relies more on the panel dimension of the data to achieve identification.

	FE OLS			IV
	(1)	(2)	(3)	(4)
Price [$$ vs $]	0.090	0.209	0.201	0.127
	(0.005)***	(0.005)***	(0.005)***	(0.018)***
	[0.059]	[0.008]***	[0.009]***	[0.050]**
Rating	0.120	0.383	0.385	0.348
	(0.014)***	(0.014)***	(0.014)***	(0.017)***
	[0.151]	[0.074]***	[0.070]***	[0.084]***
Rating^2	−0.043	−0.060	−0.063	−0.053
	(0.002)***	(0.002)***	(0.002)***	(0.003)***
	[0.021]**	[0.014]***	[0.013]***	[0.016]***
# of categories	0.135	0.025	0.028	0.011
	(0.003)***	(0.003)***	(0.003)***	(0.005)**
	[0.060]**	[0.005]***	[0.005]***	[0.008]
Log area (sq. m.)	0.069	0.063	0.055	0.497
	(0.002)***	(0.002)***	(0.002)***	(0.103)***
	[0.025]***	[0.006]***	[0.004]***	[0.273]*
CBSA FE	✓	✓	✓	✓
Brand FE		✓	✓	✓
Category FE		✓	✓	✓
Time controls	✓	✓	✓	✓
Location controls	✓	✓	✓	✓
F-stat (robust)				12.572
F-stat (cluster)				8.35
Observations	403,470	403,470	355,091	355,091
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Estimates of restaurant characteristics coefficients. Robust standard errors in round parentheses, standard errors robust to market and brand clustering in square parenthesis. IV column instruments for log restaurant area with neighbor-restaurant characteristics. Lower number of observations in the IV column due to missing instrument. Column (3) estimated on the IV sample. Coefficient on the missing price category dummy is omitted from the output, being slightly negative vs the $-category baseline and insignificant with clustered standard errors.

fixed effects. Column (4) presents the coefficient estimates in the instrumental variable regression in which the log of the restaurant area is treated as endogenous (the brand and category fixed effects are included as well). Column (4) is the preferred specification for recovering the model parameters as it is consistent with the modeling assumption of restaurant capacity optimization conditional on the unobserved characteristic realization. Column (3) shares the specification with column (2), but uses IV sample for estimation. IV sample is smaller than the FE OLS sample since the instrument is impossible to construct for some restaurants due to missing data or the absence of neighbor-restaurants.

The covariate coefficients across different specifications have consistent signs and mostly similar magnitudes. The coefficient on the $$ price category dummy is positive relative to the $ price category baseline across all specifications. This result highlights the fact that the price category is likely to reflect both the price and the unobserved quality of the restaurant and should not be surprising. The price coefficient goes up in magnitude from column (1) to column (2) upon the inclusion of brand and cuisine category dummies, suggesting that the price category is a stronger quality signal among the non-branded restaurants. The explanation is likely similar for the rating coefficient, which goes up upon the inclusion of brand and cuisine category fixed effects too. Across all specifications, the coefficient on the square of rating is negative, indicating a decreasing return to improving the restaurant rating. Additionally, ratings closer to 5 are likely to come from relatively new restaurants with fewer reviews and, relatedly, lower visit counts and lower estimated mean utilities. The number of categories, a measure of the restaurant's cuisine diversity, is positively related to the mean product utility. Again, this coefficient goes down in magnitude once the fixed effects are included.

The main effect of interest is the coefficient on the log of the restaurant area, which is a measure of the restaurant's capacity. As described in Section 4.2 the modeling assumption is that firms choose the capacity endowed with the knowledge of their unobserved characteristic ξ_r. If firms with higher values of ξ_r are likely to select into areas with higher commercial rent, they are also likely to choose lower capacity, which can translate into a negative bias in the log area coefficient estimates in column (2) of Table 6. Similarly, firms with higher values of ξ_r may find it difficult to operate on a larger scale, which would again transmit into a smaller capacity and a negative bias in the log area coefficient estimate. To account for these endogeneity issues, an instrumental variables strategy is used: column (4) of Table 6 reports the estimates with BLP-like instruments (characteristics of neighbor-restaurants) used for log-area similar to those used in Davis (2006b) for price. Neighbor-restaurants are defined to be all restaurants within a 1-km radius; the average of rating, the average cuisine categories count and the share of same-category food places among neighbor-restaurants are used as characteristics of these immediate competitors. Constructing the instruments is not always possible given missing data on restaurants, thus the reduction in observations from 403,470 in OLS specifications to 355,091 in the IV specification. The resulting estimate of 0.497 for the log area coefficient is substantially higher in magnitude than the corresponding FE OLS estimate. At the same time, the IV estimates are noisier, still, the log area coefficient is significant at the 5% (10%) level when standard errors robust to heteroskedasticity (market- and brand- clustering) are used respectively. The first stage F-statistic for excluded instruments equal 12.572 (8.35) in the respective specifications, reflecting relatively strong instruments. Also, the similarity of estimates in columns (2) and (3) suggests that the difference in the log area coefficient between the FE OLS and the IV estimate is not driven by sample selection due to the missing instrument. For completeness, Table 16 in Appendix B reports the first stage estimates: negative coefficients on average neighbor rating and the share of neighbors with the same cuisine, and a positive coefficient on the average count of neighbors' cuisine categories.

With the standard notes of caution regarding the IV strategy, I proceed to use the recovered coefficient on the measure of restaurant capacity for estimating markups on the restaurant level.

5.2 Firm side

5.2.1 Estimation procedure

Markups The maximization in eq. (6) implied by the firms' equilibrium capacity choice yields the following expression for the markups:

$$(p^* - mc)_r = \left(\left. \frac{\partial q_r \left(a_r, a^*_{-r}, \{l(r)\}_{r\in m}, \{\delta_r^{-a}\}_{r\in m} \right)}{\partial a_r} \right|_{a_r = a^*_r} \right)^{-1} \times \text{Rent}_{l(r)}, \tag{7}$$

which allows me to estimate the markups on the restaurant level subject to the availability of commercial rental rates data in the restaurant's locality[18], since the first term on the right can be computed using the estimated demand system, and the second term is data. Specifically, the total change in visits[19] with respect to a marginal increase in area is computed via numerical differentiation, and the $\text{Rent}_{l(r)}$ faced by a restaurant is approximated by the mean observed commercial rent among the listings in the same ZIP code.

Price-category-specific fixed costs With the recovered vector of $(p^* - mc)_r$ at hand, the vector of π^*_r realizations in eq. (4) can be computed, leading to the following estimation equation:

$$\begin{aligned} \sum_{t=0}^{\infty} \varphi^t \pi^*_r &= FC(\theta_r) + \left(\sum_{t=0}^{\infty} \varphi^t \pi^*_r - \mathbb{E}\left[\sum_{t=0}^{\infty} \varphi^t \pi^*_r \mid \theta_r, \{n(\theta)\}_{\theta\in\Theta} \right] \right) \\ &= FC(\theta_r) + u_r, \end{aligned} \tag{8}$$

where the disturbance terms u_r capture the mean-zero deviation of the realized profits from the expected type-specific profits in a given market. Notice that the expectation operator is taken with respect to the distribution of profits given by the equilibrium strategies of the firms upon market entry[20]. Given this estimating equation, one obtains the type-specific fixed costs in a regression of the recovered profits on the type-dummies. Since markets are sampled from the population of interest, and the assignment of firm-types is correlated within a market, clustering the standard

[18] The commercial rent is not available for *all* localities, thus not all markups can be recovered. At the stage of studying alternative firm location configurations, I replace missing restaurant markups with the local median recovered markup.
[19] Made by the entire population, observed through ACS
[20] And, potentially, with respect to equilibrium-selection probability distributions as well.

