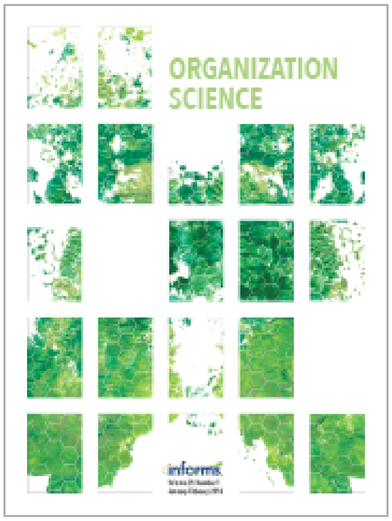

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Let Us Not Speak of Them, But Look and Pass? Organizational Responses to Online Reviews

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Abstract. In a world where five stars have become the standard for evaluating many transactions and consumers turn to the crowd for guidance when making a wide variety of choices, organizations cannot dismiss online reviews as inconsequential. And whereas we know a lot about how organizations respond to reviews online, there has been a lack of systematic evidence showing how organizations behave in response to online feedback once their screens are turned off. This paper leverages a novel combination of insights from a lab-in-the-field experiment, an archival study, and two rounds of qualitative interviews in the French restaurant industry to examine online and offline responses to reviewer feedback. We identify characteristics of the review, the restaurant, and the respondent that influenced when restaurants in our sample were more likely to align their actions online and offline and when they were more likely to decouple them—that is, posting an online response promising to take corrective action while having no intention to change how the restaurant operates "in real life." We conclude by speculating on potential mechanisms behind our respondents' reactions and discussing our contribution to the literature on producer reactivity and the symbolic management of change.

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Keywords: social evaluations • producer reactivity • decoupling • online reviews • mixed methods • experiments • hospitality

Introduction

Thanks to advances in information technology, our decisions as consumers are increasingly informed by online reviews—that is, unsolicited evaluations published on the internet by consumers intending to appraise the products and/or services provided by organizations. Today, we turn to "the crowd" for guidance, not only when making relatively inconsequential choices, such as where to eat or which movie to see, but also for deciding which doctor we should consult or to which job we should apply.[1] As the number of industries not affected by online reviews continues to shrink (Dellarocas 2003, Fourcade and Healy 2017) and the volume of online reviews generated each day continues to grow (Olson and Waguespack 2020, Botelho 2024), organizations find themselves in a position where it is difficult to ignore the opinions consumers express online. Most prior work examining producer reactivity to online reviews has tended to focus on the most apparent form of response: whether and how organizations respond to a review *online* (Wang et al. 2016, Proserpio and Zervas 2017, Chevalier et al. 2018, Wang et al. 2021). Yet posting an online response is only the most conspicuous form of reaction an organization might embrace. After all, an online review includes feedback from relevant stakeholders and, as such, represents an opportunity for an organization to learn (Dahlin et al. 2018) and engage in substantive changes to its practices *offline*, similar to how they might respond to a professional critic (Sharkey et al. 2023).

Literature on producer reactivity has illustrated a number of strategic actions firms may adopt in response to more traditional forms of evaluations, such as rankings, scores, and ratings produced by expert critics and other well-reputed intermediaries (Martins 2005). These actions range from substantive changes to organizational practices (e.g., Jin and Leslie 2003, Chatterji and Toffel 2010) to ceremonial actions aimed at gaming the system (e.g., Espeland and Sauder 2007, Ody-Brasier and Sharkey 2019) and at maintaining a positive organizational image, in some cases using rhetorical efforts alone (e.g., Elsbach 2003, Zavyalova et al. 2012). A broader literature on response strategies to external pressures (Oliver 1991, Crilly et al. 2012, Durand et al. 2019) has thoroughly discussed the tendency for organizations to engage in the symbolic management of strategic change via framing and decoupling (Fiss and Zajac 2006, Bromley and Powell 2012). According to this work, there may be a disconnect between framing versus action, saying versus doing, rhetoric versus substance. This disconnect is likely to exacerbate in the case of online reviews, where the potential for two types of responses—one posted online and one enacted offline—creates an opportunity for organizations to decouple their walk from their talk. Whereas decoupling has been documented in the context of pressures by traditional stakeholders, should we also observe it in the case of online reviews?

The answer to this question is far from trivial. On the one hand, one may argue that the scattered and potentially conflicting concerns raised by a collection of amateur evaluators (Orlikowski and Scott 2014, Sharkey et al. 2023) can be brushed off quickly once the screens are turned off. Organizations in such cases might feel safe to dismiss a customer's call for corrective action and opt instead to "look and pass," a reference from Dante's "Inferno" about ignoring remarks from critics the listener considers to be unqualified. On the other hand, offline responses may be more easily monitored by a dispersed and pseudonymous crowd, and the online context is well-known for its ability to make disapproval "faster, hotter, and more linked in," to borrow a line from Wang et al. (2021, p. 275). In other words, when an organization *disingenuously* promises to address an issue brought up by a customer but, in fact, takes no corrective action, there is a nonnull probability that future customers who find the same fault will hold the organization accountable for breaking its promise, tarring it with the reputation of a repeat offender (Etter et al. 2019, Wang et al. 2021).

In this paper, we aim to contribute to this line of research by providing systematic evidence of the circumstances under which organizations are more or less likely to align or decouple their online promises and offline actions. By shifting the focus from examining the menu of responses organizations have available when dealing with online reviews (Karunakaran et al. 2022) to investigating how organizations integrate (or not) their online and offline responses, we aim to go beyond the question of *whether* firms align or decouple and identify *when* they are most likely to embrace one strategy or the other. In other words, we ask: "When do online and offline responses to reviews differ, and why?"

Because of the exploratory nature of our inquiry, we followed an inductive approach, iterating across different data sources and methods to form a better understanding of the phenomenon under investigation (Glaser and Strauss 1999, Charmaz 2006). For our empirical context, we chose the restaurant industry (Simonson and Rosen 2014, Luca 2016, Favaron et al. 2022)—where reviews are abundant and consequential for organizations—and focused our attention on France, a country well-known for its culinary tradition (Rao et al. 2003, Fauchart and von Hippel 2008). To overcome the obvious empirical challenge of observing offline reactions to online reviews, we designed and administered a lab-in-the-field experiment to restaurants in the French edition of the Michelin Guide. We gave participants in the experiment a vignette describing an online review they might have received, manipulated a number of review features, and observed the effects of our treatments on participants' intention to take corrective action *offline*. We next collcted information about the *online* behavior of the restaurants who participated in our experiment, namely, the responses our participants issued in reaction to the TripAdvisor reviews they received up to the day of our experiment. Combining manual coding with a machine learning (ML)–based classification model, we learned about the extent to which their online responses to reviewer feedback communicated a promise of corrective action. We then matched results of the archival study with results of the experiment to observe the conditions under which the online and offline responses of our sample restaurants were aligned or decoupled. Finally, to better situate our findings and elaborate the underlying mechanisms, we leveraged qualitative data collected in two rounds of semistructured interviews with restaurant managers, owners, and chefs.

Together, our findings paint a picture that contrasts with the idea of organizations being "in effect, micromanaged by the crowd" (Karunakaran et al. 2022, p. 186), pushing them to attend to its immediate complaints and short-term demands at the expense of their long-term goals. Instead, we suggest that organizations strategically select how much they promise to address the concerns expressed by reviewers rhetorically through their online responses and how much they align these rhetorical claims with substantive changes to their offline practices, in the form of corrective action. Our results show that the extent to which online and offline responses to reviews differ depends on a number of factors at the level of the restaurant, the review, and the organization member handling the review. We uncover instances in which organizations are receptive to taking action, both online and offline, in response to feedback, as well as instances in which they limit or avoid any response, rhetorical or otherwise. We also document cases of decoupling in which online promises of corrective action are paired with limited intention to act offline. We even find circumstantial evidence of organizations avoiding an online response while, at the same time, taking action offline to correct the underlying issue. This broad and diverse array of responses to reviews in our sample allows us to identify a number of specific factors that appear to influence the strategies organizations select in response to any given review.

Theoretical Background

The phenomenon of online reviews is relatively new compared with more traditional forms of evaluations, such as rankings produced by expert critics and other well-reputed intermediaries (Sharkey et al. 2023). Different from traditional evaluations, online reviews arrive "via slingshot without warning, respite, regulation, or accountability" (Orlikowski and Scott 2014, p. 889). They are produced by laypersons who self-select into the role of critics (Botelho 2024) and have a documented tendency to provide partial accounts (Etter et al. 2019). The disproportionate prevalence of extreme reviews is among the most robust empirical findings in the literature: Consumers are more likely to post a review after a negative or very positive experience compared with an average one (Li and Hitt 2008, Luca and Zervas 2016). And this is true for books (Chevalier and Mayzlin 2006), movies (Dellarocas and Narayan 2006), home products (Moe and Schweidel 2012), and physicians (Gao et al. 2015), as well as for restaurants and hotels (Fradkin et al. 2015). As online reviews grow in number and prominence, organizations find themselves in a position where it is difficult to ignore the opinions consumers express online. For instance, in the restaurant industry, where consumers increasingly rely on online reviews for their purchasing decisions (Simonson and Rosen 2014), a one-star decrease in Yelp ratings has been argued to lead, on average, to a 5%–9% reduction in revenues (Luca 2016). The effects of reviews are also tangible outside the hospitality and travel industries. Reviews on websites such as Glassdoor and Indeed, for example, have been argued to influence firms' reputations and recruitment outcomes.[2]

Firms evaluating how to respond to online criticism face an obvious dilemma. On the one hand, publicly engaging with online commentary may help minimize its negative externalities, as it allows the organization to have a say in the matter. After all, the reviewed organization is only one of many actors (e.g., existing and potential customers, competitors) that have access to the evaluation provided by the reviewing customer (Etter et al. 2019). At the same time, a public response may "draw attention to, and increase scrutiny of, issues regarding which consumers have expressed disapproval" (Wang et al. 2016, p. 136). It may also be interpreted as overly defensive, pushing consumers to side with complainers instead of with the organization being reviewed (Ashforth and Gibbs 1990). This apparent trade-off—between minimizing externalities and attracting attention—has stimulated recent scholarly interest in producer reactivity, with a focus on uncovering the conditions under which organizations are more or less likely to respond online (Wang et al. 2016, Wang et al. 2021) and when providing a response can be more or less beneficial (Proserpio and Zervas 2017, Chevalier et al. 2018, Ananthakrishnan et al. 2023).

Of course, publishing a response intended to manage online criticism rhetorically is only the most conspicuous form of response an organization might undertake. Similar to comments raised by a professional intermediary (e.g., Sharkey et al. 2023) or concerns raised by relevant stakeholders (e.g., Huising 2015, Augustine 2021), online reviews can also push organizations to change their practices substantively. Documenting *how* organizations change their practices in response to online feedback is no easy pursuit, however. The obvious empirical challenge is to observe such behavior, which may explain the paucity of work in this domain. The few exploratory studies that have included offline responses to online reviews have hence chosen to rely on qualitative methods (i.e., Orlikowski and Scott 2014, Rahman 2021, Karunakaran et al. 2022). For instance, the pioneering 2014 study by Orlikowski and Scott relied on interviews with a heterogeneous set of informants and a rich set of archival materials to investigate how valuation practices and outcomes differ depending on whether the valuation is produced by a traditional intermediary entity (the Automobile Association) or an online review aggregator (TripAdvisor). Hoteliers interviewed by the authors suggested that they revise their everyday practices based on the feedback provided by reviews. More recently, Rahman (2021) combined interviews, archival data, and ethnographic work, with the aim of examining how evaluated actors react to the implementation of a rating system on a labor platform. They found these actors reacted in one of two ways: by experimenting to improve their rating scores or by constraining their activity on the platform to preserve scores earned previously. Probably the most comprehensive study to date is the one by Karunakaran et al. (2022). The authors drew insights from interviews, field observations, and other qualitative data sources to examine how organizations in the emergency response and hospitality industries respond to online reviews and social media commentary. Their findings suggest that producers have a menu of responses available; that is, they engage with comments online, recalibrate risk by not responding or being overcautious in what they write, redeploy resources to address the issues raised, and redefine service from long-term priorities to short-term demands. This is particularly consequential for organizations, as they risk losing perspective on their long-term trajectory (see also Chu 2021).

