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A Strategic Approach on Expert Evaluations: Three Essays on Restaurant Guides

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ABSTRACT

In today's information-saturated world, the consumption choices made by individuals and social actors are increasingly shaped by evaluations provided by critics, experts, or end-users. These evaluations play a crucial role in determining the success or failure of products and services, as well as in shaping the reputations and careers of those who offer them in the market. Evaluators thus act as powerful agents of social stratification across various sectors.

This dissertation aims to analyze the social construction of evaluations and the role of gatekeepers in our society. Specifically, it focuses on ratings and evaluations in the culinary field, where critics and gastronomic guides hold positions of authority. The first two chapters explored how these actors influence consumer preferences and construct and legitimize their roles within the culinary field. The third chapter investigates producers' reactions to changes in their ratings, exploring the influences of repeated evaluation activities. Through the analysis of the criteria used in evaluations, the dynamics of mutual influence among experts' evaluation outcomes, and the managerial responses to online consumer reviews, this dissertation aims to reveal these processes, flows, and influences by examining the relationship between local and global levels through both qualitative and quantitative methods.

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INTRODUCTION

Contemporary society is characterized by the growing prevalence and salience of evaluations that shape social and economic outcomes (Sharkey, Kovacs, & Hsu, 2023). They influence individual and organizational decision-making in production, consumption, and overall social interactions. For example, consumers rely on historical consumers' evaluations to make purchasing decisions (Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010), while producers use ranking in media lists to identify reliable partners (Chung, Singh, & Lee, 2000; Podolny, 1994). In the meantime, evaluated organizations demonstrate dynamic responsiveness, implementing strategic adjustments to their services and products in pursuit of improved evaluations (Sauder & Lancaster, 2006).

Evaluations can take various forms (Sharkey et al., 2023). As shown in Figure 1.1, basic formats include textual descriptions (e.g., movie reviews, book critiques), numerical ratings or scores (e.g., firm credit ratings, Rotten Tomatoes), rankings (e.g., QS university rankings), or lists and awards (e.g., “ten breakthrough technologies,” the Academy Awards). Complex combinations of these formats also exist, such as matrix representations (e.g., Gartner's Magic Quadrant), ratings paired with textual descriptions (e.g., Metacritic ratings and reviews), or lists integrated with ratings or rankings (e.g., Wine Spectator's top 100 wines). These diversified evaluation formats reflect the evaluators' preferences for imposing a hierarchical market structure.

Insert Figure 1.1 about here

The plurality of evaluation formats and criteria results from the plurality of evaluators. Expertise is one of the most critical distinctions between evaluators. Expert evaluators and amateur evaluators differ in their knowledge base and information processing (Boulongne,

Cudennec, & Durand, 2019). Experts' knowledge structures "are characterized by many links among elements and by the formation of abstract representations, all of which become unitized with frequent activation" (Peracchio & Tybout, 1996). While amateur evaluators may focus more on surface-level attributes, expert evaluators are better at identifying underlying attributes and making sense of novelty (Kovács & Hannan, 2010; Shafto & Coley, 2003). The elaborate expertise enables expert evaluators to shape public taste, including that of amateurs, by establishing "a canon of rules and standards", setting aesthetic trends, and determining legitimate taste (Lane, 2013; Vincent, 2018).

Another critical distinction between evaluators is the level of units that produce evaluations. Individual evaluators differ from organizational evaluators in terms of breadth of coverage and standardization of process. Due to limited time and resources, individual evaluators are less likely to produce evaluations at regular intervals or across diverse locations compared to organizational evaluators, resulting in narrower coverage. On the other hand, organizational evaluators must train employees to ensure consistent evaluations, making their outputs more systematic and stable. Individual evaluators, however, are more vulnerable to social influencing processes, particularly in adjusting their judgments to align with those expressed by others (de Nooy, 1999; Festinger, 1954).

This dissertation will focus on the expert organizations who publish rated lists (hereafter, expert rating organizations) as instances of authoritative evaluators wielding substantial institutional influence. The first two chapters investigate the determinants shaping these organizations' evaluative outcomes, while the third chapter analyzes the consequent impact of such assessments on evaluated producers. Through both quantitative and qualitative analysis approaches, this dissertation aims to illuminate both the antecedents and consequences of expert rating organizations' evaluations.

Chapter One demonstrates that expert rating organizations exhibit strategic

interdependence, with their evaluation outcomes reflecting strategic decisions on optimal distinctiveness. This study investigates the level of imitation between the two expert rating organizations in 4662 evaluations spanning 454 restaurants between 2017-2022. Results reveal that both expert rating organizations imitated each other's coverage and rating of producers to a different extent, suggesting a relational and dynamic strategy in their optimal distinctiveness. Furthermore, the analysis identifies culinary experiences as key determinants of restaurant guides' optimal distinctiveness strategies, including organizational status, market knowledge accumulation, and order of entrance into the market.

Chapter Two aims to understand how expert rating organizations navigate internal similarities/differences in their evaluation outcomes across diverse locations. In contrast to the ideal scenario where expert rating organizations provide independent and coherent evaluations, this study identifies discrepancies in evaluation outcomes across host countries. To explain these discrepancies, three hypotheses involving cultural and economic factors are tested. First, expert rating organizations encounter cultural barriers that lead to the "penalization" of countries with dissimilar cultural contexts. Second, they exercise discretionary power to shield the home country from economic competition posed by other host countries in the international market. Lastly, the presence of competing expert rating organizations contributes to strategic "penalization" in evaluations. This chapter clarifies the organizational constraints and strategic interests of expert rating organizations in shaping market social hierarchies, enhancing our understanding of the inequalities embedded in their evaluation outcomes.

Chapter Three examines how evaluated organizations navigate the opportunities and risks in their status change, focusing on organizational public responses to consumer reviews as a significant strategy for adjusting their primary market. The analysis advances two central propositions: producers experiencing status elevation demonstrate an increased propensity to engage with consumer reviews while adopting more positive response tonality, whereas

producers undergoing status decline exhibit decreased response rates but heightened positivity in their communications. Empirical analysis of organizational responses to consumer reviews on Dianping.com, examining 108 Michelin-starred restaurants across major Chinese cities from 2017 to 2022, largely supports these predictions. This research extends scholarly understanding of how organizations strategically recalibrate their primary market identification in response to status fluctuations.

This dissertation makes several significant contributions to our understanding of evaluations in contemporary society, with a particular focus on expert rating organizations as distinctive institutional actors. In an era where evaluations increasingly shape social and economic outcomes (Sharkey et al., 2023), this research offers novel insights into both the antecedents and consequences of expert evaluations across diverse geographical contexts within the culinary industry.

First, this dissertation extends the literature on evaluating organizations by conceptualizing expert rating organizations as strategic actors embedded in complex competitive landscapes. While traditional perspectives have characterized evaluators across three dimensions including information intermediaries, creators of comparative orderings, and mechanisms for surveillance and control (Rindova, Martins, Srinivas, & Chandler, 2018), our findings show how information intermediation is strategically curated rather than neutral; how comparative orderings reflect competitive positioning among evaluators themselves; and how surveillance mechanisms embed the strategic interests of the evaluators. This builds upon emerging work on the strategic behavior of market intermediaries (Bowers & Prato, 2019; Durand & McGuire, 2005; Olson & Waguespack, 2020) by revealing how expert rating organizations' pursuit of optimal distinctiveness shapes their evaluative practices across multiple dimensions. The thesis thus contributes to scholarship on "rankings entrepreneurship" (Rindova et al., 2018) by illuminating how evaluators strategically navigate tensions between

distinctiveness and legitimacy to establish and maintain their institutional authority.

Second, this research advances institutional theory by revealing how evaluators construct and reproduce market hierarchies across national boundaries. Chapter Two's analysis of cross-national evaluation discrepancies reveals that expert rating organizations do not provide uniformly objective assessments but instead exercise discretionary power influenced by cultural and economic factors. This finding resonates with the "surveillance and control" perspective of evaluations, which emphasizes how rankings subject organizations to political and economic interests. By identifying specific mechanisms through which expert rating organizations embed inequalities in their evaluation outcomes – cultural barriers, economic protection, and evaluator competition – this dissertation offers a more nuanced understanding of the institutional constraints and power dynamics that shape market social hierarchies in global contexts.

Third, this dissertation contributes to strategic management literature by examining organizational responses to status shifts in their responses to consumer reviews. The findings in Chapter Three enhance our understanding of the "changing nature of intermediation" in contemporary markets, where traditional expert evaluations coexist alongside consumer reviews and other forms of assessment (Sharkey et al., 2023). By examining how organizations strategically navigate this complex evaluative landscape, this research addresses a critical gap in understanding the interplay between multiple forms of evaluation in shaping organizational behavior.

Fourth, methodologically, this dissertation employs a mixed-methods approach combining quantitative analysis of evaluation outcome data with qualitative insights to decode evaluation criteria, evaluation process, and potential strategic intent. By triangulating between these approaches, the research overcomes the limitations of studying evaluations solely through outcome data or process observations, particularly important given the opaque nature of expert

rating organizations' decision-making processes (Lane & Opazo, 2024). This approach responds to calls for more sophisticated methodologies in studying the multifaceted nature of evaluations and their consequences, especially in contexts where the criteria for judgment combine technical, aesthetic, and cultural elements.

Finally, by synthesizing insights across three complementary studies, this dissertation offers a more complete theoretical framework for understanding evaluations as both reflections and drivers of market dynamics. It challenges two assumptions: that evaluations merely reflect objective quality assessments and that expert rating organizations function identically. Our findings reveal substantial differences among expert rating organizations in their market knowledge, status, and entrance timing, which directly shape their optimal distinctiveness strategies. These evaluations emerge from complex institutional processes involving cultural barriers, economic protectionism, and competition conditions. As markets increasingly depend on evaluations to organize economic activity, this research provides important insights into evaluation production, contextual variation, and organizational strategic responses, thus deepening our understanding of how markets function with expert rating organizations.

CHAPTER ONE

Culinary Experiences and Optimal Distinctiveness: Competition between Restaurant Guides in China

INTRODUCTION

While much is known about how expert rating organizations play an important role in mediating markets (Sauder & Lancaster, 2006; Zuckerman, 1999), less is questioned about audiences' underlying assumptions to trust these organizations. Expert rating organizations are expected and trusted to produce evaluations with objectivity and independence (Blank, 2007; Sharkey et al., 2023). But recent studies indicate that expert rating organizations face increasing pressure from heightened competition and existential threats (Durand & McGuire, 2005; Sharkey et al., 2023). To maintain audience attention and improve survival chances, expert rating organizations have been found to self-generate changes in their evaluation outcomes, intentionally increasing the dynamics of candidates' social hierarchy (Bowers & Prato, 2019).

Recognizing the goal of expert rating organizations to maintain survival and relevance in the market, it is plausible that their evaluation outcomes are not as objective and independent as audiences might wish. Therefore, the important question is: what factors may influence their evaluation? How the evaluation outcomes of expert rating organizations may be dependent on these factors? Connecting to the strategy literature, I propose that two sources of influential factors can be expected from both external peers and internal activities. I will emphasize the external source of competitors in this chapter and discuss the internal source of cross-country activities in the next chapter.

When there are competitors, expert rating organizations face a dual challenge: they must align their evaluation outcomes with competitors to avoid credibility issues while maintaining distinctions to attract attention and mitigate competition in the same market niches. This delicate balance stems from institutional pressures for conformity and strategic imperatives for differentiation. Substantial divergence from competitors' evaluations risks undermining the organization's legitimacy, as audiences question the evaluation outcome's credibility and informativeness, thereby eroding trust in expert rating organizations' professionalism within

this field. Conversely, complete isomorphism with competitors renders the focal evaluator's contribution redundant, diminishing its added value among stakeholders who seek distinctive insights, potentially leading to the singularity of the culinary field. In response, expert rating organizations may closely observe each other's outcomes and strategically adjust their evaluations to reflect certain levels of similarity or difference (Olson & Waguespack, 2020).

Optimal distinctiveness – the imperative to be both 'similar to' and 'different from' peers – is a key research focus in management and organizational studies. It emphasized the strategic balance between similarity and differentiation from competitors (Deepphouse, 1999), which serves as a suitable perspective in understanding the levels of similarity or difference in evaluations of expert rating organizations. Recent scholars have expanded the scope of optimal distinctiveness to various levels of analysis, including categories and products (Durand & Kremp, 2016; Navis & Glynn, 2010; Tauscher, Zhao, & Lounsbury, 2022). Recent boundary-exploring questions include: Do organizations pursue heterogeneous optimal distinctiveness? What shaped organizations' ability and motivation to optimize their distinctiveness? Is optimal distinctiveness a dynamic equilibrium that changes over time?

Achieving optimal distinctiveness is particularly crucial for expert rating organizations. Expert rating organizations are recognized as a cohesive group sharing common values that uphold established norms among diverse market actors (Meyer & Rowan, 1977; Zuckerman, 1999). However, cohesion may not always be the case. Recent research on film or video game reviews by professional media entities provides strong evidence of the differentiation effects brought by the mere observation of competitors' opinions (Olson & Waguespack, 2020). As "gatekeepers", expert rating organizations compete intensely to capture audiences' attention and maximize the resources they can mobilize (Durand & McGuire, 2005; Rao, Monin, & Durand, 2003). Given that the value of their offerings stems from distinct and credible perspectives, a high degree of similarity between their evaluations could undermine their

uniqueness. In contrast, low similarity may raise concerns about their credibility by reducing audience trust in the individual expert rating organizations or heightening perceptions of uncertainty within the evaluation system (Cook, Hardin, & Levi, 2005; Slovic, 1993). This is precisely the mechanism of the competition between expert rating organizations and the one I investigated in this study, which documents the dynamism of two restaurant guides' strategic imitations. This research proposes that optimal distinctiveness operates across multiple levels, including both the decision to imitate the coverage of candidates and the decision to imitate the rating of candidates. Empirically, I investigate the imitation behaviors between the Michelin Guide and the Black Pearl Guide regarding their 4662 evaluations on both coverage and rating of 454 restaurants over a period of six years.

The culinary industry represents an exemplary market context characterized by high uncertainty, where cultural goods – specifically fine dining experiences – possess aesthetic value with implicit qualifications and quantifications (Lane & Opazo, 2023). This domain is particularly suitable for examining evaluative processes because expert rating organizations routinely publish assessments with deliberately opaque criteria. The inherent implicitness of these evaluative frameworks diminishes external stakeholders' capacity for effective oversight of rating methodologies, thereby increasing the likelihood that rating organizations will strategically imitate competitors' evaluation outcomes while maintaining the appearance of independent judgment (Haunschild & Miner, 1997). Such institutional dynamics reveal how ambiguity in evaluation criteria simultaneously provides legitimacy to expert evaluators while creating conditions where convergent evaluations emerge despite claims of distinctive methodologies.

On average, I found that expert rating organizations exhibit a higher degree of imitation in candidate coverage than candidate rating, with a tendency to increase imitation in coverage and decrease imitation in rating. Furthermore, I proposed that expert ratings of organizations'

culinary experiences (i.e., status, market knowledge, and order of entrance) are plausible in explaining these variations in optimal distinctiveness. Higher status signals superior evaluation quality, diminishing the need for imitation. Market knowledge facilitates efficient and effective candidate selection, reducing the likelihood of imitation. Moreover, the first-mover advantage enables setting evaluation benchmarks and building audience loyalty, decreasing the necessity of imitation.

In the subsequent sections, I first introduce the detailed characteristics of the empirical setting to provide necessary background information about the evolution of culinary expert rating organizations in China between 2017-2022. I then build on the existing work on expert rating organizations and optimal distinctiveness to develop hypotheses concerning the linkage between the heterogeneous culinary experience of expert rating organizations and the imitation of evaluation. Finally, I discuss the longitudinal data, and the methodologies employed in the empirical analyses. I present results and elaborate on their implications for strategic interaction between expert rating organizations.

RESTAURANT GUIDES AND THE CHINESE GASTRONOMY

In 19th-century France, expert rating organizations played a pivotal role in shaping the modern gastronomy industry (Ferguson, 1998). They rely on extensive knowledge of the culinary industry's history, commonly shared cooking practices and conventions, and strict standards for aesthetic discrimination to establish a clear distinction between high-status and low-status restaurants. Through rating restaurants, they differentiate people's dining behaviors, exacerbate these distinctions, and consolidate fragmented appetites and tastes into one social order. This social order, satisfying the desire for distinction among producers and consumers, became a guiding force for major actors in the gastronomy market (Vincent, 2018). Producers seek a higher standing in this social hierarchy to attract customers and build a reputation, and

customers consume not only the quality of food but also the cultural narratives and traditions in the social order to signal their social status and distinction, reinforcing the gastronomic institution.

The Michelin Guide was established in France in 1900 and was the first to rank restaurants nationwide. Ever since its establishment, it has solidified its position as a preeminent culinary guide in France and has exerted its dominance over the gastronomy industries of other European countries (Lane, 2013).

Unlike in some countries where the Michelin Guide reviews all restaurants in the nation, in other countries, it focuses on major cities only. The Michelin Guide entered Shanghai in 2017 as the first trial in mainland China, following its previous entries in New York in 2005 and Tokyo in 2008. Initially, the reactions from local audiences were the same – they complained about the Michelin Guide’s lack of local tasters (James, 2019). However, unlike people in other countries who gradually recognized this guide, the Chinese did not fully embrace it. In response, the Black Pearl Guide emerged in 2018, aiming to become the premier restaurant guide that caters to Chinese tastes (refer to Figure 1.2 for their entries in the same Chinese cities). Developed by Meituan, the owner of China’s largest online customer review platform (Dianping.com), the Black Pearl Guide claimed to possess superior knowledge of Chinese audiences and gained significant influence in the culinary scene.

Insert Figure 1.2 about here

Despite differences in cultural backgrounds and tastes, both culinary guides take a similar process of evaluating restaurants in China: anonymous visits by inspectors, expert evaluations with consistent criteria, the final coverage of restaurants, and a rating of covered restaurants ranging from one to three (stars/diamonds). In the past five years, “Black Pearl’s influence

resonates just as much, if not more, than Michelin's; dozens of the restaurants listed in 2020 saw online orders and dine-in sales surge, and they all managed to weather COVID-19-induced lockdowns" (Wang, 2023). Therefore, this context provides an ideal opportunity to study the strategic competition of multiple expert rating organizations under the increasing proliferation era of market intermediaries.

The coexistence of both guides in China represents a necessary but insufficient condition for the competition between expert rating organizations. They demonstrated a strong aspiration to tap into the same market, as the fine dining industry in China reached a transaction volume of 55.9 billion yuan (around 7.3 billion euros) (Xinhua, 2023). While the Black Pearl Guide has consistently aimed to represent Chinese tastes since its inception, the Michelin Guide strategically partnered with WeChat, the largest social media platform in China with over one billion active users, for digital marketing exclusively in the Chinese language since 2018. Furthermore, the Michelin Guide has expanded its reach by posting on a popular online streaming platform (bilibili.com) whose primary users are between 25-35 years old. As noted by Kamran Vossoughi, the CEO of Michelin China, "the attempt (for posting on bilibili.com) is our digital effort to target the newest generation of consumers, young people, in order to reach as many people as possible in the Chinese market" (Shi, 2021).

RESTAURANT GUIDES' IMITATION STRATEGIES AND THEIR CULTURAL EXPERIENCES

Both the Michelin Guide and the Black Pearl Guide are attentive to the evaluation of each other by strategically imitating opinions from the competitor. According to the optimal distinctiveness in the management literature, the optimal strategy for organizations is to achieve a balance between being similar and being different from peers in strategic choices (Deephouse, 1999; Zhao, Fisher, Lounsbury, & Miller, 2017; Zhao & Glynn, 2022). On the one hand, being

similar helps organizations display that they are legitimate players in this field, reducing the cognitive punishments of illegitimacy from exchange partners (DiMaggio & Powell, 1983; Suchman, 1995). Mimetic isomorphism also suggests that organizations mimic or take well-established and successful organizations as a reference to minimize uncertainty (DiMaggio & Powell, 1983). On the other hand, a firm with a different strategic position alleviates the intense competition for limited resources in the center of the market, increasing organizations' competitive advantages (Carroll, 1985; Hotelling, 1929). When a firm takes a distinct position from its rivals, it can benefit from local monopoly in the under-exploited market niches (Baum & Singh, 1994). Therefore, the theory's main argument is that firms should be at an intermediate level of differentiation to realize sustainable competitive advantage.

In the field of organizational theory, expert rating organizations are well recognized as “gate-keepers” and/or “taste-makers” for maintaining the market social hierarchy by rewarding and punishing candidates (Hsu, 2006; Lounsbury & Rao, 2004; Sharkey et al., 2023). However, their strategic role in the face of competition has not received significant attention. While some qualitative studies have indirectly hinted at competition between expert rating organizations in the context of macro institutional change, such as the interplay between traditional and innovative social activists within the French nouvelle cuisine, including restaurant guides (Rao et al., 2003), explicit exploration of competition among expert rating organizations remains limited.

The competition of both guides in evaluating Chinese gastronomy turns out to be a good setting. Both restaurant guides follow an ordered hierarchy format, which distinguishes them from an unordered award-based format. As a result, restaurant guides face strategic decisions at two levels: the level of imitation in candidate coverage and the level of imitation in candidate rating. The former decision grants restaurants membership in an exclusive group, highlighting a dichotomy between the nature of elitism and democracy (Johnston & Baumann, 2007;

Mennell, 1996). On the other hand, the latter decision involves hierarchical rating among these members, aiming to establish more nuanced distinctions within the elite restaurant group. Recognizing the different strategic emphases behind both layers of evaluation strategy, expert rating organizations are likely to maintain various optimal distinctiveness.

Furthermore, it is worth noticing that expert rating organizations are neither identical nor static in the strategic choices of imitation. Rather, the decisions are relational and dynamic. Specifically, the Michelin Guide holds a higher status from long-term operations in international markets. In contrast, the Black Pearl Guide, established in China, is well-nested in the country's sophisticated culinary culture, which has as "strong, prestigious elite culinary traditions originally tied to a central government and an urban elite" as the French cuisine (Ferguson, 1998), and the Michelin Guide needs local culinary experiences to accumulate market knowledge of Chinese restaurants and to provide suitable evaluations. Additionally, being the first-mover to enter a city's culinary market gives the Michelin Guide (the Black Pearl Guide) an advantage of preempting customers' space. Therefore, their divergent culinary experiences lead to varying costs and benefits in imitating each other's evaluation, shaping the competitive strategies and positions of the two guides.

Status and Imitation Strategies

Drawing on the work of Podolny (1993), I view the market of reviewers as socially constructed, where the social status of an expert rating organization influences the relative opportunities available to them. In circumstances where the judgment process of expert rating organizations is imperfectly observable and uncertain, there is a reasonable positive correlation between status and the quality of evaluation (Podolny, 2005). Consequently, a higher-status expert rating organization will imitate less than a lower-status competitor because it will likely have a higher perceived evaluation quality than a lower-status peer. In contrast, a lower-status expert rating

organization is more likely to model itself after a higher-status peer to mitigate market uncertainty by imitating the evaluation to be perceived as more credible (Bitektine, 2011; DiMaggio & Powell, 1983).

Meanwhile, status can also be one of the consequences of expert rating organizations' imitation in evaluation. According to social cognition theory, competence is a distinct and important cue for an actor to be perceived as high status (Carrier, Louvet, Chauvin, & Rohmer, 2014; Fiske, Cuddy, Glick, & Xu, 2018). When an expert rating organization imitates its competitor's evaluation, it displays less sophisticated tastes and appears to possess lower cultural capital, a key source of an expert rating organization's competence (Bourdieu, 1984; Kim & Dellaposta, 2021). The more an expert rating organization imitates its competitor's evaluation, the less competence and the lower the status they will be perceived.

One of the most distinguished heterogeneities between the Michelin Guide and the Black Pearl Guide lies in their respective statuses. Since the Michelin Guide entered Hong Kong and Macau in 2009, Dianping launched a filtering label of "Michelin restaurant" for its platform users to identify restaurants that received Michelin star(s). This function became popular among the Michelin Guide followers because it enabled them to simultaneously view the expert rating organization's evaluation together with the online customer reviews. After Black Pearl's first publication in 2018, the platform added another "Black Pearl restaurants" label next to the previous one. Upon observing its brand being associated with the Black Pearl Guide, the Michelin Guide required Meituan to stop using "Michelin restaurant" as a label on the Dianping platform, to stop highlighting the Michelin star rating of the restaurants listed in the Black Pearl Restaurant Guide, and to remove promotional articles of the Black Pearl Restaurant involving "Michelin" or "the Michelin Guide" (Guo, 2019). This disassociation strategy is commonly employed to protect organizational status, which is difficult to obtain but can easily be compromised through association with lower-status actors, suggesting that status matters in the

competition between expert-rating organizations (Podolny, 2005). Based on previous arguments, I propose that:

Hypothesis 1: The higher the status of a restaurant guide, the less it will imitate its competitors' evaluations and recommendations.

Market Knowledge and Imitation Strategies

Expert rating organizations heavily rely on their market knowledge and expertise to claim the authority to judge (Sharkey et al., 2023). Emphasizing the capability of publishing authoritative evaluations, I define the market knowledge of expert rating organizations as the information of contextualized candidates and practices so that they can efficiently and effectively screen local candidates, evaluate them, and communicate the evaluations to the audience, ultimately contributing to higher perceived credibility among the audience.

The evaluation by expert rating organizations in broad industries usually takes the two-stage decision-making process, with the first stage screening candidates and the second stage selecting and rating candidates (Gensch, 1987; Payne, 1976). Extensive market knowledge of local market actors provides reviewers with abundant and diverse information to perceive and formulate opportunities in the market, such as identifying potential candidates, thereby enhancing the efficiency of candidate screening and reducing the need for imitation. The market knowledge also enables reviewers to evaluate candidates with contextualized rationales embedded in the local “business climate, cultural patterns, structure of the market system”, increasing the perceived credibility of evaluation and decreasing the need for imitation (Johanson & Vahlne, 1977). Thus, a reviewer with higher market knowledge can screen the candidates more efficiently in the first stage and have higher perceived credibility in the second stage, both of which will decrease the likelihood of imitating the evaluation from competitors.

A common critique expert rating organizations face in internationalization is the perceived deficiency in their understanding of local market dynamics within the international markets. The Michelin Guide insists on judging different cuisines with the same standard internationally, which is against the widespread belief that “different genres of *cuisine* require judgments based on different criteria” (Lane, 2013). For example, in New York City, “many wonder if the Michelin critics (who may as well be secret agents for all the mystery shrouding them) will be able to evaluate the more ‘laid-back’ American dining scene objectively” (Draoulec, 2005). Likewise, in Japan, “with all the doubts about Michelin’s understanding of Japanese tastes, some chefs say a rating in the guide has become a liability. Kunio Tokuoka, head chef at the high-end restaurant Kitcho, said the main Tokyo branch of his restaurant refused a listing in the Michelin Guide for fear of turning off customers seeking authentic Japanese cuisine” (Fackler, 2008). In China, “as in France, visible cultural enthusiasm is tempered, channeled, and contained by authoritative culinary and gastronomic codes”, which is as refine and complex as the French cuisine (Ferguson, 1998). The Chinese Black Pearl Guide argues that its major competitive advantage over the Michelin Guide lies in its local market knowledge, encompassing the history and conventions of Chinese cuisine, the diverse regional tastes of Chinese customers, and familiarity with the local restaurant landscape.

However, Bouty, Gomez, & Drucker-Godard (2013) observed that although there were some unfavorable criticisms in the first two years after the Michelin Guide’s entrance to New York and Tokyo, public attitudes toward the Michelin Guide’s evaluation shifted as the Michelin Guide operated longer in the cities. Therefore, the increase in market knowledge became a possible explanation for the change in expert rating organizations’ behavior and the changes in public perception. And I hypothesize that market knowledge would be another crucial dimension:

Hypothesis 2: The more market knowledge a restaurant guide accumulates, the less it will imitate its competitors' evaluations and recommendations.

Order of Entrance and Imitation Strategies

The first-mover advantage theory works well in the competition between expert rating organizations. In general, market pioneers have greater market shares (Robinson, 1988; Robinson & Fornell, 1985) as they are likely to become a “prototype”, receive less resistance from potential customers, be more efficient in marginal advertising activities, gain insights into the customer preference formation process, and achieve economies of scale (Carpenter & Nakamoto, 1989; Comanor & Wilson, 1979; Lieberman & Montgomery, 1988). Furthermore, the first-mover advantage is especially more salient among advertising-intensive industries and customer-facing industries than industrial industries, which aligns well with the realm of expert rating organizations that primarily disseminate their services through mass media channels (Kerin, Varadarajan, & Peterson, 1992; Robinson, 1988).

A first-mover expert rating organization can preempt the space of audiences by introducing the first institutional hierarchy of the market candidates, thereby establishing itself as the benchmark against which subsequent entrants are evaluated (Alpert & Kamins, 1994). It can also build audience awareness of its brand, collect information on audiences' preference change through feedback, and raise the perceived switching cost of audiences by inducing specialized knowledge investment from the audiences. Extensive research demonstrates that first-movers enjoy a sustainable competitive advantage in market shares without any condition to imitate the second-mover (Szymanski, Troy, & Bharadwaj, 1995; Urban, Carter, Gaskin, & Mucha, 1986).

In contrast, when entering a market characterized by uncertainty, the late entrant can economize the search costs through mimetic isomorphism of the existing incumbent

(DiMaggio & Powell, 1983). There is a second-mover advantage in mimicking the behavior of the early entrants because the mimetic cost is lower than the innovation cost (Banerjee, 1992). In the specific context of expert rating organizations, apart from the uncertainty associated with publishing divergent evaluations, there is a potential punishment of judgment bias towards the late-mover. An early entrant exerts an anchoring effect on audiences, whereby the first numerical value people encounter tends to influence their subsequent judgments (Furnham & Boo, 2011; Tversky & Kahneman, 1974). The existing social order, as ranked by the incumbent expert rating organization, can consequently bias audience judgments toward the divergent evaluations of late entrants (Bowman & Bastedo, 2011). To mitigate this biased judgment, a late-entrant expert rating organization is also motivated to conform to the existing rating.

In cities such as Hong Kong, Macau, and Shanghai, the Michelin Guide entered earlier than the Black Pearl Guide, whereas the Black Pearl Guide was the early entrant in Beijing. Both guides entered Taipei and Guangzhou in the same year (Figure 1.2). As an incumbent expert rating organization, either of them could attract the attention of restaurants and customers by publishing the first guide in a specific city. These publications preempted public attention and established the anchor influencing individuals' judgment of late entrants' evaluations. So, I hypothesize:

Hypothesis 3: In locations where a restaurant guide is the first mover, it will exhibit lower levels of imitation of its competitors' evaluations and recommendations.

DATA AND METHODS

I selected the Chinese gastronomy industry as a suitable empirical setting, which exemplifies an industry where expert rating organizations play a crucial role, and the competition among them is observable. While other countries have multiple expert rating organizations operating

simultaneously (e.g., the Good Food Guide and the Michelin Guide in the UK, or the Gault Millau and the Michelin Guide in France), no explicit competition exists between them. Moreover, these guides employ different evaluation processes or rating systems, rendering them less comparable competitors than the Michelin Guide and the Black Pearl Guide in China.

