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Abstract

Collaborating with Yelp and the City of San Francisco, we revisit a canonical example of quality disclosure by evaluating and helping to redesign the posting of restaurant hygiene scores on Yelp.com. We implement a two-stage intervention that separately identifies consumer response to information disclosure and a disclosure design with improved salience–a consumer alert. We find score posting is effective, but improving salience further increases consumer response.

JEL Codes: *D83, D12, D18*

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1 Introduction

Restaurants are regularly inspected for food safety violations and are given a hygiene score at the end of the inspections. Beginning in the late 1990s, there has been a movement to require restaurants to visibly post their hygiene scores on their doors, even if they received a passing score. Studying a mandatory posting policy in Los Angeles, Jin and Leslie (2003) show that posting hygiene scores led to higher demand for restaurants with higher scores, an increase in average hygiene scores, and a reduction in the rate of foodborne illness. Based largely on this study, hygiene posting is frequently cited as a success story of quality-disclosure policies (Fung et al., 2007).

Despite the success of the Los Angeles initiative and the broad support of public health officials, the introduction of mandatory posting is challenging from a practical perspective. For one thing, the restaurant industry opposes mandatory posting of health code violations.[1] Moreover, enforcing such a mandate could be costly, as it requires cities to deliver signs to every restaurant after each inspection and monitors the restaurant's compliance in posting the signs. Perhaps unsurprisingly, the vast majority of major U.S. cities thus still do not require mandatory posting, (the few exceptions include New York City, which has required posting since 2010). Even for cities in which local policymakers have mandated disclosure of hygiene scores, posting on doors has becomes insufficient as customers are increasingly turning to online platforms such as Yelp to search for and look up information on local businesses (Luca, 2016).

The rise of online platforms raises the opportunity to revisit the information disclosure challenge and to use a design economics lens to improve decisions about where and how disclosure is delivered. To our knowledge, ours is the first demonstration of how policymakers can partner with major online platforms to improve existing disclosure policies. This paper demonstrates how platforms can be important partners for regulators as well. In particular, online platforms can supplement traditional disclosure policies in at least three different ways. First, since customers are using online review platforms more frequently to learn about products and services, these platforms provide the opportunity to deliver information while customers are searching and learning. Second, online platforms can reduce the costs of disclosure and help to overcome political economy constraints. For example, the City of San Francisco was unwilling to mandate disclosure by restaurants, but was willing to share data for Yelp to publicly post. Third, online platforms allow for more direct and immediate measurement of responses to disclosure, and the opportunity to redesign disclosure policies based on initial responses.

With this in mind, we collaborated with Yelp and the City of San Francisco to publicly post restaurant hygiene scores on Yelp and investigated the effect of this digitized disclosure and its design on consumer restaurant demand, measured by consumer engagement on restaurants' Yelp pages. In this paper, we document the disclosure interventions and the resulting impacts.

Should we expect posting restaurant hygiene scores on Yelp to have an effect on restaurant

[1] For example, in a meeting we attended in a large U.S. city that was considering mandating disclosure, a representative of the local restaurant association voiced strong opposition to such policies.

demand? The answer is unclear. Before posting scores on Yelp, San Francisco has already made the scores publicly available—although they generally were unadvertised and potentially underutilized—on the Department of Public Health website. Moreover, if the restaurant hygiene information is already embedded in the ample consumer reviews on Yelp, the posting of hygiene scores may not provide any new information to consumers. Lastly, a growing body of research within psychology and behavioral economics suggests that the impact of disclosure depends not only on informational contents, but also on salience (Luca and Smith, 2013; Loewenstein et al., 2014). Hence, the information environment and the salience of the score posting are also expected to affect the impact of disclosure.

Our intervention proceeds in two stages. In the first stage, which begins in early 2013, Yelp starts posting hygiene scores on San Francisco restaurants. We analyze the impact of the score posting using a difference-in-differences strategy, comparing differential changes in restaurant demand after the score posting between restaurants with low hygiene scores that are more likely to be affected by the score posting (as predefined by the city) and those with higher scores.[2] To approximate demand, we drew on purchase intention measures, such as a user calling or seeking directions to a restaurant or clicks on the restaurant's own website link. We find that hygiene score posting on Yelp leads to a 13% decrease in purchase intentions for restaurants with low hygiene scores.

The literature on behavioral economics suggests that the impact of disclosure should depend on whether the information is sufficiently salient to end users. Our goal was to explore the potential of using salience as part of the design process to improve the impact of disclosure. Following the initial hygiene score posting intervention, in the second stage, we worked with Yelp in 2015 to develop a "hygiene alert"–a salient message that appears only on the Yelp pages of restaurants with low hygiene scores. Such low-score restaurants are identified by the city as having "poor" operating conditions with "high-risk" hygiene violations.

We find a further 7% decrease in purchase intentions for restaurants with low scores due to hygiene alerts, and 11% decrease in the number of reviews, nearly doubling the effect of the score posting for these businesses. On the restaurant side, although there is no evidence showing an improvement of restaurant hygiene scores across restaurants, we find a decrease in the probability that the low-score restaurants will receive low scores again after the alert. Overall, the results of this paper, taken in conjunction with the existing literature on hygiene posting, highlight the potential for online platforms and design economics to improve the efficacy of disclosure.

2 Background

2.1 Related Research

Mechanisms that inform consumers about the product quality are necessary for markets to function. Since Grossman (1981) and Milgrom (1981), a large theoretical literature has explored the conditions under which market pressure can lead firms to voluntarily disclose quality information.

[2]We also present results based on continuous scores.

However, as summarized in Dranove and Jin (2010), full unravelling can fail for reasons such as costs associated with disclosure (Matthews and Postlewaite, 1985), uncertainty about the information (Stivers, 2004; King and Wallin, 1991), liability (Polinsky and Shavell, 2010), or consumer deviations from rationality (Fishman and Hagerty, 2003; Hirshleifer et al., 2004). In practice, voluntary disclosure is far from complete (Bundorf et al., 2009; Bederson et al., 2018).

In response, governments can require businesses to disclose information. The findings on the impact of disclosure on demand are mixed. For example, after Los Angeles County mandated the posting of restaurant hygiene grade cards in 1998, Jin and Leslie (2003) find that restaurants with a grade of A made more sales than other restaurants. Bollinger et al. (2011) find that mandatory calorie posting in Starbucks in New York City led the average calories per transaction to fall. Mathios (2000) finds that sales declined for salad dressings with the highest fat after nutrition labels are mandated. However, Seira et al. (2017), studying the effect of disclosure on indebted consumers in the credit card market, find no effect of interest rate disclosure on consumer indebtedness and only modest effects of providing comparison and de-biasing information. Our paper contributes to this literature and suggests the necessity of a shift from "Does disclosure work?" to "How should disclosure be designed?".

Our paper is also closely related to the behavioral literature that explores how salience affects the consumer response to information in the field. Hastings and Weinstein (2008) find providing direct information that compares school academic achievement to lower-income families significantly increased in more parents choosing higher-performing schools. Pope (2009) finds that consumers respond to the ranking of hospitals rather than the detailed continuous scores that the ranking is based on when both forms of information are available. Luca and Smith (2013) find that college applications respond to the college ranking when the colleges are presented in the ranking order, but they do not respond to ranking when colleges are presented alphabetically with the information used to construct the ranking. We contribute to this literature by incorporating insights from the behavioral foundations of decision-making into designing disclosure policies.

The literature on salience has often emphasized the question of whether salience has an effect (Gabaix and Laibson, 2006; Chetty et al., 2009; Brown et al., 2010), typically treating salience as a binary outcome. Our paper suggests that salience does not necessarily have a binary effect (in which information is either salient or not), but is instead a matter of degree. Restaurant hygiene scores are already publicly available on the internet. The common binary perspective of salience suggests that it is sufficient to make hygiene scores available on a restaurant's Yelp page, but we find that the alert matters on top of this.

The results also speak to the recent literature that posits two potential explanations of why salience might matter (Handel and Schwartzstein, 2018). One potential mechanism is that salience operates by reducing information processing costs (e.g., reducing the amount of work people need to do to act upon information) (Caplin and Dean, 2015; Sims, 2003). A second hypothesis is that salience simply shifts attention to a particular piece of information (Schwartzstein, 2014). While not dispositive, the impact of the alert suggests that the second mechanism might be operating

and that consumers might not have been attending to certain information. To the extent that the attention channel is at work, this suggests that we should look for opportunities to make readily available information that consumers might care about, but aren't attending to, more salient, as opposed to just making the information consumers find difficult to process easier to comprehend.

2.2 The Empirical Setting

Hygiene Scores Hygiene inspections vary by city. San Francisco's Retail Food Safety Program is overseen by the San Francisco Department of Public Health (SFDPH), which administers inspections of "restaurants, markets, and all other retail food operations" such as bars, pushcarts, and bakeries. The results of the inspections, which occur unannounced, are used to calculate hygiene scores based on the site's compliances with health and safety regulations. Each inspection results in a score on a scale from 0 to 100. A restaurant that commits no violations will receive a score of 100. A restaurant with violations will have points deducted from 100 for each violation. The Department of Public Health classifies violations into three types: "high risk–violations that directly relate to the transmission of food-borne illnesses, the adulteration of food products and the contamination of food-contact surfaces; moderate risk–violations that are of a moderate risk to the public health and safety; low risk–violations that are low risk or have no immediate risk to the public health and safety." More serious violations are subject to bigger score deductions. Depending on the hygiene score, the site is categorized into one of the following operating conditions: *good* (a score above 90); *adequate* (a score between 86 and 90); *needs improvement* (a score between 71 and 85); and *poor* (a score 70 or below). In particular, restaurants are put into the poor category if inspection reveals several high-risk violations. We will also call such restaurants *low-score* restaurant. The score categories are summarized in Appendix Table A1.[3]

About Yelp Yelp is a platform where consumers can leave reviews for restaurants and other businesses. Based in San Francisco, Yelp was founded in 2004 and is part of the crowdsourcing movement. At the time of this research, Yelp is a main source of reviews for local businesses, with more than 100 million unique visitors per month and roughly 40 million reviews. San Francisco is one of the first cities for which Yelp launched restaurant reviews and is still the most active city in terms of website traffic and consumer reviews. See Luca (2016) for further discussion of Yelp.

