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On the tip of the brain: Understanding when negative reputational events can have positive reputation spillovers, and for how long

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ABSTRACT

This paper contributes to the reputation spillover literature by showing how a crisis caused by a firm's capability failure enhances the reputations of its rivals. We consider how the combination of rivals' characteristics that increase their associability with the focal firm and the extent to which the crisis is salient in the minds of stakeholders can lead to positive reputation spillovers, and we also explore how long the positive reputation spillover lasts. Using a natural experiment based on the E coli outbreak in Chipotle's Seattle restaurants, we find that the reputations of other restaurants in the Seattle region were enhanced when the E coli breakout was more salient and thus cognitively available, but only for Mexican restaurants that were geographically proximal to a Chipotle.

Managerial Summary: In this study we conducted a natural experiment based on Chipotle's 2015 E Coli breakout to explore how a firm's capability failure affects the reputation of its competitors. We found that failures due to firm practices that differentiate the firm from others in its industry result in a positive reputation spillover, but only for the firms that are the most similar, and only for as long as the failure is salient to stakeholders. Thus, the benefit to firms from a competitor's failure is only temporary, and will not be experienced equally.

Drama does not just walk into your life. Either you create it, invite it or associate with it.

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When you read about a negative event occurring, how widely do you spread the blame? For example, if you read that a pledge suffered a serious injury during a fraternity hazing incident, would that affect your view of just that particular fraternity chapter, the whole fraternity system at the school, the University in its entirety, or the fraternity system writ large? And would your perceptions of the entities beyond the local fraternity chapter be more negative, or more positive? These questions lie at the heart of research on reputation spillovers, which considers how a focal firm's actions can affect the reputations of other firms in the same category (e.g., Barnett & King, 2008; Zavyalova, Pfarrer, Reger & Shapiro, 2012)—in other words, how the drama created by one firm affects others associated with it.

A major, but generally untested assumption underlying these questions and concerns about reputation spillovers is that other firms are seen as being similar enough to the focal firm to experience a reputation spillover if they are members of the same broad category, often empirically identified as firms in the same SIC code designation or via some other externally determined categorization scheme. However, determining category membership can be complex (e.g., Durand & Paolella, 2013; Porac, Thomas, Wilson, Paton & Kanfer, 1995; Reger & Huff, 1993), and different, more specific combinations of characteristics may be used to determine the associability (Durand & Paollela, 2013) of different firms with the focal actor, which can influence whether or not others are affected by the reputation spillover.

A second frequent, but generally untested assumption in reputation spillover research is that the spillover effects will be enduring, at least to some degree. This assumption is important because it determines whether reputation spillovers really affect this intangible asset in a significant way, and whether firms should take steps to try and mitigate the potential damage, or leverage anticipated gains. However, most research on reputation spillovers has tended to focus on short-term financial outcomes such as cumulative abnormal market returns in the days following the event (e.g., Barnett & King, 2008; Gomulya & Mishina, 2017; Paruchuri & Misangyi, 2015), or on strategic actions designed to mitigate potential spillovers (e.g., Durand & Vergne, 2015; Zavyalova et al., 2012), rather than more directly assessing its effects on other firms' reputations. Further, these short-term outcomes provide little insight into whether spillover effects endure once the salience of the negative event has abated—that is, whether the event continues to affect others' reputations once the crisis is no longer cognitively available and on the "tip of stakeholders' brains."

Further, most research on reputation spillovers has focused on situations where a focal firm's negative action has negative spillover effects. We are aware of only one study where the valence of the spillover is different than the valence of the action—that is, where a negative action has a positive spillover effect on others. Piazza and Jourdan (2018) found that when the Catholic Church became embroiled in sex scandals in the U.S., other Christian denominations that were perceived as having stricter standards of conduct were able to increase their membership at the Catholic Church's expense. While they explored this effect over a long time period, the "pedophile priest" sex scandals continued to be in the news during the entire period of their study, keeping the Catholic Church's wrongdoing cognitively available (Fiske & Taylor, 1991; Tversky & Khaneman, 1973) in the minds of parishioners, and thus a continued focus of their attention. They also inferred reputational effects by observing parishioners' behaviors, rather than directly assessing Catholics' perceptions of the reputations of other denominations after the scandal broke.

In this study we test these assumptions and explore how the associability of other firms intersects with the salience of a negative event to influence the cognitive availability of the event and create a positive reputation spillover, and how long the spillover effects persist. We use a natural experiment to study changes in the reputational assessments of restaurants in Seattle following the Chipotle E coli crisis in 2015. We show that reputation spillovers are short-term events sustained only so long as new cases of illness continued to be reported on in the media, and that only the reputations of highly associable category members—in our case, geographically-proximal Mexican restaurants—were affected. We also develop theory to explain when a positive, rather than negative, reputation spillover is likely to occur.

Our study contributes to research on reputation spillovers by showing how a focal actor's negative behaviors can have a positive effect on an important intangible asset possessed by other category members. We also highlight how the cognitive availability created by categorical features and the salience of the event combine to influence spillovers, which has implications for whether and how firms should respond to competitors' misfortunes.

THEORY AND HYPOTHESES

Reputation spillovers occur in industries because stakeholders assume that firms in the same industry experience both the same environmental pressures and also share common perspectives and values (Barnett & King, 2008; Durand & Vergne, 2015; Paruchuri & Misangyi, 2015; Zavyalova et al., 2012). Barnett and King (2008: 1152) noted, "Firms are considered to be members of the same industry when the outputs they produce are closely substitutable. To produce closely substitutable outputs, firms in an industry tend to have similar characteristics and make use of similar processes. As a result, when new information is revealed about the characteristics of one firm, it reflects to some degree on all firms within its industry." They argued that these commonalities are the basis for a reputational "commons" problem that leads firms in industries that did not face problems based on shared resources to nonetheless self-regulate. However, spillover research based on the commons logic does not specify the nature of the reputational failure, which can affect whether damage occurs and the type of damage done.

Connelly and colleagues (2016) argued that crises result from two types of failure, which they labeled competency failures and integrity failures. Competency, or capability, failures refer to "specific situations where a firm falls short of technically proficient performance," while integrity, or character, failures refer to situations where "the firm's motives, honesty, and/or character fall short" (Connelly et al., 2016: 2136). Mishina, Block and Mannor (2012) argued that capability and character failures are assessed differently, and Park and Rogen (2019) found evidence that good capability and character reputations provided buffering effects with different audiences. Most of the reputation spillover literature has focused on events that may be characterized as character failures, such as moral failings (e.g., "pedophile priest" sex scandals), intentionally misleading stakeholders (e.g., financial reporting violations) or outright illegal activities (e.g., tax evasion).

