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Crowd-Driven Competitive Intelligence: Understanding the Relationship Between Local Market Competition and Online Rating Distributions

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Abstract

In this paper, we analyze how changes in local market structure affect the properties of a market's mean rating distribution. To this end, we combine demographic, socioeconomic, and Yelp restaurant review data for 372 isolated markets in the United States. Our empirical estimates demonstrate that an increase in overall competition – measured as total number of businesses in a market – leads to a broader range and to a decrease in the average of a market's mean rating distribution. The implication is that a larger market has proportionately more lower rated restaurants, whereas higher rated restaurants have relatively fewer comparable substitutes and face less competition in such a market. These effects are particularly pronounced when the analysis is limited to specific cuisine types where vertical differentiation is more natural or when we control for city-specific unobserved heterogeneity. Our findings highlight that practitioners and scholars using online mean ratings of businesses from disparate markets should account for the local market structure to judiciously analyze the relative market power of a business.

Keywords: Local Market Competition, Online Ratings, Online Offline Interplay, Geographic Heterogeneity, Competitive Market Intelligence.

JEL Classification: D43, D22, L11, M31

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1. Introduction

In the era of digitization, mean online ratings, such as Yelp ratings for restaurants, are a critical information source related to businesses in a local market. But what is the impact of local market competition on the heterogeneity of available businesses in a market? For instance, are there relatively more businesses with high mean ratings (usually on a scale from 1 to 5) in more competitive markets than in less competitive markets? Even though prior work has investigated the formation of mean ratings for businesses or the nature of particular reviews (Li and Hitt 2008, Forman et al. 2008), these studies do not inform us about the relationship between competition in a local market and the properties of a market's mean rating distribution.

This lack of such knowledge handicaps practitioners, scholars, consumers, and online review platform designers. Practitioners who rely on mean rating information as a decision variable in different contexts need to understand how the market power inferred from these mean ratings can be affected by local competition. Many banks have started to factor in mean online ratings in business loan decisions (Fernandes 2016, Huizinga 2015). As Eastern Bank states:

“Businesses with plenty of positive Yelp reviews or a strong social media following could hint at a reliable revenue stream. And that, along with more traditional information from income statements, can be a good indicator of whether the borrower will repay the loan.”

—Dan O'Malley, Head of Eastern Labs at Eastern Bank

Naturally, it is of paramount importance to understand how a loan recipient's mean rating stands relative to its competitors' mean ratings in the local market. Especially in the highly dynamic markets for restaurants, crowdsourced Yelp data can be a valuable measure to capture local economic activity at scale and in real-time – presumably much faster than government census data. In fact, this has been recognized by Yelp itself (Yelp 2017) as well as by scholars (Glaeser et al. 2017). Glaeser et al. (2017) find that the number of restaurants listed on Yelp can predict the number of restaurants reported to the Census Bureau, arguing that Yelp data can capture local market growth. Naturally, it would be

important to understand whether the growth in the number of restaurants is primarily driven by high or by low quality restaurants.

Given the ease and scale of data available on Yelp and other similar sources, a range of studies (e.g., Wang et al. 2016, Anderson and Magruder 2012, Lu et al. 2013, Kovacs et al. 2014) now consider a business's online mean rating as a good control variable and, conceivably, implicitly assume it as a proxy for market power. For a study that includes mean ratings of businesses from across markets and uses them in a manner where the relative standing among businesses matters, it is critical to examine if the local market competition poses a threat of confounding the results.

Also, while the theoretical literature (e.g., Shaked and Sutton 1987) in industrial organization (IO) has analyzed equilibrium market outcomes for vertically differentiated industries where quality provisioning is primarily tied to marginal costs (e.g., restaurants), the empirical evidence is still scant. Theory suggests that larger markets can support a greater number of firms that cover a larger quality spectrum than smaller markets, such that both tails of the distribution of available qualities grow. To the best of our knowledge, hitherto, the empirical evidence is limited to the growth in the *higher* end of the quality distribution (Berry and Waldfogel 2010). By studying how local market competition affects the dispersion in *both* tails of a market's mean rating distribution, we are able to also investigate the dynamics in the *lower* end of the service quality distribution as well as evaluate the impact on the average of the distribution.

Finally, especially in unknown markets, consumers may incorporate this additional information to make better decisions on where to spend their money and how to satisfy their needs. Online review platform designers, e.g., Yelp, can assist consumers in their decision making process by providing additional information. Traditionally, online review platforms have provided ways to filter search results based on the absolute mean ratings of businesses. Based on our results, platforms can consider providing ways to filter businesses according to the relative position their mean rating in the mean rating distribution of a market.

Accordingly, our research focuses on causally identifying the impact of the local market competition on the key properties of a market’s mean rating distribution: range and average.² However, delineating this effect may not be intuitive. In more competitive markets, the range of the distribution would increase because intense competition could lead to more higher rated businesses as well as to more lower rated businesses to serve the local market. The effect of competition on the average of the mean rating distribution is, however, less straightforward. If increasing competition leads to a disproportional increase in lower rated businesses than higher rated businesses, the average of the distribution decreases. Intuitively, though, one might expect an increase in businesses with high mean ratings because competition is generally viewed as a consumer welfare improving development.

We study this relationship in the context of the restaurant industry and analyze crowdsourced information from Yelp.com. Focusing on isolated markets, we clearly track differences in local market competitiveness and isolate the effect that these differences have on the distributions of mean ratings for the respective markets.³ Our empirical identification strategy pursues a two-pronged design. First, we employ an instrumental variable approach based on cross-sectional variation between markets to address endogeneity concerns. Second, we leverage the within-market variation of a panel dataset to control for time-constant unobservable market heterogeneity (e.g., city-specific preferences). Our results demonstrate that local market competitiveness drives the heterogeneity of available mean ratings in a market. As the local market competition increases, so does the range of mean ratings. Counterintuitively, the average of a market’s mean rating distribution decreases with increasing competition.

An immediate implication of our finding is that two restaurants with equal mean ratings differ substantially in the way they are affected by local competition depending on whether they are located in a large or in a small market. Figure 1 illustrates this in a stylized example. Based on our results we

² The range, which is a standardized measure of dispersion, embodies the difference between the very best and the very worst rating in a market simplistically and intuitively. The average as a measure of central tendency reacts to a change in either tail of the distribution (unlike other common central tendency measures, such as the median), which is critical in capturing the differences in market compositions.

³ In keeping with earlier research (Chevalier 1995, Brynjolfsson et al. 2009), we compute local market competitiveness as the number of businesses—i.e., restaurants—in a market.

depict a small (*dashed line*) market with a higher average and a lower range of mean ratings and a large market (*dotted line*) with a lower average and a higher range of mean ratings. A 4.5-star restaurant faces relatively fewer direct substitutes – i.e., restaurants with comparable ratings – in a larger than in a smaller market (*arrow (a)*). Yet, a restaurant with a 2.5 star mean rating faces relatively more direct substitutes in a larger than in a smaller market (*arrow (b)*). While that restaurant is among the worst in a smaller market, the worst choices in larger markets have even lower mean ratings (*arrow (d)*). Whereas a 4.5-star restaurant is among the elite in small markets, it is unlikely to be among the best choices in larger markets (*arrow (c)*). In essence, the restaurants would garner dissimilar pricing power in each market. In the absence of understanding the impact of the local market competition on the properties of the mean rating distribution, the way a particular restaurant is affected by competition would not be apparent.

Figure 1: Competition Faced by a 2.5- and 4.5-Star Business in Two Different Markets

2. Theoretical Background

Our empirical analyses are based on well-developed literature in IO that sheds light on the relationship between the distribution of quality and competition in a vertically differentiated market. In these markets, firms compete on the quality of the service they sell being produced through a combination of fixed and variable costs.⁴ The relationship between competition and the distribution of service quality

⁴ We recognize that online ratings might not perfectly capture service quality even though several studies argue that they actually do (e.g., Besbes and Scarsini 2018). Nevertheless, the intuition derived from economic theory provides a valuable starting point. Using an analytical model, Besbes and Scarsini (2018) investigated whether customers can infer the true quality of a product or service based on the mean rating they observe. They

depends on whether quality is produced mainly through fixed costs or mainly through variable costs (Shaked and Sutton 1987, Berry and Waldfogel 2010). If marginal costs increase in quality slowly, such that the cost of quality is primarily borne by fixed costs, a firm producing a high-quality service (*high-quality firm*) can undercut the price of the firm producing a low-quality service (*low-quality firm*), potentially driving it out the market. This leads to a limited set of firms in the market, including at least one high-quality firm but fewer or no lower quality firms.

