# CUSTOMER PREFERENCES IN SMALL FAST-FOOD BUSINESSES: A MULTILEVEL APPROACH TO GOOGLE REVIEWS DATA

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# ABSTRACT

Online reviews influence customers' decisions and present publicly available data to investigate their preferences on dining experience attributes. This study compares customer reviews of small fast-food businesses to national fast-food chains and builds executable recommendations to small businesses by analyzing 82,598 customer entries from Google Reviews. With text analysis tools and multilevel multinomial models, the study demonstrates that customer reviews for small businesses are less polarized and more positively skewed compared to chain restaurants. The findings also demonstrate the significance of four dining experience attributes: food, service, ambience, and price. The analysis suggests that among these, food and service are the most crucial qualities for fast-food restaurants. While food offerings are essential to get high ratings for small businesses, service is the primary factor in inducing customers to share their feelings. Due to positive skewness in customer ratings, small businesses need to have powerful testimonials to differentiate them from their competitors. Therefore, to build and increase customer base, small fast-food restaurants need to capture the attention of customers with food offerings and promote positive and insightful review contents with service quality.

## BIOGRAPHICAL SKETCH

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CHAPTER 1

# INTRODUCTION

Technological advancements in information and communication technology (ICT) supported the rapid development of internet applications and social media outlets. Electronic word-of-mouth (eWOM) is informal communications of consumers, and it shares either a positive or negative signal of the product or service popularity (Litvin et al., 2008; Zhang et al., 2010). Unlike traditional word-of-mouth (WOM), eWOM is more persistent, accessible, measurable, and involves multi-way exchanges of information (Cheung & Lee, 2012). With the increasing usage of social media and recommendation platforms like Yelp, TripAdvisor, and Google Reviews, it has become a critical element for consumers' decisions (Pantelidis, 2010).

eWOM communication through online consumer reviews became a reliable source of information (Gruen et al., 2006) and an essential tool for service sectors and hospitality businesses (Law et al. 2014; Li et al. 2019). Customers rely on digital channels during their decision process due to high uncertainty in these sectors. Hence, online reviews on popular platforms are an indispensable tool to influence customer choices (Mudambi & Schuff, 2010; Reimer & Benkenstein, 2016).

Traditionally, the customer base of Small and Medium-sized Enterprises (SMEs) depends on word-of-mouth and personal recommendations. With the increasing usage of technology, in 2019, 82% of customers stated that they particularly read online reviews of local businesses (Bright Local, 2019). Furthermore, more than half of the customers often search for a website of a business before visiting in person (Maru/Matchbox, 2018). Thus, online review platforms are especially important for SMEs to have a platform to expand their market recognition. eWOM is disruptive for this group of restaurants as it transforms regionally restricted evaluations to online open platforms (Beuscart et al., 2016). It can be a low-cost, compelling, and persuasive tool to acquire new customers (Reimer & Benkenstein, 2016; Zhang et al., 2010). Customers spend more time evaluating the reviews of non-luxury brands, including restaurants (Daugherty & Hoffman, 2014). Therefore, local non-luxurious restaurants would have more abilities to attract new customers by using these platforms.

Each location of a chain restaurant has the same menu, advertising, and sourcing of the products. This situation conveys information to the customers on the quality of the food and service. Due to prior knowledge and brand recognition, Luca (2011) found that customer ratings do not affect the revenues of chain restaurants. In contrast, an increase in the average score of an independent restaurant increases its overall revenue. Positive customer review creates a favorable image (Jeong & Jang, 2011) and impacts the perceived value of the restaurant's offering in a meaningful manner (Gruen et al., 2006). Thus, these online platforms ease demand to shift from chains to independent restaurants (Luca, 2011).

Average ratings for each restaurant are simplifying features for filtering choices within a local area. Low scores may cause losing potential customers during this process. The content of a review becomes essential in the second stage. Customers read reviews and decide on a restaurant based on the strength of these testimonials (Chevalier & Mayzlin, 2006; Senecal & Nantel, 2004; Zhang et al., 2010). Therefore, it is crucial for small businesses to increase their overall ratings and promote positive contextual comments for their restaurants.

