JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 59, No. 3, May 2024, pp. 1100–1140

doi:10.1017/S0022109023000248

Online Reputation and Debt Capacity

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Abstract

We explore the effects of online customer ratings on financial policy. Using a large sample of Parisian restaurants, we find a positive and economically significant relationship between customer ratings and restaurant debt. We use the locally exogenous variations in customer ratings resulting from the rounding of scores in regression discontinuity tests to establish causality. Favorable online ratings reduce cash flow risk and increase resilience to demand shocks. Consistent with the view that good online ratings increase the debt capacity of restaurants and their growth opportunities, restaurants with good ratings use their extra debt to invest in tangible assets.

I. Introduction

Online platforms dedicated to reviewing and rating businesses allow customers to express their opinions online and reach out to many potential customers at a negligible cost. Several recent studies show that their emergence has significantly impacted many businesses. For example, Luca (2016) shows that online ratings are reliable indicators of a restaurant's reputation and good predictors of its future sales. Online ratings also affect the value of larger companies catering to retail clients (Huang (2018)). Because the information in online ratings is relevant and readily available to fund providers, it can also affect companies' ability to obtain external financing. This is especially true and important for small businesses characterized by significant information asymmetry and thus potentially subject to credit rationing (Stiglitz and Weiss (1981), Diamond (1991)), which can limit their

We thank Jarrad Harford (the editor) and an anonymous referee for their valuable comments and inputs. We are grateful to Alberta Di Giuli, Denis Gromb, Thorsten Martin, José Martin-Flores, Clemens Otto, Christophe Spaenjers, Alexander Wagner, Michael Wittry, and seminar participants at CUNEF, Toulouse Business School, Neoma Business School, the Bank of France, IIMA, the 2021 Inter-Business-School Finance Seminar, and the 2021 Corporate Finance Webinar for helpful comments and suggestions. Derrien acknowledges financial support from the Investissements d'Avenir Labex (ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047).

development. In this article, we study a large panel of Parisian restaurants subject to severe information asymmetry vis-à-vis fund providers and largely exposed to online customer opinions. Using detailed information on these restaurants' online ratings and financial statements, we examine whether and how their online reputation affects their debt capacity.

Like many small businesses, restaurants do not have access to outside equity funding and must rely on internal funds or bank debt to finance their activity. Because they are often small independent firms with a relatively short lifespan (the median restaurant in our sample is 10 years old and has total assets worth 442,000 euros), their prospects are difficult to evaluate. Furthermore, the assets of restaurants are, to a large extent, intangible. For example, few restaurants own the building in which they operate. Thus, restaurants cannot use their assets as collateral in debt contracts. Instead, their capacity to raise debt hinges on their ability to generate stable cash flows. This ability depends mainly on intangible assets such as the restaurant's location or the talent of its chef, which collectively constitute the restaurant's reputation. We argue that online ratings provided by customers are a good measure of a restaurant's reputation and are therefore informative about the cash flow risk of restaurants above and beyond traditional measures like those coming from financial statements. Thus, online ratings are both available at negligible cost and valuable. Therefore, external fund providers such as banks are likely to use them as an input in their estimation of the creditworthiness of restaurants and supply more credit to those with better ratings. In line with this argument, our main prediction is that online ratings alleviate the traditional information asymmetries between restaurants and fund providers, allowing restaurants with positive online ratings to take on more debt.

To test whether and how online ratings affect the financing of small businesses like restaurants, we collect information on the online ratings of Parisian restaurants between 2007 and 2017 from TripAdvisor, France's most popular online rating platform. We observe customer ratings for a large number of restaurants that are concentrated geographically and, therefore, subject to the same fluctuations in demand (e.g., driven by the evolution of local tourism). Importantly, these restaurants generate a substantial online rating activity. The 2,474 Parisian restaurants in our sample received a total of 458,678 TripAdvisor reviews between 2007 and 2017. In addition to customer ratings, we collect important characteristics of these restaurants, such as their exact location, cuisine type, and price range. We also collect detailed data from their annual financial statements. Using these data, we first examine the link between a restaurant's online reputation and its leverage. Second, we explore the mechanisms through which good customer ratings allow restaurants to borrow more.

The main challenge in estimating the causal link between a restaurant's online reputation and its leverage is that omitted variables may drive both a restaurant's online reputation and debt. Debt increases may also lead to improvements in restaurant quality that, in turn, improve online ratings. We address this endogeneity concern using a regression discontinuity design (RDD) method. Specifically, we exploit the fact that the most salient rating available online is not the exact average of individual scores but the average score rounded to the nearest half-point. Thus, two restaurants with very close average unrounded ratings (say 3.74 and 3.76, respectively) can have different rounded ratings (in this case, 3.5 and 4.0, respectively). We focus on restaurants with unrounded ratings close to rounding thresholds (i.e., 1.25, 1.75, and 2.25). For these restaurants, the variation in the rating displayed by TripAdvisor is arguably random.

Our baseline specification is a local linear regression. We use observations with ratings in the vicinity of rounding thresholds and compare the leverage of restaurants with ratings above versus below these thresholds, controlling for restaurant fixed effects and unrounded ratings. In line with our prediction that online ratings have a causal effect on leverage, we find that the ratio of debt-to-assets of restaurants above rounding thresholds is higher than that of restaurants below rounding thresholds by 2.66 percentage points on average. This represents more than 10% of the standard deviation of this variable. We also find that restaurants increase their debt when their online reputation improves (i.e., when they cross rounding thresholds upward) but are reluctant to reduce it when their online reputation deteriorates (i.e., when they cross rounding thresholds downward).

This finding is robust to variations in the RDD specification and other robustness tests. In particular, we obtain qualitatively similar results if we use polynomial regressions instead of local linear regressions. We also repeat the RDD tests using placebo rounding thresholds. None of them is relevant to debt. We also find that our results still hold and even tend to become stronger economically when we focus on ratings that are consistently above or below rounding threshold for long periods, not only at year-end. Finally, we show that ratings manipulation does not seem to affect our results. Ratings manipulation is known to be widespread (Mayzlin, Dover, and Chevalier (2014), Luca and Zervas (2016)), which can reduce the precision of the information available to fund providers. We use a battery of tests to address this concern. First, we find that the effect of online ratings on debt is larger when ratings are more informative. Second, the link between ratings and debt is stronger when ratings are less likely to be manipulated. Third, we find that ratings manipulation to pass ratings thresholds does not seem to be widespread in our sample.[1]

In line with our hypothesis that online ratings reduce the information asymmetry between firms and providers of external financing, increasing the debt capacity of restaurants with good ratings, we find that various types of debt respond differently to online ratings. The overall increase in leverage associated with higher ratings comes mainly from a rise in bank debt. On the contrary, debt from family and friends, a common source of financing for small businesses that is much less subject to information asymmetry, reacts very little to online ratings. Also, consistent with the view that customer ratings provide new relevant information, the results are stronger for less established restaurants (i.e., restaurants that are younger or in lower price categories).

Next, we explore the channels through which good online ratings allow restaurants to have higher debt levels. We find that positive online ratings are

[1]An essential assumption of the RDD is that agents cannot precisely manipulate the forcing variable (i.e., the restaurant ratings) close to the cut-offs (Lee and Lemieux (2010)). Thus, such manipulation could bias RDD estimates and lead us to overestimate the causal effect of online ratings on debt. If this type of manipulation were prevalent, it would affect the distribution of unrounded ratings, which would be concentrated right above rounding thresholds.

associated with more stable cash flows. Using the Paris terrorist attacks of 2015 as a demand shock for restaurants, we find that restaurants with better online ratings before the shock have higher sales and cash flows in the 2 years following the shock. This result is more pronounced for restaurants catering primarily to foreign customers, who are more likely to rely on online ratings when choosing a dining venue. We further find that good customer ratings are negatively associated with cash flow volatility and with the probability of experiencing large decreases in sales or bankruptcy.

Finally, we examine how restaurants with good online ratings use the extra debt they obtain. We find that they invest in tangible assets instead of paying out dividends or increasing their cash balance. This finding is consistent with the view that the extra debt capacity allows restaurants to invest in existing growth opportunities rather than substitute additional debt for other forms of financing. These results are also consistent with another channel, according to which good customer ratings create new growth opportunities for restaurants, leading them to increase their demand for debt. We note that those two channels are not mutually exclusive. In the last part of the article, we assess the relevance of the growth opportunities channel by examining whether customer ratings directly affect customer demand. We find that online ratings affect customer demand as proxied by the monthly number of new customer reviews, mainly over short horizons (6 months or less). They also affect the sales of young restaurants.

This study shows the importance of online reputation in raising external financing. Its conclusions can be generalized to small businesses that cater to a retail clientele and larger companies specialized in consumer goods, as long as their online reputation contains information relevant for their future cash flows and which is not readily observable to providers of external financing. The article is related to the growing literature exploring the information embedded in online reviews. Overall, this literature concludes that online ratings reflect the reputation of businesses they are related to. Glaeser, Kim, and Luca (2017) show that Yelp reviews can help assess local economic dynamism in real-time, while Anderson and Magruder (2012) and Luca (2016) show that online ratings received by restaurants affect consumer demand. Related studies show that information available online, including customer ratings (Huang (2018)), employee ratings (Green, Huang, Wen, and Zhou (2019), Edmans (2011)) and opinions expressed in social media (Chen, De, Hu, and Hwang (2014)) convey value-relevant information and predict stock returns. The closest article to ours is Huang (2020), who uses loan-level data and shows that online ratings affect the probability of obtaining bank loans and their cost. However, the two papers can be considered complementary as they focus on different outcomes and employ different data sets. While Huang (2020) performs a detailed analysis of loan features, we take advantage of our rich accounting data on restaurants to establish the economic mechanism that links online reputation and debt capacity.

Our article also contributes to the extensive literature on capital structure determinants and the much more limited literature on the financing of small private companies. This literature suffers from a severe lack of data access. Among the few papers that explore the financing of young firms, Robb and Robinson (2014) show that young firms resort predominantly to bank financing. Giroud, Mueller, Stomper, and Westerkamp (2012) explore the effects of debt overhang using a sample of ski hotels. Our study adds to this literature by showing that online ratings can help mitigate the financial constraints of small businesses. It is also related to recent studies examining the linkage between intangible assets and debt financing. These include the relationship between leverage and brand perception (Larkin (2013)), the evaluation and disclosure of the value of intangible assets (Lim, Macias, and Moeller (2020)) and patent invalidations (Horsch, Longoni, and Oesch (2021)).

II. Data and Variables

A. Data Sources and Sample Construction

We use a combination of two data sources in our empirical analysis. First, we collect customer reviews and ratings from tripadvisor.com for a sample of Parisian restaurants. TripAdvisor is the most popular rating website for restaurants. In 2018, 490 million unique visitors accessed the TripAdvisor website each month. It contains 4.9 million restaurants and 730 million reviews.[2] As a comparison, TripAdvisor's competitor Yelp had 131 million unique monthly visitors and 177 million reviews.[3] In France, Paris has the largest number of restaurants rated on TripAdvisor (16,154 restaurants in Paris compared to 3,166 in Lyon and 2,181 in Marseille, as of Jan. 2019). Paris also has more rated restaurants than New York, Los Angeles, or Hong Kong (each around 10,000). Our second data source is the Diane database of Bureau van Dijk, which provides detailed accounting information for French companies filing annual financial statements at local commercial courts.[4]

To construct our sample, we start from the universe of Parisian restaurants that appear on TripAdvisor between 2007 and 2017.[5] We match this sample with the Diane database. We match restaurants either by name, physical address, telephone number, or email address and then screen manually through the resulting matched pairs to remove errors. Appendix A describes in detail the matching procedure. We find a match for 4,862 unique restaurants.[6] We restrict the sample to restaurants that do not belong to a chain such as McDonald's, as these restaurants' reputation

[2] *Source:* TripAdvisor investor presentation 2018:Q4.

[3] *Source:* Yelp website.

[4] Every company that files its financial statements in a given year appears in the Diane database that year. All French companies must file their financial statements with the local commercial court, except for a few companies below a certain size and with a specific legal status. Therefore, we can assume that there is no systematic bias in Diane's coverage.

[5] TripAdvisor was founded in 2000. However, it started to aggregate a large pool of reviews on French restaurants only a few years later. We start our sample period in 2007 because the number of Parisian restaurants referenced on tripadvisor.com (as well as the associated number of reviews) is extremely low before that year.

[6] One possible source of bias in the sample comes from the fact that the entire history of firm-level data in Diane is erased whenever the firm has ceased to exist in the French corporate registry for more than 3 years. To ensure that this survivorship bias does not affect our findings, we compare restaurants in TripAdvisor without a Diane match with those that can be matched with Diane. Matched and unmatched restaurants have very similar average ratings (3.86 vs. 3.90). Thus, a restaurant's presence in the accounting data set is unrelated to its online reputation.

reflects the franchise's reputation. We also focus on restaurants that have their main activity in the categories "licensed beverage establishment," "traditional restaurant," or "fast food restaurant." Using a more refined classification, we further eliminate restaurants in the catering, mass catering, canteen, grocery, or retail shops categories, as these are not the typical establishments rated online. We also exclude restaurants with a nonpositive book value of equity and further restrict the sample to restaurants for which we have nonmissing accounting data to compute our main dependent and independent variables. Finally, to ensure that the ratings we consider are informative, we eliminate restaurant-year observations with very few reviews (fewer than five). Appendix B shows how each restriction affects the number of unique restaurants we include in the sample. These restrictions yield a final sample of 2,474 unique restaurants from 2007 to 2017, corresponding to 8,766 restaurant-year observations.