I collected data from several sources to test the above hypotheses: (1) the evaluation publications by both institutional reviews in China between 2017 and 2022, (2) other archival data, including expert rating organizations' websites, their marketing articles on social media, and materials provided by the mass media, (3) Dow Jones's Factiva database, and (4) web-scraped data of candidate restaurants from the online customer review platform Dianping.com.

The evaluation publication is a hand-compiled database of 4662 restaurant ratings published by both expert rating organizations in China for a period of six years from 2017 to 2022. Any restaurant in a given year could be covered by none, one, or both. This database allows us to identify instances of simultaneous coverage of the same restaurants by both guides, as well as their specific ratings. Text analysis tools were employed to extract and quantify the expert rating organizations' understanding of the Chinese culinary industry from their websites and social media accounts. I utilized the Dow Jones' Factiva database to measure the frequency of their being mentioned in the mass media every year.

Dependent Variables

Imi_coverage: This is at the restaurant-reviewer-year level. It measures if the Michelin Guide's (the Black Pearl Guide's) coverage of a restaurant in a certain year is an imitation of its peer's coverage. Conditional on simultaneous coverage of a restaurant in a certain year, this measurement equals 1 if this restaurant was first covered by the other guide in the previous years. Otherwise, it equals 0. For example, if both guides covered *The Chairman* in Hong Kong in 2021 and 2022, and the Black Pearl Guide was the first to cover it since 2018, then the

Michelin Guide's coverage of *The Chairman* in 2021 and 2022 would be identified as an imitation in coverage of candidates. A higher probability of *Imi_coverage* in a reviewer-year unit means that this reviewer-year unit imitates more in covering candidates.

Imi_rating: It measures the Michelin Guide's (the Black Pearl Guide's) imitation of rating restaurants. It adopts the same logic as *Imi_coverage*. Conditional on the same rating given by both guides, this measure equals 1 if a restaurant was first evaluated with this rating by the other guide in the previous years. For example, if both guides ranked one star to *BingSheng Private Kitchen* in Guangzhou in 2020, and the Michelin Guide was the first to rank it with one star since 2018, then the Black Pearl Guide's rating of *Bingsheng Private Kitchen* with one star in 2020 would be an imitation in rating.

Independent Variables

Status: Existing research has observed that higher-status actors receive more media attention than lower-status actors (Castellucci & Ertug, 2010). I measured the status of a guide in a certain year and city by the annual frequency of it being mentioned by the media. I searched the keywords of "Michelin Guide", "Michelin Restaurant", "Black Pearl Guide", and "Black Pearl Restaurant" with both simplified Chinese and traditional Chinese in Factiva, a leading business and financial news database owned by Dow Jones. The status of reviewers is measured by annual press mentions in the local city.

Mkt_know. I measured the market knowledge of a reviewer based on its marketing articles on the social media account (i.e., the WeChat Official Account). I chose this social media because it is the most popular social media in China, and organizations actively utilize this channel to turn their followers into engaged fans (Guo, Zhang, Kang, & Hu, 2017). Both guides frequently make use of their social media accounts to release (1) news of incoming guide

publications, (2) reviews about recommended restaurants, (3) interviews with acknowledged chefs, (4) recipes of typical dishes at recommended restaurants, etc. There are 954 articles published by the Michelin Guide between 2015 and 2022, and 159 articles published by the Black Pearl Guide between 2019 and 2022. I analyzed the use of professional and expert words for Chinese cuisine on the WeChat Official Account. I (a) lemmatized the WeChat articles of both reviewers; (b) built a dictionary of professional words in Chinese cuisine, including Chinese dish names, ingredients, cooking methods, and geographical and ethnic characteristics; (c) counted the average occurrence of professional words per WeChat article; (d) accumulated the average word counts at the reviewer-year level to measure the market knowledge of each reviewer up until that year.

First_mover: This is a dummy variable. It equals 1 if the evaluation is given by a first-mover guide and 0 otherwise. A guide is identified as a first mover in a certain city if it entered the city earlier than its competitor.

Control Variables

I included some controls correlated with the heterogeneities of a reviewer (e.g., a higher-status reviewer tends to recommend restaurants with higher prices or in popular tourism cities) and with the outcome of the recommendation (e.g., a restaurant with higher prices or in a popular tourism city is more likely to be recommended because of better quality).

Customer_expenditure: It is the average spending per customer, as suggested on Dianping. For better quality, it was trimmed to range from 1 to 9999 CNY (around €0.1 to €1300). The average customer spending in a restaurant could be positively associated with a restaurant's quality, which increases the likelihood of a restaurant being recommended and ranked. It also determines a restaurant's identity, so a higher-status reviewer is more likely to recommend

expensive restaurants.

Customer_reviews: This is the total count of online reviews on Dianping each year. While the literature has demonstrated the influence of expert rating organizations on individual reviewers (Kovács & Sharkey, 2014), it is possible that expert rating organizations may also refer to online review aggregators (Sharkey et al., 2023).

Customer_rating: It is the average rating displayed on Dianping. I would like to include this control variable for the same reason as *Customer_review*. I distinguish between *Customer_review* and *Customer_rating* in that the former specifies the popularity of a restaurant among consumers and the latter represents the perceived quality of a restaurant by consumers.

Methods

The unit of observation in the analysis is every evaluation given to a particular restaurant in a given year by a given expert rating organization. Usually, a restaurant receives two evaluations by both the Michelin Guide and the Black Pearl Guide if they both enter this city, and each evaluation will be identified as an imitation or not. Because dependent variables of imitation in evaluation for all hypotheses are binary, I employed a linear probability model, a logit model, and a probit model with the panel dataset.

RESULTS

Tables 1.1 and 1.2 are the descriptive and correlational tables of key variables. On average, among all the evaluations given by both guides, 5.5% are identified as imitations in coverage. This ratio is much lower for imitations in rating (1.1%). This difference provides primary evidence that expert rating organizations adopt different optimal distinctiveness at multiple

levels.

Insert Table 1.1, Table 1.2 about here

Some trends of imitation are immediately apparent when I look at the figures. Table 1.3 displays a primary description of the overall frequency of imitation behaviors, and Figure 1.3 illustrates a breakdown of the imitation behaviors of every city. Both Table 1.3 and Figure 1.3 show that the Black Pearl Guide demonstrates a higher level of imitation of the Michelin Guide in both the coverage and rating. Notably, when considering the influence of time, both guides exhibit a consistent level of imitation in coverage over time, while the degree of imitation in rating appears to decline in some cities. This interesting phenomenon may be attributed to dynamic positioning strategies employed by the guides. As both guides establish a more extended presence in the market, they tend to maintain similarity in coverage but differentiate themselves in rating.

One heterogeneity observed from Figure 1.3 is the difference in imitation behavior between cities where the Michelin Guide entered first (Hong Kong, Macau, and Shanghai) and cities where the Michelin Guide and the Black Pearl Guide entered simultaneously (Guangzhou and Taipei). As anticipated, the Black Pearl Guide imitated the Michelin Guide's coverage more in the cities where the Michelin Guide was the first mover. In contrast, the Black Pearl Guide imitated the Michelin Guide's coverage less in Beijing, where the Black Pearl Guide had the advantage of being the first mover. These findings align with previous literature on herd behavior, suggesting that late-movers benefit from imitating early-movers' evaluations (Scharfstein & Stein, 1990).

Insert Table 1.3, Figure 1.3 about here

Figure 1.4 presents separate plots depicting the correlation between status and imitation in coverage, as well as imitation in rating. The results reveal a negative linear relationship, indicating that expert rating organizations with higher status in a specific time-space tend to engage in less imitation across both evaluation layers. Figure 1.5 illustrates the correlation between market knowledge and imitation in coverage, as well as imitation in rating. Contrary to the initial expectations, I observe a moderate positive relationship between market knowledge and imitation.

Insert Figure 1.4, Figure 1.5 about here

In Table 1.4, I regressed expert rating organizations' imitation in coverage by their heterogeneities in status, market knowledge, and order of entrance. I displayed the baseline linear probability model with control variables and year fixed-effect in Model 1. In Model 2, I added independent variables, including the log value of status, the log value of market knowledge, and the first-mover dummy. I found significant negative correlations between imitation in coverage and expert rating organization's status, market knowledge, as well as order of entrance. Model 3 and Model 4 used logit and probit models as robustness tests and verified the results in the linear probability model, providing evidence for H_1 , H_2 , and H_3 . To further control the unobservables within restaurants, I added restaurant fixed-effect in Model 5-8. Statistical results showed that H_1 and H_3 were still supported, while H_2 was not significant anymore.

I changed the dependent variable from imitation in coverage to imitation in rating and displayed the regression results in Table 1.5. I also found a robust negative relationship between imitation in rating and being a first-mover. As a consequence, H_3 is supported across all tests. However, status and market knowledge no longer predicted less imitation in rating. The differences in coefficients of Table 1.4 and Table 1.5 are not surprising, as I anticipated that

organizations could adopt different optimal distinctiveness in different layers of strategies, and the heterogeneities I proposed might be influential factors that determined these differences.

In conclusion, the analysis highlights two key findings. Firstly, I observed varying levels of imitation in both the coverage and rating layers of evaluation, with a higher level of imitation in coverage and a lower level of imitation in rating. The level of imitation in coverage shows a slight increase over time, while the level of imitation in rating decreases (Figure 1.3). Secondly, these dynamics in imitation behaviors can be understood through three crucial heterogeneities: status, market knowledge, and the order of entrance. Regression results indicate that a guide with higher status or more market knowledge will imitate less in covering candidates (Table 1.4), which is in line with organizational theory and the studies of expert rating organizations (Boulongne et al., 2019; DiMaggio & Powell, 1983). However, I did not find any significant correlation between status or market knowledge and imitation in rating. The order of entrance matters in both levels of imitation, suggesting the first-mover advantage in building up cultural capital and internalizing economic resources exclusively (Lieberman & Montgomery, 1988).

These intriguing findings suggest that expert rating organizations tend to converge on existing norms and values when they do not have sufficient market knowledge, high status, or an advantaged competitive position in the order of entrance. However, as they accumulate market knowledge, acquire high status, or become an early entrant in the market, they will imitate less and provide more independent evaluations.

DISCUSSION

The findings contribute to and extend the literature on both the dynamic competition between expert rating organizations and the optimal distinctiveness. I next discuss implications for the understanding of key issues in each of these literatures.

Contribution to Research on Expert Rating Organizations

A rising number of studies have started to focus on expert rating organizations and their strategies as the proliferation of multiple heterogeneous expert rating organizations becomes common in the same market (Sharkey et al., 2023). Bowers (2020) looked into security analysts and found that expert rating organizations strategically balance the ratings of the candidates by allocating negative ratings after giving a high rating in their candidate portfolio. Olson and Waguespack (2020) observed that expert rating organizations in the movie and video game industries delay the publication of negative evaluations during the major product marketing period. Similar to these studies, I found that restaurant guides strategically decide on the level of imitating competitors' evaluation. Furthermore, this study challenges the implicit assumption in the institutional theory literature that expert rating organizations are homogeneous by elaborating on the social competition between restaurant guides due to their heterogeneous cultural experiences. The correlation between their culinary experiences and optimal distinctiveness suggests that the evaluation of an expert rating organization is more than an expression of taste (Kim & Dellaposta, 2021). Expert rating organizations may strategically imitate the competitor's evaluation instead of applying independent standards when recommending candidates. This study also implies that the construction of agreed institutional hierarchies and the changes in existing hierarchies do not necessarily take the form of occasional events but can reside in the routinely dynamic competition between expert rating organizations in the market. The micro-level interaction between expert rating organizations uncovered in this study can lead to the macro-institutional environment's formation, evolution, or destruction (Boulongne et al., 2019).

Such analysis of expert rating organizations is particularly challenging because the competition is difficult to observe or infer due to a lack of active expert rating organizations and identifiable competitive discourses. This is the first study to provide evidence showing

how expert rating organizations compete with each other by explaining their competition with a longitudinal study of the evaluations of 454 restaurants in China across a period of six years made by the two most important expert rating organizations in this industry.

Contribution to Research on Optimal Distinctiveness

Whereas most research focused on the optimal distinctiveness of candidates under judgment and evaluation of expert rating organizations, I shift the focus to the optimal distinctiveness of expert rating organizations, and to the dynamic and various optimal distinctiveness across multiple layers of strategic choices. I emphasize the relational aspect of optimal distinctiveness and investigate how expert rating organizations imitate each other's evaluations. By distinguishing imitation in candidate coverage and imitation in candidate rating, this study extends the boundary condition of optimal distinctiveness from a universal firm strategic position to multidimensional across different strategic choices (Deephouse, 1999). Furthermore, I assume the optimal distinctiveness to be dynamic rather than static, allowing temporal influences on the decision of optimal distinctiveness (Zhao, 2022). Specifically, I look into how the optimal distinctiveness may vary as the strategic positions of organizations change over time (Cattani, Dunbar, & Shapira, 2017).

Meanwhile, I am aware of the limitations of this study. Firstly, the empirical results are restricted to the competition between two specific expert rating organizations in the Chinese gastronomy industry. I remind the audience that the generalization of our findings to other contexts should be cautious, where the importance of status, market knowledge, or order of entrance may vary. Nevertheless, given the existing limited understanding of the competition between expert rating organizations, this study at least sheds light on how expert rating organizations might decide optimal distinctiveness strategies at multiple levels and across

different heterogeneities. It is also worth noticing that although this study is a longitudinal analysis of two organizations, these are dominant expert rating organizations that captured a majority of the attention in the intermediated industry, which is typical in other contexts such as the business school rating industry (e.g., AACSB vs. EQUIS), the world university rating industry (e.g., QS World University Rankings vs. Times Higher Education World University Rankings), and other intermediated industries.

Secondly, this research is limited to direct observation of the evaluation outcomes of the two expert rating organizations. Unfortunately, both expert rating organizations are reluctant to discuss their competition strategies. While the Michelin Guide preferred to be perceived as unrivaled in the gastronomic industry, the Black Pearl Guide wanted to avoid the stigmatization of copycat. Therefore, even though they agreed to discuss the competition strategies, I would doubt their statements.

Lastly, this study establishes correlations between heterogeneities and competition strategies but does not test for causal relationships. I am open to discussions of heterogeneities causing competition strategies or vice versa, as I believe an expert rating organization can gain or lose status or market knowledge from imitating peers' evaluations. Therefore, designing experiments or finding a quasi-natural experimental setting to test the causality would be helpful.

CHAPTER TWO

Is It All a Matter of Taste? Differentiation of the Michelin Guide in Foreign Countries

INTRODUCTION

Expert rating organizations are organizations who publish evaluations in numerical rating format, usually at regular time intervals based on standardized evaluative processes and expert criteria (Lane, 2013; Sharkey et al., 2023). They reinforce existing institutional norms by rewarding legitimate producers, meanwhile enabling local contemporary attributes among producers to connect with broader historical constructs and create context-relevant evaluations (Boulongne et al., 2019; Khaire & Wadhvani, 2010). They have the authoritative power to shape the institutional environment of the market under evaluation. Examples include the inclusion of corporate governance measurements in corporate social responsibility ratings (Chatterji, Durand, Levine, & Touboul, 2016), the shift of emphasis from cultural to natural cuisines in restaurant guides (Rao et al., 2003), and adjustments of subject-specific indicator weights in university rankings (Rauhvargers, 2014).

Thanks to expert rating organizations' pursuit of objectivity and independence in the evaluation (Khaire, 2017; Sharkey et al., 2023), audiences can easily compare candidates without constraints of time or space by assuming evaluation coherence (Blank, 2007). As a consequence, expert rating organizations and their discretion authority are widely adopted in decision-making by both consumers and producers, simplifying vast amounts of producer data and disseminating information about the market's social hierarchy to a mass audience (Askin & Bothner, 2016; Jung, Sharkey, & Tan, 2024; Lewis & Carlos, 2023; Sauder & Espeland, 2009; Sauder & Lancaster, 2006).

While much is known about how expert rating organizations play an important role in mediating markets through their expected objectivity and independence, less is understood about how the evaluation outcomes may also be shaped by expert rating organizations own interests. Recent studies indicate that expert rating organizations face increasing pressure from heightened competition and existential threats (Durand & McGuire, 2005; Sharkey et al., 2023).

To maintain audience attention and increase survival chances, expert rating organizations have been found to self-generate changes in their evaluation outcomes, increasing dynamics in candidates' social hierarchy intentionally (Bowers & Prato, 2019).

Recognizing the goal of expert rating organizations to maintain survival and relevance in the market, it is plausible that their evaluation outcomes are not as objective and independent as audiences might wish. Therefore, the important question is: what factors may violate their “ideal” evaluation? How the evaluation outcomes of expert rating organizations may be influenced by these factors? Connecting to the strategy literature, I propose that evaluation biases could arise from evaluative process and practices across different locations, and from the competitive pressures they encounter. In reaction to heightened competition in existing niches, expert rating organizations often seek to expand their markets through internationalization (Bouty et al., 2013; Durand & McGuire, 2005). Although given the nature of their activity (i.e., publishing authoritative judgements of producers in a specific field), they should display a coherent system of evaluation that should not discriminate or favor specific countries at the expense of others, it is also necessary for them to adopt different evaluation activities in different locations as adaptation to local environments (Kostova & Zaheer, 1999), leading to evaluation outcome discrepancies across different locations.

In this chapter, I would like to explore this bias and investigate how expert rating organizations manage the evaluation outcome (i.e., the overall pattern and distribution of candidates' ratings) in selective countries. To do so, I examine the presence of discrepancies in their evaluation outcome across host countries. Subsequently, I propose three hypotheses involving the cultural and economic factors to explain these discrepancies.

This study aims to join the debate of expert rating organizations' strategic evaluation (Bowers & Prato, 2019; Olson & Waguespack, 2020; Sharkey et al., 2023). I seek to depict and explain the diverse evaluation outcomes of expert rating organizations across different

countries in the context of internationalization. Empirically, I will analyze the international expansion of the Michelin Guide, which has garnered significant recognition for reinforcing the hegemony of French cuisine (Lane, 2013), and address the following research questions: Did the French expert rating organization uphold its cultural hegemony unintentionally or strategically? Which specific countries were subject to its strategic preferences?

I would like to introduce our empirical setting of the gastronomy industry before going into the hypotheses. The gastronomy industry provides a rich context for examining the role of expert rating organizations, given its complex interplay between cultural heritage, culinary standards, and international market dynamics. Specifically, the Michelin Guide serves as an exemplary case for understanding how expert rating organizations may maintain cultural hegemony across different national contexts.

Michelin Guides Evaluations Across Countries

The gastronomy industry represents a typical cultural sector characterized by influential expert rating organizations, and extensive scholarly research has been conducted on the interactions among expert rating organizations, producers, and consumers within this domain (Favaron, Di Stefano, & Durand, 2022; Ferguson, 1998; Rao, Monnin, & Durand, 2003). Ever since the 19th century, the French gastronomy industry has been a modern industry embedded with distinctions and differentiation in tastes, where culinary expert rating organizations are crucial for establishing and reinforcing the social hierarchy of restaurants and chefs, turning this industry into a “gastronomic field” (Ferguson, 1998). Through long-standing social interaction of multiple stakeholders, this industry develops its own historical pattern of material practices, assumptions, values, beliefs, and rules to produce and reproduce the field of *haute cuisine*. The French cuisine preeminence and French culinary expert rating organizations later became a fashion worldwide, from Europe to North America and Asia, which boasted lavish banquets

with institutionalized standards and extraordinary techniques.

Thanks to its long history and familiarity with French haute cuisine, the Michelin Guide is undeniably the most acknowledged culinary guide among its peers (e.g. the World's 50 Best Restaurants, Zagat, Gault Millau, etc.). As one German Michelin-starred chef commented, "Michelin people are informed about cooking. The rest are mere journalists" (Lane, 2013). Unlike other gastronomic guides who primarily exert influence at a local level, the Michelin Guide has garnered an international reputation for its professionalism and reliability, commanding the respect and trust of chefs and consumers worldwide. The Michelin Guide prides itself on its stable evaluation criteria, implemented through a relative standard and institutionalized evaluation process. Newly recruited inspectors undergo intensive training by experienced inspectors with internal evaluative standards (Ho, 2019), and final decisions are "in a collegial manner, based on their respective visits to each of the restaurants over the course of the year" (Michelin Guide, 2024b). Consequently, the Michelin Guide affords us an exceptional opportunity to contrast its evaluation outcomes across diverse countries.

The familiarity of the French haute cuisine also brings controversies. The Michelin Guide is accused of its conservative tendencies and inclination to uphold French culinary hegemony within the industry. This recognition of the Michelin Guide's symbolic power and its evident preference for French culinary culture over alternative traditions provides a valuable starting point for observing potential strategic evaluations conducted by the guide across different countries. However, while the hegemony of the French cuisine is obvious, we lack knowledge of the logics behind the Michelin Guide's discrimination towards host countries.

In the following sections, I aim to provide a comprehensive study of how the Michelin Guide manages local contexts in the evaluation outcomes. I propose that the evaluation outcomes could be explained by three factors: the cultural distance, the geographical distance, and the local competition. As implied by the conceptualization of the internationalization of

expert rating organizations, I perceive the expansion of the Michelin Guide across different countries from 2009 to 2023 (Figure 2.1) as a model for analyzing the strategic evaluation of expert rating organizations in a broader sense.

Insert Figure 2.1 about here

Michelin Guide's Evaluation Outcome

The evaluation outcome by expert rating organizations refers to the overall pattern and distribution of ratings or evaluations across different entities or geographical areas. A consistent evaluation outcome would ideally reflect similar patterns of judgment across different contexts, assuming comparable quality standards (Karpik, 2010).

The evaluation outcomes in different countries are anything but uniform, even if the same expert rating evaluates the countries. In the gastronomy world, countries with similar numbers of Michelin-starred restaurants can have vastly different distributions of three-star, two-star, and one-star establishments. These discrepancies in evaluation outcomes play a significant role in determining a country's international tourism economy and ultimately contribute to international economic inequality (Castillo-Manzano, Castro-Nuño, Lopez-Valpuesta, & Zarzoso, 2021; Castillo-Manzano & Zarzoso, 2023).

A favorable evaluation outcome of a country could be multidimensional: a country would be a more attractive destination to international foodies if there is a greater number of Michelin-starred restaurants, or *ceteris paribus* if the overall distribution of Michelin-starred establishments skews towards higher ranks. Such a favorable evaluation outcome not only aids in the development and profitability of local gastronomy industries but also generates positive spill-over effects on ancillary industries, particularly within the realm of international tourism (Castillo-Manzano & Zarzoso, 2023; Daries, Moreno-Gené, & Cristobal-Fransi, 2021).

However, it is imperative to understand that the evaluations of expert rating organizations are not entirely objective, as they are partially socially and strategically constructed. The Michelin Guide has been observed to play a significant role in establishing and maintaining the hegemony of French cuisine over other cuisines (Lane, 2013). Therefore, it becomes crucial for us to delve into the reasoning behind expert rating organizations' evaluation outcomes. In the subsequent sections, I will look into the historical evaluations of the Michelin Guide and explore three logics to explain the various evaluation outcomes in different host countries.

THEORY

The Evaluation Outcomes of Expert Rating Organizations

Drawing on organizational sociology, I adopt the perspective that “quality is not something that arises automatically from the inherent characteristics of objects, but rather something that is externally imposed” (Hsu, 2006). In mediated markets, evaluators – whether individual or organizational, amateur or expert – possess the autonomy to establish and promote distinctive frameworks for value discrimination. These locally constructed value schemas engage in complex interactions, characterized by competition, substitution, and integration of diversified frameworks. Within this dynamic environment, evaluators strive to achieve broader acceptance of their evaluative criteria. When successful in establishing the legitimacy and authority of their standards, they secure positions as influential market intermediaries. Consequently, expert rating organizations often emerge as the prevailing arbiters in schema competitions, garnering both evaluative authority and mass audience attention.

However, such dominance remains contingent upon environmental shifts. Globalization, for instance, has connected candidates across diverse geographical contexts, necessitating a broader evaluative scope (Durand & McGuire, 2005). To maintain their relevance, expert rating organizations must expand their candidate pools to facilitate cross-regional comparisons. This

internationalization process, while necessary, potentially introduces systematic biases into the evaluation frameworks and subsequent incoherent evaluation outcomes.

Country Differences and Evaluation Outcomes

Cultural/cognitive distance. The cultural distance logic is grounded in the international business literature (Beugelsdijk, Kostova, Kunst, Spadafora, & van Essen, 2018). Scholars have theorized that cultural distance, as “unfavorable factors preventing the flow of information from and to the market”, is critical in organizations’ decision-making during the process of internationalization, including location choices, entry mode, standardization of practices, transfer of knowledge, performance, and others (Johanson & Vahlne, 1977; Kogut & Singh, 1988; Kostova, 1999; Tihanyi, Griffith, & Russell, 2005). When a host country is similar to the home country, the cultural distance involved in internationalization diminishes, facilitating organizations’ adaptation to the host market (Johanson & Vahlne, 1977; Kostova, 1999). Taking this perspective, I regard expert rating organizations as organizations that develop international activities facing the barriers of cultural distance in adapting to local environments (Johanson & Vahlne, 1977). I recognize the vital role that cultural context plays in the work of expert rating organizations and focus on the cultural dimension (Ferguson, 1998; Lane, 2013). Besides, the cultural distance has been rigidly tested to explain many aspects of the internationalization process, including entry sequence, entry mode, transfer of practice, and performance (Beugelsdijk et al., 2018; Tihanyi et al., 2005). I also recognize differences in language, education levels, industrial development, political systems, religions, time zones, colonial links, etc., and treat them as minor dimensions (Dow & Karunaratna, 2006).

Expert rating organizations’ evaluation outcome is based on operational activities, including shortlisting and evaluating producers. Cultural distance poses challenges for expert rating organizations in developing market knowledge for exploring potential producers and/or

understanding the merits of producers within the local context, Moreover, in cultural industries where institutions play a pivotal role in shaping notions of merit (DiMaggio & Powell, 1983), cultural distance may significantly hinder the accurate evaluation of candidates from culturally distant contexts. The more a country is different from the home country, the poorer evaluation outcome it will receive. In this case, a country would be unfavorably evaluated.

Like other expert rating organizations, the Michelin Guide adheres to a standardized procedure of evaluating restaurants, which involves a series of steps: initial selection of restaurants, anonymous visits to these establishments, comprehensive evaluation, and subsequent publication of the evaluation outcomes. It carefully recruits and trains inspectors with the guide's criteria through a systematic approach encompassing recruitment, training, and socialization. Despite the Michelin Guide's attempts to reduce its Francophone bias by eliminating certain criteria, such as “Parisian elegance” (Karpik, 2010), it remains plausible that the dominance of French culinary culture persists. The composition of local inspectors in the evaluation team is also questionable. According to an Italian inspector who worked in the Michelin Guide team for 11 years, “Senti il fiato dei francesi sul collo, sempre. Cercano di condizionare ogni scelta, anche quelle delle singole stelle” (“You feel the French breathing down your neck, always. They try to condition every choice, even those of individual stars”) (Bertera, 2023) This cultural dominance may create barriers when selecting and comprehending restaurants in other countries characterized by a considerable cultural distance from France.

Hypothesis 1: The Michelin Guide is more likely to “penalize” culturally dissimilar countries from France, while favorably evaluating culturally similar countries.

Economic protectionism. Protectionism and nationalism manifest in the efforts of a broad

range of social actors, including politicians, business leaders, employees, and consumers, to safeguard domestic industries from foreign competition within the context of globalization (Chandan & Christiansen, 2019; Enderwick, 2011). These endeavors not only unite individuals sharing a common national culture and identity but also serve to shield national industries from international rivals. Various forms of protectionist practices are commonly employed by formal institutions, particularly governments. These range from differential treatment, such as divergent regulations that advantage domestic firms over foreign ones, to outright prohibition of foreign firms in certain industries. For instance, foreign firms are excluded from participation in some Japanese and U.S. government construction projects (Porter, 2011).

Expert rating organizations, as a type of the informal institutions in the market, are regarded by scholars as “legitimizing institutions with the cultural authority to bestow symbolic capital” (Johnston & Baumann, 2007). They possess the discretion to “not select the most talented artist but choose one who harmonizes with their own concerns” (Lane, 2013; Schücking, 1974). This autonomy raises subtle yet pervasive questions regarding the underlying strategies employed by these influential organizations. Previous research on gastronomic discourses has identified a preference for elitism over democracy, suggesting that expert rating organizations focus on a minority of elite candidates (Johnston & Baumann, 2007; Mennell, 1996). Aligning with these studies, I posit that expert rating organizations are authoritative organizations capable of both adapting to and shaping their environment.

By creating a competitive advantage between the home country and its economic rival countries in the evaluated industry, expert rating organizations achieve multiple objectives. Firstly, they can proudly represent and reinforce the national culture and identity. Secondly, being associated with the reputational domestic industry in turn increase the status and credibility of expert rating organizations (Blank, 2007). Thirdly, expert rating organizations can benefit from the prosperous economic spillover effects in adjacent industries, and more

broadly, the national economy. This strategic positioning is not merely hypothetical. The establishment of the renowned Michelin Guide, for instance, was initially developed to boost car sales and, consequently, tire purchases (Michelin Guide, 2024a). By employing various evaluation outcomes across countries, expert rating organizations can strategically generate opportunities and alleviate economic competitive pressures for the host country, thereby capturing a variety of indirect benefits.

An illustrative example of protectionist policies is the French government's commitment to safeguarding and promoting the domestic film industry through measures such as screen quotas and subsidies, which limit the market share of foreign films (Messerlin & Parc, 2014). Drawing a parallel to this protectionist stance, France has expanded its share of the global gastronomic export market through diplomatic initiatives, from the "Palais de la France" at the San Francisco International Exhibition in 1915 to the inscription of its gastronomy on UNESCO's Intangible World Heritage List in 2008. This has been accompanied by a proliferation of tourist guides, public media dedicated to gastronomy, and the active involvement of politicians and mayors (Csergo, 2020; Martigny, 2010). To date, the gastronomy industry plays a two-fold role in France – internally, it unites the national community to perpetuate daily the relationship of identification with the nation; externally, it marks the national identity in the globalization which translates into economic competitive advantage (Martigny, 2010). As one of the prominent institutional entities in the promotion of French gastronomy, the Michelin Guide is both celebrated and criticized for allegedly favoring France over other countries, aligning with its patriotic mission of defending the national economy.

From the perspective of protectionism and nationalism, the economic competitive distance between the home country and the host country could be a favorable factor for more favorable evaluation outcomes. Economic competitive distance is defined as the geographic

distance between two countries, as the spatial economic model has proved that the competition effect is positively correlated with spatial distance in the gastronomic industry (d'Aspremont, Gabszewicz, & Thisse, 1979; Dupin & Wezel, 2023). Intuitively, a country is more rivalrous to France in the international gastronomy industry if they are geographically closer because of a shared market. The Michelin Guide can protect and enhance France's ability to attain sustainable competitive advantages in the global gastronomic industry by potentially "penalizing" adjacent countries in its evaluation outcomes.

Hypothesis 2a: The Michelin Guide is more likely to "penalize" countries competitively proximate to France, while favorably evaluating those more distant.