Interestingly, prior work on organizational responses to online reviews has so far failed to integrate a well-established finding from the literature on producer reactivity and organizational responses to external pressures more broadly, according to which, when faced with concerns from external stakeholders, organizations may engage in the symbolic management of strategic change (e.g., Fiss and Zajac 2006, Bromley and Powell 2012, Durand et al. 2019). According to this work, there may be a disconnect between rhetoric versus substantive changes. Online reviews are likely to exacerbate this disconnect. Decoupling may be an appealing strategy in contexts where feedback is offered in a fragmented and potentially contradictory fashion, making it difficult for consumers to ascertain how much a responding organization "walks its talk" offline. Still, offline responses are easier to monitor—and sanction—in a world where organizational actions are scrutinized by a dispersed and pseudonymous crowd. Getting caught in the act of decoupling, no matter how small the probability, would run the risk of triggering broad dissemination of disapproval in online social networks, subject to emotionally charged and potentially partial content (Etter et al. 2019, Wang et al. 2021). One might therefore expect organizations to be cautious when making promises online. They would understand that the primary audience for a response is not unhappy customers of the past, but their potential customers of the future.

To truly unravel the tensions that organizations face in such cases, it will be necessary to investigate how they navigate responses both online and offline and why they behave as they do. In this paper, we aim to do so by uncovering which contingencies would lead organizations to ensure that their online and offline responses are coherent with one another and which would lead to decoupling. Our ability to observe organizational responses is therefore fundamental, and it required us to devise an empirical strategy that would allow us to uncover typically unobservable behavior. We kickstarted our data collection by devising such a strategy.

Research Methods

To overcome the lack of observability of offline reactions to online reviews, we designed a lab-in-the-field experiment and administered it to real players in the restaurant industry in France. In the experiment, we gave participants a vignette describing an online review they might have received. We manipulated a number of review features and observed the effect our treatments had on the intention of our participants to respond to reviewers' online feedback with offline substantive changes, in the form of corrective action(s). We next collected information about the online behavior of our participants to form an understanding of the conditions under which these restaurateurs were more likely to respond to the feedback in reviews by publishing a promise to incorporate corrective action(s). We then leveraged the qualitative data we collected for the entire duration of the project to better situate our findings and elaborate on the mechanisms behind them. Overall, our data collection relied on three main data sources, as illustrated in Table 1.

Our research questions directed us toward an empirical context in which reviews were abundant and where they had been shown to have a real impact on organizational performance. The restaurant industry proved

Table 1. Overview of Data Sources

Data source	Description	Use in the analysis
Lab-in-the-field experiment	Vignette experiment administered to 192 restaurants included in the French edition of the Michelin Guide	Understand how organizations respond to reviews offline Examine how specific characteristics of a review, respondent, and organization affect the intention to act on the feedback provided
Archival data from TripAdvisor	Analysis of the 4,394 responses the same restaurants issued in reaction to the 30,422 TripAdvisor reviews received up to the day they participated in our lab-in-the-field experiment	Understand how organizations respond to reviews online Examine how specific characteristics of a review, respondent, and organization affect the propensity to respond online and, in that response, communicate an intention to take corrective action Explore coherence between offline and online responses
Interviews	45 semistructured interviews with French restaurant owners, managers, and chefs: First round of 15 interviews before quantitative data collection Second round of 30 interviews after quantitative data collection	Understand how restaurants think about online reviews Improve design of lab-in-the-field experiment (first round of interviews only) Elicit potential interpretations of quantitative findings (second round of interviews only)

Note. The table presents an overview of the three main data sources used in the paper.

ideal. Online reviews are a relevant phenomenon for restaurants, which remain the main target of reviews on platforms such as TripAdvisor and Yelp.[3] The impact of online reviews in the restaurant industry has also been documented by a number of empirical studies (Anderson and Magruder 2012, Luca 2016). Within the global restaurant industry, we decided to focus our attention on France, a country that is well-known for its culinary tradition (Rao et al. 2003, Fauchart and von Hippel 2008).

Sample

In defining our population of interest, we began with all restaurants listed in the French edition of the Michelin Guide, for a total of 4,214 restaurants. The choice of this population was driven by the need to identify a group of restaurants that was large enough to be representative of the variety of establishments that constitute this industry.[4] At the time of our study, the list of Michelin restaurants had recently been made freely accessible online. Restaurant pages displayed most of the information offered by the paper version of the guide, including inspectors' reviews, service quality, and business information. The availability of business information allowed us to get immediate access to the email addresses of 1,133 restaurants in the guide. We further acquired a database of email addresses of French restaurants from a private company, which allowed us to expand our initial data set from 1,133 to 2,877 restaurants. We contacted all 2,877 restaurants via email, only to realize that in many instances, those email addresses were outdated or wrong. This occurrence can be explained by the relatively short lifespan of restaurants in France (approximately two years), which leads to frequent changes in contact details.[5] For this reason, we decided to contact by phone all the restaurants in our initial sample. We were able to establish successful contact with 1,354 restaurants, which either confirmed the reception of the email or provided us with a different email address. A comparison between these 1,354 restaurants and the entire population of 4,214 Michelin restaurants shows, perhaps not surprisingly, that we were more successful at contacting restaurants that were in a higher price bracket, had been awarded more Michelin stars, and were located in one of the 10 largest metropolitan areas in France.

In the end, 192 restaurants participated in our study, a number that corresponds to a 14.2% response rate for the 1,354 restaurants we were able to contact, in line with other studies that used similar methodology and respondents (13.8% in Hawass 2010, 8.3% in Wilden et al. 2013). Our respondents are mainly male (62%), with an average age of 43 (minimum 21, maximum 68), and mostly owners of their own restaurants (specifically, 36% of our participants are chef-owners, 19% are owners but not chefs, 26% are chefs but not owners, and 19% are managers). To ensure that our final sample of 192 restaurants is representative of the entire population of Michelin restaurants and that the study is not affected by nonresponse bias, in Table 2, we compare respondents with nonrespondents. Results from this analysis show that there are no significant differences between respondents and nonrespondents in terms of average price, being awarded a Michelin star or a Bib Gourmand, and type of cuisine. The only dimension on which our respondents differ is the location of their restaurants, which is biased toward large metropolitan areas. This is probably not surprising in light of our research question; that is, we find it plausible that restaurants located in more urbanized areas would be more interested in participating in a study on online customer reviews. Still, it represents an important boundary condition to our study.

Data Sources

With access to 192 organizations secured, we implemented our three-pronged empirical strategy. First, we collected data on the offline behavior of restaurants in our sample through a lab-in-the-field experiment that we administered via email using the addresses gathered through the procedure detailed above. Second, we collected data on the online behavior of the very same

Table 2. Characteristics of Sample vs. Population

	Population (n = 1,354)		Respondents (n = 192)		Nonrespondents (n = 1,162)		t-test		Cohen's D
	Mean	SD	Mean	SD	Mean	SD	t	p-value	D
Average price (€)	60.15	34.01	61.43	35.24	59.94	33.81	−0.56	0.57	0.04
Michelin Stars	0.20	0.40	0.24	0.43	0.19	0.39	−1.67	0.10	0.12
Michelin Bib Gourmand	0.14	0.35	0.15	0.35	0.14	0.35	−0.13	0.89	0.03
Creative cuisine	0.57	0.50	0.59	0.49	0.56	0.49	−0.82	0.41	0.06
Large city	0.15	0.36	0.21	0.41	0.14	0.34	−2.69	0.01	0.19

Notes. We compare our sample of 192 respondents with the population of Michelin restaurants we were able to reach with our lab-in-the-field experiment. The comparison is based on observable characteristics described in the 2017 French edition of the Michelin Guide. Large city marks the cases of restaurants located in one of the 10 largest metropolitan areas in France by population (population > 230,000 as of 2013).

restaurants by examining the actual responses they issued in reaction to the TripAdvisor reviews they received up to the day they participated in our experiment. Third, we collected two rounds of interview data involving restaurant managers, owners, and chefs, with the aim of improving our quantitative data collection, making better sense of our findings, and elaborating on the mechanisms behind them. We next provide details on each of these data collection efforts.

Lab-in-the-Field Experiment. Each restaurant in our sample received an email that included a short presentation of the research project and a link to a website. Once participants clicked on the link, they were redirected to the survey through which we administered our experiment. We developed the survey through a series of iterations involving several sources. We started by familiarizing ourselves with the industry through discussion forums, blogs, articles from specialized industry press, and academic articles. We then collected and analyzed the content of a sample of online reviews and, when possible, restaurant responses, across a variety of review websites, including Google Reviews, OpenTable, TripAdvisor, and Yelp. Next, we conducted interviews with 10 qualitative informants, including restaurant managers, owners, and chefs. We used the interviews to refine our understanding of online customer reviews in the context of restaurants and select the best manipulations for our variables of interest. Based on this information, we developed a survey that we pretested on a sample of 106 restaurants, which were not included in the final sample. The pretest was useful to refine manipulations and improve the wording of our questions. We further improved the face validity of our instrument through interviews with five additional informants. We launched the experiment in the spring of 2018, when we emailed it to our population of 1,354 restaurants. All materials were in French, and we report only the literal English translations. A copy of the survey is available in the Online Appendix.

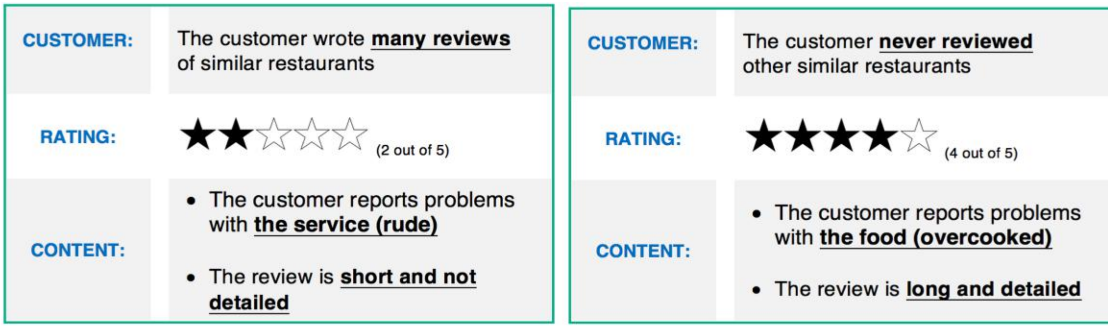
At the beginning of the survey, restaurateurs were shown a stylized online review. We introduced it as a hypothetical review received by their restaurant. We asked them to read it and then inquired about their offline response, that is, their propensity to incorporate feedback from a review by taking corrective action in the operation of their business. We measured *intention to incorporate feedback reported offline* (on a seven-point Likert scale) by asking our participants: "After having read this review, how likely is it that you would put in place some corrective actions following the customer's review (for instance, giving instructions to staff)?" The answer to this question is likely affected by a number of factors, including an individual's overall propensity to change, listen to customer feedback, or simply be subject to biases in responding. To control for these individual-specific factors, we asked our respondents to read a second review and answer the same question about their propensity to incorporate feedback with corrective action offline. Comparing how the same participant answered the same question after reading two different reviews allows us to capture how a change to a review's features generated a change in the propensity of our participants to take corrective action while removing potentially unobserved subject-level confounds (Di Stefano et al. 2015).[6]

We used the stylized review to manipulate four features that, according to our qualitative informants, could have affected the propensity of a participant to take offline action in response to a review's feedback. First, our informants agreed on the importance of the rating associated with the review. We hence decided to manipulate the extent to which the rating was *negative* by accompanying the review with a rating that was either "two out of five stars" or "four out of five stars."[7] Second, our informants suggested they would be more likely to learn from a review that provided extensive feedback in a *detailed* manner. We hence described the review as either long and detailed or short and without details. Third, our qualitative informants suggested they would be less likely to take action in response to feedback focusing on *food* rather than on service. We hence mentioned whether the customer was reporting problems about overcooked food or rude service. Fourth, our informants suggested they would be more likely to take action in response to feedback coming from a more *experienced* reviewer. We hence revealed whether the customer had written many reviews of similar restaurants in the past or had not written any before. Each participant received a random combination of the four manipulations (negative, detailed, food, experienced) in the first review and a random combination of the four manipulations in the second review, as exemplified in Figure 1.