Measuring Demand Because we do not directly observe offline restaurant demand, we use an array of metrics that measure consumer engagement on the restaurant's Yelp page to approximate purchase intentions. The first metric is the number of page views, which is the number of times consumers land on the restaurant's Yelp page. Conditional on a consumer visiting the restaurant's Yelp page, consumers can act on a few call-to-action buttons if they are interested in the restaurant. They can click on the request-for-directions button or click on the map on the restaurant's Yelp page to locate the restaurant, click on the phone number to directly call the restaurant through

[3]See https://www.sfdph.org/dph/EH/Food/Score/default.asp.

the mobile app or mobile site, or clicks on the restaurant's own external link. We sum up the number of call-to-action clicks. We call these metrics "leads," which is the second metric indicative of consumer purchase intentions. The third metric is the number of reviews left on the restaurant's Yelp page. The fourth is the number of takeout orders the restaurant receives through the Yelp platform.

Cleaner Restaurants Have Higher Demand without the Hygiene Score Posting In Figure 1, Panel A, we draw scatter plots of each restaurant's leads against its hygiene scores in the month before the posting of hygiene scores. We then fit the scatter plot with a quadratic curve. We see a positive but weak relationship between hygiene scores and leads. The quadratic fit shows that leads increase with hygiene scores but at a decreasing rate. The finding suggests that even in the absence of a hygiene score posting on Yelp, the information on restaurant hygiene conditions may have already been partially incorporated into the consumer restaurant choice, potentially through restaurant review ratings, The implication is consistent with Kang et al. (2013), who find that natural language processing of Yelp reviews can help predict hygiene violations.

To what extend are the differences in hygiene ratings reflected in other restaurant characteristics? We examine the relationship between restaurant review ratings and hygiene scores and the relationship between price categories and hygiene scores before the posting of hygiene scores. The relationships are shown in Figure 2, Panel A. Review ratings positively correlate with hygiene scores for restaurants with review ratings of three stars or above, but the relationship is noisy for restaurants less with than three stars. The figure on the right shows that the restaurants that are more expensive have higher hygiene scores on average. In addition, we show whether the restaurants with distinctively low hygiene scores are very different from an average restaurant in Appendix Figure A1, Panel A. The figure compares the distribution of restaurant review ratings and price categories between the low-score restaurants and others. The low-score restaurants (those with hygiene scores of 70 or below) clearly have worse review ratings; they are less likely to have 4-star or above ratings and are more likely to get 1.5-star ratings, but they are also most likely to have 3.5-star ratings, the median rating of all restaurants. In terms of price category, the majority of low-score restaurants have a price level of $30 or less per meal (two or fewer dollar signs).

The San Francisco Posting Initiative on Yelp In San Francisco, restaurants are not required to disclose their hygiene scores, but the SFDPH has run the online hygiene disclosure program since well before the collaboration with Yelp. While consumers can search on SFDPH's website to find the hygiene score of any restaurant operating in San Francisco, the SFDPH has found the website's utilization rate to be low.[4] At the same time, consumers have increasingly turned to review websites for restaurant information. To reflect this trend, the SFDPH provides Yelp with a weekly feed of its scores and allows Yelp to post each restaurant's hygiene score on the restaurant's Yelp page. This effort is part of Yelp's Local Inspector Value-Entry Specification (LIVES) initiative, which

[4]See https://101g-xnet.sfdph.org:8443/ords/eeopn/f?p=132:1.

allows municipalities to publish restaurant inspection information on Yelp nationwide.

The timeline of the interventions is documented in Appendix Table A2. Between January 17, 2013, and March 25, 2013, Yelp worked on the process of matching restaurants' SFDPH records and Yelp records and gradually started posting hygiene scores for the matched restaurants. We call this period the *test period*. Which restaurants have hygiene scores posted in the test period is determined by the matching process and is unrelated to the restaurant's hygiene score or Yelp page traffic. By March 25, 2013, Yelp finishes the matching records for all 3,042 restaurants in the SFDPH records and officially posts hygiene scores on these restaurants' Yelp pages. The average hygiene score of the matched restaurants is 91.3 and the standard deviation is 8.1. While 61.6% of the restaurants are in good condition (with scores above 90), 2.4% of restaurants are in poor condition (with scores less than or equal to 70).

3 The Effect of Information Disclosure

The Yelp page of a typical business with a hygiene score is shown in Figure 3. To make the hygiene score easy to access for consumers, the score, termed "health inspection," is displayed in the restaurant information box together with other restaurant attributes. The consumer can click on the score to learn more about the restaurant's hygiene violation: for example, violations found in the most recent inspection and the history of past hygiene scores.

In the following section, we examine the effects of hygiene score posting on consumers. If consumers respond to the posting of hygiene scores, we should expect consumer purchase intentions to become more sensitive to hygiene scores: that is, the posting will differentially affect restaurants with different hygiene scores. Hence, we run the following baseline specification:

$$Y_{jt} = \alpha \ln(Score_j) \times Post_t + \beta Post_t + \mu_j + \epsilon_{jt} \tag{1}$$

where $Score_j$ is restaurant j's hygiene score posted on the website at the beginning of the hygiene posting period, $Post_t$ is an indicator that equals to 1 if time period t occurs in the score posting period, μ_j is the restaurant's fixed effect, and Y_{jt} is the purchase intention metric. To help compare the sizes of effects on different outcomes, we standardized the outcomes by their mean and standard deviation during the period before the posting intervention. In the results we present in Table 1, we also control for the common linear time trend t and attribute-specific time trends, which interacts t with restaurant pre-intervention attributes such as the price category and the mean consumer review rating. The coefficient of the interactive term α in equation (1) identifies the differential changes in outcomes between restaurants with different scores.

We use the number of consumer leads and reviews as outcomes that approximate consumer demand. Although the number of page views of the restaurant's Yelp page could be an indicator of consumer interest, it is a worse measure of consumer response to the score posting. Consumers do not see the restaurant's hygiene score until they land on the restaurant's Yelp page, so we we do not expect consumers to respond to the hygiene score information before visiting the page.

Moreover, Yelp does not use hygiene scores to determine the restaurant's search ranking, so we do not expect hygiene scores to differentially affect page views after the score posting. It is possible that consumers can recall and are less likely to revisit the restaurant's Yelp page after noticing that the restaurant has a poor hygiene score, but the effect is most likely secondary. In fact, we do not find a short-term effect of score posting on page views.

The identification of differential effects of hygiene score posting on restaurants with different hygiene scores relies on the assumption that the consumer demand for these restaurants would follow the same trend if there were no intervention. We test differential pre-trends for restaurants with different hygiene scores. The results are shown in Panels A of Appendix Table A3. Using monthly standardized outcomes before the posting of hygiene scores, we do not find significant differences pre-trends. In Figure 4, we plot the weekly time trends of standardized consumer purchase intention metrics for restaurants with hygiene scores above 70 and those with scores 70 or below. We can see that the two time trends closely track each other before the posting of scores. Also, the score posting may make consumers switch from lower score restaurants to higher score ones, so we interpret our specification in equation (1) as the differential posting effect on lower score and higher scores restaurants but not the treatment effects on lower score restaurants.

In regression equation (1), we hold the value of $Score_j$ to be the restaurant's hygiene score at the beginning of the posting intervention. Potentially, the score may change after the score posting due to new inspections. We choose to use the initial score rather than the updated score after the posting period due to potential endogeneity of new scores. The mismeasurement of hygiene scores may bias the estimates of the hygiene posting effect downward.[5] The mismeasurement will be large if the new scores are very different from the old ones, so we check the changes in hygiene scores during our analysis window, three months after the start of the official posting intervention. During this period, around 38% of the restaurants have received new inspections, but the magnitudes of the score changes are small. The median absolute change in new scores relative to the original is 4%, and 83% of the restaurants have absolute changes of less than 10%.

As discussed in the posting initiative, the score posting test period is between January 17, 2013, and March 25, 2013. During this period, Yelp posted hygiene scores on the first batch of restaurants it has successfully matched between the Yelp record and the SFDPH record. Yelp continued working on matching the restaurant records and officially posted all restaurant hygiene scores on March 25, 2013.[6] We do not have information on the timing of when each restaurant's hygiene score was posted in the test period, so we included a balanced panel of all restaurants in the analysis but analyze the effects in the test period and the official posting period separately. Given the incomplete posting in the test period, we expect the effect in the test period to be slightly smaller.

[5] We expect this bias to become greater as more restaurants receive new inspections, so we focus the analysis on a relatively short time window: five months after the test posting period or three months after the official posting period.

[6] The gradual rollout is mainly due to the process of matching SFDPH restaurant records to Yelp records. The process that determines which restaurants get matched and have scores posted first is unrelated to the restaurant's hygiene scores or its Yelp page traffic.

Table 1, Panel A shows the results following regression equation (1) using monthly observations from three months before the test period to three months into the official posting period. In each column, we use the same specification that controls for the common time trend, attribute-specific trends, and restaurant fixed effects.[7] For each outcome measure, we use both standardized counts and their log-levels. As expected, the hygiene score posting makes restaurants with higher hygiene scores more attractive to consumers. In particular, with the posting of hygiene scores, a 10% increase in hygiene scores causes the number of leads to increase by 0.022 standard deviations, or by 4.0% and causes reviews to increase by 0.022 standard deviations, or by 2.5%. The point estimates for the official hygiene-posting period differ only slightly from those of the test period and the differences are not statistically significant. Besides leads and reviews, we also examine whether the score posting affects the average rating of new reviews written about the restaurant. We present the results in Appendix Table A4. We do not find that reviewer ratings to respond to the hygiene score posting.