B. TripAdvisor Variables

Our primary independent variable of interest is a restaurant's overall rating, as displayed on TripAdvisor. TripAdvisor provides individual ratings issued by customers, listed from the most recent to the oldest, as well as a summary rating, which is the one that is the most salient to internet users. Each customer review includes a restaurant rating, ranging from 1 to 5, where 1 is mediocre and 5 is excellent. For each customer review, we collect this rating and the number of previous TripAdvisor reviews posted by the same reviewer for other establishments, the review's language, and the reviewer's location (country and city). For each restaurant, we further retrieve the following information from TripAdvisor: Type of cuisine, physical address, telephone number, email address, and price range ("€": Cheap, "€€-€€€": Affordable, and "€€€€": Expensive). Figure 1 displays the sample restaurants on a map of Paris. It shows that restaurants are widespread across the city and its 20 districts.

The summary rating displayed on TripAdvisor is presented in the form of bubbles.[7] The number of bubbles ranges from one to five in half-bubble increments. For example, the restaurant Patchanka, whose TripAdvisor page appears in Appendix C, has a TripAdvisor summary rating of 5 bubbles. The summary rating corresponds to the average of all the restaurant's individual ratings, rounded to the nearest half-bubble. As shown in Appendix C, the average rating for the restaurant Patchanka is 4.85. After rounding this score to the nearest half-bubble, the restaurant's summary rating displayed by TripAdvisor (and thus observable to the public) is 5 bubbles.[8] Using the history of each restaurant's reviews, we can reconstruct the summary rating of a given restaurant at any point in time. For example, a restaurant's summary rating for 2010 uses all reviews posted up to the end of Dec. 2010.[9]

[7]In the rest of the article, we use the terms "bubbles" and "points" interchangeably when we refer to the rating scale used by TripAdvisor.

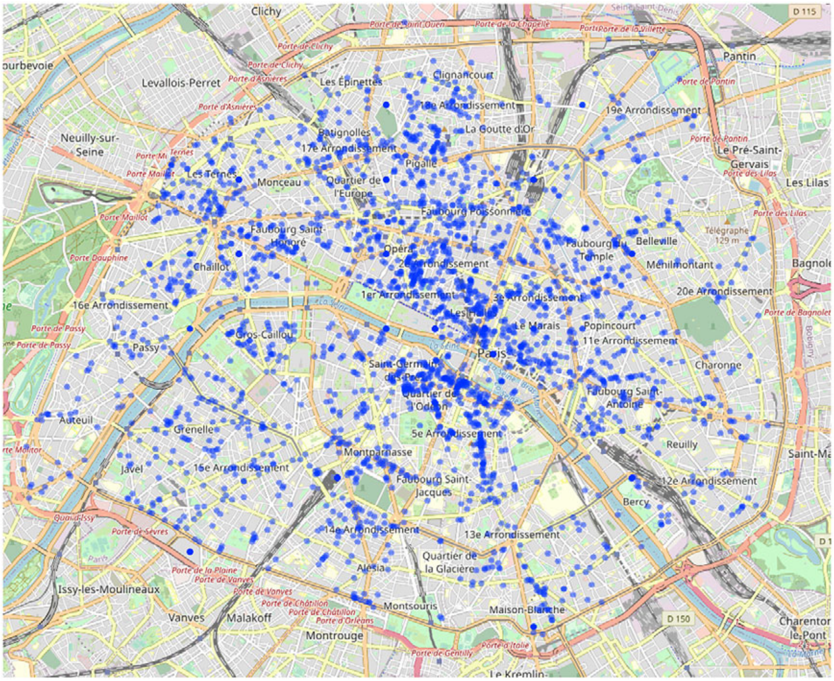
[8]In the rest of the article, we use the term "rounded rating" to refer to this summary rating, and the term "unrounded rating" to refer to the average rating across all reviews before rounding.

[9]Reviewers can also attribute optional subratings on Food, Service, Value, and Atmosphere on TripAdvisor. This information is aggregated at the restaurant level, meaning that we cannot access reviewer-specific information for these subratings.

FIGURE 1

Location of Restaurants

Figure 1 displays restaurants in the sample on a map of Paris. Each blue dot corresponds to a unique restaurant.



C. Accounting Variables

We are interested in whether and how online reputation, measured by TripAdvisor ratings, affects the leverage of restaurants. Our main dependent variable of interest is financial debt scaled by total assets. Financial debt includes bank debt and other financial debt, most of which refers to loans made to the firm by its shareholders.[10] This is broadly similar to family and friends debt in other countries. We follow previous studies on capital structure to compute our main firm-level control variables (Titman and Wessels (1988), Rajan and Zingales (1995), Lemmon, Roberts, and Zender (2008), Frank and Goyal (2009), Lemmon and Zender (2010), Bae, Kang, and Wang (2011), Campello and Giambona (2013), and Chemmanur, Cheng, and Zhang (2013)). The main control variables are firm size (defined as the natural logarithm of total assets), the natural logarithm of age (defined as one plus the number of years since the restaurant's incorporation), profitability (defined as the ratio of EBITDA to total assets), asset tangibility (defined as the ratio of tangible to total assets), asset turnover (defined as the ratio of sales to total assets), and labor expenses (defined as salaries and wages divided by total sales). All variable definitions are in Appendix D.

[10]Other financial debt also includes debt obtained through crowdfunding campaigns. However, crowdfunding is a very limited source of financing for restaurants in our sample period.

TABLE 1

Descriptive Statistics

Table 1 presents summary statistics of the sample of restaurant-year observations. The sample includes 2,474 unique Parisian restaurants between 2007 and 2017. Appendix D lists and defines the variables.

Variable	No. of Obs.	Mean	Std. Dev.	Min	0.25	Median	0.75	Max
TA_RATING	8,766	3.87	0.56	1.50	3.50	4.00	4.50	5.00
TA_RATING_UNROUNDED	8,766	3.87	0.55	1.27	3.56	3.93	4.26	5.00
TA_NUMBER_REVIEWS	8,766	111.79	186.58	6.00	18.00	48.00	124.00	2,704.00
AGE	8,766	14.79	13.37	1	5	10	20	63
TOTAL_ASSETS ('000€)	8,766	880	2,048	3	237	442	836	40,471
TANGIBLE_ASSETS	8,766	0.64	0.24	0.05	0.48	0.70	0.84	0.97
ASSET_TURNOVER_RATIO	8,766	1.72	1.03	0.13	1.01	1.47	2.16	5.62
PROFITABILITY	8,766	0.10	0.13	−0.28	0.02	0.08	0.16	0.56
LABOR_EXPENSES	8,766	0.30	0.09	0.00	0.26	0.31	0.36	0.52
TOTAL_DEBT (%)	8,766	24.11	22.86	0.00	3.50	18.07	39.60	85.99
BANK_DEBT (%)	8,766	14.23	16.85	0.00	0.01	7.34	24.01	67.78
OTHER_FINANCIAL_DEBT (%)	8,766	9.80	15.49	0.00	0.00	1.15	14.45	69.94
CASH	8,766	0.17	0.20	−1.47	0.03	0.10	0.23	1.92
LAND	8,766	0.00	0.00	0.00	0.00	0.00	0.00	0.01
BUILDING	8,766	0.05	0.14	0.00	0.00	0.00	0.00	0.83
MATERIAL, TOOLS, AND OTHER_TANGIBLE_ASSETS	8,766	0.38	0.35	0.00	0.14	0.29	0.52	2.08
DIVIDEND_DUMMY	8,766	0.03	0.16	0.00	0.00	0.00	0.00	1.00

D. Descriptive Statistics

Table 1 presents summary statistics of the main variables used throughout the empirical analysis for the sample of restaurant-year observations. All continuous variables are winsorized at the 1st and 99th percentiles. The average TripAdvisor rating of the 8,766 restaurant-year observations in the sample is 3.87. The average unrounded rating is also 3.87. The average rating is based on 112 individual reviews. Graphs A and B of Figure 2 display the distribution of rounded and unrounded ratings for the same sample of restaurant-year observations. Ratings are concentrated around 4 with few observations in the 1 and 2 categories.

About 9 in 10 restaurants in our sample use debt, with the average restaurant having total debt equal to 24.1% of total assets. Most of this debt is bank debt, equal on average to 14.2% of total assets. However, other financial debt is nonnegligible, with an average value of 9.8% of total assets. The mean (median) restaurant in our sample is small and young, with total assets of 880,000 euros (442,000 euros), and is 14.8 (10.0) years old. Tangible assets represent 64% of total assets for the average restaurant. Most of these assets (38% of total assets on average) belong to the "Materials, tools, and other tangible assets" category, including furniture and kitchen equipment.

III. Empirical Methodology

A. OLS Regressions

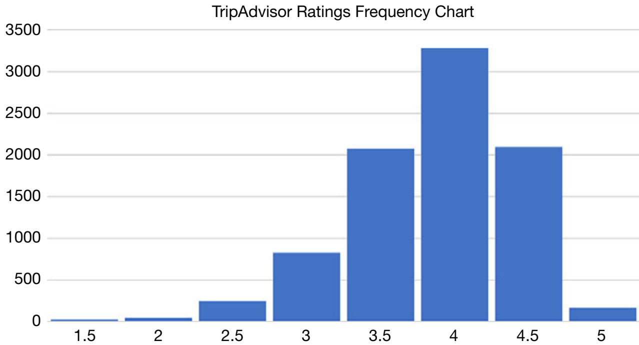
The first objective of the empirical analysis is to investigate the influence of TripAdvisor ratings on restaurant debt. Despite its limitations, we start this analysis using an ordinary least squares (OLS) specification:

FIGURE 2

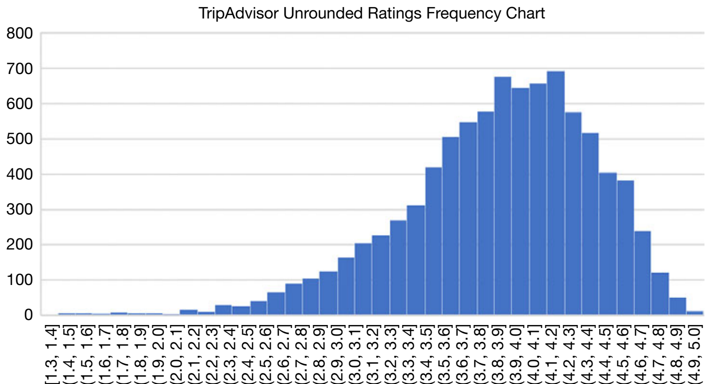
Distribution of TripAdvisor Ratings

Graph A of Figure 2 displays the frequency of (rounded) ratings across all restaurant-year observations. Graph B displays the frequency of unrounded TripAdvisor ratings across all restaurant-year observations using bins of size 0.1.

Graph A. Frequency of (Rounded) Ratings Across all Restaurant-Year Observations



Graph B. Frequency of Unrounded TripAdvisor Ratings Across All Restaurant-Year Observations Using Bins of Size 0.1



$$\text{(1)} \qquad \text{TOTAL\_DEBT}_{i,t} = \beta_0 + \beta_1 \text{TA\_RATING}_{i,t} + \beta' \mathbf{X}_{i,t-1} + \mu_t + \gamma_i + \varepsilon_{i,t},$$

where TOTAL_DEBT is the sum of bank debt and other financial debt, scaled by total assets. TA_RATING is the rounded rating displayed on TripAdvisor's website. The subscripts i and t refer to restaurants and years, respectively. $\mathbf{X}$ is a vector of lagged control variables, including size, age, profitability, asset tangibility, asset turnover ratio, labor expenses, and γ_i and μ_t are restaurant and year fixed effects, respectively. The ratings we consider are contemporaneous (i.e., they include all individual ratings between the restaurant's appearance on TripAdvisor and year-end) to the dependent variable, financial debt, measured at year-end. This is because the time needed to obtain a new loan is relatively short, so debt at a given time is likely to reflect the contemporaneous reputation of a restaurant. Restaurant fixed effects absorb time-invariant restaurant characteristics such as differences across cuisine types and districts. For example, restaurants serving French cuisine may have better access to financing due to greater cultural proximity with French banks, in line with Fisman, Paravisini, and Vig (2017), showing that cultural proximity between creditors and debtors increases the quantity of credit.

When considering a restaurant's online reputation, banks are likely to give more weight to recent ratings. To explore this possibility, we ask whether changes in cumulative ratings induced by recent (less than 1-year-old) ratings affect the level of debt by implementing a specification in first differences rather than levels.[11] In this specification, we regress changes in debt on changes in the right-hand side variables of equation (1), as described in equation (2):

$$\text{(2)}\qquad \Delta\text{TOTAL\_DEBT}_{i,t} = \beta_0 + \beta_1 \Delta\text{TA\_RATING}_{i,t} + \beta' \Delta\mathbf{X}_{i,t-1} + \mu_t + \varepsilon_{i,t},$$

where all the variables are the same as in equation (1), expressed in differences rather than levels.[12]

B. Regression Discontinuity Design

A potential issue when estimating equations (1) and (2) is that the relationship between a restaurant's online rating and its debt could arise endogenously, in which case β_1 would not reflect a causal effect of TripAdvisor ratings on restaurant debt. First, an unobservable omitted variable may influence both TripAdvisor ratings and debt. For instance, restaurants with conservative or risk-averse managers could hold more inventory for precautionary reasons, which may reduce the risk of disappointing customers if some meals on the menu are no longer available, resulting in higher customer ratings. At the same time, banks may be more willing to lend money to conservative restaurant owners. Second, causation may be reversed (i.e., financing decisions of restaurants may affect customer ratings). For instance, restaurants may borrow to make investments increasing product and service quality, which leads to better ratings.