We used the last section of the survey to collect information about the participant and the restaurant, which we combined with information available on the Michelin Guide and TripAdvisor to develop an additional set of variables. Specifically, we controlled for whether the respondent was the owner of the restaurant, whether the restaurant was located in a more touristic area, and average price, average rating, affiliation with a chain, and cuisine type. We provide a comprehensive description of the variables in Table 3 and display descriptives and correlations in Table 4. Further details on the logic behind the choice of our manipulations and the operationalization of all variables are reported in the Online Appendix.

Archival Study. Over the last two decades, TripAdvisor has emerged as the most popular review website in the hospitality industry. Founded in the United States in

Figure 1. (Color online) Examples of Stylized Reviews



Notes. The figure illustrates two potential reviews a participant might have received. We manipulated four features that, according to our qualitative informants, could have affected the propensity of a participant to incorporate the feedback provided by the review. Following the order with which they are displayed in the figure: the extent to which the review was coming from a more *experienced* reviewer, the extent to which the rating associated with the review was *negative*, the extent to which the review talked about *food*, and the extent to which the review was *detailed*.

2000, TripAdvisor currently hosts more than one billion reviews of about nearly eight million businesses and is present in 43 markets and 22 languages.[8] On TripAdvisor, every consumer, upon creation of a free account, can submit a restaurant review. Once posted, the review becomes visible to anyone visiting the website, whether or not those visitors have accounts. Interestingly, restaurants are able to follow up by responding to the review, and their responses become visible to anyone right below the text of the original review. Data from prior studies (Proserpio and Zervas 2017, Wang and Chaudry 2018) show that this feature was not frequently utilized until the late 2010s, after which it started to take off. The popularity of this feature is of pivotal importance for our study, as it allows us to examine restaurants' online reactions and connect them to the review to which they refer.

We searched TripAdvisor to identify the 192 restaurants that participated in our lab-in-the-field experiment. We were able to retrieve information for only 164 restaurants, as no TripAdvisor data were available for the remaining 28 at the time when the lab-in-the-field experiment took place. For these 164 establishments, we were able to access information about the restaurant (name, average rating, address, price range, cuisine type), the reviews it had received (text of the review, rating, date, name of reviewer, number of reviews posted by the reviewer), and the responses it had provided (text of the response, date, author of the response). For consistency with the lab-in-the-field experiment, our analyses are based on the 30,422 reviews and 4,394 associated responses that these 164 restaurants received from 2011 (the first year in which we started seeing a more consistent utilization of the response feature) until the exact day in the spring of 2018 when each of them participated in the lab-in-the-field experiment. We replicated our data collection in the spring of 2021, three years after the restaurants participated in the first study. By then, TripAdvisor data were available for 173 of the 192 participants, for a total of 42,835 reviews and 6,662 associated responses. Carrying out our analyses on this extended data set produced consistent results, as reported in the Online Appendix.

Table 5 shows selected statistics about the propensity of restaurants in our sample to respond to TripAdvisor reviews. The first interesting observation is that the majority of restaurants in our sample (68.29%) had responded to at least one review by the time they participated in the lab-in-the-field experiment. This figure reassured us that there was merit in looking at the response behavior of these restaurants, as they seemed to be quite engaged with the platform. The table further shows that despite variation in the degree to which restaurants were active on the platform, a substantial number of those in our sample had contributed to it repeatedly by the time they participated in our first study: 44.51% of restaurants had issued more than 10 responses, and 22.56% had posted over 50. Clearly, the number of responses posted by a restaurant is a function of the number of reviews received. Our data show that, on average, our respondents publicly replied to 16.10% of the reviews they received (39.86 responses over 247.54 reviews).[9]

To capture how organizations react to reviews online, however, we needed to go beyond the mere presence of a response and examine the content a response communicated. We hence built the variable *intention to incorporate feedback communicated online* to measure the extent to which an online response promises the restaurant will take corrective action. To codify this variable, we started by using a consensual assessment approach, commonly adopted to measure constructs such as creativity (Amabile 1982). With this approach, the researcher codifies the data manually by assigning a score—in this case, with the aim of evaluating the extent to which a response promised corrective action(s). To implement this approach, two independent coders labeled all responses published

Table 3. List of Variables (Lab-in-the-Field Experiment)

Variable	Measure	Operationalization
Dependent variable		
Intention to incorporate feedback reported offline	Respondent's propensity to put in place corrective actions based on feedback provided in the review	Seven-point scale, from very unlikely to very likely
Independent variables		
Rating: Negative	Review is accompanied by an extremely negative rating of 2 (vs. a marginally negative rating of 4)	Experimentally manipulated; negative = 1, zero otherwise
Review: Detailed	Review is long and detailed (vs. short and without details)	Experimentally manipulated; detailed = one, zero otherwise
Review: Food	Review reports problems with overcooked food (vs. rude service)	Experimentally manipulated; food = 1, zero otherwise
Review: Experienced	Review is written by a customer who wrote many (vs. never wrote) reviews of similar restaurants	Experimentally manipulated; experienced = 1, zero otherwise
Respondent: Owner	Respondent is the owner (vs. manager or nonowner chef) of the restaurant	Owner = 1, zero otherwise
Restaurant: Touristic	Score based on concentration of hotel rooms within the restaurant's department vis-à-vis Paris department (postal code 75)	Score between zero and one, with the Paris region representing France's most touristic area
Restaurant: Rating	Average rating of the restaurant on TripAdvisor at the time of the experiment	Average rating on a 1-to-5 scale
Restaurant: Price	Average price of the restaurant on TripAdvisor at the time of the experiment	Average price in euros
Restaurant: Chain	Restaurant is affiliated with a chain	Affiliated = 1, zero otherwise
Restaurant: Creative	Restaurant is classified by Michelin as serving creative cuisine	Creative = 1, zero otherwise

Note. The table includes a comprehensive list of the variables employed in the experimental study, including our dependent variable (*intention to incorporate feedback reported offline*) and a series of explanatory variables at the review, respondent, and restaurant levels.

Table 4. Descriptive Statistics and Correlations (Lab-in-the-Field Experiment)

Variables	Mean	SD	Min	Max	1	2
1 *Intention to incorporate feedback reported offline*	5.121	1.966	1.000	7.000	1.000	
2 *Rating: Negative*	0.478	0.500	0.000	1.000	−0.068	1.000
3 *Review: Detailed*	0.478	0.500	0.000	1.000	0.156	−0.062
4 *Review: Food*	0.481	0.500	0.000	1.000	−0.141	−0.021
5 *Review: Experienced*	0.527	0.500	0.000	1.000	0.084	0.075
6 *Respondent: Owner*	0.176	0.381	0.000	1.000	−0.011	0.017
7 *Restaurant: Touristic*	0.239	0.331	0.000	1.000	−0.098	−0.074
8 *Restaurant: Rating*	4.192	0.911	1.000	5.000	0.028	−0.062
9 *Restaurant: Price*	61.230	35.440	9.500	200.00	0.057	0.010
10 *Restaurant: Chain*	0.096	0.295	0.000	1.000	0.039	0.033
11 *Restaurant: Creative*	0.599	0.491	0.000	1.000	0.020	−0.007

Variables	3	4	5	6	8	9	10	11
3 *Review: Detailed*	1.000							
4 *Review: Food*	0.004	1.000						
5 *Review: Experienced*	0.010	−0.123	1.000					
6 *Respondent: Owner*	0.025	0.021	0.031	1.000				
7 *Restaurant: Touristic*	0.044	−0.122	0.027	−0.077	1.000			
8 *Restaurant: Rating*	−0.003	0.011	−0.107	−0.152	0.085	1.000		
9 *Restaurant: Price*	0.011	0.058	−0.020	0.077	−0.039	0.210	1.000	
10 *Restaurant: Chain*	0.064	0.015	0.091	−0.029	−0.088	−0.118	0.111	1.000
11 *Restaurant: Creative*	0.134	0.023	−0.053	−0.258	0.182	0.177	0.043	0.023

Note. The table provides descriptive statistics and correlations for all the variables from our lab-in-the-field experiment.

Table 5. Propensity of Restaurants in Our Sample to Respond to TripAdvisor Reviews

	Original data collection (spring 2018)	Extended data collection (spring 2021)
Restaurants that participated in our experiment for which TripAdvisor data are available	164	173
Average number of responses per restaurant	39.86	59.92
Restaurants with at least one response	112 (68.29%)	135 (78.03%)
Restaurants with 10 responses	73 (44.51%)	99 (57.23%)
Restaurants with >50 responses	37 (22.56%)	55 (31.79%)
Average number of reviews per restaurant	247.54	334.74
Restaurants with <50 reviews	11 (6.71%)	8 (4.62%)
Restaurants with <100 reviews	34 (20.73%)	19 (10.98%)
Restaurants with <200 reviews	82 (50.00%)	61 (35.26%)
Restaurants with >500 reviews	19 (11.59%)	36 (20.81%)

Notes. We searched TripAdvisor to identify the 192 restaurants that participated to our lab-in-the-field experiment. We were able to retrieve information for 164 restaurants only, as no TripAdvisor data were available for the remaining 28 at the time in which the experiment took place. We replicated our data collection in the spring of 2021, three years after the restaurants had originally participated in the experiment. By then, TripAdvisor data were available for 173 of the 192 participants. As a robustness test, we replicate the analysis on this extended data set. The table above displays some statistics about the propensity of these 164 and 173 restaurants to respond to TripAdvisor reviews.

by restaurants before the date when they participated in the experimental study. Responses were labeled as one if they promised to take corrective action based on the reviewer's feedback, and zero otherwise. The interrater agreement (Cohen's kappa) between the two independent coders was 74.6% before resolving the few cases in which there was a discrepancy in coding. Although promises to take corrective action are often explicit and easy to identify in management responses, our systematic examination of the text of responses revealed that in a significant portion of the responses posted by restaurants, the extent of a promise or intention is more difficult to capture. Restaurants may, for example, state that they usually take feedback into account, but they then become defensive or simply say that they would transfer the feedback to the staff. The nuanced nature of management responses convinced us to complement our manual coding of responses with a machine learning classification. ML-based classification models have been shown to perform well when trying to replicate human judgment in text (e.g., Crowston et al. 2012, Choudhury et al. 2019), images (e.g., Wang et al. 2018, Choudhury et al. 2019), and audio (e.g., Liebman et al. 2019). Hence, we decided to use the manually labeled data set to train a random forest classifier, which performs reasonably well when classifying short text (Shirani-Mehr 2014). Our goal was to find the best possible balance between the subjectivity of human judgment and the objective assessment of the machine. The additional advantage of this approach is that the output of the classifier is not a binary score for each response but a probability that each response would score one, which results in a continuous variable in the range of zero to one. These scores allowed us to more accurately capture instances of less explicit intention to incorporate offline corrective action in response to feedback. In the Online Appendix, we provide additional details on the procedure we used and show that our main results remain consistent when we replace the ML-based variable with the raw scores from the manual coding of responses. We also provide examples of coded responses.

