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Rating systems and increased heterogeneity in firm performance: Evidence from the New York City Restaurant Industry, 1994–2013

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Abstract

Research Summary: We investigate the extent to which the increasing availability of ratings information has affected heterogeneity in firm performance and, if so, what market segments are responsible for these changes. A unique dataset was constructed with restricted-access government data to examine these questions in the context of the New York City restaurant industry between 1994 and 2013. We find that firms serving tourist and expensive price point market segments experienced increasing sales discrepancies as a function of rating differentials when ratings information became more easily accessible with the advent of online rating platforms. These findings depict how the prevalence of online rating systems have shaped competition and value capture, thus providing insight into the determinants of firm performance heterogeneity.

Managerial Summary: We examine the extent to which increasing availability of ratings information has affected firm performance by estimating changes in comparative sales between New York City restaurants between 1994 and 2013. Analyses indicate that increased access to ratings information during this period had a considerable effect on comparative sales for firms serving

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the tourist and the expensive price point market segments. These results provide insights into other industries where access to evaluations and rating systems have also increased. This work suggests that online ratings have affected how firms compete and capture value, and managers have opportunities to use rating systems to their advantage.

KEYWORDS

competition, performance heterogeneity, ratings, restaurant industry, technology access

1 | INTRODUCTION

Supported by advances in digital and mobile technologies, easy access to online expert and crowd-sourced ratings information has altered how individuals make consumption choices, as well as the range of alternative options that buyers consider when making purchases (Bapna, 2017; Blank, 2007; Chen & Xie, 2005, 2008; Chevalier & Mayzlin, 2006; Dellarocas, 2003; Lu & Rui, 2017; Luca, 2016; Zhu & Zhang, 2010). In turn, the aggregate impact of individual consumers' decisions has the potential to dramatically affect market-level outcomes, such as comparative firm performance (Evans, 2008; Luca, 2016; Salganik et al., 2006). Accordingly, managers have noted the strategic importance of ratings, rankings, and evaluations in crafting their business strategies and customer relationship management procedures (Baka, 2016; Dellarocas, 2006; Ifrach et al., 2019; Mayzlin et al., 2014). Hence, understanding how the dramatic expansion of rating systems has systematically affected firm performance is a pressing issue for both strategic management scholars and practitioners.

The extent to which the increased availability and use of ratings information has systematically affected the comparative performance of competing firms in an industry remains an open question. If all relevant differences among firms and their product offerings were widely and easily known with perfect reliability, buyers could assess competing firms and their product offerings on their own. The opaqueness of market interfaces, however, complicates the assessment of comparability among firms, creating the opportunity for third parties (e.g., critics, analysts, policymakers, regulators) to provide independent assessments (Cattani et al., 2018). Third-party ratings, rankings, and other forms of categorization are important because they define which firms compete in specific markets, as well as which firms are comparable to others on various dimensions they deem important (e.g., Cattani et al., 2017; Kennedy, 2008; White, 2004). Historically, detailed information about perceptions of quality has not been easy to ascertain and measure. The advent of the Internet, however, made some of this information, particularly about mean consumer ratings, far more easily accessible (Lu & Rui, 2017). Due to advances in information technologies, rating systems have become instrumental in the identification and construction of "better" options for millions of people around the world every day. Correspondingly, buyer option-sets and subsequent decisions can be influenced by one summary parameter of quality like in Rosen's (1981) classic economics of superstars (see also Orlikowski & Scott, 2014; Sauder & Espeland, 2009).

A potential consequence of the proliferation of digital ratings, therefore, is that third party ratings increasingly influence comparative firm performance. This should not be taken for granted writ large, however, as research suggests that differences among rating systems, and even fraudulent ratings, can engender evaluative ambiguities or obfuscate core characteristics of the evaluated offerings (Cattani et al., 2018; Chatterji et al., 2016; Fleischer, 2009). Moreover, in imperfectly competitive markets, the choice parameters of buyers are multidimensional (Gergaud et al., 2015; Sands et al., 2021), and this dimensionality varies by market segment (Belton & Stewart, 2002; Zionts & Wallenius, 1976). Target consumers' need for more and better information likely varies across markets based on prior or vicarious experience or the expected value of the consumption choice. Firms also vary in their capacity and inclination to react strategically to rating systems, which may further exacerbate performance differences (Espeland & Sauder, 2007; Orlikowski & Scott, 2014). Thus, at the market level, it is an open question in the literature whether and how ubiquitous ratings may have heterogeneous effects on firms operating in different market segments.

In this article, we examine how the increasing availability of ratings information made possible by the Internet and associated technologies affected the comparative performance of firms. Our empirical setting is the New York City restaurant industry from 1994 to 2013, a period of study that purposefully envelopes the advent and diffusion of a host of online restaurant rating platforms such as *Yelp*, *TripAdvisor, and OpenTable*. To establish the set of restaurants we sample, we collected, digitized, coded, and matched time-varying New York City restaurant ratings data from print versions of the *Zagat Survey*, an early pioneer in the crowd-sourced restaurant review industry that preceded the advent and expansion period of online reviews; this allows us to study changes over the time period that envelopes the advent and proliferation of restaurant ratings information.[1] We then matched this information about New York City restaurants to performance data we derived from restricted-access administrative information about firms' financial outcomes. In bringing these data together, we developed a unique panel dataset containing two decades of New York City restaurant-year ratings observations that include granular measures of actual restaurant sales.

We operationalize competition as a network of competitor-dyad observations based on the presupposition that competition is relational and is best modeled as such (Cattani et al., 2018; Hannan & Freeman, 1977; Hawley, 1950; White, 2004). Our dataset consists of ~4.7 million competitor pair (or dyad) years, which uniquely affords us the opportunity to investigate changes in relative sales across the New York City restaurant industry over two decades. Indeed, one of the advantages of the relational modeling approach we develop in this article is that it helps us understand competitive dynamics in markets where firms compete and differentiate along many characteristics (e.g., Athey et al., 2018; Cattani et al., 2017, 2018; Lavie, 2021; Sands et al., 2021; Thatchenkery & Katila, 2021). We also use geospatial data to contextualize competitive differences by market segments that have comparatively less local information and, hence, may have a greater need for ratings information when assessing options (Besbes & Scarsini, 2018). Thus, we can investigate how more easily accessible ratings information changed competitors' sales differentials across segments of the market that may vary in their need for, and use of, such information without applying overly restrictive identifying assumptions.

Our empirical analyses yield several results about how digital ratings affect relative firm performance. As a baseline, we observe a positive relationship between favorable ratings and sales. However, we do not find evidence that comparative sales disparities have changed in the post-online restaurant rating platform entry/expansion period for New York City restaurants. Our results do, however, suggest that disparities in sales have significantly increased as a function of differences in ratings in the post-online period for restaurants located in areas that cater to tourists. A dyadic fixed-effects model is employed to define scope conditions concerning how this effect is driven, in large part, by restaurants in the most expensive price point tier. These findings are consistent with our theoretical framework in which ratings information is particularly useful and important when firms are serving market segments containing buyers with less local information and for those firms that cater to consumers who are seeking more expensive cultural/experiential goods.

Our research provides some of the first evidence concerning the extent to which the accessibility of ratings information has shaped comparative firm performance across a large market, relative to a period when such information was far less readily available. Our access to restricted government data including private firm sales information allowed us to investigate directly how the entry and expansion of online ratings have led to sales disparities between competing firms. Accordingly, we provide a market-level view of how the enhanced accessibility of rating systems has affected the distribution of value between firms and across different market segments. This focus explores and eventually establishes a tight linkage between ratings information and fundamental strategic outcomes. Additionally, by leveraging archival and interview material, our work helps to contextualize both the performance effects of rating systems and the managerial experiences around the entry and rapid expansion of digital ratings. In doing so, this research shows which market segments are most impacted by these changes, thus contributing to a growing scholarly dialogue that has underscored the complex roles that third-party evaluation plays in markets.

2 | THE EMPIRICAL SETTING: THE NEW YORK CITY RESTAURANT INDUSTRY

Our empirical goal in this article is to examine the relationship between ratings information and comparative firms' sales in the New York City restaurant industry between 1994 and 2013. For the purposes of external validity, this is a compelling strategic research site because the multiplicity of dimensions along which restaurants are (dis)similar reflects an intense competitive environment (e.g., Cattani et al., 2018). While social evaluations have been a feature of the industry since its inception, tastes and opinions are far from monolithic in a place like New York City (Davis, 2009; Hauck-Lawson & Deutsch, 2009). Thus, this empirical setting provides us with rich contextual details that allow us to take a nuanced look at the implications of the expansion of rating systems. Moreover, the restaurant industry is culturally, socially, and economically vital to the country, and to New York City in particular. In terms of economic importance, the United States restaurant industry generates approximately \$800 billion dollar in total sales, ~4% of Gross Domestic Product (GDP) (National Restaurant Association, 2019). The restaurant and food service industry also employed more than 12 million Americans in 2018 (Bureau of Labor Statistics., 2018). In New York City, restaurants account for approximately 300,000 jobs (New York State Department of Labor, 2015). The restaurant industry has long been a hotbed for female, minority, and immigrant entrepreneurship, making this a particularly important setting for those interested in business ownership within these groups (National Restaurant Association, 2016).