Countries that receive favorable evaluation outcomes from expert rating organizations gain an advantage not only in the gastronomic industry but also in related industries (Kivela & Crotts, 2006). Specifically, I identified international tourism as an important related industry. According to the former vice president of the Michelin Guide, some governments reached out to sponsor the guide for entering a country to attract international tourism (Judkis, 2021). In return, a prosperous international tourism industry also nurtures local gastronomy (Hjalager & Richards, 2003).

The development of the international tourism industry in the host country could moderate the relationship between geographical distance and evaluation "penalization". The relative competitiveness in international tourism throws a greater threat to France when the geographical proximity decreases. Consequently, as international tourism in host countries experiences growth, the evaluation "penalization" imposed by expert rating organizations would be more severe for neighboring countries than for distant ones.

Hypothesis 2b: For evaluated countries, the stronger their international tourism, the stronger the negative relationship between competitive distance and evaluation “penalization”.

Local competition. Last but not least, I shift the attention back to the external competitive environment the expert rating organizations are in. When entering new markets or countries, expert rating organizations may encounter competition from local counterparts. Under high uncertainty in the internationalization process (Johanson & Vahlne, 2009, 1977; Vahlne & Johanson, 2017), the existence of local competitors imposes constraints on the entrant expert rating's market access and anchors their strategic positioning to realize differentiation (Deephouse, 1999).

The influence of competitors' strategic positioning is evident in both stages of the evaluation process employed by the Michelin Guide – the selection of candidates and the awarding of stars (Bouty et al., 2013). Firstly, the Michelin Guide is likely to expand the pool of included candidates to remain relevant and attract market attention. In their study of AACSB's business expansion, Durand & McGuire (2005) revealed that this legitimating organization expanded its membership domain upon entering new markets in Europe, particularly in response to the presence of local competitor EQUIS. In alignment with their thoughts, we can anticipate a similar response from the Michelin Guide, which may include more restaurants to tap into broader market niches when faced with local competition.

Secondly, although seeking to attract a wider audience by expanding its candidate pool, the Michelin Guide is expected to strategically downgrade the newly included restaurants, thereby limiting their chances of achieving higher ratings within the hierarchy. According to Bourdieu (1984) and others, social actors signal their high status through exclusiveness and selectiveness in tastes. They always “distinguish themselves with an exclusive culture that rejects the cultural patterns and tastes of other groups” (Bryson, 1996). Johnston & Baumann's

(2007) study on gastronomic critics further supports this argument, illustrating how authenticity and exoticism serve as underlying values that contribute to maintaining exclusivity among high-status social groups. Consequently, downgrading candidates becomes an efficient strategy for expert rating organizations to preserve exclusiveness, signal higher status, and demonstrate greater skillfulness compared to their competitors (Kim & Dellaposta, 2021).

Considering the adjustments made in both stages of the evaluation process, it is anticipated that the Michelin Guide will relax its criteria when including candidates while strengthening its exclusivity when rating candidates, with the presence of local competition. Therefore, I propose:

Hypothesis 3: Countries with competing local guides will be more “penalized” by the Michelin Guide.

DATA AND METHODS

To test our hypotheses regarding the varying evaluation outcomes of the Michelin Guide, I conducted a quantitative analysis using country-level data from 2009 to 2023. As of November 2023, the Michelin Guide operates in 38 countries globally, assigning restaurants one, two, or three stars to indicate their quality (Michelin Guide, 2023). In 2023, 82% of the globally recognized Michelin-starred restaurants were awarded one star, 14% received two stars, and a mere 4% achieved the highest honor of three stars.

To better understand the cultural distance between the host country and the Michelin Guide’s home country, France, I used the country comparison tool provided by Hofstede Insights Ltd. (The Culture Factor Group, 2023). Additionally, I utilized OpenStreetMap data to determine the geographical distance between the two countries (OpenStreetMap, 2023). I collect country-level data, including the number of restaurants in the World’s 50 Best

Restaurants List, population, GDP, GDP per capita, household consumption, and international tourism arrivals from the World Bank, complemented by governmental statistic sources.

Dependent Variables

Focusing on the potential disparities in the Michelin Guide's evaluations across different countries, I aim to capture the potential evaluation "penalization" using four distinct measurements of the distribution of starred restaurants (Table 2.1.):

(1) High-Low ratio. Our primary measurement is a ratio between the number of three-star restaurants and the number of one-star restaurants. Understanding the relative proportion of higher-ranked restaurants in a country is straightforward. A larger value of High-Low ratio represents more preference and less penalty for the host country. I adopt Gini coefficient, skewness, and kurtosis as alternative measurements for robustness checks.

(2) Gini coefficient. This coefficient, commonly used in economics to measure income or wealth inequality, is employed here to measure the disparity in the number of stars awarded to restaurants (F. A. Cowell, 2011). A higher Gini coefficient indicates a situation where a minority of higher-ranked restaurants possess the majority of Michelin stars, implying the existence of a select number of highly regarded establishments that make the country more appealing to consumers. This measurement is a negative indicator of the evaluation "penalization".

(3) Skewness. It is computed as the adjusted Fisher-Pearson standardized moment coefficient of skewness. Generally, the evaluation outcomes of the Michelin Guide exhibit a right-skewed distribution, although there are variations in skewness among countries. A higher skewness value indicates a more significant disparity between higher-ranked and lower-ranked restaurants, suggesting a greater evaluation "penalization" for a given country.

$$G_1 = \frac{\sqrt{N(N-1)}}{N-2} \frac{m_3}{m_2^{3/2}}$$

Where:

$$m_i = \frac{1}{N} \sum_{N=1}^n (x_N - \bar{x})^i$$

(4) Kurtosis. This value quantifies the “sharpness” or peaked Ness of a distribution. In the case of Michelin-starred restaurants, the peak of the distribution consists of lower-ranked establishments, while the tail represents higher-ranked ones. Consequently, a higher kurtosis value means a greater penalty for a country.

$$G_2 = \frac{m_4}{m_2^2} - 3$$

 Insert Table 2.1 about here

A rule of thumb recommends a minimum of 50 observations for calculating stable mean and standard deviation, which are important for determining skewness and kurtosis values. In our study, I constructed a cross-sectional dataset comprising 166 country-year observations.

Independent Variables

Cultural distance. I followed the most widespread operationalization of cultural distance in the international business literature by applying the Euclidean distance measure from Hofstede’s multidimensional cultural framework (Hofstede, 1980) to capture cultural differences between The host country and the host country in a single index (Beugelsdijk et al., 2018; Kogut & Singh, 1988). To further illustrate the French people's perceived gastronomic cultural distance, I resorted to two surveys performed in 2019 and 2023 with over 1,000 respondents (Cluster-17, 2023; Gérard, Lancrey-Javal, & Prunier, 2019). Participants were requested to rate French

cuisine and other national cuisines so that I could get a ranking of the cuisines. Undoubtedly, French cuisine is the best-ranked, followed by Italian cuisine, Chinese cuisine, and so on. I use the French people's rating of cuisines as a measure of culinary cultural barrier; the higher the score, the less cultural barrier. I also consider that cuisines that were not mentioned in the poll are insignificant and unimportant, thus they are ranked at the bottom.

Competitive distance. I define competitive distance as the geographical distance between two countries, measured with the spherical distance between coordinates, specifically the latitudes and longitudes of the capital cities. It allowed for a precise measurement of the competition in the international gastronomy market between the home country and the target country under evaluation.

International tourism. This is measured by the number of international inbound tourists (overnight visitors). It provides an understanding of the extent to which a nation has attracted foreign visitors, reflecting the development and attractiveness of the international tourism industry. Given the same competitive distance as France, the country with more developed international tourism is more competitive in the international gastronomic industry.

Local competition. I identified Gault Milleu, Gambero Rosso, the Good Food Guide, Zagat, and the Black Pearl Guide as the competitors of the Michelin Guide worldwide. For any country-year observation, if a country is also under evaluation by these competitors, this dummy variable is 1. Otherwise, it is 0.

Control Variables

The number of starred restaurants. This variable is the total number of restaurants that were given at least one star in the Michelin Guide at a country-year level. As mentioned, the evaluation “penalization” is valid only when I hold the total number of restaurants equal.

The number of restaurants in the World's 50 Best Restaurants List. I included the number

of restaurants from each country featured in this list to control for the underlying quality of top-tier restaurants across countries. The World 50 Best List was the first culinary expert rating organization to adopt a global perspective in the evaluation landscape and has become increasingly influential among both chefs and consumers (Lane, 2019).

First Three-Year Operation: To account for the initial learning curve and adjustments in the Michelin Guide’s operations within a new location, this dummy variable is included as a control. It takes a value of 1 if the evaluation is published within the first three years of operation, and 0 otherwise.

Country-level controls. I controlled the population (in million), GDP (current US\$, in trillion), GDP per capita (current US\$), and household consumption (current US\$, in trillion) of every country every year to capture the demand-side of the local gastronomic industry.

Methods

Our dataset encompasses the period from 2009 to 2023 and is organized at the country-year level. Each observation represents the overall evaluation outcomes (e.g., high-low ratio, Gini coefficient, skewness, kurtosis) of Michelin-starred restaurants in each country annually, provided that the total number of starred restaurants is no less than 50. Table 2 and Table 3 show the summary of statistics and correlation matrix of main variables. I will first visualize the density of all observations to see if there are discrepancies across countries. I use OLS regression to test hypotheses because of the differences in evaluation outcomes between each country.

Insert Table 2.2, Table 2.3 about here

RESULTS

I plot the distributions of evaluation outcomes in Figure 2.2. None of the four density plots display a uniform distribution, which indicates inequality of Michelin Guide's evaluation outcomes among countries and years.

Insert Figure 2.2 about here

To further visualize the correlation between the inequality of evaluation outcomes and the cultural (geographical) difference, I conduct two-way scatter plots in Figure 2.3a, Figure 2.3b, and Figure 2.3c. Notably, Figure 2.3a reveals a negative correlation between cultural distance and evaluation outcome, contrary to H₁. Figure 2.3b supports H₂, demonstrating that countries farther from France experience lower “penalization”. However, due to a strong correlation (0.587) between cultural distance and geographic distance, I have to perform multivariate linear regressions including both independent variables in the same model (Table 2.4) to disentangle their individual effects. Figure 2.3c also suggests a moderate positive relationship between local competition and evaluation “penalization”.

Insert Figure 2.3a, Figure 2.3b, Figure 2.3c about here

Table 2.4 presents the coefficient estimates of the OLS regression models for H₁, H_{2a}, and H₃ by simultaneously adding the key independent variables. In general, the more total restaurants that are starred, the more status-disparity in the evaluation outcome, as the Michelin Guide artificially builds the hierarchy as a pyramid of a minority of higher-ranked elite chefs and a majority of lower-ranked elite chefs (Bouty et al., 2013). I included only control variables in Models 1, 5, 9, and 13. In the rest models, I introduced independent variables and identified significant effects of cultural distance across all models. The findings in Table 2.4 substantiated H₁, indicating that countries that differ more significantly from France are subject to stronger

“penalization”. This effect aligns with the existing literature in international business, highlighting the impediments posed by cultural barriers to transferring knowledge and practices across diverse contexts. The analysis also revealed a negative correlation between geographical distance and evaluation “penalization” in Models 2, 6, 10, and 14, moderately supporting expert rating organizations’ competitive distance logic (H_{2a}). The statistical findings in Table 2.4a-2.4d consistently validated H₃ by indicating stronger rating “penalization” in countries where local expert rating organizations are present.

Insert Table 2.4a-2.4d about here

Table 2.5a and 2.5b present twelve OLS models incorporating the interaction between geographical distance and international tourism, building upon models with key independent variables in Table 2.4a-2.4d. Unfortunately, only four of them (Models 18, 24, 25, and 28) yielded significant coefficients. Three of them suggest an opposite moderating effect – for any country being evaluated by the Michelin Guide, the stronger its international tourism, the weaker the negative relationship between competitive distance and evaluation “penalization”. Thus, H_{2b} is not supported.

Insert Table 2.5a, 2.5b about here

Results on the City-level

One methodological limitation of the country-level analysis stems from the Michelin Guide’s differential coverage patterns: while it evaluated most European countries as a whole, it selectively assessed specific metropolitan centers in countries such as the United States and China. This inconsistent geographical scope introduces measurement imprecision when

analyzing evaluation outcomes at the country level, particularly for partially covered countries. To address this methodological constraint, I present a comparative analysis of evaluation discrepancies across four global metropolitan centers: Paris, London, New York City, and Tokyo. These cities exhibit substantial homogeneity in economic environments, urban developments, and specifically the restaurant ecosystems and consumer demographics, thereby minimizing potential confounding variables inherent in cross-national comparisons. Furthermore, these premier global cities constitute more directly comparable competitive environments for culinary talent acquisition and consumer patronage.

Figure 2.4 illustrates the temporal evolution of high-low ratios across these four metropolitan centers from 2011 to 2016. Paris demonstrates a consistently superior ratio throughout the observation period, commencing at approximately 22.2% and concluding at 12.7%. This pattern aligns with the theoretical proposition that the Michelin Guide's country of origin receives preferential evaluation outcomes. The data also provide preliminary evidence relevant to the main hypotheses. Despite both Tokyo and New York occupying similar positions of geographical distance from Paris, New York - possessing greater cultural proximity - exhibits more favorable evaluation metrics. Similarly, while New York and London demonstrate comparable cultural affinity with Paris relative to Tokyo, London's geographical proximity appears to correlate with less favorable evaluation outcomes compared to New York. Notably, by 2016, the inter-city evaluation disparities had substantially diminished, potentially indicating a progressive standardization of assessment criteria across these diverse metropolitan markets.

Insert Figure 2.4 about here

Results on the Restaurant-level

Beyond the inequal evaluation outcomes on the country-level, I am also interested in verifying the Michelin Guide’s inequal evaluation outcomes on the restaurant-level. With detailed data of the worldwide Michelin-starred restaurants in 2023, I am able to examine the following questions as an extension of previous hypotheses: (1) the more one restaurant is different from French cuisine, the more it will be “penalized”; (2) the more one restaurant is distant to France, the less it will be “penalized”.

I scraped the publicly accessed website of the Michelin Guide¹ on July 26, 2023. A total of 3443 restaurants were listed with descriptions of the name, location, price level (1-4), and cuisine type, as well as a short review by the Michelin Guide (Figure 2.5).

Insert Figure 2.5 about here

I revised the measurement of the dependent variable to restaurant ratings, employing the same methodology to calculate cultural distance based on the national attribute of the cuisine offered by each restaurant. Furthermore, geographical distance was measured as the spherical distance between Paris and the city where the focal restaurant was situated. To ensure robustness, I replicated the analysis presented in Tables 4 and 5 while controlling for restaurant price levels and the cuisine type (French or not) with OLS, ordered Probit, and ordered Logit model. Statistical results consistently affirmed the validity of logics in H₁ (with the Hofstede cultural distance measurement) and H_{2a}, while failing to support H₃.

Insert Table 2.6 about here

DISCUSSION AND CONCLUSIONS

¹ <https://guide.michelin.com/en/restaurants/3-stars-michelin/2-stars-michelin/1-star-michelin/page/0>

This study examines the management of local contexts by expert rating organizations and uncovers evaluation outcomes among countries. I propose three potential rationales for the strategic variations in these evaluative activities. The first rationale stems from the cultural perspective in the internationalization literature, suggesting that expert rating organizations may “penalize” countries with distant cultures. The critique of undervaluing distant cultures has often been directed at expert rating organizations, as organizations encounter cultural barriers when venturing into unfamiliar contexts (Bouty et al., 2013; Lane, 2013). The second rationale draws from the competition logic in the strategy literature. I suggest that expert rating organizations may seek to safeguard their home country against competition from host countries in the evaluated international business realm by implicitly imposing unequal evaluation outcomes. However, this strategy is frequently overlooked. According to the competition logic, it is countries in closer proximity rather than those with distant cultures that face penalties. Additionally, I consider the competition among expert rating organizations and argue that the presence of local competitors leads to strategic evaluation outcome as a result of signaling status and skillfulness. All three hypotheses are supported by the primary analysis, with the first two further validated through robustness checks at both the city and restaurant levels.

Contributions

This paper contributes to the existing literature in three distinct ways. Firstly, it sheds light on the perception of expert rating organizations as strategic players in the market. Previous studies have emphasized the trust placed in expert rating organizations, unlike individual amateur reviewers, as authorities who disseminate knowledge and shape aesthetic trends for producers and consumers (Vincent, 2018). Under conditions where individuals need simplified information from mass information, expert rating organizations are particularly prevalent and

more important (Sharkey et al., 2023). This research goes a step further. It demonstrates that expert rating organizations not only provide expertise but also exercise strategic preferences in their judgments. This finding challenges the notion of purely objective and independent evaluation by expert rating organizations and reveals the influence of their strategic considerations. It uncovers unintentional “penalization” of contexts from distant cultures and highlights strategic evaluation discrimination driven by economic protectionism. These biases can have tangible consequences, such as inhibiting potential business growth for candidates, reducing the international tourism appeal of host countries, and diminishing the potential utility for customers. By illuminating these dynamics, the paper opens avenues for further exploration and discussion on the impact of expert rating organizations in shaping markets and industries.

Secondly, it shifts the focus of organizational similarities and differences from external differentiation to internal differentiation. While previous research has primarily examined how organizations balance external similarities and differences with competitors (Zhao, 2022; Zhao, Fisher, Lounsbury, & Miller, 2017; Zhao & Glynn, 2022), this study advances beyond this by recognizing that the internal activities of the same organization in different contexts are strategically divergent. This insight highlights the tension between internal differentiations and the overall commensurability of the organization. Moreover, it emphasizes how these internal differentiations reflect the strategies employed by expert rating organizations to protect the culture and economy of host countries while seeking competitive advantage in the local environment. By exploring this aspect, the paper offers a deeper understanding of the complexities of organizational dynamics.

Thirdly, the study contributes to the ongoing discussion on societal and economic inequality by organizational activities in the field of international business (Melé & Sánchez-Runde, 2013). Nascent studies have paid attention to unequal distribution of not only resource endowments (e.g. economic capital such as income and wealth) but also the access to resources

and opportunities (i.e. health & education, markets & opportunities) (Bapuji, Ertug, & Shaw, 2020). Extending this field of research, I draw attention to the role of expert rating organizations in generating and perpetuating societal and economic inequalities in the access to the international gastronomic market between countries that are evaluated. While expert rating organizations play a crucial role in ensuring fair and consistent evaluations on an international scale, I highlight the need for greater scrutiny of their judgments. By addressing this issue, the paper prompts a critical examination of the evaluation outcomes and biases that may exist within the international business community.

Last but not least, while this empirical study focuses on the culinary industry and the most prominent culinary expert rating, the implications of the research extend beyond this specific context. I believe that the insights gained from studying the Michelin Guide can be heuristic for understanding the strategic evaluations of other expert rating organizations. The arguments put forth in this study, such as cultural distance, economic protectionism, and local competition, are likely to be applicable to other industries as well. These underlying logics play a significant role in shaping the differentiation and evaluation processes employed by expert rating organizations across various contexts.

Limitations

This study, based on the case of the Michelin Guide, has certain limitations that should be acknowledged. Firstly, it is crucial to recognize that the findings of this study offer insights into the evaluation outcomes and potential strategies employed by the Michelin Guide, but they do not serve as a definitive roadmap for organizational success. Furthermore, although I tested logical arguments using a quantitative longitudinal dataset, I have to admit that I lack qualitative evidence as a cross-validation, which is difficult. Considering the potential market penalties associated with acknowledging either explicit or implicit biases in cross-country

evaluations, it is unlikely that the Michelin Guide would address such concerns in discourses. As a result, while this study effectively detects systematic patterns in the Michelin Guide's actions, its ability to determine whether these actions were deliberate or unintended remains limited due to the nature of the data.

It is also important to acknowledge that this study has a specific focus on analyzing the discrepancies of evaluative activities within organizations. While understanding the external strategic differentiation strategies would provide a broader understanding of the evaluative behavior of expert rating organizations, this research specifically examines the strategies organizations employ to balance the similarities and differences in their internal activities across different contexts. Thus, the analysis in this study only offers insights into this particular aspect of organizational activities. However, it is worth noting that future research could explore how expert rating organizations strategically evaluate candidates by considering the balance of similarities and differences with their competitors at various levels and delve into the reasons behind such evaluations.

CHAPTER THREE

Between Advancement and Retreat: Organization Responses to Consumer Reviews After Status Change

INTRODUCTION

Expert rating organizations serve as authoritative gatekeepers and tastemakers by creating a market hierarchy of producers, indicating the organizational status of the evaluated producers (Phillips & Zuckerman, 2001; Zuckerman, 1999). Organizational status – the position in the social hierarchy inferred from expert evaluations – is a critical anchoring point due to their institutionalized roles and market influence, which offer valuable insights into how organizations are perceived and assessed within their respective markets (Vincent, 2018). Distinction in organizational status explains different strategies organizations take according to their hierarchical positions as high status decreases the transaction uncertainties and provides a lens of positive interpretation for organizational deviances (Podolny, 1994, 2001; Zuckerman, 1999).

Compared to other social evaluations such as reputation or legitimacy, status has been regarded as relatively stable, not necessarily bounded to actual performance, and continuously generating competitive advantages in resource accessibility (Bitektine, Hill, Song, & Vandenberghe, 2020; Piazza & Castellucci, 2014). However, recent studies challenge the stability of status accredited by expert rating organizations. They argue that expert rating organizations are incentivized to generate dynamism in the social hierarchies and emphasize the changing aspect of status. In their research of the *Institutional Investor* magazine's All-America security analyst rankings, Bowers and Prato (2019) found that expert rating organizations deliberately introduce volatility in their evaluations to maintain audience engagement. Based on the previous two chapters of this thesis, I also found that both external peers and internal evaluation activities across locations could compromise the objectivity and independence of expert rating organizations.

A change in status within expert rating organizations' evaluations is a significant and representative event. An increase in status brings greater attention, more opportunities, and

stronger value-appropriation capabilities (Podolny, 2005). It also has side effects: increased publicity attracts untargeted consumers with varied expectations, potentially leading to broader criticisms (Kovács & Sharkey, 2014). Meanwhile, a decrease in status can cast doubt on the competence of the providers, resulting in the loss of existing consumers and resources from exchange partners.

In both cases, organizations must adapt to status changes based on their new standing in the market hierarchy. They should navigate themselves in the opportunities to enhance their competitive advantages and devise solutions to mitigate potential declines in performance. From this perspective of dynamic status, some studies have examined the impact of status shocks on organizational reactivities. For instance, Favaron et al. (2022) investigated how organizations adjust their operational activities in response to status shocks, such as offering more complex self-representations through their products and services. Similarly, Sauder & Espeland (2009) found that organizations engage in institutional activities, including interactions with expert rating organizations aimed at manipulating rankings. In alignment with these studies, the focus of this research is on their public response to consumer reviews, which is not merely a conversation with existing consumers but also a broader communication with potential consumers (Wang, Wezel, & Forgues, 2016).

Focusing on organizations' reactions to status changes as reflected in their public responses to consumer reviews, this study seeks to address the following questions: (1) Do organizations adjust their strategies for responding to consumer reviews following status changes? (2) What specific strategies do organizations experiencing status changes adopt, and how do these strategies differ between organizations experiencing status increases versus decreases? (3) What mechanisms underlie the observed differences in these responses?

I propose that organizations experiencing a status increase will enhance both the probability and the tone of their responses to consumer reviews. They will capitalize on the

opportunity to expand their market presence due to their elevated status (Benjamin & Podolny, 1999; Podolny, 1993), and they will adopt a more positive tone in their responses to mitigate common criticisms such as inconsiderateness or inauthenticity (Hahl & Zuckerman, 2014). Conversely, I suggest that organizations experiencing a status decrease will reduce their response rate to avoid perceptions of over-protestation (Ashforth & Gibbs, 1990; Veil, Petrun, & Roberts, 2012), but among the responses they make, they will adopt a more positive tone to reinforce favorable perceptions of their identity (Elsbach & Kramer, 1996).

To understand the mechanisms driving these differences, I examined changes in consumer reviews. The changes in organizational responses could be influenced by shifts in consumer feedback following a status change. Meanwhile, the shift in the composition of consumer groups could also be influential. It is plausible that organizations with a status increase emphasize replying to reviews from untargeted consumers to explore new market opportunities. In contrast, those with a status decrease primarily adjust their responses to targeted consumers.

I tested these hypotheses using data from 393,844 consumer reviews and organization responses on Dianping.com for 108 Michelin-starred restaurants in major Chinese cities between 2017 and 2022. Preliminary results support most of the hypotheses. Specifically, organizations experiencing status changes significantly altered their response strategies to consumer reviews. Organizations with a status increase raised their response probability but decreased the positivity of their responses compared to those with no status change, while those with a status decrease reduced their response probability but increased the positivity of their responses. Both mechanisms of consumer rating and consumer group are verified to be influential.

This study unveils organizational adaptation strategies to status changes. It integrates the concept of dynamic status into the literature on organizational status, arguing that status change represents a low-frequency, high-impact shock to organizations. This research significantly

enhances our understanding of the diverse strategic choices organizations make under conditions of high environmental determinism. Empirically, it aims to improve the causal understanding of organizational adaptations to status changes by employing a difference-in-difference event study method.

THEORY DEVELOPMENT

Responses To Consumer Reviews

Consumer reviews constitute a prominent and influential channel of public communication, offering extensive information about products or services that is essential for reducing transaction uncertainties. Reducing uncertainty is critical for the decision-making process of potential consumers, who rely on these reviews to anticipate the quality of their potential purchases. Empirical evidence shows that a higher average consumer rating significantly enhances local search rankings, augmenting the organization's visibility (Ursu, 2018). Positive consumer reviews with consistent consumer ratings have been shown to bring significant sales growth and organizational performance (Sun, 2012; Ye, Law, Gu, & Chen, 2011). These findings highlight the substantial economic benefits that consumer reviews can yield, emphasizing their strategic importance in organizations.

Recognizing the value of consumer reviews, managers increasingly incorporate responses to these reviews into their broader marketing communication strategies (Chen & Xie, 2008). Proactive engagement in replying to consumer reviews is a strategy to enhance consumer relations and organizational reputation. A notable study on organizational responses to consumer reviews reveals that such engagements can lead to a tangible improvement in consumer perceptions. The authors found an average increase of 0.12 stars in consumer ratings and a 12% increase in the number of consumer reviews (Proserpio & Zervas, 2017). This

indicates that, in general, responses to consumer feedback can enhance perceived service quality and stimulate increased consumer interaction and engagement. Thus, responding to consumer reviews emerges as a potent strategy for managing organizational identity, fostering enhanced consumer satisfaction, and driving organizational performance.

Nonetheless, responding to consumer reviews may not always be the best option, particularly when addressing negative feedback. Engaging with negative reviews can attract unwanted public attention to the criticisms. For organizations, especially those with limited institutional capability, ignoring and disassociating from negative issues may be more beneficial (Veil et al., 2012). Recent research has shown that organizational response to negative consumer reviews, in more and more detail, stimulates additional negative feedback (Chevalier & Mayzlin, 2006). Moreover, responses to negative reviews are often perceived as overly defensive and are suspected of being strategic legitimation efforts, leading to accusations of “protesting too much” (Ashforth & Gibbs, 1990). This negative interpretation is particularly pronounced for organizations with lower status. Consequently, organizations with varying status levels will weigh the decision to respond to consumer reviews differently, especially considering the potential risks of replying to negative feedback.

Reaction to Status Shock

A superior status position in the market hierarchy is crucial for organizations, as it secures more resources and facilitates the “Matthew effect” (Podolny, 2005). A positive change in status brings both opportunities and constraints to organizations. On the positive side, increasing status provides organizations access to valuable resources, lower costs, higher prices, and enhanced growth prospects (Podolny & Phillips, 1996). To sustain these benefits, organizations should reinforce their elevated status by selectively engaging with high-status transaction

partners and cautiously demonstrating deferential behaviors (McPherson, Smith-Lovin, & Cook, 2001; Podolny, 1994).

However, a status increase may also entail drawbacks. It can cast suspicion of being cold and inconsiderate among the mass audience (Fiske, Cuddy, & Glick, 2007; Hahl & Zuckerman, 2014). Consumers may question the motivations behind the status attainment, suspecting it involves humiliating competitors or engaging in immoral activities driven by monetary incentives. Unless organizations explicitly convey care and consideration toward consumers, such perceptions can tarnish their market identity (Hahl & Zuckerman, 2014). Additionally, an increase in status can create category ambiguities as increased publicity attracts untargeted consumers with mismatched expectations, who are more likely to share opinions about high-status producers (Kovács & Sharkey, 2014).

Organizations are likely to adopt proactive communication strategies to exploit the opportunities while mitigating potential risks. Firstly, organizations can expand the market space by addressing untargeted consumers attracted by the new status. These consumers may have varying expectations and experiences, which can result in a broader range of positive and negative feedback. Additionally, organizations need to retain satisfied consumers who contribute positively to their reputation and revenue. Retaining these consumers ensures a stable support base and helps sustain the elevated status. Organizations can convert them into loyal customers by effectively engaging with these untargeted consumers, further solidifying their market position.

Moreover, addressing skepticism regarding the organization's considerateness and authenticity is crucial. A status increase often questions the means and motivations behind the achievement. Consumers may perceive the organization as more focused on competitive success and financial gain than customer satisfaction and ethical practices. To counter these

perceptions, organizations will engage in positive communication, demonstrating genuine concern for consumer feedback and welfare.

Consequently, organizations will likely increase the probability and positivity of their responses to consumer reviews. By responding more frequently and positively, organizations can directly counteract negative perceptions of coldness and inconsideration. Positive engagement with consumer reviews reassures existing and potential customers of the organization's commitment to quality and service and enhances the overall consumer experience. This strategic approach helps maintain a favorable public image and leverage the benefits of their elevated status, ensuring long-term success and resilience in the competitive market.

H_{1a}: When an organization experiences a status increase, it will increase the likelihood of responding to consumer reviews.

H_{1b}: When an organization experiences a status increase, it will increase the expression of positive sentiment in their replies.

When organizations experience a status loss, they risk forfeiting a series of status premiums, as mentioned before (Podolny & Phillips, 1996). To mitigate the effects of this status loss, organizations must balance the benefits of engaging with consumer reviews against the potential costs of inciting further criticism. On the one hand, replying to consumer reviews could help defend their lost status and rebuild their perceived quality (Coombs, 2007). On the other hand, organizations with lower status are more susceptible to accusations of “protesting too much”, which can attract additional negative feedback and exacerbate their situation (Ashforth & Gibbs, 1990).

Organizations experiencing a status decrease often receive heightened public attention as the media draws comparisons with those whose status is rising. With status decrease during this period, their activities will be judged with less tolerance (Phillips & Zuckerman, 2001). To buffer from this heightened potential scrutiny, organizations will likely adopt a cautious approach to avoid further negative perceptions and the pitfalls of overreacting to consumer reviews. Therefore, unlike organizations with an increased status, those with a decreased status may employ a lower probability of publicly responding to unsatisfied and/or targeted consumer reviews. This strategy aims to prevent drawing negative attention or triggering adverse consequences.

However, when these organizations do respond to consumer reviews, they will likely emphasize positivity and affirmation in their replies. By selectively responding to reviews and focusing on positive engagement, they can demonstrate their commitment to improving and maintaining high standards despite declining status. This approach helps to mitigate the negative impact of the status loss, reassure existing customers, and attract new ones by showcasing the organization's resilience and dedication to quality.

