The Weight of a Star

The impact of the *New York Times* restaurant reviews on Google search queries

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Abstract

Focusing on the *New York Times* restaurant reviews and the impact that they have on individual restaurants, this paper explores the relationship between a review and a restaurant's popularity in Google search queries. The central analysis conducted is an event study that examines growth rates of Google query popularity one week prior to and four weeks after the *Times* review is published. The event study measures the initial impact of the review, but also if there is any lasting effect on the growth rate of popularity. In addition to examining the relationship between reviews and Google search, the sample of *Times* reviews was compared to New York City restaurant data at a population level to establish whether the reviews are a representative sample.

My findings reveal that the *Times* reviews have a strong impact on the average growth rate of query popularity, but that this impact does not last beyond one week. The average growth in query popularity for the first week that a review was published was 87.4%, but fell back to zero at the end of the week. However when examining the growth rates by number of stars received, growth in query popularity persists for four weeks at about 25% for three and four star restaurants. The difference in the initial growth rate also varies dramatically by the number of stars a restaurant received; more so than any variation caused by location, cuisine type, or price. I also found that the *Times* disproportionately reviews restaurants in certain neighborhoods and that serve certain cuisines when compared to the entire population of New York City restaurants.

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1. Introduction

In the world of gastronomy the *New York Times* holds a position of authority in American media that other publications strive for, but none have ever quite achieved. It is well understood that the *Times'* restaurant criticism has an impact on the establishments they choose to review, but beyond a few anecdotes from chefs and restauranteurs, that impact has never been quantified.

A good friend of mine was working at ABC Cocina, of famed French restauranteur Jean-Georges Vongerichten's empire, during its opening and refused to see me at all during the time period between when the staff spotted *Times* critic Pete Wells, and when the actual review was published. I have always been on the customer side of the restaurant industry, so it was only at that moment that I realized the importance of the *New York Times* reviews and the possibility that their impact on restaurants could be dramatic.

Search engine data was used for this study to track the search query popularity of each restaurant before and after the *Times* review was published. At a time when internet usage has surpassed 85% in the United States[1] and Google's national market share is nearly 70%[2], Google Trends has the unique capacity to capture data on the vast majority of internet users. The National Restaurant Association found that roughly half of all adults use the internet to find out about new restaurants to try[3], which reinforces the importance of studying search query data in relation to reviews.

Former *Chicago Tribune* food and wine columnist, William Rice has said, "...restaurant reviewing seems to me, without question, the least understood, the least researched, and the most difficult of the critical arts."[4] This paper seeks to provide some insight into the relationship between critics and the restaurants they review through a study of the *New York Times* reviews and the impact these reviews have on Google search queries. Through my analysis I aim to answer three questions: **(1)** Do the *New York Times* restaurant reviews have a substantial, lasting effect on Google search query popularity for the restaurants reviewed? **(2)** If so, does this impact vary by number of stars awarded, price point, location, or cuisine type of the restaurant? and **(3)** Does the *New York Times* have an implicit selection bias when choosing restaurants to review?

My findings reveal that the *Times* reviews have a strong impact on search query popularity growth rates, but that this impact does not last beyond the week the review is published. However when examining the growth rates by number of stars received, growth in query popularity persists for three and four star restaurants, and the difference in the initial growth rate varies dramatically by the number of stars a restaurant received. I was also able to conclude that the *Times* disproportionately reviews restaurants by neighborhood and cuisine type compared to all restaurants in New York City.

2. Literature Review

2.1 Relevance of Restaurant Reviews

Restaurant reviews are of particular interest because of their innate capacity to shape the field of gastronomy and the way chefs, restauranteurs, *and* consumers think about food. The value of reviews has also been attributed to the idea that recognizing and awarding outstanding restaurants creates competition and promotes a level of excellence that all restaurants will strive for.[5] Mitchell Davis, Executive Vice President of the James Beard Foundation, notes in his

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[1] Pew Research Center, *Internet Use Over Time*. Jan. 2014.

[2] Zeckman, Ashley. "Google Search Engine Market Share Nears 68%." Search Engine Watch. Incisive Media, 20 May 2014.

[3] Ong, Beng Soo. "The Perceived Influence of User Reviews in the Hospitality Industry." *Journal of Hospitality Marketing & Management* 21.5 (2012): 463-85. *Taylor & Francis Online*. 15 June 2012.

[4] Dornenburg, Andrew, and Karen Page. "Is Judging a Restaurant a Matter of Taste?" *Dining Out: Secrets from America's Leading Critics, Chefs, and Restauranteurs.* John Wiley & Sons, 1998. 53-93. Print.

[5] Ong, Beng Soo. "The Perceived Influence of User Reviews in the Hospitality Industry."

PhD dissertation that the industry values reviews because they directly affect business, both positively and negatively, and are the purest form of public relations.[6]

Reviews are also worth studying outside the sphere of chefs and restauranteurs because of the importance consumers place on their content. The impact of reviews on consumer behavior is particularly relevant now that the internet has made both traditional and user generated reviews more accessible. Past literature indicates that reviews serve as a pre-purchase decision making source of information, particularly if goods are psychologically or economically important.[7] Barrows et. al. found in a study (albeit one using a convenience sample of university employees) that restaurant reviews aid in the decision making process in the absence of past experience, recommendations from friends, and advertising.[8] Overall, the recommendation of a friend was most valued, but for those who read restaurant reviews, the reviews ranked near the top of a list of decision making factors in choosing to go to a new restaurant.

Chevalier and Mayzlin found that consumers do not rely solely on summary statistics (star ratings) when reading reviews and that lengthy reviews are regarded as particularly helpful.[9] In a telling example of the power a critic wields, Barrows et al. found that in a hypothetical situation if respondents had read a positive review, but had a negative experience at a restaurant, 30% would assume that the restaurant was just having a bad night. On the flip side, a bad review is widely believed to have the power to shut a restaurant down. In Andrew Dornenburg and Karen Page's book, *Dining Out,* one restauranteur credits former *New York Times* critic, Mimi Sheraton's no-star review of La Coupole with a decline in customers that eventually forced the restaurant to close.[10]

2.2 THE *NEW YORK TIMES* – PREMIER RESTAURANT AUTHORITY

> *"If you are in the food world, as I am, the first thing you turn to in Wednesday's New York Times is the restaurant review. Sometimes you even read it online late Tuesday night...You are compelled to read the review...because you need to know what restaurant has been anointed or trashed. You read it because the New York Times restaurant review is a topic of conversation around water coolers and in chat rooms in professional and amateur foodie circles alike... You read the reviews because you better have something to say."*[11] – Mitchell Davis, Executive Vice President of the James Beard Foundation

While my choice to study the *New York Times* restaurant reviews may be an obvious selection to some, I believe examining the publication's current position in food journalism is important to the scope of my investigation.

2.2.1 CRAIG CLAIBORNE – THE BEGINNING OF A FIELD

Craig Claiborne became the *New York Times'* food editor in 1957, during a time when papers' food sections were predominantly edited by and geared towards women. Restaurants were not regularly reviewed and there was no 'critic' staff position at any paper. What we now take for granted as an established field in journalism was at the time an offshoot of the advertising department, and Claiborne is widely credited with changing that.

Initially he authored brief lists of noteworthy restaurants, which were moved to the Weekend section in 1976 when they were no longer lists, but full reviews.[12] Americans had not been exposed to food criticism at this level of professional journalism before and Claiborne's knowledgeable and authoritative voice made them all take notice and listen. Davis notes that his reviewing style, "...bolstered by the cultural influence of the paper, gave him a dominant position in the field, which is enjoyed by the *Times* to this day."[13]

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[6] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America." Dissertation. New York University, 2009.

[7] Barrows, Clayton W., Frank P. Lattuca, and Robert H. Bosselman. "Influence of Restaurant Reviews Upon Consumers." *FIU Hospitality Review* 7.2 (1989): 84-92. *Digital Commons.* Florida International University.

[8] Barrows et al. "Influence of Restaurant Reviews Upon Consumers."

[9] Chevalier, Judith A, and Dina Mayzlin. "The Effect of Word of Mouth on Sales: Online Book Reviews." Journal of Marketing Research 43.3 (2006): 345-54. Print.

[10] Dornenburg, Andrew, and Karen Page. "The Power of a Review" *Dining Out: Secrets from America's Leading Critics, Chefs, and Restauranteurs.* John Wiley & Sons, 1998. 123-159. Print.

[11] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."

[12] Wells, Pete. "When He Dined, the Stars Came Out." *The New York Times*. The New York Times, 8 May 2012.

[13] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."