Restaurants also shape the economic, social, and cultural vitality of geographic areas. Where, how, and what we eat also signifies taste, culture, and identity, as well as how they change in time and vary between groups (Johnston & Bauman, 2007; Rao et al., 2003, 2005).

Accordingly, research has also demonstrated that housing prices are correlated with both the quantity and quality of restaurants in a neighborhood (Kuang, 2017). Some have thus argued that restaurants can be a catalyst or predictor of urban development, change, and gentrification (e.g., Carroll & Torfason, 2011; Glaeser et al., 2017; Turco, 2023; Zukin et al., 2017). Urbanist Jacobs (1961) noted long ago that residents are quick to refer to local restaurants as a sign of the vitality and appeal of their communities. Consequently, substantial scholarly research has focused on food and restaurants to study culture, creativity, categories, boundaries, work, and the attribution of valuation and meaning (Blank, 2007; Carroll & Wheaton, 2009; Demetry, 2013; Dupin & Wezel, 2023; Fine, 2008; Goldberg et al., 2016; Kovács et al., 2014; Lane, 2014; Leschziner, 2015; Opazo, 2016). As famed food critic Anthony Bourdain expressed it, "Food is everything we are" (Schulz, 2010).

2.1 | Information, technology, and ratings: A brief history of restaurant rating systems

While information technologies have only recently altered the ease with which ratings can be accessed, hungry patrons have nevertheless been searching for information about what and where to eat for a long time. The *L'Almanach des gourmands*, published in 19th century France, is often cited as the first codified review of restaurants (Blank, 2007). *Michelin*, a French tire company founded by brothers André and Edouard, published its well-known restaurant guides starting in 1900 based on the idea that cars using their tires would be used to travel to destination restaurants. *The Michelin Guide*, however, would not cover New York City for another 105 years. The first *New York Times* restaurant review was published in 1859, but restaurant-specific reviews only became a regular feature in 1962 (Wells, 2018). *The New York Times* has employed 11 head restaurant critics since then (Parker, 2016). Other New York City media outlets have followed with restaurant critics of their own. However, the limited ability of media-employed individual critics to cover large and dynamic markets meant that only a very small subset of local restaurants ever received a published review.

The scalability challenge of only using professional critics for ratings,[2] along with the attendant market opportunity for quality assessments, was first addressed in the 1980s by Nina and Tim Zagat who pioneered a "crowd-based" approach to restaurant ratings with their *Zagat Survey* guidebooks. Drawing initially on their circle of gourmet friends, the Zagats created a survey to rate restaurants on separate dimensions of quality including food, service, and décor. As the New York City culinary revolution created a market of foodies' starting in the early 1980s (Davis, 2009; McNamee, 2012), *Zagat* expanded its reach and coverage. By the 1990s, their coverage encompassed more than 1000 restaurants (Weber, 1995).[3] Indeed, *Zagat* was regarded as, "a closely followed report card for chefs and restaurateurs" who recognized that ratings had the potential to shape consumer behavior (Fabricant, 1997, p. F4).

Responding to changes in the broader technological landscape, *Zagat* initially launched an online version of their eponymous guide in 1999, but they placed their ratings behind a paywall. The strategic choice to implement a paywall system likely limited *Zagat's* diffusion and growth; however, it protected book sales, which remained the company's primary source of revenue. Cost and access restrictions, along with a comparatively limited range of restaurant coverage, left an opening for new entrants to enter the space given advances in information technologies (see Hitt & Tambe, 2007 for a study on migration to broadband and content consumption).

The digital platform *Yelp* was founded in 2004; it quickly became one of the dominant sources of online restaurant information utilizing crowd-sourced consumer ratings. *Yelp* went from an average of 0.3 million unique visitors per month in 2005 to 5.7 million in 2007 to 26 million in 2009. Hence, the period of *Yelp's* market entry and growth are reasonably construed as the period in which accessibility and use of information about the ratings of restaurants increased exponentially. It should be emphasized that even *Yelp* and other online-native platforms (e.g., Tripadvisor, OpenTable) do not and cannot cover all New York City restaurants. Every rating system entails selected samples, with the degree of selection more extreme in expert-based ratings because professional critics have only so much capacity. Notwithstanding substantial differences in coverage and form, the ratings for specific restaurants are correlated (Apple, 1998; Silver, 2014). Indeed, the biggest change to the industry over the past few decades has not been the content itself, but rather the expanded coverage of, and ease of access to, this content.

3 | MARKET SEGMENT HETEROGENEITY IN THE USE OF RATINGS INFORMATION

To the extent that ratings information affects buyer decision-making, it should follow that the expansion of access to rating systems has the potential to shape the relative performance of firms. While all consumers may realize some benefit of access to ratings information, the discriminating value of ratings information should be greater for buyers who have comparatively less first-hand experience or information about local (in either physical or conceptual space) product offerings. For these interested buyers, accessibility of ratings information should prove more influential when their decision is perceived as more economically or socially important. Hence, how rating systems affect relative firm performance may vary by market segment.

In the New York City restaurant market, tourists represent the prototypical consumer segment that has comparatively less local information and, thus, a greater need for ratings information.[4] Local residents, by contrast, have other sources of information about restaurants—be it first-hand experience, word-of-mouth, or from coverage by local media sources—that make ratings information relatively less useful. Tourists, nevertheless, represent a significant segment of restaurant-goers, and one of the main expenditures of tourists is restaurant dining (Cohen, 1984; Urry, 1990). In 2016, for example, tourists accounted for 24% of all dollars spent in restaurants in New York City (see Appendix S1). Given tourists' lack of local information about restaurants, we expect firms that serve this market segment to be more strongly impacted by ratings information.

Just as with the tourist segment (compared with locals), the relative value of ratings information should be greater for those consumers who are making particularly expensive dining decisions compared with those seeking less costly dining options. This follows because potential buyers, on average, have less first-hand knowledge about expensive offerings, and they pay more attention to ratings when they anticipate high expenditure. Moreover, the initial decision to select from a consideration set of expensive restaurants may be driven by an underlying social desire to impress others (e.g., a date or a business meeting), in which case dining at a better or the best option is entirely the point of consumption (Bagwell & Bernheim, 1996; Leibenstein, 1950). We should, therefore, expect to observe even greater sales performance implications from ratings information for firms serving the high price segment of the market.

Ultimately, we theorize that the entry and expansion of online restaurant rating systems made it far easier for consumers to access ratings information. This, in turn, increased heterogeneity in firm performance. We expect this relationship to be stronger for firms operating in market segments where their consumers have limited sources of local information. Such market segments include areas with a high concentration of tourists and for restaurants operating at the most expensive price point. Thus, the core empirical investigations driving this research are whether: (1) the increasing ease with which these ratings can be accessed due to the Internet and advances in information technology results in greater disparity in competing businesses' sales, and (2) this disparity is exacerbated in market segments that serve buyers who require more or different type of information to facilitate their decision-making. This reasoning implies the following three hypotheses concerning the advent and expansion of digital to online rating systems within the New York City restaurant industry and their performance effects:

Hypothesis 1. As the availability of information concerning the rating difference of competitors increases, *the relative disparity in sales increases between competitors.*

Hypothesis 2. As the availability of information concerning the rating difference of competitors increases, the relative disparity in sales increases between competitors *within tourist-focused market segments.*

Hypothesis 3. As the availability of information concerning the rating difference of competitors increases, the relative disparity in sales increases between competitors within tourist-focused market segments *at the expensive price-point.*

4 | ANALYTICAL CHALLENGES AND STRATEGY MODELING *N*-DIMENSIONAL COMPETITION

Our analytical objective is to determine to what extent the advent and increasing usage of ratings information have exacerbated or mitigated disparities in sales between competitors in the New York City restaurant industry. This begs the question: who is a competitor? This is among the fundamental questions in the literature that concerns competitive strategy and imperfect competition (Cattani et al., 2017; Robinson, 1933; Rothschild & Stiglitz, 1976). A market is imperfectly competitive to the extent that producers have n dimensions along with which they can differentiate themselves from others. In such markets many different competitors can be regarded as substitutes for a given purpose depending on how the choice-set is defined. Any judgment of substitutability depends on a host of context-specific particulars. Consider in our setting, for example, a Thai restaurant and a steakhouse. Are they competitors? Assume, further, they are either on the same block or across town from one another. What if they are similarly priced and have similar quality ratings? Could one consider two restaurants with different cuisines in different New York City boroughs (separated by an hour commute) substitutes? Variability in the answers to these questions highlights the difficulty in designating two entities as competitors in a multidimensional market.