A clean identification of the causal impact of customer ratings on restaurant debt hinges on finding an empirical setting in which variations in customer ratings arise exogenously to rule out omitted variables and reverse causality explanations. Thanks to the way TripAdvisor computes the overall ratings it displays on its website, we can isolate variations in restaurant ratings that are exogenous with respect to unobserved determinants of leverage. We exploit the fact that the overall rating displayed by TripAdvisor is rounded to the nearest half-bubble. This implies that some restaurants with very similar unrounded ratings end up with a half-bubble difference in the overall (rounded) rating displayed on the website, depending on whether they fall below or above a rounding threshold. For example, a restaurant with an unrounded rating of 3.74 is rounded down to 3.5 bubbles, while a restaurant with an unrounded rating of 3.76 is rounded up to 4 bubbles. However, the two restaurants have very similar unrounded ratings. Close to the rounding thresholds, variations in TripAdvisor ratings are arguably random and locally exogenous. That is, we assume that restaurants close to rounding thresholds do not choose to be

[11] We prefer this specification in differences to using a weighting scheme that would capture the decaying effect of individual ratings through time, in which weights are necessarily arbitrary.

[12] In this specification, as well as in all the specifications in differences that we use in the article, we do not include restaurant fixed effects. This is because in such regressions, restaurant fixed effects capture time-invariant changes in (rather than levels of) the dependent variable, which are unlikely to be relevant. We obtain very similar results when we add restaurant fixed effects to these regressions.

above or below the threshold, a possibility that we examine in Section IV.E. Another important assumption required for rounded ratings to affect bank debt is that banks use the ratings displayed on TripAdvisor's website to make loan decisions. In other words, banks focus on the salient but less precise rounded ratings and do not consider the information available on the website to calculate more precise unrounded scores. As we explain in greater detail in Section III.C, the idea behind this assumption is that, even if banks observe unrounded ratings, they may use the less precise rounded ratings to make their loan decisions because they know that these ratings are the ones that affect customers' decisions, and therefore restaurants' cash flows.

To exploit the difference in rounded TripAdvisor ratings for restaurants with ratings close to the discontinuities (i.e., rounding thresholds), we implement the following local linear regression around the rounding thresholds:

$$
\begin{aligned}
(3)\qquad \text{TOTAL\_DEBT}_{i,t} = {} & \beta_0 + \beta_1 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
& + \beta_2 \text{TA\_RATING\_UNROUNDED}_{i,t} \\
& + \beta_3 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
& \times \text{TA\_RATING\_UNROUNDED}_{i,t} \\
& + \beta' \mathbf{X}_{i,t-1} + \mu_t + \gamma_i + \varepsilon_{i,t},
\end{aligned}
$$

where ABOVE_VERSUS_BELOW is a dummy variable that takes the value 1 if the overall TripAdvisor rating is rounded up (i.e., the restaurant's unrounded rating is just above a discontinuity threshold) and 0 if the overall TripAdvisor rating is rounded down (i.e., the restaurant's unrounded rating is just below a discontinuity threshold). We include threshold fixed effects, which capture the average debt level of restaurants with ratings close to the various thresholds (1.25, 1.75, 2.25, 2.75, etc.). We also control for the (recentered) unrounded rating and its interaction with the ABOVE_VERSUS_BELOW dummy. **X** is a vector of lagged control variables, and γ_i and μ_t are restaurant and year fixed effects, respectively. To estimate equation (3), we restrict the sample to observations for which a restaurant is close to a rounding threshold.

The RDD estimation described in equation (3) allows us to examine the causal impact of customer ratings on debt by comparing debt ratios for restaurants that randomly fall above or below the discontinuity thresholds around which customer ratings vary exogenously. Like in the baseline OLS tests, we also run RDD regressions in first differences rather than in levels, focusing on recent changes in ratings that allow restaurants to cross rounding thresholds. These analyses examine the change in a restaurant's debt when it crosses a rounding threshold upward or downward. That is, we compare the change in debt for restaurants with a change in their average (unrounded) rating that leads them to cross a rounding threshold with restaurants experiencing a similar change in their average (unrounded) rating but that do not cross a rounding threshold. This allows us to treat situations in which restaurants cross thresholds upward and downward separately and to examine whether these two scenarios lead to symmetric changes in debt. Specifically, compared to our baseline RDD setting from equation (3), the dependent variable is the change in the ratio of total debt to total assets between years $t-1$ and t. The main independent variables are CROSS_ROUNDING_THRESHOLD_UPWARD (i.e., a dummy variable which is equal to 1 if the restaurant crosses a rounding threshold upward between years $t-1$ and t, and 0 otherwise) and CROSS_ROUNDING_THRESHOLD_DOWNWARD (i.e., a dummy variable equal to 1 if the restaurant crosses a rounding threshold downward between years $t-1$ and t, and 0 otherwise). We control for the changes in all the control variables included in equation (3). As in previous specifications, we also include year fixed effects.

Our RDD relies on local linear regressions. An alternative approach is to estimate polynomial regressions. Compared to the local linear approach, the polynomial approach uses all available data in the estimation. However, it imposes a particular functional form onto the relation between the dependent and independent variables over the entire sample, including observations far away from the cutoff points of interest, while, in fact, this relation may differ depending on the distance from the cutoff (e.g., Roberts and Whited (2013), Campello, Gao, Qiu, and Zhang (2018)). Therefore, when choosing one of the two methods, one has to trade off the statistical power and precision of the estimates. In our setting, we have several cutoff points (rounding thresholds) at our disposal, with a reasonably large number of observations in their vicinity. This implies that statistical power is unlikely to be a serious issue, hence our choice to use the local linear regression as our main specification. We nevertheless run tests using a polynomial approach. Gelman and Imbens (2019) recommend avoiding third or higher-degree polynomials when using the polynomial approach due to the sensitivity of estimates to the degree of the polynomial and the unreliability of confidence intervals. Following their recommendation, we rely on first and second-order polynomial regressions. Specifically, we run the following regressions:

$$
\begin{aligned}
\text{(4)} \qquad \text{TOTAL\_DEBT}_{i,t} = \beta_0 &+ \beta_1 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
&+ \beta_2 \text{TA\_RATING\_UNROUNDED}_{i,t} \\
&+ \beta_3 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
&\times \text{TA\_RATING\_UNROUNDED}_{i,t} \\
&+ \beta' \mathbf{X}_{i,t-1} + \mu_t + \gamma_i + \varepsilon_{i,t}
\end{aligned}
$$

and

$$
\begin{aligned}
\text{(5)} \qquad \text{TOTAL\_DEBT}_{i,t} = \beta_0 &+ \beta_1 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
&+ \beta_2 \text{TA\_RATING\_UNROUNDED}_{i,t} \\
&+ \beta_3 \text{TA\_RATING\_UNROUNDED}^2_{i,t} \\
&+ \beta_4 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
&\times \text{TA\_RATING\_UNROUNDED}_{i,t} \\
&+ \beta_5 \text{ABOVE\_VERSUS\_BELOW}_{i,t} \\
&\times \text{TA\_RATING\_UNROUNDED}^2_{i,t} \\
&+ \beta' \mathbf{X}_{i,t-1} + \mu_t + \gamma_i + \varepsilon_{i,t}.
\end{aligned}
$$

C. RDD: Underlying Assumption

A central assumption of the RDD specification is that banks base their lending decisions on rounded ratings and not on more precise unrounded ratings, although the information needed to compute them is available. The most plausible explanation for this choice is that customers, who are less sophisticated and have less time to compute unrounded ratings than banks, use rounded ratings. If customers rely on rounded ratings to choose restaurants and if their choice affects important drivers of debt capacity, like future cash flow stability, then lenders should also consider rounded ratings when they make their lending decisions.

The existing literature in psychology and management suggests that this assumption is valid. Overall, the evidence shows that consumers, who face information overload (Park and Lee (2008)) and high search costs (Siering, Muntermann, and Rajagopalan (2018)), often use simple heuristics to simplify and accelerate the decision-making process, focusing on the most salient information at their disposal (Payne, Bettman, and Johnson (1992)). This is true for online searches (Choi and Leon (2020)), and in particular for searches on restaurant websites. For example, Leitch (2018) finds that consumers spend an average of 34.5 seconds and visit 0.48 pages per session while searching for a restaurant.

Rounded ratings are very salient on the TripAdvisor website. They appear as green bubbles at the top of each restaurant page, while individual ratings necessary to compute the unrounded rating are more cumbersome to access. As shown in Appendix C, the website provides the number of ratings in each category. However, on the cell phone application, one must scroll down and go through other information (location, menu, advertising, etc.) before seeing the individual ratings needed to calculate the unrounded rating. Moreover, TripAdvisor users can apply a filter and restrict their search to restaurants with rounded ratings above 3, above 4, or equal to 5. A similar filter cannot be applied for unrounded ratings. Overall, these TripAdvisor features, together with the practices of internet users described above, make it likely that the average customer (in particular one that uses the cell phone application) relies mainly on rounded ratings to choose a restaurant.[13]

IV. Results

A. TripAdvisor Rating and Restaurant Debt: Baseline Analysis

We first analyze the relationship between TripAdvisor ratings and total debt. Figure 3 plots the average debt ratios for restaurants across different TripAdvisor ratings. The figure shows higher debt levels for restaurants with TripAdvisor ratings of 4.5 or 5. This appears to be driven chiefly by bank debt, which increases steadily with online ratings. We examine the relationship between online ratings and total debt in a multivariate setting using the OLS regression from equation (1). Here and

[13]In another context, the mutual fund literature has exploited Morningstar's presentation of mutual funds' sustainability ratings, which share common features with TripAdvisor ratings. Morningstar displays both the sustainability score of funds and their number of "globes," which depends on their percentile-based rank. Hartzmark and Sussman (2019) find that the globes are the main driver of fund flows, suggesting that investors focus on the salient globe rating and largely ignore the more detailed sustainability information. The role played by the salience of bubble ratings in our context is likely to be even stronger as the typical customer probably spends less time choosing a restaurant than an average investor spends choosing a mutual fund.

for all regressions, we cluster observations at the restaurant level to control for serial dependence across years (Petersen (2009)).

In the first column of Table 2, the dependent variable is a restaurant's total debt ratio (i.e., total debt scaled by total assets), and the independent variable of interest

FIGURE 3

Debt Ratios Across TripAdvisor Ratings

Figure 3 plots the average ratios of debt to total assets as a function of TripAdvisor ratings across all restaurant-year observations. It reports the average total debt ratio (in blue), the average bank debt ratio (in red), and the average other financial debt ratio (in green).

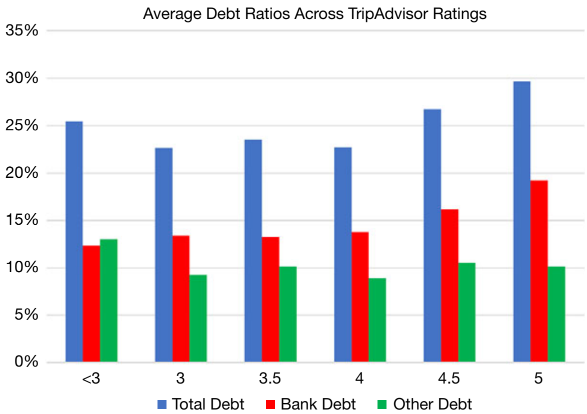


TABLE 2

TripAdvisor Ratings and Restaurant Debt: OLS Regressions

Table 2 presents OLS regressions of restaurant debt on TripAdvisor ratings and control variables using the full sample of restaurants. In column 1, we include year and restaurant fixed effects. In column 2, we use the first difference of all the variables. The dependent variable is total financial debt scaled by total assets. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Appendix D provides variable definitions. Standard errors clustered at the restaurant level are reported in parentheses. Constants are not reported for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Level	First-Difference
TOTAL_DEBT	1	2
TA_RATING	2.19**	2.11***
	(1.115)	(0.679)
ln(AGE + 1)	−18.29***	−13.31***
	(1.342)	(1.055)
ln(TOTAL_ASSETS)	3.10*	0.95
	(1.610)	(1.351)
TANGIBLE_ASSETS	14.92***	−0.56
	(2.842)	(2.114)
ASSET_TURNOVER_RATIO	−3.73***	−0.44
	(0.678)	(0.603)
PROFITABILITY	−12.12***	−3.70**
	(2.271)	(1.827)
LABOR_EXPENSES	1.78	2.24
	(5.227)	(4.022)
No. of obs.	8,766	6,982
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	No
Within R^2	0.197	0.033

is the rounded TripAdvisor rating (TA_RATING). The results reported in column 1 show that the coefficient on the TripAdvisor rating is positive and significant at the 5% level, indicating that restaurants with higher TripAdvisor ratings have more debt. The link between customer ratings and total debt is economically meaningful. A one-bubble increase in a restaurant's TripAdvisor rating is associated with an increase in total debt over total assets of 2.19 percentage points. The average restaurant has total assets of 880,000 euros. Thus, a 1-point increase in the rating is associated with an increase of about 19,300 euros in the amount of debt for the average restaurant. This amount is small in absolute terms, but it represents about 10% of the mean and of the standard deviation of financial debt in our sample. In this regression, other coefficients are in line with the existing literature. In particular, the coefficient on age is negative and statistically significant. For young firms like the restaurants in our sample, Dinlersoz, Kalemli-Özcan, Hyatt, and Penciakova (2019) and Derrien, Mésonnier, and Vuillemey (2020) document that bank debt decreases over time. Column 2 of Table 2 reports the same regressions as in column 1 in differences rather than levels. It leads to the same conclusion: A one-point increase in a restaurant's rating from one year to the next is associated with an increase in financial debt of 2.11 percentage points.