Besides examining the differential effects with respect to continuous scores, we are also interested in effects with respect to restaurants categorized by the SFDPH as having poor operating conditions. Given the high-risk hygiene violations found in the poor restaurants, it is desirable that consumers avoid such restaurants. There are 60 such restaurants, or 3%, at the beginning of the score-posting sample. We examine the differential effects using specification (1) and replace $\ln(Score_j)$ by the indicator of whether the restaurant has poor conditions, or $I(Score_j \leq 70)$. The results are shown in Panel B of Table 1. In the official posting period, we find that restaurants with hygiene scores 70 or below experience a 0.10 standard deviation reduction in the number of leads, or a 12.7% reduction, compared with restaurants with hygiene scores above 70. The effects are smaller in the test periods. The effect on the number of reviews is noisy and hence not statistically significant, but the negative impact is as expected.

To the extent that some restaurant-goers might be shifting between low-score and high-score restaurants, our estimates might overstate the effect. However, this type of spillover is likely to be small given the small fraction (fewer than 3%) of restaurants that receive alerts.

The score posting effects for restaurants with low scores can be seen intuitively in Figure 4, in which we plot the weekly trend of standardized counts of leads and reviews for restaurants with scores of 70 and below and those with scores above 70. The figures show that the two types of restaurants follow similar trends before the hygiene posting test period, but the number of leads and reviews of low-score restaurants falls below the levels of other restaurants immediately after the start of the posting test period.

[7] Effects without controlling for time trends are larger.

4 Improving Salience

4.1 The Design of Hygiene Alert

A growing economics literature has found that the impact of information depends on information salience (Mullainathan et al., 2008; Kling et al., 2012; Luca and Smith, 2013). More generally, the role of attention is one of the most robust findings from the behavioral literature (DellaVigna, 2009). This raises the possibility for policymakers to take salience and limited consumer attention into account when deciding how to operationalize a disclosure policy in the field. With this in mind, we partnered with Yelp to create a second round of interventions with increased salience, drawing attention to the hygiene information.

To attract consumers' attention, the hygiene alert, shown in Figure 3, is a message box that blocks the consumer review section of the restaurant's Yelp page. Given the salience consideration, we designed the message content to incorporate the factors known to improve the effectiveness of disclosure discussed in Loewenstein et al. (2014)—the disclosure message should be simple, standardized, and should contain information for comparison. The alert message we designed contains two key pieces of information. One is that the hygiene score is associated with food safety and is the report of government inspection. The other is that the alert is the result of the restaurant getting a score falling into the poor condition category in the most recent inspection (within six months), and the score is within the bottom 5% in the San Francisco score distribution.

The alert is also designed not to be too intrusive. Instead of a pop-up that blocks the entire business page, the alert box only blocks only the review section, which lies below essential information such as average rating, location, and the restaurant's information box, as shown in Figure 3. In web browsers, the alert box is not immediately visible on the screen when a consumer lands on the page. On mobile devices, the alert is not visible in the first screen of the page, as shown in Appendix Figure A2. Consumers who visits the page and leaves without scrolling down to see the review section will not see the alert. This includes consumers who visit the restaurant's Yelp page only to make a reservation or order a takeout without seeing the reviews. We should take into account this design feature when interpreting the size of the hygiene alert effects.

On October 20, 2015, the hygiene alert was launched simultaneously for all restaurants in San Francisco. An alternative approach would have been to randomize the posting of alerts across restaurants, which would have the benefit of creating within-city variation. However, such a scheme might confuse consumers and make it difficult for them to make inferences. In particular, if consumers see that a hygiene alert on a low-score restaurant but not on others with the similar scores, they may form wrong associations between the score and the alert. This is why we focus on a difference-in-differences strategy, comparing alert (low-score) and non-alert restaurants.

4.2 The Effect of Hygiene Alerts

We first compare the attributes of restaurants with hygiene alerts and those without. Of the 4,471 restaurants on Yelp with hygiene scores in San Francisco in October 2015, 151 restaurants have a

score of 70 or below, or 3.4%.[8] If restaurants with scores of 70 or below have very low consumer ratings, we may not need hygiene alerts to keep consumers away from them. In Figure 2, Panel B, we compare restaurant characteristics in terms of price category and posted rating. The figures shows that alert restaurants are less likely to be very expensive and are less likely to have posted ratings of 4 stars and above, but the differences are not large. Also, some restaurants with scores 70 or below have more than a thousand reviews. So consumers may not be able to distinguish alert and non-alert restaurants based simply on observed restaurant characteristics. We also show the comparison of the consumer leads between the low-score restaurants and others before the hygiene alert intervention. Before the alert, we see that distribution of the low-score restaurants is more skewed to the left compared with other restaurants. Compared with the same graph we plot for the month before the posting of hygiene scores, low-score restaurants are also shown more likely to get lower consumer leads, but the differences are are not huge. Some low-score restaurants also have sizable consumer leads.

We evaluate the effects of the alert using the same specification as the one we used for estimating the effects of score posting. We focus on the difference-in-differences strategy that compares the differential changes in consumer demand proxies after alert posting intervention starts between alert and non-alert restaurants. Using standardized outcomes, the parallel pre-trend tests do not find differential trend between alert and non-alert restaurants before the implementation of the alert, as shown in Panel B of Appendix Table A3 and in Figure 5.[9]

The launch of the hygiene alert does not interrupt hygiene score posting, so the alert effect we identify is generated by consumer responses to the alert beyond their response to the posted hygiene scores. If consumers have already paid attention to the scores and have fully incorporated the information content of the scores in their decisions, we expect no consumer response to the hygiene alert. In addition, two factors could dampen the effect of the hygiene alert. First, as discussed above, consumers will not see the alert if they do not scroll down the screen, so not all consumers landing on an alert restaurant's page may have noticed the alert. Second, as consumers take into account review ratings when they choose restaurants, more than 70% of the alert restaurants have a review rating equals to or higher than 3.5, the median posted rating on Yelp.

Using monthly data from three months before the alert launch to three months after, we evaluate the effect of hygiene alerts on the number of consumer leads and reviews. In addition, Yelp launched a delivery partnership service, Eat24, on its platform in mid-2013, so we are able to obtain the data on takeout orders for restaurants that have signed up to use Eat24. The estimates of the alert effects are presented in Table 2, identified by the coefficient of "Alert Period$\times$(Score$\leq$70)". We show the effects on consumers in column (1)–(6). We find that the posting of an alert reduces the number of consumer leads at restaurants with alert by 0.07 standard deviations, reviews by 0.10

[8]The sample size increase between 2013 and 2015 is due to the increase in the number of restaurants for which SFDPH provides hygiene records, and it is not due to restaurant entry. Comparing the hygiene score distributions between the initial score posting sample and the sample used for the hygiene alert analysis, we find no statistical difference between the two.

[9]Note that the outcome variables in their original levels differ between alert and non-alert restaurants. Figure 5 shows no difference before the alert since we have standardized the outcomes by their mean levels before the alert.

standard deviations, and orders by 0.11 standard deviations. Using log-level outcome measures, we find that the alert reduces the number of leads by 7.4%, reviews by 11.3%, and takeout orders by 12.8%. The effect on orders is not statistically significant due to the shrinking in sample size of restaurants with order data. The effects are also illustrated in Figure 5, which shows a clear pattern of negative effects on alert restaurants. The hygiene alert further reduces consumer demand at dirty restaurants, but the extra impact is slightly smaller than that of the initial score posting. In Appendix Table A5 and Appendix Figure A3, we also test the effect of the alert on review ratings and the amount (measured in dollars) per takeout order. The effects are all small and statistically insignificant.

The negative effects of the hygiene alert suggest that the alert message does deliver new information to consumers, even though consumers have already been presented with hygiene scores. But did the alert prompt consumers to pay more attention to hygiene scores in general? If the alert increases consumer attention to hygiene scores, we might expect consumers to become more sensitive to hygiene scores even at restaurants without alerts. In particular, will consumers avoid restaurants with scores just above 70, which do not have an alert displayed? To test this, we drop all alert restaurants and test whether non-alert restaurants with higher hygiene scores differentially enjoy better outcomes after the implementation of alerts. As the results in Panel A and C of Appendix Table A6 show, we do not find such an effect in the short run. In an alternative specification shown in Panel B of Appendix Table A6, we compare restaurants with scores between 60 and 70 and restaurants with scores between 70 and 80. The effect sizes identified are similar to the effects identified using the full sample. The above evidences suggests that the differential reaction of consumers to restaurants below and above the 70 cutoff is mainly driven by the alert not a better understanding of the implications of the hygiene scores.

5 Discussion

Our results contribute to the literatures on the economics of digitization, quality disclosure, and behavioral economics. By circumventing some of the typical challenges involved in mandatory disclosure, a partnership with Yelp and the City of San Francisco allows us to visibly disclose hygiene scores to consumers when they are actively searching for restaurants using review websites. The setting also allows us to vary the salience of disclosure, drawing on insights from the behavioral economics literature.

Besides consumer responses, we also examine restaurant responses to the posting of hygiene scores and alerts. We do not emphasize the restaurant response since we do not expect big impacts on the restaurants a priori. The posting of hygiene scores on Yelp is much less salient and more distant to restaurants than in situations where restaurants are required to post scores on their doors, as in Jin and Leslie (2003). Overall, we do not find temporal changes in the mean or the distribution of hygiene scores in San Francisco between 2013 and early 2016. The result doesn't change using hygiene scores in neighboring counties as the control. In particular, we do not find a reduction

in the percentage of low-score restaurants after the score posting. Notably, the hygiene alert does cause the restaurants struck by the alert to respond. In the regression in Appendix Table A7, we examine whether posting the alert reduces the probability of the low-score (score$\leq$ 70) restaurant getting a low score again. We controlled for the probability of restaurants getting out of the low-score region due to mean reversion, and we also add a comparison group of restaurants with low scores but above the 70 threshold (restaurants with scores between 70 and 85) besides controlling for the base group with scores above 85. Even though the Yelp hygiene alert is reported in the local news, we find that only the restaurants that have received the alert become less likely to get an alert again, while the restaurants that haven't received an alert do not. This could be due to the restaurants with the alerts learning about the demand shock better than other restaurants that haven't been struck by the alert.