This study aims to build executable recommendations for small fast-food businesses to improve their customer satisfaction levels. For managerial implications, the study analyzes online reviews to understand customer preferences on dining experiences and highlights the qualities that small businesses need to prioritize. In addition to that, it intends to capture differences between small business fast-food restaurants and fast-food chains. Accordingly, this study tries to answer the following questions:

1. Which dining experience attributes are significant for customer satisfaction from fast-food businesses?
2. Among these attributes, which one has the most significant impact on customer evaluations?
3. What are the differences between customer preferences from small business fast-food restaurants and fast-food chains?

To answer these research questions empirically, we followed seven major steps. Firstly, we conducted a comprehensive literature review on dining experience attributes, the credibility of online recommendations, the polarization of customer reviews, and ”opinion leaders.” Secondly, we constructed our three hypotheses related to the findings from the literature review. To test these hypotheses, we chose an appropriate online platform for data collection. Next, we collected 82,598 Google reviews from 235 chain restaurants and 387 small business restaurants and organized the dataset. In the fifth step, we applied text categorization and text stemming techniques to extract topics from the contextual data. We integrated existing literature into our findings, measured sentiment scores, and introduced new variables to the model. We created quantitative models to test the hypotheses. Based on these findings, we answered the research questions, confirmed the hypotheses, and developed recommendations for small fast-food businesses.

Our study is first to analyze data on small fast-food businesses and fast-food restaurant chains comparatively. It is also unique as the recommendations are specifically tailored to small fast-food businesses, and they are based on one of the most reliable platforms, Google Reviews.

The findings of the research demonstrate that customer reviews for small businesses are less polarized compared to chain restaurants. The positive attitudes of customers create a competitive advantage for them against restaurant chains. However, positive skewness increases competition between small fast-food businesses. They need to have both high star ratings and powerful testimonials to differentiate themselves from their local competitors. The results of online reviews suggest that food offerings are essential to capture the attention of customers. If customers mention food offerings of a small business restaurant, they are more inclined to rate the restaurant higher. However, the food attribute is not sufficient to get positive written reviews that convey customers' experiences and sentiments. According to the findings, service quality is the primary factor in eliciting positive emotions in customers and promote them to share their opinion and feelings towards a restaurant. Therefore, to differentiate in the market, to increase satisfaction levels, and to build a regular customer base, small businesses need to have fast and convenient service with friendly and responsive employees.

The remainder of this paper proceeds with a literature review, hypotheses development, data collection, methods, and results. In the final chapter, we discussed our findings, their theoretical and managerial implications, and avenues for further research.

CHAPTER 2

# LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Online customer reviews help customers to choose a restaurant that serves their preferences. As the usage of these recommendation platforms is getting more popular, research done on these topics is rapidly increasing. Most of the studies focus on the reliability of customer reviews, customer bias, review helpfulness, and effects of customer reviews on sales. There is limited research that analyzes dining experience attributes through online reviews. As our study examines customer preferences from fast-food restaurants, we decided to conduct a comprehensive literature review on dining experience attributes, and we did not limit it to online reviews. Assessing users' habits at the online recommendation platforms, learning how customers rate service or products online, and evaluate their credibility are vital for conducting fully structured research on online reviews. Hence, the following four main topics provide a comprehensive analysis of central issues related to our study: dining experience attributes, the credibility of online reviews, the polarization of customer reviews, and opinion leaders. We used findings from these studies to develop three hypotheses related to the research questions.

## 2.1 Literature Review

### 2.1.1 Dining Experience Attributes

Dining experience attributes influence customer satisfaction (Canny, 2014). Table 2.1 lists a wide range of research articles that discusses these attributes by analyzing customer surveys and online reviews. As shown in Table 2.1, researchers have agreed upon four fundamental aspects: food, service, ambiance/environment, and price.