When the cost of quality is largely borne by marginal costs, such that marginal costs increase faster than linearly in quality (Shaked and Sutton 1987), undercutting is not profitable because a low-quality firm can price near marginal costs. If the number of consumers (*market size*) is sufficiently high, pricing near marginal costs can generate enough profit to cover the fixed costs of the low-quality firm, which allows the firm to stay in the market. In this case, the outcome is that many quality levels can survive in equilibrium. As market size increases, firms proliferate such that many different quality levels become available. A larger market can thus support more low-quality firms as well as firms that offer higher qualities than the highest quality firm in a small market. Consequently, as competition increases, so does the range of different qualities available in the market. The change in the market-level average quality depends on the ratio of low- and high-quality firms entering the market. In other words, it decreases if the increase in competition is mainly driven by low- rather than by high-quality firms.

In the case of restaurants, the largest share of quality cost is linked to marginal costs—i.e., to the cost of delivering service quality or the cost of food preparation—which typically increase faster than linearly. If a chef, for example, can cater to 10 customers in a reasonable time frame at a given quality level, the only way for the restaurant to serve more people at the same quality level is to employ more chefs. If that restaurant has demand from 5 additional customers at the same quality level, it would need to employ another chef at the same skill level if it decided to cater to these customers—at the same costs as the first chef. The unused capacity, the search costs, and the training time make the 5 additional

demonstrated that, even if the mean rating of a product or service represents the aggregate of subjective opinions of past customers, future customers are still able to infer the underlying true quality of the product if they know that the mean rating is based on the subjective opinions of customers. Most importantly, the relative position of a product or a service compared to its competitors is usually preserved in mean online ratings.

customers much more costly to serve than the first 10 customers. As such, higher quality restaurants cannot stop entry of lower quality restaurants, and lower quality entry is more incentive compatible with a larger market. Thus, we hypothesize the following:

H1: The range of available restaurant mean ratings in a market increases with increasing competition.

H2: The market-level average of available restaurant mean ratings decreases with increasing competition.

However, restaurants can not only vertically differentiate but also horizontally differentiate with respect to cuisine or location (Hotelling 1929). When quality is mainly produced through variable costs, introducing horizontal differentiation, in addition to vertical differentiation, dampens the effect of competition on the range of available quality levels and on the market-level average quality. When two firms are in a market, it is more likely that both share the market by horizontal differentiation rather than pursuing vertical differentiation. For example, it is less likely for two restaurants to offer the same type of cuisine, say pizzas, than for one to offer pizzas and the other to offer hamburgers. In this case, increasing competition has a smaller effect on the range and the market-level average quality available in the market than the case of pure vertical differentiation. Therefore, we formulate our third hypothesis:

H3: The effect of competition on the range and the market-level average of available restaurant mean ratings is smaller in magnitude under horizontal differentiation than under vertical differentiation.

3. Empirical Investigation of Restaurant Ratings on Yelp

Yelp is arguably the most widely recognized platform for recording crowdsourced online ratings for all kinds of businesses, including restaurants, health care, and financial services, among others. With a current market capitalization of approximately \$3.73 billion (Yahoo Finance 2018), Yelp constitutes a global cornerstone in online consumer conversations. Naturally, scholars and practitioners are keen to understand the factors that influence these ratings (Dellarocas 2003, Li and Hitt 2008) and how online

ratings can derive big data-driven competitive intelligence (CI).⁵ Thus, Yelp is a good data source for this study, especially because the restaurants category is its hallmark.

Yelp's advantages as a data source notwithstanding, the plausibility of fake reviews posted by business owners (Mayzlin et al. 2014) threatens the credibility of the results. A sharp relief to this threat is that we did not find any evidence which suggests fake reviews are more prevalent in some markets than in others. Moreover, online review websites such as Yelp have recently started to identify and tag potential fake reviews as "not recommended" (Mukherjee et al. 2013). Obviously, we do not include these in our analysis. Reassuringly, a recent study has shown Yelp's filtering algorithm to be effective overall in identifying fakes and to represent a conservative measure in excluding suspicious reviews (Luca and Zervas 2016).

3.1. Data

Recognizing that isolating the market for a restaurant is not easy, we focus on cities that are isolated from each other and, thereby, not likely to compete with neighboring cities for market share. This approach of isolating a market is similar to Breshnahan and Reiss (1991) and Olivares and Cachon (2009). In our study, a market is isolated if it has no significant neighboring cities (more than 2,000 inhabitants) within 20 miles. Following this criterion and by utilizing a dataset provided by Collard-Wexler (2006), we have identified 372 isolated cities that are in the sample.

Using a customized web crawler, we collected a broad variety of information on each of the markets in our sample from www.city-data.com in May 2014. The data includes the following variables for each market: number of inhabitants (*POP*) as per the 2012 Census, population change since 2000 (*POPCHNG*), median age (*MEDAGE*), median income (*MEDINC*), median house value (*MEDHVAL*), median gross rent (*MEDRENT*), unemployment rate (*UNEMP*), surrounding land area (*LANDAREA*),

⁵ There is a growing literature on business intelligence and analytics (BI & A), which is often referred to as the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data (Chen et al. 2012). Naturally, because data is increasingly available to firms through online crowdsourcing, it is important to explore the ways this data can be utilized for BI & A purposes. For example, Chen et al. (2012) identify e-commerce and market intelligence as one potential application of BI & A that especially benefits from the emergence of customer-generated web content from social media platforms that enables firms to gather CI by "listening to the voice of the market."

fraction of people living in urban areas (*URBAN*), cost of living (*COSTOFLIV*), percentage of Hispanics (*PERCHISP*), percentage of American Indians (*PERCINDIAN*), percentage of Asians (*PERCASIAN*), and percentage of blacks (*PERCBLACK*). We also collected the number of restaurants (*NUMRES*), the restaurant-level mean ratings (the average of all individual ratings for a restaurant), and the total number of posted ratings (*NUMRATE*) on Yelp.com for all restaurants within these markets.

Table 1: Market-Level Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
<i>NUMRES</i> (All Restaurants)	370	40.36	34.82	1.00	289.00
<i>NUMRES</i> (Non-Fast-Food Restaurants)	355	8.9	9.7	1.00	79.00
<i>NUMRES</i> (Traditional American Restaurants)	297	4.14	4.53	1.00	41.00
<i>NUMRES</i> (Ethnic Restaurants)	362	9.48	9.3	1.00	54.00
<i>POP</i> (in 10,000 inhabitants)	371	1.11	1.08	0.26	11.89
<i>POPCHANGE</i> (since 2000)	372	0.04	0.14	-0.51	0.79
<i>MEDAGE</i>	372	36.38	6.19	20.60	58.20
<i>MEDINC</i> (in \$1,000)	372	37.03	10.56	18.52	89.73
<i>MEDHVAL</i> (in \$1,000)	372	111.78	64.74	38.09	566.80
<i>MEDRENT</i> (in \$100)	371	6.05	1.53	3.69	17.99
<i>UNEMP</i> (in % in 2014)	372	7.22	3.13	0.70	20.40
<i>LANDAREA</i> (in 100 square miles)	372	0.26	2.05	0.02	28.74
<i>URBAN</i> (% of total population)	355	0.95	0.10	0.00	1.00
<i>COSTOFLIV</i> (U.S. cost of living index)	372	84.11	10.06	76.10	194.30
<i>PERCHISP</i>	371	0.15	0.20	0.00	0.97
<i>PERCINDIAN</i>	371	0.03	0.13	0.00	1.00
<i>PERCASIAN</i>	366	0.01	0.03	0.00	0.38
<i>PERCBLACK</i>	371	0.09	0.17	0.00	0.83
<i>RESPOP</i> (number of restaurants per 10,000 inhabitants, All Restaurants)	369	40.27	24.44	1.99	235.20
<i>NUMRATE</i> (All Restaurants)	369	250.39	574.55	1.00	5676.00
<i>AVG</i> (All Restaurants)	369	3.44	0.39	1.90	5.00
<i>MINRATE</i> (All Restaurants)	369	1.45	0.73	1.00	5.00
<i>MAXRATE</i> (All Restaurants)	369	4.85	0.36	2.50	5.00
<i>RANGE</i> (All Restaurants)	369	3.41	0.88	0.00	4.00

We computed the average of the mean ratings in a market (*AVG*), the minimum (*MINRATE*), the maximum (*MAXRATE*), and the range (*RANGE*) of these mean ratings for each market. We chose the range and the average as our focal moments of the market-level mean rating distribution because of their simplicity and power in capturing the change in the heterogeneity of available mean ratings in a local market, as depicted in Figure 1. Consequently, one may judge the distance in rating score of a certain business to the best or worst option in the market based on the range. In addition, based on the

average of the mean ratings in a market, one can infer whether a business of a certain mean rating faces relatively more or relatively fewer substitutes in different markets. Finally, we computed the number of restaurants per 10,000 inhabitants (*RESPOP*) as an additional control for competitiveness in the market.⁶ Table 1 shows the summary statistics of these variables. In September 2016, we replicated the data collection scheme and combined data from www.city-data.com and Yelp.com to construct a panel dataset.