Our results suggest that the hygiene alert has increased consumer attention to the hygiene condition when they encountered. Restaurants with an alert might be improving at the margin, in the sense that they are less likely to get a second alert relative to other businesses. However, in contrast with Jin and Leslie (2003), we do not see widespread evidence of quality effects. This raises the potential that while salient disclosure through a third party seems to have some demand effect, it has not been as effective, at least in the short term, at motivating restaurant behavior. This might be in part because by increasing salience only for some businesses, the initiative had little effect at other parts of the hygiene score distribution.

In principle, demand shocks driven by the posting have the potential to affect restaurant closures as well. While our relatively short panel prevents us from doing a full analysis of this issue, our data can provide some insight into restaurant closure more broadly. In Panel A of Appendix Table A8, we regress exit decisions on the restaurant's average hygiene score during the sample period. We find that restaurants with lower average hygiene scores tend to exit at higher rates than those with higher scores, but the relationship is not statistically significant. Moreover, the correlation weakens when controlling for a restaurant's Yelp rating. In Panel B of Appendix Table A8, we look at the impact of the alert on exit decisions. In columns (1) and (2), we look at the periods before and after the alert implementation. In columns (3) and (4), we use monthly observations and control for linear and quadratic time trends to capture seasonality and common time trends of exit decisions. The effect of the alert on exit decisions is captured by the coefficients of the cross-product terms. Our point estimates suggest that the alert may drive restaurants with lower hygiene score to exit at a higher rate - while the estimates are imprecise, this suggests an area for further research.

Overall, our results suggest that policymakers and managers should think not only about what information to disclose, but also how disclosure should be designed. Moreover, we present opportunities for policymakers to partner with online platforms to improve existing disclosure policies.

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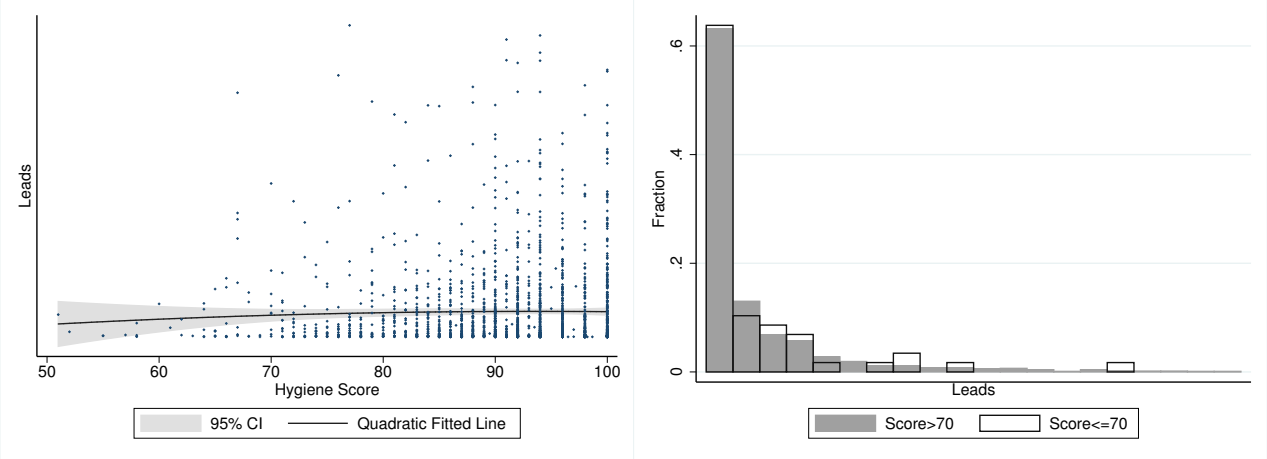
Figures and Tables

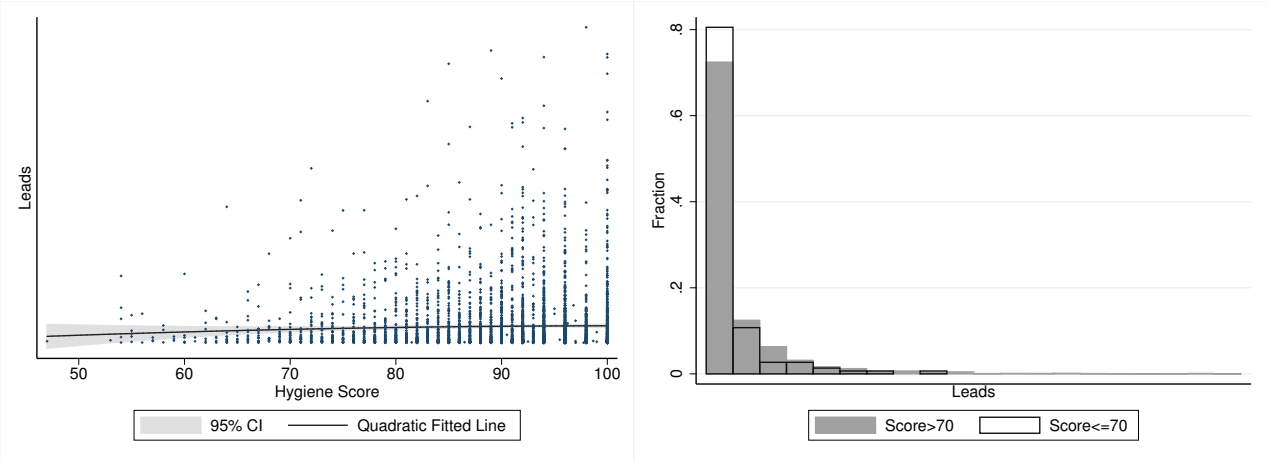
Figure 1: Baseline Relationship Between Hygiene Scores and Restaurant Leads

Panel A. Before the posting of hygiene scores



(a) (b)

Panel B. Before the posting of hygiene alerts

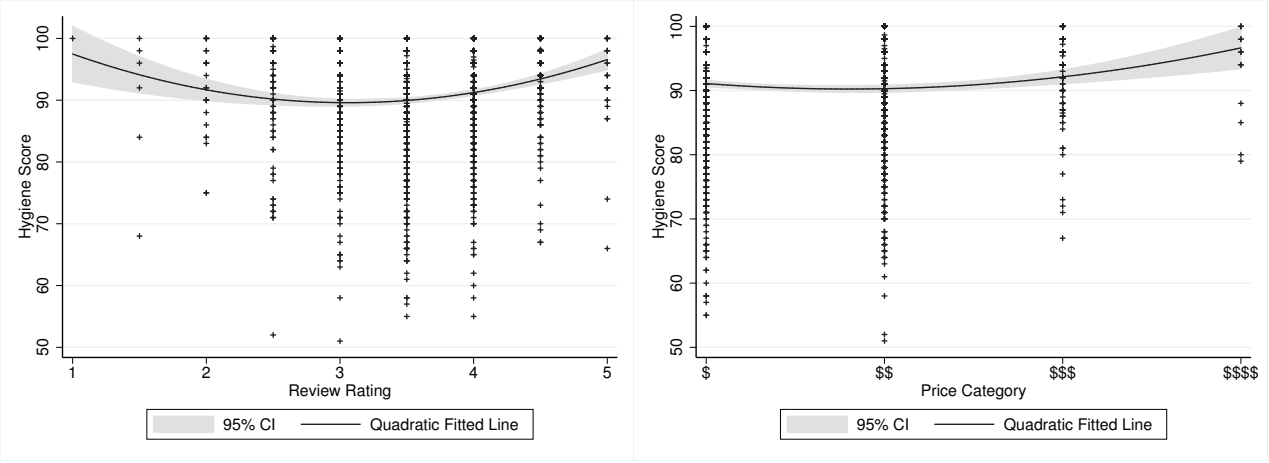


(a) (b)

Note: Panel A shows the statistics in the month before the hygiene score posting intervention. Panel B shows the statistics in the month before the hygiene alert intervention. The two figures on the left show the scatter plot of restaurant hygiene scores and restaurant leads in the month before the interventions. The scale of the y-axis is not revealed due to confidentiality. The two figures on the right compare the distribution of leads for restaurants with scores less than or equal to 70 and those above 70 in the month before the interventions.

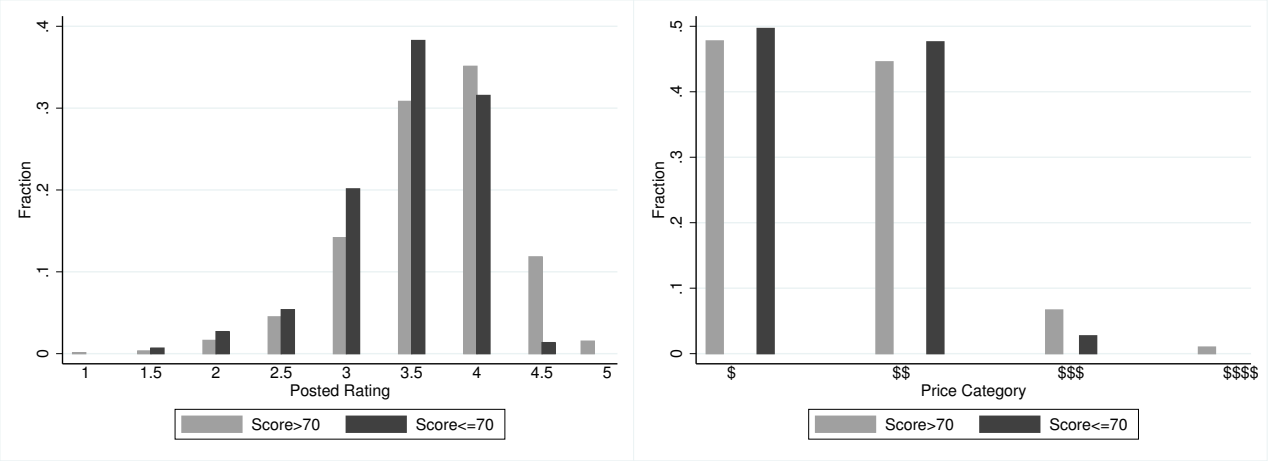
Figure 2: Baseline Relationship Between Hygiene Scores and Restaurant Characteristics