To make the archival analysis directly comparable with the lab-in-the-field experiment, we proceeded to the creation of the same variables we had previously manipulated (*negative*, *detailed*, *food*, *experienced*) or measured (*owner*, *touristic*, *rating*, *price*, *chain*, *creative*) in the experiment. We provide a comprehensive list of the variables in Table 6 with descriptives and correlations in Table 7 and further details on their operationalization in the Online Appendix.

Qualitative Data Collection. Our qualitative data collection took place over two rounds. We carried out the first round of 15 interviews at the beginning of our quantitative data collection with the aim of refining our understanding of online customer reviews in the context of restaurants and improving the design of our lab-in-the-field experiment. We carried out the second round of interviews after our quantitative data collection and analysis were complete, with the explicit goal of eliciting interpretations of findings from our qualitative informants. We were able to conduct 30 interviews with owners, chefs, and managers of restaurants both inside (four) and outside (26) our sample of 192 restaurants (see Table 8). Whereas the interviews conducted in the first round were more informal and exploratory in nature, the ones we conducted in this second round followed a precise protocol, which we include in the Online Appendix. Interviews lasted around a half hour and were mainly held by phone or videoconference. All interviews were recorded, transcribed, and translated from French to English, for a total of 515

Table 6. List of Variables (Archival Study)

Variable	Measure	Operationalization
Dependent variable		
Intention to incorporate feedback communicated online	The online response communicates the intention to put in place corrective actions based on feedback provided in the review	Score ranging from zero to one computed through an ML-based classification model
Independent variable		
Rating: Negative	TripAdvisor score, reverse coded	Five-point scale from zero (five stars) to four (one star)
Review: Detailed	Length of the review	Count of characters (log transformed)
Review: Food	Review focuses on food vis-à-vis service or other topics	Six-point score computed through an ML-based classification model
Review: Experienced	Number of reviews posted on TripAdvisor by reviewer	Count of reviews (log transformed)
Respondent: Owner	Online response is posted by owner of the restaurant	Owner = 1, zero otherwise
Restaurant: Touristic	Score based on concentration of hotel rooms within the restaurant's department vis-à-vis Paris department (postal code 75)	Score between zero and one, with the Paris region taking value of one
Restaurant: Rating	Average rating of the restaurant on TripAdvisor at the time of the review	Average rating on a 1-to-5 scale
Restaurant: Price	Average price of the restaurant on TripAdvisor at the time of the experiment	Average price in euros
Restaurant: Chain	Restaurant is affiliated with a chain (provided by participant in experiment)	Affiliated = 1, zero otherwise
Restaurant: Creative	Restaurant is classified by Michelin as serving creative cuisine	Creative = 1, zero otherwise

Note. The table includes a comprehensive list of the variables employed in the archival study, including our dependent variable (*intention to incorporate feedback communicated online*) and a series of explanatory variables at the review, respondent, and restaurant levels.

Table 7. Descriptive Statistics and Correlations (Archival Study)

Variables	Mean	SD	Min	Max	1	2
1 *Intention to incorporate feedback communicated online*	0.266	0.204	0.014	0.952	1.000	
2 *Rating: Negative*	0.617	0.938	0.000	4.000	0.580	1.000
3 *Review: Detailed*	5.770	0.643	4.234	9.123	0.307	0.229
4 *Review: Food*	−2.249	0.548	−3.900	0.400	0.305	0.300
5 *Review: Experienced*	3.108	1.563	0.000	8.104	0.026	−0.028
6 *Respondent: Owner*	0.089	0.285	0.000	1.000	−0.078	0.043
7 *Restaurant: Touristic*	4.192	0.911	0.000	4.878	0.101	0.019
8 *Restaurant: Rating*	4.349	0.334	1.000	5.000	−0.140	−0.223
9 *Restaurant: Price*	67.220	40.610	9.500	200.00	0.011	−0.124
10 *Restaurant: Chain*	0.117	0.322	0.000	1.000	0.091	−0.006
11 *Restaurant: Creative*	0.566	0.496	0.000	1.000	0.002	−0.054

Variables	3	4	5	6	8	9	10	11
3 *Review: Detailed*	1.000							
4 *Review: Food*	0.357	1.000						
5 *Review: Experienced*	0.125	0.081	1.000					
6 *Respondent: Owner*	−0.040	0.016	−0.034	1.000				
7 *Restaurant: Touristic*	0.026	0.037	0.085	−0.123	1.000			
8 *Restaurant: Rating*	−0.027	−0.041	−0.058	0.167	0.026	1.000		
9 *Restaurant: Price*	0.090	0.015	0.063	−0.323	0.034	0.240	1.000	
10 *Restaurant: Chain*	0.041	0.012	0.021	−0.147	−0.109	−0.142	0.163	1.000
11 *Restaurant: Creative*	0.023	−0.002	−0.027	0.118	0.089	0.340	−0.138	0.025

Note. The table provides descriptive statistics and correlations for all the variables from our archival study.

Table 8. Characteristics of Informants (Qualitative Data Collection, Second Round)

ID	Cuisine Type	Touristic area	Michelin guide	Michelin stars	Tripadvisor price level	Tripadvisor rating	Informant role	Quantitative sample
Informant 1	Traditional	1	1	0	4.0	4.5	Chef-owner	1
Informant 2	Seasonal	1	0	0	2.5	4.5	Chef-owner	1
Informant 3	Modern	1	0	0	4.0	4.5	Chef-owner	1
Informant 4	Traditional	1	0	0	2.5	4.0	Owner	1
Informant 5	Modern	1	1	2	4.0	4.5	Chef	0
Informant 6	Modern	1	1	0	2.5	4.5	Owner	0
Informant 7	Traditional	0	1	0	2.5	4.5	Chef-owner	0
Informant 8	Modern	1	1	0	2.5	4.5	Chef-owner	0
Informant 9	Modern	1	1	0	4.0	4.5	Manager	0
Informant 10	Modern	1	1	0	4.0	4.5	Manager	0
Informant 11	International	1	1	0	1.0	4.5	Chef-owner	0
Informant 12	Modern	0	1	0	2.5	4.5	Owner	0
Informant 13	Creative	1	1	2	4.0	4.5	Manager	0
Informant 14	Modern	1	1	1	4.0	4.5	Manager	0
Informant 15	Seasonal	0	0	0	2.5	5.0	Owner	0
Informant 16	Modern	1	1	0	4.0	4.0	Chef-owner	0
Informant 17	Creative	1	1	3	4.0	4.5	Owner	0
Informant 18	Regional	0	1	0	4.0	4.5	Owner	0
Informant 19	Modern	0	1	2	4.0	5.0	Manager	0
Informant 20	Modern	0	1	0	2.5	4.5	Chef-owner	0
Informant 21	Seasonal	0	1	0	2.5	4.5	Owner	0
Informant 22	Modern	1	1	0	4.0	4.0	Manager	0
Informant 23	Creative	1	1	1	4.0	4.5	Manager	0
Informant 24	Modern	0	1	0	2.5	4.5	Chef-owner	0
Informant 25	Seafood	0	1	0	4.0	4.5	Chef-owner	0
Informant 26	Modern	0	1	0	4.0	4.0	Chef	0
Informant 27	Modern	1	1	1	4.0	4.5	Owner	0
Informant 28	Seafood	0	1	0	2.5	5.0	Chef-owner	0
Informant 29	Modern	0	1	0	4.0	5.0	Chef-owner	0
Informant 30	Creative	0	1	1	4.0	4.5	Manager	0

Notes. We carried out the second round of interviews after our quantitative data collection and analysis were complete, with the explicit goal of eliciting interpretations of findings from our qualitative informants. We conducted a total of 30 interviews with owners, chefs, and managers. The table reports characteristics of these qualitative informants and their restaurants, including whether they were included in our quantitative study. Restaurant areas were coded as touristic if the tourism score of their department was above the median value of the sample.

minutes of recording (excluding the time devoted to introducing the study and allowing participants to express their consent to participation and recording), corresponding to 66 single-spaced pages of transcripts.

Findings

We began this paper by asking "when do online and offline responses to reviews differ, and why?" We now proceed to contrast the findings from the archival study with findings from the lab-in-the-field experiment to uncover the conditions under which online and offline responses are more or less aligned and coherent with one another. Our results reveal circumstances under which restaurants appear to be accommodating in their online responses (i.e., they are more likely to promise correction action in response to feedback) but, in fact, intend to ignore or dismiss that feedback (i.e., they express a lower intention to actually incorporate corrective actions "in real life")—a behavior we interpret as suggestive of a tendency to decouple rhetorical claims from substantive changes. Given the risks associated with decoupling in an online context—in which constituents may verify compliance and hold the restaurant accountable for their online promises—we then discuss the extent to which different moderators can temper such a tendency toward decoupling.

When Do Online and Offline Responses to Reviews Differ?

We start by reporting the results of our analyses of how organizations respond online and offline to reviews. Before we can do that, it is important to discuss a relevant selection issue that may bias our examination of online responses. In fact, our ability to observe *how* an organization responds online is conditional on *whether* the organization responds in the first place. To tackle this, we adopted a Heckman two-stage approach with some adaptations to accommodate the structure of our panel data (Heckman 1976, Wooldridge 2010, Certo et al. 2016, Wooldridge 2019). In the first stage of our adapted model, we estimate the probability of an organization responding to a review. Following the methodological framework proposed by Wooldridge (2019), we implemented a Chamberlain correlated random effects probit model, which allowed us to effectively capture unobserved heterogeneity in our unbalanced panel data, a key feature wherein the unobserved individual-specific effects may be correlated with the observed covariates and the occurrence of sample selection. This first stage therefore estimates the likelihood of an online response while accounting for the potential biases introduced by our panel data's structure and the inherent selection process. To exogenously capture the choice to respond, we identified an instrument in the survey associated with our experiment. In the survey, we had asked respondents about the frequency with which they read their reviews on TripAdvisor, on a scale from 1 to 4. We posited that such frequency of reading could serve as an exogenous factor influencing a restaurant's decision to respond to reviews; that is, this variable is likely to be associated with the propensity to respond, but not with the content or style of the response. Therefore, we incorporated *TripAdvisor frequency* into the first-stage estimation of our Heckman model and then included the *inverse Mills ratio* from the selection equation as a control in the second stage. We report the results of the first stage in the Online Appendix, where we show that the instrument has a positive effect on the propensity to respond online ($p = 0.001$) and that the inverse Mills ratio does not have a clear effect on whether such response promises to incorporate corrective action ($p = 0.328$). In the Online Appendix, we also run a number of robustness tests underscoring the robustness of our model.