Both Zagat, the restaurant discovery platform with reviews from major cities around the US (Zagat, 2020), and the AAA Diamond Rating, restaurant rating program in North America (AAA, 2020) indicate food quality, décor, and service at their rating system. Both of the platforms also provide information on the price range of restaurants. These criteria used in both rating acknowledges the importance of four fundamental attributes. Thus, customers are motivated to articulate positive electronic word-of-mouth (eWOM) for restaurants with excellent food, high-quality service, and a pleasant environment (Jeong & Jang, 2011). In addition to that, for fast-food restaurants, low prices are also critical factors in customer satisfaction (Knutson, 2000; Medeiros, 2013). To examine the relationship between main dining experience attributes and their determinants, most of the studies applied quantification methods to qualitative data. The researchers often preferred methods such as factor analysis (Bardwell et al., 2018; Hyun, 2010; Jeong & Jang, 2011; Liu & Tse, 2018), principal component analysis (Harrington et al., 2011), hierarchical value map (Ha & Jang, 2013) and correlation analysis (Ponnam & Balaji, 2014; Sulek & Hensley, 2004). To evaluate the importance of attributes on customer satisfaction, researchers preferred descriptive analysis (Knutson, 2000; Mattila, 2001; Pantelidis, 2010), regression analysis (Canny, 2014; Namkung & Jang, 2008; Parsa et al., 2012) and hierarchical regression analysis (Ryu & Han, 2010).

Studies that use online reviews to assess the relationship between dining experience attributes and customer satisfaction are either examined contextual component of reviews (Ganu et al., 2009; Gan et al., 2017; Gan & Yu, 2015; Keller & Kostromitina, 2020; Lu et al., 2011; Pantelidis, 2010) or rating of a restaurant (Bakhshi et al., 2014; Zhang et al., 2010; Zhang et al., 2014). Among the first group, three studies focused on finding determinants of customer satisfaction. They used multilevel regression models (Gan et al., 2017; Gan & Yu, 2015) and multiple correspondence analysis (Keller & Kostromitina, 2020) to assess the significance of the attributes.

Table 2.1: Dining experience attributes in the literature

| Author | Date | Data Source | Dining Experience Attributes |
|---|---|---|---|
| AAA Diamond Rating | | Online Platform | Food, décor, personal service |
| Zagat | | Online Platform | Food, décor, service |
| Bakhshi et al. | 2014 | Online Reviews (CityGrid) | Food, atmosphere, service, monetary, advertising,location, miscellany |
| Bardwell et al. | 2018 | Surveys | Food, service, menu, atmosphere |
| Canny | 2014 | Surveys | Food quality, service quality, physical environment |
| Gan et al. | 2017 | Online Reviews (Yelp) | Food, service, ambience, price, context |
| Gan & Yu | 2015 | Online Reviews (Yelp) | Food, service, décor/ambience, pricing, special contexts |
| Ganu et al. | 2009 | Online Reviews (Citysearch NY) | Food, service, ambience, price, anecdotes, miscellaneous |
| Ha & Jang | 2013 | Interviews | Low food price, prompt service, convenient location, menu variety, long business hour, drive thru, take-out service, friendly staff |
| Harrington et al. | 2011 | Surveys | Promotion, price/value, quality expectation, setting, dietary, variety/innovative characteristics |
| Hyun | 2010 | Surveys | Food quality, service quality, price, location, environment |
| Jeong & Jang | 2011 | Surveys | Food quality, service quality, atmosphere, price fairness |
| Keller & Kostromitina | 2020 | Online Reviews (Yelp) | Food, service, environmental factors |
| Knutson | 2000 | Surveys | Price, service, consistency, and location |
| Liu & Tse | 2018 | Surveys | Food, service, price/value |
| Lu et al. | 2011 | Online Reviews (OpenTable) | Food, service, ambience, price |
| Mattila | 2001 | Surveys | Food quality, service, atmosphere, value for price, location, personal recognition, memorable past experience |
| Namkung & Jang | 2008 | Surveys | Food presentation, tasty food, spatial seating arrangement, fascinating interior design, pleasing background music, reliable service, responsive service, competent employees |
| Pantelidis | 2010 | Online Reviews (London-eating) | Food, service, ambience, price, menu, décor |
| Parsa et al. | 2012 | Surveys | Food quality, service, ambience |
| Ponnam & Balaji | 2014 | Surveys | Responsiveness, gourmet taste, hospitality, food presentation, ambience, upscale image, menu variety, menu price, design & décor |
| Ryu & Han | 2010 | Surveys | Food, service, physical environment |
| Sulek & Hensley | 2004 | Surveys | Food quality, atmosphere, fairness of wait |
| Zhang et al. | 2010 | Online Reviews (Dianping) | Food quality, environment, service, cost |
| Zhang et al. (a) | 2014 | Online Reviews (Dianping) | Food taste, physical environment, employee service |
| Zhang et al. (b) | 2014 | Online Reviews (Dianping) | Food taste, environment, service, price |