H_{2a}: When an organization experiences a status decrease, it will decrease the likelihood of responding to consumer reviews.

H_{2b}: When an organization experiences a status decrease, it will increase the positive sentiment in their responses.

DATA AND METHOD

Empirical Context and Sample

I tested the hypotheses in the gastronomy industry, a typical intermediated industry where the

yearly rankings by restaurant guides receive broad attention and recognition from consumers and restaurants. Through ranking restaurants, the guides differentiate consumers' dining behaviors, exacerbate these distinctions, and consolidate fragmented appetites and tastes into one social order. This social order, satisfying the desire for distinction among restaurants and consumers, became a guiding force for major actors in the gastronomy market (Vincent, 2018). Restaurants seek a higher standing in this social hierarchy to attract consumers and build a reputation, and consumers consume not only the quality of food but also the cultural narratives and traditions in the social order to signal their social status and distinction, reinforcing the gastronomic institution.

Specifically, the Michelin Guide is one of the most prestigious restaurant guides for its historical influences in the French gastronomy industry since the 1900s and the continuous international influences in this field ever since then. Winning every Michelin star reflects a restaurant's superior market status, providing abundant resource access (Podolny, 1993). As a renowned chef who has garnered 31 Michelin stars Joël Robuchon remarked, "with one Michelin star, you get about 20 percent more business. With two stars, you do about 40 percent more business, and with three stars, you'll do about 100 percent more business". In contrast, a decline in the number of Michelin stars brings significant loss in both market status and material income. For the restaurant owners of a two-star restaurant in Hong Kong, losing one star in 2018 brought a mass drop in customer reservations and left them with only three months of runway (Chee & Reddy, 2021). In this case, gaining or losing a star from the yearly Michelin Guide announcement is perceived as a shock of status increase or status loss, which changes the perceived quality of restaurants among consumers and their willingness to consume the restaurant offerings.

At the same time, the proliferation of consumer review aggregators such as Yelp, TripAdvisor, and Dianping joined this interface between restaurants that compete for the

market space and consumers who look for more information in decision-making. According to research by Yelp, a one-star increase in the aggregated consumer rating brings a 5-9% increase in restaurant revenues (Luca, 2016). I collected data on restaurant ratings from consumers on Dianping.com, a large restaurant review platform in Asia that provides services similar to Yelp. The website was founded in 2003, with over 30 million monthly active visitors and over 20 million consumer ratings and reviews (Wu, Che, Chan, & Lu, 2015). The website is open to consumer reviews of restaurants and other consumer-oriented businesses, such as hotels, gyms, hair salons, and karaoke. After merging with another large home delivery platform, the company's 2023 gross profit was CNY 25 billion (EUR 3.2 billion).

Consumers can voluntarily leave a numerical rating of the restaurant ranging from 0.5 to 5 stars and attach written comments aside. The sample comprises 393,844 consumer reviews of 101 restaurants awarded at least one Michelin star between January 1, 2016, and March 1, 2023, in Beijing, Shanghai, or Guangzhou. Each consumer review serves as the unit of analysis. The average consumer rating is 4.38, and the average restaurant response rate is 22%.

Difference-in-Difference Event Study Design

Restaurants have to strategically allocate limited resources to a variety of operations, such as marketing management, including responses to consumer reviews, environmental settings, on-site service, and food *per se*. Identifying the effect of status change by comparing the average response probability of consumer reviews by restaurants that gained, lost, or didn't change their Michelin stars could be biased by their resource allocation adjustments in other operations rather than the effect of status change.

The yearly announcement of the Michelin star restaurants presents a unique opportunity to mitigate this issue and analyze the organizational shock resulting from status changes.

Importantly, the shock of status change is exogenous within the proposed framework, as restaurants cannot anticipate the exact timing or nature of the status change. Therefore, a difference-in-difference design is employed to investigate the differential patterns of consumer review responses between restaurants that experienced a status change and those that did not as potential counterfactuals. I also combined the difference-in-difference design with the event study method because the influence of yearly announcements on restaurants is temporal and recurring. According to the interview with the restaurant manager, restaurants are usually affected by the Michelin Guide announcement for two weeks. To fully capture the influence of status change, pre- and post-shock periods of two months are utilized to analyze restaurants' responses to consumer reviews. The difference-in-difference event study method is also helpful for analyzing the dynamic treatment effect across years, enabling us to observe evidence of organizational learning in responding to status change.

A fundamental dependent variable in this research is restaurants' decision on whether to respond to a consumer review. However, to apply the difference-in-difference event study approach, I should determine if this decision to respond to consumer reviews is before or after the exogenous shock. This determination is not easy because, for consumer reviews that firms decided not to respond to, there is no specific time stamp of the decision. This timestamp is not necessarily the same as the consumer review time stamp, as restaurants can still respond to pre-announcement consumer reviews after the announcement. I have devised two approaches to address this problem in my study.

The first approach is to use the consumer review time stamp as the determinant of pre-/post- treatment so that I understand how restaurants responded to each consumer review. I constrained the restaurant response duration conservatively by its median (38 hours, around 1.5 days) so that the review time stamp is as close to the response time stamp as possible. Only if a consumer review was responded to within 38 hours it will be identified as a timely response.

The average timely response rate is 11%, which is 11% lower than the restaurant response rate in the full sample. This approach shifts the measurement from restaurant responses to restaurant timely responses but correctly identifies the pre-/post- treatment on consumer reviews. It helps us understand if restaurants responded to consumers' reviews before and after the announcement shock differently. In the robustness check, I also used the third quantile of responding duration (123 hours, around 5 days) as the bar of timely response (Table A1, A2).

Insert Figure 3.1, 3.2 about here

The second approach generates and uses the restaurant response time stamp so that I can take a more extended observation of the organization's decision-making process. However, since I only had the time stamp for decisions of responded consumer reviews, I had to decide on a decision-making window for those consumer reviews that were not responded to. Having analyzed the time it takes for restaurants to decide to respond (or not), I found that the distribution of decision time is highly right-skewed. On average, restaurants took 453 hours to reply to a consumer review, and 75% of restaurant responses were made within 123 hours. To ensure a more extended response window for restaurants, I generated a predicted response time stamp for non-responding observations by extending the consumer review time by an extra 453 hours. In robustness checks, I also changed this response window to 123 hours (Table A3, A4).

Insert Figure 3.3, 3.4 about here

Key Variables

Dependent Variables.

Restaurant response is a binary variable in both approaches, taking the value of 1 if a

consumer review receives a response from the restaurant and 0 otherwise.

Tone in response is also a binary variable, equaling 1 if the sentiment analysis of the reply indicates a positive tone and 0 otherwise. Sentiment analysis is conducted using Google's BERT model in the Chinese language.

Independent Variables.

Post is a binary variable. In the first approach, it equals 1 if the *actual consumer review* was posted before the announcement of the Michelin Guide and 0 otherwise. In the second approach, it equals 1 if the *predicted restaurant response* was posted prior to the announcement of the Michelin Guide and 0 otherwise.

Status change is a categorical variable, distinguishing groups of restaurants that received a positive status change (status increase), those that received a negative status change (status decrease), and those that did not experience any change (no status change) in the announcement of the Michelin Guide, compared to their accredited number of Michelin stars one year before.

Control Variables.

Some review-level characteristics are controlled in that they might influence the probability of restaurant responses.

Consumer rating measures the evaluation of consumers in the review, ranging from 0.5 to 5. Existing studies have shown that organizations are more likely to respond to negative consumer reviews.

Daily review is the total number of consumer reviews of the restaurant on the same day of receiving the consumer review. It is positively correlated with the daily popularity of a restaurant, which could decrease the probability of replying to a consumer review.

Review length measures the number of words in a consumer review. Restaurants are more

likely to reply to a longer consumer review.

Insert Table 3.1 about here

RESULTS

The Effects of Status on Restaurant Responses

Since the dependent variables are binary, linear probability models (LPMs), logit, and probit regressions are employed in the analysis. Restaurant and year fixed effects are included to control for time-invariant and organization-invariant variables.

The regression results in the first approach (Table 3.2) indicate that consumer reviews posted after the Michelin Guide announcement are more likely to receive a timely response from restaurants with a status increase compared to those with no status change. Conversely, consumer reviews are least likely to be responded to in a timely manner by restaurants that experienced a status decrease. These findings are consistent across all three models and are corroborated by robustness checks using 123 hours (the third quantile of response duration) to define a timely response (Table A2).

To further understand how restaurants reply to reviews, I can examine the tone of their responses. Interestingly, restaurant restaurants that experienced a status increase are less likely to reply to consumer reviews with positive tones than those with no status change. As hypothesized, restaurant restaurants with a status decrease are more likely to reply to consumer reviews with positive tones.

These results suggest that consumer reviews receive more timely attention but less positive communication from restaurants with a status increase.

Insert Table 3.2 about here

As for the second approach, I examined the timing of restaurants' decision to respond to a consumer review or not. Allowing a decision-making window of 453 hours (mean of response duration, covering more than 85 percentile responses), results in Table 3.3 describe the summary of statistics, and Table 3.4 shows that after the announcement of status change, restaurants display the same patterns in responses to consumer reviews as the first approach. The results are consistent among all three models, and in the robustness check, I allowed the decision-making window to be 123 hours (the third quantile of response duration).

Insert Table 3.3, 3.4 about here

Mechanism I: Heterogeneity in Consumer Ratings

One plausible explanation for the changes in restaurants' responses to consumer reviews is that they are reacting to the changes in consumer ratings (Figure 3.5). This is especially prominent among those with a status increase as they are more likely to experience lower consumer ratings after the publicity. To test if this is the case, I first explored if the “paradox of publicity” phenomenon also holds where the barriers to consumers' ability to experience a high-status product are quite high. Then, I subset the main results in Table 3.2 and Table 3.4 into different consumer ratings and see the heterogeneity of restaurant responses across various consumer ratings.

I tested the argument that a positive status shock would bring popularity and untargeted audiences in an industry where the consumption barrier is relatively high in Table 3.5 (Kovács

& Sharkey, 2014). Regression results suggest that restaurants receive 0.2 fewer consumer reviews every day and 0.15 lower consumer ratings when experiencing a status increase. Restaurants experiencing a status decrease receive 1.1 fewer consumer reviews daily with no significant changes in the consumer rating. This result validates the arguments in Kovács and Sharkey (2014) that gaining higher status might lead to punishment in the average broad evaluation. Still, there has been no significant increase in popularity, indicating that the mechanism of turning someone off is more valid in this context.

Tables 6a, 6b, 7a, and 7b further examine the heterogeneous effects of restaurants in responding to consumer reviews conditional on consumer ratings. The average consumer rating is 4.37 out of 5, so I created two subsamples: a high consumer rating over 4.5 (including 4.5) and a low consumer rating lower than 4.5. On average, restaurants with status increase are more likely to reply to consumer reviews with higher consumer ratings compared to those with lower consumer ratings, while restaurants with status decrease are less likely to reply to consumers with lower ratings. The results support previous hypotheses that restaurants with a status decrease tend to protect their identity from negative consumer ratings by avoiding responses to consumer reviews, while restaurants with a status increase tend to emphasize their segmented market of consumers who leave positive ratings. But when I look into the tone of restaurant responses, I can find that restaurants with a status increase use a less positive tone if they reply to a consumer review with a higher consumer rating than a lower one. Restaurants with a status increase use a more positive tone in responses if they reply to a consumer review with a lower consumer rating than a higher one.

Mechanism II: Heterogeneity in Consumer Groups

Furthermore, existing literature revealed that the changes in consumer ratings cannot be

explained only by the denigration of high-status organizations but could also be due to the shift in consumer composition (Kovács & Sharkey, 2014). To test this mechanism, I identified targeted consumers if they had previously reviewed any Michelin-starred restaurants in the sample before the focal review (Figure 3.6). On average, 33% of the reviews were written by targeted consumers.

Table 3.8 shows regression results of consumer ratings by the number of targeted and untargeted consumers daily. Tables 3.9a, 3.9b, 3.10a, and 3.10b further examine the heterogeneous effects of restaurants in responding to consumer reviews conditional on targeted or non-targeted consumers. Interestingly, restaurants that experienced a status increase are more likely to reply to untargeted consumers than targeted consumers. In contrast, restaurants that experienced a status decrease are more likely to modify their response to targeted consumers than untargeted consumers. Further robustness checks with subsamples of the combination of two-by-two conditions also show consistent evidence of these findings (Table A3, A4, A5, A6).

DISCUSSION

This study aims to investigate how organizations react to changes in their status, specifically in terms of their responses to consumer reviews. The primary focus is on Michelin-starred restaurants, examining how a change in their Michelin status influences their likelihood of responding to consumer reviews and the tone of these responses. It reveals that Michelin-starred restaurants tend to increase the probability of replying to consumer reviews when they experience a status increase. However, the tone of their responses becomes less positive. Conversely, restaurants that experience a status decrease are less likely to reply to consumer reviews, but the tone of their responses becomes more positive. To understand the underlying

mechanisms, I conducted several subsample analyses. The results indicate that restaurants with an increased status primarily change their response behavior toward satisfied consumers and those previously untargeted by Michelin-starred restaurants. In contrast, restaurants with a decreased status predominantly adjust their responses towards dissatisfied consumers and those who were their targeted audience.

This paper makes several contributions to the study of organizational status and adaptation. It introduces a dynamic perspective of status, extending previous literature on the impact of expert rating organizations' evaluations (Espeland & Sauder, 2007; Favaron et al., 2022; Sauder & Lancaster, 2006). Empirically, it put efforts into the causation identification and employed difference-in-difference event study method to improve existing understanding from qualitative, correlational, and selective survey-based observation to quantitative, causal, and more generic strategy-based phenomenon (Elsbach & Kramer, 1996; Espeland & Sauder, 2007).

This study also contributes to existing literature on organizational adaptation to evolving institutional environments. It unveils how organizations enjoy strategic choices in managing market segments under the stringent nature of external constraints (Hrebiniak & Joyce, 1985). Incorporating the multiplicity of social evaluators provides a nuanced explanation of how organizations adapt to institutional rankings through simultaneous change in consumer reviewers (Sarta, Durand, & Vergne, 2021). It underscores the critical role of strategic communication with consumers as a pivotal choice and highlights the diversity of strategic options available, contingent on the varying competitive standings of organizations.

Like all the other studies, this paper has limitations. First, an expected instead of actual decision-making time window of no-response is used. Although there are robustness checks with two different time windows for the estimation, there is still some inaccuracy in identifying the response time. Unfortunately, this information is not accessible on any online review platforms, so future improvements in collecting this information would be useful.

Secondly, while employing BERT to measure the tone of restaurant response texts is acceptable, it may lack precision in understanding the contextual nuances of customer review replies. Future research could explore alternative methods to enhance the accuracy of tone measurement.

Most importantly, it is crucial to note that this study primarily focuses on descriptive rather than prescriptive aspects. The author has outlined status change as an antecedent of organization adaptation and the diverse strategies of organizations experiencing different status changes. However, further research should investigate the consequences for organizations actively incorporating these adaptation strategies. By examining the long-term effects on performance, reputation, and customer perceptions, researchers can provide valuable normative suggestions for organizations seeking successful navigation through status changes. Understanding the impact of these strategies will contribute to a more comprehensive understanding of the effectiveness of organizational adaptation in dynamic and evolving environments.

REFERENCES

- Alpert, F. H., & Kamins, M. A. (1994). Pioneer brand advantage and consumer behavior: A conceptual framework and propositional inventory. *Journal of the Academy of Marketing Science*, 22, 244–253.
- Ashforth, B. E., & Gibbs, B. W. (1990). The Double-Edge of Organizational Legitimation. *Organization Science*, 1, 177–194.
- Askin, N., & Bothner, M. S. (2016). Status-Aspirational Pricing: The “Chivas Regal” Strategy in U.S. Higher Education, 2006–2012. *Administrative Science Quarterly*, 61, 217–253.
- Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *Quarterly Journal of Economics*, 107, 797–817.
- Bapuji, H., Ertug, G., & Shaw, J. D. (2020). Organizations and Societal Economic Inequality: A Review and Way Forward. *Academy of Management Annals*, 14, 60–91.
- Baum, J. A. C., & Singh, J. V. (1994). Organizational Niches and the Dynamics of Organizational Mortality. *American Journal of Sociology*, 100, 346–380.
- Benjamin, B. A., & Podolny, J. M. (1999). Status, quality, and social order in the California wine industry. *Administrative Science Quarterly*, 44, 563–589.
- Bertera, M. (2023, November 15). Come diventare ispettore della “Guida Michelin”: Intervista. *La Cucina Italiana*. Retrieved from <https://www.lacucinaitaliana.it/article/come-diventare-ispettore-guida-michelin-intervista/>
- Beugelsdijk, S., Kostova, T., Kunst, V. E., Spadafora, E., & van Essen, M. (2018). Cultural Distance and Firm Internationalization: A Meta-Analytical Review and Theoretical Implications. *Journal of Management*, 44, 89–130.
- Bitektine, A. (2011). Toward a Theory of Social Judgments of Organizations: The Case of Legitimacy, Reputation, and Status. *Academy of Management Review*, 36, 151–179.
- Bitektine, A., Hill, K., Song, F., & Vandenberghe, C. (2020). Organizational Legitimacy, Reputation, and Status: Insights from Micro-Level Measurement. *Academy of Management Discoveries*, 6, 107–136.
- Blank, G. (2007). *Critics, Ratings, and Society: The Sociology of Reviews*. Rowman & Littlefield.
- Boulongne, R., Cudennec, A., & Durand, R. (2019). When do market intermediaries sanction categorical deviation? The role of expertise, identity, and competition. *Research in the Sociology of Organizations*, 65B, 67–83.
- Bourdieu, P. (1984). *Distinction: A social critique of the judgement of taste*. Routledge.

- Bouty, I., Gomez, M.-L., & Drucker-Godard, C. (2013). Maintaining an Institution: The Institutional Work of Michelin in Haute Cuisine Around the World. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2328259>
- Bowers, A. (2020). Balanced but not fair: Strategic balancing, rating allocations, and third-party intermediaries. *Strategic Organization*, *18*, 427–447.
- Bowers, A., & Prato, M. (2019). The Role of Third-Party Rankings in Status Dynamics: How Does the Stability of Rankings Induce Status Changes? *Organization Science*, *30*, 1146–1164.
- Bowman, N. A., & Bastedo, M. N. (2011). Anchoring effects in world university rankings: Exploring biases in reputation scores. *Higher Education*, *61*, 431–444.
- Bryson, B. (1996). “Anything But Heavy Metal”: Symbolic Exclusion and Musical Dislikes. *American Sociological Review*, *61*, 884–899.
- Carpenter, G. S., & Nakamoto, K. (1989). Consumer Preference Formation and Pioneering Advantage. *Journal of Marketing Research*, *26*, 285–298.
- Carrier, A., Louvet, E., Chauvin, B., & Rohmer, O. (2014). The Primacy of Agency Over Competence in Status Perception. *Social Psychology*, *45*, 347–356.
- Carroll, G. R. (1985). Concentration and Specialization: Dynamics of Niche Width in Populations of Organizations. *American Journal of Sociology*, *90*, 1262–1283.
- Castellucci, F., & Ertug, G. (2010). What’s in It for Them? Advantages of Higher-status Partners in Exchange Relationships. *Academy of Management Journal*, *53*, 149–166.
- Castillo-Manzano, J. I., Castro-Nuño, M., Lopez-Valpuesta, L., & Zarzoso, Á. (2021). Quality versus quantity: An assessment of the impact of Michelin-starred restaurants on tourism in Spain. *Tourism Economics*, *27*, 1166–1174.
- Castillo-Manzano, J. I., & Zarzoso, Á. (2023). Towards “a sky full of Michelin Stars.” *International Journal of Gastronomy and Food Science*, *32*, 100738.
- Cattani, G., Dunbar, R. L. M., & Shapira, Z. (2017). How Commitment to Craftsmanship Leads to Unique Value: Steinway & Sons’ Differentiation Strategy. *Strategy Science*, *2*, 13–38.
- Chabal, E. (2013). The Rise of the Anglo-Saxon: French Perceptions of the Anglo-American World in the Long Twentieth Century. *French Politics, Culture & Society*, *31*, 24–46.
- Chabal, E. (2016). French Political Culture in the 1970s. *Geschichte Und Gesellschaft*, *42*, 243–265.
- Chandan, H. C., & Christiansen, B. (2019). *International Firms’ Economic Nationalism and Trade Policies in the Globalization Era*. IGI Global.

- Chanlat, J.-F. (2014). Language and thinking in organization studies: The visibility of French OS production in the Anglo-Saxon OS field. *International Journal of Organizational Analysis*, 22, 504–533.
- Chatterji, A. K., Durand, R., Levine, D. I., & Touboul, S. (2016). Do ratings of firms converge? Implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37, 1597–1614.
- Chee, J., & Reddy, S. K. (2021). *The Michelin rating system: Cracking the code of the stars* (pp. 1–17) [Case Study]. Singapore Management University.
- Chen, Y., & Xie, J. (2008). Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science*, 54, 477–491.
- Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43, 345–354.
- Chung, S., Singh, H., & Lee, K. (2000). Complementarity, status similarity and social capital as drivers of alliance formation. *Strategic Management Journal*, 21, 1–22.
- Cluster-17. (2023). *Sondage pour Le Point: Quels sont les goûts culinaires des Français ?* Retrieved from <https://cluster17.com/sondage-pour-le-point-quels-sont-les-gouts-culinaires-des-francais/>
- Comanor, W. S., & Wilson, T. A. (1979). The Effect of Advertising on Competition: A Survey. *Journal of Economic Literature*, 17, 453–476.
- Cook, K. S., Hardin, R., & Levi, M. (2005). *Cooperation Without Trust?* Russell Sage Foundation.
- Coombs, W. T. (2007). Protecting Organization Reputations During a Crisis: The Development and Application of Situational Crisis Communication Theory. *Corporate Reputation Review*, 10, 163–176.
- Cowell, F. A. (2011). Analysing Inequality. In F. Cowell (Ed.), *Measuring Inequality* (p. 0). Oxford University Press.
- Csergo, J. (2020). Influence of French Cooking Globally. In H. L. Meiselman (Ed.), *Handbook of Eating and Drinking: Interdisciplinary Perspectives* (pp. 461–477). Cham: Springer International Publishing.
- d’Aspremont, C., Gabszewicz, J. J., & Thisse, J.-F. (1979). On Hotelling’s “Stability in Competition.” *Econometrica*, 47, 1145–1150.
- Daries, N., Moreno-Gené, J., & Cristobal-Fransi, E. (2021). Michelin stars shine brightly, but are they profitable? *International Journal of Gastronomy and Food Science*, 24, 100352.
- de Nooy, W. (1999). A literary playground: Literary criticism and balance theory. *Poetics*, 26,

385–404.

- Deephouse, D. L. (1999). To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management Journal*, *20*, 147–166.
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, *48*, 147–160.
- Dow, D., & Karunaratna, A. (2006). Developing a multidimensional instrument to measure psychic distance stimuli. *Journal of International Business Studies*, *37*, 578–602.
- Draoulec, P. L. (2005, September 28). Michelin rates the apple. *New York Daily News*. Retrieved from <https://www.nydailynews.com/2005/09/28/michelin-rates-the-apple/>
- Dupin, L., & Wezel, F. C. (2023). Artisanal or Just Half-Baked: Competing Collective Identities and Location Choice Among French Bakeries. *Administrative Science Quarterly*, *68*, 867–909.
- Durand, R., & Kremp, P.-A. (2016). Classical Deviation: Organizational and Individual Status as Antecedents of Conformity. *Academy of Management Journal*, *59*, 65–89.
- Durand, R., & McGuire, J. (2005). Legitimizing agencies in the face of selection: The case of AACSB. *Organization Studies*, *26*, 165–196.
- Elsbach, K. D., & Kramer, R. M. (1996). Members' Responses to Organizational Identity Threats: Encountering and Countering the Business Week Rankings. *Administrative Science Quarterly*, *41*, 442–476.
- Enderwick, P. (2011). Understanding the rise of global protectionism. *Thunderbird International Business Review*, *53*, 325–336.
- Espeland, W. N., & Sauder, M. (2007). Rankings and reactivity: How public measures recreate social worlds. *American Journal of Sociology*, *113*, 1–40.
- Fackler, M. (2008, February 24). Michelin Gives Stars, but Tokyo Turns Up Nose. *The New York Times*. Retrieved from <https://www.nytimes.com/2008/02/24/business/worldbusiness/24guide.html>
- Favaron, S. D., Di Stefano, G., & Durand, R. (2022). Michelin Is Coming to Town: Organizational Responses to Status Shocks. *Management Science*, *68*, 6925–6949.
- Ferguson, P. P. (1998). A Cultural Field in the Making: Gastronomy in 19th-Century France. *American Journal of Sociology*, *104*, 597–641.
- Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*, 117–140.
- Fiske, S. T., Cuddy, A. J. C., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*, 77–83.

- Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2018). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. In *Social Cognition*. Routledge.
- Furnham, A., & Boo, H. C. (2011). A literature review of the anchoring effect. *The Journal of Socio-Economics*, 40, 35–42.
- Gensch, D. H. (1987). A Two-Stage Disaggregate Attribute Choice Model. *Marketing Science*, 6, 223–239.
- Gérard, M., Lancrey-Javal, G., & Prunier, A. (2019). *French people's opinions on international cuisines 2019* (pp. 1–19). France: Harris Interactive.
- Guo, L., Zhang, M., Kang, K., & Hu, M. (2017). Transforming followers into fans: A study of Chinese users of the we Chat Official Account. *Online Information Review*, 41, 1029–1045.
- Guo, S. (2019, November 29). Michelin comes to Beijing: To share or to compete. *Beijing Business Today*, p. 5.
- Hahl, O., & Zuckerman, E. W. (2014). The denigration of heroes? How the status attainment process shapes attributions of considerateness and authenticity. *American Journal of Sociology*, 120, 504–554.
- Haunschild, P. R., & Miner, A. S. (1997). Modes of Interorganizational Imitation: The Effects of Outcome Salience and Uncertainty. *Administrative Science Quarterly*, 42, 472–500.
- Hjalager, A.-M., & Richards, G. (2003). *Tourism and Gastronomy*. Routledge.
- Ho, C. (2019, March 4). Interview with a MICHELIN Guide Inspector from Thailand. Retrieved February 14, 2024, from MICHELIN Guide website: <https://guide.michelin.com/th/en/article/features/anonymous-interview-with-michelin-guide-thailand-s-restaurant-inspector>
- Hofstede, G. (1980). *Culture's Consequences: International Differences in Work-Related Values*. Beverly Hills, CA: SAGE.
- Hotelling, H. (1929). Stability in Competition. *The Economic Journal*, 39, 41–57.
- Hrebiniak, L. G., & Joyce, W. F. (1985). Organizational Adaptation: Strategic Choice and Environmental Determinism. *Administrative Science Quarterly*, 30, 336–349.
- Hsu, G. (2006). Evaluative schemas and the attention of critics in the US film industry. *Industrial and Corporate Change*, 15, 467–496.
- James, F. (2019). Red (Michelin) Stars Over China: Seeking Recognition in a Transnational Culinary Field. In *Culinary Nationalism in Asia* (p. 193). Bloomsbury Publishing.
- Johanson, J., & Vahlne, J. E. (2009). The Uppsala internationalization process model revisited:

- From liability of foreignness to liability of outsidership. *Journal of International Business Studies*, 40, 1411–1431.
- Johanson, J., & Vahlne, J.-E. (1977). The internationalization process of the firm—A model of knowledge development and increasing foreign market commitments. *Journal of International Business Studies*, 8, 23–32.
- Johnston, J., & Baumann, S. (2007). Democracy versus distinction: A study of omnivorousness in gourmet food writing. *American Journal of Sociology*, 113, 165–204.
- Judkis, M. (2021, October 23). South Korea paid big money to commission its Michelin Guide. Does that mean U.S. cities could do the same? *Washington Post*. Retrieved from <https://www.washingtonpost.com/news/food/wp/2017/10/24/south-korea-paid-big-money-to-commission-its-michelin-guide-does-that-mean-u-s-cities-could-do-the-same/>
- Jung, W., Sharkey, A., & Tan, D. (2024). Corporate social responsibility at the margins: Firms' responses to marginal inclusion on the Vault Law 100 ranking. *Strategic Management Journal*. <https://doi.org/10.1002/smj.3642>
- Karpik, L. (2010). *Valuing the Unique*. Retrieved from <https://press.princeton.edu/books/paperback/9780691137100/valuing-the-unique>
- Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First-Mover Advantage: A Synthesis, Conceptual Framework, and Research Propositions. *Journal of Marketing*, 56, 33–52.
- Khaire, M. (2017). The Importance of Being Independent: The Role of Intermediaries in Creating Market Categories. In *Research in the Sociology of Organizations: Vol. 51. From Categories to Categorization: Studies in Sociology, Organizations and Strategy at the Crossroads* (pp. 259–293). Emerald Publishing Limited.
- Khaire, M., & Wadhvani, R. D. (2010). Changing landscapes: The construction of meaning and value in a new market category—Modern Indian art. *Academy of Management Journal*, 53, 1281–1304.
- Kim, M., & Dellaposta, D. (2021). The Fickle Crowd: Reinforcement and Contradiction of Quality Evaluations in Cultural Markets. *Organization Science*, 33, 2496–2518.
- Kivela, J., & Crotts, J. C. (2006). Tourism and Gastronomy: Gastronomy's Influence on How Tourists Experience a Destination. *Journal of Hospitality & Tourism Research*, 30, 354–377.
- Kogut, B., & Singh, H. (1988). The Effect of National Culture on the Choice of Entry Mode. *Journal of International Business Studies*, 19, 411–432.
- Kostova, T. (1999). Transnational Transfer of Strategic Organizational Practices: A Contextual

- Perspective. *Academy of Management Review*, 24, 308–324.
- Kostova, T., & Zaheer, S. (1999). Organizational Legitimacy Under Conditions of Complexity: The Case of the Multinational Enterprise. *Academy of Management Review*, 24, 64–81.
- Kovács, B., & Hannan, M. T. (2010). The consequences of category spanning depend on contrast. In G. Hsu, G. Negro, & Ö. Koçak (Eds.), *Categories in Markets: Origins and Evolution* (pp. 175–201). Emerald Group Publishing Limited.
- Kovács, B., & Sharkey, A. J. (2014). The Paradox of Publicity: How Awards Can Negatively Affect the Evaluation of Quality. *Administrative Science Quarterly*, 59, 1–33.
- Lane, C. (2013). Taste makers in the “fine-dining” restaurant industry: The attribution of aesthetic and economic value by gastronomic guides. *Poetics*, 41, 342–365.
- Lane, C. (2019). Reverse cultural globalization: The case of haute cuisine in one global city. *Poetics*, 75, 101350.
- Lane, C., & Opazo, M. P. (2023). From Ethnic to High-End Cuisine: Recategorization and Status Change Among Restaurants in Global Cities. *Cultural Sociology*, 17499755231172825.
- Lane, C., & Opazo, M. P. (2024). *Cultural Flows in High-End Cuisine: From the Periphery to the Center*. London: Routledge.
- Lewis, B. W., & Carlos, W. C. (2023). The risk of being ranked: Investor response to marginal inclusion on the 100 Best Corporate Citizens list. *Strategic Management Journal*, 44, 117–140.
- Lieberman, M. B., & Montgomery, D. B. (1988). First-Mover Advantages. *Strategic Management Journal*, 9, 41–58.
- Lounsbury, M., & Rao, H. (2004). Sources of Durability and Change in Market Classifications: A Study of the Reconstitution of Product Categories in the American Mutual Fund Industry, 1944-1985. *Social Forces*, 82, 969–999.
- Luca, M. (2016, March 15). *Reviews, Reputation, and Revenue: The Case of Yelp.Com* [SSRN Scholarly Paper]. Rochester, NY. <https://doi.org/10.2139/ssrn.1928601>
- Martigny, V. (2010). Le goût des nôtres: Gastronomie et sentiment national en France. *Raisons politiques*, 37, 39–52.
- McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, 27, 415–444.
- Melé, D., & Sánchez-Runde, C. (2013). Cultural Diversity and Universal Ethics in a Global World. *Journal of Business Ethics*, 116, 681–687.
- Mennell, S. (1996). *All Manners of Food: Eating and Taste in England and France from the*

- Middle Ages to the Present*. University of Illinois Press.
- Messlerin, P., & Parc, J. (2014). The Effect of Screen Quotas and Subsidy Regime on Cultural Industry: A Case Study of French and Korean Film Industries. *Journal of International Business and Economy*, 15, 56–73.
- Meyer, J. W., & Rowan, B. (1977). Institutionalized Organizations: Formal Structure as Myth and Ceremony. *American Journal of Sociology*, 83, 340–363.
- Michelin Guide. (2023). MICHELIN Guides Worldwide. Retrieved November 13, 2023, from MICHELIN Guide website: <https://guide.michelin.com/en/michelin-guides-worldwide>
- Michelin Guide. (2024a). About the Michelin Guide. Retrieved August 29, 2024, from MICHELIN Guide website: <https://guide.michelin.com/en/about-us>
- Michelin Guide. (2024b). Everything You Want to Know About the Michelin Guide Inspectors. Retrieved August 29, 2024, from MICHELIN Guide website: <https://guide.michelin.com/gb/en/article/features/everything-you-want-to-know-about-the-michelin-guide-inspectors>
- Navis, C., & Glynn, M. A. (2010). How New Market Categories Emerge: Temporal Dynamics of Legitimacy, Identity, and Entrepreneurship in Satellite Radio, 1990–2005. *Administrative Science Quarterly*, 55, 439–471.
- Olson, D. M., & Waguespack, D. M. (2020). Strategic behavior by market intermediaries. *Strategic Management Journal*, 41, 2474–2492.
- OpenStreetMap. (2023). OpenStreetMap. Retrieved November 14, 2023, from OpenStreetMap website: <https://www.openstreetmap.org/>
- Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance*, 16, 366–387.
- Peracchio, L. A., & Tybout, A. M. (1996). The Moderating Role of Prior Knowledge in Schema-Based Product Evaluation. *Journal of Consumer Research*, 23, 177–192.
- Phillips, D. J., & Zuckerman, E. W. (2001). Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. *American Journal of Sociology*, 10, 379–429.
- Piazza, A., & Castellucci, F. (2014). Status in Organization and Management Theory. *Journal of Management*, 40, 287–315.
- Podolny, J. M. (1993). A Status-Based Model of Market Competition. *American Journal of Sociology*, 98, 829–872.
- Podolny, J. M. (1994). Market Uncertainty and the Social Character of Economic Exchange.