3.2 Yelp Ratings Across Markets

The validity of the causal inferences from the cross-sectional analysis that follow rests on an assumption: Yelp mean ratings for restaurants, which are aggregates of random individual reviews posted by geographically dispersed customers, follow an identical data-generation mechanism. To evaluate whether the idiosyncrasies of reviewers introduce any peculiarities in the distribution of the mean ratings across locations, we check for consistency in the distributions with respect to market structures.⁷ In particular, we present evidence that a mean rating distribution of a market with a particular number of restaurants is independent of the geographic location. This, in turn, improves our confidence in the assumption that unobservables affecting the key features of a mean rating distribution in a market remain time invariant. As typical, our causal inferences from the panel data fixed effects model are threatened by this assumption.

We create bins of cities according to the number of restaurants in a city. If the data generation process is internally consistent, the mean rating distributions should be similar across cities with a comparable number of restaurants instead of being a collection of differently shaped distributions. To systematically assess the mean rating distributions of cities within a bin, we first categorize cities into bins of 10

⁶ A relevant concern in isolating the effects of competition is that cities with an identical number of restaurants can have different levels of competitiveness because of different population sizes. This can be addressed by controlling for *RESPOP*. We are indebted to an anonymous reviewer for suggesting this additional control variable.

⁷ If the motivation to post reviews is altruism—to help other consumers discern the quality of the restaurant—then subjectivity won't be an issue. If, however, consumers' intentions are to express themselves and declare what they are, what they feel, and what they think, then those posting may not express themselves objectively. Besbes and Scarsini (2018), through a rich comprehensive analytical framework, demonstrate that even in the case of subjective expressions, the mean ratings—average of individual ratings—converge to the underlying objective quality under a pragmatic set of assumptions.

restaurants. We have one bin with cities consisting of 11 to 20 restaurants, cities of the next bin consisting of 21 to 30 restaurants, and so forth. We design a bootstrapping program that randomly draws two cities from a bin, compares the cities' distributions, puts the two cities back into the bin, and repeats this procedure 2,000 times. We employ the Kolmogorov-Smirnov test to determine if distributions of the two cities are equal. If the cities' mean rating distributions are consistent within the bins, we expect to find substantial shares of equal distributions per bin.

The line “%Equal” of Table 2 reports the percentage of the 2,000 Kolmogorov-Smirnov tests performed by the bootstrapping program that yielded an insignificant difference in the distributions (on a 95% confidence level). The percentages of equal distributions within the bins range from 86.75% in the bin of cities with 51 to 60 restaurants to 96.45% in the bin of cities with 21 to 30 restaurants. Although the lowest value of 86.75% is already quite substantial, the highest consistency of distributions within a bin becomes apparent for the two bins with the cities. Thus, we find substantial internal consistency of mean rating distributions within bins across our whole dataset.

Figure 2: Sample of Distributions from Bin 30

We present an example of sets of distributions in Figure 2. In the appendix, we present results of correlation analyses suggesting that the insights provided in this study might also extend beyond online ratings from Yelp to other sources of online ratings, such as Zagat.

Table 2: Results for Distribution Tests Within City Bins

Cities with...	11 to 20 Restaurants	21 to 30 Restaurants	31 to 40 Restaurants	41 to 50 Restaurants	51 to 60 Restaurants	61 to 70 Restaurants	71 to 80 Restaurants	81 to 90 Restaurants
% Equal	96.45	96.45	96.05	94.65	86.75	92.7	94.75	95.15
# Cities	79	81	56	33	30	23	13	9

Note: Equal means equal distributions at a 95% confidence level. The value of 96.45 means that 96.45% of all 2,000 Kolmogorov-Smirnov tests have yielded insignificant differences in the distributions of the cities with 11 to 20 restaurants.

4. Empirical Model

To investigate our focal effect, we first use a cross-sectional estimation model:

$$Y_m = \beta_0 + \beta_1 LN_NUMRES_m + \zeta X_m + \epsilon_m \quad (1)$$

where the subscript m represents a market, X_m is a vector of market-level control variables, and ϵ_m is the random error term.⁸ The dependent variables in this equation are the range of the mean ratings in a market (*RANGE*) and the average of the mean ratings in a market (*AVG*), respectively. The key variable of interest in equation (1) is the number of restaurants (*LN_NUMRES*) as a measure of competition in a market (Chevalier 1995, Brynjolfsson et al. 2009). Although this measure of competition does not account for each firm's market share, it reliably captures market entries and exits and is correlated with market concentration, especially for restaurants where marginal costs grow nonlinearly.⁹ We let this variable be the natural log of the number of restaurants in a market. Next, we estimate a panel data regression specification that allows us to control for market-level heterogeneity:

$$Y_{mt} = \beta_0 + \beta_1 LN_NUMRES_{mt} + \zeta X_{mt} + D_m + \epsilon_{mt} \quad (2)$$

where t identifies the time of observation for market m of our dependent variables Y , of *LN_NUMRES*, and of our vector of market-level control variables X . To utilize the advantage of the panel structure of the data, we estimate both fixed and random effects models.

In the fixed effects model, D_m represents a set of dummy variables indicating market-level fixed effects.

Fixed effects models allow for arbitrary correlations of the market-level fixed effects with the vector of

⁸ The vector of controls comprises MEDAGE, MEDINC, MEDHVAL, MEDRENT, UNEMP, LANDAREA, URBAN, COSTOFLIV, PERCHISP, PERCINDIAN, PERCASIAN, PERCBLACK, and RESPOP.

⁹ We revisit the market share issue in our robustness checks. We calculate the Herfindahl-Hirschmann Index (*HHI*) based on a restaurant's number of reviews.

control variables, i.e., $E(D_m|X_m) \neq 0$ (Wooldridge 2010). Because of its focus on only within-market variation, this model specification controls for all the time-invariant unobservable heterogeneity (e.g., city-specific preferences of raters). Thus, the fixed effects model allows us to address endogeneity concerns meaningfully and robustly (Allison 2005). However, in this model specification, time-constant control variables cannot be included in X_{mt} , and there is no β_0 . In the random effects model, D_m is a market-specific random element, similar to ϵ_{mt} (Wooldridge 2010). This assumes that market-level effects D_m are uncorrelated with the control variables X_m , but it allows for the inclusion of time-constant control variables.

4.1. Identification

Naturally, it is challenging to establish a causal relationship between, on the one hand, competition measured as the number of restaurants and, on the other, the range or the average of a market's mean rating distribution. Although controlling for a wide range of market-level variables improves our confidence in the cross-sectional model, unobservables may still exist that simultaneously affect the formation of the online ratings of restaurants and the number of restaurants in a market. For instance, the mere existence of online ratings may intensify competition in local markets. This, in turn, might influence firm behavior and obstruct the identification of the causal effect of competition on the mean rating distribution. As a result, we need an exogenous source of variation in the number of restaurants in a specific market to properly identify the effect of the number of restaurants on the range and average of a market's mean rating distribution.

As our first IV, we use total deposits of local FDIC-insured bank branches in 2014 (deposits and branches data come from FDIC's website). We aggregate the deposits from the local branches at the city level for all the cities in our sample to compute this IV. FDIC deposits represent the local lending capacity and are used widely in the finance literature to account for access to business loans in local areas (Butler and Cornaggia 2011). More importantly, this variable has been established as a major driver of local businesses (Guiso et al. 2004) and is unlikely to be related to the mean ratings of restaurants. Not surprisingly, it is highly and significantly correlated with LN_NUMRES , as shown in Table A3 in the appendix.

As our second IV, we collected the number of real estate and rental and leasing firms (*REAL_EST*) in 2014 from the U.S. census business pattern data (sector 53 of the NAICS industry code) from www.census.gov. Because restaurants generally have the option to buy or rent their property, it seems natural that the number of restaurants in a city would be positively correlated with the number of real estate and rental and leasing firms. The high and statistically significant correlation in this connection, as shown in Table A3, corroborates this.¹⁰ Also, it is quite unlikely that the number of real estate and rental and leasing firms would be directly related to the mean ratings of restaurants.¹¹

5. Empirical Results

Table 3 presents the regression estimates of our model with *RANGE* and *AVG*, respectively, as the dependent variables. Columns (1) to (4) report cross-sectional results of OLS and 2SLS estimations of equation (1). Columns (5) to (8) present results from panel data estimations of equation (2) with fixed effects (FE) on the city level and random effects (RE). Across the estimates, we find a significant and positive impact of *LN_NUMRES* on *RANGE*, supporting H1. We also find that *LN_NUMRES* has a significant negative effect on *AVG*, supporting H2.