Table 9 reports the results of our analyses of how organizations respond online and offline to reviews. Model 1 shows the results of our archival study, with *intention to incorporate feedback communicated online* as the dependent variable (including the inverse Mills ratio from the first stage), whereas Model 2 reports the results of our lab-in-the-field experiment, with *intention to incorporate feedback reported offline* as the dependent variable. For both models, we ran an ordinary least squares (OLS) regression with fixed effects, as well as a generalized least squares (GLS) regression with random effects. We then employed the Hausman test (Hausman 1978) to observe whether the coefficients changed significantly across the

Table 9. Organizational Responses to Reviews, Online and Offline

	Model 1 Intention to incorporate feedback communicated online (archival study)	Model 2 Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.098 (0.005, $p = 0.000$)	−0.364 (0.180, $p = 0.043$)
Review: Detailed	0.043 (0.007, $p = 0.000$)	0.693 (0.185, $p = 0.000$)
Review: Food	0.036 (0.006, $p = 0.000$)	−0.704 (0.206, $p = 0.001$)
Review: Experienced	0.000 (0.002, $p = 0.803$)	0.335 (0.180, $p = 0.063$)
Respondent: Owner	−0.034 (0.014, $p = 0.014$)	−0.740 (0.379, $p = 0.051$)
Restaurant: Touristic	0.069 (0.035, $p = 0.051$)	−0.007 (0.431, $p = 0.987$)
Restaurant: Rating	0.044 (0.068, $p = 0.520$)	0.037 (0.129, $p = 0.775$)
Restaurant: Price	0.000 (0.000, $p = 0.657$)	0.004 (0.004, $p = 0.344$)
Restaurant: Chain	0.070 (0.040, $p = 0.081$)	0.016 (0.562, $p = 0.977$)
Restaurant: Creative	−0.006 (0.023, $p = 0.781$)	0.082 (0.307, $p = 0.789$)
Constant	−0.143 (0.278, $p = 0.605$)	4.807 (0.608, $p = 0.000$)
N	4,394	302
Within R^2	0.380	0.209
Chi square	1,568.899	46.928

Notes. The table documents the effect of our independent variables on two dependent variables: first, the extent to which the online response on TripAdvisor communicates an intention to incorporate feedback (Model 1, GLS regression with random effects, including the inverse Mills ratio from the first stage, which we report in the Online Appendix), and second, the extent to which the restaurant reported an intention to incorporate feedback in response to our lab-in-the-field experiment (Model 2, GLS regression with random effects). The *N* for Model 2 is equal to 302 despite having data on a total of 364 scenarios (see endnote 6) because not all restaurants provided information on two control variables, namely, *owner* and *chain*. Because the observations are restaurant-review pairs, we estimated robust standard errors clustered at the restaurant level in all models. For Model 1, we further controlled for the year in which the response was published to rule out unobserved time-varying heterogeneity. We report standard errors and *p*-values below the coefficient estimates.

two specifications, and successfully passed it for all models. We hence report results from the random-effects specification only. Because the observations are restaurant-review pairs, which may lack independence (Cameron et al. 2011), we estimate robust standard errors clustered at the restaurant level in all models. For Model 1, we further control for the year in which the response was published to rule out unobserved time-varying heterogeneity.

Results from a comparison of Model 1 and Model 2 suggest a certain degree of incoherence between online and offline responses when reviews are accompanied by a more negative rating, as well as when their content mostly focuses on food. Specifically, our data show that the more *negative* the rating associated with a review, the higher the likelihood an organization will promise to take corrective action when issuing an online response (Model 1: $\beta = +0.098$, $p < 0.001$; +36.84% compared with the average likelihood of making such a promise), and the lower its intention to incorporate offline corrective action offline (Model 2: $\beta = -0.364$, $p = 0.043$; −7.11% compared with the average level of such an intention). A similar pattern can also be observed for reviews mostly focused on *food*, where we observe a positive effect on intentions communicated online (Model 1: $\beta = +0.036$, $p < 0.001$; +13.53%), but a negative effect on intentions reported offline (Model 2: $\beta = -0.704$, $p = 0.001$; −13.75%).

Online and offline responses appear more coherent when reviews are more *detailed*, a case in which we observe a positive effect on both intentions communicated online (Model 1: $\beta = +0.043$, $p < 0.001$; +16.17%) and intentions reported offline (Model 2: $\beta = +0.693$, $p < 0.001$; +13.53%). Results from our analyses suggest coherence also in the behavior of *owners* but, interestingly, in exactly the opposite way, as owners seem *less* likely to incorporate corrective actions in either what they communicate online (Model 1: $\beta = -0.034$, $p = 0.014$; −12.78%) or what they report offline (Model 2: $\beta = -0.740$, $p = 0.051$; −14.45%).

We also note a higher propensity to promise corrective action in online responses among restaurants located in a more *touristic* area (Model 1: $\beta = +0.069$, $p = 0.051$; +25.94%) and to some extent also for those affiliated with a *chain* (Model 1: $\beta = +0.070$, $p = 0.081$; +26.32%), and we see a somewhat higher intention to incorporate corrective action offline when feedback comes from more *experienced* reviewers (Model 2: $\beta = +0.335$, $p = 0.063$; +6.54%).

Taken together, our results reveal three main patterns. First, restaurants appear to be generally accommodating in their online responses; that is, most of the features we examined tended to have a positive effect on promises to take corrective action in response to the feedback in a review. This is not surprising in light of what we heard in the field. When asked about online reviews, our qualitative informants elaborated extensively on the many reasons why a restaurant should address them online. They remarked how important it is to make customers feel heard and that they have a responsibility to their patrons ("We want to show those who leave us reviews or those who simply consult them that we are present, we are active, and we take the reviews into consideration"). They discussed an imperative to manage what is said about their establishments online so as to reduce negative externalities and protect their reputation ("I think that those who overlook review management are missing something very important because they are not managing the restaurant's image on the web"). Our informants also brought up some strategic motives behind the choice to respond, such as search engine optimization, and using responses to prevent concerns from future customers ("When we respond to a negative review, we don't do it so much for the person who wrote it but, rather, for potential future customers. If the latter only saw a negative review, they would be exposed to only one point of view, which is a negative one. Instead, if we respond, we can mitigate the negative perception").

A second pattern we observed in our data is an inclination for owners to go against this general tendency toward being accommodating in their online responses by exhibiting a coherently lower propensity to "listen to customers," both online and offline. In our interviews with owners, we noticed how they seemed to take a more pragmatic approach to assessing the difficulty and cost of responding to feedback with substantive corrective action(s). They put considerable emphasis on the many reasons why they could not implement changes based on the feedback provided through reviews, including practical considerations associated with lack of time or the message getting lost ("Restaurant owners are not necessarily involved in the kitchen or service. Thus, if sometimes they do not implement any practical action, it might be because they are not able to do it"), but also emotional considerations associated with the psychological cost of dealing with reviews ("Psychology plays a major role. You know that, after you have worked for 10 hours and you receive an unfair review, you will tend to close your eyes and ignore such a review"). Interestingly, when it came to their online reactions, these informants emphasized the importance of using online responses to educate customers ("I also try to teach something to my customers: I always point out that you cannot pursue quality, quantity, and prices at the same time. At a certain point, you are forced to make a choice: we generally keep our prices and quality, even if this is sometimes at the expense of quantity"). We also consistently heard them talk about their role as buffers between their customers and their team in the restaurant ("When the review is disparaging to the staff, I point this out to the customer and say that it is not appropriate to write such reviews"). We consistently observed them speaking for their team and using responses as a tool to explain what happened and deflect responsibility from their employees. As one informant explained: "I trust my team more than the customer."

A third general pattern emerging from our analysis is related to the fact that under some circumstances, restaurants appear to decouple their rhetorical claims from the substantive changes they enact in their organizational practices. Faced with reviews that mostly focus on food and when confronted with more negative ratings, restaurants appear accommodating in their online responses (i.e., they make more online promises to take corrective action) but are de facto more dismissive of the feedback (i.e., they express a lower intention to take corrective action offline). When it came to this type of feedback, our qualitative informants seemed to be caught between a rock and a hard place. Concerns about the negative spillovers that could originate from reviews that are more negative or that speak directly to core aspects of a restaurant's offering pushed our informants to respond to these reviews online, thus explaining why restaurants tend to be accommodating in their online responses. Concerns about the extent to which these reviews can be trusted as accurate sources of feedback, on the other hand, justified the observed reticence to initiate corrective actions based on the feedback conveyed. Our informants suggested there is also an inclination to turn a blind eye to feedback related to areas perceived as requiring more technical knowledge ("You must know that there is a kind of person who wants to teach me how to cook, even if I have had the restaurant for 33 years and have been in the business for 40 years") and choices related to food ("Once, a customer complained that there was too much lemon in a lemon custard. Another time, a customer told me that I used frozen food in my restaurant, as they saw some white traces on the bread, but they didn't realize that those were simply traces of flour"). But they also discussed a tendency to discount the informational value of reviews that appear overly negative ("Overly extreme reactions should be disregarded because they are just something purely emotional and not logical") and need to be contextualized ("Sometimes, people arrive at the restaurant and they have already had a bad day. So, we try not to take the review directly, but, rather, we put it in the context of all the other reviews, and we judge the globality of them"). Our informants also explicitly mentioned the psychological costs associated with dealing with more negative reviews, which they described as "demotivating," "a tough blow to take," and something that "makes you feel nervous," with a chef openly telling us: "Negative reviews are perceived by restaurants as something very violent. They are violent for the entire team. We generally finish working between midnight and 2 a.m. Reading a negative review once you get back home makes you sick."

These findings illustrate a classic case in which organizations respond to constituents' demands by decoupling ceremonial and substantive compliance—organizations appear accommodating in their online responses but are dismissive in their offline reactions. As one informant lucidly articulated: "It is clear that for the majority of the restaurants, it is way easier to tell the customer that they will take into account their comments and make changes, even if, in reality, such restaurants are not willing to do so. The reason why they answer that way is that online reviews represent a public thing: thus, no restaurant will ever try to publicly go against the customer. So, restaurateurs will try to be polite and please the customer even though they will not necessarily make actual changes because they do not agree with the customer, or they do not have enough resources to bear the changes, or again they are simply not willing to make changes. In general, just as customers can say whatever they want in an online review, so can restaurateurs who reply in whatever way they want behind the screen." However, engaging in decoupling may be particularly risky in our context, given the risk associated with overpromising when talking to a wide audience that could potentially verify substantive compliance. As one informant put it: "If there is already a review on a particular aspect, future customers will tend to pay particular attention to it when they are at the restaurant." In other words, although the single customer who complained online can decide not to visit the restaurant again, new customers who read online reviews can observe restaurants' responses. These customers may also form expectations based on how restaurants respond (or not) to customers who complained in the past. In our qualitative analysis, this aspect emerged quite clearly, with our informants explicitly mentioning that a reason to respond to reviews online was to prevent potential complaints from future customers ("Answers to reviews are not meant for customers who have complained but for future customers. Therefore, when an establishment responds adequately and positively to criticism, this has an influence on future customers who will not necessarily repeat the same complaint"). For this reason, we would expect restaurants to be cautious in the way they make promises online because they understand that what they write is going to be scrutinized by potential future customers, who may have a chance to verify compliance.

What Moderates the Tendency Toward Decoupling Online and Offline Responses?

We now examine how the tendency toward decoupling that we remarked for reviews with more negative ratings is moderated by other review-, respondent-, and restaurant-level characteristics. Such a focus is justified by the fact that reviews accompanied by more negative ratings represent an interesting empirical puzzle. On the one hand, our results suggest that they elicit a tendency toward decoupling, with organizations appearing accommodating in their online responses but dismissive in their offline reactions. On the other hand, reviews with more negative ratings are likely to draw more attention, thus increasing the risk that future customers may hold the restaurant accountable for any promise they make online. This increases the risks associated with decoupling online promises from offline actions, thus making it interesting to examine whether other factors among those we examined may counteract this tendency and temper the strong emotional reaction restaurants seem to have when faced with particularly harsh reviews.[10]

In keeping with the exploratory nature of our inquiry, we next report results of a series of analyses in which we interact the extent to which the rating associated with the review is *negative* with the features we previously discussed at the level of reviews (*detailed*, *food*, *experienced*—see Table 10), respondents (*owner*—see Table 11), and restaurants (*touristic*, *rating*, *price*, *chain*, *creative*—see Table 12). All tables replicate Table 9, with the addition of these moderating effects. As such, they display the results of our archival study in Model 1 (with *intention to incorporate feedback communicated online* as the dependent variable and including the inverse Mills ratio from the first stage) and results of our lab-in-the-field experiment in Model 2 (with *intention to incorporate feedback reported offline* as the dependent variable). As before, we ran both an OLS regression with fixed effects and a GLS regression with random effects, but we only report the random-effects specification based on the results of a Hausman test. In the interest of space, we only report the main coefficients of interests in the tables that follow. We include the full tables in the Online Appendix.