His legacy extends beyond his writing for the *Times* and his high standards of conduct in the field of restaurant criticism have become *the* standard across publications. First, he refused to accept free meals in return for a review, insisting all meals be paid for by the *Times*, which is a principle maintained to this day. Second, he visited a restaurant at least three times before publishing a review, which Wells confirms has been standard practice ever since.[14] Finally, Claiborne insisted on complete anonymity which Davis credits as one of the major factors that distinguished the *Times'* reviews and was the driving force behind the paper's ascent in the field of gastronomy.

In more recent years the *Times* critic still proves to be the most influential in the nation. Dornenburg and Page were surprised to find that when they asked chefs across the country about the media with the strongest influence on their restaurants, "without exception, it was the *New York Times* that top chefs from coast to coast cited."[15] Chef Andrew Carmellini believes the *Times* reviews carry a legitimacy that other reviews do not[16], and Blue Hill chef/owner Dan Barber refers to the *Times* critic as "the most powerful restaurant critic in the country" and the "only reviewer who really matters."[17] Davis summarizes nicely when he says "The *New York Times* restaurant review remains the loudest voice because it has so much capital invested in its position and because influential people on *both sides* of the swinging door care what the *New York Times* reviewer has to say."[18] This prominent position in the field of food journalism makes the *New York Times* particularly worthy of study in this paper.

2.3 Other Sources of Restaurant Criticism

In trying to understand how the *New York Times* dominates the field of restaurant criticism I also came across substantial literature describing why other publications and sources of reviews have failed to become as widely read or influential. Priscilla Ferguson argues that there are three types of food critics: the plebiscite, the tribunal, and the judge[19], but neither the Plebiscite nor the Tribunal has been able to knock the *Times* from its dominant position as judge.

The Zagat guide is the most well-known form of the plebiscite, publishing an annual guide based on aggregated consumer surveys. There are a number of issues with the Zagat guide, but the most alarming is its lack of a verification process to establish that reviewers have actually been to the restaurant. In a similar vein the brief comments included in the guide are often so generic they could apply to any restaurant, and the 30-point scales have been extrapolated from actual survey responses recorded on a three point scale.[20] Beyond the questionable numbers in the Zagat guide, the real issue with the plebiscite is the underlying assumption that average opinions are of value in judgements of taste.

The newer 'critic' to fit the plebiscite model is Yelp, a website where anyone can post reviews of restaurants (and other businesses) that include a star ranking as well as the option to write out a full critique. One advantage Yelp has over Zagat is the limitless space for Yelpers to describe their experience and thereby give a more accurate portrayal of the restaurant. More importantly though, writing for *and* browsing Yelp.com are free compared to the roughly $15 that Zagat charges for its guide. But again, the issue with Yelp is that the opinion of many does not necessarily equate to a knowledgeable or trustworthy opinion. Davis points out that following the underlying logic of Yelp and Zagat, the restaurant that would satisfy the most people is McDonalds.

In addition to the plebiscite, Ferguson also describes the tribunal, which consists of an expert panel of judges who convene behind closed doors and publish restaurant criticism collectively. Michelin is the most well-known and influential tribunal, but has failed to take hold and exert as much influence in New York City as it has in Paris. Tribunals operate slowly and often fail to keep up with new restaurants and trends, which in Michelin's case has led to a reputation for traditionalism and 'Frenchness' in its selection of restaurants. A number of prominent chefs have gone so far as to return their Michelin stars because they feel that if they don't cater to the rigid expectations people have of what a Michelin starred restaurant is, customers will leave unhappy with the experience. John Colapinto

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[14] Lehman, Susan. "Restaurant Critic Pete Wells on How He Does His Job." Times Insider. The New York Times, 16 Feb. 2015. Web.
[15] Dornenburg, Andrew, and Karen Page. "The Power of a Review"
[16] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."
[17] Barber, Dan. "The Mouth That Matters." Gourmet 1 Oct. 2007: 80-82. Print.
[18] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."
[19] Ferguson, Priscilla Parkhurst. "Michelin in America." *Gastronomica: The Journal of Food and Culture* 8.1 (2008): 49-55. *JSTOR*. Web.
[20] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."

notes in an interview with a Michelin inspector that five years after coming to New York, Michelin has “failed to knock the *Times* from its perch as the premier arbiter of restaurants in the city, or to outsell the Zagat guide.”[21]

The final category of critic in Ferguson’s taxonomy is the judge, which is the role that the *New York Times* critic assumes. While I have established the *Times’* dominance in the field of food journalism, Ferguson adds that the power of the judge lies in their audience and “the great reach of a major international paper [that] gives the Judges who write for it undeniable clout.”[22] Historically, diners needed the judge because they did not have the detailed knowledge of food that consumers have today. The *Times* began covering restaurants at an opportune moment when the American public was desperately in need of a judge, and no other newspapers at the time were publishing quality food writing. It was the first publication to value and dedicate significant resources to food criticism and the enduring influence of the food critic can now be largely attributed to the esteemed reputation of the *Times* as a whole. Barrows et al. found that “...it is more important... where the review is printed rather than who actually wrote it”[23] which speaks to Ferguson’s point that much of the authority a critic has comes from writing for a major international newspaper. Both the historical dominance of the *Times* and the failure of other publications and critics to challenge its authority highlight the validity of studying the *Times’* reviews in particular.

2.4 The Power of Google Trends

With increased internet usage across the country and the emergence of Google as the leading search engine (to the extent that in 2006, Google was added to the Merriam Webster and Oxford English Dictionaries as a transitive verb[24]), Google Trends data is becoming increasingly relevant and robust. Because the data is relatively new and only dates back to 2004, there are relatively few academic papers using this dataset.

In a study of the modeling ability of Trends data, Vosen and Schmidt found that Google Trends data was a more accurate forecasting model and predictor of private consumption than traditional survey-based indicators when compared to actual aggregate consumption. Their model using Trends data collected on various consumption categories outperformed models using both the University of Michigan Consumer Sentiment Index (MCSI) and the The Conference Board’s Consumer Confidence Index (CCI).[25] They explained their findings by highlighting that while “macroeconomic variables [income, wealth, interest rates] indicate consumers’ *ability to spend* and survey-based indicators try to capture consumers’ *willingness to spend*, the Google indicator intends to provide a measure for consumers’ *preparatory steps to spend* by employing the volume of consumption-related search queries.”[26] Historically both of these indices have been highly regarded standards for gauging consumer sentiment and are widely cited by economists, government agencies, and academics. Vosen and Schmidt’s findings challenge the accuracy of established survey based indicators of economic confidence and highlight the power of leveraging Google Trends as a new data source.

Kulkarni et al. found results similar to Vosen and Schmidt, but within a single industry. Their study was based on the idea that because online search requires action on the part of the consumer, search query popularity can serve as a good indicator of interest or buzz for a topic or product. Their research concluded that search volume is a good measure of consumer interest in the motion picture industry and because films can be researched before they premier, the data has significant forecasting power to accurately predict post-launch sales.[27]

Past research focused on specific industries forms a foundation that is the basis for my research, but perhaps the most relevant to my topic was a study conducted by Hyunyoung Choi and Google’s own Chief Economist, Hal Varian. They illustrate the forecasting value of search query data in relation to retail, automotive, and home sales, and travel. Their findings in the travel industry are particularly relevant due to the fact that both travel and dining can be broadly categorized as leisure activities. Using visitor data from the Hong Kong Tourism Board and Google Trends data on search queries for cities in China, Choi and Varian created a model that predicted total visitors per

[21] Colapinto, John. "Lunch with M. - Undercover with a Michelin Inspector." *The New Yorker.* Condé Nast, 23 Nov. 2009. Web.

[22] Ferguson, Priscilla Parkhurst. "Michelin in America."

[23] Barrows et al. "Influence of Restaurant Reviews Upon Consumers."

[24] Lombardi, Candace. "Google Joins Xerox as a Verb." *CNET News*. CBS Interactive, 6 June 2006. Web.

[25] Vosen, Simeon, and Torsten Schmidt. "Forecasting Private Consumption: Survey-based Indicators vs. Google Trends." *Journal of Forecasting* 30 (2011): 565-78. *Business Source Complete*. Web.

[26] Vosen, Simeon, and Torsten Schmidt. "Forecasting Private Consumption: Survey-based Indicators vs. Google Trends."