Comparing the OLS and 2SLS estimates shows a substantial difference in magnitude between the models with *RANGE* as the dependent variable; both Wooldridge's score test and the regression-based test (Wooldridge 2010) reject the null that *LN_NUMRES* is exogenous.¹² In interpreting the coefficients, if we compare a market with 20 competitors (the 25th percentile) to a market with 53 competitors (the

¹⁰ In considering the strength of our IVs, an adjusted R^2 of 0.6509 for *LN_NUMRES* for the first-stage regressions indicates a strong correlation between our IVs and the number of restaurants in a market. This is also reflected by a high F statistic (61) for the joint significance of our IVs, which is well above any critical value for weak IVs (Stock and Yogo 2005). Wooldridge's robust score test of overidentification indicates an insignificant test statistic, implying that our IVs are uncorrelated with the error term. We find qualitatively the same pattern for all cross-sectional estimates.

¹¹ One caveat to both of our IVs is that richer cities might systematically differ from poorer cities in ways that influence the bank assets of the local population and the entry of real estate agents. If this systematic difference manifests in dependent variables, our IVs could become weaker. Fortunately, the observables—median income, house value, gross rent, and cost of living—of a city arguably account for such a systematic difference and give us confidence in the conditional independence of the IVs. In addition, as mentioned earlier, the fixed effects model complements our identification strategy by accounting for unobserved time-constant heterogeneities.

¹² To mitigate endogeneity concerns for the RE model for All Restaurants with *RANGE* as the dependent variable, we conducted an RE estimation with IVs, and the results remain qualitatively unchanged. Wooldridge's score tests and the regression-based tests for the remaining cross-sectional models in Table 3 to 5 cannot reject the null hypothesis that *LN_NUMRES* is exogenous.

75th percentile), the range of mean ratings is between 0.654 (OLS) and 0.444 (2SLS)

$\left(0.444 = 0.456 * \ln\left(\frac{53}{20}\right)\right)$ larger in the market with 53 competitors.

Table 3: Regression Results for All Restaurants

	OLS	2SLS IV 2 nd Stage	OLS	2SLS IV 2 nd Stage	RE	RE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RANGE	RANGE	AVG	AVG	RANGE	AVG	RANGE	AVG
<i>LN_NUMRES</i>	0.671*** (0.064)	0.456*** (0.066)	-0.115** (0.045)	-0.081** (0.034)	0.620*** (0.058)	-0.10*** (0.036)	1.153*** (0.304)	-0.462* (0.262)
<i>MEDAGE</i>	-0.008 (0.006)	-0.015** (0.006)	0.006* (0.003)	0.007** (0.004)	-0.006 (0.005)	0.007*** (0.003)	-0.039** (0.020)	0.0280** (0.014)
<i>MEDINC</i>	0.008 (0.005)	0.008 (0.005)	-0.005 (0.004)	-0.005 (0.004)	0.006 (0.004)	-0.005** (0.002)	0.016 (0.010)	0.001 (0.005)
<i>MEDHVAL</i>	-0.002** (0.001)	-0.001** (0.001)	0.001 (0.000)	0.001 (0.000)	-0.001*** (0.001)	0.0007** (0.000)	-0.005 (0.003)	0.002 (0.001)
<i>MEDRENT</i>	-0.049 (0.046)	-0.022 (0.046)	0.047 (0.031)	0.043 (0.030)	-0.039 (0.037)	0.0321** (0.016)	-0.078 (0.070)	-0.001 (0.032)
<i>UNEMP</i>	-0.018 (0.018)	-0.018 (0.020)	0.010 (0.011)	0.010 (0.010)	-0.018 (0.012)	0.001 (0.006)	-0.015 (0.015)	0.001 (0.007)
<i>LANDAREA</i>	0.693 (0.469)	1.098** (0.495)	0.716*** (0.257)	0.652** (0.264)	0.018 (0.012)	0.002 (0.003)	— —	— —
<i>URBAN</i>	0.011 (0.013)	0.01710* (0.010)	0.001 (0.004)	0.000 (0.004)	0.600 (0.380)	0.286 (0.201)	— —	— —
<i>COSTOFLIV</i>	0.020** (0.009)	0.018** (0.009)	-0.004 (0.004)	-0.004 (0.004)	0.0105* (0.006)	-0.004* (0.003)	-0.027 (0.017)	-0.013 (0.008)
<i>PERCHISP</i>	-0.183 (0.200)	-0.220 (0.217)	-0.054 (0.110)	-0.048 (0.114)	-0.092 (0.151)	-0.044 (0.081)	-3.505** (1.725)	-0.072 (0.796)
<i>PERCINDIAN</i>	0.075 (0.669)	-0.224 (0.704)	-0.255 (0.358)	-0.207 (0.360)	-0.112 (0.727)	-0.182 (0.316)	-5.886* (2.993)	-1.230 (1.739)
<i>PERCASIAN</i>	-1.225 (1.029)	-1.523 (1.075)	1.497 (1.127)	1.545 (1.115)	-0.201 (1.075)	1.131 (0.762)	2.387 (3.471)	-1.594 (1.885)
<i>PERCBLACK</i>	0.024 (0.239)	0.065 (0.245)	-0.156 (0.151)	-0.163 (0.149)	0.102 (0.179)	-0.141 (0.117)	-1.639 (3.247)	-0.995 (1.343)
<i>RESPOP</i>	0.000 (0.002)	0.00313* (0.002)	0.000 (0.001)	0.000 (0.001)	0.001 (0.002)	0.000 (0.001)	-0.012 (0.009)	0.010 (0.007)
Constant	-0.561 (1.051)	-0.082 (1.075)	3.076*** (0.511)	3.000*** (0.478)	0.418 (0.735)	3.576*** (0.380)	4.878** (1.986)	4.546*** (1.203)
<i>N</i>	348	348	348	348	696	696	696	696
<i>R</i> ²	0.387	0.364	0.085	0.082	0.355	0.082	0.106	0.057

Note: *** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses. *LANDAREA* and *URBAN* drop out in the FE models due to insufficient variation in time. The IVs for *LN_NUMRES* in the 2SLS models are 2014 deposits of local FDIC-insured bank branches (*FDIC*) and the number of real estate and rental and leasing firms (*REAL_EST*) of the respective markets.

Although the effect of LN_NUMRES on AVG is smaller in magnitude, it is still economically significant. For instance, the average rating in a market with 53 restaurants (75th percentile) is between 0.112 (OLS) and 0.079 (2SLS) lower than in a market with 20 restaurants (25th percentile).

Comparing the OLS and 2SLS estimates shows a substantial difference in magnitude between the models with $RANGE$ as the dependent variable; both Wooldridge's score test and the regression-based test (Wooldridge 2010) reject the null that LN_NUMRES is exogenous.¹³ In interpreting the coefficients, if we compare a market with 20 competitors (the 25th percentile) to a market with 53 competitors (the 75th percentile), the range of mean ratings is between 0.654 (OLS) and 0.444 (2SLS) $\left(0.444 = 0.456 * \ln\left(\frac{53}{20}\right)\right)$ larger in the market with 53 competitors. Although the effect of LN_NUMRES on AVG is smaller in magnitude, it is still economically significant. For instance, the average rating in a market with 53 restaurants (75th percentile) is between 0.112 (OLS) and 0.079 (2SLS) lower than in a market with 20 restaurants (25th percentile).

The coefficients for LN_NUMRES in the FE estimations (columns (7) & (8)) are substantially larger for both $RANGE$ and AVG as dependent variables. For $RANGE$ as the dependent variable, the magnitude of the coefficient more than doubles (0.456 vs. 1.153) compared to the 2SLS results. This magnitude suggests that, controlling for unobserved market-level heterogeneity, when the number of restaurants in a market increases by 10%, $RANGE$ for that market increases by 0.11. For AVG as the dependent variable, the difference in the coefficient for LN_NUMRES between the cross-sectional and the panel results is even larger. Here, the magnitude of the coefficient for the FE model increases by more than five times (-0.081 vs. -0.462) compared to the 2SLS model. A 10% increase in LN_NUMRES in a market relates to a decrease in the average of that market's mean rating distribution by -0.044 .

In explicating the economic significance of the estimates, particularly the cross-sectional ones, it is worth noting that the restaurant industry, as a whole, might be too broad to quantify the relationship

¹³ To mitigate endogeneity concerns for the RE model for All Restaurants with $RANGE$ as the dependent variable, we conducted an RE estimation with IVs, and the results remain qualitatively unchanged. Wooldridge's score tests and the regression-based tests for the remaining cross-sectional models in Table 3 to 5 cannot reject the null hypothesis that LN_NUMRES is exogenous.

between competition and the properties of a market's mean rating distribution. The industry comprises everything from fast food restaurants like McDonald's and Burger King to "classical" restaurants like Red Lobster and Applebee's, and it is questionable whether these restaurants are competing in the same segment. If, indeed, they operate in different segments, the question arises whether vertical differentiation and heterogeneous consumer preferences for services apply to fast food outlets. As discussed in section 2, restaurants may also horizontally differentiate their service offerings. As such, if a small market supports just two restaurants, one is unlikely to observe, for example, two vertically differentiated Traditional American Restaurants. It is more likely that the second restaurant is horizontally differentiated by offering Chinese cuisine, for example.¹⁴ Because these two restaurants would be monopolists in their specific cuisine, we would not expect to observe a broader range and a lower average of a market's mean rating distribution in this context.¹⁵

5.1. Evidence from Non-Fast-Food Restaurants and Traditional American Restaurants

To limit the impact of horizontal differentiation, we re-estimated our models on a subsample from our original dataset including only restaurants that we characterize as Non-Fast-Food Restaurants, as well as a subsample of restaurants from one specific category: Traditional American Restaurants. We assigned restaurants that were categorized by Yelp as American (traditional), American (new), Italian, Steak, and Seafood to the subsample of Non-Fast-Food Restaurants; and restaurants that were categorized as American (traditional) to the subsample of Traditional American Restaurants. Tables 4 and 5 display the cross-sectional data and panel data estimation results for our models with *RANGE* and *AVG*, respectively, as the dependent variables. Columns (1) to (4) report cross-sectional results of OLS and 2SLS estimations of equation (1). Columns (5) to (8) present results from panel data estimations of equation (2).