Panel A. Before the posting of hygiene scores



(a) (b)

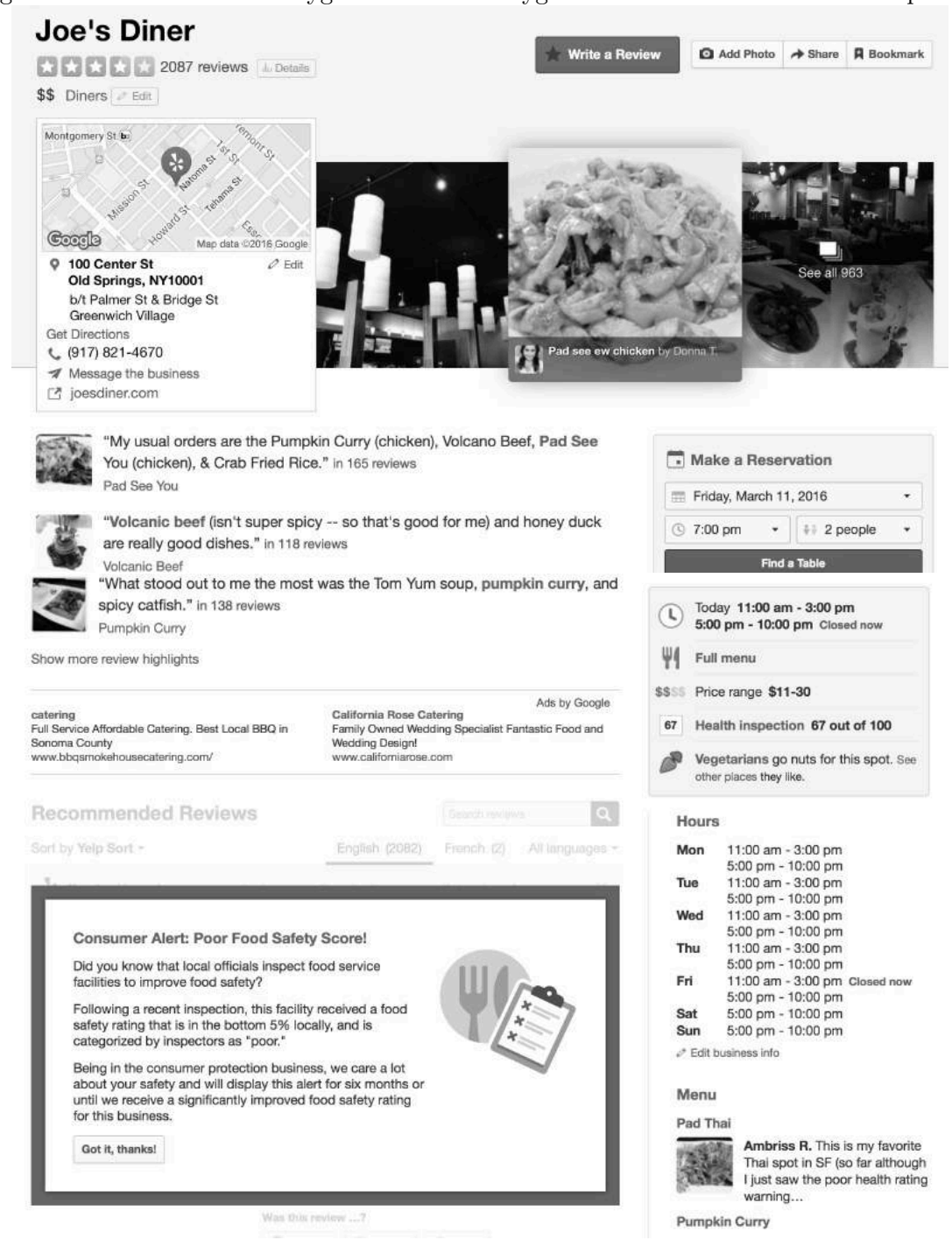
Panel B. Before the posting of hygiene alerts



(a) (b)

Note: The two figures in Panel A shows the scatter plot of restaurant hygiene scores and displayed review rating (on the left) and the price category of the restaurant (on the right) before the posting of hygiene scores, fitted with quadratic curves. The two figures in Panel B compares the distribution of restaurant displayed review ratings and price category for restaurants with scores less than or equal to 70 and those above 70 before the implementation of hygiene alerts. There are 151 alert restaurants and 4,471 non-alert restaurants.

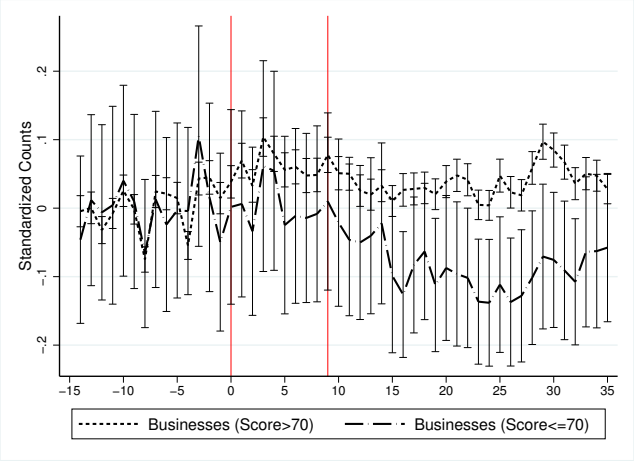
Figure 3: Screenshot of the Hygiene Score and Hygiene Alert on a Restaurant's Yelp Page



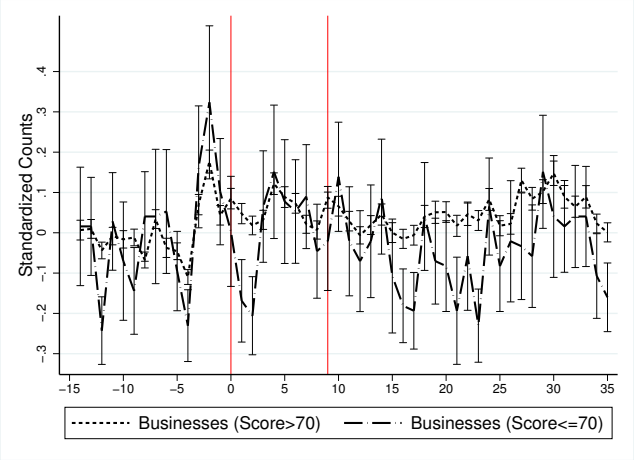
Note: The figure above shows the hygiene alert on a restaurant's Yelp page. The hygiene score, 67, is shown in the information box on the right. The hygiene alert blocks the consumer reviews section. The alert is visible only to users who scroll to read reviews. Consumers can get more information, such as specific hygiene violations during the restaurant inspection, by clicking the "Health Inspection" link next to the score.

Figure 4: The Impact of Posting on Purchase Intentions

Panel A. Weekly consumer leads: 10/11/2012 - 9/25/2013



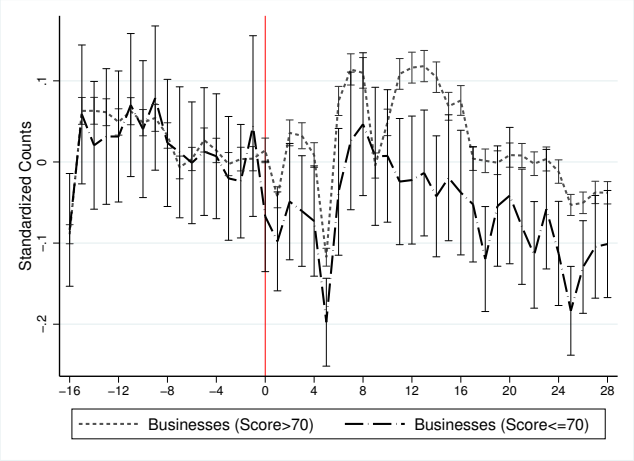
Panel B. Weekly number of reviews: 10/11/2012 - 9/25/2013



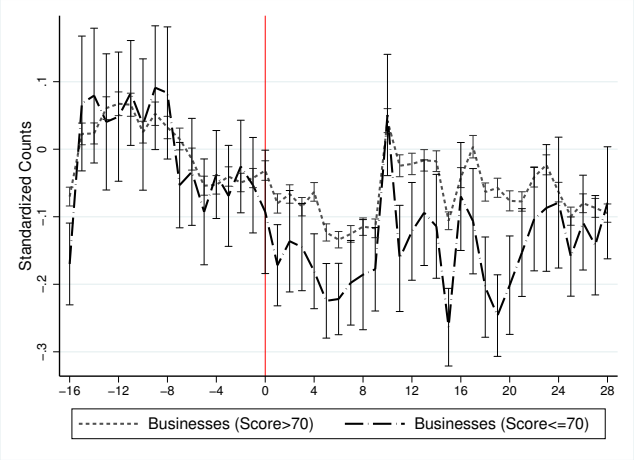
Note: The figures plot the standardized weekly counts of consumer leads (Panel A) and reviews (Panel B) with standard error bars separately for businesses with hygiene scores above 70 and businesses with hygiene scores of 70 or below. Consumer leads consist of calls to businesses through the Yelp app or mobile website, clicks on the business's URL on its Yelp page, and clicks on the direction request button or the business's map on its Yelp page. The standardization is done using the sample mean and standard deviation within 15 weeks before the score posting interventions. The two vertical lines represent the start of the health score posting test period on 1/17/2013 and the official posting period on 3/25/2013.