- Administrative Science Quarterly*, 39, 458–483.
- Podolny, J. M. (2001). Networks as the pipes and prisms of the market. *American Journal of Sociology*, 10, 33–60.
- Podolny, J. M. (2005). *Status Signals*. Princeton University Press.
- Podolny, J. M., & Phillips, D. J. (1996). The Dynamics of Organizational Status. *Industrial and Corporate Change*, 5, 453–471.
- Porter, M. E. (2011). *Competitive Advantage of Nations: Creating and Sustaining Superior Performance*. Simon and Schuster.
- Proserpio, D., & Zervas, G. (2017). Online Reputation Management: Estimating the Impact of Management Responses on Consumer Reviews. *Marketing Science*, 36, 645–665.
- Rao, H., Monin, P., & Durand, R. (2003). Institutional Change in Toque Ville: Nouvelle Cuisine as an Identity Movement in French Gastronomy. *American Journal of Sociology*, 108, 795–843.
- Rauhvargers, A. (2014). Where Are the Global Rankings Leading Us? An Analysis of Recent Methodological Changes and New Developments. *European Journal of Education*, 49, 29–44.
- Rindova, V. P., Martins, L. L., Srinivas, S. B., & Chandler, D. (2018). The Good, the Bad, and the Ugly of Organizational Rankings: A Multidisciplinary Review of the Literature and Directions for Future Research. *Journal of Management*, 44, 2175–2208.
- Robinson, W. T. (1988). Sources of Market Pioneer Advantages: The Case of Industrial Goods Industries: *Journal of Marketing Research (JMR)*. *Journal of Marketing Research (JMR)*, 25, 87–94.
- Robinson, W. T., & Fornell, C. (1985). Sources of Market Pioneer Advantages in Consumer Goods Industries. *Journal of Marketing Research (JMR)*, 22, 305–317.
- Sarta, A., Durand, R., & Vergne, J.-P. (2021). Organizational Adaptation. *Journal of Management*, 47, 43–75.
- Sauder, M., & Espeland, W. N. (2009). The Discipline of Rankings: Tight Coupling and Organizational Change. *American Sociological Review*, 74, 63–82.
- Sauder, M., & Lancaster, R. (2006). Do Rankings Matter? The Effects of U.S. News & World Report Rankings on the Admissions Process of Law Schools. *Law & Society Review*, 40, 105–134.
- Scharfstein, D. S., & Stein, J. C. (1990). Herd Behavior and Investment. *American Economic Review*, 80, 465–479.
- Schücking, L. L. (1974). *The Sociology of Literary Taste*. University of Chicago Press.

- Shafto, P., & Coley, J. D. (2003). Development of Categorization and Reasoning in the Natural World: Novices to Experts, Naive Similarity to Ecological Knowledge. *Journal of Experimental Psychology: Learning Memory and Cognition*, *29*, 641–649.
- Sharkey, A., Kovacs, B., & Hsu, G. (2023). Expert Critics, Rankings, and Review Aggregators: The Changing Nature of Intermediation and the Rise of Markets with Multiple Intermediaries. *Academy of Management Annals*, *17*, 1–36.
- Shi, C. (2021, November 26). The Michelin Guide's Sixth Year in Mainland China: Continuing to Promote the Healthy Development of the Restaurant Industry. *Jiemian Global*. Retrieved from <https://www.jiemian.com/article/6853059.html>
- Slovic, P. (1993). Perceived Risk, Trust, and Democracy. *Risk Analysis*, *13*, 675–682.
- Suchman, M. C. (1995). Managing Legitimacy: Strategic and Institutional Approaches. *Academy of Management Review*, *20*, 571–610.
- Sun, M. (2012). How Does the Variance of Product Ratings Matter? *Management Science*, *58*, 696–707.
- Szymanski, D. M., Troy, L. C., & Bharadwaj, S. G. (1995). Order of entry and business performance: An empirical synthesis and reexamination: Journal of Marketing. *Journal of Marketing*, *59*, 17.
- Taeuscher, K., Zhao, E. Y., & Lounsbury, M. (2022). Categories and narratives as sources of distinctiveness: Cultural entrepreneurship within and across categories. *Strategic Management Journal*, *43*, 2101–2134.
- The Culture Factor Group. (2023). Country comparison tool. Retrieved November 14, 2023, from <https://www.hofstede-insights.com/country-comparison-tool>
- Tihanyi, L., Griffith, D. A., & Russell, C. J. (2005). The effect of cultural distance on entry mode choice, international diversification, and MNE performance: A meta-analysis. *Journal of International Business Studies*, *36*, 270–283.
- Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*, 1124–1131.
- Urban, G. L., Carter, T., Gaskin, S., & Mucha, Z. (1986). Market Share Rewards to Pioneering Brands: An Empirical Analysis and Strategic Implications. *Management Science*, *32*, 645–659.
- Ursu, R. M. (2018). The Power of Rankings: Quantifying the Effect of Rankings on Online Consumer Search and Purchase Decisions. *Marketing Science*, *37*, 530–552.
- Vahlne, J.-E., & Johanson, J. (2017). From internationalization to evolution: The Uppsala model at 40 years. *Journal of International Business Studies*, *48*, 1087–1102.

- Veil, S. R., Petrun, E. L., & Roberts, H. A. (2012). Issue Management Gone Awry: When Not to Respond to an Online Reputation Threat. *Corporate Reputation Review*, *15*, 319–332.
- Vincent, A. (2018). *Shaping Tastes: Authority versus Democracy, Professionals versus Amateurs*. 1–7.
- Wang, T., Wezel, F. C., & Forgues, B. (2016). Protecting Market Identity: When and How Do Organizations Respond to Consumers' Devaluations? *Academy of Management Journal*, *59*, 135–162.
- Wang, Z. (2023, April 5). Black Pearl Vs. Michelin Guide: Culture and Controversy In China's Luxury Cuisine Industry. *Jing Daily*. Retrieved from <https://jingdaily.com/michelin-guide-vs-black-pearl-china-luxury-cuisine/>
- Wu, C., Che, H., Chan, T. Y., & Lu, X. (2015). The Economic Value of Online Reviews. *Marketing Science*, *34*, 739–754.
- Xinhua. (2023, October 6). Exquisite dining a sizzling new trend in China. *China Daily*. Retrieved from <https://www.chinadaily.com.cn/a/202310/06/WS6520ca85a310d2dce4bb9491.html>
- Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*, 634–639.
- Zhao, E. Y. (2022). *Optimal Distinctiveness: A New Agenda for the Study of Competitive Positioning of Organizations and Markets*. Cambridge: Cambridge University Press.
- Zhao, E. Y., Fisher, G., Lounsbury, M., & Miller, D. (2017). Optimal distinctiveness: Broadening the interface between institutional theory and strategic management. *Strategic Management Journal*, *38*, 93–113.
- Zhao, E. Y., & Glynn, M. A. (2022). Optimal Distinctiveness: On Being the Same and Different. *Organization Theory*, *3*, 1–15.
- Zhu, F., & Zhang, X. (Michael). (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing*, *74*, 133–148.
- Zuckerman, E. W. (1999). The Categorical Imperative: Securities Analysts and the Illegitimacy Discount. *American Journal of Sociology*, *104*, 1398–1438.

TABLES AND FIGURES

Table 1.1. Summary of Descriptives

	Mean	SD	Min	Max	N
Imi_coverage	.055	.227	0.000	1	4662
Imi_ranking	.011	.105	0.000	1	4662
Status(log)	3.550	1.390	0.693	6.506	4328
Market_know(log)	5.491	.503	4.171	6.051	4208
First_mover	.449	.497	0.000	1	4662
Customer_rating	4.425	.263	2.500	5	3974
Customer_reviews	364.428	525.587	1.000	4993	3974
Customer_expenditure	893.156	701.720	0.000	6593.823	3974

Table 1.2. Correlational Table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Imi_coverage	1							
(2) Imi_ranking	0.329	1						
(3) Status(log)	-0.144	-0.054	1					
(4) Market_know(log)	0.059	0.020	0.033	1				
(5) First_mover	-0.186	-0.056	0.371	-0.162	1			
(6) Customer_rating	0.051	-0.001	0.105	-0.082	0.058	1		
(7) Customer_reviews	0.029	0.047	-0.242	-0.053	0.018	-0.071	1	
(8) Customer_expenditure	0.129	0.027	0.051	0.079	0.060	0.238	-0.257	1

Table 1.3. The Frequency of Imitation by the Michelin Guide and the Black Pearl Guide

	Coverage Size		Imitation in Coverage		Imitation in Ranking	
	M	B	M	B	M	B
2017	106	-	-	-	-	-
2018	139	147	-	37	-	21
2019	151	137	1	42	0	8
2020	195	153	11	41	5	3
2021	211	154	11	45	0	5
2022	222	151	13	54	6	6

Table 1.4. Regression Results, Dependent Variable = Imitation in Coverage

VARIABLES	(1) LPM	(2) LPM	(3) Logit	(4) Probit
Status(log)		-0.009** (0.004)	-0.198** (0.093)	-0.096** (0.046)
Market_know(log)		-0.112** (0.053)	-3.598*** (1.338)	-1.573*** (0.605)
First_mover		-0.072*** (0.008)	-1.692*** (0.243)	-0.763*** (0.105)
Customer_rating	0.019* (0.011)	0.037*** (0.013)	1.046*** (0.317)	0.508*** (0.162)
Customer_reviews	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Customer_expenditure	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Constant	-0.134*** (0.048)	0.363* (0.219)	15.099* (8.164)	6.027 (3.710)
Observations	4,012	3,492	3,007	3,007
R-squared	0.027	0.071		
Year FE	Yes	Yes	Yes	Yes
Restaurant FE	No	No	No	No

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

Table 1.4 (continued) Regression Results, Dependent Variable = Imitation in Coverage

VARIABLES	(5) LPM	(6) LPM	(7) Logit	(8) Probit
Status(log)		-0.014** (0.007)	-0.425** (0.203)	-0.236** (0.109)
Market_know(log)		-0.013 (0.061)	-2.378 (1.923)	-1.297 (0.985)
First_mover		-0.101*** (0.010)	-3.109*** (0.402)	-1.689*** (0.177)
Customer_rating	0.011 (0.013)	0.016 (0.014)	0.945 (1.074)	0.626 (0.597)
Customer_reviews	0.000*** (0.000)	0.000* (0.000)	0.001*** (0.001)	0.001*** (0.000)
Customer_expenditure	0.000* (0.000)	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)
Constant	-0.181*** (0.059)	0.029 (0.236)	11.636 (12.422)	5.891 (6.494)
Observations	4,012	3,492	611	611
R-squared	0.311	0.359		
Year FE	Yes	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes	Yes

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

Table 1.5. Regression Results, Dependent Variable = Imitation in Ranking

VARIABLES	(9) LPM	(10) LPM	(11) Logit	(12) Probit
Status(log)		-0.001 (0.002)	-0.286 (0.218)	-0.097 (0.076)
Market_know(log)		-0.004 (0.021)	0.218 (2.386)	-0.034 (0.840)
First_mover		-0.009*** (0.003)	-1.126** (0.542)	-0.421** (0.187)
Customer_rating	0.001 (0.005)	-0.000 (0.006)	0.038 (0.866)	-0.014 (0.316)
Customer_reviews	0.000*** (0.000)	0.000** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Customer_expenditure	0.000** (0.000)	0.000** (0.000)	0.001*** (0.000)	0.000*** (0.000)
Constant	-0.014 (0.022)	0.026 (0.095)	-5.204 (15.759)	-1.785 (5.537)
Observations	4,012	3,492	3,007	3,007
R-squared	0.010	0.009		
Year FE	Yes	Yes	Yes	Yes
Restaurant FE	No	No	No	No

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

Table 1.5 (continued). Regression Results, Dependent Variable = Imitation in Ranking

VARIABLES	(13) LPM	(14) LPM	(15) Logit	(16) Probit
Status(log)		-0.000 (0.003)	-0.021 (0.344)	-0.011 (0.192)
Market_know(log)		-0.003 (0.026)	-2.454 (3.086)	-1.292 (1.597)
First_mover		-0.012** (0.005)	-1.671*** (0.640)	-0.893*** (0.277)
Customer_rating	0.006 (0.006)	0.004 (0.005)	0.792 (2.372)	0.532 (1.213)
Customer_reviews	0.000*** (0.000)	0.000*** (0.000)	0.006*** (0.002)	0.003*** (0.001)
Customer_expenditure	0.000 (0.000)	0.000 (0.000)	0.003* (0.002)	0.002** (0.001)
Constant	-0.061** (0.026)	-0.009 (0.105)	4.506 (22.655)	1.668 (11.255)
Observations	4,012	3,492	216	216
R-squared	0.103	0.123		
Year FE	Yes	Yes	Yes	Yes
Restaurant FE	Yes	Yes	Yes	Yes

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

Table 2.1. Favorable/Unfavorable measurement of the evaluation outcome

	High-Low ratio	Gini coefficient	Skewness	Kurtosis
Evaluation Outcome	Favorable	Favorable	Unfavorable	Unfavorable

Table 2.2. Summary of Statistics

	Mean	SD	Min	Max	N
High-Low ratio	.051	.028	0.009	.157	166
Gini	.153	.024	0.116	.22	166
Skewness	2.183	.375	1.231	2.951	166
Kurtosis	4.05	1.789	0.201	8.077	166
Cultural Distance	52.382	25.343	0.000	93.973	174
Cuisine Distance A	8.511	4.422	1.000	12	174
Cuisine Distance B	8.167	4.33	1.000	12	174
Geographical Distance	3041.36	3834.756	0.000	10733.752	174
Local competitor	.724	.448	0.000	1	174
Total restaurants	235.428	164.626	51.000	638	166
World 50 Best	2.701	2.225	0.000	8	174
Population	180.734	365.631	4.839	1412.36	162
GDP	4.33	5.568	0.194	25.463	162
GDP per capita	44666.477	18073.319	4550.474	92101.47	162
Private consumption	2.317	3.297	0.080	15.9	159
International tourism	62.001	65.455	0.250	217.88	152

Table 2.3. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Kurtosis	1																
(2) Skewness	0.991	1															
(3) Gini	-0.886	-0.87	1														
(4) High-Low ratio	-0.616	-0.592	0.898	1													
(5) Cultural Distance	-0.349	-0.388	0.41	0.386	1												
(6) Cuisine Distance A	0.21	0.232	-0.355	-0.357	0.23	1											
(7) Cuisine Distance B	0.031	0.012	-0.247	-0.38	0.402	0.825	1										
(8) GeoDistance	-0.693	-0.704	0.841	0.772	0.587	-0.394	-0.165	1									
(9) Local competitor	0.248	0.245	-0.292	-0.27	-0.134	0.069	0.214	-0.292	1								
(10) Total restaurants	0.027	0.032	0.065	0.037	-0.488	-0.716	-0.507	0.073	0.163	1							
(11) World 50 Best	0.148	0.211	0.086	0.304	-0.276	-0.238	-0.515	0.011	-0.025	0.233	1						
(12) Population	-0.514	-0.535	0.673	0.72	0.513	-0.312	-0.3	0.593	-0.216	-0.202	-0.056	1					
(13) GDP	-0.479	-0.443	0.688	0.773	0.485	-0.113	-0.124	0.641	0.075	-0.105	0.324	0.579	1				
(14) GDP per capita	0.016	0.036	-0.248	-0.425	-0.014	0.488	0.578	-0.296	0.321	-0.158	-0.205	-0.591	-0.187	1			
(15) First 3-year operation	-0.209	-0.206	0.196	0.112	0.245	-0.072	0.012	0.281	-0.248	-0.19	-0.169	0.22	-0.012	0.032	1		
(16) Private consumption	-0.384	-0.336	0.575	0.664	0.405	-0.022	-0.056	0.544	0.134	-0.099	0.401	0.371	0.969	-0.04	-0.054	1	
(17) International tourism	-0.158	-0.099	0.402	0.578	-0.246	-0.498	-0.723	0.156	-0.003	0.307	0.729	0.387	0.511	-0.401	-0.060	0.483	1

Table 2.4a. OLS model on the Evaluation Penalty by Country Differences

VARIABLES	(1) H-L ratio	(2) H-L ratio	(3) H-L ratio	(4) H-L ratio
Total restaurants (log)	-0.006*** (0.002)	-0.017*** (0.003)	-0.014*** (0.003)	-0.015*** (0.003)
World 50 Best	0.004*** (0.001)	-0.000 (0.001)	0.003*** (0.001)	0.002 (0.001)
Population (log)	-0.003 (0.039)	-0.038 (0.028)	-0.033 (0.034)	-0.042 (0.033)
GDP (log)	0.082* (0.042)	0.073** (0.029)	0.089** (0.036)	0.106*** (0.034)
GDP per capita (log)	-0.008 (0.039)	-0.039 (0.027)	-0.031 (0.033)	-0.035 (0.032)
Private consumption (log)	-0.058*** (0.014)	-0.014 (0.012)	-0.034*** (0.013)	-0.037*** (0.012)
International tourism (log)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.009*** (0.003)
Cultural Distance (log)		-0.025*** (0.003)		
Cuisine Distance A			-0.002*** (0.000)	
Cuisine Distance B				-0.003*** (0.001)
Geographical Distance (log)		0.010*** (0.001)	-0.000 (0.001)	-0.001 (0.001)
Local Competitor		-0.008*** (0.003)	-0.012*** (0.004)	-0.009** (0.004)
Constant	0.119 (0.531)	0.679* (0.370)	0.535 (0.454)	0.649 (0.441)
Observations	143	143	143	143
R-squared	0.763	0.872	0.804	0.823
Year FE	Yes	Yes	Yes	Yes

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

Table 2.4b. OLS model on the Evaluation Penalty by Country Differences

VARIABLES	(5) Gini	(6) Gini	(7) Gini	(8) Gini
Total restaurants (log)	-0.002 (0.002)	-0.014*** (0.002)	-0.015*** (0.003)	-0.013*** (0.003)
World 50 Best	0.003*** (0.001)	-0.001 (0.001)	0.002* (0.001)	0.001 (0.001)
Population (log)	0.002 (0.037)	-0.034 (0.022)	-0.031 (0.030)	-0.040 (0.032)
GDP (log)	0.102** (0.040)	0.091*** (0.024)	0.104*** (0.033)	0.126*** (0.034)
GDP per capita (log)	0.006 (0.036)	-0.027 (0.022)	-0.018 (0.030)	-0.024 (0.031)
Private consumption (log)	-0.084*** (0.012)	-0.036*** (0.012)	-0.052*** (0.013)	-0.060*** (0.012)
International tourism (log)	-0.006*** (0.002)	-0.006*** (0.002)	-0.007*** (0.002)	-0.014*** (0.004)
Cultural Distance (log)		-0.027*** (0.002)		
Cuisine Distance A			-0.003*** (0.000)	
Cuisine Distance B				-0.004*** (0.001)
Geographical Distance (log)		0.010*** (0.001)	-0.001 (0.001)	-0.001 (0.001)
Local Competitor		-0.009*** (0.003)	-0.014*** (0.004)	-0.010*** (0.004)
Constant	0.030 (0.497)	0.633** (0.298)	0.520 (0.407)	0.622 (0.426)
Observations	143	143	143	143
R-squared	0.668	0.844	0.768	0.779
Year FE	Yes	Yes	Yes	Yes

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

Table 2.4c. OLS model on the Evaluation Penalty by Country Differences

VARIABLES	(9)	(10)	(11)	(12)
	Skewness	Skewness	Skewness	Skewness
Total restaurants (log)	0.041 (0.040)	0.222*** (0.052)	0.328*** (0.053)	0.248*** (0.073)
World 50 Best	-0.039* (0.021)	0.024 (0.020)	-0.020 (0.024)	0.004 (0.025)
Population (log)	0.096 (0.599)	0.538 (0.466)	0.529 (0.538)	0.653 (0.604)
GDP (log)	-1.918*** (0.622)	-1.670*** (0.505)	-1.762*** (0.593)	-2.221*** (0.625)
GDP per capita (log)	-0.028 (0.599)	0.378 (0.463)	0.253 (0.531)	0.340 (0.593)
Private consumption (log)	1.566*** (0.275)	0.867*** (0.321)	0.959*** (0.338)	1.182*** (0.323)
International tourism (log)	0.145*** (0.043)	0.155*** (0.050)	0.175*** (0.061)	0.287*** (0.092)
Cultural Distance (log)		0.397*** (0.050)		
Culinary Cultural Distance A			0.056*** (0.008)	
Culinary Cultural Distance B				0.065*** (0.014)
Geographical Distance (log)		-0.146*** (0.027)	0.020 (0.019)	0.030 (0.021)
Local Competitor		0.100* (0.055)	0.179*** (0.057)	0.106* (0.061)
Constant	2.514 (8.214)	-3.972 (6.407)	-4.814 (6.930)	-5.210 (7.672)
Observations	143	143	143	143
R-squared	0.525	0.681	0.677	0.652
Year FE	Yes	Yes	Yes	Yes

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

Table 2.4d. OLS model on the Evaluation Penalty by Country Differences

VARIABLES	(13) Kurtosis	(14) Kurtosis	(15) Kurtosis	(16) Kurtosis
Total restaurants (log)	0.274 (0.189)	1.248*** (0.237)	1.571*** (0.251)	1.278*** (0.329)
World 50 Best	-0.252** (0.098)	0.078 (0.095)	-0.156 (0.111)	-0.043 (0.119)
Population (log)	0.161 (2.823)	2.431 (1.990)	2.288 (2.507)	2.903 (2.787)
GDP (log)	-9.260*** (3.014)	-7.849*** (2.262)	-8.587*** (2.833)	-10.658*** (2.950)
GDP per capita (log)	-0.645 (2.822)	1.462 (1.994)	0.803 (2.479)	1.216 (2.736)
Private consumption (log)	7.873*** (1.350)	4.110*** (1.516)	4.948*** (1.618)	5.873*** (1.535)
International tourism (log)	0.634*** (0.202)	0.712*** (0.228)	0.787*** (0.279)	1.325*** (0.411)
Cultural Distance (log)		2.072*** (0.239)		
Cuisine Distance A			0.249*** (0.038)	
Cuisine Distance B				0.308*** (0.062)
Geographical Distance (log)		-0.708*** (0.135)	0.116 (0.090)	0.167* (0.100)
Local Competitor		0.515** (0.245)	1.090*** (0.268)	0.646** (0.267)
Constant	14.337 (38.827)	-26.791 (27.616)	-20.266 (34.149)	-26.953 (37.132)
Observations	143	143	143	143
R-squared	0.528	0.707	0.659	0.645
Year FE	Yes	Yes	Yes	Yes

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

Table 2.5a. OLS model on the Moderation of International Tourism

VARIABLES	(17) H-L ratio	(18) H-L ratio	(19) H-L ratio	(20) Gini	(21) Gini	(22) Gini
Total restaurants (log)	-0.019*** (0.003)	-0.017*** (0.003)	-0.016*** (0.004)	-0.014*** (0.003)	-0.015*** (0.003)	-0.012*** (0.004)
World 50 Best	-0.000 (0.001)	0.002 (0.001)	0.001 (0.001)	-0.001 (0.001)	0.002 (0.001)	0.001 (0.001)
Population (log)	-0.043 (0.029)	-0.044 (0.036)	-0.044 (0.034)	-0.036 (0.023)	-0.033 (0.030)	-0.037 (0.032)
GDP (log)	0.072** (0.030)	0.088** (0.037)	0.103*** (0.035)	0.091*** (0.025)	0.103*** (0.034)	0.129*** (0.034)
GDP per capita (log)	-0.044 (0.029)	-0.043 (0.035)	-0.039 (0.034)	-0.029 (0.022)	-0.021 (0.030)	-0.019 (0.031)
Private consumption (log)	-0.009 (0.013)	-0.026* (0.014)	-0.034** (0.014)	-0.035*** (0.012)	-0.050*** (0.014)	-0.063*** (0.013)
Cultural Distance (log)	-0.024*** (0.003)			-0.026*** (0.002)		
Cuisine Distance A		-0.001** (0.001)			-0.003*** (0.001)	
Cuisine Distance B			-0.003*** (0.001)			-0.004*** (0.001)
Geographical Distance (log)	0.014*** (0.003)	0.009** (0.005)	0.002 (0.005)	0.011*** (0.004)	0.001 (0.005)	-0.005 (0.005)
International tourism (log)	0.005 (0.006)	0.013 (0.008)	-0.003 (0.010)	-0.004 (0.007)	-0.004 (0.009)	-0.020** (0.008)
GeoDist (log)*IntTourism (log)	-0.001 (0.001)	-0.002** (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)
Local Competitor	-0.007** (0.003)	-0.008* (0.004)	-0.008* (0.004)	-0.009*** (0.003)	-0.013*** (0.004)	-0.011*** (0.004)
Constant	0.731* (0.389)	0.641 (0.480)	0.674 (0.454)	0.649** (0.302)	0.538 (0.408)	0.593 (0.424)
Observations	143	143	143	143	143	143
R-squared	0.873	0.810	0.824	0.844	0.768	0.780
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 2.5b. OLS model on the Moderation of International Tourism

VARIABLES	(23)	(24)	(25)	(26)	(27)	(28)
	Skewness	Skewness	Skewness	Kurtosis	Kurtosis	Kurtosis
Total restaurants (log)	0.178** (0.073)	0.270*** (0.059)	0.172** (0.077)	1.035*** (0.333)	1.349*** (0.284)	0.953*** (0.356)
World 50 Best	0.017 (0.017)	-0.041** (0.020)	-0.013 (0.020)	0.046 (0.081)	-0.236** (0.103)	-0.116 (0.101)
Population (log)	0.431 (0.448)	0.297 (0.509)	0.417 (0.586)	1.911 (1.904)	1.407 (2.416)	1.895 (2.721)
GDP (log)	-1.686*** (0.475)	-1.786*** (0.563)	-2.409*** (0.601)	-7.924*** (2.112)	-8.677*** (2.743)	-11.460*** (2.867)
GDP per capita (log)	0.260 (0.440)	-0.029 (0.500)	0.010 (0.573)	0.891 (1.868)	-0.269 (2.371)	-0.193 (2.659)
Private consumption (log)	0.959*** (0.249)	1.142*** (0.258)	1.464*** (0.224)	4.553*** (1.165)	5.645*** (1.313)	7.076*** (1.122)
Cultural Distance (log)	0.425*** (0.051)			2.208*** (0.251)		
Cuisine Distance A		0.070*** (0.010)			0.300*** (0.048)	
Cuisine Distance B			0.093*** (0.013)			0.426*** (0.063)
Geographical Distance (log)	-0.063 (0.106)	0.235** (0.115)	0.315*** (0.115)	-0.336 (0.497)	0.930 (0.571)	1.382** (0.567)
International tourism (log)	0.314* (0.186)	0.539*** (0.195)	0.812*** (0.198)	1.486* (0.883)	2.167** (0.980)	3.567*** (0.993)
GeoDist (log)*IntTourism (log)	-0.020 (0.022)	-0.044* (0.022)	-0.057** (0.022)	-0.095 (0.101)	-0.166 (0.110)	-0.244** (0.109)
Local Competitor	0.132** (0.064)	0.265*** (0.074)	0.190** (0.077)	0.717** (0.293)	1.277*** (0.355)	0.975*** (0.364)
Constant	-3.793 (6.044)	-1.709 (6.871)	-3.085 (7.804)	-21.333 (25.680)	-11.111 (32.574)	-17.229 (36.241)
Observations	143	143	143	143	143	143
R-squared	0.690	0.699	0.678	0.712	0.671	0.666
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 2.6. Regression results of the Restaurant Ranking by Country Differences