Key to negative reputation spillovers are that the negative action is perceived as self-serving, within an actor's control, and that others are also likely to be doing the same thing (Barnett & King, 2008; Gomulya & Mishina, 2017; Park & Rogen, 2019). However, what if the negative action is the outcome of capability failings that result from taking different actions than those taken by others in the industry? In other words, what if the action is less likely to be shared by others in the same category because the firm differentiated itself by adopting non-standard practices, and it is these practices that have led to the crisis? We argue that in this situation the spillover dynamics are likely to be different. Since social evaluations are made compared to some referent (March & Simon, 1958; Mishina, Dykes, Block & Pollock, 2010; Porac, Wade &

Pollock, 1999), a given level of performance can look better or worse depending on how well or poorly the comparative referents perform, and how similar they are perceived to be to the focal actor (Cattani, Porac & Thomas, 2017; Porac et al., 1999). If a category member demonstrates a major capability failure associated with their differentiating actions, other firms will look better not because they enhanced their performance, but because their comparative referent did something different and worse, making them appear better by comparison.

In our research context, Chipotle Mexican Restaurants—whose slogan "food with integrity" reflects the value it puts on using healthy ingredients—has differentiated itself by using ingredients that are unadulterated by antibiotics or chemical additives, that are locally sourced whenever possible, and that are cooked on site (Figart, 2017). One consequence of this is that managing its supply chain and food production becomes exponentially more difficult compared to firms who source their ingredients from centralized suppliers, and who often use ingredients that have been cooked to some degree before arriving at the restaurant, and can thus be reheated or finished on site. The E coli breakout in October of 2015 that rocked Chipotle has been widely attributed to the complexities of its operation (Walker & Merkley, 2017)—that is, it was attributed to capability failures associated with its values and differentiation strategy. Thus, we expect Chipotle's crisis will have positive, rather than negative reputation spillover effects.

Associability. Prior research has established audience perceptions of shared category membership increases the associability among firms (Cattani et al., 2017; Durand & Paollela, 2013) that can result in reputation spillovers (Barnett & King, 2008). However, simply sharing a broad category affiliation with a firm in crisis may not be enough to understand the full influence of the reputation spillover. There are an enormous set of dimensions audiences can use to classify firms as similar or dissimilar (Cattani et al., 2017), and "categorical boundaries are contingent upon the specific audience constructing them" (Cattani et al., 2017: 71). Thus, dimensions unique to each research context and audiences' decision making are likely to influence whether a firm is included in a stakeholder's "consideration set" (Pollock et al., 2008;

Roberts & Lattin, 1997) for making comparative assessments. When making decisions and evaluations, stakeholders use simplifying criteria to first reduce the set of possible options (Vergne, 2012), and then choose from among the firms remaining in their consideration set. Consequently, stakeholders may assess firms within the same broad category differently (Durand & Paollela, 2013; Paruchuri & Misangyi, 2015).

Although Chipotle can be classified in a number of different ways (e.g., Mexican restaurant, fast food, or inexpensively priced), its core identity is based on its cuisine—Mexican food—that is made salient by its name. As such, we argue that Chipotle will be a comparative referent for other Mexican restaurants, and that its capability failure will enhance perceptions of other Mexican restaurants' capabilities, and thereby their reputations. However, given the large number of Mexican restaurants in Seattle, cuisine type alone is unlikely to be sufficient to make a restaurant cognitively available. We argue geographic proximity is likely to be another relevant criterion for creating the consideration set from which to choose restaurants, and the basis on which to make comparative evaluations (Silva, 2016). While individuals can travel anywhere within a city to go to a restaurant, more often than not they will choose restaurants within reasonable proximity to where they live. Thus, they will be most familiar with the restaurants in their area, and these restaurants will form the consideration set to whom Chipotle will be compared. We therefore expect Mexican restaurants that are geographically proximal to a Chipotle restaurant will have the greatest associability with Chipotle, and will benefit the most from the positive reputation spillover resulting from Chipotle's crisis. We therefore hypothesize,

Hypothesis 1: Given the salience of the event, a firm's differentiation-based capability failure will have a positive reputation spillover on highly associable category members.

Salience. We also argue reputation spillover effects will only persist as long as the event precipitating the spillover continues to be salient, or cognitively available to the stakeholders making the assessments (Fiske & Taylor, 1991; Pollock, et al., 2008). Thus, for a negative event such as a capability failure to affect others' reputations, both the event and the firms affected have to be cognitively available (Fiske & Taylor, 1991; Tversky & Khaneman, 1973) and easily recalled together in order for the event to influence perceptions of the other firms.

Extreme and frequently occurring stimuli tend to be more cognitively available because they are figural, or stand out relative to the typical flow of information, and therefore are more easily recalled when making assessments (Khaneman, 2011; Taylor & Fiske, 1975). Thus, a firm's capability failure is likely to be easily recalled and factor into stakeholders' assessments of other category members while the crisis associated with the failure is playing out. However, since reputations need to be continually reinforced (Pollock et al., 2015; Washington & Zajac, 2005), when the crisis abates it will become less salient and its influence will weaken, eventually ceasing to factor into stakeholders' assessments of other category members. Thus, any reputation spillover effects are likely to diminish and disappear once the failure ceases to be salient.

In our research context, we argue Chipotle's crisis will be salient and cognitively available as long as the media keeps reporting about its E Coli cases. The media influences public attention and discourse (Carroll & McCombs, 2003; Pollock et al., 2008), and will continue to report on stories as long as they perceive them to be newsworthy. While their problems did not end once new cases ceased to be reported, the lack of new cases led the media to turn its attention elsewhere, and the E coli outbreak thus became less salient and less cognitively available when assessing restaurants other than Chipotle. We therefore expect that the positive reputation spillover effect to geographically-proximal Mexican restaurants will diminish as media coverage declines. We therefore hypothesize,

Hypothesis 2: Given category members' high associability, the lower the salience of the differentiation-based capability failure the weaker the positive reputation spillover.

RESEARCH METHODS

Research context, data sources and sample

We tested our hypotheses using a natural experiment derived from real events (Dunning, 2012; Shadish et al., 2002). In contrast to an experiment, where subjects are randomly assigned to different situations, “naturally” occurring events such as natural disasters or terrorist attacks also assign subjects to different conditions, such as the condition where the subjects are affected by the event and the condition where subjects are not affected by the event. This assignment process by naturally occurring events is called “as-if randomization” (Dunning, 2012: 10) and is considered “plausibly as good as random” because it allows researchers to have confidence that the differences in the outcome variable could be plausibly attributed to the treatment. Dunning (2012) also pointed out that this assignment technique rules out endogenous explanations for group differences (e.g., self-selection bias) and balances the treatment and control groups with regard to observable and unobservable variables.