[27] Kulkarni, Gauri, P.K. Kannan, and Wendy Moe. "Using Online Search Data To Forecast New Product Sales." Decision Support Systems 52.(2012): 604-611. ScienceDirect. Web.

month. When compared to actual visitor numbers the fit of the model had an R^2 value of 0.733, which indicates their model explains 73.3% of the variation in actual visitor numbers.[28] Across the various industries studied, they found that autoregressive models including relevant Trends data outperform models that do not include search engine data by five to twenty percent.[29]

Investigating the *New York Times* impact on search queries and *subsequent sales* at the restaurants reviewed is not within the scope of this study, but the fact that this link has been established at an aggregate consumption level and within a variety of industries (some more similar to the restaurant industry than others) motivates my research and substantiates my findings.

3. DATA

3.1 THE *NEW YORK TIMES* REVIEWS

Currently there is no public database of historical *New York Times* restaurant reviews, but from 1994 onwards they are all archived on the *Times'* website. I manually and entered each review into a database and coded variables that the *Times* provides in the review: price range, address, cuisine, and of course the number of stars. For a detailed list of variables and categories see Appendix A.

I drew my sample of reviews from the time period from April 2010 to February 2015, which includes the reviews of two critics: Sam Sifton, who was critic for two years, and his successor and current critic, Pete Wells who took over the position in November 2011. During this five year period 228 reviews were published, all of which were included in the initial dataset.

Each review includes a star ranking of the restaurant and a detailed write up that often addresses topics like note-worthy dishes, service, ambience, décor, etc. The *New York Times'* awards stars on a scale of 0-4, with the following equivalencies:

★★★★ - Extraordinary, ★★★ - Excellent, ★★ - Very Good, ★ - Good, and [ZERO] - Satisfactory/Poor

The bottom of each review contains the following explanation: "**WHAT THE STARS MEAN** Ratings range from zero to four stars and reflect the reviewer's reaction primarily to food, with ambiance, service and price taken into consideration." Current critic Pete Wells says that this short sentence is the only written guideline he has ever seen or heard of for determining the number of stars a restaurant receives.[30]

3.2 GOOGLE TRENDS

Google Trends data was collected individually for each restaurant using the name of the restaurant as the keyword input. All results were collected during a three day period from March 16, 2015 to March 18, 2015. Google Trends allows the user to selectively limit the data displayed by geography, time period, and a number of broad content categories. For this paper, results were limited to the United States due to the fact that the *Times* is a national paper and, though the restaurant reviews are perhaps more relevant to readers in the NYC metro area, they are still read by a large audience outside of New York. The time period was limited from March 2010 to March 2015 in an attempt to reduce the influence of low internet and/or search engine usage prior to 2010. In 2004, which is the earliest date Google Trends data is available, only 60% of adults in the United States used the internet, whereas by 2010 that number had reached 80%.[31] This time period also allows search data to be captured one month prior to the first review in my sample, and one month after the final review.

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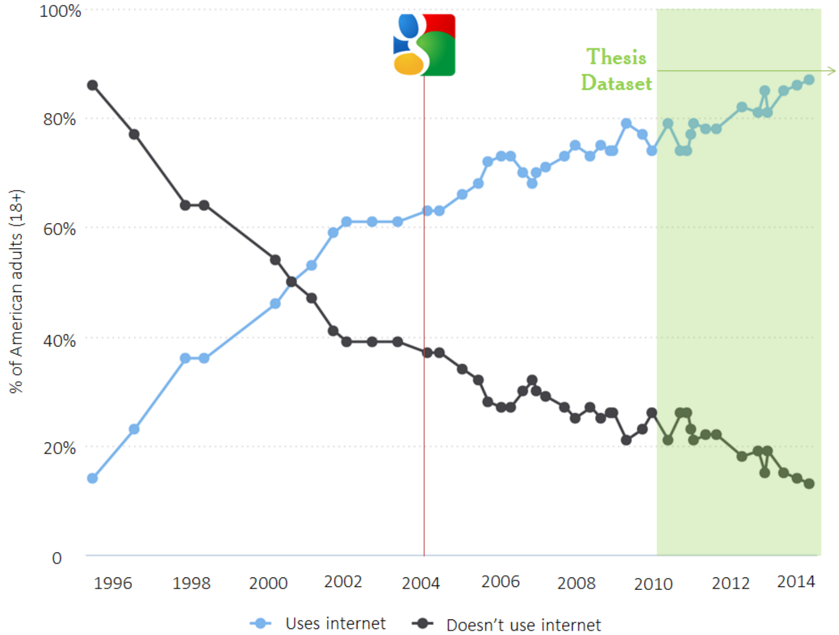
[28] Choi, Hyunyoung, and Hal Varian. "Predicting The Present With Google Trends." Economic Record 88.(2012): 2-9. Business Source Premier. Web. 2 May 2015.

[29] Choi, Hyunyoung, and Hal Varian. "Predicting The Present With Google Trends."

[30] Wells, Pete. "Our Readers See Stars, and Ask Why." *Diner's Journal*. The New York Times, 13 Mar. 2012. Web.

[31] Pew Research Center. "Internet Use Over Time."

FIGURE 1 – INTERNET USAGE IN THE U.S.



Because Google Trends only collects data on the search queries that Google receives, the company's share of the search engine market was also an important factor in determining the time period for data collection. In 2004 the percentage of search engine users that reported using Google was 47%, but by 2012 that number was 83%.[32]

The output for all Trends data is an indexed value of the ratio of searches for the specific keyword to the total number of searches. The highest level of popularity a restaurant's keyword receives over the observed time period is assigned a value of 100 and all other values are indexed from zero to 100 accordingly. The indexed values are provided by Trends as weekly averages. In the case where there is enough data to produce a time series, but not at the weekly level, Trends automatically reports the data as monthly averages.

The ratio of keyword searches to total searches controls for changes in total search volume over time. The indexed value essentially represents the popularity of the keyword over time. For this paper, all keywords are the names of the individual restaurants reviewed. Because the popularity values are indexed from 0 to 100 for each restaurant the indexed values cannot be compared across the various restaurants. In order to address this issue and understand the impact of the *Times* reviews, growth rates of search popularity were calculated; this is explained further in Section 5. The combined database of *Times* reviews and Google Trends data allowed me to address the first two questions proposed in the introduction: **(1)** Do the *New York Times* restaurant reviews have a substantial, lasting effect on Google search query popularity for the restaurants reviewed? **(2)** If so, does this impact vary by number of stars awarded, price point, location, or cuisine type of the restaurant?

3.3 DEPARTMENT OF HEALTH AND MENTAL HYGIENE INSPECTION RESULTS

To address the third question of whether the *Times* had reviewed a representative sample of New York City restaurants, I had to find a way to acquire restaurant data on New York City at the population level. I wanted to examine the *Times* sample of restaurants over the past five years in relation to the New York City population by cuisine type and location. Every restaurant in New York City has at least one unannounced inspection per year conducted by the Department of Health and Mental Hygiene (DOHMH) and receives a letter grade result. The City of New York recently launched an initiative to provide public data in an accessible format online and through NYC OpenData website I was able to access the database of all DOHMH inspections, which in addition to the letter grades, includes the full address of each restaurant and categorization by cuisine type.

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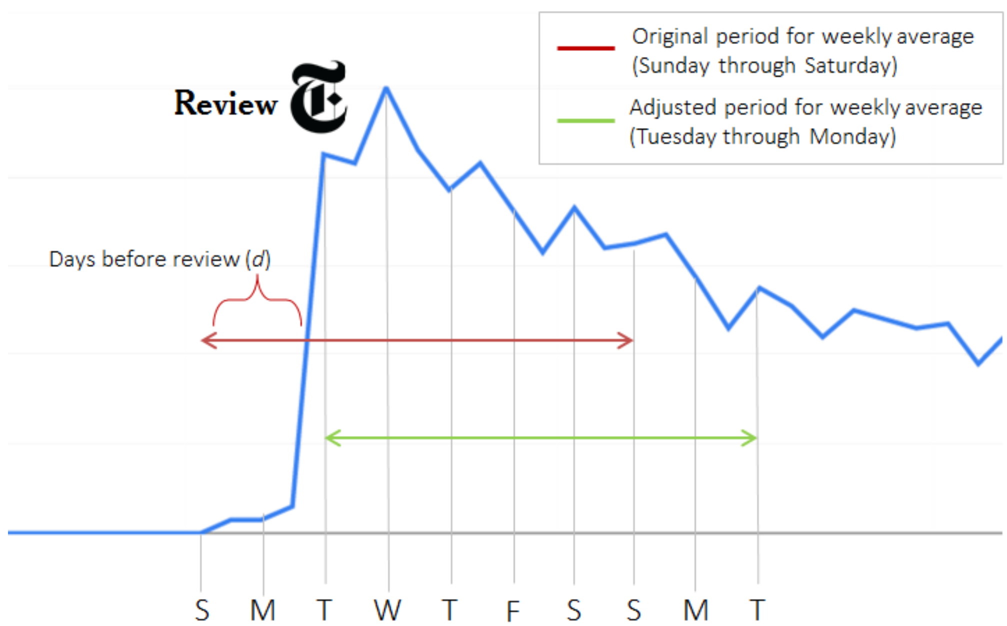
[32] Purcell, Kristen, Joanna Brenner, and Lee Rainie. "Search Engine Use 2012." *Pew Internet & American Life Project*. Pew Research Center, 9 Mar. 2012. Web.