Figure 5: The Impact of the Hygiene Alert on Purchase Intentions

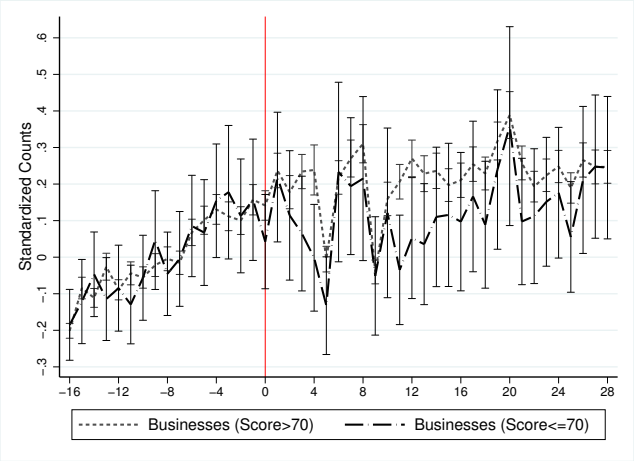
Panel A. Weekly consumer leads: 7/1/2015 - 5/9/2016



Panel B. Weekly number of reviews: 7/1/2015 - 5/9/2016



Panel C. Weekly number of takeout orders: 7/1/2015 - 5/9/2016



Note: The figures plot the standardized weekly counts of consumer leads (top figure), reviews (middle figure), and takeout orders (bottom figure) with standard error bars separately for businesses with hygiene scores above 70 and businesses with scores of 70 or below. The standardization is done using the sample mean and standard deviation within 16 weeks before the hygiene alert interventions. The vertical line represents the week that the hygiene alert was implemented (10/20/2015).

Table 1: The Impact of Score Posting on Purchase Intentions

Panel A. *Differential effects by Ln(Score)*

	(1) Standardized # of Leads	(2) Ln(# of Leads)	(3) Standardized # of Reviews	(4) Ln(# of Reviews)
Posting Test Period× Ln(Score)	0.219***	0.397***	0.224***	0.248**
	(0.053)	(0.108)	(0.0917)	(0.110)
Posting Period× Ln(Score)	0.211***	0.431***	0.183*	0.178*
	(0.061)	(0.126)	(0.099)	(0.093)
N	16,409	16,409	15,491	15,491

Panel B. *Differential effects by the 70 cutoff*

	(1) Standardized # of Leads	(2) Ln(# of Leads)	(2) Standardized # of Reviews	(4) Ln(# of Reviews)
Posting Test Period× (Score≤70)	-0.056***	-0.116*	-0.066	-0.066
	(0.020)	(0.068)	(0.048)	(0.066)
Posting Period× (Score≤70)	-0.101***	-0.127*	-0.083	-0.069
	(0.035)	(0.067)	(0.066)	(0.055)
N	16,409	16,409	15,491	15,491

Note: All linear regression specifications control for restaurant fixed effects, period dummies (test period and posting period), a linear time trend, and attribute-specific linear time trends. The attribute-specific trends are the interaction terms between time trend and restaurant attributes, including price category and the posted star rating of the restaurant before the score posting intervention. Standard errors are clustered at the business level. The regressions use monthly data at the business level between 10/16/2012 and 6/20/2013, from three months before the test period started on 1/17/2013 to three months after the official posting period started on 3/25/2013. Month 0 starts on 1/17/2013, and we assume 31 days for each month. The test period lasts a little less than two months, and we take months 0-1 as the test period and 2-4 as the posting period. The hygiene score of a restaurant is its score as of the most recent inspection before 1/17/2013. Among all restaurants, 2,038 have hygiene scores above 70, and 60 have scores of 70 or below. Dependent variables are standardized by the mean and standard deviation during the period before score posting. We drop restaurants that have never received any review in the entire sample period in the regression for reviews, which causes the drop in the sample size in columns (3) and (4). Standard errors in parentheses, clustered at the business level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2: The Impact of the Hygiene Alert on Purchase Intentions

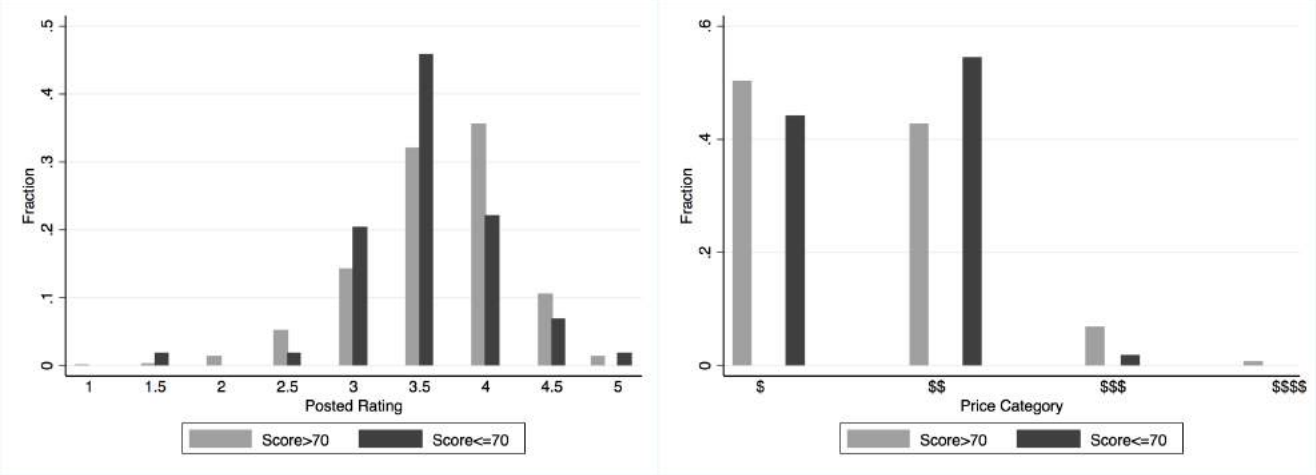
	(1) Standardized # of Leads	(2) Ln(# of Leads)	(3) Standardized # of Reviews	(4) Ln(# of Reviews)	(5) Standardized # of Orders	(6) Ln(# of Orders)
Alert Period× (Score≤70)	-0.066***	-0.074**	-0.098***	-0.113***	-0.111	-0.128
	(0.025)	(0.036)	(0.031)	(0.037)	(0.073)	(0.120)
Alert Period	0.009***	-0.033***	-0.038***	-0.051***	0.043*	0.0216
	(0.003)	(0.009)	(0.009)	(0.012)	(0.024)	(0.0303)
N	26,911	26,911	24,359	24,359	5,011	5,011

Note: The specifications in columns (1)-(6) are the same as in Table 1. The regressions in columns (1)-(6) use monthly data at the business level between 7/1/2015-1/31/2016, from three months before to three months after the implementation of the hygiene alert on 10/20/2015. Month 0 starts on 10/20/2015, and we assume 31 days for each month. The hygiene score of a restaurant is its score as of most recent inspection before 10/20/2015. Among all restaurants, 4,336 have hygiene scores above 70, and 149 have scores of 70 or below. Dependent variables are standardized by the mean and standard deviation during the period before the hygiene alert. The drop in sample size in the regression for reviews is due to dropping restaurants with no reviews in the sample period. Only restaurants that have signed up on Yelp's EAT24 platform have takeout order data available, so we have a much smaller sample for regressions in columns (5) and (6). *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

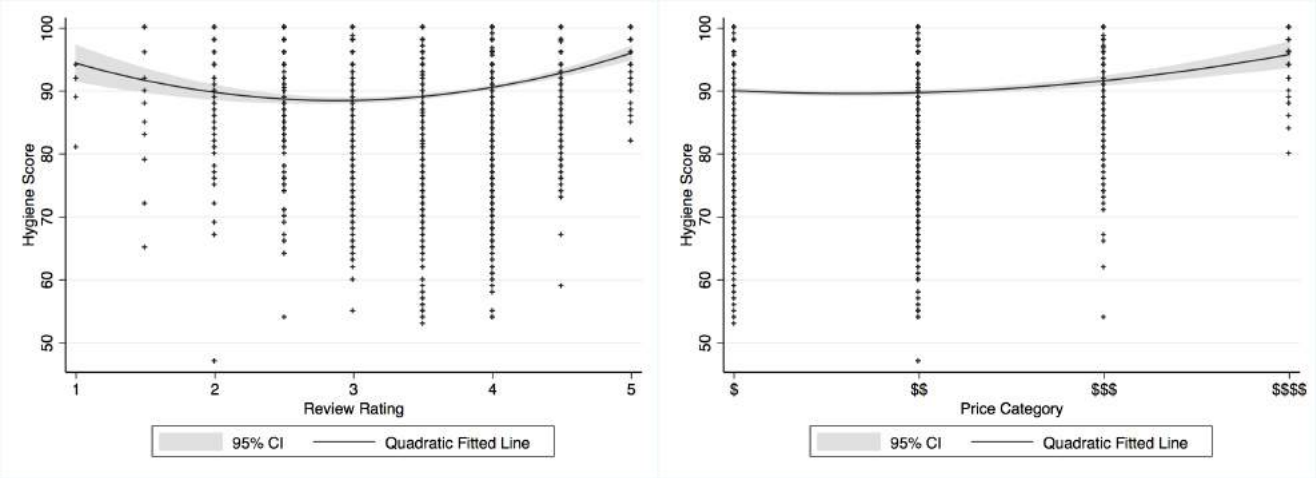
Online Appendix for Digitizing Disclosure: The Case of Restaurant Hygiene Scores

Figure A1: Baseline Relationship Between Hygiene Scores and Restaurant Characteristics

Panel A. Distribution of restaurant characteristics by the low-score cutoff (before the score posting)