The attribute of food contains information on food quality, variety of menu, healthy options, taste, and freshness (Medeiros, 2013; Namkung & Jang, 2007). According to studies, food is a primary variable that influences a customer's memory (Pantelidis, 2010), and it is considered an essential component of the restaurant experience (Namkung & Jang, 2007). Food attributes are seen as equally important to all restaurant-goers regardless of the type of restaurant (Bardwell et al., 2018). According to the findings of Ganu et al. (2009), food offerings have the highest impact on the perception of a restaurant, and reviews of delis and pizzerias mostly focus on the quality of food.

The attribute of service includes information on the speed of service, friendliness and responsiveness of employees, delivery service, and qualities of service employees (Medeiros, 2013; Namkung & Jang, 2007; Pantelidis, 2010). These interactions have a substantial impact on customers' evaluations at online reviews (Huang et al., 2014; Jeong & Jang, 2011; Namkung & Jang, 2007). Service quality is the significant determinant of building trust between a restaurant and customers (Hyun, 2010) and has a powerful influence over the meal experience (Zhang et al., 2014). Compared to the overall dining experience, the speed of service is more important for quick service restaurants (Parsa et al., 2012).

Spatial layout, interior design, color, music, cleanliness, and restaurant amenities are the main drivers of ambiance attributes (Namkung & Jang, 2007). In North America, the existence of parking lots and comfortable ambiance positively influences customer satisfaction (Kong et al., 2016). According to Medeiros (2013), the importance of ambiance is negatively correlated to fast-food restaurants. This relationship confirms an American appreciation for lower-end dining establishments with a comfortable ambiance.

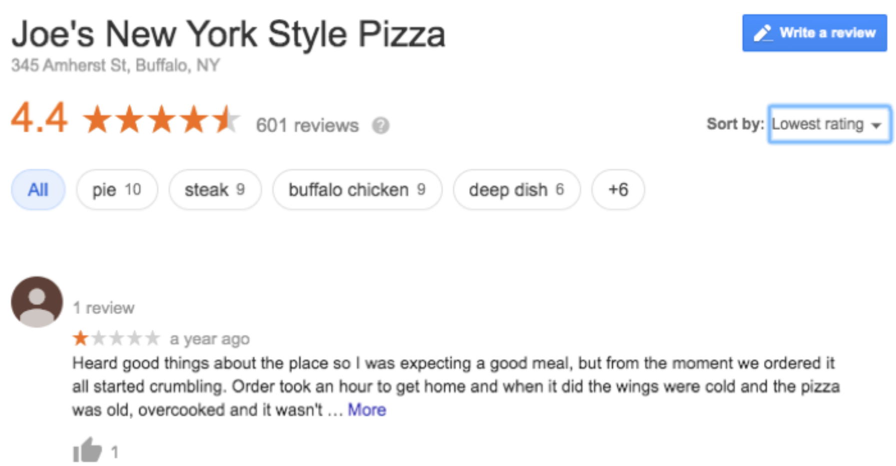
Price is the final attribute that considered to be essential for customer satisfaction. Unsurprisingly, customers complain more about prices of expensive restaurants (Ganu, 2009). According to multiple studies, price is not a significant and critical motivator for customers to write eWOM (Hyun, 2010; Jeong & Jang, 2011; Zhang et al., 2014). However, for fast-food restaurants, pricing might be a determinant of customer satisfaction (Knutson, 2000; Medeiros, 2013).