Specifically, we test our hypotheses in the context of the E coli outbreak that occurred in Chipotle’s Seattle restaurants from October 16, 2015 to December 1, 2015. At least fifty customers reported falling ill during this period, and all Chipotle restaurants in the Seattle area were voluntarily shut down for approximately eleven days during this period. Using this incident as a natural experimental setting, we followed Shadish and colleagues’ (2002) longitudinal design, where we collected information on treatment and control groups in the pre-crisis, crisis, and post-crisis periods, and consider whether the effects of the treatment continue to persist after the treatment is withdrawn.

In particular, we use data on restaurant reviews hosted on Yelp.com—a third-party, review-hosting social media platform—to operationalize stakeholders’ perceptions of restaurant’s reputations. Yelp was founded in 2004 as a way for consumers to provide reviews of their experiences and give potential customers insights to use in making their dining decisions. Yelp’s expansive platform engages a wider group of consumers other outlets have been unable to reach (Kovács et al 2013; Johnston & Bauman 2007). Yelp is also the most prominent social media platform for restaurant reviews; by the end of Q2 2017 it hosted approximately 135 million cumulative reviews from 83 million unique visitors to Yelp’s website by desktop computer, and another 74 million visitors through its mobile website (Yelp 2017). Due to its popularity, acceptance and use by so many consumers, and the fact that it is a direct reflection of stakeholders' perceptions, we chose Yelp reviews as our indicator of other firms' reputations.

Yelp also provides a good interactive setting to observe the exchange of information among consumers and businesses. Each consumer review hosted on Yelp.com is time-stamped and maintained publicly on the site at all times for transparency. For each restaurant, Yelp provides relevant information such as its name, address, overall star rating, cuisine type, price range, hours of operation, delivery and reservation options. We will discuss some of these attributes in detail later in this section. Additionally, Yelp has other relevant features for each posting, including review date, review rating, and review content for each restaurant under study. To address issues of fake reviews, Yelp examines each review using its proprietary filtering algorithm to filter fraudulent or seemingly deceptive reviews (Luca and Zervas 2016). We rely on Yelp's system to filter out deceptive messages and use only filtered reviews in this study.

We selected a twenty-four week observation window for our study—the eight weeks before the E coli outbreak, the eight weeks when E coli cases were reported, and the eight weeks afterward, and collected weekly data on a sample of 2,672 restaurants in the Seattle metropolitan area. We dropped the observations for Chipotle restaurants, as our hypotheses are about the effects of their E coli breakout on other restaurants. We split the observation of the restaurants in the sample into weekly spells to accommodate time-varying factors in the analysis. Further, we dropped the restaurant-week spells for which there are no ratings (and correct for this selection in the analytical technique as described later). This resulted in 22,137 restaurant-week observations. In addition to the Yelp data, we also collected data from *ABI/INFORM*, the *U.S. Census Bureau*, and the *National Oceanic and Atmospheric Administration* to construct our measures.

Dependent variable

We measured *category member reputation* as the average Yelp review ratings the focal restaurant received in a given week. Each review rates a restaurant on a scale of 1 to 5 stars: 1star signifies low satisfaction and 5 stars signifies high satisfaction. Figure 1 shows a distribution of the review ratings for restaurants in our sample. Illustrating the relevance of Yelp reviews to our research context, a reviewer of Qdoba, another Mexican restaurant whose business model is similar to Chipotle's, stated: "Didn't start regularly going here until the Chipotle E. coli crisis. Benefits of going here over the rival U-District Chipotle: 1. Good, free parking lot, 2. Open an hour later, 3. No E. coli." Consistent with prior studies using Yelp ratings (e.g., Hu et al., 2009), the review ratings in our dataset have a J-shaped distribution, suggesting that reviewers generally tend to have a positive bias in their ratings. Of the 29,500 total reviews during our study period, 9.04% give a 1-star rating, 9.10% of reviews give a 2-star rating, 12.60% of reviews give a 3-star rating, 27.28% of reviews give a 4-star rating, and 41.61% of reviews give a 5-star rating.

Independent variables

We used three explanatory variables to capture the salience of the failure event and the associability of category members: salience, same industry sub-type, and geographic proximity. *Salience* is measured as a count of news articles published in the 26 major newspapers tracked in the *ABI/INFORM* database for each of the weeks in our observation window. In order to be included, the article had to contain the words "Seattle," "Chipotle" and "E coli." The higher the count, the more salient Chipotle's capability failure and the ensuing crisis were likely to be. The number of articles ranged from 0 to 43 articles in a given week. Because Chipotle sells Mexican cuisine, we coded *same category* as a dichotomous variable, where all Mexican restaurants in our sample were coded one and all other restaurants were coded zero. We measured *geographic proximity* as a dichotomous variable coded one if the focal restaurant is proximal to a Chipotle restaurant based on sharing the same zip code, and zero otherwise.

Control variables

Our control variables can be classified into three groups: restaurant attributes, location attributes, and weekly weather attributes. For restaurant attributes, we controlled for the characteristics that might affect that week's restaurant ratings. These controls included the *cumulative average Yelp rating* of the restaurant up to the week prior the current week; the *number of reviews* that week, measured as a count representing the total number of reviews for a given restaurant in the focal week; and *public firm*, an indicator variable coded 1 if the firm was publicly-traded and zero otherwise. We also controlled for the *price range of each restaurant*. Yelp uses four categories to classify a restaurant's price level, which is the approximate cost per person for a meal including one drink, tax and tip: $ = inexpensive, $$ = moderately expensive, $$$ = expensive, and $$$$ = very expensive. Chipotle's price range is $. We used the $$ range as the reference group and included indicator variables for each of the other three price categories. We also controlled for the *fast food* category, of which Chipotle is a member, by including an indicator variable that is coded one if the restaurant is a fast food restaurant. Finally, we also controlled for the *age of the restaurant*. Since many of the restaurants were small and privately-held, we followed the prior literature (Kovács et al 2013) and used the number of weeks since the first review was written as a proxy measure of the restaurant's age.