Despite the number of dimensions along which restaurants can compete, business owners must make strategic decisions that consider, to varying degrees, their competition however defined. Consumers and critics, in turn, form their evaluations and make consumption decisions with reference to some set of (perhaps implicit) comparable options that may be similar on some dimensions and differ on, or are ambiguous with respect to, others (Askin & Mauskapf, 2017; Bian et al., 2022; Cattani et al., 2018; Fleischer, 2009; Greenberg, 2021; Sands et al., 2021; Zuckerman, 1999). When a customer considers what to eat for lunch, for example, distance to work may be a plausible filter she imposes as far as she prefers to minimize travel time and cost. She may also have in mind a relative price range, and a floor for product quality. With these parameters defined, she may, however, be open to a variety of options that reflect combinations of these parameters on any given day. This example is for one discrete consumption choice, which has been the topic of considerable study going back to McFadden (Manski, 2001), but is not the focus here. Rather, the number of dimensions along which one might consider options as substitutes over the course of a day, let alone a year, is greater—thus, revealing the limitations of a matching-approach when considering daily, monthly, or yearly differentials.

Given the conceptual challenges described above, we begin with a risk set in which all restaurants in New York City theoretically compete, and we then put structure around this question with the rich data collected and described in the subsequent section.[5] Provided the relational nature of competition, we conceptualize competition here as a matrix, $\boldsymbol{M}$, with a risk-set of $\left(\frac{N(N-1)}{2}\right)_t$ competitive dyads. As such, we will hypothesize that the aggregation of consumers' choices indicates substantial cross-firm sales implications. This reflects that the "action of all on the common supply give rise to a *reciprocal relation* between each unit and all others, if only from the fact that what one gets reduces by that the amount what the others can obtain" (Hawley, 1950, p. 202, emphasis added). Importantly, this approach does not require a priori answers to the question of who is a competitor? which would demand a great deal of the researcher and for which sound science is lacking. Instead, the dyadic approach makes relatively limited assumptions in treating every dyad pair as a competitive interaction of equal weight, even if this may induce some noise and be computationally intensive. Pragmatically, since we obtained government permission to utilize an extensive amount of restricted-access data, this affords us the ability to overcome the limitations of, and need for, imposing match-based constraints because we do not need to pre-specify sets of competitors.

5 | DATA

Our data collection and compilation process began with a United States Census Bureau Federal Statistical Research Data Center (RDC) application for access to restricted-access administrative data for private firms' total value of sales information. The proposal specified the research question, the required administrative variables and their intended use, as well as the researcher-provided data (e.g., restaurant ratings and characteristics) we would need to merge to run analyses specified in the proposal.[6]

For the ratings information, we purchased historical editions of *Zagat* guides for New York City for the study window. New York City was *Zagat's* first and largest market, thus providing the largest number of observations for the longest time-series, which covered both the pre- and post-online rating system entry and expansion periods. We were able to find the long out-of-print *Zagat* volumes through an extensive search at used bookstores and other online resale outlets such as *eBay* and *Amazon*. Given the unstandardized physical specifications of *Zagat* guides (3.8 × 8.5 inches—which was considered a feature that would allow them to be more conveniently held in a pocket), we deconstructed the guide page-by-page and then scanned them. Scanned pages were then converted into an editable format using OCR software. Algorithmic and human coding ensued to fix conversion errors, particularly those associated with the unique characters and symbols used in *Zagat*. Thus, for each non-chain *Zagat* rated-restaurant-year entry,[7] we created a data point capturing its name, address, the brief (often snarky) description of the restaurant that was curated by a *Zagat* editor to represent the essence of the crowd-based ratings and qualitative reviews; the average price for a meal with drink and tip; the cuisine category; and quantitative ratings for food, décor, and service on a 30-point scale. We linked these observations over time to construct our panel dataset of New York City restaurants and their by-year *Zagat* ratings (1994–2013). Given inconsistencies in naming conventions across our various data sources, the next steps of our dataset construction necessitated cleaning and matching of observations with usable data.[8] Following extensive data cleaning, processing, and matching to our two-decade panel of restaurants with corresponding ratings information, we conducted descriptive and graphical analyses to explore variable distributions. This stage informed the construction of all variables described in subsequent sections.

6 | MEASURES

6.1 | Outcome

The outcome measure used in this study is the urban CPI-deflated difference in sales between restaurants i and j in year t. These data are restricted access government data from the BR consisting of detailed private businesses information. Our outcome variable thus represents yearly sales performance differences for private firms.

6.2 | Predictors

6.2.1 | Ratings

To measure restaurant ratings, we use the *Zagat* survey. The number of survey respondents that contributed ratings grew increasingly larger throughout the years.[9] *Zagat* volumes were historically released in the final quarter of the previous calendar year (i.e., the 2006 New York City *Zagat Survey* went on sale in October 2005). Hence, the reviews used here are lagged slightly more than one calendar year and are updated (time-varying) yearly. We created an overall restaurant rating based on the mean of a restaurant's food, décor, and service scores (Cronbach $\alpha = 0.84$[10]), and then calculated the difference between restaurant i's and j's rating in year $t-1$. As noted above, we also find that *Zagat* ratings measures are strongly correlated with *Yelp* ratings, which is in line with evidence from related prior work related to this topic. For example, Kovács et al. (2014) found that *Zagat* ratings measures are strongly correlated with *Yelp* ratings, and within restaurant ratings are very highly correlated year-over-year. To further corroborate this finding, we linked all available *New York Times'* critic ratings by restaurant-year to *Zagat* ratings between 1994 and 2013 and found the two to be correlated ($r = .45$, exact p-value = .0000). Likewise, using 2016 data, we linked *Yelp* and *Tripadvisor* New York City area ratings, and found that the pair-wise correlation was $r = .52$ (exact p-value = .0000).

What all these ratings correlations imply is that, while each platform may differ in its taxonomic structure and business logic and are therefore not analytically interchangeable, they tend to agree about the underlying quality of restaurants—something that media coverage of New York City restaurant ratings has noted as well (e.g., Apple, 1998; Silver, 2014). However, the assumption that these ratings do converge should not be taken for granted since research has documented other empirical settings in which this is not the case (e.g., Chatterji et al., 2016). Nevertheless, our analyses suggest that the rating platforms in the New York City restaurant industry are generally consistent in a way that allows for the use of *Zagat* ratings as a proxy for the ratings given by, or which might have been given by, other platforms if they had existed for a longer period. As the *New York Times* noted in their 1998 coverage of *Zagat's* 20th anniversary, "the top restaurants chosen by Zagat's amateurs do not vary markedly from those chosen by the pros, whether critics, food writers or restaurateurs. That is not surprising, since the pros influence the amateurs to start with" (Apple, 1998, p. F1). Put differently, if restaurant quality is considered a partially socially constructed latent variable, then the various rating platforms should be correlated. This is precisely what we, and others, have observed in analyzing these data. For the purposes of our empirical investigation, therefore, we use *Zagat* ratings as the proxy measure of quality from these sources, which crucially allows us to have an observable source of ratings information for the era prior to digital rating platform entry and expansion.

6.2.2 | Tourist market segment

Tourists are a significant force in the restaurant industry, accounting for a quarter of the $9.1 billion in sales volume at food and drinking establishments in 2016 (Gonzalez-Rivera, 2018). In an ideal analytical setup, a researcher would be able to perfectly measure directly, over time, the proportion of a restaurant's customers in terms of where they live along with other demographic information. Absent this information, we extrapolate those areas frequented by tourists by identifying areas with a high concentration of hotels relative to city residents. We took several steps to ensure construct validity (see Appendix S1 for additional detail). First, we tabulated the 20 largest hotels by available beds in New York City by zip code. Every single one of the largest hotels is located in a zip code denoted here as a tourist neighborhood. Because these hotels tend to be double-occupancy, and Manhattan's occupancy rate has hovered between 75% and 85%, the number of hotel rooms provides a reasonable lower bound of the number of tourists in an area at a given time. Second, using population data from the US Census, we calculated the ratio of residents in the zip codes denoted as tourist versus those in areas typically regarded as residential. This coding scheme provides a reasonable if indirect means of designating places in New York City as tourist-concentrated. This procedure ultimately generated a tourist area designation that encompasses many of the great tourist sites of New York City, including: the Broadway Theater District, Times Square, the southern part of Central Park, and the World Trade Center/Freedom Tower. Thus, from a face-validity perspective, we observe that popular characterizations of New York City tourist sites correspond to our coding schema (e.g., Lee, 2003).