¹⁴ This intuition is supported by Neven and Thisse (1989), who found that firms differentiate maximally in the horizontal dimension when the range of qualities a market can accommodate for is small.

¹⁵ In fact, we see a strong effect of the number of restaurants on horizontal differentiation when regressing the number of restaurants on the number of cuisines as a measure of horizontal differentiation.

For the cross-sectional estimations, the estimated β_1 coefficients for the effect of *LN_NUMRES* on *RANGE* for Non-Fast-Food Restaurants are positive (OLS: 1.107 (s.e. = 0.067), 2SLS: 1.009 (s.e. = 0.127)), highly significant, and between about 1.6 times (OLS) and 2.2 times (2SLS) larger than the estimated coefficients for All Restaurants presented in Table 3. For Traditional American Restaurants, significance levels are qualitatively unchanged, and the magnitude of the coefficient increases again (β_1 : OLS: 1.175 (s.e. = 0.091), 2SLS: 1.021 (s.e. = 0.167)).

Table 4: Regression Results for Non-Fast-Food Restaurants

	OLS	2SLS IV 2 nd Stage	OLS	2SLS IV 2 nd Stage	RE	RE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	<i>RANGE</i>	<i>RANGE</i>	<i>AVG</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>
<i>LN_NUMRES</i>	1.107*** (0.067)	1.009*** (0.127)	-0.15*** (0.056)	-0.19*** (0.053)	1.139*** (0.053)	-0.14*** (0.045)	1.422*** (0.184)	-0.338** (0.155)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Constant	-1.871 (1.221)	-1.728 (1.224)	3.380*** (0.897)	3.440*** (0.889)	-0.953 (0.869)	2.891*** (0.523)	0.953 (2.624)	2.937** (1.329)
<i>N</i>	326	326	326	326	652	652	652	652
<i>R</i> ²	0.566	0.563	0.062	0.060	0.551	0.083	0.35	0.078

Note: *** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses. *LANDAREA* and *URBAN* drop out in the FE models due to insufficient variation in time. The IVs for *LN_NUMRES* in the 2SLS models are 2014 deposits of local FDIC-insured bank branches (*FDIC*) and the number of real estate and rental and leasing firms (*REAL_EST*) of the respective markets.

The effect of *LN_NUMRES* on the average of a market's mean rating distribution for Non-Fast-Food Restaurants is significant and negative. The estimated coefficients of -0.15 (s.e. = 0.056) (OLS) and -0.19 (s.e. = 0.053) (2SLS) for *LN_NUMRES* are also around 1.3 times and 2.3 times larger than the coefficients for All Restaurants presented in Table 3, which suggests a non-negligible effect of the number of restaurants in a market on the average mean rating. For example, if we compare a market with 3 Non-Fast-Food Restaurants (the 25th percentile) to a market with 11 Non-Fast-Food Restaurants (the 75th percentile), the average of a market's mean rating distribution decreases by between 0.195 (OLS) and 0.247 (2SLS). Considering that the mean value of *AVG* is 3.58 for Non-Fast-Food Restaurants, this change falls between 5.4% and 6.9%.

For the panel data, we find qualitatively unchanged results for Non-Fast-Food Restaurants, presented in columns (5) to (8) of Table 4. Again, for the models with market-level fixed effects (columns (7) and

(8)), the coefficients for *LN_NUMRES* are substantially larger than the OLS and 2SLS estimates for the models with both *RANGE* and *AVG* as dependent variables. The magnitude of β_1 in the FE model suggests that when the number of restaurants in a market increases by 10%, *RANGE* for that particular market increases on average by 0.13. For *AVG* as the dependent variable, a 10% change in *LN_NUMRES* relates to a decrease in the average of a market's mean rating distribution by -0.032 .

For cross-sectional estimations of Traditional American Restaurants, the magnitude of the coefficients substantially increases again (*LN_NUMRES*: -0.28 (s.e. = 0.077) (OLS) and -0.33 (s.e. = 0.095) (2SLS)), as illustrated in columns (3) and (4) of Table 5, meaning that an increase in the number of Traditional American Restaurants from the 25th percentile (1 Traditional American Restaurant) to the 75th percentile (4 Traditional American Restaurants) decreases the average of a market's mean rating distribution by between 0.39 and 0.46. The results of the panel data estimations for Traditional American Restaurants (columns (5) to (8) in Table 5) remain qualitatively unchanged compared to All Restaurants and Non-Fast-Food Restaurants; however, the coefficient for the FE model with *AVG* as the dependent variable slightly misses statistical significance. This could be due to a substantially lower number of observations compared to the other two restaurant categories.

Table 5: Regression Results for Traditional American Restaurants

	OLS	2SLS IV 2 nd Stage	OLS	2SLS IV 2 nd Stage	RE	RE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	<i>RANGE</i>	<i>RANGE</i>	<i>AVG</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>
<i>LN_NUMRES</i>	1.175*** (0.091)	1.021*** (0.167)	-0.28*** (0.077)	-0.33*** (0.095)	1.153*** (0.070)	-0.18*** (0.053)	1.186*** (0.157)	-0.141 (0.121)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Constant	-1.568 (1.127)	-1.425 (1.103)	4.123*** (1.097)	4.169*** (1.082)	-0.550 (0.879)	3.144*** (0.767)	-4.977* (2.826)	1.115 (1.495)
<i>N</i>	258	258	258	258	502	502	502	502
<i>R</i> ²	0.560	0.554	0.112	0.110	0.534	0.102	0.389	0.046

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, Robust standard errors in parentheses. *LANDAREA* and *URBAN* drop out in the FE models due to insufficient variation in time. The IVs for *LN_NUMRES* in the 2SLS models are 2014 deposits of local FDIC-insured bank branches (*FDIC*) and the number of real estate and rental and leasing firms (*REAL_EST*) of the respective markets.

5.2. The Effect of Horizontal Differentiation

To test H3 from section 2, we limit the impact of vertical differentiation and focus on the impact of horizontal differentiation. For this, we re-estimate our models on a subsample of our original dataset

including only restaurants categorized as Ethnic Restaurants, e.g., Chinese, Greek, or French, to name only a few.¹⁶ Ethnic Restaurants of different types compete in the horizontal rather than in the vertical dimension. Thus, the key idea is that an increase in the number of Ethnic Restaurants in a market increases horizontal competition. In small isolated markets, where a limited number of Ethnic Restaurants of the same cuisine type—e.g., Chinese—exists, the presence of vertical competition is virtually absent for the same cuisine type. Therefore, it is more likely that two horizontally differentiated restaurants will be of comparable quality and, consequently, one will not observe a high-quality Chinese and a low-quality Greek restaurant in such a market. Thus, when focusing on Ethnic Restaurants only, we expect to see an insignificant effect, possibly smaller in absolute terms, of *LN_NUMRES* on both *AVG* and *RANGE*. To isolate the effect of the pure increase in the number of restaurants from the increase in cuisine types, we additionally control for the natural log of the number of different Ethnic cuisine types (*LN_ECT*). To compute *LN_ECT*, we count the available restaurant categories in the subsample of Ethnic Restaurants for each market.

Table 6: Regression Results for Ethnic Restaurants

	OLS	2SLS IV 2 nd Stage	OLS	2SLS IV 2 nd Stage	RE	RE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	<i>RANGE</i>	<i>RANGE</i>	<i>AVG</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>
<i>LN_NUMRES</i>	1.030***	0.726***	-0.098	-0.109	0.884***	-0.0773	1.059***	0.0101
	(0.137)	(0.239)	(0.089)	(0.126)	(0.090)	(0.056)	(0.24)	(0.137)
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Constant	0.28232	0.44977	4.584***	4.590***	0.399	3.504***	3.593	1.211
	(1.1721)	(1.171)	(0.896)	(0.873)	(0.909)	(0.632)	(2.903)	(1.366)
<i>N</i>	338	338	338	338	333	333	333	333
<i>R</i> ²	0.436	0.432	0.038	0.038	0.488	0.038	0.286	0.036

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, Robust standard errors in parentheses. *LANDAREA* and *URBAN* drop out in the FE models due to insufficient variation in time. The IVs for *LN_NUMRES* in the 2SLS models are 2014 deposits of local FDIC-insured bank branches (*FDIC*) and the number of real estate and rental and leasing firms (*REAL_EST*) of the respective markets.