For location attributes, we controlled for the *number of Mexican restaurants* and the *number of all other restaurants* in the focal restaurant's zip code, as captured in the Yelp data, and the following demographic data, also by zip code: *total population*, *median age of all households*, *number of people who did not graduate from high school* and *mean household income*. These characteristics could influence consumer behavior (Reynolds & Wells 1977) and their engagement with user-generated content including review ratings on online social media (Sorce et al., 2005). Chipotle also voluntarily closed its restaurants for 11 days following the E coli outbreak. We included a dummy variable, *Chipotle closed*, coded 1 for the weeks Chipotles were closed. Finally, we included the *number of rain days* in a week and the *average weekly temperature* to account for any potential effects weather may have had on review ratings.

Method of Analysis

One challenge we faced is that each restaurant is not necessarily reviewed each week, resulting in some restaurant/week observations having no reviews. Assigning a zero to these observations would be inconsistent with the 1 to 5 ratings scale and does not accurately reflect perceptions of the restaurant. Instead, we coded the observation's value as missing and corrected for this potential sample selection bias using a Heckman selection model. In the first-stage model we predicted whether a restaurant had a review in a given week using a random-effects probit model. We used the total review ratings on Yelp that week as an instrument to predict being reviewed (β=0.0005; p-value=0.000), and also included all our control variables. We computed the Heckman correction factor from this analysis and included it as an additional control variable in the second-stage analysis. It was not significant in any of the models, suggesting selection bias is not a concern. In addition, it created some collinearity issues when we included it in the models, and our results did not change when it was excluded. Thus, we do not include the Heckman correction in the models presented below. We employed random-effects linear regression with robust standard errors based on restaurant in our primary analysis. We used random effects models because many of our independent measures are time-invariant, making fixed effects specifications inappropriate.

RESULTS

The summary statistics and bivariate correlations are presented in the supplemental Table 1, and the results of our primary regression analyses are presented in Table 2. We have also included a supplemental data file, available on the *Strategic Management Journal* Website, which includes a Chipotle press release and tables and graphs for the additional analyses reported here. Model 1 of Table 2 includes only the control variables; Model 2 adds the two explanatory variables *Geographic proximity* and *Same category*; and Model 3 adds their interaction. None of these terms were significant.

[Insert Tables 1 & 2 about here]

Model 4 introduces the *Salience* of Chipotle's crisis as additional variable, but it is not significant. Model 5 introduces the interaction of *Salience* and *Same category*. The interaction is significant at p=0.07. This interaction is graphed in Figure 2 and shows that increases in the Salience of Chipotle's capability failure is associated with higher positive ratings of Mexican restaurants, but not with non-Mexican restaurants. Model 6 introduces the interaction between *Salience* with *Geographic proximity*, but it is not significant.

Model 7 includes the two-way interactions between all of our independent variables, and Model 8 adds the three-way interaction between Salience, Geographic proximity and Same category. The two-way interaction between Salience and Same category is positive and the p-value is 0.07. The three-way interaction term is positive and the p-value is 0.06. This interaction effect is graphed in Figure 3, and shows that the increasing salience of Chipotle's crisis enhanced reputations the most for restaurants in the same industry sub-type and geographic location as a Chipotle. [1] These findings support Hypothesis 1, that when another firm's capability failure is salient, only firms with greater associability will experience positive reputation spillovers.

[Insert Figure 3 about here]

To further test Hypothesis 1, we re-ran our analyses using other, broader categorical dimensions that could be used to categorize these restaurants—fast food and being the same price range. The results of these analyses are included in Tables 1 and 2 of the supplemental file. As these results show, neither the two-way interaction between *Salience* and *Fast food* nor the three-way interaction between *Fast food*, *Salience* and *Geographic proximity* were significant. We performed the same analysis using *Price range*, and neither interaction was significant. Taken together, these results support Hypothesis 1.

The results presented in Model 8 of Table 2 and Figure 3 also support Hypothesis 2, that the positive reputation spillover effects for highly associable firms will diminish as the salience of the crisis declines, as only the line for geographically-proximal Mexican restaurants has a significant positive slope as the number of articles increases. In the range of our salience data, their reputations increased from 3.1, on average, for no Saliency to 3.6 for highest Salience, an effective increase of 16.3 percent compared to their reputations during the non-crisis periods. To put this in context, the week the crisis started a score of 3.1 ranked a restaurant 746th in our

[1] Even though the slope of the line for other geographically proximal restaurants was negative in Figure 3, it is not statistically significant (p=0.53); it therefore should be treated as flat.

sample, and a score of 3.6 ranked 656th—a jump of 90 restaurants. If a restaurant had a score of 4.0, an increase of .5 stars would result in a 136 restaurant jump in the rankings.

Because there were no mentions of E coli associated with Chipotle prior to the outbreak, to further test Hypothesis 2 we dropped the pre-crisis period observations from our analysis and re-ran our models. The results of this analysis are presented in Table 3 in the supplemental file. The results are identical to the ones presented here and show that the interaction of *Salience* with *Same category* in Model 5 is significant at p=0.09, and the three-way interaction in Model 8 is significant at p=0.07. This interaction, graphed in Figure 1 in the supplemental file, again shows that the reputation of other geographically-proximal Mexican restaurants increased as the salience of Chipotle's capability failure increased. Because the observation window only includes the crisis and post-crisis periods, this interaction implies that the reputation bump that occurred during the crisis period vanished when Salience decreased in the post-crisis period. These findings support H2.

Robustness tests

We also performed several robustness tests. First, while the earlier models did not include the selection correction factor, we included it in the analysis and the results (see Table 4 in the supplemental file) are similar to the ones presented here. Second, we also considered whether specific distance radii, rather than zip code, affected our findings. We found that the geographic distance effects decreased as the radius increased, and disappeared when the radius exceeded 5.00 miles (see Table 5 in the supplemental file).

Third, instead of using the single Yelp rating to assess stakeholder reactions, we content analyzed the reviews using Linguistic Inquiry Word Count (LIWC) (Pennebaker et al., 2007), which included pre-validated dictionaries for capturing positive and negative affective language, and used these scores to measure diners' perceptions of restaurants. We coded a review as positive if the ratio of positive to total affective language (positive plus negative affective words) was greater than 65 percent, and negative if the ratio of negative to total affective language was greater than 65 percent. All other reviews were coded as neutral. We then used the Janis-Fadner coefficient of imbalance (Deephouse, 2000; Janis & Fadner, 1965) to calculate a measure of the overall affective language of a restaurant's reviews for each week, which ranged from -1 (all negative) to all positive (+1), and used this measure as our dependent variable. Our results were consistent with the results presented here (see Table 6 in the supplemental file).