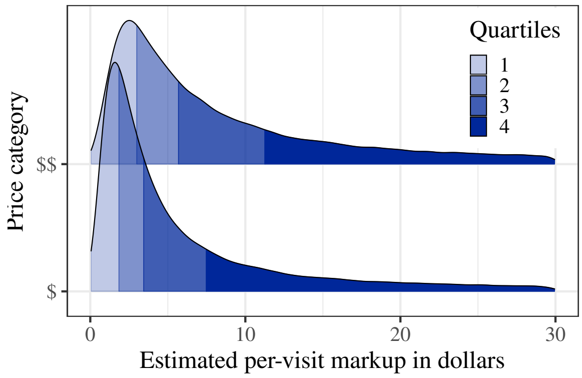


Figure 3: Distribution of estimated markups, broken down by price category. Restaurants with missing price category omitted.

Price	*Mean*	*Q10*	*Q25*	*Med*	*Q75*	*Q90*
$	8.19	1.09	1.87	3.74	9.14	22.45
$$	11.64	1.86	3.22	6.60	15.05	30.47

Table 7: Summary statistics for the distribution of markups broken down by price category. Restaurants with missing price category omitted.

errors on the market level is necessary in such an estimation. Alternatively, in my preferred specification, I explicitly model the realization of the disturbance term as a sum of market-specific error v_m and firm-specific error e_r, $u_r = v_m + e_r$, imposing the across-market condition $\mathbb{E}\left[v_m\right] = 0$. In that specification I estimate the type-specific fixed costs using a regression of the realized profits on type- and market fixed effects, enforcing the average market fixed effect to be equal to zero.

One parameter that is required to compute the left-hand side of estimating equation (8) is the discount rate φ, which I can not recover from the available data. I calibrate this parameter to fit the monthly restaurant survival probability. The range of yearly failure rates reported by the industry press ranges from as low as 17% (e.g. Forbes (2017)) to as high as 40% (e.g. CNBC (2016)), implying monthly survival probabilities from 0.927 to 0.985. Carefully computed estimates appear to be more on the low side of the range (Parsa et al. (2005) find 26.16% first-year failure rate, Luo and Stark (2014) find 19% and 17% failure rates for limited- and full-service restaurants respectively). Thus I perform the estimation of fixed costs under a range of conservative assumptions about the discounting rate: $\varphi \in \{0.965, 0.97, 0.975\}$.

5.2.2 Estimation results

Markups Figure 3 plots the estimated markup distribution by the observed restaurant price category, and Table 7 tabulates the respective summary statistics. The median markup among the $ restaurants is estimated to be 3.74 dollars per visit. For the restaurants in the $$ price category, the median is about 75% higher and stands at 6.69 dollars per visit. The markup distributions are skewed to the right: as can be observed in Figure 3, the right tails are heavy for both price categories. Also, the mean markups for the $ category (8.19 dollars) and for the $$ category (11.645 dollars) are both substantially higher than the respective median markups. These observations indicate that while the majority of restaurants charge relatively low markups, a small fraction of firms enjoys substantial profits per visit, driving the industry-mean averages higher. To give these estimates a perspective, according to industry press (see, e.g. On The Line (2019)) a typical restaurant makes

	$\varphi = 0.965$		$\varphi = 0.97$		$\varphi = 0.975$	
	(1)	(2)	(3)	(4)	(5)	(6)
FC($)	$371,584.2^{***}$	$281,733.3^{***}$	$433,514.9^{***}$	$328,688.8^{***}$	$520,217.9^{***}$	$394,426.6^{***}$
	(14,056.5)	(6,655.4)	(16,399.2)	(7,804.3)	(19,679.1)	(9,606.7)
FC($$)	$642,361.6^{***}$	$550,886.6^{***}$	$749,421.9^{***}$	$642,701.1^{***}$	$899,306.2^{***}$	$771,241.3^{***}$
	(28,825.6)	(9,285.5)	(33,629.9)	(10,888.4)	(40,355.9)	(13,403.0)
CBSA FE		✓		✓		✓
Observations	269,507	269,507	269,507	269,507	269,507	269,507
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: Fixed cost estimates. Columns (2), (4), (6) report estimates with across-market zero average profit condition enforced. CBSA-clustered standard errors in parentheses. Only the restaurants with non-missing price category are included in the estimation.

$111,860.70 in monthly sales, and net profit margins are around 6.1 % (see Forbes (2018)), implying a typical monthly profit of roughly $6823.5, while, for reference, the median recovered monthly profit of a restaurant in my sample stands slightly higher at $7419.8. As another sanity check, Table 17 in Appendix B reports details on the relationship between estimated markups, estimated restaurant quality and observed restaurant characteristics, establishing three intuitive correlations. First, restaurant quality is negatively related to markups. Second, restaurants with higher price category have higher markups. Third, restaurants with higher ratings have lower markups.

Overall, the estimated markups appear reasonable, and, given the lack of detailed pricing information on the restaurant levels, these estimates are likely to be the best measures of restaurant profitability with the data I have available.

Fixed costs Table 8 reports the price category-specific fixed costs recovered off the expected zero-profit equilibrium conditions. Specifications (1), (3) and (5) use across-firm variation, imposing the zero average profit condition for every type (price category) of firms. Specifications (2), (4) and (6) use the across-market variation of average firm profits and impose the across-market zero average profit condition for every firm type. The estimated fixed costs are systematically lower in the latter specifications compared to those with the same discounting rate, but no market fixed effects. This suggests that markets with more firms exhibit higher profits as well, and the estimates without market fixed effects don't account for such differences, placing equal weight on all firms. As a result, these estimates are higher compared to FE estimates, which instead place equal weight on all markets. As my preferred estimates, I use the results of fixed-effect specifications, relying on across-market variation to recover the fixed costs.

The fixed cost of opening a $-priced restaurant is estimated to be 328,689 dollars in my preferred specification ($\varphi = 0.97$, market FE), while the fixed cost estimate of opening a $$-priced restaurant is almost 2 times higher, standing at 642,701 dollars. For comparison, the industry press typically mentions startup costs between $225k for a smaller restaurant and $785k for a larger one (see e.g. Seek Capital (2019) and Lightspeed (2020)). As a note of caution, some of the costs included in the startup costs breakdown are actually not *fixed* costs and may be recovered in case of failure (for example, furniture or kitchen equipment). At the same time, the startup costs reported by the press do not include the income a business owner forgoes by concentrating on the restaurant opening.

Overall, the industry benchmarks seem consistent with the fixed cost estimates I recovered using the zero-profit condition. These estimates will be instrumental for assessing the magnitude of the social cost of excessive entry, which is often associated with free-entry industries, see Mankiw and Whinston (1986).

6 Alternative firm location configurations

In order to look into the efficiency of firm location configurations, I develop a framework that utilizes the recovered structural parameters to determine the magnitudes and sources of welfare losses. The framework consists of efficiency criteria, a computational approach to the exploration of alternative configurations, and a perturbation method that provides guidance into the relative importance of inefficiency sources.

Efficiency criteria are total profits for the firms and the equivalent variation in distance costs for consumers. The computational method performs a greedy search for welfare improvements, at each step shifting a single firm location or switching locations of a firm pair so that the efficiency criteria are increased. The perturbation method explores the welfare consequences of altering the status quo location configuration by either a single firm shift or a single firm switch. Profitable individual shifts indicate either information frictions or welfare-reducing differentiation. Unprofitable and welfare-increasing shifts point to firms' business stealing incentives. Profitable location switches indicate imperfect firm-location sorting, which can be attributed to miscoordination or separate ownership.

The exploration of alternative firm location configurations demonstrates sizeable efficiency losses: in a median market spatial reconfiguration can improve the consumer welfare metric by 7.73%, while at the same increasing total industry profits by 8.51%. The welfare improvements are associated with increasing restaurant quality in low-variety areas and areas located further away from the mean consumers. At the same time, the abundance of profitable deviations indicates points at differentiation incentives, which are not aligned with social welfare maximization, as a force that has a substantial influence on the inefficient status quo configurations. Firm location switches provide lower profit increases than individual deviations, which is indicative of miscoordination / separate ownership being less important in shaping firm location configurations.