3.4 Adjustments to the Data

Google Trends returns data at the weekly level, specifically from Sunday through Saturday, but the *Times* reviews are published Tuesday online and Wednesday in print. Therefore the weekly averages from Google Trends are an incorrect measure of the search volume *after* the review is published because they include two days (Sunday and Monday) before the review is published. It is assumed that including these two days (*d*) brings down the weekly average because the review would have no impact on the search queries before it is published. Because the reviews are published on Tuesday, the adjustment essentially manipulates the data so that weekly averages are calculated from Tuesday through Monday rather than Sunday through Saturday. The adjustment has been represented graphically below:

Figure 2 – Adjustment to Time Period for Weekly Average



Using the following values, I derived a formula to adjust the raw Google Trends averages to more accurately reflect when the *Times* reviews are published.

G_x = Google Trends weekly index value for Week (*x*)
G_{t-1} = Google Trends weekly index value for Week (*t-1*)
G_t = Google Trends weekly index value for Week (*t*)
d = days in Week (t) before the review was published

The assumption with my adjustment formula is that those days (*d*) have an actual Google Trends value of G_{t-1} because they occur before the review has been published and are artificially lowering the week (*t*) average (G_t). So to find the actual Google Trends value for the week after the review, the following adjustment formula was used:

$$G_x = \frac{7 \cdot G_t - d \cdot G_{t-1}}{7 - d}$$

In the same way that G_t is artificially low because of the few days included in the average that occur before the review, the weekly average for week (*t+1*) is artificially high because the days in the beginning of the week are actually part of that initial week after the review. For this reason, the adjustment formula has also been applied to the Google Trends values for the weeks following the review so that all the data is essentially shifted *d* number of days.

A similar issue presents itself for the restaurants that have monthly Google Trends data because the *Times* reviews were often published mid-month, so the raw Google Trends values are not an accurate representation of search query popularity before and after the review. A similar formula was applied, though in this case the assumption is that those days (*d*) in Month (*t*) have an actual Google Trends value of (G_{t-1}). An additional assumption that each month has thirty days was made to standardize the formula. For a more detailed explanation of both formulas see Appendix B.

In the future, when week *t* and its corresponding Google Trends value G_t are referred to, they represent the exact week after the review is published and the relative popularity of the restaurants' search query after the review rather than the deflated average from the Google Trends raw output.

4. Analysis

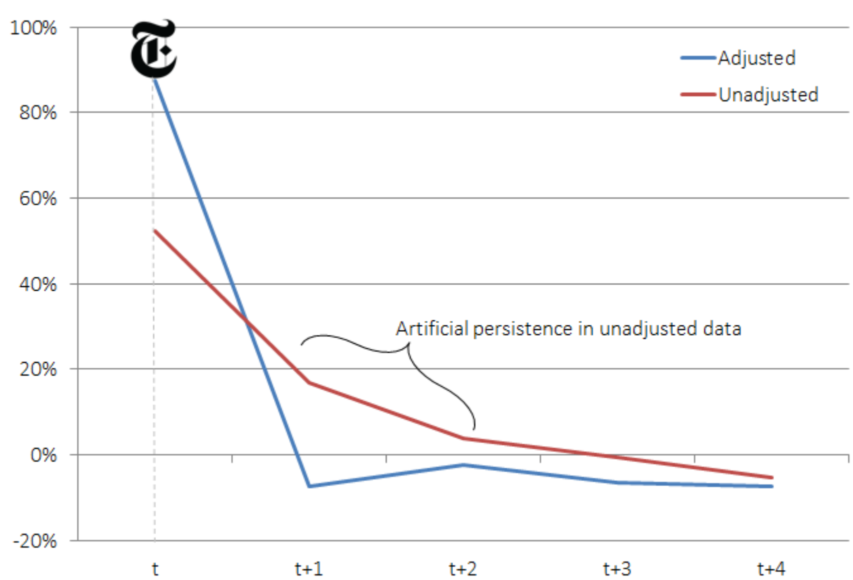
Google Trends provides an indexed value of the volume of keyword search queries compared to the total volume of search queries over a specified time period. As previously noted, I restricted the Trends data collection to the United States and the time period of March 2010 to March 2015. In order to conduct an event study to understand the impact of the reviews, I computed growth rates based on the change in Trends index values over time. The period of my analysis is one week prior to the review to four weeks after to measure whether any impact is lasting. Growth rates between indexed values therefore represent the changing popularity of a search term (in this case, a restaurant) rather than the total or absolute search volume for the term.

4.1 Growth Rate Calculation

Because Trends provides an indexed value of the average popularity of a query relative to the total number of searches that week, the raw weekly averages for each restaurant cannot be compared. Computing the growth rates over time of these values makes them comparable, and shows the longevity of any impact. Where week *t* is the week the review was published and the six days after, and week *t-1* is the week before, all growth rates were calculated in reference to week *t-1* as the historical value. In order to measure any lasting effect, the time period included in this analysis is the week before the review through the fourth week after the review is published.

Because of the time series discrepancy of the Trends data, I first analyzed the larger series of weekly data to see if there were any outcomes that would inform my analysis of the monthly data. Looking at average growth rates around the date of the review it became clear that there was no persistent impact on search query popularity beyond the week that the review was published. The comparison between average growth rates calculated with the adjusted data and unadjusted data can be seen below in Figure 3.

Figure 3 - Adjusted v. Unadjusted Growth Rates



4.1.1 Monthly Stacking

Under the assumption that the average monthly data was an aggregation of weekly data, and the impact of the *Times* reviews was obscured because of the aggregation, the dataset that included monthly data was adjusted. I manipulated the data to essentially stack the indexed Trend value higher in the beginning of the month when the review was published (the data had already been adjusted to assume the review was published at the beginning of the month – see Section 3.4).

In this adjustment, the monthly data is corrected to assume that the impact of the review is observed only during the week the review came out and that the actual indexed value of search query popularity fell during the weeks after the review. In order to correct the smoothing effect of averaging the data at a monthly level, the formula used assumes 4.3 weeks per month and adjusts the monthly value to a single Google value for the week of the review. The scale of this data then matches the rest of the data at the weekly level. I assume that the values for the four weeks after the review are equal to month t+1 values from the original Trends output.

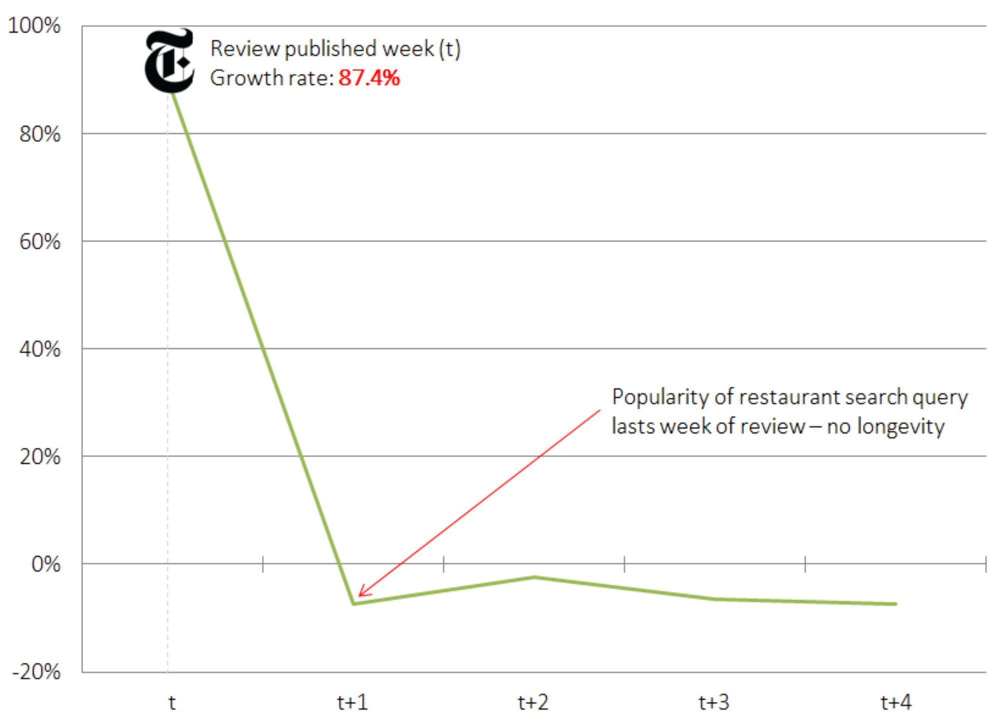
$$G_x = 4.3G_t - 3.3G_{t+1}$$
$$G_{t+1}, G_{t+2}, G_{t+3}, G_{t+4} = \ Monthly\ G_{t+1}$$

This correction assumes quick decay in the popularity of restaurant searches, which was based off of analyzing average growth rates from the weekly dataset. However, this monthly stacking will slightly minimize any lasting impact that may be exposed analyzing the grown rate by price, location, and cuisine. However, because the amount of data that I have applied the stacking correction to is relatively small (less than 35% percent) my findings should not be greatly altered. Finally, the growth rates for the monthly-adjusted-to-weekly dataset were calculated. After this adjustment, all Google Trends data is now on the same time scale and can be compared because of the growth rate calculation.