B. TripAdvisor Ratings and Restaurant Debt: Regression Discontinuity Tests

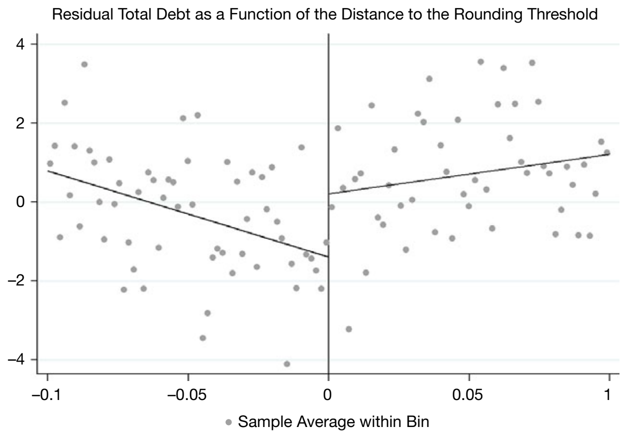
We now study the relation between TripAdvisor ratings and financial debt in the RDD setting. The logic of the RDD framework is that close to the rounding thresholds used by TripAdvisor (1.25, 1.75, etc.), variations in customer ratings are randomized and locally exogenous to restaurant debt and other restaurant characteristics. By comparing restaurants with similar ratings just above versus just below the rounding thresholds, we capture the effect of an exogenous half-bubble change in TripAdvisor ratings on restaurant debt. To ensure that we compare restaurants with similar ratings, we restrict the sample to restaurant-year observations with unrounded ratings within 0.10 of rounding thresholds. We choose this window size following the Mean Squared Error optimal point estimation procedure proposed by Calonico, Cattaneo, and Titiunik (2014). This procedure yields an optimal bandwidth of 0.098, hence our bandwidth choice of [−0.10, +0.10] around rounding thresholds. However, we use alternative bandwidths in the robustness tests below. In the resulting sample of restaurant-year observations, from which we exclude observations for which the unrounded rating is precisely equal to the rounding threshold, 1,657 ratings are rounded up, and 1,808 ratings are rounded down. Figure 4 provides a graphical analysis of residual total debt for restaurants just above and below rounding thresholds (i.e., 1.25, 1.75, 2.25, 2.75, 3.25, 3.75, 4.25, and 4.75). It shows a discontinuous jump in total debt around the thresholds, suggesting a causal effect of ratings on leverage.

Appendix E presents regressions of ABOVE_VERSUS_BELOW, a dummy variable that takes the value 1 if the restaurant is above a rounding threshold, on lagged values of our main control variables (column 1) as well as total debt (column 2). In both regressions, the coefficients are insignificant, indicating that none of the variables predict whether a restaurant is above versus below a rounding threshold.

FIGURE 4

Residual Total Debt Around Discontinuous Changes in TripAdvisor Ratings: Local Linear Regression

Figure 4 shows the average residual total debt on both sides of the rounding thresholds, focusing on the data points close to the rounding thresholds (i.e., with a maximum absolute distance to the rounding threshold of 0.10). It plots the average residual total debt in each of the bins. To select the number of bins, we use the mimicking variance evenly spaced method using spacings estimators (Calonico et al. (2014)). Residual total debt is the residual of the estimation of equation (3) excluding ABOVE_VERSUS_BELOW, TA_RATING_UNROUNDED, and TA_RATING_UNROUNDED × ABOVE_VERSUS_BELOW.



These results support the assumption that, close to the rounding thresholds used by TripAdvisor, variations in online ratings are exogenous.

The first column of Table 3, Panel A reports the results of the RDD regressions presented in equation (3). The independent variable of interest is ABOVE_VERSUS_BELOW, a dummy variable equal to one if the restaurant's rating is above a rounding threshold (conditional on being within [−0.10, +0.10] around it). The ABOVE_VERSUS_BELOW coefficient is 2.66 and is statistically significant at the 1% level. This indicates that restaurants with unrounded ratings above the discontinuity, for which the displayed rating is rounded up, have a debt-to-asset ratio 2.66 percentage points higher than restaurants with unrounded ratings below the rounding thresholds, for which the displayed rating is rounded down. Given that being rounded up versus down leads to a half-bubble difference in TripAdvisor ratings, the economic effect in the RDD setting is about twice as large as it is in the OLS regression. The coefficients of interest in these regressions reflect both the endogenous relationship between the online reputation of a restaurant and its debt and the effect of perceived differences in reputation due to the construction of online ratings. While the RDD coefficient captures only the latter effect, the OLS coefficient reflects both. The comparison of OLS and RDD coefficients suggests that endogeneity biases the OLS coefficient downward or that the relation between reputation and debt is not uniform and is more pronounced for restaurants with ratings close to rounding thresholds.

In column 2, we repeat the tests of column 1, focusing on changes rather than levels to study how recent changes in a restaurant's online reputation affect its ability to raise new debt. To do so, we examine a restaurant's debt change when it crosses a rounding threshold upward or downward. We compare the change in

TABLE 3

TripAdvisor Ratings and Restaurant Debt: Regression Discontinuity Design

Column 1 in Panel A of Table 3 presents the regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW and control variables described in equation (3) restricting the sample to restaurant-year observations with unrounded ratings in a bandwidth of [−0.10;+0.10] around rounding thresholds. Column 2 presents the regression of changes in debt on dummy variables indicating whether a restaurant crossed a rounding threshold upward or downward in the last year and changes in control variables between years $t-2$ and $t-1$. The sample is restricted to restaurant-year observations with changes in unrounded ratings smaller than 0.25. Panel B presents a regression discontinuity analysis based on a polynomial approach, using a first-degree polynomial in column 1 and a second-degree polynomial in column 2, as described in equations (4) and (5). Regressions in Panel B use the full sample of restaurant-year observations. Control variables are the same as in Table 2 and described in Appendix D. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Debt Levels for Restaurants Just Above or Below Rounding Thresholds

	Level	Difference
TOTAL_DEBT	1	2
ABOVE_VERSUS_BELOW	2.66*** (0.938)	
CROSS_ROUNDING_THRESHOLD_UPWARD		2.63** (1.074)
CROSS_ROUNDING_ THRESHOLD_DOWNWARD		−1.46 (0.907)
No. of obs.	3,465	6,668
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	No
Rounding threshold fixed effects	Yes	Yes
Within R^2	0.169	0.035

Panel B. Polynomial Regression Discontinuity Design

	Order 1	Order 2
TOTAL_DEBT	1	2
ABOVE_VERSUS_BELOW	2.00*** (0.627)	2.82*** (0.843)
No. of obs.	8,648	8,648
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	Yes
Within R^2	0.196	0.196

debt for restaurants crossing a rounding threshold to the change in debt for restaurants experiencing similar changes in their unrounded ratings without crossing a rounding threshold, which allows us to isolate the effect of crossing a threshold. For this test, we keep only observations with changes in unrounded ratings smaller than 0.25 because large changes in unrounded ratings may not be exogenous. However, unlike in the specification in levels, there is no guidance on how to choose the maximum acceptable change in unrounded rating from one year to the next. We choose 0.25 because this is the maximum difference between an unrounded rating and the closest corresponding rounded rating. However, the results are similar, with a maximum change in unrounded ratings of 0.10.

In column 2 in Panel A of Table 3, the coefficient on CROSS_ROUNDING_THRESHOLD_UPWARD is positive, statistically significant, and of a similar magnitude to the coefficient on the ABOVE_VERSUS_BELOW dummy in column 1. The coefficient on CROSS_ROUNDING_THRESHOLD_DOWNWARD is negative but not statistically significant, and its magnitude is lower than the coefficient on CROSS_ROUNDING_THRESHOLD_UPWARD. This suggests that the sensitivity of leverage to online ratings is larger for increases than decreases. Improved online reputation allows restaurants to take on more debt. On the contrary, restaurants may be reluctant to reduce their debt when their online reputation deteriorates. Doing so would reduce their short-term cash flows when their future cash flows are already more uncertain due to less favorable customer reviews.

Finally, we consider a regression discontinuity analysis based on a polynomial approach. Following Gelman and Imbens (2019), we report results with first and second-order polynomials. The corresponding graphical analyses in Graphs A and B of Figure 5 show a discontinuous jump in debt between restaurants just below the rounding thresholds and those just above the thresholds with both specifications. Panel B of Table 3 reports the results of polynomial regressions. In both columns, the coefficient on ABOVE_VERSUS_BELOW is positive and statistically significant at the 1% level. The magnitude of the coefficients is roughly similar to the one obtained using the local linear approach.

C. RDD Tests: The Role of Ratings Stability

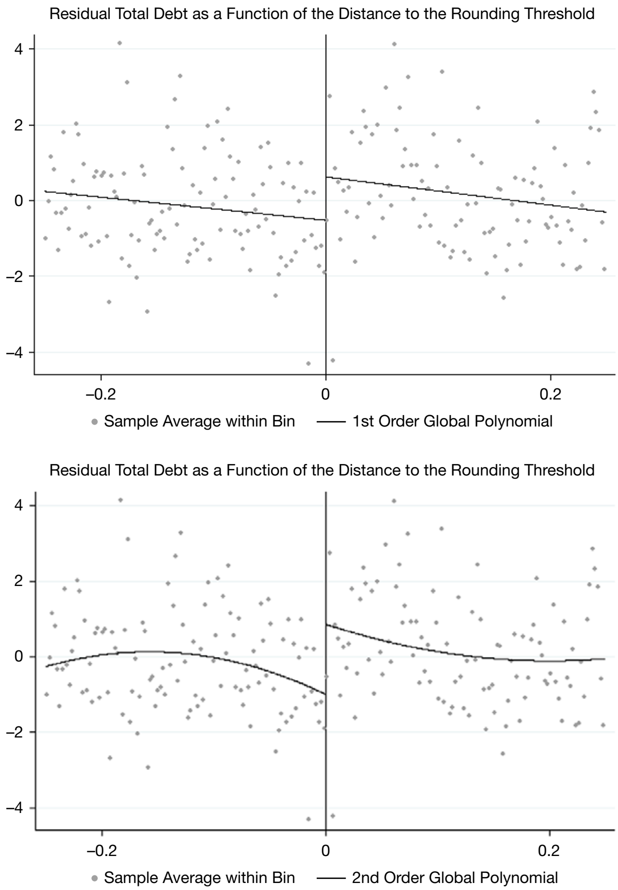
Online ratings (and whether they fall above or below a rounding threshold) are measured at the end of the year. A restaurant above a rounding threshold at the end of the year may have fallen above and below a rounding threshold, possibly several times, over the year. Since restaurants can raise debt at any point in time, not only at year-end, such movements around rounding thresholds may add noise to the estimation. To address this concern, we focus on restaurants that stay in the same position relative to their rounding threshold for a significant fraction of the year. We run RDD tests separately for subsamples of restaurants sorted by two different proxies for rating stability. First, each time a customer posts a new review, we calculate the updated unrounded rating and count the number of times it is above or below a rounding threshold over the year. A restaurant is considered to have high rating stability if its unrounded rating stays in the same position relative to the rounding threshold more than 75% of the time it receives a new review within the year. As an alternative measure, we classify a restaurant as having high rating stability if its unrounded rating has been in the same position relative to the threshold in the last 6 months of the year.

Table 4 reports the results of the local linear regressions of Panel B of Table 3 separately for subsamples of restaurants sorted by the two proxies for rating stability. Columns 1 and 3 report the results for restaurants with low rating stability and columns 2 and 4 for restaurants with high rating stability. The results are similar for the two proxies. They show that the coefficient on ABOVE_VERSUS_BELOW is statistically significant (at the 1% level) only in the subsamples of restaurants with high rating stability. The economic effect is also substantially larger in the subsamples of restaurants with high rating stability than in the baseline RDD tests in Table 3. An exogenous increase of 0.5 bubbles is associated with total debt higher by about 8.0% of total assets. Thus, ratings stability seems an essential factor in the relation between online ratings and leverage. This can be because focusing on restaurants with stable ratings allows to obtain less noisy estimates, as discussed above.

FIGURE 5

Residual Total Debt Around Discontinuous Changes in TripAdvisor Ratings: Polynomial Approach

Graph A (B) of Figure 5 shows the average residual total debt on both sides of the rounding thresholds. It plots the average residual total debt in each of the bins. To select the number of bins, we use the mimicking variance evenly spaced method using spacings estimators (Calonico et al. (2014)). Residual total debt is the residual of the estimation of equation (4) ((5)) excluding ABOVE_VERSUS_BELOW, TA_RATING_UNROUNDED, and TA_RATING_UNROUNDED × ABOVE_VERSUS_BELOW (and, in Graph B, TA_RATING_UNROUNDED^2, and TA_RATING_UNROUNDED^2 × ABOVE_VERSUS_BELOW). The order of the polynomial used in the regression is 1 (2). Graph B shows the average residual total debt on both sides of the rounding thresholds. It plots the average residual total debt in each of the bins. To select the number of bins, we use the mimicking variance evenly spaced method using spacings estimators (Calonico et al. (2014)). Residual total debt is the residual of the estimation of equation (5) excluding ABOVE_VERSUS_BELOW, TA_RATING_UNROUNDED, and TA_RATING_UNROUNDED × ABOVE_VERSUS_BELOW, TA_RATING_UNROUNDED^2, and TA_RATING_UNROUNDED^2 × ABOVE_VERSUS_BELOW. The order of the polynomial used in the regression is 2.



D. RDD: Robustness Tests

In this section, we conduct additional tests to assess the robustness of the RDD results. First, we examine the robustness of our results to alternative bandwidths. In the baseline tests of Table 3, we use a bandwidth of [−0.10, +0.10] around rounding thresholds, justified by Calonico et al. (2014) bandwidth selection procedure. Panel A of Table 5 presents local linear regression results restricting the sample to

https://doi.org/10.1017/S0022109023000248 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109023000248 Published online by Cambridge University Press

TABLE 4

RDD Tests for Restaurants with High Versus Low Rating Stability

Table 4 presents the results of our main regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW and control variables (column 1 in Panel A of Table 3) estimated for subsamples of restaurants with unrounded ratings in a bandwidth of [−0.10;+0.10] around rounding thresholds and sorted by rating stability. The dependent variable is the ratio of total financial debt over total assets. In columns 1 and 2, a restaurant has high rating stability if its unrounded rating has been in the same position relative to the rounding threshold more than 75% of the time within the year. In columns 3 and 4, a restaurant has high rating stability if its unrounded rating has been in the same position relative to the rounding threshold in the last 6 months of the year. Control variables are the same as in Table 2 and described in Appendix D. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TOTAL_DEBT	Low Rating Stability A 1	High Rating Stability A 2	Low Rating Stability B 3	High Rating Stability B 4
ABOVE_VERSUS_BELOW	0.78 (1.512)	7.73*** (2.512)	1.17 (1.373)	8.68*** (2.997)
No. of obs.	2,367	1,098	2,437	1,028
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes	Yes
Within R^2	0.151	0.155	0.140	0.160

restaurant-year observations with unrounded ratings ranging from [−0.04, +0.04] to [−0.14, +0.14] around rounding thresholds. For the sake of brevity, we report only the coefficients for ABOVE_VERSUS_BELOW throughout the table. The coefficients are positive in all specifications but are statistically significant at conventional levels only for larger bandwidths (0.10 and above). However, when we restrict the sample to stable ratings (using either of the two measures of ratings stability), we observe, like in Panel A, that the magnitude of coefficients increases. The coefficients are also very stable across bandwidths and statistically significant at conventional levels for all bandwidths. Overall, the inference from our baseline test in Table 3 is robust to alternative bandwidths.