Finally, we also assessed whether the differences in the number of reviews published while new E coli cases were being reported could have influenced the ratings relative to different periods (see the supplemental file for graphs). We collected data on the number of reviews and the distribution of reviews during the periods before, during and after the crisis, and found that both Mexican and non-Mexican restaurants experienced decreases in the number of reviews during the crisis period relative to the other two periods, and that non-Mexican restaurants experienced a greater decline than Mexican restaurants. Thus, Mexican restaurants' rating frequency was consistent with broader trends. We also found that during the crisis period Mexican restaurants' ratings went up because they received fewer 1, 2 and 3 star ratings, but there was no difference in 4 and 5 star ratings received, suggesting that it was more likely those who gave negative to mediocre ratings perceived them as "less bad."

DISCUSSION

In this study we explored when and how a firm's capability failure affects the reputations of other firms in the same industry. Using a natural experiment based on Chipotle's E coli outbreak in Seattle, we found that Chipotle's capability failure associated with its differentiating practices had a positive reputation spillover, but only for restaurants specializing in the same cuisine that were also geographically proximal to a Chipotle, and only while the media kept the capability failure salient. These findings contribute to our understanding of reputation spillovers, and show how negative events at one firm can have positive consequences for its rivals.

Theoretical Contributions

Prior reputation spillover research has primarily focused on how one firm's crisis can have negative consequences for other firms in the same industry category, based on the idea that firms in the same industry category share a commons with respect to social approval assets such as reputation, and that because they make use of similar resources and employ similar processes, what befalls one industry member is likely to befall others (Barnett & King, 2008; Paruchuri & Misangyi, 2015). Limited research in this area has considered the nature of the negative event, though, and whether the factors underlying the event are in fact shared.

We contribute to this literature by developing theory to explain when positive, rather than negative reputation spillovers are likely to occur. We suggest that when the reasons for the crisis are related to practices that differentiate firms from others in their category, their failures will more likely be attributed to the individual firm, rather than to common failings shared by the category, resulting in a positive reassessment of other category members' reputations. In contrast, failures assumed to be driven by characteristics widely shared within the industry category are more likely to result in the negative spillovers observed in prior research (e.g., Barnett & King, 2008; Paruchuri & Misangyi, 2015). We did not develop specific hypotheses testing this argument because our context only offered one kind of spillover; however, when our results are observed alongside other reputation spillover findings, including other research finding positive spillover effects due to character failures (Piazza & Jourdan, 2018), the logic underpinning our conjecture is supported. Future research in other contexts should continue to tease out the dimensionality of reputations and the spillover events that can affect them.

Our study also contributes to the reputation spillovers literature by testing assumptions about when and why a firm's crisis is likely to affect other category members' reputations. Recent research has begun to explore factors that can influence spillovers, such as the substantive and ceremonial actions industry members take (Zavyalova et al., 2012), or the characteristics of the event, perpetrator and industry bystanders (Paruchuri & Misangyi, 2015). We add to this literature by focusing on how combinations of categorical characteristics that increase the associability between the focal firm and other firms lead stakeholders to include these other firms in their consideration sets (Pollock et al., 2008; Roberts & Lattin, 1997), and the consequences for how they are assessed.

However, associability alone is not sufficient. We also show that the associability of other category members has to combine with the salience of the failure to create the cognitive availability required for the spillover to occur. We also show that reputation spillovers are temporary, and only likely to endure while the focal firm's failure is salient to audiences making assessments. This finding is practically as well as theoretically important, because it suggests that whether positive or negative, other category members should not overreact to reputation spillovers, since any benefits or costs are likely to be temporary. Future research in other contexts should continue to explore the complex combination of salience and category characteristics that can affect whether and how a negative event affects others' reputations.

A final contribution of our study is that we directly assess the effects of a negative event on other actors' reputations. Most prior research has not attempted to directly assess the effects of scandals or other negative events on others' reputations. Rather, they have measured other factors, such as market (e.g., Karpoff, Lee & Martin, 2008; Paruchuri & Misangyi, 2015; Piazza & Jourden, 2018) and media (Zavyalova et al., 2012) reactions, or the actions taken by other firms to protect themselves from the negative effects of potential spillovers (Arthaud-Day et al., 2006; Barnett & King, 2008; Gomulya & Mishina, 2017). Thus, while reputations are theorized about, there are typically treated as an unspecified mediator in the empirical analyses. We directly consider customers' assessments of other category members before during and after the event, and examine whether and why other firms' reputations are influenced. We contribute to the literature by showing how reputations, rather than outcomes presumed to be affected by changes in reputation, are influenced by others' negative actions.

Limitations and Future Research

Like any study, ours has limitations that create the opportunity for future research. One limitation is that we studied a single event in a single geographic location. While our approach allowed us to conduct a natural experiment that offers unique insights, at the same time it limits the generalizability of our findings. Future research in other contexts and focusing on different types of crises or negative events should be conducted to confirm and extend our findings.

A second limitation of our study is that we rely on Yelp ratings as our measure of firm reputation. The Yelp data offer a number of advantages in terms of its longitudinal nature, ubiquity, and direct reflection of customer perceptions, and our results were confirmed using an alternative, content analysis-based measure. However, it is still a single-item indicator of an individual's overall satisfaction with a restaurant. Thus, we are unable to assess its reliability, and it does not allow us to distinguish among the factors influencing a restaurant's reputation. Future research using other, more specific measures of capability and character reputations should be conducted.

A third limitation is that we have made assumptions about the extent to which the differentiating characteristic that led to the capability failure is known. However, as noted above our results are consistent with our theory and contrast with those of other studies whose contexts do not fit our theory. Nonetheless, future research should explicitly test this argument.

CONCLUSION

Actions can have reputational consequences for those beyond the perpetrator. In this study we have explored how negative events at one firm can have positive reputational consequences for other category members. In doing so we have refocused attention on the salience of the action and associability of the category members when assessing other members' reputations. Our findings suggest that scholars studying the effects of scandals, wrongdoing and the dynamics of reputation creation and repair should more carefully consider these factors when theorizing about and assessing the factors that influence reputation creation and destruction.

REFERENCES

Arthaud-Day, M. L., Certo, S. T., Dalton, C. M. D., & Dalton, D. R. 2006. A changing of the guard: Executive and director turnover following corporate financial restatements. *Academy of Management Journal*, 49: 1119–1136.

Barnett, M. , & King, A. 2008. Good fences make good neighbours: A longitudinal analysis of an industry self-regulatory instititutions. *Academy of Management Journal*, 51(6):1150–1170.