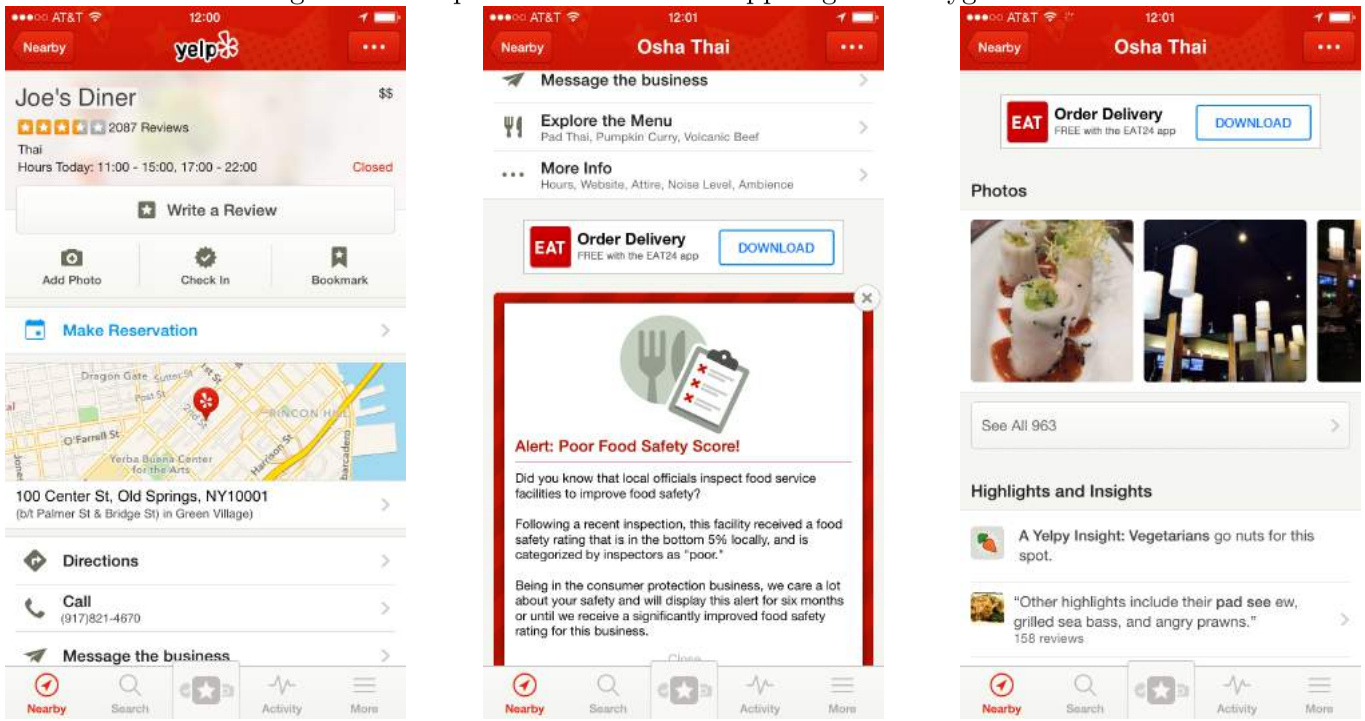


Panel B. Relationship between restaurant hygiene scores and restaurant characteristics (before the hygiene alert)



Note: **1** The two figures in Panel A shows the scatter plot of restaurant hygiene scores and displayed review rating (on the left) and the price category of the restaurant (on the right) before the posting of hygiene scores, fitted with quadratic curves. **2** The two figures in Panel B compares the distribution of restaurant displayed review ratings and price category for restaurants with scores of less than or equal to 70 and those above 70 before the score posting program.

Figure A2: Yelp Restaurant Mobile App Page with Hygiene Alert

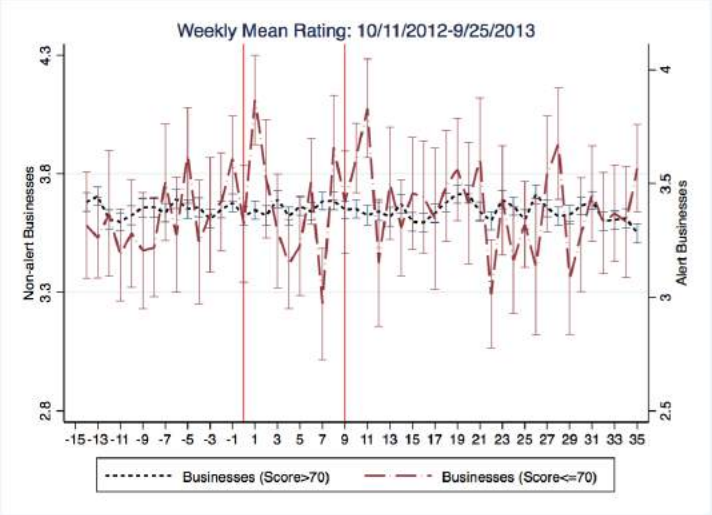


A. Top of the App Screen B. Scrolling Down the App Screen C. After Closing the Hygiene Alert Box

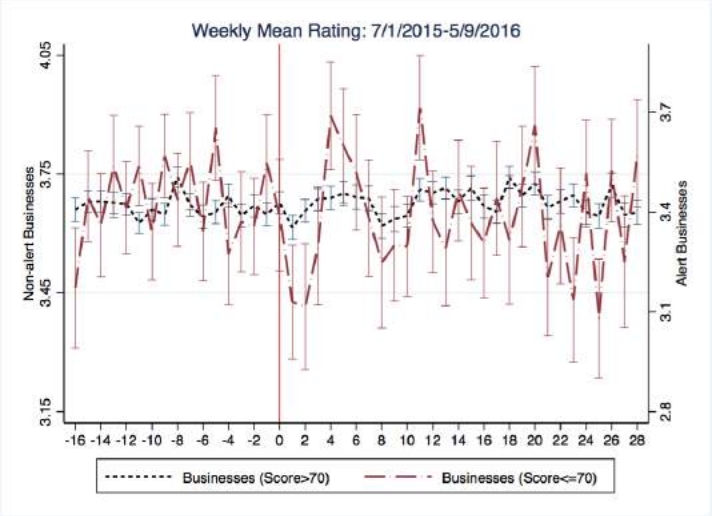
Note: In the mobile app, the hygiene alert blocks the photos and reviews section. The alert is not visible to the consumers who do not scroll down the page.

Figure A3: The Impact on Yelp Ratings

Panel A. Effects of score posting



Panel B. Effects of hygiene alerts



Note: **1** The figures plot the weekly average rating of new reviews left on the restaurant's page and the average trustworthiness of these reviews with standard error bars separately for businesses with scores of 70 and below and businesses with scores above 70. **2** The two vertical lines in the top figure represent the week that the hygiene score posting is launched in the test period (1/17/2013) and officially (3/25/2013). The vertical line in the bottom figures represents the week that the hygiene alert is implemented (10/20/2015).

Table A1: Hygiene Score Categories and Interpretations

- High risk: Violations that directly relate to the transmission of foodborne illnesses, the adulteration of food products ,and the contamination of food-contact surfaces.
- Moderate risk: Violations that are of a moderate risk to the public health and safety.
- Low risk: Violations that are low risk or have no immediate risk to the public health and safety.

Score	**Operating Condition Category**	**Inspection Findings**
>90	Good	• Typically, only lower-risk health and safety violations observed • May have high-risk violations
86-90	Adequate	• Several violations observed • May have high-risk violations
71-85	Needs Improvement	• Multiple violations observed • Typically, several high-risk violations
Less than or equal to 70	Poor	• Multiple violations observed • Typically, several high-risk violations

Note: The above table is replicated from the website of the San Francisco Department of Public Health (https://www.sfdph.org/dph/EH/Food/Score/default.asp)

Table A2: Two Interventions in San Francisco and the Population of Restaurants Directly Affected

	Intervention	Effective Time	Yelp Efforts and Restaurants Affected
1	Hygiene scores are posted on Yelp	(Test period) 2013/1/17–2013/3/25	• Yelp publicly announces the hygiene score posting program on its official blog and on various media outlets • Hygiene scores are posted on the Yelp pages of San Francisco restaurants matched with SFDPH records
		(Official posting period) 2013/3/25–present	• Hygiene scores are posted on the Yelp pages of all San Francisco restaurants matched with SFDPH records
2	A hygiene alert is issued for restaurants with poor operating conditions	2015/10/20–present	• Consumer alerts are posted on 151 restaurants identified as having poor operating condition by the SFDPH in the most recent inspection within 6 months (hygiene score$\leq$70).

Table A3: Pre-trend Tests Before Interventions

Panel A. Pre-trend tests before the hygiene score posting intervention

	(1) Standardized # of Leads	(2) Standardized # of Reviews	(3) Rating
$t \times \ln(Score)$	0.042	-0.129	0.069
	(0.043)	(0.0854)	(0.151)
t	-0.179	0.618	-0.301
	(0.192)	(0.385)	(0.679)
$\ln(Score)$	0.480**	-0.091	1.127***
	(0.238)	(0.301)	(0.358)
N	6,149	5,806	4,400

Panel B. Pre-trend tests before the hygiene alert intervention

	(1) Standardized # of Leads	(2) Standardized # of Reviews	(3) Rating	(4) Standardized #Orders
$t \times (Score \leq 70)$	0.005	-0.033	0.046	0.0165
	(0.013)	(0.165)	(0.057)	(0.033)
t	-0.026***	-0.422***	-0.0005	0.103***
	(0.002)	(0.031)	(0.011)	(0.0110)
$(Score \leq 70)$	0.010	0.062	-0.081	0.0330
	(0.082)	(0.421)	(0.134)	(0.194)
N	13,600	12,262	9,780	2,529

Standard errors in parentheses, clustered at the business level. * p<0.10, ** p<0.05, *** p<0.01

Note: **1** This table reports linear regression results investigating the differential pre-trends before the hygiene score posting intervention (Panel A) and the hygiene alert intervention (Panel B). **2** The samples for the regressions in Panel A are monthly observations at the business level during the three months before the hygiene score posting test period started on 1/17/2013. The samples for Panel B are monthly observations at the business level during the three months before the hygiene alert program started on 10/20/2015.