4.2 Average Growth Rates

To understand the overall impact of the *New York Times* restaurant reviews on restaurant search query popularity, I calculated the average growth rates over the specific time period. The results are displayed in Figure 4 and it is immediately clear that (1) there is a strong and immediate impact and (2) it does not persist beyond the week of the review.

Figure 4 – Average Growth Rates



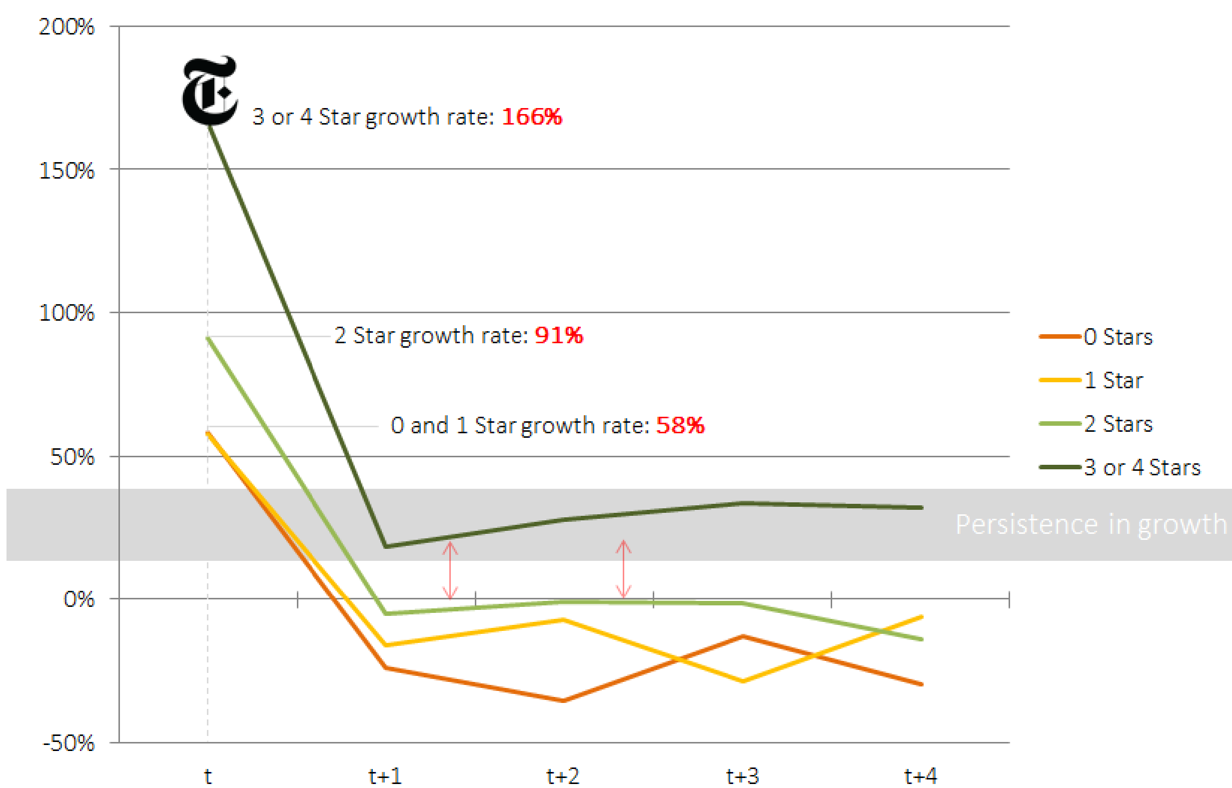
4.3 GROWTH RATES BY CATEGORIES

The next step to understand the impact of the reviews was to analyze the average growth rates by the four categories mentioned prior: stars received, price point, location, and cuisine type. For all the regressions conducted in the following sections, categories are dummy variables, so the coefficients represent the average growth rate and the regression tests for statistical significance.

For the category of stars, restaurants that received three and four stars were grouped together due to a small sample of four star restaurants (n=5). Each category (one star, two stars, etc.) was a dummy variable in a regression with the growth rate from week (t-1) to week (t) as the dependent variable to check for statistical significance. The full output of this regression can be seen in Appendix C.

Two observations become immediately apparent in Figure 3 below: (1) the initial growth rate varies dramatically based on the number of stars a restaurant receives and (2) there *is* persistence in growth as highlighted by the grey rectangle. Search query popularity for those restaurants that received 0-1 star grows by 58%, for those restaurants that received 2 stars query popularity grows 91%, and most substantially for restaurants that received 3 or 4 stars query popularity grows 166%.

FIGURE 3 – AVERAGE GROWTH RATES BY STARS RECEIVED



Perhaps the more important, but less obvious insight that this graph reveals is that the growth in search query popularity actually persists for restaurants that received 3 or 4 stars. This indicates that the *New York Times* reviews have a significant and *lasting* impact specifically on restaurants that received 3 or 4 stars. The persistence is highlighted on the graph with a grey rectangle, where growth rates remain above zero for the four weeks after the review is published. While it seems that stars are the driving force behind the varying growth rates, I also examined the influence of price point, location, and cuisine type.

When represented graphically, it appeared as though growth rates by the various price points varied significantly. The low ($) price point in particular had a much higher average growth rate for week (*t-1*) to week (*t*) than all the other price points. However, the sample size for this price point is small (n=7) and upon further analysis I found that the one dollar sign ($) price point has a much lower average week (*t-1*) index value than all the price points ,which explains why comparatively the initial growth in query popularity for this price point seemed so high.

Because the sample was so small for the lower price point, I decided to convert the dummy variables for each price level to a single continuous variable. The *New York Times* specifies a range of dollar amounts for each price level, so to create a continuous variable I used the midpoint dollar value and assigned it to the various price levels. To determine which category was a larger driver of variation in the growth rates, I regressed number of stars and the continuous price variable on growth rate from (*t-1*) to (*t*). When both stars and price were included in the regression, the coefficient for price was still statistically significant, but much smaller than the coefficients for the levels of star ranking indicating that the stars still have a greater impact on variation in growth rates.

For the location category, my original dataset had eleven neighborhoods coded as dummy variables. However, when I regressed all eleven neighborhood variables on growth rate (*t-1*) to (*t*), a number of coefficients were statistically insignificant. I still believed that location could be a factor in explaining variation in growth rates, so the neighborhoods were recoded into broader areas: uptown, midtown, downtown, and outside of Manhattan. When I conducted the second regression with the broader location categories, all coefficients (average growth rates) were statistically significant. Again, to understand whether the variation in growth rates was better explained by the location of a restaurant or the stars it received, I ran a bivariate regression with broad neighborhood dummy variables and star dummy variables as the predictors, and growth rate from (*t-1*) to (*t*) as the dependent variable. Similarly to the price category, coefficients for location became statistically insignificant in the bivariate regression, while all coefficients for the star dummy variables remained significant. This again means that stars are a more important explanation for variation in growth rates than both price and location of a restaurant.

Finally, I believed the type of cuisine that a restaurant serves would be a major factor in the variation between the query growth rates. To investigate this hypothesis, ten cuisine categories were regressed as dummy variables on growth from week (*t-1*) to week (*t*). As was the case with my initial neighborhood categories, a number of the average growth rates by cuisine were statistically insignificant. The cuisine types were recoded into four broader categories: American, Asian, European, and Other. When these four categories were regressed on growth the results returned statistically significant results. However, when I conducted a bivariate regression including stars, the coefficients for cuisine type were no longer significant.