VARIABLES	(29) OLS	(30) OLS	(31) OLS	(32) Ordered Logit	(33) Ordered Logit	(34) Ordered Logit	(35) Ordered Probit	(36) Ordered Probit	(37) Ordered Probit
Price Level	0.274*** (0.014)	0.277*** (0.014)	0.277*** (0.014)	2.204*** (0.143)	2.219*** (0.143)	2.223*** (0.143)	1.162*** (0.071)	1.174*** (0.071)	1.177*** (0.072)
French Cuisine	0.040 (0.031)	0.062** (0.029)	0.064** (0.030)	0.225 (0.154)	0.353** (0.146)	0.372** (0.147)	0.126 (0.085)	0.185** (0.081)	0.199** (0.082)
Cultural Distance (log)	-0.011** (0.005)			-0.080*** (0.031)			-0.032* (0.017)		
Cuisine Distance A		-0.001 (0.005)			-0.024 (0.029)			-0.003 (0.016)	
Cuisine Distance B			0.001 (0.004)			-0.000 (0.020)			0.007 (0.011)
Geographical Distance (log)	0.025*** (0.006)	0.020*** (0.005)	0.019*** (0.006)	0.172*** (0.040)	0.136*** (0.034)	0.129*** (0.035)	0.090*** (0.020)	0.075*** (0.018)	0.070*** (0.019)
Local competitor	-0.003 (0.025)	-0.013 (0.025)	-0.015 (0.025)	0.043 (0.132)	-0.019 (0.131)	-0.030 (0.131)	0.040 (0.073)	0.011 (0.073)	0.003 (0.073)
Threshold parameter estimates									
q ₁				10.807*** (0.612)	10.655*** (0.591)	10.648*** (0.597)	5.806*** (0.315)	5.769*** (0.307)	5.759*** (0.310)
q ₂				12.619*** (0.618)	12.463*** (0.596)	12.455*** (0.602)	6.769*** (0.322)	6.730*** (0.314)	6.721*** (0.317)
Constant	0.100 (0.067)	0.116* (0.066)	0.118* (0.067)						
Observations	3,081	3,081	3,081	3,081	3,081	3,081	3,081	3,081	3,081
R-squared	0.098	0.097	0.097						

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

Table 3.1. Descriptive Statistics (first approach)

	Mean	SD	Min	Max	1	2	3	4	5	6
1.Timely response	0.11	0.32	0	1	1					
2.Tone	0.16	0.36	0	1	-0.10	1				
3.Post	0.49	0.50	0	1	0.02	0.01	1			
4.Consumer rating	4.37	0.87	0.5	5	0.05	0.09	-0.02	1		
5.Daily review	5.41	4.51	1	84	-0.00	0.07	0.09	0.04	1	
6.Review length	150.49	160.88	0	4678	-0.01	-0.00	0.04	-0.05	0.03	1

Table 3.2. Regressions on Response Probability and Tone (first approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Response OLS	Response Logit	Response Probit	Tone OLS	Tone Logit	Tone Probit
Status Decrease	-0.042*** (0.011)	-0.837*** (0.191)	-0.392*** (0.089)	0.348*** (0.037)	3.310*** (0.256)	1.742*** (0.140)
Status Increase	-0.026*** (0.003)	-0.303*** (0.041)	-0.178*** (0.023)	0.075*** (0.008)	0.857*** (0.076)	0.440*** (0.043)
Post	-0.008*** (0.002)	-0.154*** (0.033)	-0.103*** (0.019)	0.037*** (0.005)	0.578*** (0.078)	0.286*** (0.043)
Status Decrease*Post	-0.051*** (0.016)	-0.226 (0.229)	-0.226* (0.118)	0.132*** (0.042)	0.123 (0.253)	0.239 (0.149)
Status Increase*Post	0.018*** (0.003)	0.303*** (0.056)	0.171*** (0.031)	-0.061*** (0.010)	-0.809*** (0.107)	-0.415*** (0.060)
Customer Rating	0.007*** (0.001)	0.110*** (0.016)	0.051*** (0.009)	0.026*** (0.002)	0.396*** (0.038)	0.194*** (0.021)
Daily Review	-0.000* (0.000)	-0.005 (0.003)	-0.004** (0.002)	-0.000 (0.001)	-0.002 (0.007)	-0.000 (0.004)
Review Length	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-0.014** (0.005)	-2.631*** (0.183)	-1.494*** (0.095)	0.390*** (0.029)	-1.574*** (0.223)	-0.748*** (0.126)
Observations	105,077	63,288	63,288	22,070	16,854	16,854
R-squared	0.385			0.324		
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.3. Descriptive Statistics (second approach)

	Mean	SD	Min	Max	1	2	3	4	5	6
1.Restaurant response	0.22	0.41	0	1	1					
2.Tone	0.16	0.36	0	1	-	1				
3.Post	0.50	0.50	0	1	0.03	0.02	1			
4.Consumer rating	4.37	0.87	0.5	5	-0.00	0.08	-0.02	1		
5.Daily review	5.41	4.49	1	84	0.01	0.04	0.13	0.05	1	
6.Review length	149.90	161.16	0	4678	0.01	-0.01	0.03	-0.05	0.04	1

Table 3.4. Regressions on Response Probability and Tone (second approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Response OLS	Response Logit	Response Probit	Tone OLS	Tone Logit	Tone Probit
Status Decrease	-0.034** (0.014)	-0.702*** (0.155)	-0.375*** (0.075)	0.209*** (0.044)	2.671*** (0.377)	1.305*** (0.204)
Status Increase	-0.059*** (0.003)	-0.824*** (0.047)	-0.463*** (0.026)	0.084*** (0.008)	1.007*** (0.090)	0.505*** (0.049)
Post	-0.031*** (0.002)	-0.627*** (0.035)	-0.356*** (0.020)	0.017*** (0.005)	0.355*** (0.075)	0.150*** (0.040)
Status Decrease*Post	-0.044** (0.017)	-0.230 (0.219)	-0.045 (0.121)	0.310*** (0.052)	0.597* (0.350)	0.553*** (0.201)
Status Increase*Post	0.035*** (0.003)	0.658*** (0.059)	0.332*** (0.033)	-0.063*** (0.010)	-0.864*** (0.107)	-0.432*** (0.060)
Customer Rating	-0.001 (0.001)	-0.027* (0.016)	-0.032*** (0.009)	0.019*** (0.002)	0.259*** (0.035)	0.126*** (0.019)
Daily Review	-0.002*** (0.000)	-0.041*** (0.005)	-0.025*** (0.003)	0.001 (0.001)	0.002 (0.007)	0.003 (0.004)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.060*** (0.006)	-1.010*** (0.155)	-0.546*** (0.087)	0.505*** (0.028)	-0.745*** (0.218)	-0.285** (0.120)
Observations	102,599	58,712	58,712	22,224	16,937	16,937
R-squared	0.654			0.321		
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.5. Regressions on Consumer Rating and Daily Consumer Reviews

VARIABLES	(1) Consumer Rating OLS	(2) Consumer Rating Ordered Probit	(3) Consumer Rating Ordered Logit	(4) Daily Reviews OLS
Status Decrease	0.039 (0.033)	0.076 (0.050)	0.130 (0.085)	0.186 (0.149)
Status Increase	0.008 (0.009)	0.003 (0.011)	-0.004 (0.019)	0.583*** (0.042)
Post	0.032*** (0.007)	0.055*** (0.009)	0.087*** (0.015)	0.195*** (0.027)
Status Decrease*Post	-0.058 (0.046)	-0.074 (0.067)	-0.095 (0.113)	-1.094*** (0.158)
Status Increase*Post	-0.046*** (0.012)	-0.057*** (0.015)	-0.090*** (0.026)	-0.197*** (0.054)
Daily Review	0.002** (0.001)	0.003*** (0.001)	0.007*** (0.002)	
Review Length	-0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	
/cut1		-2.976*** (0.078)	-5.775*** (0.137)	
/cut2		-2.661*** (0.078)	-4.975*** (0.135)	
/cut3		-2.584*** (0.077)	-4.791*** (0.135)	
/cut4		-2.396*** (0.077)	-4.362*** (0.134)	
/cut5		-2.274*** (0.077)	-4.095*** (0.134)	
/cut6		-1.931*** (0.077)	-3.394*** (0.134)	
/cut7		-1.684*** (0.077)	-2.926*** (0.134)	
/cut8		-0.975*** (0.077)	-1.706*** (0.134)	
/cut9		-0.464*** (0.077)	-0.879*** (0.133)	
Constant	4.627*** (0.040)			0.844*** (0.065)
Observations	105,077	105,077	105,077	33,802
R-squared	0.037			0.413
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table 3.6a. Regressions on Response Probability subsampled by consumer rating (first approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	High: OLS	Low: OLS	High: Probit	Low: Probit	High: Logit	Low: Logit
Status Decrease	-0.058*** (0.012)	-0.009 (0.021)	-1.085*** (0.237)	-0.377 (0.339)	-0.537*** (0.112)	-0.125 (0.153)
Status Increase	-0.020*** (0.003)	-0.034*** (0.005)	-0.214*** (0.050)	-0.459*** (0.075)	-0.122*** (0.029)	-0.269*** (0.042)
Post	-0.008*** (0.002)	-0.009*** (0.003)	-0.157*** (0.041)	-0.179*** (0.057)	-0.097*** (0.023)	-0.125*** (0.032)
Status Decrease*Post	-0.028 (0.019)	-0.089*** (0.029)	0.161 (0.278)	-0.975** (0.428)	-0.010 (0.143)	-0.640*** (0.217)
Status Increase*Post	0.023*** (0.004)	0.010* (0.005)	0.356*** (0.069)	0.205** (0.098)	0.185*** (0.039)	0.131** (0.054)
Customer Rating	0.032*** (0.005)	0.003** (0.002)	0.420*** (0.071)	0.047* (0.026)	0.231*** (0.041)	0.018 (0.014)
Daily Review	-0.000** (0.000)	-0.000 (0.000)	-0.007* (0.004)	-0.005 (0.007)	-0.005** (0.002)	-0.004 (0.004)
Review Length	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Constant	-0.143*** (0.025)	0.005 (0.008)	-6.426*** (0.680)	-1.684*** (0.220)	-3.368*** (0.302)	-0.991*** (0.124)
Observations	68,241	36,836	36,134	20,493	36,134	20,493
R-squared	0.400	0.369				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.6b. Regressions on Response Tone subsampled by consumer rating (first approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	High: OLS	Low: OLS	High: Probit	Low: Probit	High: Logit	Low: Logit
Status Decrease	0.427*** (0.046)	0.220*** (0.057)	3.673*** (0.320)	2.536*** (0.498)	2.003*** (0.174)	1.255*** (0.259)
Status Increase	0.102*** (0.010)	0.024** (0.012)	1.069*** (0.092)	0.317** (0.144)	0.573*** (0.052)	0.138* (0.079)
Post	0.047*** (0.006)	0.018** (0.008)	0.673*** (0.094)	0.334** (0.143)	0.349*** (0.052)	0.148** (0.074)
Status Decrease*Post	0.088* (0.050)	0.210*** (0.068)	0.242 (0.333)	0.597 (0.478)	0.246 (0.193)	0.510* (0.269)
Status Increase*Post	-0.073*** (0.013)	-0.036** (0.016)	-0.921*** (0.126)	-0.558*** (0.204)	-0.489*** (0.072)	-0.284*** (0.110)
Customer Rating	0.044*** (0.012)	0.018*** (0.003)	0.562*** (0.128)	0.300*** (0.065)	0.313*** (0.074)	0.139*** (0.034)
Daily Review	-0.000 (0.001)	0.000 (0.001)	-0.004 (0.008)	0.005 (0.015)	-0.001 (0.005)	0.003 (0.009)
Review Length	0.000** (0.000)	-0.000 (0.000)	0.000** (0.000)	-0.000 (0.000)	0.000** (0.000)	-0.000 (0.000)
Constant	0.343*** (0.068)	0.395*** (0.043)	-2.224*** (0.673)	-1.161*** (0.325)	-1.266*** (0.389)	-0.510*** (0.179)
Observations	14,802	7,268	10,995	5,300	10,995	5,300
R-squared	0.350	0.289				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.7a. Regressions on Response Probability subsampled by consumer rating (second approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	High: OLS	Low: OLS	High: Probit	Low: Probit	High: Logit	Low: Logit
Status Decrease	-0.068*** (0.016)	0.030 (0.026)	-1.092*** (0.192)	0.031 (0.258)	-0.614*** (0.093)	0.014 (0.129)
Status Increase	-0.054*** (0.003)	-0.069*** (0.005)	-0.788*** (0.058)	-0.894*** (0.081)	-0.439*** (0.033)	-0.522*** (0.044)
Post	-0.033*** (0.002)	-0.030*** (0.003)	-0.716*** (0.045)	-0.551*** (0.057)	-0.413*** (0.026)	-0.310*** (0.032)
Status Decrease*Post	-0.035* (0.020)	-0.066** (0.033)	-0.075 (0.259)	-0.500 (0.438)	0.006 (0.145)	-0.130 (0.221)
Status Increase*Post	0.042*** (0.004)	0.021*** (0.006)	0.841*** (0.076)	0.378*** (0.096)	0.425*** (0.043)	0.199*** (0.054)
Customer Rating	0.028*** (0.005)	-0.007*** (0.002)	0.557*** (0.086)	-0.109*** (0.025)	0.308*** (0.049)	-0.074*** (0.014)
Daily Review	-0.002*** (0.000)	-0.001*** (0.000)	-0.046*** (0.006)	-0.036*** (0.009)	-0.028*** (0.004)	-0.022*** (0.005)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-0.087*** (0.023)	0.079*** (0.009)	-6.332*** (0.661)	0.009 (0.194)	-3.334*** (0.319)	0.035 (0.116)
Observations	66,658	35,941	28,950	20,138	28,950	20,138
R-squared	0.679	0.621				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.7b. Regressions on Response Tone subsampled by consumer rating (second approach)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	High: OLS	Low: OLS	High: Probit	Low: Probit	High: Logit	Low: Logit
Status Decrease	0.262*** (0.057)	0.089* (0.050)	3.110*** (0.556)	1.603** (0.734)	1.574*** (0.289)	0.689** (0.336)
Status Increase	0.104*** (0.010)	0.045*** (0.012)	1.233*** (0.115)	0.607*** (0.159)	0.630*** (0.061)	0.295*** (0.087)
Post	0.015** (0.006)	0.021** (0.009)	0.343*** (0.091)	0.357*** (0.134)	0.142*** (0.049)	0.154** (0.070)
Status Decrease*Post	0.335*** (0.063)	0.272*** (0.071)	0.804 (0.526)	1.289* (0.700)	0.644** (0.288)	0.848** (0.341)
Status Increase*Post	-0.055*** (0.013)	-0.087*** (0.016)	-0.845*** (0.130)	-1.125*** (0.204)	-0.414*** (0.073)	-0.600*** (0.111)
Customer Rating	0.052*** (0.011)	0.009*** (0.004)	0.632*** (0.130)	0.135** (0.053)	0.344*** (0.075)	0.066** (0.029)
Daily Review	0.003*** (0.001)	-0.002 (0.001)	0.016** (0.008)	-0.029** (0.015)	0.012** (0.005)	-0.012 (0.008)
Review Length	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)
Constant	0.410*** (0.066)	0.477*** (0.042)	-2.305*** (0.684)	-0.405 (0.290)	-1.232*** (0.391)	-0.140 (0.165)
Observations	14,877	7,347	11,101	5,323	11,101	5,323
R-squared	0.349	0.299				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.8. Regressions on the Probability of Targeted Consumers

VARIABLES	(1)	(2)
	Daily Targeted Consumer OLS	Daily Untargeted Consumer OLS
Status Decrease	0.090 (0.073)	0.096 (0.127)
Status Increase	0.221*** (0.020)	0.362*** (0.035)
Post	-0.001 (0.014)	0.196*** (0.023)
Status Decrease*Post	-0.398*** (0.087)	-0.696*** (0.135)
Status Increase*Post	-0.067** (0.026)	-0.131*** (0.045)
Daily Review		
Review Length		
Constant	0.030 (0.042)	0.814*** (0.063)
Observations	33,802	33,802
R-squared	0.138	0.444
Restaurant FE	Yes	Yes
Year FE	Yes	Yes

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

Table 3.9a. Regressions on Response Probability subsampled by targeted consumer (first approach)

VARIABLES	(1) Targeted: OLS	(2) Untargeted: OLS	(3) Targeted: Probit	(4) Untargeted: Probit	(5) Targeted: Logit	(6) Untargeted: Logit
Status Decrease	-0.054*** (0.017)	-0.034** (0.014)	-1.089*** (0.310)	-0.670*** (0.243)	-0.503*** (0.151)	-0.319*** (0.111)
Status Increase	-0.022*** (0.005)	-0.027*** (0.003)	-0.294*** (0.070)	-0.310*** (0.051)	-0.159*** (0.040)	-0.188*** (0.029)
Post	-0.012*** (0.003)	-0.006** (0.002)	-0.235*** (0.057)	-0.116*** (0.041)	-0.149*** (0.032)	-0.083*** (0.023)
Status Decrease*Post	-0.066*** (0.025)	-0.040** (0.021)	-0.376 (0.383)	-0.150 (0.288)	-0.285 (0.207)	-0.190 (0.143)
Status Increase*Post	0.015*** (0.006)	0.020*** (0.004)	0.287*** (0.096)	0.321*** (0.069)	0.169*** (0.054)	0.178*** (0.038)
W						
Customer Rating	0.007*** (0.002)	0.007*** (0.001)	0.119*** (0.031)	0.108*** (0.019)	0.057*** (0.018)	0.050*** (0.011)
Daily Review	-0.001 (0.000)	-0.000 (0.000)	-0.008 (0.007)	-0.004 (0.004)	-0.006 (0.004)	-0.004* (0.002)
Review Length	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Constant	-0.012 (0.010)	-0.015** (0.006)	-3.044*** (0.362)	-2.465*** (0.211)	-1.728*** (0.182)	-1.406*** (0.112)
Observations	37,053	68,024	19,015	39,838	19,015	39,838
R-squared	0.388	0.386				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.9b. Regressions on Response Tone subsampled by targeted consumer (first approach)

VARIABLES	(1) Targeted: OLS	(2) Untargeted: OLS	(3) Targeted: Probit	(4) Untargeted: Probit	(5) Targeted: Logit	(6) Untargeted: Logit
Status Decrease	0.326*** (0.053)	0.324*** (0.052)	3.252*** (0.454)	3.192*** (0.331)	1.671*** (0.222)	1.681*** (0.190)
Status Increase	0.083*** (0.013)	0.069*** (0.009)	0.859*** (0.130)	0.823*** (0.095)	0.462*** (0.073)	0.415*** (0.053)
Post	0.026*** (0.008)	0.043*** (0.006)	0.393*** (0.146)	0.658*** (0.094)	0.177** (0.078)	0.333*** (0.052)
Status Decrease*Post	0.174*** (0.061)	0.139** (0.058)	0.587 (0.405)	0.085 (0.339)	0.517** (0.231)	0.211 (0.203)
Status Increase*Post	-0.057*** (0.017)	-0.061*** (0.013)	-0.660*** (0.186)	-0.853*** (0.133)	-0.336*** (0.104)	-0.441*** (0.074)
Customer Rating	0.024*** (0.004)	0.026*** (0.003)	0.386*** (0.067)	0.404*** (0.045)	0.204*** (0.038)	0.194*** (0.025)
Daily Review	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.014)	-0.003 (0.009)	-0.000 (0.008)	-0.000 (0.005)
Review Length	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.366*** (0.046)	0.378*** (0.039)	-1.898*** (0.427)	-1.537*** (0.275)	-0.962*** (0.236)	-0.722*** (0.155)
Observations	7,549	14,521	5,027	11,135	5,027	11,135
R-squared	0.359	0.309				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.10a. Regressions on Response Probability subsampled by targeted consumer (second approach)

VARIABLES	(1) Targeted: OLS	(2) Untargeted: OLS	(3) Targeted: Probit	(4) Untargeted: Probit	(5) Targeted: Logit	(6) Untargeted: Logit
Status Decrease	-0.022 (0.021)	-0.040** (0.019)	-0.525** (0.231)	-0.781*** (0.211)	-0.275** (0.119)	-0.414*** (0.099)
Status Increase	-0.043*** (0.005)	-0.066*** (0.003)	-0.550*** (0.078)	-0.967*** (0.059)	-0.303*** (0.044)	-0.546*** (0.033)
Post	-0.030*** (0.003)	-0.033*** (0.002)	-0.612*** (0.059)	-0.652*** (0.044)	-0.356*** (0.034)	-0.365*** (0.025)
Status Decrease*Post	-0.034 (0.029)	-0.050** (0.022)	-0.035 (0.356)	-0.338 (0.281)	0.100 (0.194)	-0.138 (0.155)
Status Increase*Post	0.027*** (0.006)	0.040*** (0.004)	0.580*** (0.101)	0.727*** (0.073)	0.302*** (0.057)	0.364*** (0.041)
Customer Rating	-0.003 (0.002)	-0.001 (0.001)	-0.049 (0.033)	-0.018 (0.019)	-0.048*** (0.019)	-0.025** (0.011)
Daily Review	-0.003*** (0.000)	-0.001*** (0.000)	-0.055*** (0.010)	-0.035*** (0.006)	-0.032*** (0.006)	-0.022*** (0.003)
Review Length	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.059*** (0.012)	0.059*** (0.007)	-1.499*** (0.303)	-0.821*** (0.182)	-0.817*** (0.166)	-0.437*** (0.104)
Observations	35,973	66,626	18,684	36,005	18,684	36,005
R-squared	0.645	0.662				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3.10b. Regressions on Response Tone subsampled by targeted consumer (second approach)

VARIABLES	(1) Targeted: OLS	(2) Untargeted: OLS	(3) Targeted: Probit	(4) Untargeted: Probit	(5) Targeted: Logit	(6) Untargeted: Logit
Status Decrease	0.221*** (0.067)	0.158*** (0.050)	2.739*** (0.596)	2.151*** (0.579)	1.347*** (0.307)	1.039*** (0.300)
Status Increase	0.096*** (0.013)	0.076*** (0.010)	1.096*** (0.152)	0.953*** (0.113)	0.567*** (0.082)	0.471*** (0.061)
Post	0.008 (0.009)	0.022*** (0.006)	0.239* (0.142)	0.402*** (0.089)	0.070 (0.074)	0.185*** (0.048)
Status Decrease*Post	0.333*** (0.081)	0.346*** (0.063)	0.741 (0.505)	1.049* (0.583)	0.644** (0.290)	0.780** (0.310)
Status Increase*Post	-0.057*** (0.017)	-0.065*** (0.012)	-0.765*** (0.184)	-0.893*** (0.134)	-0.372*** (0.103)	-0.453*** (0.074)
Customer Rating	0.015*** (0.004)	0.020*** (0.003)	0.252*** (0.067)	0.265*** (0.042)	0.129*** (0.037)	0.128*** (0.022)
Daily Review	0.001 (0.001)	0.001 (0.001)	0.003 (0.013)	0.001 (0.008)	0.003 (0.008)	0.003 (0.005)
Review Length	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Constant	0.466*** (0.046)	0.505*** (0.038)	-1.269*** (0.422)	-0.637** (0.266)	-0.564** (0.230)	-0.228 (0.146)
Observations	7,568	14,656	5,011	11,288	5,011	11,288
R-squared	0.359	0.305				
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Figure 1.1. Evaluators and evaluation formats

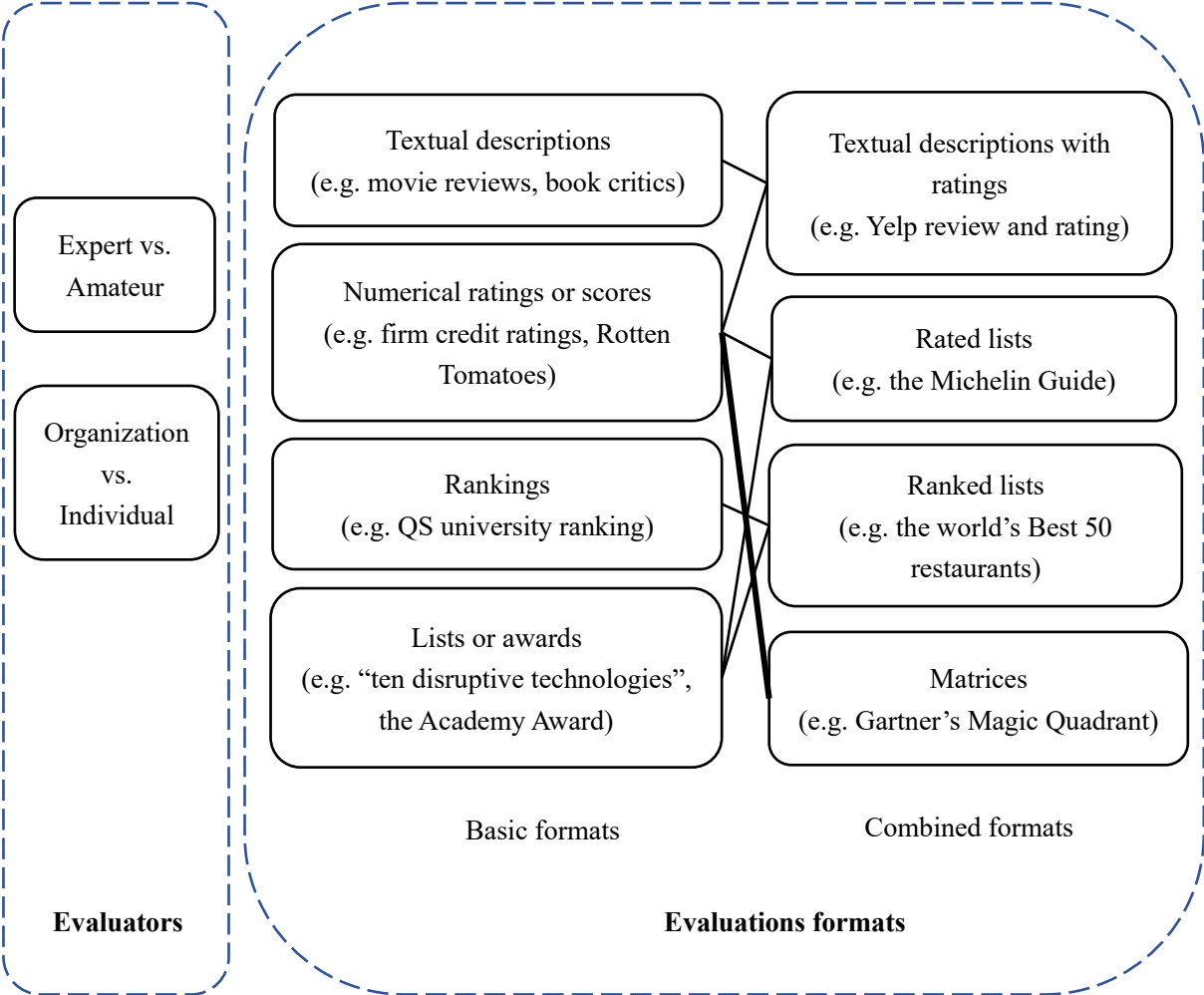


Figure 1.2. Timeline of both guides' entrance in China

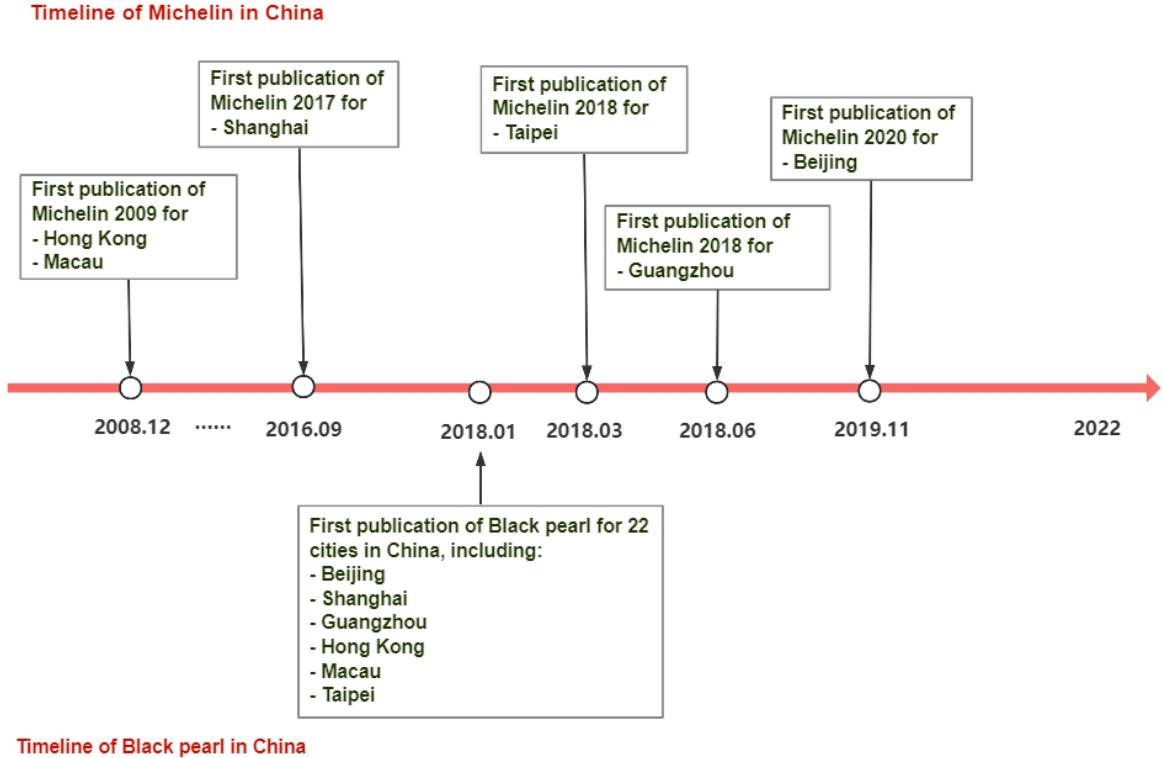


Figure 1.3. The imitation behaviors in coverage and ranking

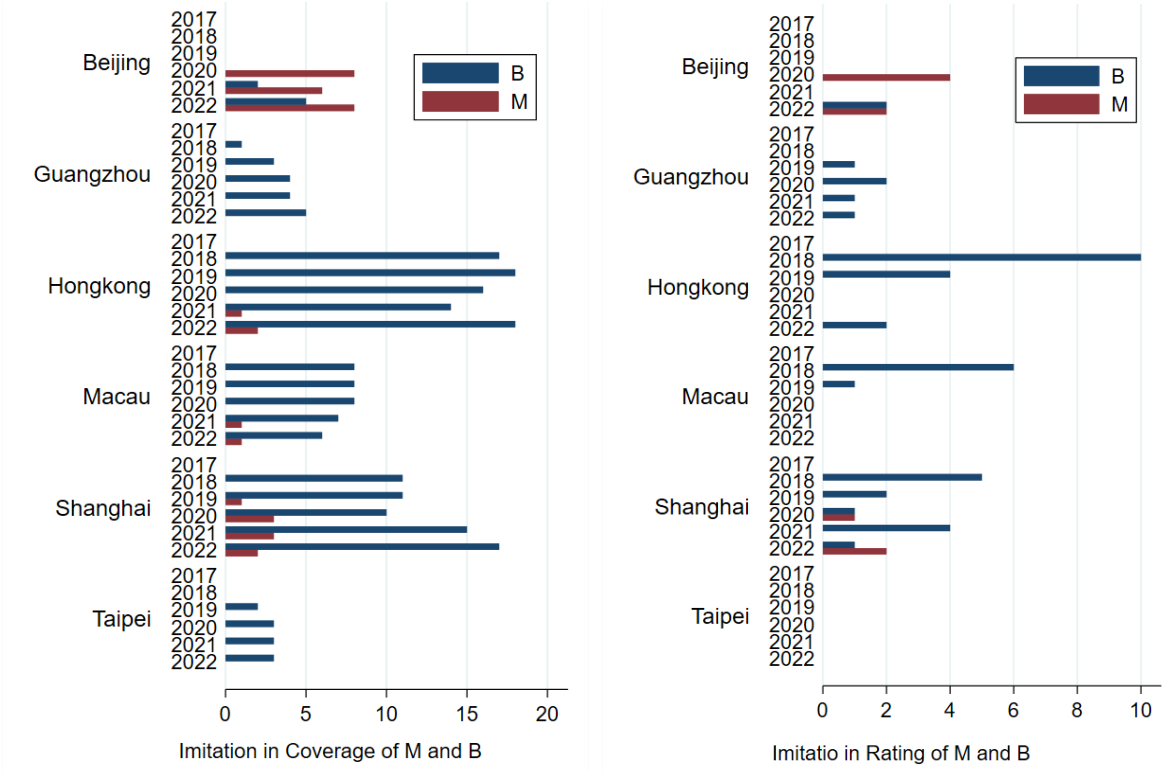


Figure 1.4. Expert rating organizations' Status and Imitation in Evaluation

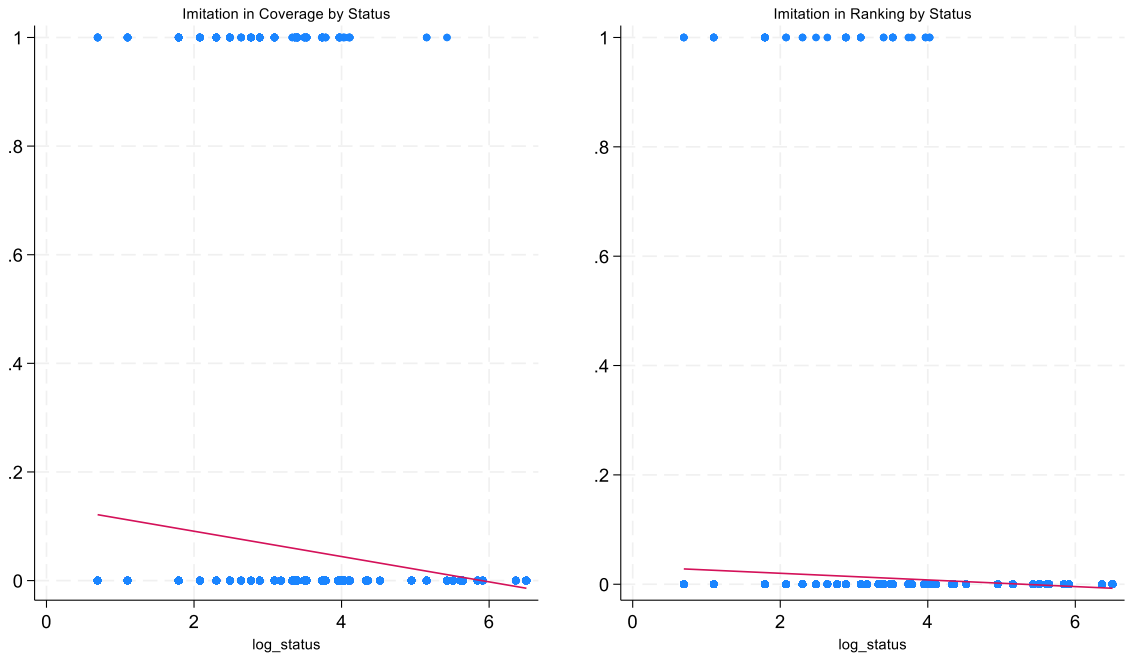


Figure 1.5. Expert rating organizations' Market Knowledge and Imitation in Evaluation