Table 6 shows the estimation results for the subsample of Ethnic Restaurants. For *AVG* as the dependent variable, in line with our expectations, the effect of *LN_NUMRES* is insignificant in all model

¹⁶ We included all restaurants from a total of 21 different ethnic restaurant types based on the categorization provided by Yelp. The restaurant types are Austrian, Chinese, Cuban, French, German, Greek, Hawaiian, Indian, Italian, Japanese, Korean, Sushi Bars, Latin American, Middle-Eastern, Mediterranean, Mexican, Spanish, Thai, Turkish, Asian Fusion, and Vietnamese. We thank the AE for suggesting this analysis.

specifications. The magnitude of the coefficient is moderate for the cross-sectional models and small for the RE and FE models. For *RANGE* as the dependent variable, the effect of *LN_NUMRES* is significant and positive in the panel as well as in the cross-sectional models, but, by and large, smaller compared to the corresponding coefficients reported in Tables 3, 4, and 5. Intuitively, this could explain why some Ethnic Restaurants, regardless of local market competition, constantly hover around a 3-star mean rating and rarely achieve a rating higher than 4 stars. For Chinese restaurants, for instance, the average mean rating is 3.11 compared to an average mean rating of 3.44 for the full sample. Nevertheless, we still find a medium effect of *LN_NUMRES* on *RANGE* under horizontal differentiation. This might be explained by idiosyncratic quality differences pertaining to different Ethnic Restaurant types and by theoretical findings of Zeithammer and Thomadsen (2013), who find that under certain conditions, two horizontally differentiated restaurants also differentiate vertically. In summary, comparing the coefficients from Table 6 (horizontal case) with those from Tables 4 and 5 (vertical case), H3 is supported.

5.3. Further Analyses

In the following, we would like to get insights into the mechanism that drives the change of the dispersion in the distribution. Therefore, we compute the median, minimum, and maximum as well as the 10th percentile, 20th percentile, 30th percentile, 40th percentile, 60th percentile, 70th percentile, 80th percentile, and 90th percentile of the rating distribution for each isolated market and estimate our model for our three focal restaurant categories with these percentiles as dependent variables.

If the range of the mean rating distribution increases and the average of a market's mean rating distribution decreases, we would expect to find a negative effect for the median and for all percentiles left to the median where the absolute magnitude of the negative effect should be strongest for the minimum rating and decreasing for increasing percentiles. For the percentiles above the median, the sign and magnitude of the expected coefficients depend on two opposing effects. The increase in the range of the mean ratings should lead to a positive effect, whereas the decrease of the average of a market's mean rating distribution should lead to a negative effect (where the former increases with increasing percentiles and the latter remains constant). Therefore, we would expect to find a decreasing

absolute magnitude of the negative effect for increasing percentiles, and possibly a conversion to a positive sign for the highest percentiles. Figure 3 shows the estimates (diamond symbols) as well as the 95% confidence intervals (vertical lines) from 2SLS models with the percentiles on the x-axis as dependent variables for our focal restaurant categories.

Figure 3: Estimated Coefficients on LN_NUMRES for Different Percentiles of the Mean Rating Distribution as Dependent Variables

The estimated coefficients are negative for the lower percentiles, decrease in absolute magnitude for increasing percentiles, and turn positive for the highest percentiles. This suggests that a disproportionately high decrease in ratings for the lower percentiles of the mean rating distribution leads to the decrease in the average of a market's mean rating distribution. In other words, larger markets exhibit a disproportional increase in lower rated restaurants than smaller markets. In addition, the negative effect on the minimum rating and the positive effect on the maximum rating rule out that the increase in the range of the mean rating distribution is solely attributable to an increase in restaurants with either high or low mean ratings.

Recognizing the benefit of calculating the Herfindahl-Hirschman Index (HHI) in a market but realizing that the market shares are often not available, we investigate whether crowdsourced online ratings can compute an HHI -like measure that captures competition in a market. This not only obviates the missing

data problem of the rarely available information on market shares to compute the *HHI* but also ensures that our results are not driven by the operationalization of the market competition measure.

We conduct a simple OLS regression substituting *LN_NUMRES* with *HHI* as an explanatory variable. Because we cannot observe market shares of restaurants, we calculate the *HHI* based on the number of ratings a restaurant receives. It is reasonable to assume that the number of ratings a restaurant receives has a positive correlation with the market share of a restaurant because a restaurant that establishes a customer base over time also sees its number of ratings increasing. To the best of our knowledge, we are the first to calculate the *HHI* in this way based on crowdsourced data. Ultimately, inferring whether our computation of the *HHI* based on the number of reviews is equivalent to the calculation based on real market shares is not possible in this case. We can, however, check whether the results using the alternative calculation of the *HHI* are consistent with the results in our baseline estimation in section 5.

We calculated the *HHI* at the city level by summing the total squared percentage market shares of ratings for each restaurant, normalized between 0 and 1.¹⁷ An *HHI* of 0 indicates high competition, and 1 indicates a perfect monopoly. Reassuringly, we find that *LN_NUMRES* is statistically, significantly, and substantially negatively correlated to our computation of the *HHI* (Pearson's $\rho = -0.7622$). This means that a higher *HHI*, where 1 equals a pure monopoly, is associated with a lower value for *LN_NUMRES*. Thus, we expect coefficients for *HHI* with an opposite sign compared to those for *LN_NUMRES* in our baseline model. Indeed, the results for this analysis largely remain qualitatively unchanged from our baseline model, as depicted in Table A4 in the appendix.

5.4. Robustness Checks

One might argue that our results are affected by the truncation of our key variables of interest. The market-level average of mean ratings (*AVG*) can only take values between 1 and 5, and the range of mean ratings takes values between 0 and 4. We consider this specific characteristic of our variables by estimating Tobit versions of all our cross-sectional IV models.¹⁸ All the resulting coefficients are larger

¹⁷ For instance, if there are two restaurants in the market, each with 200 individual ratings, the *HHI* is calculated as $\frac{50(\%)^2 + 50(\%)^2}{10000} = 0.5$.

¹⁸ The results of all robustness checks are available upon request.

in absolute magnitude than the respective coefficients from the linear regression models except for one model. We are confident, therefore, that the results presented in Tables 3 through 5 can be interpreted as a lower boundary for the real effects rather than being driven by the truncation of our key variables of interest.

Yelp may not cover all restaurants in a specific location and may, therefore, represent an inappropriate measure of local market competition. To address this concern, we collected data on the number of restaurants for each of our isolated markets on Yellowpages.com and compared this to the number of restaurants collected from Yelp.com. Although the resulting average number of restaurants on Yellowpages.com (46.0) is larger than the average number on Yelp (40.1),¹⁹ these two measures are highly correlated ($\rho = 0.959$), and our results of the cross-sectional models do not change if we substitute the natural log of the number of restaurants collected on Yelp.com with the natural log of the number of restaurants collected on Yellowpages.com.

Another potential concern is that our results are driven by restaurants with only a few very positive or very negative ratings. For example, the owner (or their friends) of a newly opened restaurant posting a five-star rating would almost certainly increase the observable range of mean ratings. The same applies if the competitors of a newly opened restaurant in turn post very negative ratings. We address this issue by limiting our dataset for the cross-sectional models to restaurants that received at least two or at least five reviews, respectively. We observe the same pattern for the effect of *LN_NUMRES* on the average of a market's mean rating distribution.

Even though the range of mean ratings in a market increases with further competition, this might not result in more competitive markets offering a larger number of different mean ratings. To dispel this, we use the discreteness of the star rating system on Yelp.com and count the number of different mean ratings available in a market. In this rating system, ratings are measured in full and half stars, ranging from 1 star for the lowest to 5 stars for the highest rating level, which gives us a total of nine potential

¹⁹ One potential explanation is that, due to the crowd-driven nature of the Yelp data-generation process, it reflects restaurant closures much more promptly than Yellow Pages. The Yellow Pages listings were collected in September 2014.

mean rating levels for each restaurant. Per sections 5 and 5.1, we would expect to see a higher number of different mean ratings in more competitive markets. Because this number is an ordinal variable, we use an ordered logistic regression model (as well as a generalized ordered logistic regressions) to analyze the relationship between this variable and the number of competitors in a market. Reassuringly, we see increased odds of having a higher number of available mean ratings with *LN_NUMRES*.