6.2.3 | Exogenous information shock: Online restaurant review market entry and expansion

Yelp was founded in 2004, and quickly became the leader in online restaurant ratings and reviews (see also Luca, 2016). At roughly the same time, *Tripadvisor* expanded in the restaurant evaluation market, as did *OpenTable*, even though their primary business had been and remains reservation coordination (see Appendix S1). Hence, we code a dummy variable that distinguishes the pre- and post-online restaurant rating platform entry period around this time. The functional form implied by our theoretical argument noted above need not be discrete in nature. That is, information in this setting is not a discrete shock but rather a continuous treatment, as noted in the earlier discussion of rating systems. Moreover, *Yelp* expanded to new international markets in 2010, including countries such as France, Germany, and Spain, which constitute important source countries for New York City tourism and would have allowed those consumers to more effectively access and use restaurant ratings when traveling to New York City. Hence, we specify a second binary variable indicating the post-2010 online restaurant rating platform expansion period, as it is plausible that the ratings effect became more pronounced over time. Finally, we created a continuous variable in which all years before 2005 are coded as 0 (i.e., pre-online restaurant rating platform entry), 2005 == 1, 2006 == 2, ..., 2013 == 9.

6.2.4 | Interactions to test hypotheses

A baseline test of the impact of ratings information employs a two-way interaction between the (lagged) rating scale differential and the respective variable indicating: (a) the online restaurant ratings platform market entry (2005+) period, (b) the expansion period (2010+), or (c) the continuous measure. The second hypothesis is tested with a three-way interaction between location (both restaurants in an area with a high tourist concentration), the (lagged) ratings scale differential, and the respective variable indicating the online restaurant rating platform market entry period (2005+), its expansion period (2010+), or the continuous measure denoting greater online restaurant rating platform adoption and usage. Finally, the third hypothesis adds an indicator variable denoting that both restaurants are in the highest price-tier ($$$$), corresponding to the "very expensive" price point designated by *Zagat*. We employ a four-way interaction as it provides a statistical test of the relevant differences in quality by market segments (*tourist* by *expensive*) in a specific period.

6.3 | Controls

6.3.1 | Competitor geo-distance

In theory, substitutability should decrease with distance (Athey et al., 2018; Rosen, 1981). Hence, we measure geodetic distance between all dyadic pairs of restaurants. We also specify binary measures denoting that they are both in the same borough (Manhattan) where the density of competitors is greatest. Supplemental analyses not presented with the main text include zip or tract code fixed-effects and yield similar estimates.

6.3.2 | Competitor cuisine category overlap

A dimension for potential substitutability in this setting is cuisine type. The models presented below use the *Zagat* cuisine classification. For estimation and disclosure/confidentiality reasons, we combined sub-forms of cuisines together (e.g., Northern and Southern Italian). In total, we created 18 cuisine categories, as well as a summary measure to denote category similarity or difference. In models not presented here for disclosure reasons, we operationalized two competitors as occupying the same category with varying levels of specificity. In the most granular model (>80 categories), we defined two restaurants as similar in cuisine category if and only if the two competitors' classifications were identical. The results of that exercise yielded similar results to those presented in the main tables.

6.3.3 | Notable owners and "top-lists"

To account for managerial effects, we coded a binary variable from *Zagat* that designates whether a restaurant had a notable owner insofar as it was owned by a celebrity chef or had a renowned restaurateur associated with it. Having a celebrity chef in the ownership team may also indicate the restaurant has operational and marketing skills or advantages such as cheaper/free publicity that are likely to increase sales. Indeed, a notable owner sets the blueprint for a restaurant (Baron et al., 1999) and is likely to garner attention from critics and the popular press. Thus, this variable also helps us account for some of the idiosyncratic advantages that derive from celebrity in competitive markets (Rindova et al., 2006).

In each *Zagat* guide there are lists that provide sets of top-rated restaurants within particular categories or use-cases. These lists include being a "noteworthy newcomer" or "trendy." Many of these dimensions are not measured directly in surveys, leaving them up to editorial discretion. In turn, there is a positive correlation between notable ownership and being on a top list, net of quality. As with the notable owner variable, this measure is time invariant for theoretical and practical reasons. Theoretically, if status effects are durable, being on a top list should have a lasting effect. Pragmatically, many of these lists do not change that markedly in time, and those that do often have too few cases for robust estimation and disclosure review thresholds. It should be noted that quality ratings, notable ownership, and being on a top list are correlated, albeit modestly, ranging from $r = .22$ to $r = .36$ ($p < .0001$).

6.3.4 | Price

The total value of sales for restaurants is a function of two primary parameters: the number of customers served and the average sale price per customer. Price is also both a signal, and endogenous reflection, of underlying product quality (Roberts et al., 2011). Additionally, Luca and Reshef (2021) demonstrate restaurants receive less favorable consumer ratings when their prices are higher. Accordingly, we control for the ratio of competitor i's and j's prices, where price reflects the average sale price per customer for dinner including one drink and tip. This average estimate is not for a specific meal (e.g., popular item, tasting menu, prix fixe), but rather constitutes an overall average meal cost that is derived from survey responses from all consumers rating a particular restaurant in a given year. Note that for the purposes of our hypothesis testing, we denote the most expensive price-tier in subsequent tables as "$$$$," which reflects the market stratifications provided by *Zagat* and later *Yelp*. All price figures are deflated using the urban CPI for cross-year comparability.

TABLE 1 Summary statistics for selected variables.

Variable	Mean/(SE)
Post-online platform entry/expansion period (2005+)	0.6217 (0.485)
Post-online platform entry/expansion period (2010+)	0.27 (0.4439)
Pre-online platform entry period = 0, post-online platform entry/expansion period (2005 = 1, ..., 2013 = 9)	3.039 (3.079)
Restaurant *i* and *j* both located in a tourist area	0.1259 (0.3317)
Restaurant *i* and *j* both in the $$$$ price tier	0.0305 (0.172)
Restaurant *i*, but not *j*, featured on "top list"	0.0839 (0.2772)
Restaurant *i*, but not *j*, has a notable owner	0.1428 (0.3498)

Note: Interaction terms not presented to ensure disclosure confidentiality. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

6.3.5 | Time trend effects

We also include linear time trend effects to account for general trends in competitive differences or market conditions, and as a basis of distinguishing the period effect triple-differences that are of interest here. In analyses not reported here, we also estimated models with polynomial time trend effects, which had no bearing on the period effect results presented below. Simple descriptive statistics permissible by disclosure rules are included in Table 1.[11]

7 | ANALYTICAL MODEL

We tested our hypotheses by specifying OLS models predicting Urban CPI-deflated sales differentials between competitors *i* and *j* as:

$$
\begin{aligned}
Y_i - Y_j = {} & \beta_1 \left(\text{Rating scale}_i - \text{Rating scale}_j\right)_{t-1} + \beta_2 \left(\text{Notable owner}_{i \neq j}\right) + \beta_3 \left(\text{Top list}_{i \neq j}\right) \\
& + \beta_4 (\text{Post} - \text{online rating platform entry/expansion period}) \\
& + \beta_5 \left(\text{Rating scale}_i - \text{Rating scale}_j\right)_{t-1}^{*} (\text{Post} - \text{online rating platform entry/expansion period}) \\
& + \beta_6 (\mathbf{X}) + \theta + \varepsilon_{i,j,ij}
\end{aligned}
$$

In this model, $[Y_i - Y_j]_t = [X_{in} - X_{jn}]_t = 0$ is the special case of perfect substitution insofar as there are no differences between two competitors. This model is used to establish a baseline concerning the period effects. The first and second hypotheses rely on three-way and four-way interactions, respectively, that build on this specification. $\boldsymbol{X}$ refers to the matrix of controls described above, and θ represents a time trend to help clarify interpretation of the period effects of interest by excluding alternative interpretations concerning secular trends or economic conditions. Given the matrix of 4.7 million dyads employed in this study to model potential competitors, observations are not independent, and half the possible dyads are dropped given they are symmetric duplicates. Due to government restricted-access data disclosure requirements, exact cell sizes cannot be disclosed; actual numbers are, thus, rounded.

Based on our analyses of intra-class correlations, we use standard errors that are multiway clustered to account for the non-independence of observations along *i and j* and *ij* dimensions

(Cameron et al., 2011). We develop models progressively, adding the interaction terms to tests the hypotheses after building intuition with simpler models. For robustness, we also specify the final model in a fixed-effects (within dyad) framework. This model accounts for all dyadic competitor time-invariant characteristics including brand equity and comparative starting positions (or imprints) that may explain sales differentials.

8 | PRESENTATION OF FINDINGS

8.1 | Baseline rating difference effects and tests of Hypothesis 1

Table 2 presents OLS regression coefficients from the repeated cross-sectional dyadic competitor matrix. Following recent calls (e.g., Benjamin et al., 2018) and to facilitate easier assessment on the part of the reader, we present exact *p*-values to four digits in parentheses, where *p*-values are based on multi-way clustered standard errors. All reported estimates are in $1000s of urban CPI-deflated dollars. As variables are normally distributed and the outcome is comparative sales, the coefficients can be interpreted as the disparity in (deflated) sales associated with a one-unit increase in a predictor.