The rest of this section describes the details of the developed framework for efficiency investigation, lays out the results and provides a discussion.

6.1 Efficiency criteria

I study the efficiency of firm location configurations through the lens of two welfare metrics, that separately represent consumer and firm welfare in a given market. The firm-side welfare metric is straightforwardly defined as total industry profits. In a less standard fashion, the consumer-side metric captures consumer welfare in an alternative market configuration by the *alternative-equivalent* level of distance costs that makes the average consumer indifferent between facing that distance cost level under the status quo configuration and switching to the alternative. If for a certain alternative configuration, the respective alternative-equivalent distance cost level exactly equals the actual estimate of the distance cost, this alternative configuration is welfare-equivalent to the status quo from the consumer point of view. Levels of alternative-equivalent distance costs lower than the actual estimates indicate that the alternative configuration is preferred to the status quo, while higher alternative-equivalent distance costs indicate a reduction in consumer welfare. The difference between the alternative-equivalent and the actual levels of distance costs thus shares the interpretation with the equivalent variation from the standard demand theory Mas-Colell et al. (1995, Chapter 3).

For a formal definition of consumer welfare, consider market m and two firm location configurations: the status quo configuration s and the alternative one a. Let $U_{ma}(\rho_m)$ be the average expected consumer utility under the alternative market configuration a and the actual estimated distance cost level ρ_m. Next, similarly, let $U_{ms}(\cdot)$ be the function that maps distance cost levels into the average expected consumer utility under the status quo market configuration s. Now consider the value ρ^*_{ma} of distance costs such that $U_{ms}(\rho^*_{ma}) = U_{ma}(\rho_m)$. The value ρ^*_{ma} makes the average consumer exactly indifferent between the status quo market configuration s when distance costs are equal to ρ^*_{ma} and the alternative market configuration a and the actual distance cost level ρ_m. In turn, the difference $\rho^*_{ma} - \rho_m$ captures the change in consumer welfare associated with the switch from status quo s to alternative a. If $\rho^*_{ma} - \rho_m < 0$, the alternative configuration is equivalent to a reduction in distance costs, an improvement for the consumer. If, to the opposite, $\rho^*_{ma} - \rho_m > 0$, the average consumer is hurt by the switch to the alternative configuration a. $\rho^*_{ma} - \rho_m$ is thus similar to the equivalent variation welfare metric from the standard demand theory (the change in wealth at current prices that leads to the same level of consumer utility as the considered change in prices).

When exploring the alternative market configurations in my empirical setting, I use the consumer choice model introduced in Section 4 to compute average consumer welfare levels $U_{ms}(\cdot), U_{ma}(\rho_m)$, and to find the value of ρ^*_{ma} that solves equation $U_{ms}(\rho^*_{ma}) = U_{ma}(\rho_m)$ for a given market m and configurations s, a. That is, the computation of average consumer utility recognizes the observed spatial heterogeneity of consumers and the unobserved variation in consumer tastes captured by the logit shocks:

$$U_{ma}(\rho_m) = \int \mathbb{E}\left[\max_{r\in a}\left[\rho_m d(h,r) + \delta_r + \varepsilon_{i(h)r}\right]\right] \mathrm{d}F_m(h)$$
$$U_{ms}(\rho_{ma}) = \int \mathbb{E}\left[\max_{r\in s}\left[\rho_{ma} d(h,r) + \delta_r + \varepsilon_{i(h)r}\right]\right] \mathrm{d}F_m(h)$$

where $\mathbb{E}\left[\max_{r\in a}\left[\rho_m d(h,r) + \delta_r + \varepsilon_{i(h)r}\right]\right]$ and $\mathbb{E}\left[\max_{r\in s}\left[\rho_{ma} d(h,r) + \delta_r + \varepsilon_{i(h)r}\right]\right]$ are the inclusive values of consumers characterized by home location h under alternative configuration a (paired with the actual distance cost ρ_m) and status quo configuration s (paired with the distance cost level ρ_{ma}) respectively. The weights $F_m(h)$ denote the empirical distribution of consumers across home locations observed in the data. Conditional on the home location, the inclusive value computation is standard, see Train (2009, Chapter 3); while I find the distance cost parameter ρ^*_{ma} solving $U_{ms}(\rho^*_{ma}) = U_{ma}(\rho_m)$ numerically.

Note that my proposed definition of consumer welfare metric does not permit aggregating welfare of firms and consumers into a single measure due to the difference in units; I choose such a definition due to the absence of firm-level price information in my data[21]. For this reason, exploring alternative configurations is complicated by the need to consider the firm and consumer sides separately and I use multi-objective optimization when searching for welfare-improving configurations.

6.2 Efficiency-improving configurations

I begin the exploration of alternative firm location configurations by searching for a configuration that improves market efficiency by increasing both consumer welfare and total industry profits. While such a maximization problem is hard, I design an approximation algorithm and interpret the resulting improvements as lower bounds on feasible welfare improvements.

6.2.1 Algorithmic approach

The search for the firm location configuration that maximizes a single welfare metric (either total profits or the consumer welfare) can be decomposed into two steps: choosing a set of locations, and assigning firms to these locations. The latter assignment step can be formulated as a non-linear integer programming[22], which is known to be NP-complete, see, for example, Schrijver (1998, Chapter 18). The two-step optimization problem is thus NP-complete as well, although the outer search for a set of locations can further increase the computational complexity. In practice, non-linear integer programming problems are solved using heuristic methods, see Papadimitriou and Steiglitz (1998). I follow this practice and design a heuristic optimization algorithm accounting for

[21] Such an approach is not uncommon in similar settings without monetary values assigned to choices, e. g. Agarwal et al. (2020).

[22] See Appendix C.1 for details.

the multi-objective nature of optimization.

The designed algorithm aims at the step-wise improvement of welfare metrics on both consumer and firm sides of the market. The algorithm begins with the status quo location configuration, on each step the market configuration is randomly altered, and the alteration is retained if both welfare metrics are increased. The algorithm finishes after a pre-specified number of iteration steps is completed or once the computational time budget is exhausted.

Two features of the algorithm are worth noticing: the use of randomization (in a way reminiscent of the *simulated annealing* technique described in van Laarhoven and Aarts (1987)) and its greedy local search (a characteristic shared by multiple combinatorial heuristics, see Aarts and Lenstra (1997)). While, in principle, every local alteration can be considered on each step of the algorithm in search for the best local alteration, I use randomization to speed up each step of the procedure. The algorithm's greediness is in turn useful as a way of ensuring that the resulting location configuration is, in fact, welfare-improving compared to the status quo, without relying on the structure of the maximization problem.

To improve the welfare metrics on each algorithm step, I use two types of location configuration alterations inspired by the standard approaches in local search in combinatorial approximation (see Aarts and Lenstra (1997)): firm shifts and firm pair switches. Of course, a firm pair switch can be equivalently represented by two firm shifts, however, in practice, the algorithm proceeds faster, when firm switches are allowed. Due to the remaining computational constraints, I use the computation time budget finish criterion of 4 hours of runtime to stop the optimization in each of the explored markets.

Comparing the welfare metrics in the best alternative market configuration and the status quo configuration is informative of the welfare loss magnitudes that can be accrued specifically to firm locations. Several notes of caution are necessary. First, the best alternative configuration results from an algorithm that only approximates the actual welfare-optimal configuration, thus, the generated improvement can only be interpreted as the lower bound on attainable welfare improvements[23]. On the other hand, the total profit improvement does not account for unobserved firm preferences regarding locations, and a richer model would be necessary to incorporate such preferences. While firm owners are in fact likely to have unobserved location preferences, some of these preferences can be interpreted as "biases" given that a large fraction of owners are entrepreneurs, and I focus the analysis on the only objective measure of firm success that is available in my setting – firm profits. Third, the search for alternative configurations I propose does not involve the re-pricing by the firms. One reason for such a partial approach is the lack of detailed information about firm prices, that prevents carefully modeling the pricing decisions.