Review Features. First, we explore whether different review features affected the tendency to decouple online and offline responses to negative reviews. Results in Table 10 suggest that this may be the case. A comparison of Model 1 and Model 2 suggests that the tendency to decouple responses to negatively rated reviews (i.e., *increased* intention communicated online together with *decreased* intention reported offline, as per Table 9) clearly emerges when such reviews are written in a less detailed fashion. This is how the coefficient of the main effect of *negative* is to be interpreted in the presence of the interaction term between *detailed* and *negative* in the same regression model. In other words, the copresence of a positive effect of *negative* on online responses in Model 1a (β = +0.091) and a negative effect of *negative* on offline responses in Model 2a (β = −0.462) provides evidence of decoupling when reviews are negatively rated and *less* detailed. The same pattern surfaces for reviews whose content is *less* focused on food (cf. the positive coefficient for *negative* in Model 1b, β = +0.097, vis-à-vis the negative coefficient for *negative* in Model 2b, β = −0.486) as well as for reviews written by *less* experienced reviewers (cf. the positive coefficient for *negative* in Model 1c, β = +0.093, vis-à-vis the negative coefficient for *negative* in Model 2c, β = −0.574). Our results further suggest that the tendency to decouple online and offline responses attenuates if the negatively rated reviews are written in a more *detailed* fashion, as shown by a comparison of coefficients in Model 2a, where the negative main effect of *negative* (β = −0.462) is partially offset by the positive interaction with *detailed* (β = +0.212, even if the estimate is less precise). This is also the case if negatively rated reviews focus on *food* (cf. Model 2b, where the negative coefficient of *negative*, β = −0.486, is partially offset by the positive coefficient of the interaction term, β = +0.254, again with a loss in estimate precision) and are written by more *experienced* reviewers (cf. Model 2c, where the negative coefficient of *negative*, β = −0.574, is partially offset by the positive coefficient of the interaction term, β = +0.393, also, in this case, with a less precise estimate).

Taken together, these results suggest that substantiating the negative rating—by writing the review in a more detailed fashion, commenting about food, or simply being a more experienced reviewer—attenuates the tendency to decouple and makes restaurants marginally more willing to incorporate the provided feedback. As one informant put it, "A review has much more impact when a person has justified it well and written it well because it means they have thought it through." Conversely, restaurants tend to disregard feedback that lacks context and appears groundless. In the words of one informant, "There are often negative reviews that provide no justification. When there is no explanation from the customer, it is difficult for the restaurateur to care about the customer's opinion because, after all, there is not much to do in practice. It may be that the customer did not like it and that the restaurant is not in their style, but if they do not explain the reason for their statement, it is difficult for the restaurateur to pay attention to it."

Respondent Role. Second, we explore whether the role our respondent has in the restaurant—namely, whether they were owners or employees of the restaurants (managers or employed chefs)—influenced the tendency to decouple online and offline responses to negative reviews. Results from a comparison of Model 1 and Model 2 in Table 11 suggest that the tendency to decouple responses to negatively rated reviews (i.e., *increased* intention communicated online together with *decreased* intention reported offline, as per Table 9) clearly emerges when responses to such reviews are issued by staff members rather than restaurant owners. Again, this is how we interpret the coefficient of the main effect of *negative* given the presence of the interaction term

Table 10. The Moderating Effect of Review Features

Panel A: Detailed		
	Model 1a Intention to incorporate feedback communicated online (archival study)	Model 2a Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.091 (0.026, p = 0.000)	−0.462 (0.252, p = 0.067)
Review: Detailed	0.042 (0.006, p = 0.000)	0.596 (0.252, p = 0.018)
Review: Detailed × *Rating: Negative*	0.001 (0.004, p = 0.777)	0.212 (0.393, p = 0.589)
Constant	−0.129 (0.267, p = 0.630)	4.865 (0.618, p = 0.000)
N	4,394	302
Within R^2	0.380	0.214
Chi square	1,882.284	46.840

Panel B: Food		
	Model 1b Intention to incorporate feedback communicated online (archival study)	Model 2b Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Review: Negative	0.097 (0.011, p = 0.000)	−0.486 (0.249, p = 0.051)
Review: Food	0.037 (0.008, p = 0.000)	−0.826 (0.270, p = 0.002)
Review: Food × *Rating: Negative*	0.000 (0.004, p = 0.913)	0.254 (0.411, p = 0.536)
Constant	−0.141 (0.275, p = 0.608)	4.842 (0.614, p = 0.000)
N	4,394	302
Within R^2	0.380	0.209
Chi square	1,606.613	52.816

Panel C: Experienced		
	Model 1c Intention to incorporate feedback communicated online (archival study)	Model 2c Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Review: Negative	0.093 (0.007, p = 0.000)	−0.574 (0.302, p = 0.057)
Review: Experienced	−0.001 (0.002, p = 0.526)	0.149 (0.248, p = 0.548)
Review: Experienced × *Rating: Negative*	0.002 (0.001, p = 0.198)	0.393 (0.409, p = 0.336)
Constant	−0.132 (0.268, p = 0.622)	4.863 (0.607, p = 0.000)
N	4,394	302
Within R^2	0.380	0.213
Chi square	1,604.912	45.993

Notes. The table documents the moderating effect of negative ratings on the relationship between review features (*detailed*, *food*, *experienced*) and *intention to incorporate feedback communicated online* (Model 1) and *intention to incorporate feedback reported offline* (Model 2). As before, we ran two GLS regressions with random effects and robust standard errors clustered at the restaurant level. For Model 1, we also include year fixed effects and the inverse Mills ratio from the first stage. All models include controls at the review, respondent, and restaurant levels. In the interest of space, the tables only report the main coefficients of interest. We include the full tables in the Online Appendix. We report standard errors and p-values below the coefficient estimates.

between *owner* and *negative* in the same regression model. In other words, the copresence of a positive effect of *negative* on online responses in Model 1 (β = +0.109) and a negative effect of *negative* on offline responses in Model 2 (β = −0.406) provides evidence of decoupling when the organizational member responding to negatively rated reviews is *not* the restaurant owner. The tendency to decouple online and offline reactions to negative reviews appears to be attenuated when it is the *owner* who directly responds to them,

Table 11. The Moderating Effect of Respondent Role

	Model 1 Intention to incorporate feedback communicated online (archival study)	Model 2 Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.109	−0.406
	(0.007, p = 0.000)	(0.196, p = 0.039)
Respondent: Owner	−0.015	−0.854
	(0.014, p = 0.289)	(0.370, p = 0.021)
Respondent: Owner × Rating: Negative	−0.021	0.269
	(0.008, p = 0.007)	(0.517, p = 0.603)
Constant	−0.149	4.819
	(0.264, p = 0.571)	(0.603, p = 0.000)
N	4,394	302
Within R^2	0.382	0.210
Chi square	1,636.165	50.779

Notes. The table documents the moderating effect of negative ratings on the relationship between respondent role (*owner*) and *intention to incorporate feedback communicated online* (Model 1) and *intention to incorporate feedback reported offline* (Model 2). As before, we ran two GLS regressions with random effects and robust standard errors clustered at the restaurant level. For Model 1, we also include year fixed effects and the inverse Mills ratio from the first stage. All models include controls at the review, respondent, and restaurant levels. In the interest of space, the tables only report the main coefficients of interest. We include the full tables in the Online Appendix. We report standard errors and p-values below the coefficient estimates.

with a marginal *decrease* in the intention communicated online ($\beta = -0.021$) and a marginal *increase* in the intention reported offline ($\beta = +0.269$, even if the estimate loses in precision). In other words, owners appear to exercise more caution with decoupling in response to negatively rated reviews, probably in consideration of the higher risks of getting "caught" overpromising from a position where their claims are more carefully scrutinized, and they have the agency to engage in corrective actions.

We have already seen in Table 9 that owners tend to be more dismissive of feedback, both online and offline. Once we consider how owners modulate their responses based on how negative the rating accompanying the review is, we observe how their tendency to be more dismissive of feedback seems to be mostly driven by less negative reviews (cf. the negative coefficient for *owner* in both Model 1 and Model 2), thus suggesting that when the rating is particularly harsh, owners may be moved to stop and think about the feedback conveyed in the review without necessarily realizing it or acknowledging this in the open. This resonates with some of the accounts we heard during our qualitative interviews, when our informants suggested that sometimes reviews may trigger action unconsciously ("All negative reviews are somehow taken into account, even if unconsciously. Some details remain engraved in our minds, and we tend not to repeat the same mistake again").

Restaurant Characteristics. Third, we explore whether different restaurant characteristics altered the tendency to decouple online and offline responses to negative reviews. Results in Table 12 suggest that this may be the case. Starting with the location of the restaurants, results from a comparison of Model 1 and Model 2 suggest that the tendency to decouple responses to negatively rated reviews (i.e., *increased* intention communicated online together with *decreased* intention reported offline, as per Table 9) clearly emerges when the recipient of such reviews is a restaurant located in a *less* touristic area. This is our interpretation of the coefficient of the main effect of *negative* in the presence of the interaction term between *touristic* and *negative* in the same regression model. In other words, the copresence of a positive effect of *negative* on online responses in Model 1a (β = +0.095) and a negative effect of *negative* on offline responses in Model 2a ($\beta = -0.593$) provides evidence of decoupling when the recipient of a negatively rated review is a restaurant located in a less touristic area. Interestingly, the tendency to decouple online and offline reactions to negatively rated reviews seems to be completely reversed for restaurants located in a *more* touristic area, as shown by a comparison of coefficients in Model 2a, where the negative main effect of *negative* ($\beta = -0.593$) is more than compensated by the positive interaction with *touristic* ($\beta = +0.941$). In other words, restaurants located in more touristic areas exhibit a lower propensity to decouple and an increased propensity to incorporate corrective action in response to feedback provided by the review. This is not surprising given that consumers may more heavily rely on review websites in more touristic areas; that is, tourists may use TripAdvisor more heavily than residents when choosing a restaurant, a feature that, for restaurants, may trigger increased dependence on reviews to bring in customers. As one informant put it, "Reviews allow people to get a sense of a certain establishment. In other words, reviews are able to trigger consumption." They consistently mentioned the need to reflect on criticism ("Restaurateurs often respond to online reviews because