Carroll, C. E., & McCombs, M. 2003. Agenda setting effects of business news on the public's images and opinions about major corporations. *Corporate Reputation Review*, 6: 36–46.

Cattani, G., Porac, J. F., Thomas, H. 2017. Categories and competition. *Strategic Management Journal*, 38: 64-92.

Connelly, B. L., Ketchen, D. J., Gangloff, K. A., & Shook, C. L. (2016). Investor perceptions of CEO successor selection in the wake of integrity and competence failures: A policy capturing study. *Strategic Management Journal*, 37(10), 2135-2151.

Deephouse, D. L. 2000. Media reputation as a strategic resource: An integration of mass communication and resource based theories. *Journal of Management*, 26: 1091-1112.

Durand, R., & Paolella, L. 2013. Category stretching: Reorienting research on categories in strategy, entrepreneurship, and organization theory. *Journal of Management Studies*, 50(6): 1100–1123.

Durand, R., & Vergne, J-P. 2015. Asset divestment as a response to media attacks in stigmatized industries. *Strategic Management Journal*, 36, 1205-1223.

Figart, DM. 2017. Delving into the food supply chain: The case of fresh tomatoes. In *Stories of Progressive Institutional Change*. Palgrave Macmillan, Cham

Fiske, S. T., & Taylor, S. E. 1991. Social cognition. New York: McGraw Hill.

Gomulya, D., & Mishina, Y. 2017. Signaler credibility, signal susceptibility, and relative reliance on signals: How stakeholders change their evaluative processes after violation of expectations and rehabilitative efforts. *Academy of Management Journal*, 60(2): 553-584.

Hu, N., Zhang, J., & Pavlou, P. A. (2009). Overcoming the J-shaped distribution of product reviews. *Communications of the ACM*, 52(10), 144-147.

Janis, I. L., & R. Fadner 1965. The coefficient of imbalance. In H. Lasswell, N. Leites, & Associates (Eds.), Language of Politics: 153-169. Cambridge, MA: MIT Press.

Johnston J, Baumann S (2007) Democracy versus distinction: A study of omnivorousness in gourmet food writing. *American Journal of Sociology,* 113:165–204.

Karpoff, J. M., Lee, S. D., & Martin, G. S. 2008. The consequences to managers for financial misrepresentation. *Journal of Financial Economics*, 88: 193–215.

Kovács, B., Carroll, G. R., & Lehman, D. W. (2013). Authenticity and consumer value ratings: Empirical tests from the restaurant domain. *Organization Science*, 25(2), 458-478.

Luca, M., & Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science*, 62(12), 3412-3427.

March, J.G., & Simon, H.A. 1958. *Organizations*. New York, NY: Wiley.

Mishina, Y., Block, E. S., & Mannor, M. J. 2012. The path dependence of organizational reputation: How social judgment influences assessments of capability and character. *Strategic Management Journal*, 33: 459–477.

Mishina, Y., Dykes, B.J., Block, E.S. & Pollock, T.G. 2010. Why good firms do bad things: The effects of high aspirations, high performance and prominence on the incidence of corporate illegality. *Academy of Management Journal*, 53(4): 701-722.

Park, B., Rogen, M. 2019. Capability reputation, character reputation and exchange partners' reactions to adverse events. *Academy of Management Journal*, Forthcoming.

Paruchuri, S. & Misangyi, V. F. 2015. Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. *Academy of Management Journal*, 58(1): 169-194.
Reynolds, F. D., & Wells, W. D. (1977). *Consumer behavior*. New York: McGraw Hill.
Piazza, A. & Jourdan, J. 2018. When the dust settles. The consequences of scandals for organizational competition. *Academy of Management Journal*, 61(1): 165-190..
Pollock, T.G., Lee, P.M., Jin, K. & Lashley, K. 2015. (Un)Tangled: Exploring the asymmetric co-evolution of new VC firms' reputation and status. *Administrative Science Quarterly*, 60(3): 482-517.
Pollock, T. G., Rindova, V. P., & Maggitti, P. G. 2008. Market watch: Information and availability cascades among the media and investors in the U.S. IPO market. *Academy of Management Journal*, 51(2): 335–358.
Porac, J., Thomas, H., Wilson, F., Paton, D. & Kanfer, A. 1995. Rivalry and the industry model of Scottish knitwear producers. *Administrative Science Quarterly*. 40(2): 203-227.
Porac, J. F., Wade, J. B., & Pollock, T. G. 1999. Industry categories and the politics of the comparable firm in CEO compensation. *Administrative Science Quarterly*, 44: 112–144.
Reger, R. K., & Huff, A. S. 1993. Strategic groups: A cognitive perspective. *Strategic Management Journal*, 14: 103-124.
Roberts, J.H. & Lattin, J. M. 1997. Consideration: Review of research and prospects for future insights. *Journal of Marketing Research*, 34 (3): 406-410.
Sorce, P., Perotti, V., & Widrick, S. (2005). Attitude and age differences in online buying. *International Journal of Retail & Distribution Management*, 33(2), 122-132.
Silva, R. (2016). Competition and demand effects of geographic distance to rivals. *The Service Industries Journal*, 36(1-2), 37-57.
Taylor, S. E., & Fiske, S. T. 1975. Point of view and perceptions of causality. *Journal of Personality and Social Psychology*, 32: 439–445.
Tversky, A., & Kahneman, D. 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, 5: 207–232.
Vergne, J. P. 2012. Stigmatized categories and public disapproval of organizations: A mixed-methods study of the global arms industry, 1996–2007. *Academy of Management Journal*, 55(5), 1027-1052.
Walker, R. & Merkley, G. 2017. Chipotle Mexican Grill: Food with integrity. *Kellogg School of Management Case KEL979*, Northwestern University.
Washington, M., & Zajac, E. J. 2005. Status evolution and competition: Theory and evidence. *Academy of Management Journal*, 48: 282–296.
Yelp. (2017). Yelp Reports Second Quarter 2017 Financial Results. Accessed October 1, 2017. http://www.yelp-ir.com/news-releases/news-release-details/yelp-reports-second-quarter-2017-financial-results
Zavyalova, A., Pfarrer, M. D., Reger, R. K., & Shapiro, D. L. 2012. Managing the message: The effects of firm actions and industry spillovers on media coverage following wrongdoing. *Academy of Management Journal*, 55(5): 1079–1101.