[23] Similarly, since the algorithm maximizes total profits and the consumer welfare metric simultaneously, the resulting improvement corresponds to a single point on the Pareto-frontier of alternative allocations.

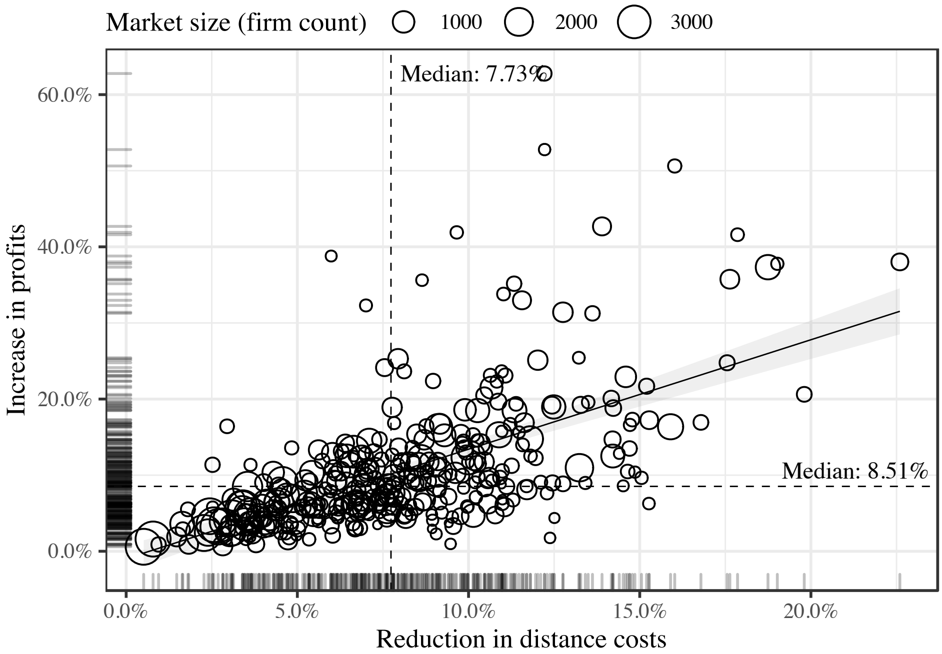


Figure 4: Joint distribution of profit and consumer welfare changes (best alternative vs status-quo configurations). Each observation represents a single market, dot sizes reflect the market firm count.

At the same time, the lack of repricing stage allows me to concentrate specifically on the location configurations and isolate their impact on welfare.

6.2.2 Results

Using the designed approximation algorithm, I document the bounds on welfare improvement. Then, I study the differences between the best alternative location configuration and the status quo configuration by comparing them across markets and along several dimensions that capture characteristics of these configurations. These characteristics reflect the within-market relationship between restaurant and location characteristics and provide guidance on the desirable configuration features that can serve as policy goals.

Figure 4 presents information on the magnitudes of consumer welfare and total industry profits improvement provided by the best alternative configuration compared to the status quo configuration across a sample of markets with 100-4000 firms[24]. To simplify the across-market comparisons, I translate the welfare improvement into percentage units. That is, Figure 4 plots the percent-difference between the alternative-equivalent and the actual distance costs ($(\rho^*_{ma} - \rho_m)/\rho_m$) against the percent-change in total industry profits.

In the median market, the total profits are 8.51% higher in the best alternative configuration compared to the status quo configuration. There is substantial variation in profit increases associated

[24]For computational reasons, I only use 355 smaller markets (out of the initial 387 markets) in the exploration of alternative configurations at this point.

with switching to the best alternative configuration: from 3.14% at the 0.1-quantile to 19.63% at the 0.9-quantile. In turn, the consumer welfare increase in the median market is equivalent to a 7.73% decrease in distance costs under the status quo firm location configuration. The 0.1-quantile to 0.9-quantile range is 3.58% to 12.50%, wider than the the profit-increase range. There is a positive association between the improvements to firm profits and consumer welfare, represented by the upward-sloping linear fit in Figure 4, suggesting that the changes in location configurations tend to evenly split the increased surplus between consumers and firms, rather than primarily benefiting one side of the market.

Features that capture market size (firm count, area and population) are not predictive of the welfare changes brought by the alternative market configurations, which is reflected by the lack of significant coefficients in the first two columns of Table 18 in Appendix C. This fact suggests that markets with more participants are not characterized by more efficient location configurations, and neither are markets that are smaller in area where the variation in location configuration is, in principle, smaller. More intricate market features are responsible for welfare improvements. At the same time, I find that the type of alterations on the path from the status quo location configuration to the best alternative *does* vary with the count of firms in the market, as one can observe from column (4) of Table 18. Specifically, the negative coefficient of -33.98 on the log firm count indicates that, in smaller markets, a larger fraction of alterations are firm shifts compared to the medium-sized markets. The positive coefficient of 2.51 on the square of log firm count, however, indicates a U-shaped relationship between firm count and the share of shift-type alterations applied to location configurations in search for welfare improvements. These results suggest that the welfare losses in medium-sized markets are mostly generated by imperfect firm-location matches, while smaller and larger markets are more likely to have firms located in positions that are detrimental to welfare per se. A note of caution for these interpretations is the fact that the search for welfare improvements varies with market size (see column (3) of Table 18), and, thus, the described regularities, to some extent reflect the variation in algorithm execution across markets of different sizes as well.

How do the best alternative configurations differ from the status quo ones bring? The answer to this question can be informative of the goals that the policies should pursue in an attempt to correct welfare losses associated with firm location configurations. Table 9 provides guidance, summarizing how characteristic features of markets change in the best alternative configuration compared to the status quo.

To construct this table, I consider the market features that describe how firms heterogeneous along the quality and markup dimensions (reflected by the parameters δ_r and $(p - c)_r$ recovered on the estimation stage) are matched towards locations[25] that differ in local restaurant count, local population density and average distance to consumers. These firm characteristics reflect

[25] In the data, each Census Block Group is a location for the purposes of this section.

	Dependent variable:					
	Correlation between quality and			Correlation between markups and		
	Rest. count (1)	Pop. dens. (2)	W. distance (3)	Rest. count (4)	Pop. dens. (5)	W. distance (6)
Alt. config [vs status-quo]	-0.040^{***} (0.004)	-0.002 (0.006)	0.030^{***} (0.004)	-0.011^{*} (0.006)	-0.005 (0.006)	0.042^{***} (0.003)
CBSA FE	✓	✓	✓	✓	✓	✓
Observations	710	710	710	710	710	710
R^2	0.940	0.915	0.979	0.951	0.934	0.926
Adjusted R^2	0.879	0.829	0.957	0.901	0.868	0.853
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 9: Changes in market characteristics associated with the switch from status-quo to best alternative configurations. W. distance refers to average distance from a given restaurant to consumers. Standard errors robust to heteroskedasticity and CBSA clustering reported in parentheses.

the value to consumers (δ_r) and firm owners ($(p^* - mc)_r$), while location characteristics reflect local competition and proximity to consumers. The characteristics were chosen to be in line with the market dimensions captured by the model: spatial differentiation, lack of unobserved taste heterogeneity, and varying firm profitability types. Table 9 reports how the correlations between firm and location characteristics differ between the best alternative and the status quo configuration.