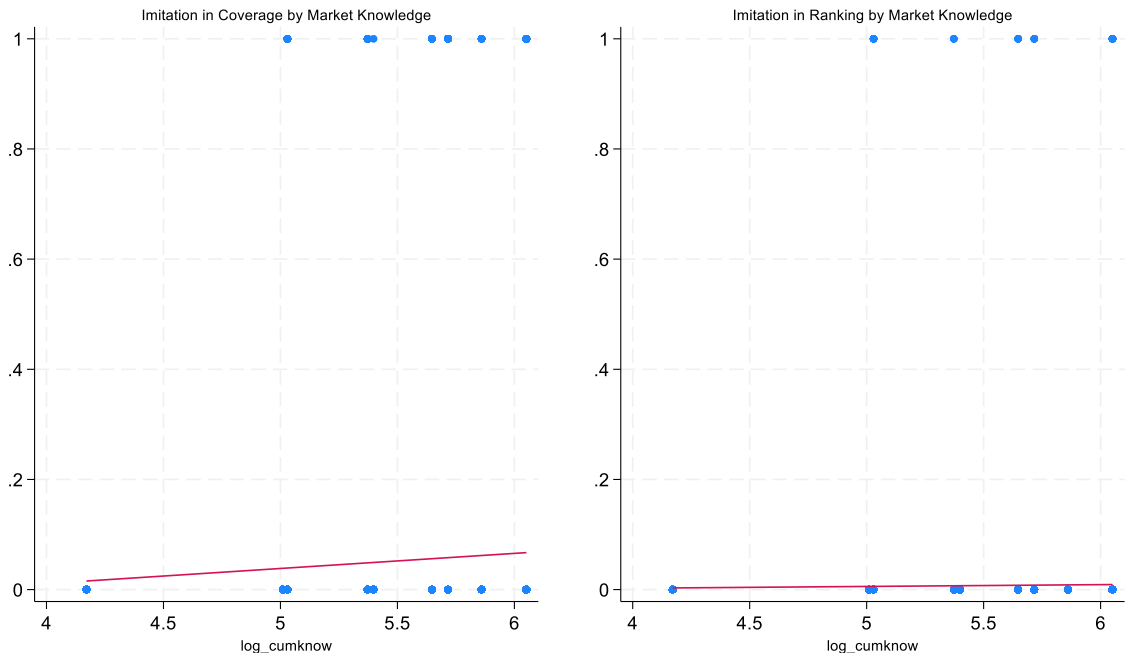


Figure 2.1. Timeline of Michelin Guide's Internationalization

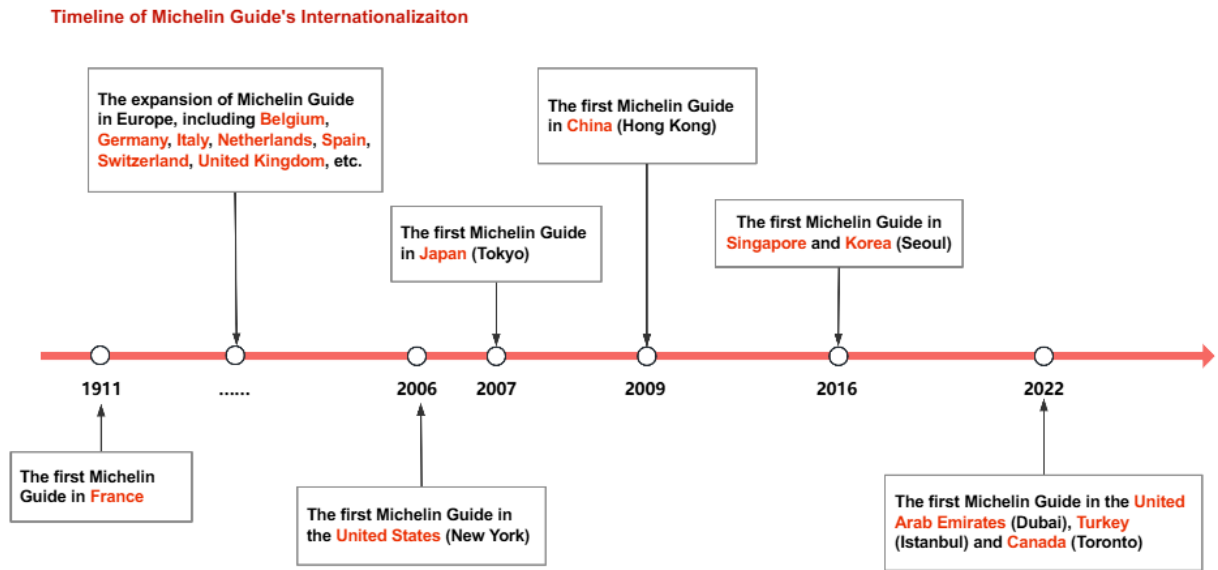


Figure 2.2. Density plot of Evaluation Penalty

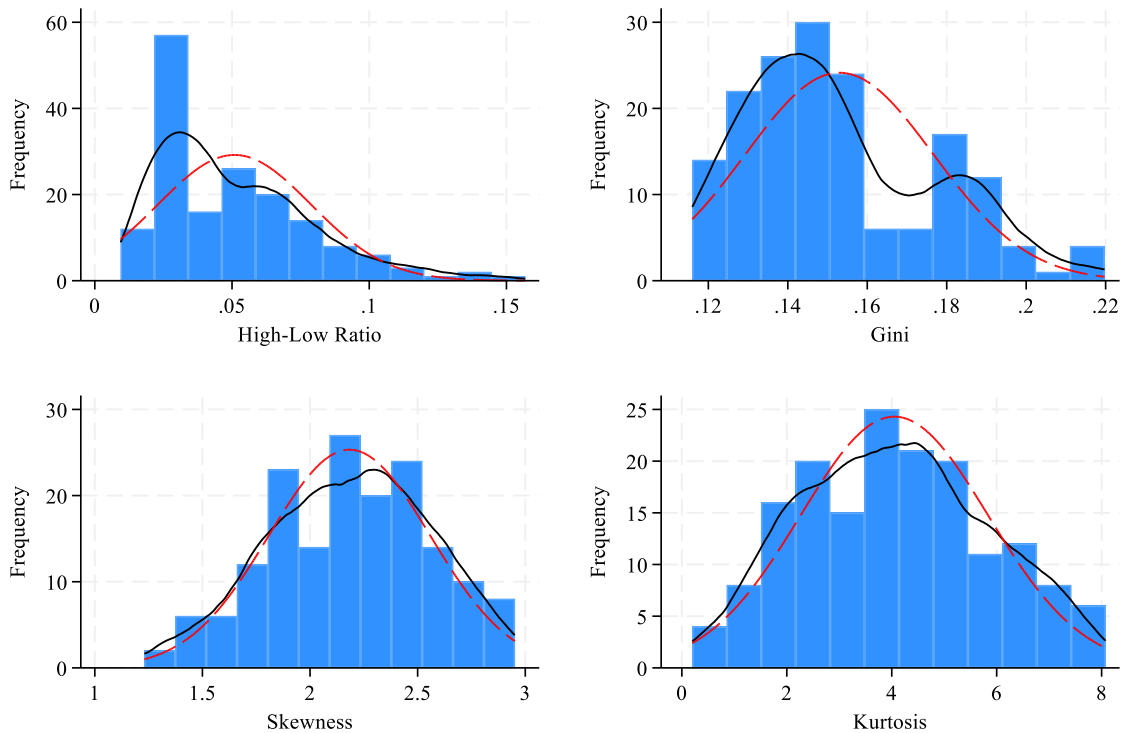


Figure 2.3a. Evaluation Penalty by Cultural Distance

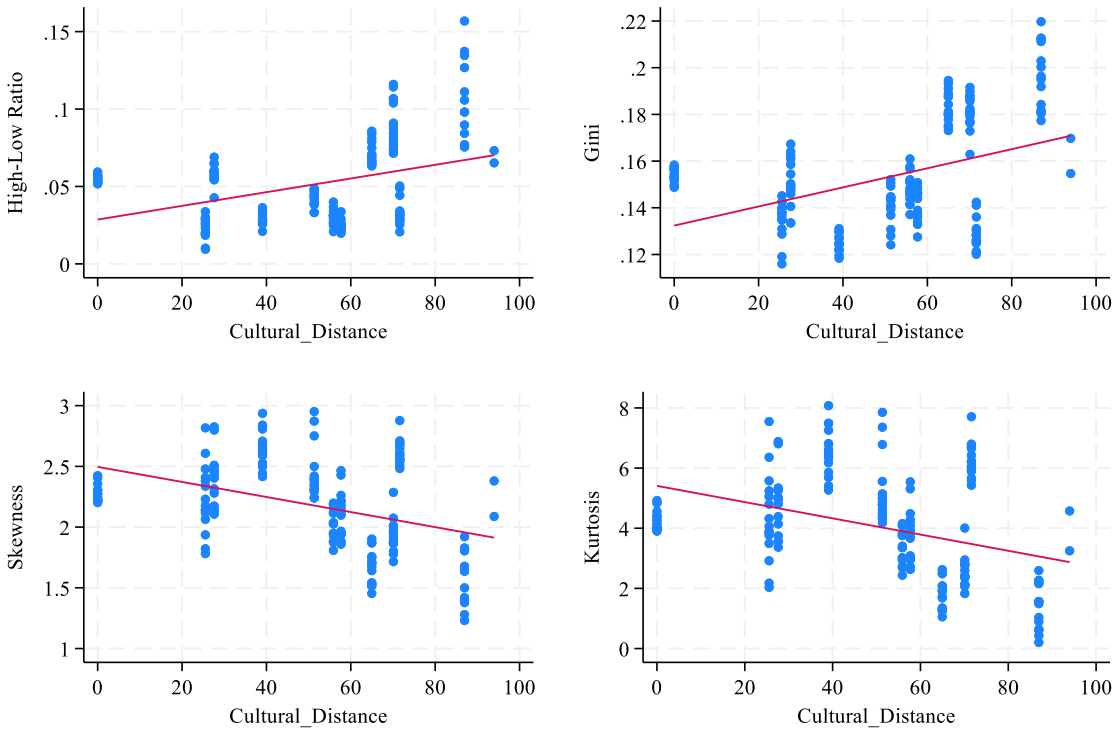


Figure 2.3b. Evaluation Penalty by Geographical Distance

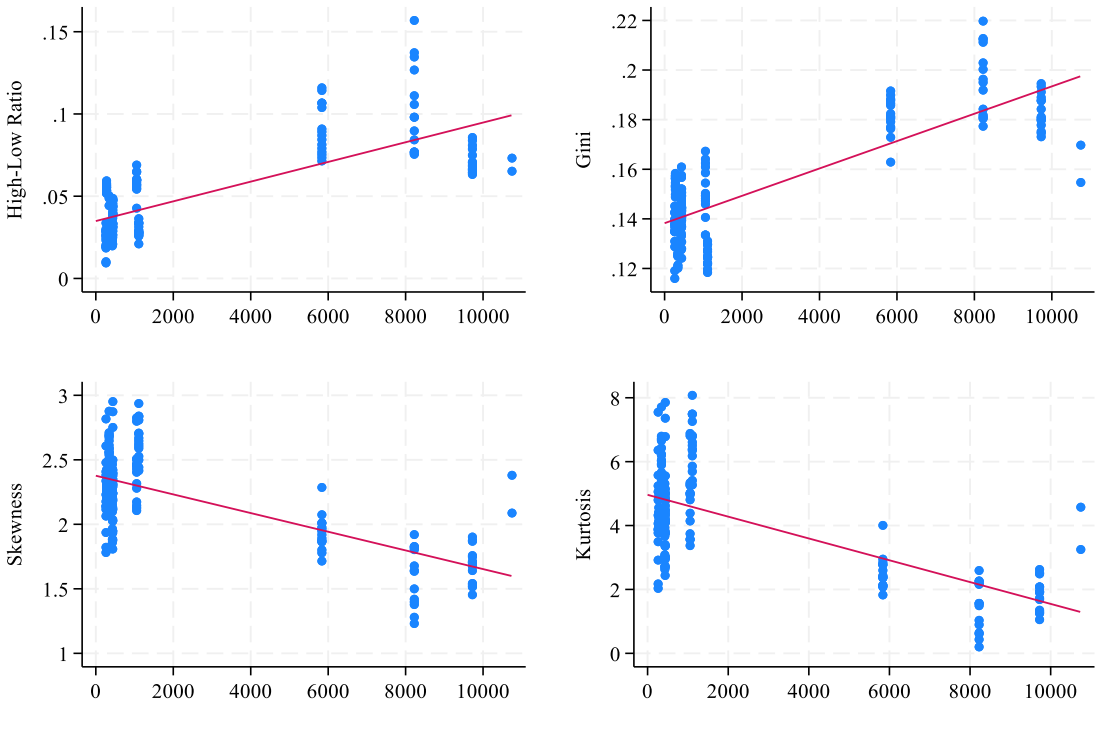


Figure 2.3c. Evaluation Penalty by Local Competition

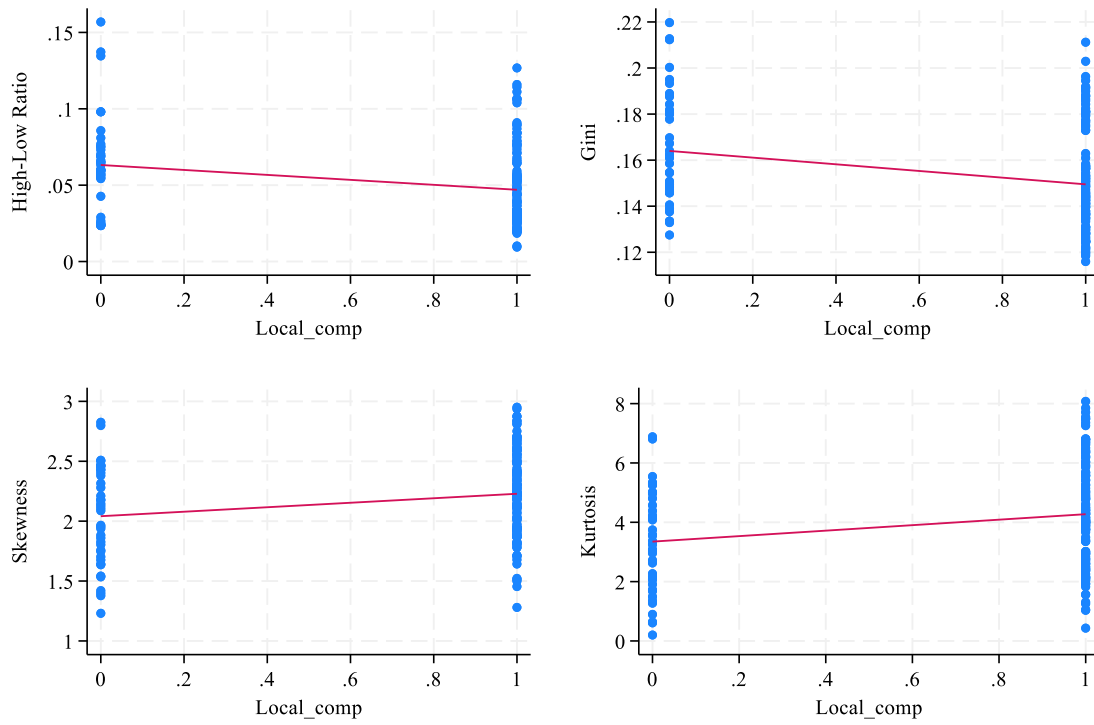


Figure 2.4. The Michelin Guide Website

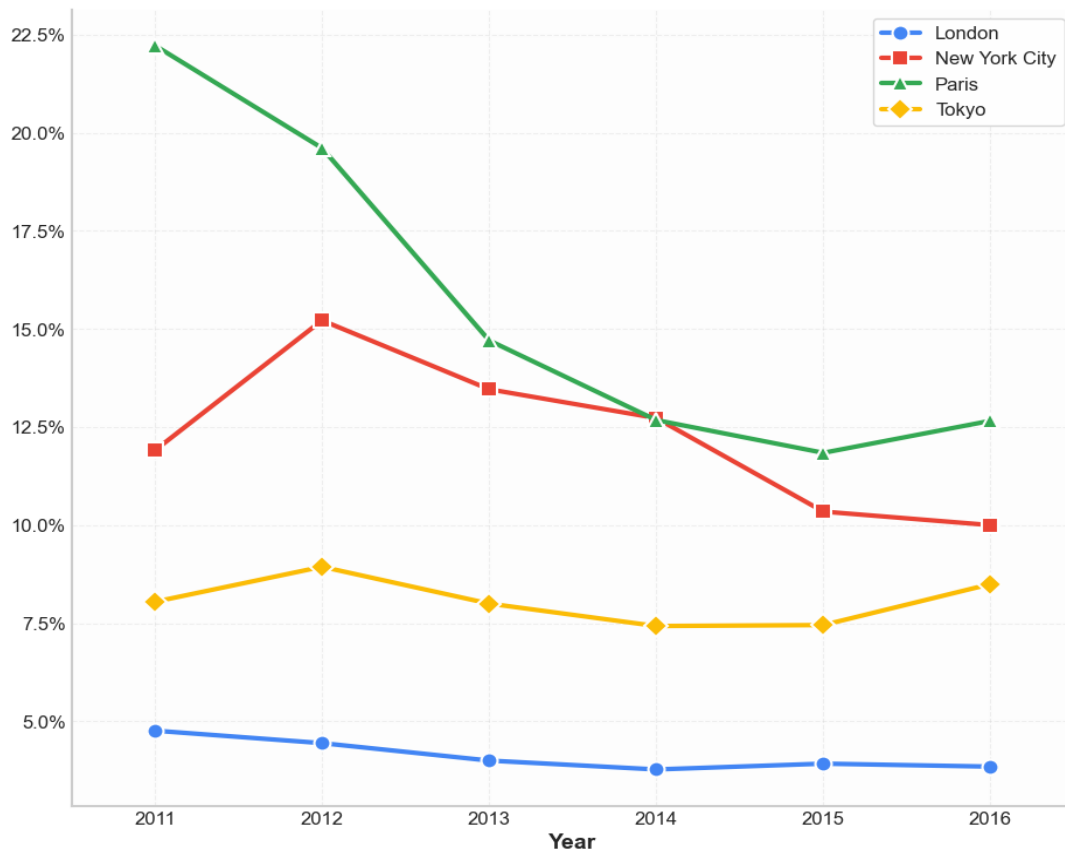


Figure 2.5. The Michelin Guide Website

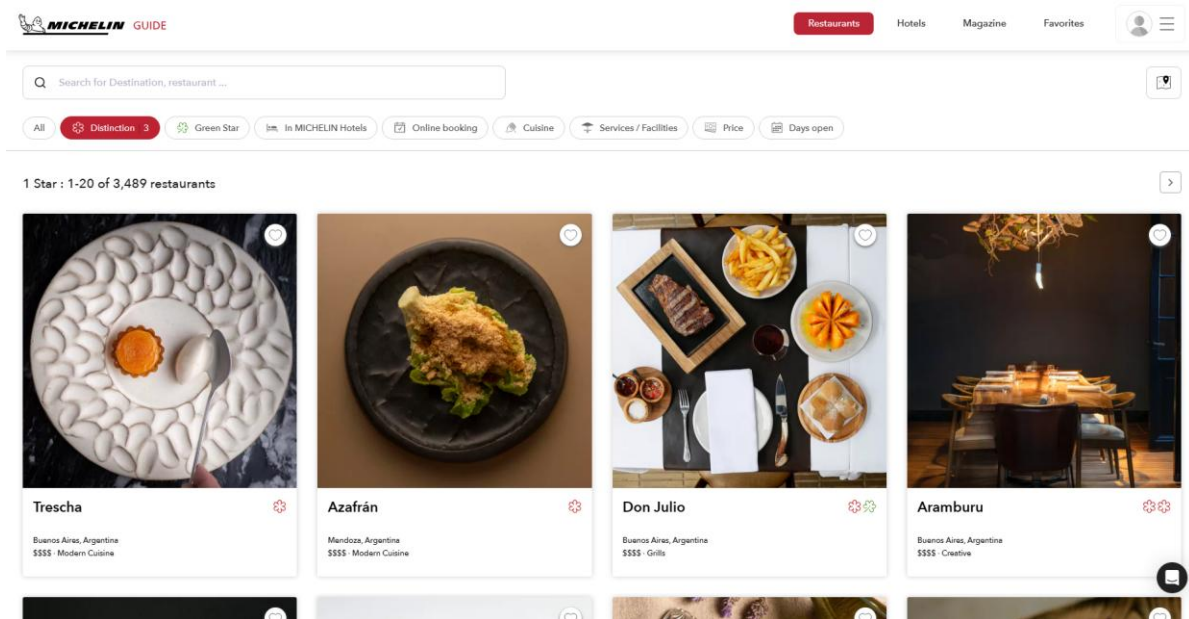


Figure 3.1. The Probability of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on timely response within 38 hours)

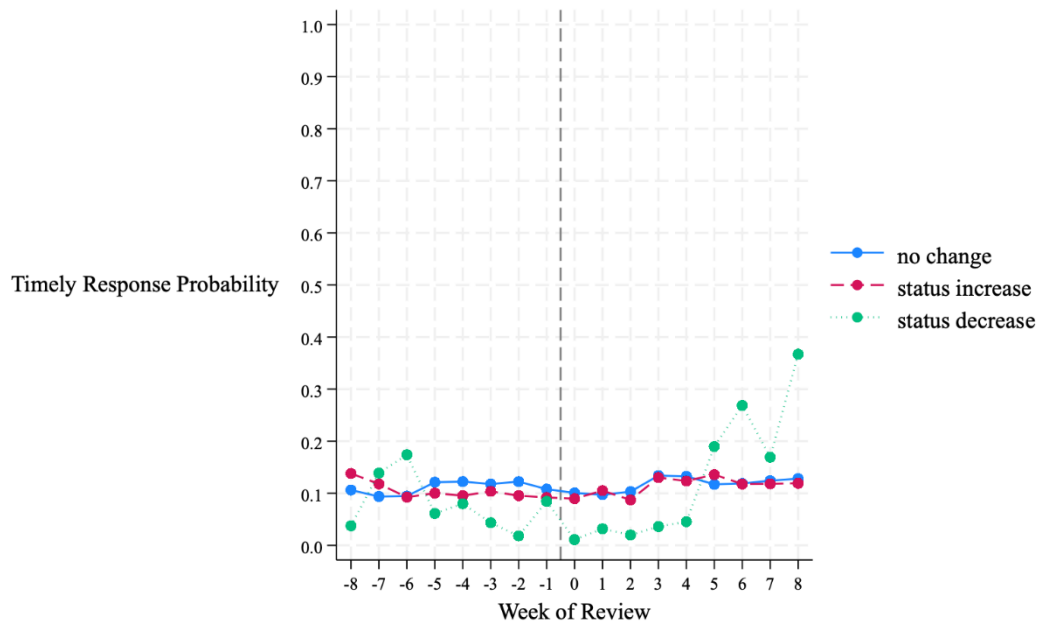


Figure 3.2. The Tone of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on timely response within 38 hours)

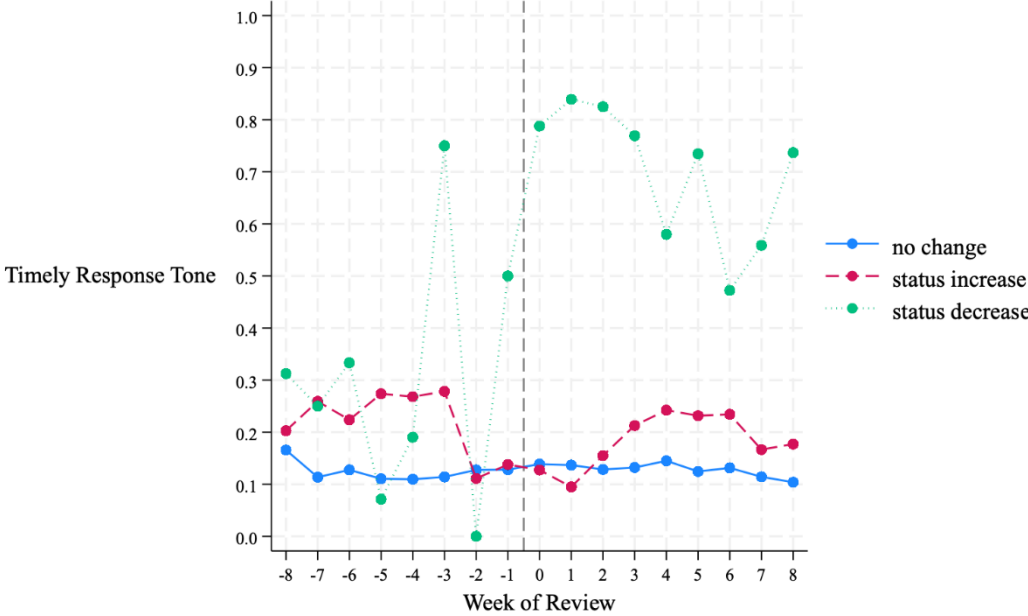


Figure 3.3. The Probability of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on allowed response window 453 hours)

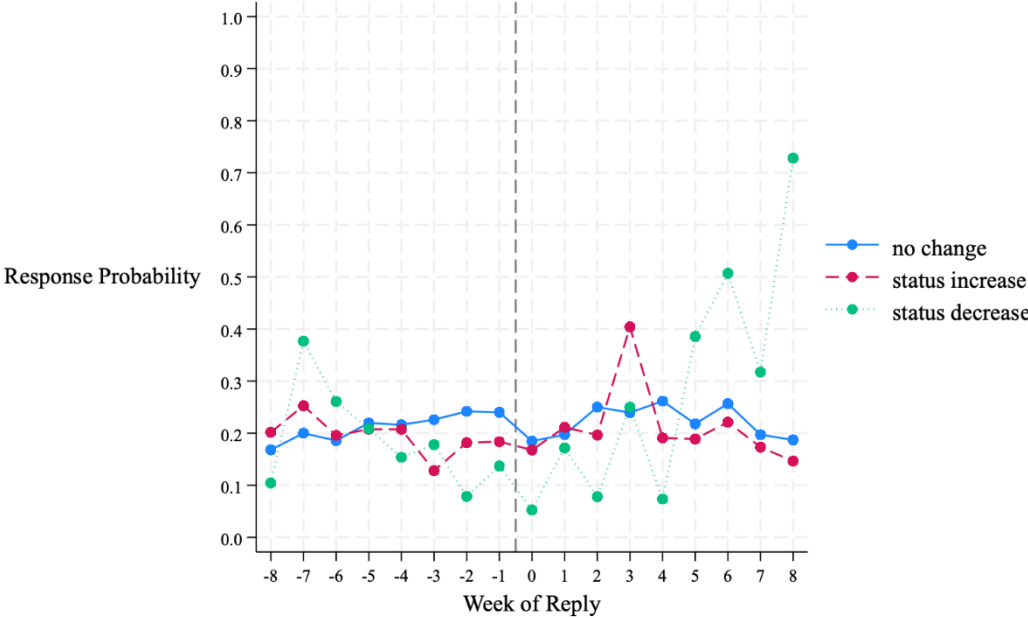


Figure 3.4. The Tone of Response (positive) per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on allowed response window 453 hours)