Table A4: The Impact of Score Posting (Log vs. Negative Binomial, Effects on Ratings)

Panel A. Differential effects by Ln(Score)

	(1) Ln(# of Leads)	(2) # of Leads	(3) Ln(# of Reviews)	(4) # of Reviews	(5) Mean Rating
Test Period× Ln(Score)	0.397***	0.378***	0.247**	0.333***	0.059
	(0.108)	(0.078)	(0.109)	(0.125)	(0.199)
Posting Period× Ln(Score)	0.431***	0.390***	0.192**	0.281**	-0.073
	(0.126)	(0.069)	(0.0931)	(0.115)	(0.175)
N	16,409	16,409	15,499	15,499	11,8380
Fixed Effects	Business	Business	Business	Business	Business
Model	Linear	Negative Binomial	Linear	Negative Binomial	Linear

Panel B. Differential effects by the 70 score cutoff

	(1) Ln(# of Leads)	(2) # of Leads	(3) Ln(# of Reviews)	(4) # of Reviews	(5) Mean Rating
Test Period× (Score≤70)	-0.116*	-0.129***	-0.0661	-0.100	0.024
	(0.068)	(0.047)	(0.0651)	(0.071)	(0.107)
Posting Period× (Score≤70)	-0.127*	-0.158***	-0.0797	-0.110*	0.086
	(0.067)	(0.041)	(0.0548)	(0.065)	(0.089)
N	16,409	16,409	15,499	15,499	11,830
Fixed Effects	Business	Business	Business	Business	Business
Model	Linear	Negative Binomial	Linear	Negative Binomial	Linear

a. Standard errors in parentheses, clustered at the business level. * p<0.10, ** p<0.05, *** p<0.01

b. All regressions have controlled for period dummies, a linear time trend, and attribute-specific linear time trends. The results are similar without controlling for the time trends.

Note: **1** Panel A reports regression results examining the differential effects of the hygiene score posting on consumer activities based on log-levels of hygiene scores, and Panel B reports results based on the 70 score cutoff. **2** The regressions use the same sample as the ones reported in Table 1. Results of the alternative negative binomial specification are reported.

Table A5: The Impact of Hygiene Alerts (Log vs. Negative Binomial, Effects on Ratings and Orders)

Panel A. Effects on leads and reviews.

	(1) Ln(# of Leads)	(2) # of Leads	(3) Ln(# of Reviews)	(4) # of Reviews	(5) Mean Rating
Alert Period× (Score≤70)	-0.074**	-0.094***	-0.113***	-0.144***	-0.101
	(0.036)	(0.021)	(0.0370)	(0.040)	(0.072)
Alert Period	-0.033***	-0.0095	-0.0505***	-0.060***	-0.011
	(0.009)	(0.0074)	(0.0123)	(0.015)	(0.027)
N	26,911	26,911	24,359	24,359	18,999
Fixed Effects	Business	Business	Business	Business	Business
Model	Linear	Negative Binomial	Linear	Negative Binomial	Linear

Panel B. Effects on take-out orders.

	(1) Ln(# of Orders)	(2) # of Orders	(3) Value per Order ($)
Alert Period× (Score≤70)	-0.128	-0.147**	0.480
	(0.120)	(0.066)	(0.722)
Alert Period	0.0216	0.0525	0.581
	(0.0303)	(0.0375)	(0.804)
N	5,011	5,011	4,179
Fixed Effects	Business	Business	Business
Model	Linear	Negative Binomial	Linear

a. Standard errors in parentheses, clustered at the business level. * p<0.10, ** p<0.05, *** p<0.01

b. All the regressions have controlled for period dummies, a linear time trend, and attribute-specific linear time trends. The results are similar without controlling for the time trends.

Note: **1** The regressions use the same sample as the ones reported in Table 2. Results of the alternative negative binomial specification are reported. **2** This table shows that the hygiene alert has no effect on the mean rating of trustworthiness of new reviews left for the restaurant or on the value of the orders consumers placed.

Table A6: Analysis with Alternative Sample and Alert Threshold

Panel A. Use sample of restaurants above the alert threshold. Test impacts on restaurants with score (70,75] and (75,100].

	(1) Standardized # of Leads	(2) Standardized # of Reviews	(3) Standardized # or Orders
Alert Period ×(Score≤75)	0.0117	0.0118	0.0603
	(0.0216)	(0.0305)	(0.144)
Alert Period	0.00957***	-0.0388***	0.0411
	(0.00310)	(0.00871)	(0.0254)
N	26116	23518	4697
Fixed Effects	Business	Business	Business
Model	Linear	Linear	Linear

Panel B. Compare the impact on restaurants restaurants just above (70,80] and just below (60,70]the alert threshold.

	(1) Standardized # of Leads	(2) Standardized # of Reviews	(3) Standardized # of Orders
Alert Period ×(Score≤70)	-0.0893***	-0.0992***	-0.167
	(0.0293)	(0.0345)	(0.104)
Alert Period	0.0104	-0.0341*	0.0886
	(0.00979)	(0.0204)	(0.0595)
N	3329	3088	878
Fixed Effects	Business	Business	Business
Model	Linear	Linear	Linear

Panel C. Use the sample of restaurants above the alert threshold. Test differential impacts on restaurants with respect to hygiene scores.

	(1) Standardized # of Leads	(2) Standardized # Reviews	(3) Standardized # Orders
Alert Period ×Ln(Score)	0.0103	-0.0845	-0.438
	(0.0115)	(0.0644)	(0.282)
Alert Period	0.00902***	0.343	2.010
	(0.00321)	(0.290)	(1.265)
N	26116	23518	4697
Fixed Effects	Business	Business	Business
Model	Linear	Linear	Linear

Standard errors in parentheses, clustered at the business level. * p<0.10, ** p<0.05, *** p<0.01

Note: The regressions use the same sample as the those reported in Table 1. In this section, we conduct robustness and placebo tests using alternative samples and placebo cutoffs for hygiene alerts.

Table A7: Do Alerts Improve Future Scores?

	(1) (Score≤70)	(2) (Score≤70)
(LagScore≤70)×1st Inspection After Alert	-0.114**	-0.233***
	(0.0527)	(0.0757)
(70<LagScore≤85)×1st Inspection After Alert	0.0140	0.0248
	(0.0136)	(0.0187)
(LagScore≤70)	-0.182***	0.0424
	(0.0257)	(0.0495)
(70<LagScore≤85)	-0.00138	-0.00739
	(0.00598)	(0.0137)
1st Inspection After Alert	-0.000282	-0.00573
	(0.00449)	(0.0145)
Month Dummies	x	x
Linear Time Trend (by month)	x	x
Business Fixed Effects	x	x
	15,754	8,209

Standard errors in parentheses, clustered at the business level. * p<0.10, ** p<0.05, *** p<0.01

Note: **1** The table reports panel regression results that investigate hygiene score changes for restaurants with a score of 70 or below in the previous inspection. **2** The sample in column (1) consists of all inspections before the alert period and the first inspection after the alert. The sample in column (2) only includes the last inspection before the alert period and the first inspection after the alert.

Table A8: Effects of Hygiene Alerts on Restaurant Exit

Panel A. Cross-sectional Regression

	$I(Exit_i)$			
	(1)	(2)	(3)	(4)
$ScoreEverBelow70$	0.0032	-0.0009		
	(0.0180)	(0.0184)		
$Ln(\overline{Score_{i,mth}})$			-0.0938	-0.0732
			(0.0622)	(0.0644)
$\overline{ReviewRating_{i,mth}}$		-0.0225**		-0.0210**
		(0.0092)		(0.0092)
$Constant$	0.0231	0.112**	0.447	0.436
	(0.0238)	(0.0496)	(0.282)	(0.290)
Price Category Dummies	X	X	X	X
N	3,817	3,705	3,817	3,705

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Note: **1** The regressions in Panel A analyzes whether restaurants with lower hygiene scores are more likely to exit during the sample period. **2** We focus on the sample of 3,817 restaurants for which we observe hygiene scores since January 2014 and are operating in January 2014. **3** $ScoreEverBelow70$ is an indicator of whether the restaurant has ever received a hygiene score 70 or below between January 2014 and December 2016. $\overline{Score_{i,mth}}$ and $\overline{ReviewRating_{i,mth}}$ are average monthly ratings between January 2014 and December 2016. **4** The number of observations in columns (2) and (4) is less than 3,817 since some restaurants do not have review ratings.

Panel B. Panel Regression

	$I(Exit_{i,regime})$		$I(Exit_{i,mth})$	
	(1)	(2)	(3)	(4)
$ScoreEverBelow70 \times AlertPeriod$	0.00027		0.0045*	
	(0.0134)		(0.0026)	
$ScoreEverBelow70$	0.00763		-0.0005	
	(0.0233)		(0.0009)	
$Ln(\overline{Score_{i,mth}}) \times AlertPeriod$		-0.0204		-0.0112**
		(0.0363)		(0.00442)
$Ln(\overline{Score_{i,mth}})$		-0.0961		0.0012
		(0.0678)		(0.0015)
$AlertPeriod$	0.0275***	0.459	-0.0016*	0.0491**
	(0.0055)	(0.305)	(0.0009)	(0.0200)
$Constant$	-0.0022	0.0916	0.0010**	-0.0043
	(0.0063)	(0.164)	(0.0004)	(0.0066)
Price Category Dummies	X	X	X	X
Linear and Quadratic Time Trend			X	X
N	7,473	7,473	129,401	129,401

Standard errors in parentheses, clustered at the restaurant level. * p<0.10, ** p<0.05, *** p<0.01

Note: **1** The table in Panel B show the effects of the hygiene alert intervention on restaurant exits. Note that since we cannot obtain historical hygiene score data before the hygiene score posting intervention, we are not able to analyze analyze the effect of the hygiene score posting on exits. **2** We focus on the sample of 3,817 restaurants on which we observe hygiene scores since January 2014 and are operating in January 2014. Among all restaurants, 417 restaurants, or 10.9%, have exited between January 2014 and December 2016. The unit of observation in column (1) and (2) is a restaurant is a given "regime" (before or after the hygiene alert intervention). To control for general time trend due to seasonality or restaurant aging, we use restaurant monthly data in column (3) and (4) and control for linear and quadratic time trend. **3** $ScoreEverBelow70$ is a dummy variable indicating whether the restaurant's hygiene score has hit 70 or below in the given regime or a quarter. $\overline{Score_{i,mth}}$ is the average of the restaurant's monthly hygiene scores. The sample average of score is 90, and its log value is 4.5. $AlertPeriod$ is the indicator of the period after the hygiene alert intervention.