From these bivariate regressions (the full output of all these bivariate regressions can be found in Appendix D) it is evident that the primary driver of variation in growth rates is the number of stars a restaurant receives in the review. This insight further underscores the *New York Times*' strong influence in the field of restaurant criticism. Not only does publishing the review drive up the popularity of searches for the restaurant, the star ranking each review includes also dictates exactly how much the popularity of queries for a restaurant will increase.

4.4 Implicit Selection Criteria

The database that I created for this paper includes the 228 restaurants reviewed by the *New York Times* over a period of time from April 2010 to February 2015. I wanted to investigate whether these restaurants were a representative sample of the New York City restaurant landscape as a whole with regard to cuisine type, and location. The Department of Health and Mental Hygiene database of restaurant inspection results was used to understand the breakdown of restaurants by location and cuisine type at the population level. Because mandatory unannounced inspections occur *at least* once per year, the original DOHMH database covers every restaurant in New York City including smaller establishments that sell food like roadside hotdog and pretzel carts. In order to make my comparison of restaurants more accurate, I excluded single item stands and food carts from the population data (see Appendix E for list of exclusions). After exclusions, the population dataset includes 17,667 restaurants in the five boroughs of New York City.

Dividing the *Times* sample by cuisine type and location results in relatively small sample sizes for the subcategories (in some cases n<20), so I decided not to conduct z-tests to measure differences in proportions. Rather, I selected 5% as a threshold of difference that would be interpreted as significant in terms of over- or under-representation (i.e. if the difference between total NYC and *Times* proportions is greater than |5%| I interpreted the result as significant).

Current restaurant critic Pete Wells, claimed in an interview that when choosing restaurants to review he "look[s] for something a little unusual, like a neighborhood that isn't really on the foodie radar, or a cuisine that hasn't reached market saturation yet"[33] and since he penned roughly 65% of the *Times* reviews sampled for this paper we can see if that statement is true.

In the comparison of proportions by cuisine, all the restaurants in both the *Times* sample and New York City population were grouped into ten categories. Early in the analysis when I had only calculated the *Times* proportions, one observation that stood out was the complete lack of reviews of African restaurants, but compared to the 1% of all restaurants in New York City that are African this apparent exclusion is not far off from being representative. The two cuisines that are actually underrepresented in the reviews are Chinese and Latin American/Spanish. The two over-represented cuisines in the sample are French and Italian restaurants. Table 1below details the results of cuisine proportion comparisons.

TABLE 1 – SAMPLE/POPULATION COMPARISON BY CUISINE

Cuisine	NYT Proportion	NYC Proportion	Difference
French	11.1%	2.0%	**9.2%**
Chinese	5.3%	14.1%	**-8.8%**
Latin American/Spanish	10.2%	17.9%	**-7.7%**
Italian	15.1%	8.6%	**6.5%**
American	30.7%	35.4%	-4.7%
European	6.7%	3.4%	3.2%
Japanese	7.1%	4.4%	2.7%
Asian	7.1%	5.7%	1.4%
African	0.0%	1.0%	-1.0%
Mediterranean/Mid. Eastern/Indian	6.7%	7.6%	-0.9%

To Wells' credit, these cuisine categories do not include fusion, avant-garde, molecular gastronomy and the likes as their own categories. Restaurants that are experimental or serve a new interpretation of traditional cuisine for example, are included in the count of their overarching cuisine type, suppressing some of the possible differentiation. Additionally, it is not as easy to categorize cuisine as it is to group the restaurants by a more concrete variable like zip code, so some of the restaurants could arguably be included in multiple categories.

Looking at representation by location, I first examined the data at the borough level. Comparison of the proportions can be seen in Table 2.

TABLE 2 – SAMPLE/POPULATION COMPARISON BY BOROUGH

Borough	NYT Proportion	NYC Proportion	Difference
Manhattan	84.0%	41.0%	**43.0%**
Queens	3.1%	22.4%	**19.3%**
Brooklyn	11.1%	24.2%	**13.1%**
Bronx	0.4%	8.6%	**-8.1%**
Staten Island	0.4%	3.7%	-3.3%

The NYT Proportion column indicates the percentage of restaurants reviewed that were in each borough. The NYC Proportion column shows the percentage of all the restaurants in New York City in each borough. From this analysis it is clear that the *Times* over-represents Manhattan by about 40%, and under-represents Queens, Brooklyn, and the Bronx.

Because of the high concentration of restaurants reviewed in Manhattan, I chose to look at a breakdown of neighborhoods within Manhattan and compare the *Times* sample to the proportion of restaurants in each

[33] Lehman, Susan. "Restaurant Critic Pete Wells on How He Does His Job."

neighborhood as a population. Neighborhoods were determined by zip codes, so the comparison between sample and population is accurate. Results are below in Table 3.

TABLE 3 – SAMPLE/POPULATION COMPARISON BY NEIGHBORHOOD (MANHATTAN)

Neighborhood	NYT Proportion	NYC Proportion	Difference
Gramercy	20.1%	8.53%	**11.6%**
Soho	12.2%	3.69%	**8.5%**
Upper Manhattan	0.5%	8.88%	**-8.4%**
Midtown	14.8%	22.64%	**-7.8%**
Upper East Side	9.5%	13.56%	-4.0%
West Village	7.4%	4.01%	3.4%
Lower Manhattan	12.2%	9.49%	2.7%
East Village/LES	9.0%	7.39%	1.6%
Upper West Side	4.2%	5.52%	-1.3%
Chelsea	10.1%	8.94%	1.1%

Of the neighborhoods within Manhattan the differences in proportions are certainly much less than 43%, however there are still some neighborhoods that have disproportionate coverage in the *Times*. Specifically, Midtown and Upper Manhattan restaurants are under-represented in the sample of restaurants reviewed and Soho and Gramercy restaurants are over-represented.

The most significant difference however is almost 12% in the Gramercy neighborhood, where 20% of the restaurants reviewed by the *Times* are located, but only 8.5% of total restaurants are located. I was interested in trying to explain the biased representation of this area, specifically the 10003 zip code which has a higher concentration of restaurants reviewed than any other zip code. As it turns out, this zip code is part of a U.S. Census Bureau tract where the median household income is $153,472[34] which almost exactly aligns with the $158,186 median household income of online *New York Times* readers, and is still incredibly close to the $173,807 median HHI of the traditional print *Times* subscribers.[35]

5. DISCUSSION

The scope of this paper does not include an investigation into *why* some of the relationships I have uncovered exist, but in this section I propose a number of possible explanations for my findings.

The first significant finding was that on average, search query popularity for restaurants increased 87.4% the week after the *New York Times* review was published. However, this large impact on query popularity does not persist for more than that initial week. I believe this strong immediate impact and lack of persistence has to do with the fact that the *Times* publishes a new restaurant review every week. Subscribers who regularly read the reviews are likely aware that they are published weekly and keep up with the most recent review that comes out. If they decide to Google a restaurant it would likely be for the one most recently reviewed, suggesting that a search for that restaurant would be isolated to the initial week (*t*) before the next review comes out. This would explain why for every restaurant reviewed, the spike in search query popularity occurs during week (*t*) and does not persist after that week. Even if it is assumed that not all people read the restaurant reviews regularly, someone who visits the site for the first time will be directed to the most recent review before reviews from prior weeks since articles are sorted by date. Both of these instances would explain the initial growth in query popularity for week (*t*), but also why the effect does not persist beyond one week.

I also believe that readership may have something to do with the variation in growth rates by number of stars. It seems reasonable to assume that most people who read the restaurant reviews have done so before and are likely aware of the lack of three and four star reviews (and if not, they would still know from the scale that more stars are

[34] "Median Income by ZIP Code Based on U.S. Census Bureau Data." Median Income Across the US. WNYC. Web.
[35] *The New York Times Media Kit.* The New York Times. Web.

better). In my five year sample of 228 reviews, only five restaurants received four stars and twenty restaurants received three stars. Therefore, because three and four star reviews are scarcer, their impact is more substantial when they *are* published. Google Trends measures the popularity of a restaurant as a search term, not the number of people who read reviews, which means that for a restaurant to have higher search popularity on Google there had to be something about the review that caused the reader to investigate the restaurant further. If readers consistently see reviews for one and two star restaurants, a four star review is more of an exception and they may go out of their way to find out more about the restaurant.

A second finding revealed in the analysis of growth rates by number of stars is that the growth rate of query popularity persists for four weeks after the review is published at around 25% for three and four star restaurants. This may also be attributed to readers recognizing that these reviews are exceptions and seeking out information on three and four star restaurants even if they are not the most recently reviewed. The lack of persistence for zero, one, and two star restaurants may be because one and two star reviews are fairly run-of-the-mill and consumers lose interest once a new review is published. Because three and four star reviews are exceptional, consumers seek them out and search for more information even if the review isn't current, which explains the persistent growth four weeks after the publication of a three or four star review.