Models one through ten estimate baseline rating difference effects on firm sales disparities (Hypothesis 1). The first model includes only the coefficient for the comparative restaurant rating differential as it predicts differences in competitors' sales. The estimate is $333,000, with an exact *p*-value of .0000. As a point of reference, a standard deviation in the scale is slightly greater than four; this implies a one standard deviation rating difference corresponds to more than $1,300,000 in comparative sales. This result is the performance consequence of a basic rating disparity, which captures potential quality differences between restaurants and the publicization and increased accessibility of these differences. We note that this is an upperbound estimate, which decreases in subsequent models with the inclusion of additional controls. Model two adds the variable denoting that competitor i but not j was at some point featured on a top list. (The inverse of this measure, as well as the off-diagonal values, are not informative and thus omitted.) This coefficient is large, implying a sales differential of $1,866,000 net of the difference in rating (exact *p*-value = .0013). Model three, in turn, adds an intersection effect (Goodman, 2002; Greenberg, 2014; Greenberg & Mollick, 2017) denoting that competitor i but not j has a notable owner. As above, the inverse and off-diagonal values are omitted. The estimate is $1,517,000 (exact *p*-value = .0000) in comparative revenue, net of the rating difference and being featured on a top list. Including this measure reduces the top list estimate, and it reduces the size of the comparative rating difference estimate. This is not surprising as the three measures are correlated, as noted above. Notable owners offer a restaurant experience that is more highly rated. But that is only a portion of the producer effect observed here. In our 55 interviews with restaurateurs and review of historical material, we observe that notable owners often have an advantage via cheaper marketing activities. For example, a new restaurant by a notable owner is often featured in the media on lists such as "hot new restaurants" and "tough tickets" even before the crowd or experts have rendered a rating.

Model four includes extensive controls including geodesic dyadic distance between competitors, cuisine category similarity, borough, comparative average meal price of i/j, and a time trend. It also introduces control variables for both restaurants being co-located in a tourist area and the dummy variable denoting the post-online platform entry (2005+) period. Neither of these coefficients are statistically significant at conventional levels. However, with their addition and the

TABLE 2 OLS regression estimating difference in competitors' sales in thousands of urban CPI-deflated US dollars.

Variable	1	2	3	4	5	6	7	8	9	10
Diff in *i*'s and *j*'s rating	333 (.0000)	310.2 (.0000)	280.5 (.0000)	134.8 (.0000)	134.6 (.0000)	161.7 (.0000)	143.5 (.0000)	119.8 (.0002)	144.9 (.0000)	128.1 (.0001)
i but not *j* featured on "top list"		1866 (.0013)	1328 (.0135)	1316 (.0148)	1318 (.0147)	1323 (.0142)	1321 (.0145)	1308 (.0155)	1315 (.0149)	1312 (.0152)
i but not *j* has a notable owner			1517 (.0000)	1480 (.0000)	1480 (.0000)	1477 (.0000)	1478 (.0000)	1483 (.0000)	1480 (.0000)	1482 (.0000)
Both *i* and *j* located in a tourist area				−394.1 (.0646)	−394.2 (.0644)	−395.2 (.0638)	−394.4 (.0643)	−371.2 (.0812)	−372.9 (.0798)	−371.8 (.0807)
Post-online platform entry/expansion period (2005+)				10.57 (.9388)		2.49 (.9856)		10.9 (.9367)	3.46 (.9799)	
Post-online platform entry/expansion period (2010+)					−39.96 (.7838)		−43.3 (.7658)			−42.76 (.7683)
Diff in $i - j$ rating * post-online platform entry/expansion period (2005+)						−51.61 (.0996)			−47.5 (.1312)	
Diff in $i - j$ rating * post-online platform expansion (2010+)							−46.49 (.1617)			−43.5 (.1896)
Diff in $i - j$ rating * both in tourist area								111.8 (.0036)	108.3 (.0053)	110.1 (.0043)
Year trend	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	325	955.8	682.4	681.1	686.7	620.5	627.3	632.2	581.4	587.9
N (rounded)	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000	4,730,000

Note: Exact *p*-values to four digits in parentheses, based on multi-way clustered standard errors. Controls include: Distance, co-location in Manhattan, cuisine category, average price per meal cost ratio. Other models not reported include zip or tract FEs, time polynomials, and fine-grained cuisine category measures; all yield comparable results. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

other controls, the rating scale difference effect is reduced by more than half compared with Model one to \$134,800 (exact p-value = .0000). If we interpret this more modest figure with respect to a one standard deviation difference in ratings as we did earlier, this implies there is an approximately \$550,000 comparative sales differential. Model five, in turn, repeats this exercise with the dummy variable denoting the restaurant rating platform expansion period (2010+); that is, the period when *Yelp* dramatically grew its domestic and international user base, thereby diffusing restaurant ratings information further. In both models, the online restaurant rating platform entry or expansion coefficients are not statistically significant at conventional levels. When coupled with a control for the time trend, this suggests that sales differentials are not explained simply by time, secular shifts, or time-varying and broader economic conditions. These models also shed light on the competitive dynamics that characterize the industry. For example, net of controls, restaurants founded by notable owners earn approximately \$1.5 million more than restaurants without a notable owner. This owner effect is so large that restaurants with notable owners with a 50th percentile rating earn more than restaurants with a 75th percentile rating without a notable owner. Indeed, a restaurant that is not owned by a notable restaurateur would need a rating equal to or greater than the 91st percentile rating to be statistically indistinguishable in sales relative to a restaurant with a notable owner at the 50th percentile of the rating scale. The evidence also suggests that restaurants featured on a top list earn, on average, approximately \$1.32 million more than those that are never featured on a top list, net of controls.

In Model six, we include an interaction term between the comparative rating difference and the online restaurant rating platform entry period starting in 2005. Model seven includes an interaction term between the comparative rating and online restaurant rating platform expansion period starting in 2010. The interaction term displays a small effect size ($b = -\$51,610$; exact p-value = .0996), and the expansion period estimate also displays a small point estimate with a 95% confidence interval that encompasses zero ($b = -\$46,490$; exact p-value = .1617). Hence, we do not observe a reliable market-level sales effect that has changed significantly over time, and we do not find evidence to support Hypothesis 1.

In Model eight, we introduce an interaction between the comparative rating difference and the measure denoting that both competitors are located in a tourist area. The estimate for this variable is \$111,800 (exact p-value = .0036). It suggests that ignoring the period of online rating platforms entry or expansion, rating differentials matter more in a context where consumers have less local information about eating options, on average. This estimate provides preliminary support for Hypothesis 2. However, it is only a partial test. Models 9 and 10 add the interaction terms for the rating scale differential and the post-online platform entry (2005+) and expansion (2010+) periods with the variable denoting tourist markets. Including these measures does not substantially alter the effect observed in the tourist area segment and helps build intuition for subsequent models.

8.2 | Tests of Hypotheses 2 and 3

Models 11 and 12 in Table 3 provide direct tests of Hypothesis 2. Model 11 includes a three-way interaction for i and j's rating difference when they both were located in a tourist area in the post online restaurant rating platform period (2005+). These effects are also plotted in Figure 1. Model 12, in turn, uses the online restaurant rating platform expansion (2010+) period measure instead. In both models, the moderation effect is strongly evident. The three-way interaction effect in Model 11 (2005+) is \$119,000 (exact p-value = .0086), and in Model 12 (2010+) it is \$132,500 (exact p-value = .0070). These estimates imply that the ratings information effect is

TABLE 3 OLS regression estimating difference in competitors' sales in thousands of urban CPI-deflated US dollars as a function of tourist area market segment.