The RDD tests above exploit the fact that, close to the rounding thresholds used by TripAdvisor (1.25, 1.75, etc.), variations in customer ratings are exogenous to restaurant debt and other restaurant characteristics. If this assumption is correct, we should not observe any effect of being above versus below other thresholds than those TripAdvisor uses to construct its ratings. To confirm this, we run placebo RDD tests where we define the ABOVE_VERSUS_BELOW dummy respective to alternative thresholds. Specifically, we consider placebo thresholds that are either 0.15 bubbles below (i.e., 1.10, 1.60, and 2.10) or 0.15 bubbles above (i.e., 1.40, 1.90, and 2.10) the "true" rounding thresholds used by TripAdvisor. We also consider placebo thresholds strictly at half bubbles (i.e., 1.5, 2, and 2.5). Panel B of Table 5 reports the results of RDD tests using the same specifications as in column 1 in Panel B of Table 3 but with the three sets of placebo rounding thresholds instead of the actual rounding thresholds. The coefficient on ABOVE_VERSUS_BELOW is small (even negative in the first column) and statistically insignificant in the three cases. This confirms that the RDD tests are valid only around TripAdvisor's thresholds, reinforcing our conclusion that the link between online ratings and restaurant debt is causal.

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TABLE 5

TripAdvisor Ratings and Restaurant Debt: RDD Robustness Tests

Panel A of Table 5 presents the results of estimating the RDD specification of equation (3) using alternative bandwidths around rounding thresholds. Results are reported for all the restaurant-year observations with ratings within the bandwidth and for the subsamples of restaurants with high rating stability. We only report the coefficients for Above versus Below throughout the panel for brevity. Panel B presents RDD tests using placebo rounding thresholds. The sample is restricted to restaurants with unrounded ratings in the bandwidth [−0.10;+0.10] around the rounding thresholds for each placebo threshold. In all panels, control variables are the same as in the baseline regression (column 1 in Panel A of Table 3) and described in Appendix D. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. RDD Tests with Alternative Bandwidths

Bandwidth	Full Sample	High Rating Stability A	High Rating Stability B
0.04	1.38 (1.745) Obs: 1,380	6.36* (3.659) Obs: 424	8.20* (4.392) Obs: 404
0.06	1.38 (1.166) Obs: 2,104	6.92** (2.848) Obs: 665	7.53** (3.407) Obs: 620
0.08	1.23 (1.035) Obs: 2,791	8.35*** (2.778) Obs: 890	9.80*** (2.939) Obs: 821
0.10	2.66*** (0.938) Obs: 3,465	7.73*** (2.512) Obs: 1,098	8.68*** (2.997) Obs: 1,028
0.12	2.92*** (0.837) Obs: 4,191	5.74*** (2.290) Obs: 1,316	7.51*** (2.699) Obs: 1,226
0.14	2.65*** (0.768) Obs: 4,862	5.08** (2.183) Obs: 1,544	6.79** (2.608) Obs: 1,433

Panel B. RDD Tests with Placebo Rounding Thresholds

	Alternative Rounding Threshold		
	+0.15	−0.15	0.5
TOTAL_DEBT	1	2	3
ABOVE_VERSUS_BELOW	−0.38 (0.934)	0.53 (0.947)	0.60 (0.668)
No. of obs.	3,392	3,653	3,446
Controls of Panel A	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes
Within R^2	0.172	0.197	0.168

E. Potential Rating Manipulation and Rating Informativeness

A common concern when using online ratings is manipulation. Restaurant owners may improve ratings by manipulating them by posting fake reviews. Such manipulation can affect the interpretation of earlier results if restaurant owners are more likely to engage in ratings manipulation when they are willing to raise debt. In this section, we run several tests to address this concern. First, we verify that previous results hold in two situations in which ratings manipulation is less likely to be a concern. These tests appear in Table 6.

In Panel A of Table 6, we partition the sample into two groups based on the number of reviews. We reestimate the local linear regression in column 1 of Table 3, Panel B for the two subsamples. The rationale of this test is that ratings manipulation is more difficult when the overall rating is based on a larger number

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TABLE 6

Ratings Manipulation

Panel A of Table 6 presents the results of our main RDD regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW, and control variables (column 1 in Panel A of Table 3) estimated separately for restaurants with a low number of reviews (i.e., below the median) and restaurants with a high number of reviews (i.e., above the median) in columns 1 and 2, respectively. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Panel B presents the results of our main RDD regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW and control variables (column 1 in Panel A of Table 3) estimated separately for restaurants sorted by measures of the dispersion of individual ratings. The measure of rating dispersion is indicated at the top of each column. In columns 5 and 6, we partition the sample based on whether the fraction of individual ratings in the "1" category is below or above the median. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Panel C the results of our main RDD regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW and control variables (column 1 in Panel A of Table 3) partitioning the sample according to whether the contribution of reviews by infrequent reviewers to the restaurant's unrounded rating is below or above the median. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Panel D reports the results of a McCrary (2008) density test, in which we regress the probability mass of observations in each 0.05 interval on a dummy variable that indicates intervals just above a rounding threshold. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Cross-Sectional Tests Based on the Number of Reviews

TOTAL_DEBT	Number of Reviews: Below Median (< 48)	Number of Reviews: Above Median (≥ 48)
	1	2
ABOVE_VERSUS_BELOW	1.76 (1.527)	3.68*** (1.229)
No. of obs.	1,730	1,735
Baseline controls	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	Yes
Rounding threshold fixed effects	Yes	Yes
Within R^2	0.113	0.159
p-value of one-sided Wald test of coefficient equality	0.094	

Panel B. Cross-Sectional Tests Based on the Dispersion of Individual Ratings

TOTAL_DEBT	Standard Deviation of Individual Ratings		% of Occurrence of the Most Prevalent Rating		% of Individual Ratings in the "1" Category	
	Low	High	Low	High	Low	High
	1	2	3	4	5	6
ABOVE_VERSUS_BELOW	3.42** (1.431)	2.18 (1.374)	1.70 (1.379)	3.22** (1.460)	4.42*** (1.460)	2.47* (1.383)
No. of obs.	1,723	1,722	1,723	1,722	1,723	1,722
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.179	0.177	0.154	0.227	0.214	0.149
p-value of one-sided Wald test of coefficient equality	0.17		0.175		0.075	

Panel C. Cross-Sectional Tests Based on the Weight of Potentially "Fake" Reviews

TOTAL_DEBT	Effect of Infrequent Reviewers on the Rating: Below Median (< 0.01)	Effect of Infrequent Reviewers on the Rating: Above Median (≥ 0.01)
	1	2
ABOVE_VERSUS_BELOW	5.28*** (1.521)	0.40 (1.425)
No. of obs.	1,730	1,735
Baseline controls	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	Yes
Rounding threshold fixed effects	Yes	Yes
Within R^2	0.201	0.141
p-value of one-sided Wald test of coefficient equality	0.003	

Panel D. McCrary Test

Probability Mass of the Interval	
Interval is just above the discontinuity	−0.001 (0.005)
No. of obs.	74
R^2	0.0005

of reviews. The number of fake positive reviews needed to affect a rating based on many reviews is larger than when the average rating is based on a few reviews. The results reported in columns 1 and 2 show that the coefficient on ABOVE_VERSUS_BELOW is positive and significant only for the subsample of restaurants with a number of reviews above the median (i.e., above 48). On the contrary, the coefficient is not statistically significant for restaurants with few reviews. The Wald test of coefficient equality indicates that the coefficient is statistically larger for the subsample of restaurants with many reviews. This finding suggests that the positive association between TripAdvisor ratings and debt is more pronounced when ratings manipulation is more complicated.

More generally, while every review submitted by customers represents a noisy signal of a restaurant's reputation, the aggregation of individual ratings should provide less noisy information.[14] When based on many individual reviews, the overall rating should therefore be more informative and less affected by noisy or fake reviews. Thus, this finding is also consistent with the view that fund providers assess TripAdvisor signals (ratings) based on the quality of the signals and make their lending decisions accordingly.

Aggregate ratings are also likely to be more informative when they reflect a greater consensus among customers. For example, individual ratings may be more dispersed when a restaurant owner is seeking to compensate for negative customer reviews by posting positive reviews. We explore this possibility using two measures of the dispersion of individual ratings. The first measure is the standard deviation of individual ratings. The second measure is the frequency of the most prevalent individual rating. This measure takes higher values when the consensus among customers is stronger. In Panel B of Table 6, we reestimate our baseline regression separately for different subsamples of restaurants sorted by our measures of the dispersion of individual ratings. For both measures, the positive association between TripAdvisor ratings and debt is more pronounced when the dispersion of individual ratings is low. However, Wald tests suggest that coefficients in the subsamples are only marginally significantly different (*p*-values are 17% and 17.5% for the difference in coefficients between column 1 vs. column 2 and column 3 vs. column 4, respectively).

In columns 5 and 6, we sort the sample based on the fraction of ratings in the "1" category (i.e., the worst possible rating). Very low ratings may raise concerns about the restaurant's quality and discourage risk-averse customers. The results show that the positive association between TripAdvisor ratings and debt is more pronounced when the percentage of ratings in the "1" category is low (the *p*-value of the Wald test for the difference between the two coefficients is 7.5%).

To further alleviate ratings manipulation concerns, we design a test in which we seek to identify fake reviews more directly. To do so, we consider reviews posted by "infrequent" reviewers (i.e., reviewers with 0 or 1 previous review posted on TripAdvisor). These reviews are likely to be posted by fake accounts whose only

[14]Subrahmanyam and Titman (1999) highlight the importance of serendipity in information acquisition. This refers to the way investors gather valuable information in their day-to-day activities. They further observe that while this serendipitous information may be noisy it can provide a helpful signal, when it is aggregated across many stockholders.

purpose is to inflate a restaurant's rating. They represent 12% of reviews and are above the unrounded ratings of the restaurants they refer to by about 0.2 on average, in line with the intuition that at least some are manipulative. For each restaurant year, we calculate the difference between the rating with and without reviews by infrequent reviewers. We then partition the sample into two subgroups depending on whether the difference is larger or smaller than the median and reestimate our baseline regression for the two subsamples. Panel C of Table 6 reports the results.

The link between online ratings and debt appears only in column 1, in which we consider ratings that are less affected by reviews posted by infrequent reviewers. In the other subsample, in which infrequent reviewers affect the overall rating to a larger extent, the link between ratings and debt is economically and statistically insignificant. This suggests that lenders can detect manipulative ratings.

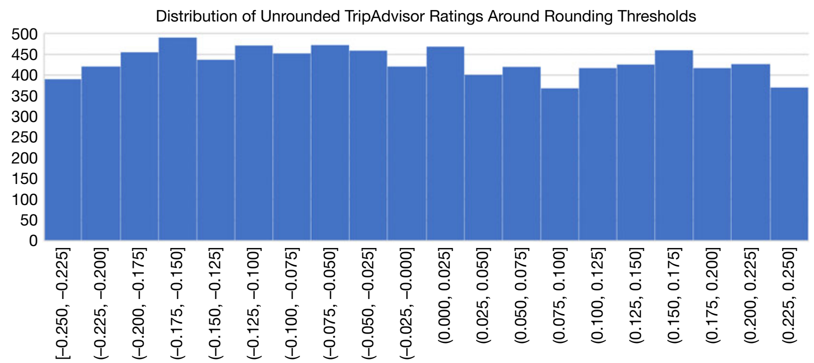
Next, we analyze potential manipulation to cross rounding thresholds, which could bias RDD estimates. An essential assumption of the RDD is that agents cannot exactly manipulate the forcing variable (i.e., the restaurant's unrounded rating) near the thresholds (Lee and Lemieux (2010)). Lee (2008) argues that, even if manipulation exists, an exogenous discontinuity still permits random treatment assignment if firms cannot precisely control the forcing variable. In our context, manipulation would violate the identification assumption of the RDD if it were both widespread and related to debt issuance. That is if restaurant owners with ratings below rounding thresholds systematically issued manipulative ratings to cross rounding thresholds before raising new debt.

Such manipulation would affect the distribution of ratings, leading to a large concentration of unrounded ratings just above rounding thresholds. To test this, we run a McCrary (2008) density test. We allocate each unrounded rating to bins of width 0.05, and we regress the number of observations in each bin on a dummy variable equal to one for bins just above the rounding thresholds. As reported in Panel D of Table 6, the number of observations in bins just above rounding thresholds is not significantly higher than that of other bins. This is in line with the evidence in Figure 6, which shows no abnormal concentration of restaurants

FIGURE 6

Density Plot of Unrounded TripAdvisor Ratings Around Rounding Thresholds

Figure 6 plots a histogram of the distribution of unrounded TripAdvisor ratings around the rounding thresholds (1.25, 1.75, 2.25, and so on) across 20 equal-sized bins.



just above rounding thresholds (vs. just below). Overall, it appears that manipulation, if existent, is not precise or widespread enough to invalidate the identifying assumption of our RDD.