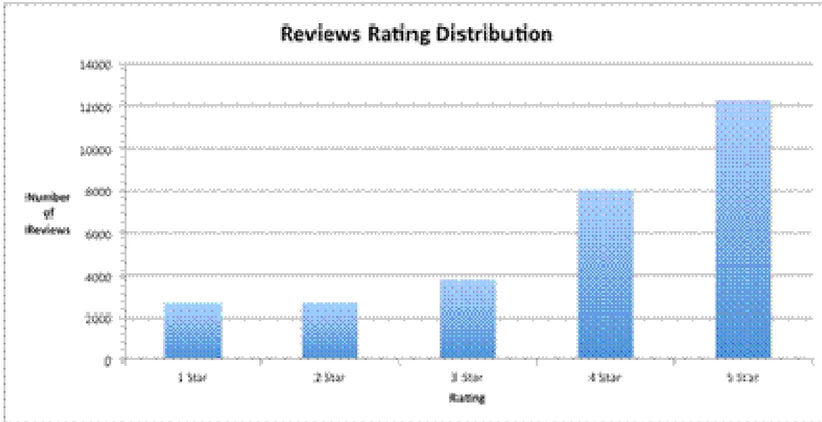

Figure 1: Distribution of Review Ratings

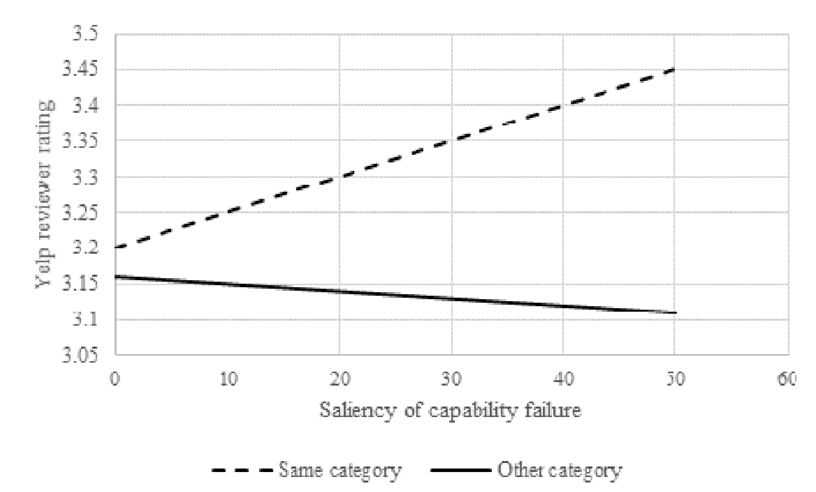

Figure 2: Graph of interaction between Saliency of capability failure and Same category

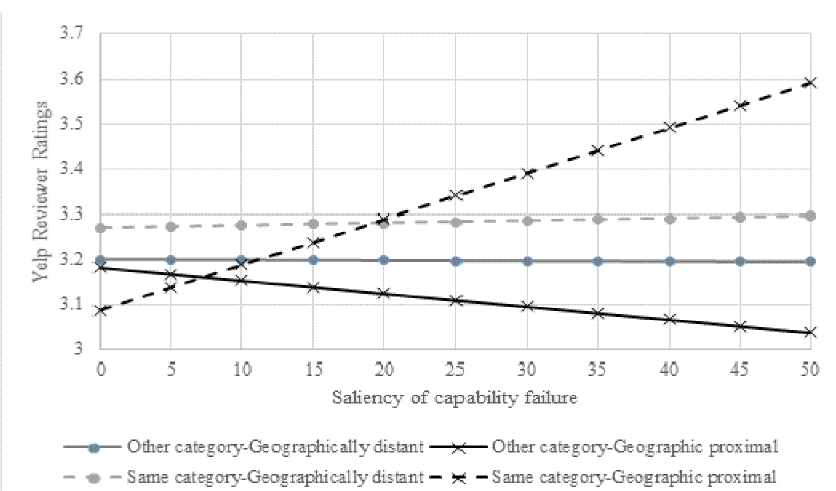

Figure 3: Graph of 3-way interaction

Table 1: Simple bivariate correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1.Dependent variable	3.78	1.19												
2. Chipotle closed	0.08	0.27	0.01											
3.Cumulative rating	3.71	0.87	0.25	0.00										
4.Number of reviews	1.90	1.84	0.05	-0.01	0.11									
5.Public firms	0.02	0.13	-0.11	-0.00	-0.15	-0.04								
6.Fast food	0.02	0.16	-0.09	-0.00	-0.16	-0.05	0.27							
7.Price range $	0.30	0.46	0.02	0.00	-0.01	-0.09	0.05	0.22						
8.Price range $$$	0.07	0.25	0.02	0.00	0.05	0.05	0.04	-0.04	-0.18					
9.Price range $$$$	0.01	0.11	0.02	0.00	0.04	0.01	-0.01	-0.02	-0.07	-0.03				
10.Restaurant age	281.92	189.96	-0.08	-0.00	-0.08	-0.03	0.04	0.04	0.04	0.07	0.02			
11.Other restaurants in ZIPCODE	143.92	71.49	-0.04	-0.02	-0.02	0.13	0.03	-0.04	0.00	0.10	0.02	0.08		
12.Mexican restaurants in ZIPCODE	6.19	3.76	0.01	-0.02	0.03	0.02	-0.01	-0.03	-0.04	0.04	0.01	-0.06	0.42	
13.Median age of households	35.69	4.57	0.01	0.00	0.00	0.00	0.04	-0.01	-0.05	0.01	-0.02	0.04	-0.01	-0.24
14.Number of HS non-graduates	202.76	269.18	0.01	-0.01	-0.01	-0.07	0.00	0.02	0.10	-0.08	-0.02	-0.08	-0.26	0.04
15.Mean household income	89.77	18.41	0.04	0.00	0.07	0.01	-0.03	-0.03	-0.14	0.05	0.01	0.03	-0.25	0.03
16.Total population	26.93	13.27	0.01	0.00	0.02	-0.08	-0.03	0.01	0.06	-0.09	-0.04	-0.07	-0.31	0.37
17.Average weekly temperature	54.39	8.00	-0.01	-0.09	-0.01	0.04	0.01	0.00	0.01	-0.01	-0.01	0.03	-0.05	-0.33
18.Number of rainy days	3.66	2.09	0.01	0.31	0.02	-0.02	0.00	0.00	0.01	0.00	0.01	-0.01	0.03	0.23
19.Salience of capability failure	5.87	9.35	-0.01	0.07	0.02	-0.02	-0.01	-0.00	0.01	0.01	-0.01	-0.01	0.01	0.07
20. Same category	0.06	0.24	0.01	0.00	-0.05	-0.04	0.01	0.04	0.01	-0.07	-0.03	-0.02	-0.05	0.04
21.Geographic proximity	0.42	0.49	-0.04	-0.01	-0.03	0.10	0.06	0.03	0.01	0.06	0.01	0.03	0.44	0.23
22.Salience*same category	0.35	2.72	0.01	0.04	-0.02	-0.02	0.00	0.01	0.00	-0.03	-0.01	-0.02	-0.02	0.03
23.Salience*geographic prox.	2.48	6.72	-0.02	-0.04	-0.02	0.03	0.02	0.02	0.01	0.03	0.00	0.01	0.20	0.16
24. Same category* geographic prox.	0.02	0.15	-0.01	0.00	-0.03	-0.02	-0.00	0.01	0.00	-0.04	-0.02	-0.02	0.05	0.04
25. 3-way interaction	0.15	1.80	0.01	0.01	-0.01	-0.02	-0.00	-0.00	0.01	-0.02	-0.01	-0.01	0.03	0.04