Another possible explanation is that other media outlets cover restaurants that the *Times* critic has awarded three or four stars. Again this has to do with the idea that these reviews (and restaurants) are the exception and may be especially worthy of coverage. Davis found that a large proportion of other publications will actually cover not just the restaurant, but the actual *Times* review and comment on the critic's opinion as an article or story.[36] If this is the case the *Times* can be credited as the catalyst, with the persistence in growth coming from indirect coverage of the restaurant in other publications. My study does not explain *why* the query popularity increases or persists in certain cases, only that it does, but these seem like reasonable explanations in the absence of other evidence.

This paper also does not investigate whether the *New York Times* tailors its restaurant reviews to its readership, but that could be the reason for the clear selection bias towards certain neighborhoods and cuisine types. While I did not have a way to divide the entire New York City population by the four price levels the *Times* uses in its reviews I analyzed the proportions *within* the sample and 77% of the restaurants reviewed are in the third ($$$) and fourth ($$$$) tier price points – which in exact dollar terms indicates that a meal at any of these restaurants would cost over forty dollars (excluding drinks and tip).[37] According to the *Times'* media kit, median household income for online and print subscribers is roughly $160,000, so the tendency to review higher priced restaurants again may be to appeal to its readership. It is worth noting that the *Times* has no obligation to provide a perfectly representative sample of New York City restaurants.

Another explanation for the disproportionate coverage is that the *Times* has other food/dining columns that include coverage of restaurants but are entirely separate from the star-ranked reviews that the critic writes. In this paper, the only reviews examined were written by the restaurant critic and always included a star ranking. It would be an interesting continuation of this study to look at all the restaurants the *Times* has profiled and see if this sample is more representative than just the critic's reviews.

6. Conclusions

The main objective of my research was to show that the *New York Times* restaurant reviews have a statistical impact on popularity of the restaurant in Google search queries. Through this study I have shown that it not only has an impact, but a substantial immediate one at that. On average, search popularity for restaurants reviewed in the *Times* increases by 87.4% the week that the review is published. However, at an aggregate level, this impact is short-lived and does not persist beyond the week of the review.

Through my efforts to understand the change in search query popularity at a more detailed level, I found that the main driver of variation in the growth rates is the number of stars a restaurant receives from the *Times*. Restaurants that received three or four stars saw their query popularity increase 166%, while restaurants that received two stars saw an increase of 91%, and restaurants that received one or no stars a 58% increase. The scope of my study also investigated whether search query popularity was influenced by cuisine, location, or price, but in every case

[36] Davis, Mitchell. "A Taste for New York: Restaurant Reviews, Food Discourse, and the Field of Gastronomy in America."

[37] *The New York Times Restaurant Key: Prices*. Dining & Wine. The New York Times. Web.

bivariate regression analysis revealed that the underlying driver of variation was still the number of stars a restaurant received. I also found that the impact of a *Times* review does have a lasting impact for restaurants that were awarded three or four stars. Growth rates of keyword popularity remain at roughly 25% for four weeks after the review was published.

Finally, I was able to identify that the restaurants reviewed by the *New York Times* are not a representative sample of New York City restaurants. The *Times* over represents the borough of Manhattan, specifically the neighborhoods of Gramercy and Soho. Perhaps not surprisingly, restaurants that serve French or Italian cuisine are also dramatically oversampled. On the flipside, Queens, Brooklyn, and the Bronx are underrepresented in the *Times* coverage as are restaurants serving Chinese and Spanish/Latin American cuisine.

6.1 Implications for Restaurants

The most significant implications of this study affect the overall restaurant industry. Restaurants already want to be reviewed by the *New York Times* for a number of reasons, but given the profound impact reviews have on restaurant search popularity, management has an even greater incentive to get the *Times* critic in the door. Though I did not directly link increased search popularity to increased sales in this study, prior literature suggests it is a very likely relationship. However, a restaurant can neither buy nor request a review, which means encouraging the *Times* critic to visit primarily has to be done by creating hype and maintaining a certain level of relevance in the overall food environment of New York City. Wells said himself that some restaurants become mandatory to review because you hear so much about them, most often because they are backed by a celebrity chef or restaurateur, and want to see what they're like for yourself.[38]

The second major implication, derived from the first, is the inherent value of being able to recognize and influence the *New York Times* critic. In the context of my study, if a restaurant can affect the number of stars they are awarded by providing an above-average experience, they also manipulate the growth in popularity of the restaurant in Google search queries (particularly if they are awarded three or four stars). Anecdotes from chefs and restauranteurs abound about what it's like behind the swinging door once a critic is spotted. Dan Barber described the paramount attention to detail that pervaded every aspect of Blue Hill when he and the staff thought former *Times* critic, William Grimes, was in the building (ironically it was not actually Grimes, but instead a loyal customer who Barber partially credits for Blue Hill's two star review)[39]. During her stint as *Times* critic, Ruth Reichl famously penned a two part review of Le Cirque, noting dramatic changes in the experience from her first three incognito visits to subsequent visits after the staff had recognized her.[40] Obviously critics' efforts to stay anonymous are to prevent this from happening, but nowadays anyone can Google Pete Wells and his photo comes up. Jeffrey Tascarella, food and beverage manager at the Nomad said, "In the back of every restaurant, I guarantee, there is a board with all the thank you notes – and a picture of Pete Wells"[41] which speaks to the increasingly difficult task of remaining anonymous.

6.2 Future Research

This study has shown that the *New York Times* restaurant reviews have a large impact on Google search queries. A more consequential study would be to investigate the link between a review in the *New York Times* and revenue growth (or decline). This suggested research would, in addition to the insights on search queries provided in this paper, quantify the economic impact for restaurants of the *Times* dominant position in the field of restaurant criticism.

[38] Lehman, Susan. "Restaurant Critic Pete Wells on How He Does His Job."
[39] Barber, Dan. "The Mouth That Matters."
[40] Reichl, Ruth. "Restaurants." New York Times 29 Oct. 1993. Web.
[41] Tascarella, Jeffrey, and Laura Wagstaff. "The Inside Scoop on How Restaurants Work." Taste Talks. Wythe Hotel, Brooklyn. 13 Sept. 2014. Panel Discussion.

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APPENDIX A – VARIABLES AND CATEGORIES

The following variables were included in the database of restaurant reviews:

Review Date	Street Address
Restaurant Name	ZIP Code
NY Times Stars	Neighborhood (string)
Critic	Neighborhood (dummy)
Price Point	Area (string)
Cuisine Type (string variable)	Area (dummy)
Cuisine Type (dummy variables)	Borough
Broader Cuisine Type (string)	Google Trends Index Values (week t-1, to week t+4)
Broader Cuisine Type (dummy)	Growth Rates

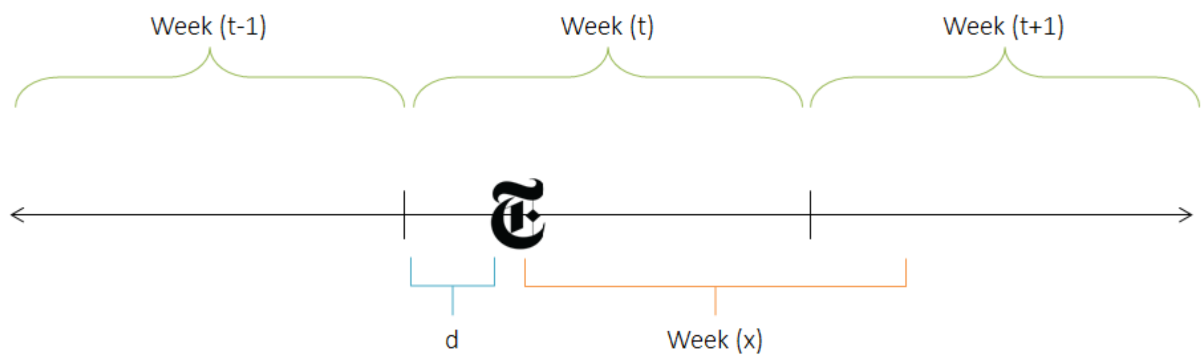
For cuisine type, the **bold** labels represent categories that were used in my analysis, and the subcategories below are the cuisines that were included within those categories.