Similar to our binning strategy introduced earlier, we also test whether our empirical baseline results hold if we compare cities from different bins. We again utilize our bootstrapping program that randomly draws two cities with replacement—this time each from a different bin (representing disparate city sizes)—and tests for differences in the market-level average rating and in the range of ratings. Running the program for 2,000 rounds, we find that cities from bin 20 have a higher average rating in at least 50.9% of cases (when compared to cities from bin 30) and at most in 59.8% percent of cases (when compared to cities from bin 40). Similarly, the range of ratings of cities from bin 20 is smaller in at least 52.75% of cases (when compared to cities from bin 30) and at most in 67.7% of cases (when compared to cities from bin 40).²⁰

Despite the robust empirical evidence supporting Yelp’s mean ratings, we still would like to consider the confounding effect of the rater’s motivation—particularly social influence—on rating distributions. Dai et al. (2017) found that rating distributions on Yelp.com are not plagued by the J-shaped distribution that normally indicates a tendency to rate when opinions are extreme. Nevertheless, to exclude this concern and to account for social influence on ratings, we implement a debiasing approach proposed by Dai et al. (2017). Using Yelp data, they discovered that a social influence bias increases with the number of ratings a restaurant obtains. The authors developed and implemented an aggregation mechanism to construct an optimal mean—a weighted average based on the number of ratings of a restaurant—that accounts for social influence. We applied this strategy to the mean ratings of the restaurants in our basic model and found that the conclusions remain qualitatively unchanged. In

²⁰ It is worth noting that, in the absence of statistical power enjoyed by parametric tests because of distributional assumptions, the observed level of consistency is reassuring. After all, the cost of fewer assumptions in nonparametric tests is that they are generally less powerful than their parametric counterparts.

addition, we considered only restaurants with similar numbers of ratings (e.g., restaurants with less than 10 ratings, less than 25 ratings, and 10 to 20 ratings). The results remained qualitatively unchanged.

In addition to social influence on ratings, we wanted to rule out that ratings follow a certain trend over time. Our identification of the effect of *LN_NUMRES* on *AVG* and *RANGE* might be plagued by this time trend if it is correlated with *LN_NUMRES*. To exclude these concerns, we collected time series data on all individual customer-level reviews for all restaurants in our original sample in December 2015. First, we conducted run tests that verified whether a time series followed a random order or whether it exhibited some trend. A *run* is defined as the sequences of consecutive observations above or below the sample median; the number of runs relative to the total number of observations indicates whether a variable follows a random order or a trend (Madansky 1988). According to the run test, only a small proportion of sampled restaurants (<15%) follows a time trend. Second, we correlated the results of the run test with *LN_NUMRES*; it turns out that the number of restaurants in a given restaurant market is not correlated with a time trend. For further robustness, we estimated a logit model with a dummy variable as regressand that indicates whether a time series follows a trend, and indicator variables for the city bins from section 3.2 as regressors, including the same control variables as in our main model. None of the city bins significantly influenced whether or not the ratings of a restaurant followed a time trend.

6. Conclusion and Discussion

By analyzing how changes in local market competition influence a market's distribution of mean ratings, we demonstrate that local market competition is a driver of the heterogeneity of available mean ratings in a market. We find evidence that increasing competition leads to a broader range of mean ratings and to a decrease in the average of a market's mean rating distribution. These effects are particularly pronounced when we limit our analysis to specific restaurant types that have no significant opportunities for horizontal differentiation and when we control for unobserved market heterogeneity. Analogous to this, when there are no significant opportunities for vertical differentiation, these effects partially vanish. We rule out time-constant unobservable heterogeneity at the city level (such as preferences or framing of the raters) as a potential driver of our results. Relatedly, our empirical

examination offers credence to using Yelp mean ratings from across markets and reveals the consistency of the data-generation process.

The empirical IO literature has documented that increasing competition leads to an increase in the dispersion in the *higher* end of the service quality distribution (Berry and Waldfogel 2010), yet, the effect on the dispersion in the *lower* end of the distribution has been neglected. We extend this result as we find that the dispersion in the *lower* end of the service quality distribution actually exceeds that of the *higher* end. Moreover, literature on BI & A (as suggested by Chen et al. 2012) can build on the evidence presented here—in particular, Yelp’s mean ratings form an internally consistent data source for conducting CI activities. Supplementary analyses provided in the appendix support the claim that the insights of this study might also extend beyond online ratings from Yelp to other sources of online ratings, including Zagat. Yelp’s online rating data also comes with advantages over traditional IO measures of quality (e.g., curated ratings for restaurants (Berry and Waldfogel 2010), the number of branches and employees to measure a bank’s quality (Cohen and Mazzeo 2010, Dick 2007)) with respect to availability and granularity.

Our results also come with nontrivial managerial implications, especially for gathering CI. As depicted in Figure 1, when increasing the number of restaurants in a market, the consequences for a restaurant with a 2.5 star mean rating are distinct from the consequences for a restaurant with a 4.5 star mean rating. In our data sample, a restaurant with a mean rating of 2.5 stars faces almost 30% more competition from substitutes in markets with 51 to 60 restaurants (approximately the 75th percentile) than in markets with 21 to 30 restaurants (approximately the 25th percentile). In contrast to this, a restaurant with a mean rating of 4.5 stars faces about 5% less competition in markets with 51 to 60 restaurants than in markets with 21 to 30 restaurants.²¹ Therefore, restaurants with similar mean ratings should ideally be assessed differently if they operate across markets with dissimilar numbers of competitors. Furthermore, restaurant chains, operating in markets with dissimilar structures but seeking to maintain homogeneous appeal to customers at each of their restaurants, should hyper-differentiate

²¹ We calculate these estimates by determining the differences in relative frequency of a particularly rated restaurant between bin 30 (21 to 30 restaurants) and bin 60 (51 to 60 restaurants).

based on local market competition. All else being equal, in larger markets—with 50 restaurants, for example—“classical” restaurant chains like Applebee’s and Red Lobster face disproportionately more competition from restaurants at the lower end of the rating scale than they do in smaller markets. Consequently, it would be beneficial for such a chain to pursue strategies recognizing increased competition from lower end competitors in a larger market; the strategies in a smaller market need to be conducive to being one of the higher end providers.

The results presented in this paper have implications for everyday life, too. In general, people who prefer restaurants with very high mean ratings will find more suitable matches in larger markets. However, people should not randomly choose a restaurant there because larger markets are home to disproportionately more restaurants with low mean ratings than smaller markets. In other words, the broader range of available mean ratings comes at the expense of lower averages of the mean rating distributions in larger markets. This result emphasizes the importance of online review websites and other mechanisms to prescreen businesses in large markets to better serve consumer preferences.

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Appendix

Investigating the Correlation Between Yelp and Zagat Online Ratings

In June and July 2015, we collected data on curated ratings for 28 major U.S. cities with a total of 4,993 restaurants from Zagat.com, a company that looks back on a long-standing history of providing restaurant ratings made by enlisted critics.¹ A series of correlation analyses and regressions on a matched sample of restaurants with Yelp and Zagat ratings reveal that Yelp and Zagat mean ratings exhibit a significantly strong and positive correlation.

Correlations between Yelp ratings and Zagat's food ratings are on average 0.4918 and significant ($p < 0.0001$), as depicted in Table A1. The strength of the correlations, when considered on a city-by-city level, ranges from a minimum of $\rho = 0.2948$ to $\rho = 0.7627$ and remains significant throughout. For all 28 cities in our matched sample, the comparatively low value of 0.2948 for San Diego is the only value below 0.3, and most cities—comprising 4,238 out of the total 4,993 restaurants in our matched sample—are above 0.4. We also conducted separate correlation analyses for different cuisine types such as American, Barbeque, Burger, and Chinese and found that correlations ranged from $\rho = 0.7026$ for Barbeque to $\rho = 0.3511$ for Chinese. These values are above conventional thresholds of medium ($\rho = 0.3$) and large ($\rho = 0.5$) correlation effect sizes (Cohen 1992). To account for differences in rating scales (Zagat ratings are given on a scale from 1 to 30 and Yelp ratings on a scale from 1 to 5), we transposed Zagat ratings onto a scale from 1 to 5 and repeated the same correlation analysis. The results remained qualitatively and, by and large, quantitatively unchanged. To verify that the strong correlations were not driven by a higher number of reviews, we calculated separate correlations for restaurants with different numbers of reviews. Correlations ranged from $\rho = 0.3253$ for restaurants with fewer than 25 reviews to $\rho = 0.4881$ for restaurants with fewer than 1,100 reviews. However, the group of restaurants with fewer than 25 reviews comprised only 110 restaurants out of 4,993 total.

¹ We utilized undergraduate research assistance to manually match every restaurant between Yelp and Zagat.