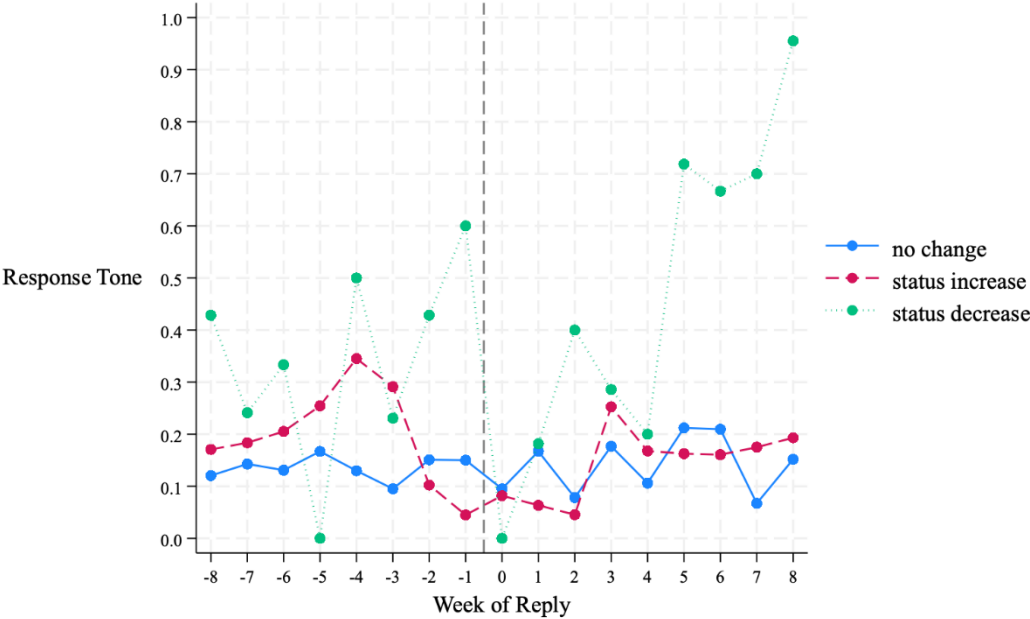


Figure 3.5. The average consumer rating per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements

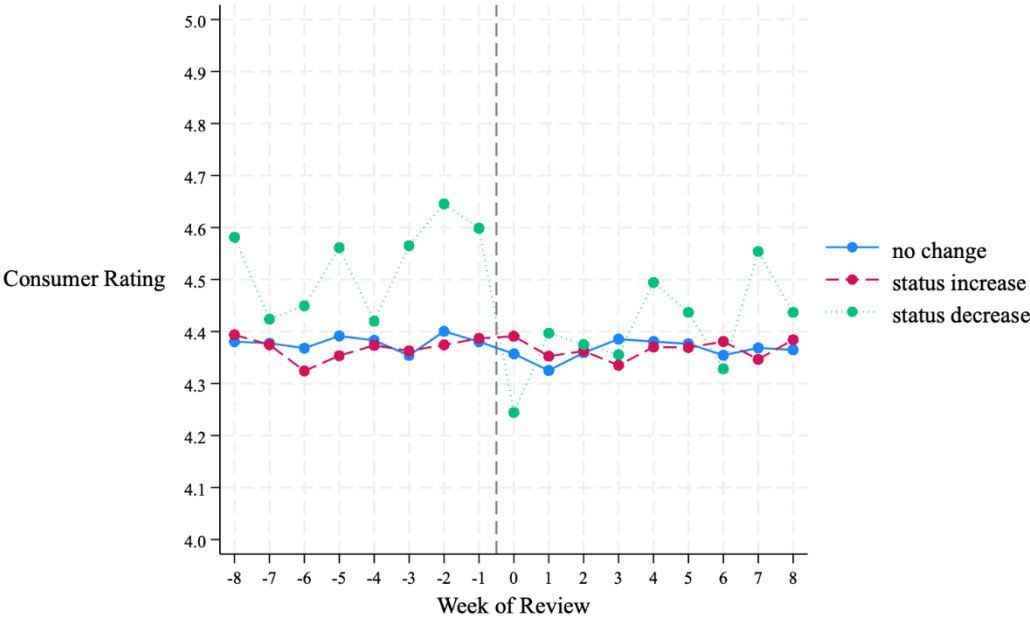
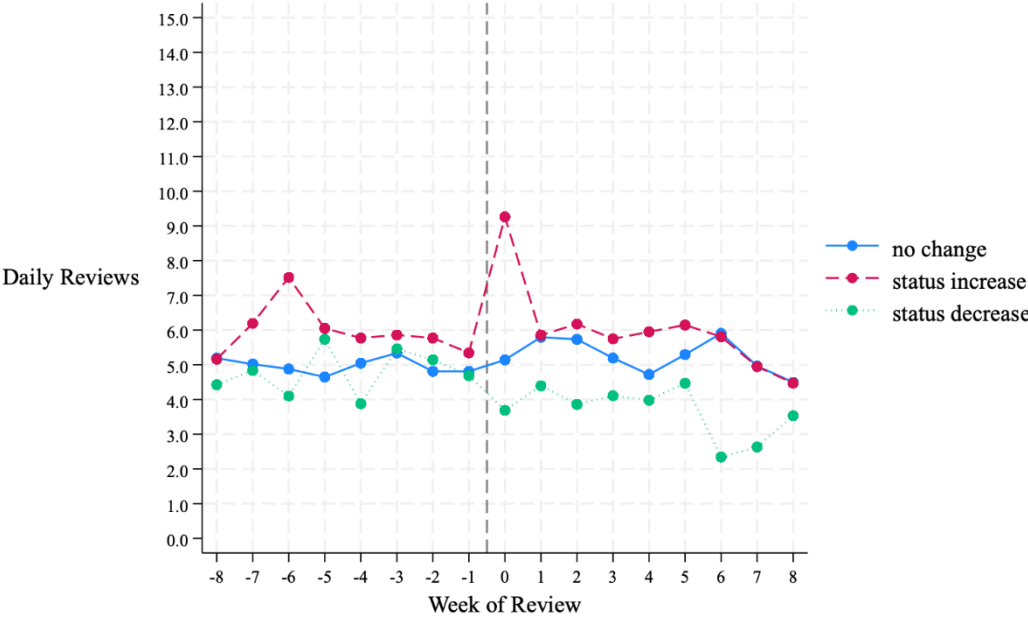


Figure 3.6. The average daily reviews per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements



APPENDICES

Table A1. Regression on Timely Response and Tone of response (Identification with 123 hours, third quantile of response duration)

VARIABLES	(1) Response OLS	(2) Response Logit	(3) Response Probit	(4) Tone OLS	(5) Tone Logit	(6) Tone Probit
Status Decrease	0.149*** (0.014)	0.631*** (0.107)	0.387*** (0.057)	0.408*** (0.022)	3.105*** (0.184)	1.750*** (0.103)
Status Increase	-0.009*** (0.003)	-0.113** (0.049)	-0.045* (0.026)	-0.063*** (0.008)	-0.440*** (0.097)	-0.263*** (0.052)
Post	0.012*** (0.002)	0.189*** (0.029)	0.093*** (0.016)	-0.013*** (0.004)	-0.104* (0.063)	-0.053 (0.035)
Status Decrease*Post	-0.124*** (0.021)	-0.941*** (0.160)	-0.538*** (0.094)	0.108*** (0.038)	0.659*** (0.211)	0.343*** (0.125)
Status Increase*Post	0.028*** (0.004)	0.384*** (0.056)	0.186*** (0.032)	0.036*** (0.009)	0.341*** (0.110)	0.164*** (0.062)
Customer Rating	0.006*** (0.001)	0.090*** (0.016)	0.042*** (0.009)	0.028*** (0.002)	0.466*** (0.043)	0.222*** (0.023)
Daily Review	-0.001*** (0.000)	-0.010*** (0.003)	-0.007*** (0.002)	0.001* (0.001)	0.009 (0.008)	0.007 (0.005)
Review Length	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-0.043*** (0.006)	-3.026*** (0.165)	-1.744*** (0.090)	-0.054*** (0.012)	-3.580*** (1.045)	-1.705*** (0.418)
Observations	105,672	66,616	66,616	21,697	16,511	16,511
R-squared	0.520			0.341		
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A2. Regression on Restaurant Response and Tone of response (Identification with 123 hours, third quantile of response duration)

VARIABLES	(1) Response OLS	(2) Response Logit	(3) Response Probit	(4) Tone OLS	(5) Tone Logit	(6) Tone Probit
Status Decrease	-0.048*** (0.014)	-0.838*** (0.159)	-0.437*** (0.076)	0.209*** (0.044)	2.671*** (0.377)	1.305*** (0.204)
Status Increase	-0.056*** (0.003)	-0.777*** (0.046)	-0.437*** (0.026)	0.084*** (0.008)	1.007*** (0.090)	0.505*** (0.049)
Post	-0.030*** (0.002)	-0.584*** (0.035)	-0.331*** (0.020)	0.017*** (0.005)	0.355*** (0.075)	0.150*** (0.040)
Status Decrease*Post	-0.018 (0.018)	0.031 (0.228)	0.073 (0.124)	0.310*** (0.052)	0.597* (0.350)	0.553*** (0.201)
Status Increase*Post	0.036*** (0.003)	0.643*** (0.059)	0.324*** (0.033)	-0.063*** (0.010)	-0.864*** (0.107)	-0.432*** (0.060)
Customer Rating	-0.002 (0.001)	-0.028* (0.016)	-0.034*** (0.009)	0.019*** (0.002)	0.259*** (0.035)	0.126*** (0.019)
Daily Review	-0.002*** (0.000)	-0.037*** (0.005)	-0.023*** (0.003)	0.001 (0.001)	0.002 (0.007)	0.003 (0.004)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.055*** (0.006)	-1.098*** (0.155)	-0.593*** (0.086)	0.505*** (0.028)	-0.745*** (0.218)	-0.285** (0.120)
Observations	104,754	59,827	59,827	22,224	16,937	16,937
R-squared	0.652			0.321		
Restaurant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A3-1. Regressions on Response Probability subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: OLS	(2) Targeted High: OLS	(3) Untargeted Low: OLS	(4) Untargeted High: OLS
Status Decrease	0.017 (0.032)	-0.097*** (0.019)	-0.032 (0.026)	-0.034** (0.016)
Status Increase	-0.027*** (0.008)	-0.018*** (0.006)	-0.038*** (0.006)	-0.021*** (0.004)
Post	-0.011** (0.005)	-0.013*** (0.004)	-0.008** (0.004)	-0.006** (0.003)
Status Decrease*Post	-0.145*** (0.045)	-0.022 (0.030)	-0.049 (0.037)	-0.027 (0.025)
Status Increase*Post	0.000 (0.009)	0.023*** (0.007)	0.015** (0.007)	0.023*** (0.005)
Customer Rating	0.004 (0.003)	0.012 (0.008)	0.002 (0.002)	0.044*** (0.006)
Daily Review	0.001 (0.001)	-0.002*** (0.001)	-0.000 (0.000)	-0.000 (0.000)
Review Length	-0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-0.006 (0.016)	-0.025 (0.040)	0.010 (0.010)	-0.207*** (0.033)
Observations	13,196	23,857	23,640	44,384
R-squared	0.381	0.399	0.365	0.402
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A3-2. Regressions on Response Probability subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: Logit	(2) Targeted High: Logit	(3) Untargeted Low: Logit	(4) Untargeted High: Logit
Status Decrease	0.006 (0.449)	-2.000*** (0.462)	-0.755 (0.512)	-0.651** (0.276)
Status Increase	-0.370*** (0.122)	-0.241*** (0.086)	-0.525*** (0.096)	-0.204*** (0.062)
Post	-0.227** (0.094)	-0.239*** (0.072)	-0.155** (0.072)	-0.113** (0.051)
Status Decrease*Post	-1.938*** (0.705)	0.634 (0.521)	-0.347 (0.585)	-0.007 (0.330)
Status Increase*Post	0.047 (0.164)	0.407*** (0.119)	0.307** (0.123)	0.340*** (0.084)
Customer Rating	0.072 (0.055)	0.159 (0.117)	0.037 (0.029)	0.565*** (0.090)
Daily Review	0.011 (0.009)	-0.021** (0.010)	-0.013 (0.009)	-0.004 (0.004)
Review Length	-0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-2.559*** (0.451)	-4.855*** (1.151)	-1.337*** (0.255)	-7.208*** (0.847)
Observations	6,533	11,307	13,059	22,707
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A3-3. Regressions on Response Probability subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: Probit	(2) Targeted High: Probit	(3) Untargeted Low: Probit	(4) Untargeted High: Probit
Status Decrease	0.059 (0.213)	-1.038*** (0.245)	-0.298 (0.231)	-0.333*** (0.126)
Status Increase	-0.209*** (0.068)	-0.122** (0.049)	-0.313*** (0.054)	-0.123*** (0.035)
Post	-0.154*** (0.052)	-0.141*** (0.041)	-0.111*** (0.040)	-0.073** (0.029)
Status Decrease*Post	-1.061*** (0.387)	0.295 (0.291)	-0.367 (0.284)	-0.087 (0.165)
Status Increase*Post	0.052 (0.092)	0.221*** (0.067)	0.184*** (0.068)	0.172*** (0.047)
Customer Rating	0.036 (0.031)	0.085 (0.068)	0.014 (0.016)	0.312*** (0.052)
Daily Review	0.006 (0.005)	-0.013** (0.006)	-0.010* (0.005)	-0.004* (0.002)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-1.504*** (0.243)	-2.508*** (0.499)	-0.788*** (0.147)	-3.801*** (0.380)
Observations	6,533	11,307	13,059	22,707
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A4-1. Regressions on Response Tone subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: OLS	(2) Targeted High: OLS	(3) Untargeted Low: OLS	(4) Untargeted High: OLS
Status Decrease	0.222*** (0.075)	0.454*** (0.072)	0.203** (0.097)	0.374*** (0.062)
Status Increase	0.042** (0.020)	0.105*** (0.016)	0.008 (0.015)	0.100*** (0.012)
Post	0.025* (0.014)	0.023** (0.011)	0.015 (0.010)	0.056*** (0.008)
Status Decrease*Post	0.237** (0.092)	0.064 (0.076)	0.213** (0.108)	0.132* (0.068)
Status Increase*Post	-0.047* (0.027)	-0.059*** (0.022)	-0.026 (0.020)	-0.078*** (0.016)
Customer Rating	0.023*** (0.006)	0.056*** (0.019)	0.017*** (0.004)	0.038*** (0.015)
Daily Review	0.000 (0.002)	-0.000 (0.002)	0.001 (0.002)	-0.001 (0.001)
Review Length	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)
Constant	0.435*** (0.071)	0.169 (0.109)	0.325*** (0.058)	0.413*** (0.089)
Observations	2,631	4,918	4,637	9,884
R-squared	0.352	0.378	0.260	0.341
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A4-2. Regressions on Response Tone subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: Logit	(2) Targeted High: Logit	(3) Untargeted Low: Logit	(4) Untargeted High: Logit
Status Decrease	3.205*** (1.218)	3.624*** (0.557)	2.233*** (0.645)	3.488*** (0.396)
Status Increase	0.491** (0.237)	1.038*** (0.161)	0.166 (0.190)	1.056*** (0.113)
Post	0.420* (0.255)	0.364** (0.181)	0.332* (0.177)	0.785*** (0.112)
Status Decrease*Post	1.034 (1.105)	0.325 (0.536)	0.500 (0.624)	0.388 (0.441)
Status Increase*Post	-0.648* (0.337)	-0.670*** (0.228)	-0.502* (0.265)	-1.001*** (0.155)
Customer Rating	0.450*** (0.142)	0.692*** (0.218)	0.273*** (0.074)	0.495*** (0.160)
Daily Review	-0.007 (0.029)	0.001 (0.015)	0.012 (0.018)	-0.008 (0.010)
Review Length	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)
Constant	-1.575** (0.696)	-3.804*** (1.161)	-1.241*** (0.392)	-1.590* (0.842)
Observations	1,641	3,144	3,407	7,616
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Table A4-3. Regressions on Response Tone subsampled by consumer rating and targeted consumer (first approach)

VARIABLES	(1) Targeted Low: Probit	(2) Targeted High: Probit	(3) Untargeted Low: Probit	(4) Untargeted High: Probit
Status Decrease	1.470*** (0.436)	1.981*** (0.283)	1.086*** (0.370)	1.885*** (0.230)
Status Increase	0.239* (0.130)	0.589*** (0.092)	0.052 (0.103)	0.556*** (0.064)
Post	0.175 (0.129)	0.185* (0.100)	0.151 (0.092)	0.411*** (0.062)
Status Decrease*Post	0.850* (0.454)	0.279 (0.303)	0.469 (0.371)	0.346 (0.268)
Status Increase*Post	-0.318* (0.182)	-0.369*** (0.129)	-0.258* (0.142)	-0.531*** (0.089)
Customer Rating	0.242*** (0.076)	0.401*** (0.125)	0.122*** (0.038)	0.274*** (0.093)
Daily Review	-0.002 (0.016)	0.001 (0.009)	0.008 (0.010)	-0.003 (0.006)
Review Length	-0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)	0.000* (0.000)
Constant	-0.776** (0.374)	-2.181*** (0.662)	-0.584*** (0.219)	-0.908* (0.488)
Observations	1,641	3,144	3,407	7,616
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Table A5-1. Regressions on Response Probability subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: OLS	(2) Targeted High: OLS	(3) Untargeted Low: OLS	(4) Untargeted High: OLS
Status Decrease	0.078** (0.037)	-0.091*** (0.025)	-0.027 (0.033)	-0.051** (0.021)
Status Increase	-0.049*** (0.008)	-0.040*** (0.006)	-0.080*** (0.006)	-0.060*** (0.004)
Post	-0.023*** (0.006)	-0.034*** (0.004)	-0.034*** (0.004)	-0.033*** (0.003)
Status Decrease*Post	-0.133** (0.055)	0.032 (0.033)	-0.003 (0.040)	-0.073*** (0.025)
Status Increase*Post	0.004 (0.010)	0.038*** (0.007)	0.033*** (0.007)	0.044*** (0.005)
Customer Rating	-0.007** (0.004)	0.011 (0.007)	-0.006*** (0.002)	0.037*** (0.006)
Daily Review	-0.001* (0.001)	-0.004*** (0.001)	-0.001*** (0.000)	-0.002*** (0.000)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Constant	0.071*** (0.019)	-0.005 (0.037)	0.085*** (0.011)	-0.135*** (0.030)
Observations	12,820	23,153	23,121	43,505
R-squared	0.612	0.673	0.631	0.685
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A5-2, continued. Regressions on Response Probability subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: Logit	(2) Targeted High: Logit	(3) Untargeted Low: Logit	(4) Untargeted High: Logit
Status Decrease	0.484 (0.309)	-1.432*** (0.337)	-0.648 (0.496)	-0.913*** (0.224)
Status Increase	-0.504*** (0.127)	-0.569*** (0.101)	-1.160*** (0.109)	-0.884*** (0.072)
Post	-0.427*** (0.094)	-0.777*** (0.078)	-0.642*** (0.073)	-0.696*** (0.056)
Status Decrease*Post	-1.149* (0.697)	0.858* (0.439)	0.292 (0.653)	-0.544* (0.318)
Status Increase*Post	0.116 (0.157)	0.904*** (0.135)	0.580*** (0.124)	0.823*** (0.093)
Customer Rating	-0.115** (0.056)	0.261* (0.136)	-0.109*** (0.029)	0.716*** (0.112)
Daily Review	-0.018 (0.012)	-0.081*** (0.013)	-0.044*** (0.011)	-0.035*** (0.006)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)
Constant	-0.758** (0.380)	-4.697*** (0.988)	0.393* (0.236)	-7.308*** (0.909)
Observations	6,600	9,610	12,785	18,143
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Table A5-3, continued. Regressions on Response Probability subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: Probit	(2) Targeted High: Probit	(3) Untargeted Low: Probit	(4) Untargeted High: Probit
Status Decrease	0.251 (0.174)	-0.754*** (0.177)	-0.278 (0.216)	-0.544*** (0.111)
Status Increase	-0.309*** (0.071)	-0.301*** (0.057)	-0.662*** (0.058)	-0.500*** (0.041)
Post	-0.250*** (0.053)	-0.453*** (0.045)	-0.353*** (0.041)	-0.399*** (0.032)
Status Decrease*Post	-0.466 (0.337)	0.576** (0.256)	0.218 (0.316)	-0.276 (0.178)
Status Increase*Post	0.072 (0.089)	0.464*** (0.075)	0.296*** (0.069)	0.414*** (0.052)
Customer Rating	-0.075** (0.031)	0.144* (0.079)	-0.075*** (0.016)	0.396*** (0.063)
Daily Review	-0.011 (0.007)	-0.049*** (0.008)	-0.027*** (0.006)	-0.022*** (0.004)
Review Length	-0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)
Constant	-0.445** (0.220)	-2.486*** (0.495)	0.280** (0.142)	-3.830*** (0.426)
Observations	6,600	9,610	12,785	18,143
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Table A6-1. Regressions on Response Tone subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: OLS	(2) Targeted High: OLS	(3) Untargeted Low: OLS	(4) Untargeted High: OLS
Status Decrease	0.185** (0.072)	0.309*** (0.107)	-0.052 (0.084)	0.207*** (0.057)
Status Increase	0.082*** (0.021)	0.107*** (0.017)	0.016 (0.015)	0.104*** (0.013)
Post	0.031** (0.014)	-0.008 (0.011)	0.017 (0.011)	0.025*** (0.008)
Status Decrease*Post	0.296*** (0.106)	0.258** (0.114)	0.353*** (0.104)	0.407*** (0.071)
Status Increase*Post	-0.105*** (0.027)	-0.034 (0.022)	-0.069*** (0.020)	-0.064*** (0.016)
Customer Rating	0.013** (0.006)	0.040** (0.018)	0.008* (0.004)	0.057*** (0.014)
Daily Review	-0.001 (0.002)	0.002 (0.002)	-0.002 (0.002)	0.003** (0.001)
Review Length	-0.000 (0.000)	0.000** (0.000)	-0.000 (0.000)	0.000 (0.000)
Constant	0.496*** (0.068)	0.344*** (0.107)	0.412*** (0.058)	0.429*** (0.085)
Observations	2,667	4,901	4,680	9,976
R-squared	0.372	0.374	0.262	0.342
Restaurant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table A6-2. Regressions on Response Tone subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: Logit	(2) Targeted High: Logit	(3) Untargeted Low: Logit	(4) Untargeted High: Logit
Status Decrease	2.867** (1.417)	3.281*** (0.823)	2.443*** (0.455)	2.440*** (0.845)
Status Increase	1.040*** (0.270)	1.265*** (0.196)	0.271 (0.210)	1.235*** (0.143)
Post	0.545** (0.257)	0.065 (0.174)	0.278* (0.160)	0.444*** (0.107)
Status Decrease*Post	0.879 (1.209)	0.518 (0.716)	0.000 (0.000)	1.539* (0.882)
Status Increase*Post	-1.404*** (0.352)	-0.601*** (0.229)	-0.898*** (0.264)	-0.944*** (0.162)
Customer Rating	0.235* (0.133)	0.540** (0.223)	0.111* (0.059)	0.672*** (0.163)
Daily Review	-0.025 (0.027)	0.016 (0.015)	-0.028 (0.018)	0.014 (0.009)
Review Length	-0.000 (0.000)	0.001** (0.000)	-0.000 (0.000)	0.000 (0.000)
Constant	-0.920 (0.654)	-2.888** (1.197)	-0.390 (0.350)	-2.201*** (0.851)
Observations	1,656	3,133	3,407	7,746
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Table A6-3. Regressions on Response Tone subsampled by consumer rating and targeted consumer (second approach)

VARIABLES	(1) Targeted Low: Probit	(2) Targeted High: Probit	(3) Untargeted Low: Probit	(4) Untargeted High: Probit
Status Decrease	1.210** (0.488)	1.717*** (0.431)	1.301*** (0.258)	1.246*** (0.427)
Status Increase	0.529*** (0.142)	0.678*** (0.107)	0.111 (0.114)	0.622*** (0.076)
Post	0.218* (0.128)	-0.016 (0.092)	0.124 (0.085)	0.203*** (0.058)
Status Decrease*Post	0.769 (0.494)	0.457 (0.408)	0.000 (0.000)	1.006** (0.462)
Status Increase*Post	-0.720*** (0.186)	-0.293** (0.128)	-0.482*** (0.143)	-0.468*** (0.090)
Customer Rating	0.136* (0.071)	0.301** (0.128)	0.051 (0.033)	0.370*** (0.093)
Daily Review	-0.010 (0.015)	0.011 (0.009)	-0.011 (0.010)	0.011* (0.006)
Review Length	-0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.000 (0.000)
Constant	-0.445 (0.350)	-1.546** (0.675)	-0.167 (0.204)	-1.196** (0.487)
Observations	1,656	3,133	3,407	7,746
Restaurant FE				
Year FE	Yes	Yes	Yes	Yes

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

Figure A1. The Probability of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on timely response within 123 hours)

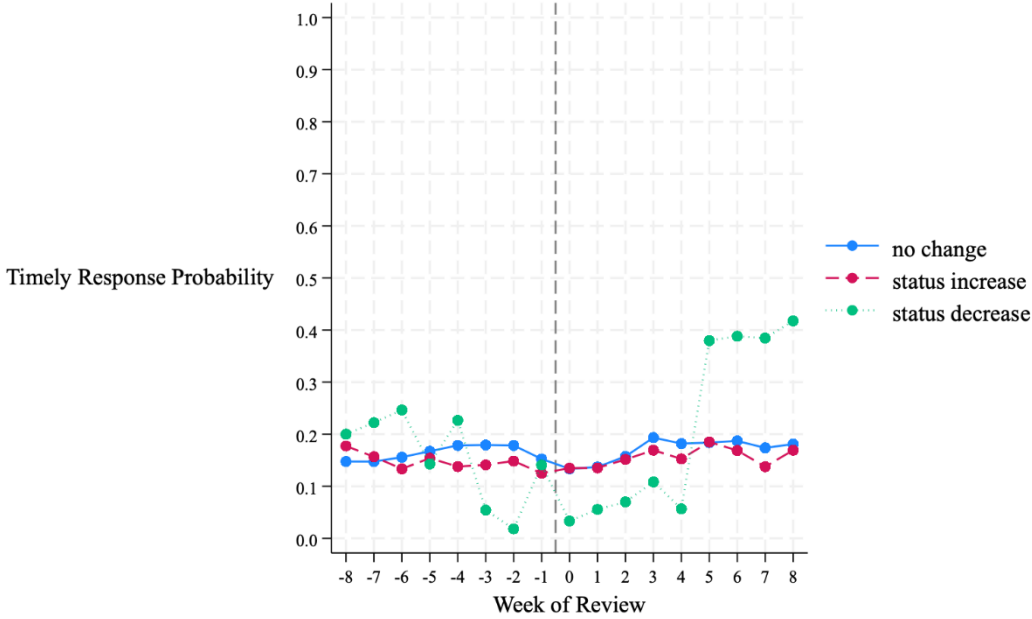


Figure A2. The Tone of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on timely response within 123 hours)

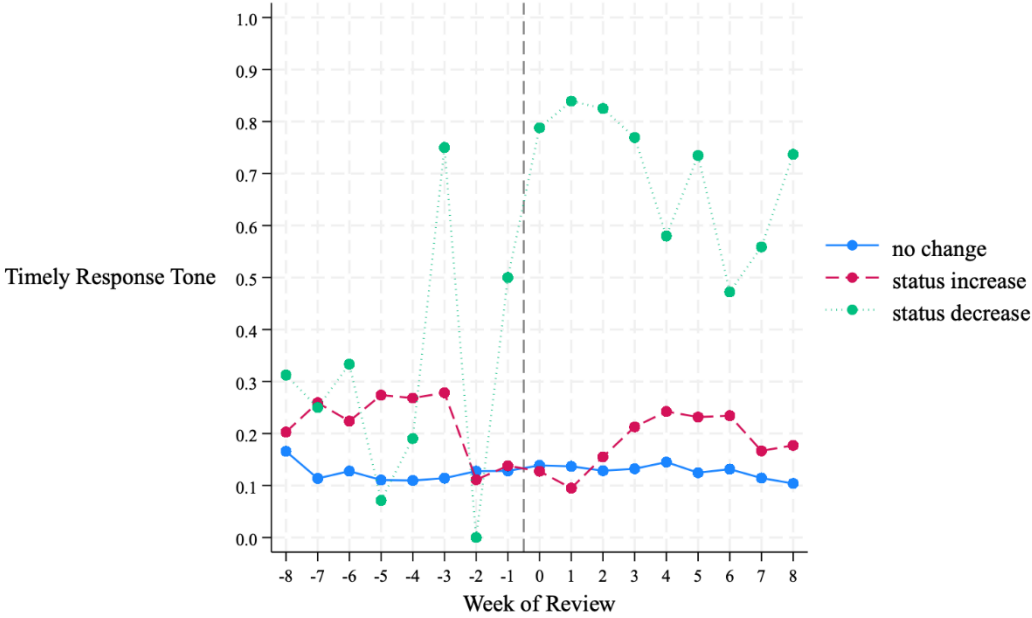


Figure A3. The Probability of Response per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on allowed response window 123 hours)

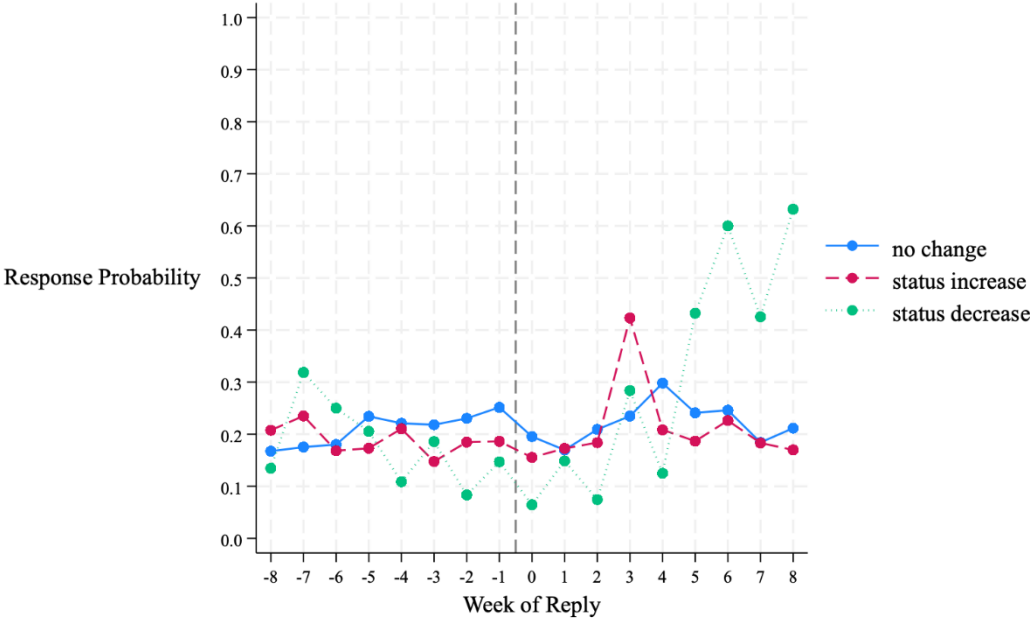


Figure A4. The Tone of Response (positive) per week for restaurants experiencing status increase, status decrease, or no status change before and after the announcements (based on allowed response window 123 hours)