Variable	11	12
Diff in *i*'s and *j*'s rating	155.8 (.0000)	132.5 (.0001)
i but not *j* featured on "top list"	1315 (.0149)	1310 (.0154)
i but not *j* has a notable owner	1483 (.0000)	1484 (.0000)
Both *i* and *j* located in a tourist area	−343.5 (.1108)	−419.3 (.0534)
Post-online platform entry/expansion period (2005+)	13.54 (.9164)	
Post-online platform entry/expansion period (2010+)		−63.25 (.6455)
Diff in $i - j$ rating * post-online platform entry/expansion period (2005+)	−65.1 (.0318)	
Diff in $i - j$ rating * post-online platform expansion (2010+)		−60.7 (.0590)
Diff in $i - j$ rating * both in tourist area	45.24 (.2077)	81.64 (.0323)
Both *i* and *j* located in tourist area * post-online platform entry/expansion period (2005+)	−57.75 (.8052)	
Diff in rating * both *i* and *j* located in tourist area * post-online platform entry/expansion period (2005+)	119 (.0086)	
Both *i* and *j* located in tourist area * post-online platform expansion (2010+)		177.6 (.4973)
Diff in rating * both *i* and *j* located in tourist area * post-online platform entry/expansion period (2010+)		132.5 (.0070)
Year trend	Yes	Yes
Controls	Yes	Yes
F	500.9	505.7
N (rounded)	4,730,000	4,730,000

Note: Exact *p*-values to four digits in parentheses, based on multiway clustered standard errors. Controls include: Distance, co-location in Manhattan, cuisine category, average price per meal cost ratio. Other models not reported include zip or tract FEs, time polynomials, and fine-grained cuisine category measures; all yield comparable results. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

getting larger with time in market segments where consumers' external information is limited. Thus, the models presented in Table 3 and Figure 1 provide support for Hypothesis 2. As our theorizing indicated, however, there is reason to believe that other market sub-segments may also have a greater need for, and reliance on, ratings information.

In Table 4, we turn to this matter as a test of our third hypothesis. These models entail a four-way interaction between the tourist market, competitor rating differential, the period effects denoting the online restaurant rating platform entry period, and an intersection effect denoting that both competitors were in the most expensive price-tier ($$$$).[12] Model 13 in Table 4 is similar in form (a repeated cross-sectional competitor matrix) as our previous models, and it indicates a large interaction term of $406,100 (exact *p*-value = .0036). To facilitate interpretation of these results, we linearly graphed the coefficients of the equation in Figure 2. The *y*-axis reflects deflated sales differentials. Because of the larger magnitude and range of the rating differences on competitors' sales differentials, it is worth noting that the scale is denominated in $200,000. The *x*-axis represents the difference in the competitors' ratings. Given the range and scale of values, and to make the graphic intuitive, the top graph in Figure 2 illustrates disparities for restaurants located in

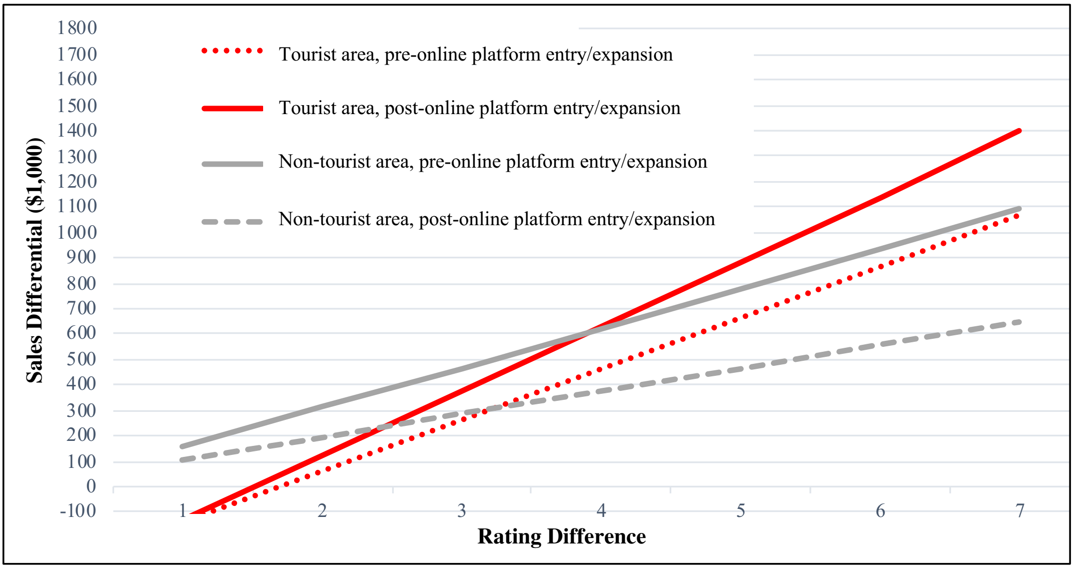

FIGURE 1 Competitor sales differentials as a function of their rating difference by tourist area market segment in the pre- and post-online rating platform entry/expansion period. The *y*-axis represents Urban CPI-deflated competitor sales differentials in 1000s of US Dollars. Rating scale difference denotes difference in competitors' *Zagat* rating scale. Estimates from regression Model 11 in Table 3 with 3-way interaction that includes the post-online platform entry/expansion entry (2005+) period. The estimates used in the above figure includes all the controls noted in text for Model 11. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

tourist areas in the pre- and post-online restaurant rating platform entry/expansion periods separated by price tier. The graphic illustrates the substantial returns to better ratings for those competitors in tourist areas offering the highest priced products in the post-online platform entry/expansion (2005+) period, while the pattern of effects in non-tourist areas appears to be far less definitive. With respect to slope comparisons, the pre- and post-$$$$ slopes are statistically different in tourist areas for quality scale values above one standard deviation. In non-tourist areas the same comparison does not indicate a reliably different slope.

Model 14 provides a test of robustness specifically designed to address empirical concerns related to un-observables by including competitor-dyad fixed effects. The four-way interaction effect in this model is $205,400 (exact p-value = .0003). An advantage of this model is that it absorbs dyadic-specific factors such as initial advantages and imprints that may not vary in time, and therefore provides a particularly powerful basis of comparison.[13] Indeed, this models the situation where two restaurants compete with each other before the online rating platform market entry or expansion periods, as well as after as a function of these period differences and rating disparities updated in time. Ultimately, these results are consistent with those presented in the repeated cross-sectional pooled competitor dyad models.

8.3 | Supplementary analyses and contextualizing our investigation

To help us better understand underlying changes in the market during this time and how such changes may affect our interpretation of the results, we also examined a complete restaurant-year panel for all restaurants listed in the 1994–2013 *Zagat* guidebooks. We note that this

TABLE 4 OLS/FE regression estimating difference in competitors' sales in thousands of urban CPI-deflated US dollars as a function of tourist area market *t* and price tier sub-segments.

Variable	13	14
Diff in *i*'s and *j*'s rating	148.2 (.0000)	91.26 (.0000)
i but not *j* featured on "top list"	1316 (.0148)	
i but not *j* has a notable owner	1480 (.0000)	
Both i and *j* located in tourist area	−329.5 (.0969)	
Both *i* and *j* in $$$$ price tier	−356.6 (.389)	−127.2 (.3279)
Diff in *i* – *j* rating * post-online platform entry/expansion period (2005+)	−64.69 (.0305)	−23.7 (.0497)
Diff in *i* – *j* rating* both in tourist area	48.46 (.1676)	46.78 (.0442)
Both *i* and *j* located in tourist area * post-online platform entry/expansion period (2005+)	−46.41 (.8349)	16.78 (.8675)
Diff in *i* – *j* rating * both *i* and *j* located in tourist area * post-online platform entry/expansion period (2005+)	107.7 (.0143)	12.45 (.5163)
Post-online platform entry/expansion entry (2005+)	13.1 (.9178)	12.43 (.8125)
Diff in *i* – *j* rating * both *i and j* in $$$$ price tier	349.2 (.0003)	47.55 (.0766)
Post-online platform entry/expansion period (2005+) * both *i* and *j* in $$$$ price tier	−65.87 (.8882)	197.3 (.1639)
Both *i* and *j* located in tourist area * both *i* and *j* in $$$$ price tier	63.51 (.8982)	137.7 (.3987)
Post-online platform entry/expansion period (2005+) * both *i* and *j* in $$$$ price tier * *i* – *j* rating diff	−39.11 (.6806)	11.53 (.7361)
Both *i* and *j* in $$$$ price tier * both *i* and *j* in a tourist area * *i* – *j* rating diff	−293 (.0088)	−98.55 (.0077)
Post-online platform entry/expansion period (2005+) * both *i* and *j* in $$$$ price tier * both *i* and *j* in a tourist area	−219.2 (.7167)	5.213 (.9801)
Both *i* and *j* located in tourist area * post-online platform entry/expansion period * in the same price * *i* – *j* rating diff	406.1 (.0036)	205.4 (.0003)
Year trend	Yes	Yes
Time-invariant controls	Yes	No
Time-varying controls	No	Yes
Dyad FEs	No	Yes
F	421.1	12.28
N (rounded)	4,730,000	4,730,000

Note: Exact *p*-values to four digits in parentheses, based on multiway clustered standard errors. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

supplemental dataset was constructed completely outside the RDC for the purposes of these post hoc analyses, which allows us to discuss years/market segments without disclosure concerns related to the comingling of confidential data. Analyses of these data at the firm-year level underscore some other notable changes that took place during our two decades of study. We