	13	14	15	16	17	18	19	20	21	22	23	24
14.Number of HS non-graduates	0.13											
15.Mean household income	-0.09	-0.46										
16.Total population	-0.52	0.20	0.21									
17.Average weekly temperature	0.01	0.01	-0.01	0.00								
18.Number of rainy days	0.00	0.00	0.00	0.00	-0.46							
19.Saliency of capability failure	-0.01	0.00	0.00	0.01	-0.22	0.40						
20. Same category restaurant	-0.01	0.02	0.05	0.05	-0.01	0.00	0.05					
21.Geographic proximity	-0.28	-0.29	0.06	-0.05	-0.02	0.01	0.00	0.00				
22.Salience*same category	-0.01	0.01	0.02	0.02	-0.04	0.08	0.21	0.52	0.00			
23.Saliencyegeographic prox.	-0.13	-0.13	0.02	-0.02	-0.13	0.24	0.58	0.00	0.43	0.13		
24. Same category* geographic prox.	-0.04	-0.05	0.03	-0.00	-0.00	-0.00	0.00	0.63	0.18	0.34	0.09	
25. 3-way interaction	-0.02	-0.03	0.02	-0.00	-0.03	0.05	0.14	0.33	0.09	0.66	0.24	0.53

Table 2: Results of random-effects linear regression specification

	1	2	3	4	5	6	7	8
Restaurant Characteristics								
Chipotle closed	0.036	0.036	0.037	0.040	0.040	0.040	0.040	0.040
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
	[0.20]	[0.20]	[0.20]	[0.16]	[0.16]	[0.16]	[0.16]	[0.16]
Cumulative rating	0.076	0.076	0.076	0.077	0.076	0.077	0.076	0.076
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Number of reviews	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
	[0.19]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.19]	[0.18]
Public firms	-0.821	-0.815	-0.816	-0.815	-0.816	-0.815	-0.818	-0.817
	(0.097)	(0.097)	(0.097)	(0.097)	(0.097)	(0.097)	(0.097)	(0.097)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Fast food indicator	-0.579	-0.578	-0.579	-0.576	-0.576	-0.576	-0.577	-0.576
	(0.081)	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Price range_$	0.163	0.161	0.161	0.161	0.162	0.161	0.162	0.161
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Price range_$$$	0.165	0.169	0.168	0.169	0.169	0.169	0.169	0.168
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Price range_$$$$	0.204	0.208	0.207	0.207	0.207	0.206	0.206	0.205
	(0.155)	(0.155)	(0.155)	(0.154)	(0.154)	(0.154)	(0.154)	(0.154)
	[0.19]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]
Restaurant age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Location characteristics								
Other restaurants in ZIP CODE	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	1	2	3	4	5	6	7	8
	[0.11]	[0.24]	[0.24]	[0.25]	[0.26]	[0.25]	[0.25]	[0.25]
Other Mexican restaurants in ZIP CODE	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.04]	[0.04]	[0.04]
Median age of households	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	[0.28]	[0.49]	[0.49]	[0.49]	[0.48]	[0.50]	[0.48]	[0.49]
Number of HS non-graduates	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Mean household income	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Total population	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.21]	[0.18]	[0.17]	[0.19]	[0.19]	[0.18]	[0.18]	[0.18]
Weather characteristics								
Average weekly temperature	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.96]	[0.99]	[0.99]	[0.89]	[0.87]	[0.91]	[0.89]	[0.90]
Number of rainy days	-0.003	-0.003	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	[0.45]	[0.44]	[0.43]	[0.69]	[0.69]	[0.68]	[0.69]	[0.68]
Theoretical variables								
Same category		0.041	0.075	0.041	0.005	0.041	0.039	0.071
		(0.058)	(0.074)	(0.058)	(0.062)	(0.058)	(0.076)	(0.078)
		[0.49]	[0.31]	[0.48]	[0.94]	[0.48]	[0.61]	[0.36]
Geographic proximity		-0.041	-0.035	-0.041	-0.040	-0.028	-0.022	-0.018
		(0.035)	(0.036)	(0.035)	(0.035)	(0.036)	(0.037)	(0.037)
		[0.25]	[0.33]	[0.25]	[0.25]	[0.43]	[0.55]	[0.63]
Same category* Geographic proximity			-0.089				-0.090	-0.166
			(0.119)				(0.119)	(0.126)
			[0.46]				[0.45]	[0.19]

	1	2	3	4	5	6	7	8
Salience of capability failure				-0.001	-0.001	-0.000	-0.000	-0.000
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
				[0.28]	[0.14]	[0.97]	[0.72]	[0.94]
Salience * Same category					0.006		0.006	0.001
					(0.003)		(0.003)	(0.004)
					[0.07]		[0.07]	[0.90]
Salience * Geographic proximity						-0.002	-0.002	-0.003
						(0.002)	(0.002)	(0.002)
						[0.19]	[0.18]	[0.08]
Salience*Same category*Geo.proximity								0.012
								(0.007)
								[0.06]
_cons	3.111	3.158	3.156	3.159	3.161	3.156	3.156	3.156
	(0.202)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.205)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	22,168	22,137	22,137	22,137	22,137	22,137	22,137	22,137
Model Fit: Wald chi-square	379	380	381	384	387	385	389	392
Model improvement								
Comparison model		vs. 1	vs. 2	vs.2	vs.4	vs. 4	vs. 4	vs.7
Chi-square improvement		1.79	0.56	1.15	3.28	1.74	5.64	3.54
Significance of improvement (p-values)		0.41	0.45	0.23	0.07	0.18	0.17	0.06

Notes: standard errors are in ( ) parentheses and p-values are in [ ] parentheses.