Table A1: City-Level Correlation Between Yelp and Zagat Ratings

	Number of Restaurants	$corr(Yelp, Zagat)$
All Cities	4,993	0.4918
Atlanta, GA	266	0.4066
Austin, TX	256	0.6028
Baltimore, MD	317	0.5125
Boston, MA	197	0.433
Charleston, SC	76	0.5318
Charlotte, NC	62	0.3306
Chicago, IL	169	0.4481
Dallas, TX	94	0.5137
Denver, CO	266	0.4381
Houston, TX	381	0.4591
Las Vegas, NV	242	0.5045
Los Angeles, CA	258	0.4134
Miami, FL	117	0.4728
Minneapolis, MN	201	0.5822
Nashville, TN	48	0.3343
New Orleans, LA	172	0.4367
New York City, NY	399	0.4513
Orlando, FL	55	0.498
Philadelphia, PA	160	0.5765
Scottsdale, AZ	132	0.3962
Portland, OR	276	0.4254
Providence, RI	57	0.5686
San Antonio, TX	97	0.3563
San Diego, CA	352	0.2948
Savannah, GA	24	0.7627
Seattle, WA	80	0.4765
Tampa, FL	64	0.3794
Washington, DC	175	0.5161

Note: All correlations are significant at 1% except for Nashville, Tennessee, which is significant at 5%.

We also conducted a series of regressions of Yelp ratings on Zagat's food ratings to show that Zagat's rating is a strong predictor of Yelp ratings, as depicted in Table A2. These included regressions with neither city-level nor cuisine-level FE (column (1)), with only city-level FE (column (2)), with only cuisine-level FE (column (3)), and with both FEs combined (column (4)). Although Zagat features scores for food, service, and decor, the food score is the strongest predictor for Yelp ratings.

Table A2: Regression Analysis of Yelp and Zagat Ratings

	(1)	(2)	(3)	(4)
VARIABLES	<i>YELP</i>	<i>YELP</i>	<i>YELP</i>	<i>YELP</i>
<i>ZAGAT_FOOD</i>	0.30672*** (0.01269)	0.30651*** (0.01689)	0.33795*** (0.02009)	0.33711*** (0.01388)
<i>ZAGAT_DECOR</i>	−0.03818*** (0.00899)	−0.04765*** (0.01194)	−0.05363*** (0.013)	−0.06279*** (0.00962)
<i>ZAGAT_SERVICE</i>	0.08336*** (0.01433)	0.10904*** (0.02326)	0.04960*** (0.01615)	0.07680*** (0.01516)
CITY-LEVEL FE		✓		✓
CUISINE-LEVEL FE			✓	✓
CONSTANT	2.36212*** (0.04151)	2.30064*** (0.06913)	2.40582*** (0.05763)	2.45632*** (0.05766)
<i>N</i>	4,991	4,991	4,832	4,832
R ²	0.22674	0.2046	0.21414	0.33666

Note: *** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses. For ease of interpretation we employ Zagat ratings transposed onto a scale of 1 to 5.

Table A3: First-Stage Results *LN_NUMRES*

	All Restaurants	Non-Fast-Food Restaurants	Traditional American Restaurants
VARIABLES	<i>LN_NUMRES</i>	<i>LN_NUMRES</i>	<i>LN_NUMRES</i>
<i>REAL_EST</i>	0.008***	0.009***	0.009***
	(0.003)	(0.004)	(0.004)
<i>FDIC</i>	0.007***	0.006***	0.004*
	(0.002)	(0.002)	(0.003)
<i>MEDAGE</i>	−0.018***	−0.022***	−0.021***
	(0.005)	(0.006)	(0.006)
<i>MEDINC</i>	−0.004	−0.001	−0.002
	(0.004)	(0.004)	(0.004)
<i>MEDHOUSEVAL</i>	−0.001	−0.002	−0.001
	(0.001)	(0.001)	(0.001)
<i>MEDGROSSRENT</i>	0.051	0.102**	0.087**
	(0.042)	(0.044)	(0.039)
<i>UNEMP</i>	0.010	0.032**	0.026**
	(0.017)	(0.013)	(0.013)
<i>LANDAREA</i>	1.007***	0.56492*	0.692***
	(0.313)	(0.291)	(0.246)
<i>URBAN</i>	0.027***	0.038***	0.029***
	(0.009)	(0.007)	(0.011)
<i>COSTOFLIV</i>	0.002	−0.005	−0.006
	(0.007)	(0.008)	(0.009)
<i>PERCHISP</i>	0.035	−0.119	−0.210
	(0.223)	(0.184)	(0.203)
<i>PECINDIAN</i>	−0.119	−0.705	−0.058
	(0.549)	(0.590)	(0.635)
<i>PERCASIAN</i>	−0.775	−0.346	−1.39463*
	(0.973)	(0.822)	(0.776)
<i>PERCBLACK</i>	−0.026	−0.307*	−0.542**
	(0.166)	(0.184)	(0.218)
<i>RESPOP</i>	0.010***	0.054***	0.102***
	(0.002)	(0.009)	(0.015)
Constant	1.969***	1.017	0.523
	(0.649)	(0.777)	(0.844)
<i>N</i>	348	326	258
<i>F</i>	61	46	42
Adjusted R ²	0.6509	0.6577	0.6952

Note: *** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses.

Table A4: OLS Results with *HHI* as a Substitute for *LN_NUMRES*

	All Restaurants		Non-Fast-Food Restaurants		Traditional American Restaurants	
VARIABLES	<i>RANGE</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>	<i>RANGE</i>	<i>AVG</i>
<i>HHI</i>	−4.09456***	0.37792**	−2.98058***	0.33172*	−2.46366***	0.57596***
	(0.33122)	(0.18874)	(0.12863)	(0.19319)	(0.17797)	(0.18137)
<i>MEDAGE</i>	−0.01198*	0.00806**	−0.02379***	0.01351**	−0.01042	0.00954
	(0.00621)	(0.00399)	(0.00834)	(0.00569)	(0.00996)	(0.00796)
<i>MEDINC</i>	0.00706	−0.00524*	0.01554**	−0.00494	0.01147	−0.01192**
	(0.00509)	(0.00316)	(0.00617)	(0.00463)	(0.00781)	(0.00555)
<i>MEDHOUSEVAL</i>	−0.00102	0.00056	−0.00320***	−0.0001	−0.00252**	0.00006
	(0.00085)	(0.00056)	(0.00115)	(0.00081)	(0.00106)	(0.001)
<i>MEDGROSSRENT</i>	−0.03067	0.03923	−0.01619	0.08541*	0.0194	0.08253
	(0.04)	(0.02788)	(0.05356)	(0.04448)	(0.06419)	(0.05273)
<i>UNEMP</i>	−0.00311	0.00878	−0.00823	0.01124	−0.00489	0.0129
	(0.01513)	(0.00897)	(0.01943)	(0.01231)	(0.01963)	(0.01869)
<i>LANDAREA</i>	0.71415*	0.61416**	0.25153	0.28602	0.30657	0.00403
	(0.4211)	(0.25093)	(0.54457)	(0.28018)	(0.58379)	(0.40599)
<i>URBAN</i>	0.01577**	−0.00065	0.03533***	0.0047	−0.01784	0.01518**
	(0.00774)	(0.01024)	(0.01084)	(0.00745)	(0.01277)	(0.00739)
<i>COSTOFLIV</i>	0.01268	−0.00322	0.01569	−0.00709	0.01451	−0.00877
	(0.01014)	(0.00554)	(0.01038)	(0.00873)	(0.00895)	(0.0099)
<i>PERCHISP</i>	−0.09125	−0.05317	0.06725	−0.06877	0.25718	−0.25037
	(0.1928)	(0.11298)	(0.22904)	(0.17576)	(0.29507)	(0.25085)
<i>PECINDIAN</i>	−0.41117	−0.136	−1.89270***	−0.11202	−2.12335*	0.05796
	(0.74308)	(0.42753)	(0.68884)	(0.61128)	(1.25061)	(0.74799)
<i>PERCASIAN</i>	−0.85474	1.53683*	−1.32652	−0.07333	−0.98811	−0.90042
	(0.87113)	(0.79783)	(1.40469)	(0.68741)	(0.89416)	(0.82001)
<i>PERCBLACK</i>	0.06905	−0.17061	0.38287	0.03344	0.41769	−0.01785
	(0.24058)	(0.14322)	(0.36327)	(0.27678)	(0.41772)	(0.36196)
<i>LOC_POP</i>	0.00275*	−0.00081	0.02025***	−0.00066	0.03378**	0.00546
	(0.00144)	(0.00106)	(0.00503)	(0.00432)	(0.01478)	(0.01014)
CONSTANT	2.66901***	2.65958***	2.18665*	2.87798***	1.2073	3.46059***
	(1.00051)	(0.5724)	(1.25547)	(0.88325)	(1.13029)	(1.06617)
<i>N</i>	348	348	326	326	258	258
<i>R</i> ²	0.45496	0.06653	0.58449	0.05126	0.50028	0.09666

Note: *** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses.

References in the Appendix

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