F. Online Ratings and Restaurant Debt: Complementary Tests

In this section, we provide complementary tests to further characterize the effect of TripAdvisor ratings on restaurant debt. More precisely, we test predictions related to our hypothesis that online ratings increase the debt capacity of restaurants by reducing the information asymmetry between restaurants and providers of external financing. Our tests focus on i) the type of debt that should be more affected by online ratings and ii) the restaurants for which online ratings should have a larger impact on debt capacity.

First, we decompose restaurant debt into its two components: i) bank debt and ii) other financial debt, primarily from family and friends. Both debt types are important funding sources for restaurants, representing respectively about 14% and 10% of total assets in our sample (see Table 1). However, bank debt is more sensitive to information asymmetry than debt from family and friends. Suppose favorable online ratings reduce information asymmetry between restaurants and lenders. In that case, they should mainly lead to increases in bank debt and have a smaller or even negative impact on debt from family and friends.[15] In Panel A of Table 7, we repeat our baseline regression replacing total financial debt with its two components: bank debt (column 1) and other financial debt, similar to debt from family and friends (column 2). In line with our prediction and the preliminary evidence in Figure 3, the association between debt and online ratings is significantly positive only for bank debt.

Next, we study whether our main results exhibit cross-sectional heterogeneity. If online ratings affect restaurant debt because they provide useful information about restaurants' financial health, the results should be more pronounced when financial health is more uncertain. Thus, we expect that customer ratings are less important quality signals for older and more expensive restaurants, which are more established. To test this hypothesis, we reestimate the baseline regression of Table 3, Panel B on different subsamples of firms sorted by restaurant age and price range. The results are reported in Panel B of Table 7. Columns 1 and 2 show that the coefficient on ABOVE_VERSUS_BELOW is positive and statistically significant only for young restaurants (below the median age of 10 years). In columns 3–5, we estimate the regression separately for each price category assigned by TripAdvisor.[16] The coefficient on ABOVE_VERSUS_BELOW is large for restaurants in the

[15]Small businesses like restaurants also tend to use debt from family and friends as a last resort when they have exhausted their bank debt capacity. In unreported OLS regressions using the entire restaurant sample, we find that larger restaurants tend to have more bank debt and less debt from family and friends. This suggests that, as they become less financially constrained, restaurants replace debt from family and friends with bank debt.

[16]In our sample, 77% of restaurants-year observations are in the affordable category, while 11.5% and 11.5% of the observations are in the cheap and expensive categories, respectively.

TABLE 7

TripAdvisor Ratings and Restaurant Debt: Additional Tests

Panel A of Table 7 presents local linear regressions of bank debt and other financial debt on the dummy variable ABOVE_VERSUS_BELOW, equal to 1 if a restaurant is above a rounding threshold and 0 otherwise, and control variables, in columns 1 and 2, respectively. The sample is restricted to restaurants with unrounded ratings in the bandwidth [−0.10; +0.10] around rounding thresholds. Panel B presents the results of our main RDD regression of restaurant debt on the dummy variable ABOVE_VERSUS_BELOW, and control variables (column 1 in Panel A of Table 3) estimated separately for young (i.e., below or equal to the median age) and old restaurants (i.e., above the median age) and for restaurants in the cheap, affordable, and expensive price categories. All regressions include year, restaurant, and rounding threshold fixed effects. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Bank Debt and Other Financial Debt

	Bank Debt	Other Financial Debt
	1	2
ABOVE_VERSUS_BELOW	1.84**	0.80
	(0.773)	(0.652)
No. of obs.	3,465	3,465
Baseline controls	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	Yes
Rounding threshold fixed effects	Yes	Yes
Within R^2	0.198	0.046

Panel B. Age and Price Range

TOTAL_DEBT	Restaurant Age		Price Range		
	Young	Old	Cheap	Affordable	Expensive
	1	2	3	4	5
ABOVE_VERSUS_BELOW	3.58***	0.72	3.69	2.51**	0.64
	(1.303)	(1.259)	(2.879)	(1.095)	(2.332)
No. of obs.	1,766	1,699	394	2,628	352
Baseline controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes	Yes	Yes
Within Adj. R^2	0.322	0.086	0.280	0.193	0.250
p-value of one-sided Wald test (1) > (2)	0.038				
p-value of one-sided Wald test (3) > (5)				0.083	

cheap and affordable categories but statistically significant only for the latter. It is small and statistically insignificant for expensive restaurants. The Wald test shows that the coefficient in column 3 (cheap restaurants) is significantly larger than the coefficient in column 5 (expensive restaurants) at the 10% level.

These results suggest that online ratings reduce information asymmetry between firms and lenders, allowing restaurants with favorable ratings to increase their (bank) debt, particularly when they face high information asymmetry. They are consistent with the view that good online ratings increase the supply of credit to restaurants, allowing them to realize their current growth opportunities. Another possibility, however, is that good online ratings directly affect customer demand and create new growth opportunities for restaurants, which raise new debt to invest in these new growth opportunities. This could explain why the debt of young restaurants, which have a greater growth potential, is more sensitive to online ratings. In the next two sections, we explore the mechanisms through which online ratings affect debt capacity.

G. The Cash Flow Risk Channel

This section explores the mechanisms through which good customer ratings allow restaurants to have higher debt levels. Prior studies suggest that intangible assets such as patents are increasingly used as collateral (Loumioti (2012), Mann (2018)). Unlike patents, good customer ratings cannot be pledged as collateral as they cannot be repossessed or redeployed in case of financial distress. While customer ratings cannot be used as collateral, they can still contribute to increasing a firm's ability to borrow. Larkin (2013) shows that the brand perception of listed companies reduces their cash flow volatility and increases their operating performance in periods of economic downturn. Like brand perception, online reputation may reduce the riskiness of restaurants' cash flows, thereby reducing their ex ante probability of default and increasing their debt capacity.

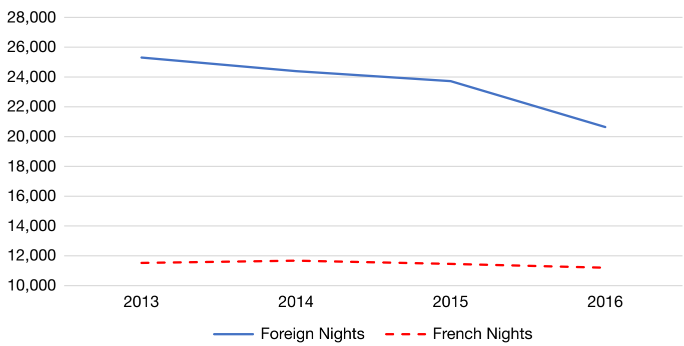
To explore this possibility, we first examine whether favorable customer ratings reduce cash flow risk. We hypothesize that good online ratings protect restaurants against economic downturns characterized by a decrease in overall demand. We rely on an exogenous demand shock with a large effect on the entire industry concentrated in a short time period, the terrorist attacks in Paris in 2015, and we analyze whether restaurants with good online ratings experienced better operating performance after this shock.[17] To illustrate the relevance of these events for local tourism, we plot the annual number of hotel nights in Paris from 2013 to 2016. Figure 7 shows a decline in the number of nights in 2015 and 2016, particularly among foreign tourists.

In Panel A of Table 8, we exploit the terrorist attack shock in difference-in-differences tests in which we examine the sales and cash flows of restaurants after

FIGURE 7

Nights in Parisian Hotels in 2013–2016

Figure 7 shows the annual number of hotel nights by domestic (red dashed line) and foreign (solid blue line) guests from 2013 to 2016. The numbers on the *y*-axis are in thousands. Data source: Comité Régional du Tourisme Paris Ile-de-France.



[17]On Jan. 7, 2015, an armed attack at the Parisian office of the satirical magazine Charlie Hebdo killed 12 people and injured 11 others. Related attacks occurred in Paris on Jan. 7–9, 2015. The coordinated terrorist attacks on 6 Parisian locations on Nov. 13, 2015, killed 130 and injured 494 people. Following the attacks, the state of emergency was declared throughout the country.

TABLE 8

TripAdvisor Ratings and Cash Flow Risk

Panel A of Table 8 presents OLS regressions of performance measures on POST_TERRORIST_ATTACK (a dummy variable that takes the value 1 in 2015, 2016 and 0 in 2013, 2014) and its interaction with GOOD_TA_RATING (a dummy variable that takes the value 1 if a restaurant's TripAdvisor rating is greater than 3.5 and 0 otherwise as of end of 2014) and control variables of Table 2 (except profitability). All regressions include year and restaurant fixed effects. Panel B presents the same regression as in Panel A, column 3, estimated separately for two subsamples of restaurants sorted by their proportion of foreign clientele. We partition the sample into two groups based on the median value of the percentage of reviews written in French (columns 1 and 2) and the median value of the percentage of reviewers located in France (columns 3 and 4). All regressions include year and restaurant fixed effects. Panel C presents OLS regressions of future cash flow volatility and the next-year probability of experiencing a significant drop in sales on GOOD_TA_RATING (a dummy variable that takes the value 1 if a restaurant's TripAdvisor rating is greater than 3.5 and 0 otherwise) and control variables in column 1, 2, and 3, respectively. All regressions include year, cuisine, arrondissement (district), and business type fixed effects. The control variables are the same as in the regression of Table 2. Panel D presents OLS regressions of restaurant probability of survival on GOOD_TA_RATING (a dummy variable that takes the value 1 if a restaurant's TripAdvisor rating is greater than 3.5 and 0 otherwise) and control variables. We consider three measures of restaurant closure which are indicated at the top of each column. All regressions include year and restaurant fixed effects. Panels C and D are estimated for the entire sample period. The control variables are the same as in the regression of Table 2. Appendix D provides variable definitions. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. TripAdvisor Ratings and Resilience to Economic Shocks

	ln(SALES)		PROFITABILITY	
	1	2	3	4
POST_TERRORIST_ATTACK		−0.05*** (0.017)		−0.02*** (0.005)
POST_TERRORIST_ATTACK × GOOD_TA_RATING	0.03** (0.016)	0.04** (0.016)	0.02*** (0.006)	0.02*** (0.006)
No. of obs.	5,385	5,385	5,393	5,393
Baseline controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
Restaurant fixed effects	Yes	Yes	Yes	Yes
Within Adj. R^2	0.114	0.114	0.038	0.041

Panel B. TripAdvisor Ratings and Resilience to Cash Flow Shocks – Foreign Versus French Clientele

PROFITABILITY	Proportion of Foreign Clientele (Based on Language Used)		Proportion of Foreign Clientele (Based on Reviewer Location)	
	Low	High	Low	High
	1	2	3	4
POST_TERRORIST_ATTACK × GOOD_TA_RATING	0.01 (0.009)	0.03*** (0.009)	0.01 (0.010)	0.02*** (0.009)
No. of obs.	2,745	2,648	2,710	2,683
Baseline controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes
Within Adj. R^2	0.048	0.044	0.035	0.057
p-value of one-sided Wald test (2) > (1)	0.054			
p-value of one-sided Wald test (4) > (3)			0.075	

Panel C. Future Cash Flow Volatility and Sales Drop

	Future Cash Flow Volatility	Future Sales Drop
	1	2
GOOD_TA_RATING	−0.44** (0.205)	−0.01** (0.005)
No. of obs.	4,227	8,636
Baseline controls	Yes	Yes
Year fixed effects	Yes	Yes
Cuisine fixed effects	Yes	Yes
District fixed effects	Yes	Yes
Business type fixed effects	Yes	Yes
Adj. R^2	0.142	0.023

Panel D. Probability of Survival

	TA Closed	Diane Stopped Operating	Diane Liquidation
	1	2	3
GOOD_TA_RATNG	−0.80* (0.417)	−1.08** (0.479)	−0.58** (0.291)
No. of obs.	8,766	8,766	8,766
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes
Within Adj. R^2	0.0104	0.019	0.006

versus before the shock (i.e., in 2015–2016 vs. 2013–2014) for restaurants with good online ratings before the shock (at the end of 2014) versus other restaurants. To be able to perform the difference-in-differences tests in Table 8, we adjust the specifications used thus far in two ways. First, we depart from the RDD setting because limiting the analysis to restaurants with ratings close to rounding thresholds at the time of the terrorist attacks would reduce sample size significantly. Second, we create a dummy variable capturing "good ratings," which we define as ratings above 3.5.[18] In Dec. 2014, approximately half of the restaurants in the sample had good ratings.

In the first column of Panel A of Table 8, we regress the natural logarithm of sales on the interaction between the POST_TERRORIST_ATTACK dummy, equal to one in 2015 and 2016, and the GOOD_TA_RATING dummy. The coefficient on this interaction variable is positive and significant, indicating that restaurants with good online ratings are more resilient to the demand shock than other restaurants. In column 2, we run the same regression, excluding year fixed effects and adding the POST_TERRORIST_ATTACK dummy in the regression instead. As expected, the coefficient on this variable is negative and significant, indicating that the average restaurant not in the "good rating" category faces a decrease in sales in the 2015–2016 period. Again, the coefficient on the interaction variable is positive and significant. It indicates that having a good rating almost eliminates the negative effect of the demand shock on sales. This effect is similar in columns 3 and 4 of the table, in which we examine the impact of the demand shock on profitability. The coefficient of the interaction variable is positive and significant (column 3). Column 4 shows that being in the "good rating" category allows restaurants to completely offset the negative effect of the demand shock on profitability (the sum of the coefficients on POST_TERRORIST_ATTACK and POST_TERRORIST_ATTACK × GOOD_TA_RATING is equal to 0).