Table 12. The Moderating Effect of Restaurant Characteristics

	Panel A: Touristic	
	Model 1a Intention to incorporate feedback communicated online (archival study)	Model 2a Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.095 (0.006, $p = 0.000$)	−0.593 (0.223, $p = 0.008$)
Restaurant: Touristic	0.049 (0.036, $p = 0.173$)	−0.411 (0.468, $p = 0.380$)
Restaurant: Touristic × *Rating: Negative*	0.014 (0.020, $p = 0.475$)	0.941 (0.556, $p = 0.090$)
Constant	−0.134 (0.276, $p = 0.627$)	4.953 (0.612, $p = 0.000$)
N	4,394	302
Within R^2	0.380	0.210
Chi square	1,860.703	52.106
	Panel B: Rating	
	Model 1b Intention to incorporate feedback communicated online (archival study)	Model 2b Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.128 (0.043, $p = 0.003$)	−1.328 (0.502, $p = 0.008$)
Restaurant: Rating	0.053 (0.062, $p = 0.396$)	−0.096 (0.124, $p = 0.438$)
Restaurant: Rating × *Rating: Negative*	−0.007 (0.010, $p = 0.488$)	0.231 (0.123, $p = 0.061$)
Constant	−0.181 (0.253, $p = 0.473$)	5.371 (0.561, $p = 0.000$)
N	4,394	302
Within R^2	0.380	0.207
Chi square	1,742.647	59.553
	Panel C: Chain	
	Model 1c Intention to incorporate feedback communicated online (archival study)	Model 2c Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.095 (0.005, $p = 0.000$)	−0.385 (0.198, $p = 0.052$)
Restaurant: Chain	0.052 (0.046, $p = 0.252$)	−0.082 (0.644, $p = 0.898$)
Restaurant: Chain × *Rating: Negative*	0.022 (0.017, $p = 0.183$)	0.181 (0.445, $p = 0.684$)
Constant	−0.140 (0.283, $p = 0.621$)	4.835 (0.616, $p = 0.000$)
N	4,394	302
Within R^2	0.381	0.208
Chi square	2,684.289	46.926
	Panel D: Price	
	Model 1d Intention to incorporate feedback communicated online (archival study)	Model 2d Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.074 (0.011, $p = 0.000$)	−0.913 (0.427, $p = 0.033$)
Restaurant: Price	−0.001 (0.000, $p = 0.075$)	−0.002 (0.005, $p = 0.763$)
Restaurant: Price × *Rating: Negative*	0.000 (0.000, $p = 0.023$)	0.009 (0.006, $p = 0.144$)
Constant	−0.105 (0.272, $p = 0.701$)	5.158 (0.637, $p = 0.000$)

Table 12. (Continued)

Panel D: Price		
	Model 1d Intention to incorporate feedback communicated online (archival study)	Model 2d Intention to incorporate feedback reported offline (lab-in-the-field experiment)
N	4,394	302
Within R^2	0.383	0.217
Chi square	1,879.349	49.032

Panel E: Creative		
	Model 1e Intention to incorporate feedback communicated online (archival study)	Model 2e Intention to incorporate feedback reported offline (lab-in-the-field experiment)
Rating: Negative	0.112	−0.122
	(0.006, p = 0.000)	(0.275, p = 0.657)
Restaurant: Creative	0.030	0.280
	(0.023, p = 0.195)	(0.328, p = 0.392)
Restaurant: Creative × Rating: Negative	−0.033	−0.404
	(0.008, p = 0.000)	(0.351, p = 0.250)
Constant	−0.185	4.644
	(0.280, p = 0.508)	(0.614, p = 0.000)
N	4,394	302
Within R^2	0.387	0.219
Chi square	2,272.596	47.704

Notes. The table documents the moderating effect of negative ratings on the relationship between restaurant characteristics (*touristic, rating, price, chain, creative*) and *intention to incorporate feedback communicated online* (Model 1) and *intention to incorporate feedback reported offline* (Model 2). As before, we ran two GLS regressions with random effects and robust standard errors clustered at the restaurant level. For Model 1, we also include year fixed effects and the inverse Mills ratio from the first stage. All models include controls at the review, respondent, and restaurant levels. In the interest of space, the tables only report the main coefficients of interest. We include the full tables in the Online Appendix. We report standard errors and p-values below the coefficient estimates.

they have to, but then the heart of the matter is an in-depth operational reflection aimed at improving the restaurant. Taken to the extreme, this reflection can even lead the restaurant to take responsibility for the mistake") and acknowledged how sometimes mere exposure to feedback may trigger change, even if unconsciously ("When a restaurant receives criticism, it is inevitably exposed to it, and thus, it is made aware of it. This leads the restaurant to make changes, and this process might be even unconscious"). Put simply, restaurants in touristic areas cannot really "afford" to decouple because visibility to their review-dependent customers means they can be more easily held accountable for their promises.

Results from a comparison of Model 1 and Model 2 further suggest that the tendency to decouple responses to negatively rated reviews (i.e., *increased* intention communicated online together with *decreased* intention reported offline, as per Table 9) characterizes restaurants that exhibit a *lower* average rating (cf. the coefficient for *negative* in Model 1b, β = +0.128, vis-à-vis Model 2b, β = −1.328) and are *not* affiliated with a chain (cf. the coefficient for *negative* in Model 1c, β = +0.095, vis-à-vis Model 2c, β = −0.385). The tendency to decouple online and offline responses to negatively rated reviews is instead attenuated for restaurants with *better* average ratings (cf. Model 2b, where the negative main effect of *negative*, β = −1.328, is partially offset by the positive interaction with *rating*, β = +0.231) and for restaurants that *are* affiliated with a chain (cf. Model 2c, where the negative main effect of *negative*, β = −0.385, is partially offset by the positive interaction with *chain*, β = +0.181, even if with a loss in the precision of the estimate). We interpret these results as suggestive of the fact that decoupling may be attenuated when responses to negatively rated reviews are likely to be given more attention, thus making restaurants more accountable for any promise they commit to online. This is the case for restaurants that are part of restaurant groups—and, hence, more closely scrutinized from a variety of stakeholders—as well as for restaurants that have a stronger track record—thus making the single negative review, and its response to it, more noticeable.

Finally, the tendency to decouple responses to negatively rated reviews does not seem to be substantially mitigated depending on a restaurant's price point (cf. Model 2d, where the negative coefficient of *negative*, β = −0.913, is minimally if at all counteracted by the positive coefficient of the interaction with *price*, β = +0.009) or affected at all by the cuisine type of the restaurant (cf. Model 2e, where the coefficient estimates do not substantially differ depending on whether the restaurant serves a more or less creative cuisine).

Discussion

In a world where five stars have become the standard for evaluating many transactions, organizations cannot dismiss online reviews as inconsequential. In this paper, we contrast what restaurants communicate in their online responses to reviews with how they intend to respond "in real life"—that is, what they *say* they will do versus what they *intend* to do. To summarize our findings, we treat the choices of how to respond to feedback online and offline as orthogonal and give rise to the four possible scenarios depicted in Figure 2. The diagonal cases represent situations in which online and offline responses are coherent with one another, whereas the off-diagonal cases illustrate cases when online and offline responses differ. Results from our three-pronged empirical enquiry into the behavior of French restaurants provide us with evidence about the circumstances under which their behavior was in line with each of these quadrants, depending on features of the review, role of the respondent, and characteristics of the restaurant.

Quadrant 1 ("acceptance") depicts a case in which organizations are receptive to the feedback conveyed through reviews, both online and offline. Not only do they believe themselves better off by addressing the underlying issue in the open; they are more likely to evaluate the need for corrective action. Results from our analyses suggest this may be the case when reviews are written in a more detailed fashion (cf. results from Table 9). Our results also corroborate the idea that this may be the quadrant occupied by restaurants located in touristic areas when addressing reviews accompanied by more negative ratings (cf. results from Table 12), given their higher reliance on online reviews as a tool to capture potential demand and the increased risks associated to decoupling in areas where customers may more easily hold them accountable for their promises.

Quadrant 2 ("impression management") describes a case in which we should observe substantive promises of corrective action online but a limited intention to implement those actions offline. This quadrant best describes the reaction to reviews that mostly focused on food (cf. results from Table 9), with our informants suggesting an inclination to turn a blind eye to reviewer feedback related to an organization's defining features, as food is for a restaurant, because these often require some technical knowledge to be fully appreciated. This is also the general behavior displayed by organizations in our sample when addressing reviews that are more negatively rated (cf. results from Table 9), with a reported tendency to discount the informational value of the feedback they convey because of the high psychological costs involved with managing particularly harsh criticism. Interestingly, results of our moderation analyses show that bad ratings can be more easily stomached when they accompany reviews that are (i) better articulated, as is the case for negative reviews that are more detailed, provide comments about food, or are written by more experienced reviewers (cf. results from Table 10), or (ii) likely to be given particular attention, as is the case for negative reviews of restaurants affiliated with a chain or with a

Figure 2. Summary of Findings

		Offline response: Does the organization report an intention to incorporate corrective action?	
		Yes	No
Online response: Does the organization promise to incorporate corrective action?	Yes	**Acceptance** *This quadrant represents the reaction to more detailed reviews and the behavior of restaurants located in touristic areas when addressing reviews accompanied by more negative ratings.*	**Impression management** *This quadrant represents the reaction to reviews focusing on food and reviews accompanied by more negative ratings, unless they are well-articulated, or likely to be given particular attention.*
	No	**Quiet action** *Some evidence suggests this quadrant may represent the reaction of restaurant owners to reviews accompanied by more negative ratings.*	**Dismissal** *This quadrant represents the average reaction of restaurant owners.*

Notes. The figure provides a systematization of our findings on the conditions under which online and offline responses align or differ. We report instances in our data that are suggestive of the behaviors in each quadrant.

stronger track record (cf. results from Table 12). In these cases, the reaction of restaurants in our sample tended toward acceptance.

Organizations positioned in quadrant 3 ("quiet action") would limit their online promises in response to a review while, at the same time, taking steps to correct the underlying issue offline, thus engaging in what we define as quiet action. We did not observe clear evidence of this behavior across restaurants in our sample, even if we collected some evidence that the behavior of restaurant owners may tend toward this quadrant when they are reacting to harsh criticism (cf. results from Table 11). In those instances, in fact, we observed evidence of some marginally higher willingness to incorporate corrective action offline coupled with some marginally lower willingness to commit to it online. We speculate this behavior may take place in cases in which restaurants may have an incentive to deflect attention from the negative commentary while, at the same time, addressing its root causes so as to avoid the risk that negative feedback resurfaces in the future.

Finally, quadrant 4 ("dismissal") illustrates a case in which organizations limit or avoid responding to calls for corrective action, both online and offline. On average, owners of restaurants in our sample tended to behave in line with this strategy in that they appeared to be more dismissive both online and offline (cf. results from Table 9). If we assume that their promises bear more weight because they should be in the position to implement any change that they communicate, it seems rational for them not to overcommit online but, rather, to use the response to explain to customers why certain feedback cannot be taken into consideration. To us, they seemed concerned with maintaining a coherence between what the restaurant says online and what it does offline, but without the need to please the crowd, which we observed for restaurants located in touristic areas. In this sense, they did not seem to mind standing up for their restaurants and engaging with reviews in ways that could be perceived as dismissive.

Overall, our findings suggest that the choice to manage reviewers' concerns *online* is associated with cases in which the single review is more likely to stand out: reviews that are more detailed, and hence occupy more real estate on a restaurants' TripAdvisor page; reviews for restaurants located in touristic areas, where consumers rely more heavily on review platforms; reviews about food, and hence touching upon the core of what the restaurant does; and reviews that are accompanied by a more negative rating, and hence more likely to catch the attention of a reader. Online engagement may help reduce concerns about the extent to which more visible reviews may generate negative externalities (Proserpio and Zervas 2017, Chevalier et al. 2018) and threaten the very identity of the establishment (Wang et al. 2016). On the other hand, we observe how the choice to dismiss an online review transcends the single review and is a rather a respondent-specific feature, with restaurant owners trying not to commit to changes online. Limiting online engagement, or avoiding it altogether, may be an effective strategy to deflect attention from the average review, consistent with prior work showing that managerial responses spur an increase in reviewing activity (Proserpio and Zervas 2017).