Several estimates in Table 9 are worth noticing. First, I find that the correlation between restaurant quality and restaurant count on the local level is lower in the best alternative configuration, as reflected by the statistically significant -0.04 coefficient in column (1). I interpret this finding as evidence that best alternative configurations better trade-off quality and the number of options available to local consumers: in the alternative configuration locations with a smaller number of local options are characterized by higher restaurant quality as compared to the status quo. Second, I find that the correlation between restaurant quality and weighted distance to consumers is higher in the alternative configuration constructed in search for welfare-improvement. Specifically, the correlation goes up by 0.03 from its status quo value, that is, higher quality restaurants are shifted *away* from the consumers. This finding is consistent with the first result: when higher quality restaurants are shifted to locations that are further away from consumers on average but benefit those local consumers, who suffer from long travel distances and a low number of local options. At the same time, the shifted restaurant benefit are likely to benefit from lower local competition and lower rental costs, which can create extra profits. Next, the correlation between markups and weighted distance to consumers is higher in the best alternative configuration as one can observe from column (6) in Table 9: restaurants with lower markups are shifted to locations in closer proximity to consumers. This is consistent with the [marginally insignificant] negative coefficient in column (4): markups in option-rich locations are lower in the best alternative configurations compared to the status quo. Finally, insignificant coefficients in columns (2) and (5) indicate that the relationship between restaurant characteristics and the population density in the immediate proximity is not an important determinant of the welfare level.

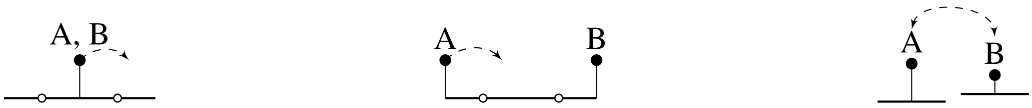
Overall, results reported in Table 9 suggest that the welfare-increasing firm location configuration differ from the status quo configurations by two key features: higher restaurant quality in option-poor and more remote locations, and lower markups in option-rich and more accessible locations. Thus improving quality in remote locations (which likely provides welfare improvement to initially disadvantaged consumers) and ensuring that markups are low in option-rich locations could potentially be the goals of policy set to improve both consumer and firm welfare. It should, however, be noted, that one should be especially cautious of the potential repricing that could happen if the alternative configurations were realized. More detailed data and a correspondingly more intricate model of firm behavior is required to account for such equilibrium changes, which I leave as a direction for further research.

6.3 Sources of efficiency losses

The algorithmic search for welfare-improving firm location configurations puts a lower bound on welfare losses and suggests the changes in spatial market structure that policy work can promote to restore firm position efficiency. However, it is not informative of the incentives issues that generate welfare losses. To provide evidence on the economic sources of efficiency losses, I design a set of tests based on small perturbations of the status quo market configurations. The perturbation consequences allow assessing the relative importance of business-stealing incentives, market power considerations and imperfect firm-location sorting. Section 6.3.1 describes the conceptual framework for analyzing perturbations, Section 6.3.2 reports the results indicative of differentiation incentives being the most pronounced source of efficiency losses.

6.3.1 Conceptual framework

Business-stealing vs market power The theoretical literature on spatial competition beginning with the classic paper by Hotelling (1929) has identified several key frictions that result in inefficient firm location configurations. First, conditional on a vector of prices, firms prefer to locate closer to the average consumer, stealing business from the competitor, which results in minimal differentiation, see Tirole (1988, Chapter 7). Minimal differentiation, originally alluded to by Hotelling (1929), results in aggregate distance costs that are too high compared to the social optimum. Figure 5a illustrates this for the case of a linear market: for fixed prices, firms A and B prefer to be located in the middle of the market (the black dot), while the empty dots correspond to firm positions that minimize total distance costs incurred by consumers. Second, recognizing that positions in close proximity result in intense price competition, firms prefer to locate further from one another, which can result in maximal differentiation as shown by d'Aspremont et al. (1979). In that case, again, the distance costs incurred by consumers are inefficiently high. For the case of the



(a) Market dominated by business-stealing incentives. Firm A shift is consumer-welfare increasing and unprofitable.

(b) Market dominated by market power considerations. Firm A shift is consumer-welfare increasing and profitable.

(c) Market with imperfect firm-location sorting. Location switch is consumer-welfare increasing and jointly profitable.

Figure 5: A conceptual representation of market frictions in one-dimensional market space.

linear market firms located at market boundaries, as shown in Figure 5b.

These two extreme cases of minimal and maximal differentiation share a common prediction: firms' individual deviations from equilibrium locations result in increased consumer welfare. To see this, consider a shift in the location of firm A in Figures 5a and 5b (indicated by the dashed arrow) and note that consumers benefit from these shifts[26].

Predictions regarding consequences for the deviating firm profits, however, are different for the markets dominated by business-stealing and market power effects. In the case where the business-stealing dominates the market and leads to minimal differentiation, a firm that is shifted away from the average consumer loses market share and experiences a decrease in profits, as does the shifted firm A in Figure 5a. When the market power considerations dominate and push firms to extreme differentiation as in Figure 5b, a shift in firm A's location is in fact profitable for the shifted firm as its market share increases conditional on fixed prices.

I use this observation regarding the different directions of profit changes of shifted firms in case of dominating business-stealing and market power effects to design a perturbation approach that suggests, which of the two forces is more important in my empirical context. Specifically, in each sample market, I consider a set of alternative market configurations that differ from the status quo by a position of exactly one firm. I then record the consequences of such perturbations in terms of the consumer welfare change and the shifted firm profit change. I interpret the increased profits of shifted firms as evidence of market power considerations and decreased profits – as evidence of business-stealing incentives leading firm to location configurations, such that deviations result in the loss of market share. While the resulting evidence is not fully conclusive, it provides intuition and benefits from the simplicity of implementation.

Imperfect firm-location sorting Firm differentiation beyond locations in the market space and non-uniform distribution of consumers are immediate features of my empirical setting not captured by traditional models of spatial competition. The recent theoretical research has considered relaxing both the uniform density assumption (e.g. Anderson et al. (1997)) and the firm homogeneity assumption (e.g. Vogel (2008)). To the best of my knowledge, the framework with both non-

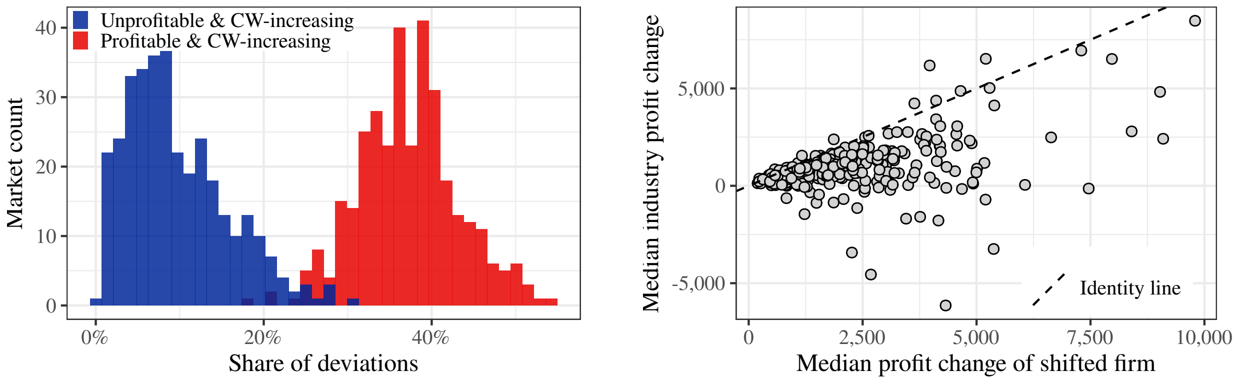
[26]This is true for any shift of firm A from the middle of the line segment as in Figure 5a. For the shift from the endpoint as in Figure 5b, the shift needs to place firm A far enough from the other endpoint, where firm B is located, in order for consumers to benefit from lower distance costs.

uniform consumer density and firm heterogeneity beyond location choices is yet to be explored by the spatial competition literature. However, some intuition on additional sources of location configurations inefficiency can be gained from the entry and trade research. For example, Nocke (2006) considers the setting in which entrepreneurs of heterogeneous productivity select a market to enter; markets are isolated, which can be viewed as a special case of non-uniform consumer density. Nocke (2006) establishes positive sorting: more productive entrepreneurs select into larger markets. Under certain conditions, similar results have been established in the trade literature, see, e.g., Okubo et al. (2010) or Kokovin et al. (2020). The sorting of firms to locations is, however, not necessarily efficient, when firms are differentiated and the set of available locations is limited. Consider Figure 5c, in which there are two available business spots, and firm A is located in a market region with lower consumer density than firm B's region, although firm A's product is of higher quality. For fixed prices, exchanging A and B's locations would be jointly profitable and consumer-welfare increasing: more consumers would buy the good (due to increased quality) in the more dense region, while a lower amount of consumers would stop buying the good (due to lower quality) in the less dense area. A jointly profitable location switch requires coordination, which may be impossible when firms are separately owned. Still, the inefficient sorting of firms to locations is an equilibrium outcome if each spot can support a single firm only[27]. I attempt to assess such sorting inefficiencies by perturbation exercises similar to the ones aimed at detecting business-stealing and market power considerations. Specifically, I perturb the status quo market allocations by pair-wise location switches and record the profitability of such switches for the firm pairs. I then use the magnitudes of the profit changes to provide evidence on the relative strength of incentive issues (business-stealing and market power) versus the miscoordination issues (imperfect firm-location sorting).