American	**Latin American/Spanish**
Barbecue	Mexican
Steakhouse	Brazilian
Hamburgers	Caribbean
American	Spanish/Tapas
Asian	**Chinese**
Korean	**French**
Southeast Asian	**New American**
Thai	Contemporary
European	**Mediterranean, Middle Eastern, Indian**
English	Greek
Scandinavian	**Italian**
Eastern European	Pizza
German	Seafood
Japanese	
Sushi	

The neighborhood categories were determined in order to map distinct areas that the *Times'* reviews covered by zip codes of the restaurants. Categories in parentheses are the area categories used for the analysis in Section 5.3.

Brooklyn (Outside Manhattan) – 11201, 11206, 11211, 11215, 11217, 11222, 11235, 11231, 11249
Chelsea (Midtown) – 10001, 10011
East Village/Lower East Side (Downtown) – 10009, 10002
Gramercy (Midtown) – 10010, 10003
Lower Manhattan (Downtown) – 10004, 10005, 10007, 10013, 10282
Midtown (Midtown) – 10016, 10017, 10018, 10019, 10036
Soho (Downtown) – 10012
West Village (Downtown) – 10014
Upper East Side (Uptown) – 10021, 10022, 10075, 10028, 10065
Upper West Side (Uptown) – 10023, 10024
Other (Outside Manhattan *except one restaurant in Harlem which was included in the Uptown category) – 10027, 10304, 10462, 11101, 11105, 11355, 11367
The Other category includes Queens, Harlem, Staten Island, and the Bronx.

Appendix B – Adjustment Formulas



The visualization above underscores the issue with the raw output from Google Trends. The problem lies in the fact that for Week (t), the weekly average includes the index values for those days (d) before the review was published. In order to correct for that, I essentially recalculated the average for what is indicated above as Week (x) and that became the adjusted Week (t) value used in my growth rate analysis.

G_x = Google Trends weekly index value for Week (x)
G_{t-1} = Google Trends weekly index value for Week (t-1)
G_t = Google Trends weekly index value for Week (t)
d = days in Week (t) before the review was published

In order to make the adjustment calculation I assumed that the G value for days (d) was equal to the weekly average from the week prior (G_{t-1}) since the review has not yet been published.

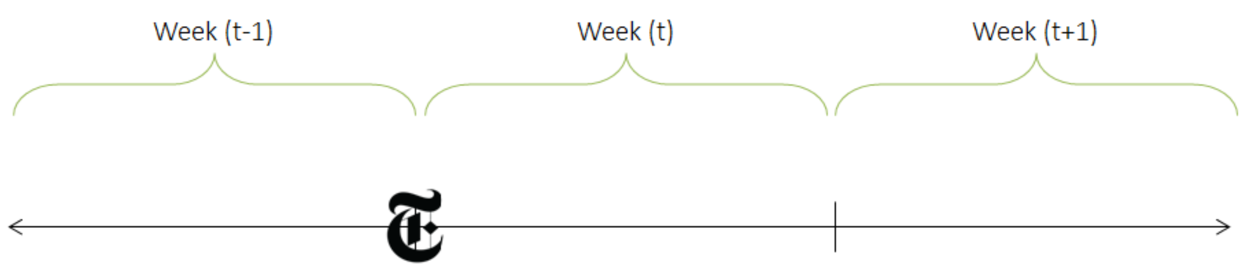
We know that G_t is an average of the index values for days before (d) and the days (7-d) after the review.

$$G_t = \frac{d \cdot G_{t-1} + (7-d) \cdot G_x}{7}$$

Then, to find the Google Trends index value for Week (x) the formula is manipulated and all the known variables can be entered to calculate G_x:

$$G_x = \frac{7 \cdot G_t - d \cdot G_{t-1}}{7-d}$$

This formula essentially manipulates the data to look as follows:



With the review directly between weeks, growth rates from week to week are a more accurate assessment of the impact of the *Times* review.

The formula below follows the same logic, but was used to adjust the monthly data. I assumed that each month has thirty days in order to apply the same formula to all the data. It was also assumed that the three weeks following week (*t*) had Google index values equivalent to the month after the review, Month (*t-1*).

G_x = Google Trends weekly index value for Month (x)
G_{t-1} = Google Trends weekly index value for Month (t-1)
G_t = Google Trends weekly index value for Month (t)
d = days in Week (t) before the review was published

$$G_x = \frac{30 \cdot G_t - d \cdot G_{t-1}}{30 - d}$$

APPENDIX C – REGRESSION OUTPUT: GROWTH RATE AND STARS

Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.666[a]	.443	.431	1.059877192

a. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	157.450	4	39.362	35.041	.000[c]
	Residual	197.708	176	1.123		
	Total	355.158[d]	180			

a. Dependent Variable: Growth (t-1) to (t) ADJ (all weekly)

b. Linear Regression through the Origin

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Stars_0	.580	.274	.119	2.120	.035
	Stars_1	.576	.144	.225	3.994	.000
	Stars_2	.909	.112	.455	8.087	.000
	Stars_3AND4	1.665	.226	.414	7.370	.000

APPENDIX D – OUTPUT OF BIVARIATE REGRESSIONS

Regression Output 1 – Stars and Price Regressed on Growth Rate

Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.685[a]	.469	.453	1.038441990

a. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, PriceContinuous

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	166.444	5	33.289	30.870	.000[c]
	Residual	188.713	175	1.078		
	Total	355.158[d]	180			

a. Dependent Variable: Growth (t-1) to (t) ADJ (all weekly)

b. Linear Regression through the Origin

c. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, PriceContinuous

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	PriceContinuous	-.020	.007	-.722	-2.888	.004
	Stars_0	1.475	.410	.303	3.599	.000
	Stars_1	1.523	.357	.594	4.266	.000
	Stars_2	1.891	.358	.947	5.289	.000
	Stars_3AND4	2.827	.459	.704	6.157	.000

Regression Output 2 – Stars and Location Regressed on Growth Rate

Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.670[a]	.448	.426	1.064210446

a. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, Area_Uptown, Area_Outside, Area_Downtown

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	159.228	7	22.747	20.085	.000[c]
	Residual	195.930	173	1.133		
	Total	355.158[d]	180			

a. Dependent Variable: Growth (t-1) to (t) ADJ (all weekly)

b. Linear Regression through the Origin

c. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, Area_Uptown, Area_Outside, Area_Downtown

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Area_Outside	-.155	.253	-.041	-.614	.540
	Area_Downtown	.112	.188	.046	.597	.552
	Area_Uptown	-.135	.261	-.034	-.516	.606
	Stars_0	.587	.301	.121	1.950	.053
	Stars_1	.581	.169	.226	3.440	.001
	Stars_2	.910	.160	.456	5.688	.000
	Stars_3AND4	1.648	.240	.410	6.856	.000

*Area_Midtown was excluded as a predictor because of colinearity with Area_Downtown

Regression Output 3 – Stars and Cuisine Regressed on Growth Rate

Model Summary

Model	R	R Square[b]	Adjusted R Square	Std. Error of the Estimate
1	.673[a]	.453	.431	1.059218733

a. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, Broad_Asian, Broad_Other, Broad_European

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	161.061	7	23.009	20.508	.000[c]
	Residual	194.096	173	1.122		
	Total	355.158[d]	180			

a. Dependent Variable: Growth (t-1) to (t) ADJ (all weekly)

b. Linear Regression through the Origin

c. Predictors: Stars_3AND4, Stars_2, Stars_1, Stars_0, Broad_Asian, Broad_Other, Broad_European

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Broad_European	-.192	.190	-.080	-1.006	.316
	Broad_Asian	-.283	.236	-.082	-1.199	.232
	Broad_Other	.142	.251	.038	.564	.573
	Stars_0	.644	.301	.132	2.141	.034
	Stars_1	.656	.185	.256	3.557	.000
	Stars_2	1.007	.154	.504	6.553	.000
	Stars_3AND4	1.785	.251	.444	7.117	.000

*Broad_American was excluded as a predictor because of colinearity with the other cuisine predictors.

Appendix E – Exclusions from DOHMH Population Dataset

Cuisine	Count
Australian	14
Bagels/Pretzels	168
Bakery	705
Bottled beverages, including water, sodas, juices, etc.	72
Café/Coffee/Tea	1,897
Chicken	411
Delicatessen	319
Donuts	486
Fruits/Vegetables	8
Hamburgers	433
Hotdogs	35
Hotdogs/Pretzels	16
Ice Cream, Gelato, Yogurt, Ices	329
Juice, Smoothies, Fruit Salads	290
Not Listed/Not Applicable	16
Nuts/Confectionary	6
Other	916
Pancakes/Waffles	17
Pizza	1,152
Salads	48
Sandwiches	448
Sandwiches/Salads/Mixed Buffet	261
Soups	3
Soups & Sandwiches	55
Vegetarian	102