Next, we replicate the regression of column 3 of Panel A, accounting for the nationality of reviewers. Restaurants that cater mainly to a foreign clientele are likely to be the most affected by the terrorist attacks because the decrease in Parisian hotel nights is concentrated in the foreign category (as seen in Figure 7). Moreover, foreign tourists may be less informed than locals and rely more on online platforms like TripAdvisor to choose restaurants. If good customer ratings insulate restaurants from demand shocks, their effect should be more pronounced for restaurants that depend more on foreign customers. We identify exposure to foreign tourists by the percentage of TripAdvisor reviews written in a language other than French (about one-third of the total number of reviews). Alternatively, we identify the reviewer's nationality based on the reviewer's location. In Panel B of Table 8, we repeat the third column of Panel A, splitting the sample according to whether the restaurant's foreign clientele is above or below the median using the two methods described above (the language of the review in columns 1 and 2 and the reviewer's location in columns 3 and 4). The previous finding that good TripAdvisor ratings improve the resilience of restaurants to exogenous shocks like terrorist attacks is valid only for restaurants that depend on foreign clients.

[18]In unreported tests, we find similar results if we define "good ratings" as ratings above 4.

In Panel C of Table 8, we examine whether good online ratings reduce future cash flow volatility and the probability of experiencing significant sales drops, which capture more idiosyncratic shocks than systematic shocks due to terrorist attacks. In column 1, we run a regression of forward-looking cash flow volatility computed as the standard deviation of a firm's annual profitability (EBITDA scaled by total assets) over a 3-year window on TripAdvisor ratings and control variables. We include a series of fixed effects in the regression to control for cross-sectional differences in cuisine types, districts, and restaurant types. Unlike in previous tests, we do not include restaurant fixed effects in the regression. The average restaurant in our sample has 4 years of data, three of which are used to compute the forward-looking cash flow volatility, significantly reducing the time-series dimension of the regression. Column 1 shows that the coefficient on GOOD_TA_RATING is negative and statistically significant, consistent with good customer ratings reducing the riskiness of a restaurant's cash flows. In column 2, the dependent variable is a dummy variable equal to one if, in a given year, a restaurant experiences a change in sales scaled by total assets in the bottom 5% of the distribution. The results show that the coefficient on GOOD_TA_RATING is negative and statistically significant at the 5% level, indicating that restaurants with good online ratings are less likely to experience a significant drop in sales.[19]

Finally, in Panel D of Table 8, we ask whether TripAdvisor ratings are related to the survival of restaurants, measured with three different variables. To construct the first one (TA_CLOSED), we identify restaurants that stop receiving TripAdvisor reviews in a given year (and the following years). We then check manually that these restaurants closed permanently using additional internet sources. We obtain 96 confirmed cases of restaurant closures. We create a dummy variable equal to 1 in the last year a restaurant is present in our restaurant-year sample and 0 in other years. The second and third variables are based on data from Diane, which identifies companies that stop operating (142 cases in our sample) and companies that are liquidated (60 cases). Although the exact timing of the closure or liquidation is uncertain, we consider the last year in which accounting data are available in Diane as the restaurant's last year of operation. We then create two dummy variables, DIANE_STOPPED_OPERATING and DIANE_LIQUIDATION, equal to 1 that year for restaurants in the two categories. The results reported in Panel D show that the coefficient on GOOD_TA_RATING is negative and statistically significant in the three columns, consistent with good customer ratings reducing the risk of restaurant closure.

H. Online Ratings, Investment, and Customer Demand

In this section, we further explore the mechanisms behind our main findings. The results from the previous section show that good customer ratings decrease restaurants' cash flow risk, allowing them to take on more debt. Another nonmutually exclusive possibility is that good customer ratings create growth opportunities and improve future growth, leading to increased demand for debt.

[19]In unreported tests, we find that good online ratings are not statistically associated with the probability of experiencing a significant jump in sales, indicating that the effect of online ratings is asymmetric.

In other words, in the latter channel, online ratings affect the demand for debt from restaurants, while in the former channel, they affect the debt supply of banks. Both channels predict that restaurants with good ratings should use their new debt to invest. Under the credit supply channel (which we also call the cash flow stability channel), good online ratings increase the debt capacity of restaurants and allow them to realize existing investment opportunities. In contrast, the new growth opportunities (or demand) channel predicts that online ratings create new investment opportunities.

We consider three ways restaurants with good online ratings can use their extra debt capacity. They can invest, substitute debt for equity by initiating or increasing dividend payments, or increase cash reserves.[20,21] Since this test aims at exploring how restaurants use the debt they obtain as a result of improved ratings, we use two-stage least square regressions. By contrast, a simple regression of debt usage on new debt would capture the correlation between the entire amount of new debt (not only the part of it that is the consequence of improved ratings) and firm policies. In such a setting, new debt would be endogenous, as it could be determined together with the dependent variables by unobserved variables or even caused by the dependent variables. By instrumenting debt with the ABOVE_VERSUS_BELOW variable, we ensure that TripAdvisor ratings cause the predicted debt we use in the second stage regression.[22] We have already established that this instrument is relevant, as it affects bank debt. To satisfy the exclusion restriction, it needs to affect the dependent variable only through its effect on debt. In other words, it needs to be the case that restaurants with improved customer ratings invest (or pay a dividend, or increase their cash balance, etc.) because they can raise new debt.

Table 9 reports the second-stage regressions. In all regressions, the main independent variable is the predicted value of debt from the first stage. In Panel A of Table 9, the extra debt explained by online ratings is not associated with the ratio of cash and equivalents to total assets or dividend payments.[23] However, it is positively associated with the level of tangible assets. Thus, restaurants with favorable TripAdvisor ratings appear to use their extra debt capacity to invest. In Panel B of Table 9, we explore this further by splitting tangible assets into their main components: land, building, installations and materials, and other tangible

[20]By reducing cash-flow risk, good ratings may actually decrease the need to hold cash for precautionary motives. Consistent with this argument, Larkin (2013) finds that brand perception is associated with higher leverage and lower cash holdings. However, her sample contains large and publicly listed companies. By contrast, our sample consists of small unlisted firms for which cash is very important for business transactions with suppliers and customers (e.g., Mun and Jang (2015)). An increase in debt capacity can therefore allow restaurants to increase their cash balance, thereby gaining flexibility in their working capital management.

[21]Restaurants could also use bank debt to reduce debt from family and friends. Results in Table 7 show that this is not the case.

[22]In the first stage, we regress total debt on the variable ABOVE_VERSUS_BELOW and the same controls as in equation (3) estimated in Table 3, except that we exclude (lagged) TANGIBLE_ASSETS from the control variables because (current) TANGIBLE_ASSETS is one of the dependent variables in this analysis, as well as the interaction term between ABOVE_VERSUS_BELOW and the unrounded rating. In the (unreported) first-stage regression, the coefficient on ABOVE_VERSUS_BELOW is 2.06, with a t-statistic of 3.38 and the F-statistic of the regression is 11.42.

[23]Only 3% of our restaurant-year observations have nonzero dividends.

TABLE 9
Debt Use

Panel A of Table 9 presents the second stages of 2SLS regressions of balance sheet and cash flow statement items scaled by lagged total assets on the predicted value of debt. In the first stage, total debt is regressed on the dummy variable ABOVE_VERSUS_BELOW, equal to 1 if a restaurant is above a rounding threshold and 0 otherwise, and the same control variables as in equation (3) except TANGIBLE_ASSETS. Appendix D provides the variable definitions. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Use of Debt

	Cash	Dividend Dummy	Tangible Assets	Intangible Assets
	1	2	3	4
PREDICTED_TOTAL_DEBT	−0.20	−0.26	1.25***	0.30
	(0.330)	(0.442)	(0.422)	(0.212)
No. of obs.	3,465	3,465	3,465	3,465
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes
Within Adj. R^2	0.101	0.016	0.321	0.160

Panel B. Decomposition of Tangible Assets

	Land	Building	Installation, Materials, and Other Tangible Assets
	1	2	3
PREDICTED_TOTAL_DEBT	−0.00	0.34**	0.78**
	(0.001)	(0.149)	(0.357)
No. of obs.	3,465	3,465	3,465
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes
Within Adj. R^2	0.013	0.031	0.296

assets. The results show that building, installations and materials and other tangible assets, which correspond to the kind of investments a growing restaurant makes (i.e., tables and chairs and kitchen equipment), increase with debt.

Overall, consistent with the two channels, Table 9 indicates that restaurants with good customer ratings invest more in tangible assets. These investments should allow restaurants to maintain or improve their quality, and perhaps affect their revenues. To explore their effect on sales, we run regressions of the natural logarithm of sales on the ABOVE_VERSUS_BELOW dummy and control variables. The first column of Panel A of Table 10, reports the result of this regression. The coefficient on ABOVE_VERSUS_BELOW is positive but not statistically significant. We then split our sample based on restaurant age and reestimate the regression of column 1 of Panel A of Table 10. The rationale for this sample split is that mature restaurants will likely operate at full capacity. As a result, these restaurants cannot scale up linearly following an increase in online reputation. Instead, their reaction may be to raise prices, but perhaps cautiously, if they anticipate that the effect of recent ratings will be short-lived. This explanation is less likely for less mature restaurants still in their growth phase and which have not yet reached their full capacity. In line with this conjecture, the results from column 2 show that the coefficient on ABOVE_VERSUS_BELOW is statistically significant at the 5% level for the subsample of young restaurants, indicating a significant increase in sales for young restaurants with ratings rounded up. On the contrary, we do not observe a significant increase in sales for old restaurants.

In Panel B of Table 10, we reestimate the regressions of Panel A, focusing on future sales at longer horizons ($t + 1$ and $t + 2$). The results show that the coefficient on ABOVE_VERSUS_BELOW is positive but not statistically significant. When we split our sample between young and mature restaurants, we find that the coefficient is positive and larger for the sample of young restaurants but not statistically significant at conventional levels.[24]

TABLE 10

TripAdvisor, Customer Demand, and Restaurant Sales

Panel A of Table 10 presents RDD regressions of the natural logarithm of sales at the end of year *t* on ABOVE_VERSUS_BELOW, a dummy variable equal to 1 if a restaurant is above a rounding threshold and 0 otherwise, and control variables. In columns 2 and 3, we reestimate the regression of column 1 separately for subsamples of restaurants sorted by age (above or below the median). Panel B presents the same regressions as Panel A, using the natural logarithm of sales at 1-year and 2-year horizons as dependent variables. Panel C presents the results of estimating RDD regressions of the number of monthly reviews over horizons varying from 1 to 12 months as dependent variables. Unlike in Panels A and B, in which we rely on yearly data, in Panel C, we use the same RDD as in our main tests but with monthly data. We only report the coefficients for ABOVE_VERSUS_BELOW throughout the panel for brevity. All regressions include year and restaurant fixed effects. Appendix D provides the variable definitions. Standard errors clustered at the restaurant level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Customer Ratings and Sales in Year t

	ln(SALES)		
	Full Sample	Young	Old
	1	2	3
ABOVE_VERSUS_BELOW	0.02 (0.016)	0.04** (0.019)	0.02 (0.029)
No. of obs.	3,406	1,731	1,675
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes
Within Adj. R^2	0.147	0.111	0.198
p-value of one-sided Wald test (1) > (2)		0.038	

Panel B. Customer Ratings and Sales in Years t ± 1 and t ± 2

	ln($SALES_{t+1}$)			ln($SALES_{t+2}$)		
	All	Young	Old	All	Young	Old
	1	2	3	1	2	3
ABOVE_VERSUS_BELOW	0.01 (0.021)	0.01 (0.028)	−0.01 (0.035)	0.01 (0.030)	0.03 (0.043)	−0.02 (0.040)
No. of obs.	2,374	1,175	1,199	1,626	779	847
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Rounding threshold fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Within Adj. R^2	0.0619	0.0278	0.105	0.0603	0.0308	0.119

(continued on next page)

[24]Higher sales are not the only manifestation of restaurant growth. In fact, successful restaurants tend to operate at full capacity, and one way to realize their growth opportunities is for their owner to open a new restaurant. Diane reports the ultimate ownership of firms, but this information is sparse, in particular for small companies like the restaurants in our sample. We observe the ultimate ownership of 642 restaurants. Among them, 102 restaurants have a common ultimate owner, and we observe the first year of operation of 17 of them. In the year these 17 restaurants open, the TripAdvisor rating of the restaurants owned by the same ultimate owners is 3.73, compared to 3.57 for restaurants with multiple owners in

TABLE 10 (continued)

TripAdvisor, Customer Demand, and Restaurant Sales

Panel C. Customer Ratings and Customer Demand

Horizon	Above Versus Below
1 month	0.03* (0.017) Obs: 19,624
2 months	0.04** (0.019) Obs: 15,643
3 months	0.06*** (0.021) Obs: 14,882
4 months	0.07*** (0.022) Obs: 14,301
5 months	0.05** (0.021) Obs: 13,879
6 months	0.04* (0.020) Obs: 13,444
7 months	0.02 (0.019) Obs: 13,084
8 months	0.00 (0.022) Obs: 12,802
9 months	−0.01 (0.020) Obs: 12,553
10 months	0.03 (0.020) Obs: 12,330
11 months	0.01 (0.020) Obs: 12,077
12 months	0.01 (0.021) Obs: 11,845

One of the specific predictions of the growth opportunities channel is that customer demand increases when online ratings improve, leading restaurants to increase their debt level and investments. Thus, under the growth opportunities channel, the increase in customer demand should materialize quickly following good online ratings. To test this prediction, one would need to observe demand at a high frequency. We do not observe sales at a frequency higher than annual, but we observe online reviews in real-time. We proxy for customer demand using the monthly number of TripAdvisor reviews received by a restaurant, making the reasonable assumption that customer demand in a given month is correlated with the observed number of reviews from customers in the same month. This allows us to explore how online ratings affect customer demand at relatively short horizons. To do so, we use the same RDD setting as in our main tests but at the monthly level.

years with no new restaurant opening. This result should be interpretated with care because of the small sample size. However, it suggests that growth can happen through the opening of new restaurants, and that online ratings can be a driver of this type of growth.