It should be noted that in order to precisely differentiate between the sources of inefficiency, one would need to fully specify a structural model of location choice and price setting, simulate the model *without* price setting (to isolate the business-stealing incentives), simulate the model *with* price setting to evaluate the additional welfare losses due to market power, and simulate the model under joint ownership to isolate the impact of imperfect firm-location sorting. My approach can be viewed as a first-order approximation aimed at simplicity of implementation, designed specifically for markets with a large number of competing firms and limited by the lack of price information.

Excessive entry Additionally, to quantify the extent of excessive entry along the lines of Mankiw and Whinston (1986) or Salop (1979), I perform an exploration of market configurations with a reduced number of firms compared to the status quo. Specifically, in each sample market, I sequentially delete random firms and then reallocate the remaining ones by shifts and switches until

[27] This intuition can be expected to hold even without the limited set of locations if firms are horizontally differentiated beyond location: if firm A was to individually shift location to the denser region, price competition would follow, potentially rendering the individual shift unprofitable.



(a) Distribution of deviation type shares across sample markets.

(b) Relationship between shifted firm profit changes and total market profit changes.

Figure 6: Consequences of individual firm shifts across sample markets.

the initial levels of consumer welfare and total profits are restored. Once the deletion-reconfiguration procedure is finished, I compute the total number of firms removed without reducing the welfare metrics. Given the fixed cost estimates obtained above, this number provides guidance into the total losses associated with the excessive entry.

6.3.2 Results

I first report the results on one-shift market configuration perturbations that capture the strength of business-stealing versus market power incentives resulting in the inefficiency of firm positioning. Next, I compare the consequences of individual firm shifts versus pairwise switches, shedding light on the importance of firm-location sorting in determining the efficiency of location configurations.

Business-stealing vs market power Figure 6a depicts the across-market variation in the share of individual firm shifts that result in the increase in consumer welfare and the shifted firm's profit loss (blue) or the shifted firm's profit increase (red). In that figure, the red histogram is almost entirely to the right of the blue one, reflecting a higher percentage of profitable location shifts across most of the sample markets. In an average market, 37.1% of firm shifts result in higher firm profit and higher consumer welfare, while only 8.2% of shift result in lower firm profit and higher consumer welfare. Given the intuition developed using simple spatial competition models in Section 6.3.1, this finding suggests that the incentives to differentiate and obtain market power are relatively more important in shaping market outcomes compared to the business-stealing incentives. Figure 6b provides another piece of evidence. In that graph, each observation corresponds to a single market, and the median increase in total industry profits is plotted against the shifted firm profits, conditional on the location shift being profitable. In most of the markets, the median increase in industry profits is lower than the median increase in firm individual profits, which is reflected by the dashed identity-line lying above most of the observations. That is, profitable location shifts result in the market being reallocated in favor of the shifted firm at the cost of the competitors' profits as in Figure 5b depicting a market with *maximal differentiation* shaped by market power considerations. I interpret this fact as further evidence of the firms' desire to differentiate shaping inefficient location configurations.

Table 20 in Appendix C provides further information on the across-market variation of the location configuration consequences. Details to notice are: (i) very modest consumer welfare changes corresponding to individual location shifts, an expected finding given the high firm count in the studied markets; (ii) the median profitable location shift leading to a \$3776.95-increase in the shifted firm monthly profits. Given such relatively low profit changes, one could also suspect that the studied firms are not perfectly informed of certain subtleties of market demand conditions, and the existence of profitable deviations reflects information frictions. While this may be plausible in the markets with many small entrepreneurs, studying information frictions is out of the scope of the present paper.

Imperfect firm-location sorting I use a simple comparison between welfare metrics changes corresponding to individual firm shifts and firm location switches to determine the relative importance of incentive issues and imperfect firm-location matching. Table 10 reports the result of such a comparison. The first panel (all shifts/switches) depicts the across-market variation of welfare metric changes that correspond to a median shift or switch, when *all* perturbations within each market are considered. Firm location switches are more beneficial compared to the firm shifts than location shifts for consumers, affected (shifted or switched) firms and market profits. However, this observation likely reflects the fact that, on average, firm switches simply affect allocations less than firm shifts, while firm shifts are again, on average, unprofitable and welfare-destroying. Perturbations that are more suggestive of the relative strength of incentive and sorting issues are the ones that are profitable and consumer-welfare increasing, reflected in the second panel of Table 10. That panel shows that conditional on the perturbation being profitable and beneficial for consumers, shifts improve consumer welfare, firm and total profits more than switches. The comparison of shift and switch perturbation is thus suggestive of firm sorting across locations being relatively less important than incentive issues in rendering firm location configurations inefficiency.

Excessive entry As a quantification of the excessive entry, Figure 7 reports the across-market distribution of the share of firms that can be removed without a decrease in either consumer welfare or total market profits (after a reconfiguration of the market through shifts or switches). In the median market, 7.20% can be harmfully removed; across markets, the share can be as low as 0.6% and as high as 21.3%. Table 11 maps these results into total fixed costs savings that could be saved if redundant firms were removed from the market. Savings are sizeable and amount to \$ 7.26 bn. However, since the estimated savings do not reflect the equilibrium adjustment in the firm location configurations which would occur under the reduced entry, the actual gains of entry restrictions are likely to be lower. As suggested above, a structural model of the industry, with a fully-specified location and price choice, is required to incorporate such an adjustment. Given the data limitations

		Pert. type	*Q10*	*Q25*	*Median*	*Q75*	*Q90*	*Mean*	*SD*
All shifts / switches									
	% CW change $\times 10^5$	Shifts	-3.8	-2.1	-0.9	0.0	1.1	-1.2	2.9
		Switches	-0.8	0.0	0.6	1.6	3.5	1.0	2.8
	Firm profit change	Shifts	-986.8	-549.4	-178.6	-33.5	0.0	-319.6	1153.4
		Switches	-38.2	-1.4	44.2	197.1	489.0	0.9	2197.2
	Industry profit change	Shifts	-287.0	-105.3	-20.9	4.0	47.8	-58.5	688.2
		Switches	-101.5	-6.7	32.1	138.1	338.3	32.3	443.2
Profitable & CW-increasing shifts / switches									
	% CW change $\times 10^5$	Shifts	10.3	16.4	25.8	44.1	70.6	34.8	28.0
		Switches	7.0	11.1	19.4	34.5	53.9	27.5	28.1
	Firm profit change	Shifts	651.2	1102.6	2038.1	3370.7	4866.6	3287.3	12555.1
		Switches	433.1	759.5	1568.5	2859.8	4515.4	2525.9	4216.9
	Industry profit change	Shifts	-221.3	198.5	660.3	1300.1	1955.7	858.1	6345.9
		Switches	-33.3	200.7	508.1	1078.1	2068.5	830.5	3306.5

Table 10: Comparison of configuration perturbation types (shifts and switches) consequences. Summary statistics report variation of median perturbation consequence across markets. Consumer welfare (CW) is measured by percent reduction in alternative-equivalent distance costs versus the status-quo distance costs.

in the current paper, I leave this as an exciting opportunity for further research.