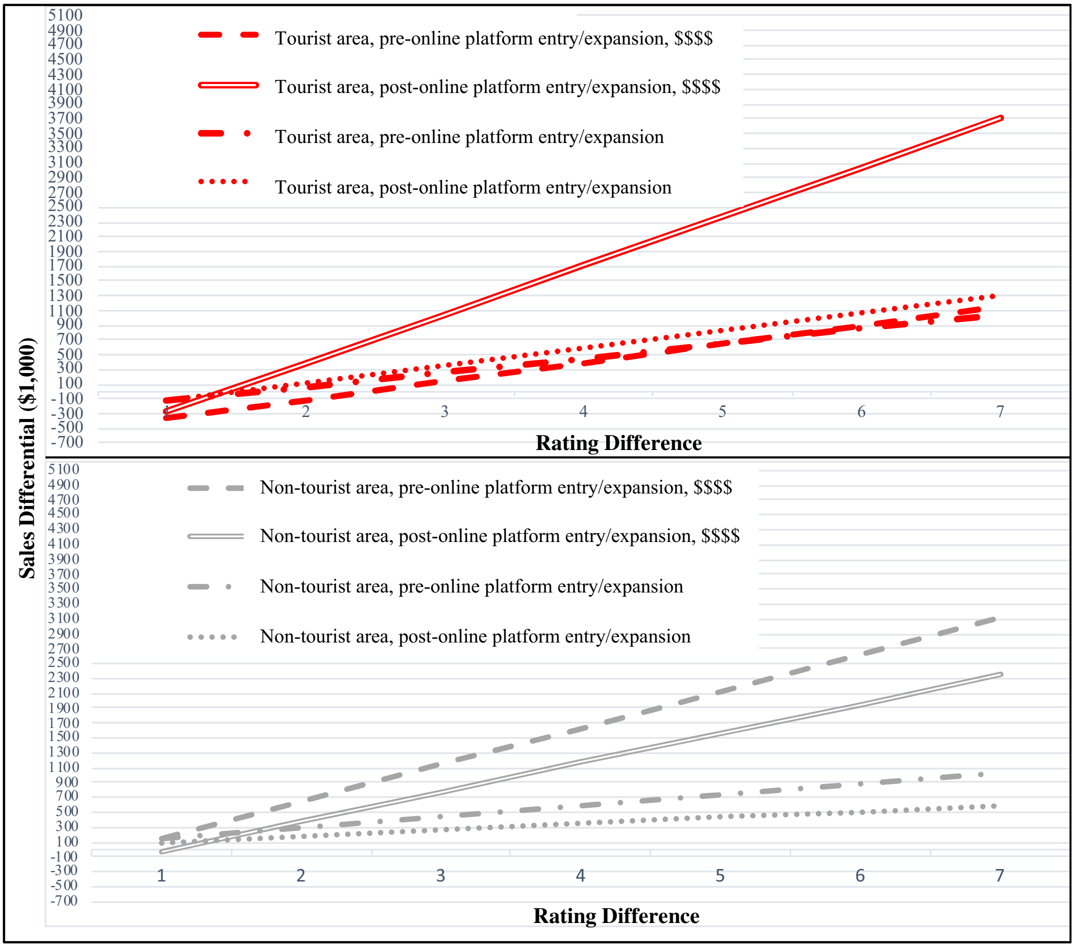

FIGURE 2 Competitor sales differentials as a function of rating differences by tourist area and price tier market segments in the pre- and post-online rating platform entry/expansion period. The *y*-axis represents Urban CPI-deflated competitor sales differentials in 1000s of US Dollars. Rating difference denotes difference in competitors' *Zagat* rating. Top figure derived from estimates from regression Model 14 in Table 4 with 4-way interaction that includes the post-online platform entry/expansion entry (2005+) period and price tier dummy variable denoting that both competitors are in the $$$$ price tier, or not. Source material US RDC restricted access administrative data and *Zagat* volumes 1994–2013.

observe that the number of restaurants covered in the *Zagat* guidebooks increased along with the growth in the population of New York City, and mean restaurant ratings have steadily inflated: 21% of restaurants had a *Zagat* rating of less than 15 (out of 30) from 1994 to 1999, 11% 2000–2004, 8% 2005–2009, and 4% 2010–2013 (see Appendix S1). While ratings inflation has been identified elsewhere in the literature, some of it has been attributed to buyer behavioral changes (e.g., Filippas et al., 2022), but this may also be consistent with work such as Chatterji and Toffel (2010) who find differences in firm responses to positive and negative ratings. We should consider it plausible that the reduction in low restaurant ratings may also be driven by supply-side responses wherein restaurateurs seek to avoid unfavorable ratings. Indeed, our analyses provide some evidence that favorable ratings have been positively correlated with restaurant survival throughout our period of study. It is plausible that rating-exit relationships have changed after online ratings became available, but we do not clearly observe any distinct effects on survival between market segments over time.[14]

These supplementary analyses offer some general insight into the developments in the restaurant evaluation industry during this time, as well as inform additional robustness checks. Additional models were thus estimated to account for possible alternative interpretations of the patterns observed here. As noted with our main analyses, we controlled for time effects in various ways to account for secular trends and alternative period effects. Other specifications yield similar results and enhance our confidence in the primary approach. For example, in an alternative model to those presented in Table 4, we allow all post-online platform entry/expansion years to vary linearly. These analyses indicate that the effect is increasing in the post-online platform entry/expansion period by \$24,130 per year from 2005 to 2013 (exact p-value = .0025), which is in line with our main results. Consistent with these findings, a New York City restaurateur we interviewed reflected on the increased importance of receiving and maintaining favorable ratings, stating that: “It's not about ego. That's how you make money.”

9 | DISCUSSION

Tracing the origins of performance heterogeneity among firms has been the central topic in strategy research (Barney, 1986; Nelson, 1991; Peteraf, 1993; Porter, 1980, 1985), and the growing importance of third-party rating systems across a variety of industries raises new questions as to their influence in shaping firm performance. To this end, our in-depth analysis of rating systems elucidates “the role that third-parties can play in influencing value creation and capture in product markets” (Cattani et al., 2017, p. 84). By leveraging special access to government-restricted data, we examined the extent to which increasing availability of ratings information, facilitated by the entry and expansion of online restaurant rating platforms, led to greater disparity levels in sales among restaurants in New York City between 1994 and 2013.

Our work provides important context-specific evidence concerning the much larger question about whether the Internet has exacerbated sales performance disparities between competitors as consumers are more easily informed about others' perceptions as to what are better, or the best, options. Explaining how and why the impact of rating systems varies across firms within the same industry is among the key questions we face in an ever increasingly digitized world of ratings, rankings, and evaluation (Blank, 2007; Bowers & Prato, 2019; Chu & Noh, 2019; Espeland & Sauder, 2007; Rindova et al., 2018; Sauder & Espeland, 2009; Sauder & Lancaster, 2006). As we show in this article, unpacking these differences entails delineating conditions under which such differential impact can be observed. Our results indicate that the effects of rating systems on how firms capture value may be contingent on the particulars of a given market segment. Prior research examining topics related to ratings, rankings, and evaluations has focused on other cultural settings, including beer and wine (e.g., Benjamin & Podolny, 1999; Frake, 2016), books (e.g., Kovács & Sharkey, 2014; Wang et al., 2018), and movies (e.g., Ferriani et al., 2009; Hsu, 2006; Olson & Waguespack, 2020). Science, particularly the natural sciences, and the legal context, have also proven fruitful research sites (e.g., Sauder & Espeland, 2009; Sauder & Lancaster, 2006). So, while we examined within-industry differences in market segments and show that they matter, cross-industry comparisons may also suggest other differences in how firms are able to capture value. This boundary condition concerning to what degree ratings information affects market outcomes may depend on the extent to which a setting exhibits the following features: (near) zero marginal costs, endogeneity in evaluation, a high correlation between producer status and product quality and pricing, and the range of parameters that are plausible differentiators (see also Lamont, 2012; Zuckerman, 2012). Provided restaurant multidimensionality corresponds to frictions in buyer beliefs about substitutability, this article's setting may yield conservative estimates of ratings effects compared with other markets. In contexts with non-zero marginal costs, there is a ceiling on the extent to which one firm can capture all available rents, and contexts with a lower correlation between producer status and quality may exhibit less competitive disparities as ratings information increases.