Our findings also suggest that not all reviews that stand out as worthy of attention, or that are going to be brushed off online, will receive the same treatment offline. What makes the quadrants on the left different from those on the right is the receptivity of an organization to the feedback provided by the consumer, which, in turn, disposes them to responsive actions. Restaurants may be intrinsically more open to feedback because they tend to be reviewed more often. But they may also resist feedback, as exemplified by the case of restaurant owners, who, despite having the agency, may lack the *willingness* (Bundy et al. 2013) or *ability* to enact substantive changes based on considerations about costs and benefits (Durand et al. 2019). Consumers also have a role to play in that they can write reviews in a way that makes them easier to accept, as for detailed reviews, or more difficult to swallow, as with reviews accompanied by a more negative rating or that touch upon core defining features, as food is for a restaurant. We read this evidence as suggestive of the fact that our decision makers may be affected by the emotions triggered by the feedback—something we know has the potential, under certain circumstances, to override cognitive processing and deliberative decision making altogether (Loewenstein and Lerner 2003).

Conclusions

In this paper, we combine the insights of a lab-in-the-field experiment, an archival study, and two rounds of qualitative interviews to uncover the circumstances under which organizations are more or less likely to align or decouple their online and offline response to reviews. Together, our findings suggest that organizations in our sample strategically select the extent to which they address the concerns expressed by reviewers rhetorically by promising online to take corrective action and the extent to which they align these rhetorical claims with substantive changes to their organizational practices. More specifically, our results show that the extent to which online and offline responses to reviews differ depends on a number of factors at the level of the restaurant and the review, as well as the organizational member who is handling the review. We document cases of alignment between online and offline responses, as well as cases of decoupling, in the form of online promises to take corrective action coupled with limited intention to follow through offline. We also collect some circumstantial evidence of occasions in which organizations may appear to ignore a review online while, at the same time, taking action to address the underlying issue offline.

We believe our study makes several contributions to literature on producer reactivity. First, we provide systematic evidence of what Karunakaran et al. (2022) define as diffractive reactivity, or the tendency for organizational actors to address online reviews, and social media commentary more broadly, by producing scattered and equivocal responses. Contrary to the idea that organizations are "in effect, micromanaged by the crowd" (Karunakaran et al. 2022, p. 186) to the point of losing perspective on their long-term trajectory (Chu 2021), our findings suggest a more nuanced take on how organizations respond to being evaluated online. Our analyses suggest that organizations in our sample carefully modulate their responses to reviews based on the risks associated with misaligning online promises and offline practices. In this sense, our findings challenge the prevailing view of online pressures as predominantly destabilizing forces that divert resources or displace long-term priorities. This is more evident in cases where organizations demonstrate awareness of critical contextual factors, such as the nature of their customer base and the anticipated reputational impact of online reviews—cf. our findings about restaurants located in more touristic areas. It also becomes apparent when key decision makers, deeply invested in the organization's long-term strategy, are actively engaged in shaping the responses to these external pressures—cf. our findings about owners.

We further contribute to this stream of work by documenting how the pervasive nature of online ratings, coupled with the rapid proliferation of review platforms, places organizations under significant pressure to comply to constituents' demands. Compared with influential rankings, heterogeneous and idiosyncratic online ratings might appear less likely to prompt substantive change and reconfiguration of practices in organizations. Yet our results show that online reviews can act as powerful triggers of change: we witnessed circumstances in which corrective substantive changes were put in motion discretely, as well as circumstances in which changes in practice were perfectly aligned with rhetorical promises. Our findings also uncover cases of purely rhetorical compliance—in other words, instances of decoupling. These instances connect the literature on producer reactivity with work on the symbolic management of strategic change (Edelman 1992; Elsbach and Sutton 1992; Westphal and Zajac 1994, 2001; Fiss and Zajac 2006; Bromley and Powell 2012). In our empirical context, decoupling emerged when characteristics of the single review made it more likely to attract the attention of consumers while, at the same time, more difficult to digest and process emotionally for producers. Under these circumstances, organizations may find themselves in a precarious position. Consumers exposed to outstanding reviews may, in fact, be more likely to monitor the extent to which organizations align rhetorical claims with substantive changes so that failing to strategically assess and substantively respond to this feedback can lead to a loss of legitimacy and credibility in the eyes of their stakeholders (Etter et al. 2019, Wang et al. 2021).

From a practical standpoint, our findings offer helpful insights to the main stakeholders involved in the production and dissemination of reviews. For customers who post their reviews, we show how, while giving a very negative score or criticizing a restaurant's core offering may be a signal that is easily interpreted by other customers, it will not spur an establishment to substantively address the underlying issue, which may be acceptable if the review is mostly intended for future customers, but not ideal if the goal is to trigger change on the part of the establishment under review. Results from our analyses also suggest that under some conditions, online reviews are carefully examined and promptly incorporated by organizations, thus making the case for writing detailed reviews and reviewing restaurants that need reviews to capture demand in touristic areas. For the organizations whose activities are under scrutiny, we bring attention to the importance of responding to online reviews by highlighting the different strategies their peers might employ. Notably, our findings suggest the importance of alignment between organizational functions when assessing how to address reviews. Whereas in the hospitality sector it is generally advisable to invest in dedicated functions that manage relations with clients (Greenberg et al. 2024), our study cautions that these functions may sometimes overshadow the strategic and long-term priorities of the organization. In the context of our study, we observed that when responding to negative reviews, managers were more prone to overpromising compared with owners, who actively defended the organization's identity and upheld the efforts of their staff, even if this meant standing up to their customers. Whereas our study does not track the long-term consequences of a misalignment between online promises and offline practices, it is reasonable to speculate that sustained discrepancies could lead to negative consequences, particularly in industries where firms are under constant scrutiny. In such environments, relying solely on impression management tactics might eventually erode trust and credibility, underscoring the need for authentic and consistent engagement both online and offline. Finally, our work has implications for platforms that connect reviewers on one side and organizations to be reviewed on the other, as we provide evidence of the importance of their role in shaping how those organizations behave.

We believe our work also makes an empirical contribution in that it provides an example of how to integrate different methods with the aim of building and testing theory in a full-cycle approach to research (Cialdini 1980, Fine and Elsbach 2000, Chatman and Flynn 2005, Ranganathan 2018, Di Stefano and Micheli 2023). We show how one can complement different methods to gain a better understanding of a relatively unexplored phenomenon (cf. the first round of qualitative interviews) that is difficult to uncover (cf. the administration of the lab-in-the-field experiment), lacks systematic evidence (cf. our engagement with TripAdvisor reviews and responses), and requires a better understanding of the underlying mechanisms (cf. the choice of conducting interviews to make sense of the results of our quantitative examination). In this sense, we attempt to solve the problem of testimony (King et al. 2021) by integrating different methods in pursuit of consilience (Wilson 1998).

In terms of future research, we believe it would be extremely interesting for future work to further explore (and test) the mechanisms behind the effects we uncovered. For instance, future research could develop a better understanding of the role of emotions in the choice to incorporate feedback in the form of corrective action. Another promising research direction has to do with the interplay between online reviews and expert ratings—a topic that we would like to investigate further in the future. We know a lot about how organizations react to the feedback provided by experts (Jin and Leslie 2003, Rao et al. 2003, Espeland and Sauder 2007, Chatterji and Toffel 2010, Waguespack and Sorenson 2011) and are starting to know more about how they deal with the feedback provided by consumers (Piezunka and Dahlander 2015, Wang et al. 2016, Etter et al. 2019, Wang et al. 2021). What would be interesting to examine next is how these different types of evaluations interact (Sharkey et al. 2023). We recognize that it would be difficult to rely on archival data to disentangle the effect of online ratings relative to expert ratings because the two may affect one another, and organizations are simultaneously exposed to both. To address this identification challenge, future work could explore the possibility of running an experimental study where participants receive different evaluations from these two sources so as to disentangle how the two evaluation systems act in isolation, as well as in conjunction with one another.

Of course, our study is not immune to limitations. First, whereas the grounded nature of our research provides the undeniable benefit of better internal and construct validity (Di Stefano and Gutierrez 2019), this comes at the expense of generalizability beyond our study's setting. We hope future research will help us extend our findings more broadly by studying online and offline responses to negative feedback in a variety of contexts. Second, our analysis focuses on the intention to incorporate corrective action online and offline, but it does not allow us to observe actual changes to organizational processes in response to a review. The closest we were able to get was our lab-in-the-field experiment, which allowed us to move away from the "front region" of self-presentation as it is vehiculated online and more toward the "back region" of what happens behind the scenes (Goffman 1959). Still, future work could get closer to observing real action by leveraging a more creative array of data sources. Progress in computational linguistics, for instance, may make it possible to study the evolution of menus over time in response to themes evoked in reviews. Qualitative work could further help disentangle the process through which these changes take place and the motivations guiding different establishments.

Our journey among restaurants, chefs, and critics started with the goal of understanding how organizations respond, online and offline, to feedback provided in online reviews, a phenomenon that is growing in relevance by the day. Along the way, we encountered what we believe are interesting findings showing that organizations modulate the way they address online feedback, as they are well aware that it is in their best interest to manage it and that they are doing so in a context in which their actions can be carefully scrutinized by a dispersed and pseudonymous crowd. Despite the increasing pressure for compliance, organizations in our sample exhibited clear decoupling tendencies when facing online customer reviews that upset them. It is under these circumstances that we witnessed them being more likely to "look and pass" on the opportunity to engage with, and learn from, the online sentiments shared in customer reviews.

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Endnotes

[1] See, for instance, Capoccia (2018).

[2] See for instance, Daneshkhu (2018) and Widdicombe (2018).

[3] See, for instance, Pattison (2009) and https://www.yelp-press.com/company/fast-facts/default.aspx.

[4] The Michelin Guide traditionally covers a variety of establishments, from high-end restaurants that are awarded up to three Michelin stars for culinary excellence to restaurants deserving a "Bib Gourmand" for serving quality food at a reasonable price (entrée, plat, and dessert for €33 (37) or less in France (Paris); two courses and dessert/glass of wine for $40 or less in the United States). In recent years, the guide has also started to award Michelin stars to less formal and more affordable establishments, as in the famous case of the Bangkok street food vendor (see Chatikavanij 2019). This change is consistent with a recent trend in fine dining, with restaurants becoming "less formal, more social venues rather than formal temples of gastronomy" (see Hoffower 2019).

[5] According to industry experts, the lifespan of restaurants in France has been declining in the last decades. In 2014, it was estimated to be around two years and possibly even shorter in Paris (Bouleau 2014).

[6] Around 90% of the 192 participants answered questions related to both reviews, whereas the others answered questions for the first review only. In our analyses, we include data on all 364 reviews for which we were able to collect information. As a robustness test, we replicated the analysis, excluding participants who answered questions for the first review only, with consistent results.

[7] We discuss this choice at length in the Online Appendix, with our informants recommending the use of a two-star rating (as opposed to a one-star rating) to increase realism and suggesting they would perceive a four-star rating as marginally negative, in line with a reported tendency to inflate review scores and consider everything below five as indicative of a negative evaluation (Wolff-Mann 2016).

[8] See https://tripadvisor.mediaroom.com/us-about-us.

[9] When inspecting these figures, we found it interesting to observe that this percentage had increased over time. We noticed an increase from an average of 18.47% to an average of 22.53% if we compared the year before and the year after each restaurant participated in our experiment. This latter pattern pushed us to consider the possibility that our experiment "treated" participants and made them more likely to respond to reviews online. We explored this conjecture in a robustness test, reported in the Online Appendix, where we fail to show any effect of this unintended potential "intervention."

[10] The case of decoupling responses to reviews focusing on food does not elicit a similarly strong tension, as these reviews are not necessarily given more attention compared to those focusing on service. Also, prior work suggests that potential customers rarely go beyond the surface of ratings (Bright Local 2024) and that negative reviews are more likely to affect purchase decisions (Rozin and Royzman 2001, Basuroy et al. 2003, Chevalier and Mayzlin 2006, Sen and Lerman 2007).

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