6.4 Policy suggestions

The welfare losses due to inefficient firm location configurations I report in Section 6.2.2 suggest sizeable gains to policy interventions. Which interventions are likely to be successful? First, since the perturbation method points at local market power as an important determinant of welfare losses, more restrictive zoning arrangements in relatively central areas within a market can provide a remedy to excessive differentiation. Lower differentiation will likely imply lower markup levels in locations accessible to many consumers, a desirable market feature, as suggested by the best alternative firm configurations. At the same time, since in the best alternative configurations higher-quality restaurants are located in areas with relatively few food service options, improved food service quality standards in relatively underserved neighborhoods may be beneficial, potentially financed by within-market across-neighborhood subsidies.

7 Conclusion

This paper attempts to evaluate the efficiency of firm location configurations in the context of the food service industry. While it is well-known that several economic forces (business stealing, differentiation incentives, and excessive entry) can render location configurations inefficient, there has

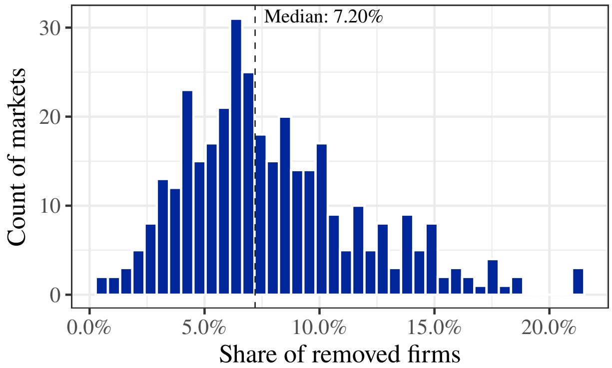


Figure 7: Distribution the share of firms removed from sample markets without diminishing consumer welfare or total market profits.

Price	*Fixed cost*	*Removed*	*Savings*
$	328,688.8	9,483	3.12 bn
$$	642,701.1	6,444	4.14 bn
Both		15,927	7.26 bn

Table 11: Estimate of FC savings by price category of restaurants removed without diminishing consumer welfare or total market profits.

been, to the best of my knowledge, no estimate of the resulting welfare losses in the restaurant sector, potentially, due to data limitations and the complexity of solving for the optimal configuration.

Overcoming these limitations, I assemble a comprehensive dataset on locations, foot-traffic, and characteristics of restaurants across 387 US urban markets, as well as consumer residency patterns, and local commercial real estate rental rates. I then estimate consumer preferences parameters with regards to travel distance and restaurant characteristics, markups on the restaurant level, and entry fixed costs using a structural model of ex-ante zero expected profits entry and a capacity choice game played by the firms. The structural estimation leverages the dataset advantages (a combination of micro- and aggregate data on consumer choices, availability of restaurant-level characteristics, and local rental rates) and compensates for the important limitation of unobservable prices faced by consumers.

I then set up an algorithm that mitigates the complexity of the search for the optimal location configuration and produces a lower bound for unrealized profits and consumer welfare. In a median market, the best firm reordering results in an 8.51% increase in profits and a simultaneous 7.73% growth of a consumer welfare metric. The best alternative configurations are characterized by increasing restaurant quality in underserved areas and lower markups in the areas that are accessible to many consumers.

To determine the economic forces that lead to inefficient market configurations, I use a perturbation method that marginally changes the status quo configurations and determines the consequences for firms and consumers. Through the perturbation method, I find out that most of the individual firm shifts, that are consumer-welfare increasing, are also profitable for the shifted firms. When viewed through the lens of simple spatial competition models, this finding indicates that firm differentiation incentives are strong in most of the studied markets.

At the same time, market entry levels are higher than optimal. In total, almost 16 thousand firms can be removed from the studied markets without any loss to consumer welfare or total industry profits if the remaining firms are properly reallocated across the market space. Potential savings amount to more than $7 billion.

Overall, by exploring the efficiency of food service firm location configurations across multiple US urban markets I contribute to the literature on spatial competition and the research on the restaurant industry. Specifically, I collect the most comprehensive dataset on the food service places, including granular information on quantity and costs. Then, I develop a methodological framework to study the efficiency of location configurations and provide the first estimate of welfare losses associated with the suboptimal firm positions. Finally, through the perturbation method, I shed light on the economic sources of the losses due to location configurations and suggest potential policy remedies. It is necessary to mention several directions for further research. First, endogenizing the firms' pricing decisions would allow to incorporate the repricing stage into the search for alternative configurations. Second, an explicit model of the location choice game would permit a full evaluation of spatially-targeted policies like entry restrictions, subsidies for operating in underserved areas, or local quality controls. These important improvements remain to be explored.

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A Appendix for Section 3

A.1 Figures

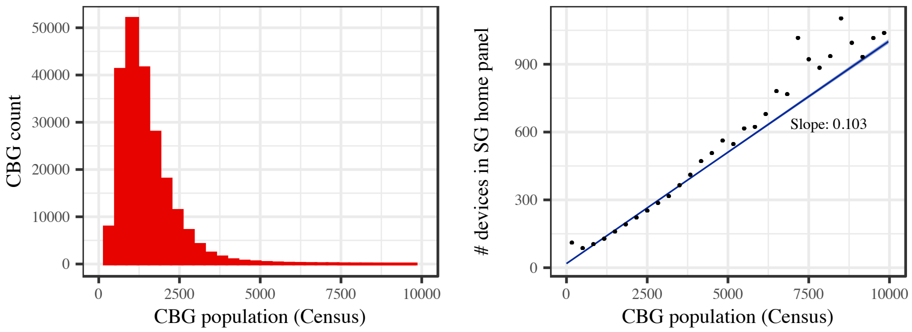

Figure 8: Distribution of Census Block Groups by population; relationship between population count and the number of user devices residing in a given CBG according to Safegraph.

A.2 Tables

	Q10	*Q25*	*Median*	*Q75*	*Q90*	*Mean*	*SD*
Area (sq.km.)	1597.32	2566.34	4810.54	8640.72	14407.33	7049.28	7707.55
Pop. (in 1000s)	106.86	143.39	243.85	560.29	1371.88	629.42	1117.54
CBG count	75.00	97.00	164.00	354.00	959.80	410.50	708.51
Rest. count	163.40	217.50	400.00	937.00	2363.20	1042.86	1875.16
Mean price	3.21	3.29	3.35	3.47	3.56	3.38	0.16
Mean rating	1.33	1.36	1.40	1.48	1.56	1.43	0.10

Table 12: Summary statistics for market areas (CBSAs) used in estimation.

Name	*Location*	*Characteristics*	*Visits*	*Visitors' home CBG*	*Area*	*Rent*
PizzaHub	(42.0, -87.7)	$, 3.0, 'pizza'	169	{391290211004: 11, 391290204002: 10, . . . }	102.02	12.00

Table 13: Example restaurant record

Home CBG	*Device count*	*Population count*
391290211004	192	2001
391290204002	998	1102
391290217002	160	795
391290214022	246	1992

Table 14: Extract of CBG-level data on Safegraph sample device count and Census population.