That is, we ask whether being above a rounding threshold is associated with a greater number of monthly reviews at horizons varying from 1 to 12 months, controlling for the usual restaurant characteristics and fixed effects. Panel C of Table 10 reports the coefficient on ABOVE_VERSUS_BELOW in each of the 12 regressions. It is positive and statistically significant for horizons up to 6 months, but its magnitude decreases and it loses its statistical significance at longer horizons. In line with the prediction of the growth opportunities channel and with the findings of Luca (2016), who shows a link between online ratings and quarterly revenues, this indicates that online ratings affect customer demand at short horizons.

To sum up, the evidence on the effect of online ratings on cash flow risk from the previous section is consistent with a cash flow stability (or credit supply) channel. The results on the use of debt and subsequent sales are consistent both with a credit supply channel and a growth opportunities channel, and the evidence on the short-term demand effects of online ratings is in line with the growth opportunities channel. These tests suggest that both mechanisms are at play when explaining the relationship between online ratings and leverage.

V. Conclusion

The expansion of online customer review websites such as TripAdvisor has improved the information on product quality as it is easily accessible to a large audience at a negligible cost. This article examines the implications of online customer ratings for financial and investment policies. Using a large sample of Parisian restaurants, we document that good TripAdvisor ratings increase restaurants' debt capacity as measured by higher leverage. As the most salient rating displayed online is rounded to the closest half-bubble, we can identify the causal impact of customer ratings on debt using a RDD that exploits locally exogenous variations in customer ratings.

Consistent with customer ratings allowing restaurants to have higher debt levels through a reduction in cash flow risk, we find that good customer ratings reduce cash flow volatility and increase the resilience of restaurants to economic shocks. In particular, restaurants with good customer ratings resist better during the demand shock that follows the Paris terrorist attacks of 2015. We further explore how restaurants use the new debt they raise thanks to their good online ratings. We find that restaurants with higher online scores invest in tangible assets instead of increasing dividend payments or improving their cash balance. This finding is consistent with restaurants exploiting unrealized growth opportunities thanks to increased debt capacity and good online ratings creating new growth opportunities.

Overall, the results indicate that customer ratings have implications for corporate policies. Online ratings appear to be a relevant source of information about restaurants' financial health and ability to support debt financing, especially for restaurants with shorter track records. These results apply to restaurants and small businesses that cater to retail customers and large companies in consumer-goods industries, as long as online ratings contain useful information about their prospects. The implications of our results are twofold. First, firms can benefit from an improved online reputation by attracting new customers and improving access to external funds. Second, external funding providers like banks can benefit from paying attention to online customer ratings to reduce information asymmetry in the screening of borrowers and determine their creditworthiness.

Appendix A. Matching Procedure Between TripAdvisor and Diane

In Appendix A, we start from the universe of Parisian restaurants listed on TripAdvisor over the 2007–2017 period (around 14,000). We look for a unique match in the Bureau van Dijk financial database Diane of Parisian restaurants active over the same period. We first match unique restaurants using their physical address (street name, number, and district) and then manually screen the matched pairs to validate the matching (using the three different company names provided by the database). Matching errors can arise from the restaurant's physical address not matching the one of the company the restaurant belongs to if the restaurant is a subsidiary or is incorporated at a physical address that does not correspond to the one on TripAdvisor. Addresses can also differ between TripAdvisor and the financial database when a restaurant is located at a street corner so that at least 2 different streets can refer to its location. Finally, multiple restaurants can be located at the same address (for instance, in a mall). We find a unique match for 2,507 TripAdvisor restaurants based on their physical addresses.

We match the remaining restaurants using their names and then manually screen the matched pairs to validate them. The financial database provides three different names we can match with the restaurant's name on TripAdvisor. Not all private companies directly refer to the restaurant's name as referenced on TripAdvisor in their tax reports. Moreover, when a restaurant name is too generic, the chance of obtaining a wrong match increases markedly. We first look for exact name matches. Then, for restaurant names with no matches, we look for the best match using a fuzzy matching technique (Stata command *matchit* with a similarity score cut-off superior or equal to 90%). We find a unique match for 2,148 TripAdvisor restaurants based on restaurant names.

For the remaining unmatched TripAdvisor restaurants, we look for their financial database counterparts using their telephone or email addresses. We then screen the matched pairs manually to identify relevant ones (based on other information, like the Diane and TripAdvisor restaurant names). We find a unique match for 200 and 5 TripAdvisor restaurants based on the telephone number and email address, respectively. In total, we find a unique match for 4,862 unique TripAdvisor restaurants.

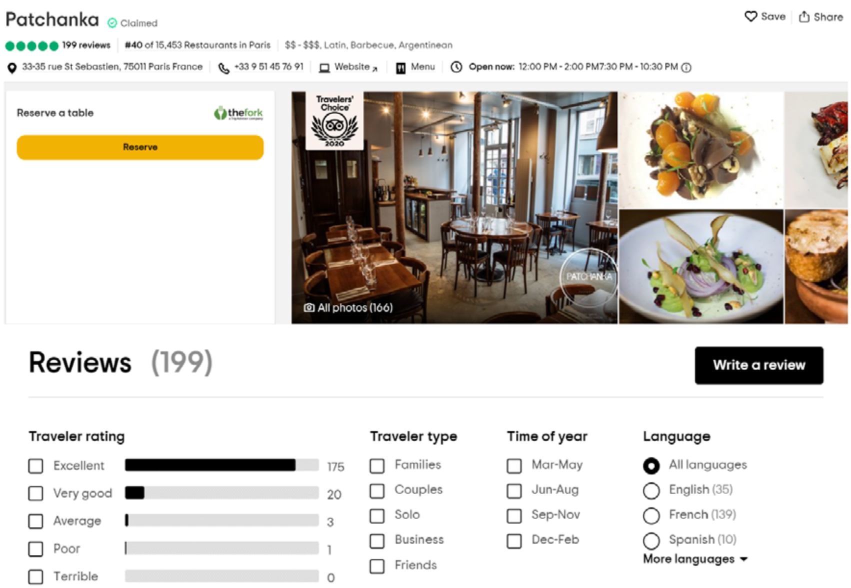
Appendix B. Sample Construction

Appendix B shows how each criterion used to select restaurants affects the number of restaurants in the final sample used in the empirical analysis.

Restrictions	Unique Restaurants
Unique TripAdvisor restaurants with a unique Diane match	4,862
At least one review posted on TripAdvisor over the sample period	4,585
Drop chain restaurants (McDonald, Pizza Hut, Subway,…)	4,493
Drop restaurants whose main activity is not: "Traditional Restaurant," "Fast Food Restaurant," or "Licensed Beverage Establishment"	3,895
Drop restaurant-year observations with missing accounting data we require to compute our main dependent and independent variables for years t and $t-1$. Drop restaurant-year observations with negative equity	2,658
Keep restaurants with more than five reviews	2,474

Appendix C. Computation of TripAdvisor Rounded and Unrounded Overall Ratings

In Appendix C, we reconstruct the ratings of Parisian restaurants displayed on TripAdvisor using the entire history of individual ratings for each restaurant in the sample. The overall bubble rating displayed on TripAdvisor reflects the average of all individual bubble ratings for a restaurant, and it is rounded to the nearest half-point. To illustrate how TripAdvisor calculates a restaurant's overall rating, we consider the following restaurant, *Patchanka*. We present below an extract of the restaurant's TripAdvisor page as of the end of Dec. 2020. The TripAdvisor overall rating presented to the website's users is 5.



This rating is based on 199 customer ratings. The unrounded mean of the ratings given by the reviewers is $(175 \times 5 + 20 \times 4 + 3 \times 3 + 1 \times 2 + 0 \times 1)/199 = 4.85$. After rounding to the nearest half-point, we obtain 5. This is the rating TripAdvisor displays on that date. In the empirical analysis, we compute TA_RATING for year t and restaurant i in the same way as TripAdvisor. That is, as the average across all the ratings a restaurant has received between its first customer review and the end of year t, rounded to the nearest half-point (5 in this case). TA_RATING_UNROUNDED corresponds to the unrounded average (4.85 in this case).

Appendix D. Variable Definitions

ABOVE_VERSUS_BELOW: Dummy variable equal to 1 (0) for a restaurant with unrounded ratings above (below) 1 of the rounding thresholds (1.25, 1.75, 2.25, …). Source: TripAdvisor.

AGE: Number of years since incorporation. Source: Diane.

ASSET_TURNOVER_RATIO: Sales scaled by total assets. Source: Diane.

BANK_DEBT: Bank debt divided by total assets. Source: Diane.

BUILDING: Book value of buildings. Source: Diane.

CASH: Cash and equivalent scaled by lagged total assets. Source: Diane.

CASH_FLOW_VOLATILITY: Standard deviation of EBITDA scaled by total assets over 3 years (between years t and $t+2$). Source: Diane.

CROSS_ROUNDING_THRESHOLD_DOWNWARD: Dummy variable equal to 1 if the restaurant crosses a rounding threshold downward. Source: TripAdvisor.

CROSS_ROUNDING_THRESHOLD_UPWARD: Dummy variable equal to 1 if the restaurant crosses a rounding threshold upward. Source: TripAdvisor.

CUISINE_TYPE: Cuisine types as indicated by TripAdvisor: "French," "Italian," "Japanese," "South-American," "Indian," "Middle East," "Mediterranean," "Other Asian" (Chinese, Thai, Vietnamese, or Cambodian), "Other." Source: TripAdvisor.

DIANE_LIQUIDATION: Dummy variable equal to 1 for restaurants that are liquidated according to Diane in the last year in which their accounting information is available. Source: Diane.

DIANE_STOPPED_OPERATING: Dummy variable equal to 1 for restaurants that stopped operating, according to Diane, in the last year in which their accounting information is available. Source: Diane.

DROP_IN_SALES: The drop in sales over total assets between year $t-1$ and year t is in the bottom 5% of the distribution. Source: Diane.

GOOD_TA_RATING: Dummy variable equal to 1 if a restaurant's rating is greater than 3.5. Source: TripAdvisor.

INTANGIBLE_ASSETS: The sum of start-up costs, R&D, concession, patents, goodwill, other intangible assets, and advances to intangible assets, scaled by total assets. Source: Diane.

LABOR_EXPENSES: Salaries and wages scaled by sales. Source: Diane.

LAND: Book value of land. Source: Diane.

MATERIALS, TOOLS, AND OTHER_TANGIBLE_ASSETS: Book value of Materials, tools, and other tangible assets. Source: Diane.

OTHER_FINANCIAL_DEBT: Other financial debt scaled by total assets. Source: Diane.

POST_TERRORIST_ATTACK: Dummy variable equal to 1 in 2015 and 2016, 0 in 2013 and 2014.

PRICE_RANGE: TripAdvisor's classification into cheap, affordable, and expensive. The variable takes the value 1, 2, and 3, respectively, when the price-range category is "€," "€€–€€€," and "€€€€," respectively. Source: TripAdvisor.

PROFITABILITY: EBITDA scaled by total assets. Source: Diane.

ROA: Net income scaled by total assets. Source: Diane.

SALES: Sales. Source: Diane.

TOTAL_ASSETS: Total assets. Source: Diane.

TA_CLOSED: Dummy variable equal to 1 in the last year in which a restaurant obtains TripAdvisor reviews, and 0 in other years. We first identify restaurants that stop receiving TripAdvisor reviews and then manually check whether they closed using other internet sources. Source: TripAdvisor.

TA_NUMBER_REVIEWS: Number of reviews received by restaurant *i* as at the end of year *t* and used to compute TA_RATING. Source: TripAdvisor.

TA % FRENCH_REVIEWS_LANGUAGE: For restaurant *i* and year *t*, proportion of the reviews written in French. Source: TripAdvisor.

TA % FRENCH_REVIEWS_LOCATION: For restaurant *i* and year *t*, proportion of the reviews written by reviewers residing in France. Source: TripAdvisor.

TA_RATING: For year *t* and restaurant *i*, average rating across all the reviews a restaurant has received as at the end of year *t*, rounded to the nearest 0.5. Source: TripAdvisor.

TA_RATING_UNROUNDED: For year *t* and restaurant *i*, average rating across all the reviews a restaurant has received as at the end of year *t*. Source: TripAdvisor.

TANGIBLE_ASSETS: Sum of land, buildings, plant & equipment, other tangible assets, PP&E in progress, and prepayment of tangible assets, scaled by total assets. Source: Diane.

TOTAL_DEBT: Bank debt plus other financial debt, scaled by total assets. Source: Diane.

Appendix E. The Determinants of Being Above Versus Below a Rounding Threshold

Appendix E presents regressions of ABOVE_VERSUS_BELOW, a dummy variable equal to 1 if a restaurant is above a rounding threshold and 0 otherwise, on lagged values of restaurant debt and other control variables. Control variables are the same as in Table 2 and described in Appendix D. For expositional convenience, coefficient estimates are reported after multiplying the dependent variables by 100. Standard errors clustered at the restaurant level are reported in parentheses.

ABOVE_VERSUS_BELOW	1	2
TOTAL_DEBT		0.06
		(0.067)
ln(AGE)	0.05	0.07
	(0.042)	(0.044)
ln(TOTAL_ASSETS)	−0.01	−0.01
	(0.045)	(0.045)
TANGIBLE_ASSETS	0.07	0.05
	(0.069)	(0.074)
ASSET_TURNOVER_RATIO	0.03	0.03
	(0.022)	(0.022)
PROFITABILITY	−0.09	−0.08
	(0.080)	(0.079)
LABOR_EXPENSES	−0.21	−0.21
	(0.158)	(0.157)
No of obs.	3,465	3,465
TA_RATING_UNROUNDED	Yes	Yes
Year fixed effects	Yes	Yes
Restaurant fixed effects	Yes	Yes
Rounding threshold fixed effects	Yes	Yes
Within R^2	0.656	0.656

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