The extent to which rating systems shape organizational behavior by leading managers to adjust to match ratings criteria (e.g., Favaron et al., 2022; Pollock et al., 2018; Sauder & Espeland, 2006; Sauder & Lancaster, 2006; Sharkey & Bromley, 2015) suggests that the expansion of rating systems can both provide opportunities for differentiation and lead to isomorphism. Collectively, these considerations reflect important issues for future research as they will allow us to develop a better understanding of the impact of rating systems on strategic management across settings. Likewise, the fact that fake ratings have become increasingly prevalent as the variety of rating platforms has continued to expand raises new questions about the legitimacy of ratings and how managers should respond (e.g., Anderson & Magruder, 2012; Cattani et al., 2018; Luca, 2016; Luca & Zervas, 2016; see also Guynn & Chang, 2012; Streitfeld, 2012). Ensuring a favorable client experience is increasingly regarded as vital by organizations engaging in electronic commerce as it correlates with ratings, and sales by implication. In the context of restaurants, we find that notable restaurateurs were correlated with higher ratings, placement on top lists, and greater comparative sales, seemingly corroborating the idea that management matters on several margins. In many firms, this entails functional roles devoted entirely to managing social media, customer, support, and online ratings (Proserpio & Zervas, 2017). Indeed, some of the restaurateurs we interviewed indicated that in weekly staff meetings they often discuss customer reviews as a basis for gauging in real time various facets of their performance. One New York City restauranteur emphasized, "we talk about it every Tuesday morning." Another one of the chef-owners that we spoke to, who was even particularly adamant that she did not want her vision for the restaurant to be distracted by ratings, still went on to underscore that: "My front-of-the-house general manager's responsibility is to read those things." Others also stressed the need to reach out to dissatisfied customers who might give particularly bad ratings and pen especially caustic reviews—a feature that *Yelp* introduced in 2009 (Cain Miller, 2009, p. B8; see also Wang et al., 2016). Others discussed the need to consider customer product experience by offering frills or promotions to early users to garner high ratings (Kuksov & Xie, 2010). Firms that do not have this social marketing savvy and relational management capabilities are likely at a competitive disadvantage as the digital interface between the firm and consumers becomes more dynamic.

Another managerial implication of this study is that as information on competitors becomes more granular—and recommendation systems incorporate this information to make it more easily communicated to those with less local information such as tourists—it is plausible that information technology may lessen sales disparities among competitors by enabling greater horizontal differentiation at the business-level, which is consistent with work suggesting long-tail effects (e.g., Brynjolfsson et al., 2010; Fleder & Hosanagar, 2009). This, in turn, demands that managers make strategic positioning decisions and engage in meaning-making to capture value.

Likewise, there may be upstream consequences of persistent heterogeneity in firm performance within particular market segments as this can impact the economic well-being of the value-chains and communities in which these firms operate. Wilmers (2017), for example, studies how consumers for higher end goods drive disparities in employees' pay. Our article considers a similar question as it pertains to disparities in firm sales, which, in turn, is a key lever that leads to disparities in employee hiring and pay. In conjunction, such possibilities highlight that the supply-side effects of third-party evaluation have been, thus far, notably absent from the literature in strategic management.

10 | CONCLUSION

Our research helps to build upon existing theory and extend our knowledge about the strategic impact of the rise of rating systems. We build on previous work related to ratings, showing with unique quantitative data, how ratings drive substantial differences in competitors' sales performance; how this effect is shaped by enormous changes in information technology; and which market segments are particularly susceptible to information effects (i.e., heterogeneous effects) that explain increasing sales disparities for a specific subset of competitors. Second, this research focuses on a specific market over time, rather than just at the product-level, thereby showing directly how information technology effects can shape the competitive landscape for both firms and entire markets, in addition to specific products that prior research has considered (e.g., Li & Hitt, 2008; Oestreicher-Singer & Sundararajan, 2012). Importantly, this work provides estimates of competitive implications of one of the biggest informational shocks in recent years: the widespread diffusion of online ratings information.

We show that to understand the importance and impact of ratings information effects one must consider the nature of competition within particular market segments. In general, we find little evidence that across the entire market online restaurant rating platforms increased disparities in sales between New York City restaurants, even though we do see a baseline positive relationship between favorable ratings and sales. It stands to reason that buyers have always preferred higher rated options, and, in turn, higher rated restaurants have greater sales. However, for firms that compete in those market segments where their customers have a greater need for ratings information due to less local information or more substantial expenditures, there is considerable evidence that sales disparities have increased dramatically in those periods with easier access to ratings information.

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DATA AVAILABILITY STATEMENT

The data used in this study are confidential and restricted-access administrative data. The first author received special sworn access to analyze the data, pursuant to a rigorous and pre-specified proposal. However, the first author was not able to remove any data from a secure government research facility.

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ENDNOTES

[1] In what seems like prescient use of language, a 1989 *New York Times* article about *Zagat* described how: "Many restaurateurs believe the Zagats (Nina and Tim) perform a valuable service by giving *democratic assessments* of eating places. Others, however, question the method" [emphasis added] (Hall, 1989, p. C1).

[2] In August of 2016, *The New York Times* ceased its coverage of restaurants (and other cultural institutions) in the Tri-State area outside New York City. Though mourned by many, this business decision reflected the constraints related to the cost of expert-based ratings and the limits such a system imposes on scalability. Even if an expert reviewer eats out five times per week and dines at a restaurant multiple times before submitting a review, as *New York Times* critic Pete Wells does (Parker, 2016), there is a clear and costly ceiling on the number of ratings and reviews that can be written by such experts.

[3] *Zagat* focused on full-service restaurants. It was never designed to cover all chain restaurants, bars, bodegas, food stands/trucks, or pop-ups in the same way that decentralized digital platforms like *Yelp* would later be able to do more effectively (see Appendix S1).

[4] For an alternative approach concerning those who frequent a restaurant see Cai et al. (2009). These authors used an experiment coupled with a post-treatment survey of those experimental participants to determine how observable ranking information of dishes influenced consumer ordering behavior. They then surveyed the experimental participants and interacted the experimental treatment variables with an indicator for frequenting the restaurant at least six times. The interaction term in their LPM was −0.0004 (SE = 0.0002), with a constant value of 0.043. This suggests a slight (in substantive terms) moderation effect for inferred familiarity on experimentally manipulated consumption choices in the presence of ranking information.

[5] For government disclosure review purposes only, we also estimated models at the firm-level. Results were consistent with those presented below. However, such a firm-level analysis does not allow for the calculation of similarity and difference metrics that are vital given the network conceptualization of competition used here.

[6] We note in advance of our analyses that there are restrictions imposed on the use and reporting of the government data used here. First, the researcher is circumscribed by her ex-ante proposal. Second, there are strict rules pertaining to where and what data can be analyzed. Third, there are strict data disclosure rules and requirements (see https://web.archive.org/web/20170211213119/https://www.census.gov/content/dam/Census/programs-surveys/sipp/methodology/RDCDisclosureRequestMemo.pdf).

[7] *Zagat's* focus on non-chain restaurants in New York City remained throughout our period of investigation, which never exceeded 14% of its by-year coverage. There was an expansion of its chain coverage over time alongside its stable expansion of coverage. Nevertheless, chain restaurants have been relatively less common in New York City compared with other places in the country. Note also that Luca's (2016) work on *Yelp* ratings in Washington State focuses explicitly on the effect of ratings access in areas where chain restaurants are/were more prevalent, which offers detailed consideration of these issues.

[8] Other than the challenges obtaining administrative approval for disclosure and standard issues around matching, Haltiwanger et al. (2017) point out a variety of challenges in using these sorts of government restricted data, such as missing observations or inconsistent year-over-year coding. The BR revenue data have limitations that would pose challenges in different settings, but our interest in non-chain restaurants make it an ideal candidate for this project (see Haltiwanger et al., 2017, p. 17). While it was a labor-intensive process, we were able to overcome some of the potentially inherent data limitations by linking observations by-hand to

ensure that we only kept observations with reliable data. Our sample, then, can plausibly reflect a bias to firms with reliable tax filings.

[9] Note that in *Zagat*, the number of restaurant-specific reviews is not observable. However, prior research suggests that quality ratings have an appreciable effect (e.g., Lu et al., 2013; Luca, 2016; Wu et al., 2015).

[10] These ratings are so highly correlated that including each rating separately induces multicollinearity. We thus obtain similar results if we select just one dimension. Our approach seeks to provide a more comprehensive assessment by including these different dimensions in an overall restaurant rating.

[11] See also the material available in the Appendix S1 for a variety of disclosable descriptive and summary measures.

[12] As indicated earlier, for the purposes of confidentiality and disclosure requirement we report only models with multi-way interactions. We did, however, receive government approval for qualitative disclosure to confirm that subsample analyses provide results that are consistent, with respect to direction and significance of our variables of interest, with those presented in the main tables.

[13] These models include a very large number of fixed effects. We also estimated this model conditional on price tier ($$$$) with a 3-way interaction. Results are consistent with those presented here. Again, government disclosure rules make related sub-sample analysis presentation complicated. However, employing the full sample with interaction terms to test predictions also allows for a simpler basis of calculating tests of differences.

[14] Supplemental survival analyses consider not only the correlation between a given firm's ratings and their likelihood of exit holding constant the market-level mean rating, but also the relative changes in ratings for individual firms, to include the restaurant's ratings compared with their own average lifetime rating and their year-over-year rating change. See Appendix S1.

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