B Appendix for Section 5

B.1 Estimation algorithm

for m **in** M **do**
  function `Objective`$_m$ (ρ_m):
    $\{\delta_r\}_{r\in m} \leftarrow$ invert market shares given ρ_m
    $\bar{\boldsymbol{g}}(\rho_m) \leftarrow$ evaluate sample analogs of eq. (3)
    $Q_m(\rho_m) \leftarrow \bar{\boldsymbol{g}}'\boldsymbol{W}\bar{\boldsymbol{g}}$ for a positive definite matrix $\boldsymbol{W}$
    return $Q_m(\rho_m)$
  $\hat{\rho}_m \leftarrow$ **minimize** `Objective`$_m$ (ρ_m) **wrt** ρ_m
  $\{\delta_r\}_{r\in m} \leftarrow$ invert market shares given $\hat{\rho}_m$
end
$\hat{\alpha}_m, \hat{\beta}, \hat{\lambda}, \hat{\gamma}^B, \hat{\gamma}^C \leftarrow$ **estimate** $\delta_r = \alpha_m + x_r'\beta + \gamma_r^B + \gamma_r^C + l'_{CBG(r)}\lambda + \xi_r$

Algorithm 1: Estimation of ρ_m, α_m, β, λ, γ^B and γ^C

B.2 Tables

	Dependent variable:			
	ρ_m			
	(1)	(2)	(3)	(4)
Log market area	−0.627***			−0.352***
	(0.189)			(0.112)
Log market area^2	0.014***			0.007***
	(0.004)			(0.002)
Log firm count		−0.114***		−0.085
		(0.029)		(0.056)
Log firm count^2		0.011***		0.009**
		(0.002)		(0.004)
Log market pop.			−0.198***	0.064
			(0.053)	(0.120)
Log market pop.^{2}			0.009***	−0.002
			(0.002)	(0.005)
Observations	387	387	387	387
R^2	0.059	0.471	0.452	0.595
Adjusted R^2	0.054	0.468	0.449	0.589
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15: Relationship between market characteristics and the estimated distance costs. Robust standard errors reported in parentheses.

	Log area (sq. m.)
Average neighor rating	−0.006
	(0.004)
	[0.005]
Average neighor # of categories	0.056***
	(0.005)
	[0.007]
Share of neighbors with same cuisine	−0.114***
	(0.016)
	[0.021]
CBSA FE	✓
Brand FE	✓
Category FE	✓
Time controls	✓
Location controls	✓
Observations	355,091
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 16: First stage estimates of coefficients on excluded instruments in the IV regression of restaurant quality on characteristics. Robust standard errors in round parentheses, standard errors robust to market and brand clustering in square parentheses.

	Dependent variable:	
	δ_r	$(p^* - mc)_r$
	(1)	(2)
$(p^* - mc)_r$	-0.031^{***}	
	(0.002)	
Price [$$ vs $]		0.250^{***}
		(0.038)
Rating		-1.014^{***}
		(0.069)
Rating^2		0.213^{***}
		(0.019)
CBSA FE	✓	✓
Brand FE	✓	✓
Category FE	✓	✓
Observations	322,810	322,837
R^2	0.401	0.133
Adjusted R^2	0.399	0.132
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 17: Relationship between (1) restaurant quality and estimated markups; (2) estimated markups and restaurant characteristics. Standard errors robust to market and brand clusterting in parentheses.

C Appendix for Section 6

C.1 Optimal firm-location match as an integer programming problem

Consider a market m with a fixed set of firms $\{r\}_{r \in 1,\dots,R}$ and a fixed set of locations $\{l\}_{r \in 1,\dots,L}$. Let x_r be a variable taking the value in $\{l\}_{r \in 1,\dots,L}$ and indicating the location assigned to firm r. Given a function $\pi(\boldsymbol{x})$ that maps firm location configurations into total profits, the profit maximization problem can be written as

$$\begin{aligned} \text{maximize} \quad & \pi(\boldsymbol{x}) \\ \text{subject to} \quad & \boldsymbol{I}\boldsymbol{x} \leqslant \boldsymbol{L} \\ & \boldsymbol{x} \geqslant \boldsymbol{0} \\ & \boldsymbol{x} \in \mathbb{Z}^R, \end{aligned}$$

which, without further constraints on the functional form of $\pi(\cdot)$ corresponds to a canonical form of the integer programming problem. The consumer-welfare maximization problem can be represented in a similar fashion. In my market reconfiguration problem, both total profits and consumer welfare are maximization objectives.

C.2 Tables

	Dependent variable:			
	Profits change (%) (1)	CW change (%) (2)	Iterations (3)	Share of shifts (%) (4)
Log firm count	−17.72	10.90	4,545.03***	−33.98***
	(41.51)	(11.27)	(952.31)	(12.55)
Log firm count^2	1.50	−1.10	−335.95***	2.51**
	(3.17)	(0.88)	(77.74)	(1.05)
Log market area	−72.71	−3.18	−725.14	−13.45
	(47.89)	(11.40)	(687.72)	(9.39)
Log market area^2	1.62	0.08	16.30	0.31
	(1.07)	(0.26)	(15.41)	(0.21)
Log market pop.	101.65	−6.20	1,313.14	5.71
	(91.09)	(24.30)	(2,049.70)	(28.23)
Log market pop.^{2}	−4.04	0.32	−53.78	−0.17
	(3.52)	(0.95)	(82.29)	(1.14)
Observations	355	355	355	355
R^2	0.01	0.12	0.58	0.25
Adjusted R^2	-0.01	0.10	0.57	0.24
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Relationship between market characteristicswelfare improvements and optimization procedure execution features.Robust standard errors reported in parentheses.

	Dep. var.: corr. between rest. count and pop. density	
	(1)	(2)
Alt. config [vs status-quo]	−0.002	−0.141
	(0.004)	(0.161)
× Log market area		0.004
		(0.006)
× Log market pop.		0.006
		(0.021)
× Log firm count		−0.004
		(0.020)
CBSA FE	✓	✓
Observations	710	710
R^2	0.975	0.975
Adjusted R^2	0.950	0.950
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 19: Change in correlation between population density and restaurant count associated with the switch from status-quo to best alternative configurations. Standard errors robust to heteroskedasticity and CBSA clustering reported in parentheses.

	Q10	*Q25*	*Median*	*Q75*	*Q90*	*Mean*	*SD*
All deviations							
Market share ↑	0.418	0.439	0.465	0.495	0.523	0.468	0.042
Profit ↑	0.388	0.410	0.438	0.468	0.495	0.440	0.043
Profit ↓, CW ↑	0.027	0.051	0.082	0.133	0.181	0.097	0.061
Profit ↑, CW ↑	0.297	0.330	0.371	0.406	0.452	0.372	0.060
% CW change $\times 10^5$	-3.817	-2.062	-0.942	-0.017	1.082	-1.232	2.918
Firm profit change	-986.807	-549.447	-178.615	-33.549	0.000	-319.606	1153.377
Industry profit change	-286.952	-105.333	-20.868	3.980	47.849	-58.487	688.184
Profitable deviations							
Market share ↑	0.703	0.788	0.865	0.911	0.955	0.843	0.099
Profit ↑	1.000	1.000	1.000	1.000	1.000	1.000	0.000
Profit ↓, CW ↑	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Profit ↑, CW ↑	0.703	0.788	0.865	0.911	0.955	0.843	0.099
% CW change $\times 10^5$	5.746	8.846	16.465	29.031	50.223	23.354	21.433
Firm profit change	583.733	1028.341	1719.981	2951.521	4538.415	3776.951	21532.187
Industry profit change	48.504	387.491	825.035	1417.936	2374.101	1933.400	12396.521
Profitable & CW-increasing deviations							
Market share ↑	1.000	1.000	1.000	1.000	1.000	1.000	0.000
Profit ↑	1.000	1.000	1.000	1.000	1.000	1.000	0.000
Profit ↓, CW ↑	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Profit ↑, CW ↑	1.000	1.000	1.000	1.000	1.000	1.000	0.000
% CW change $\times 10^5$	10.295	16.363	25.799	44.089	70.603	34.833	28.047
Firm profit change	651.152	1102.588	2038.098	3370.748	4866.584	3287.318	12555.068
Industry profit change	-221.272	198.497	660.314	1300.095	1955.725	858.052	6345.876

Table 20: Across-market summary statistics on the consequences of median individual deviations. Consumer welfare (CW) is measured by percent reduction in alternative-equivalent distance costs versus the status-quo distance costs.