Overall, fast-food restaurants that have high-quality food (Ganu, 2009; Namkung & Jang, 2008; Pantelidis, 2010; Zhang et al., 2014) and great service (Cuizon, 2018; Ponnam & Balaji, 2013; Yuksel & Yuksel 2002; Zhang et al., 2014) with good value for money (Knutson, 2000; Medeiros, 2013) at a clean and nice ambiance (Canny, 2014; Ryu & Han, 2010) satisfy customer needs and have more positive eWOM (Hyun, 2010; Zhang et al., 2014).

### 2.1.2 Evaluating the Credibility of Online Reviews

The importance of eWOM is well-recognized in marketing communications. Online platforms provide aggregated ratings for each product/service based on reviewers' input to convey an overall impression to other customers. This unique feature of eWOM offers a representation of how previous customers have reacted to each product/service and eases the choice process for customers (Cheung et al., 2009). These online recommendations influence consumers' product and service choices and purchasing behaviors (Chevalier & Mayzlin, 2006; Senecal & Nantel, 2004). Although aggregated rating includes both high and low scores, it is possible to have a high average rating with multiple negative reviews (Figure 2.1). Therefore, customers do not solely rely on aggregated scores; they read and respond to review contents (Chevalier & Mayzlin, 2006). Recommendation consistency between reviews is positively related to eWOM review credibility, and this can influence consumers' review adoption (Cheung et al., 2009). Consumers also prefer long reviews, and the presence of a real photo increases the credibility of the information in the entry (Park & Nicolau, 2015). The more information a reviewer reveals on their identity, the more credible content is (Couzin & Grappone, 2013). In addition to this, customers assess the credibility of online reviews by comparing them to their own experiences (Zhang et al., 2010).

Figure 2.1: Negative review example from Google Reviews




Attribution theory explains how individuals make causal inferences to satisfy their need to understand social events. There are two types of causes: personal causes and environmental situations (Heider, 1958; Jones & Davis, 1965; Kelley, 1967). In the case of eWOM, product/service-related factors would be environmental (external) situations, whereas non-product/service-related factors would be personal (internal) causes (Qui et al., 2012). If a review is solely based on personal reasons, readers may not consider it as accountable (Sen & Lerman, 2007). Similarly, negative reviews on utilitarian products perceived more useful than hedonic products. Thus, customer reviews of functional products are considered more persuasive (Sen & Lerman, 2007).

As hedonic and utilitarian values influence customer satisfaction and behavioral intentions, both of these play a vital role in the choice of fast-food consumption (Nejati & Moghaddam, 2013; Ryu et al., 2010). In the context of fast-food restaurants, utilitarian values have a more substantial influence on the behavioral intentions of customers (Nejati & Moghaddam, 2013). Therefore, reviews on fast-food restaurants can be considered more persuasive among readers compared to quality restaurants.

### 2.1.3 Polarization of Customer Reviews

Individuals with exceptionally good or exceptionally bad experiences are more likely to post their reviews online (Dellarocas & Narayan, 2006; Hu et al., 2009; Moon et al., 2014). Most reviewers tend to have very favorable or very unfavorable opinions toward the service (Litvin et al., 2008). Customers mostly decide on a restaurant based on eWOM, and they choose an option that they favor. Hence, they have a favorable opinion about the restaurant before the experience, and they are more inclined to write a positive review (Hu et al., 2009; Moon et al., 2014). Previously posted views and rating environments also affect a reviewer's decision on whether or not to post a review, and they influence the content of the post (Moe & Schweidel, 2012). Negative reviews at online platforms elicit emotions of anger and disappointment and drive customers to share their experiences openly online (Verhagen et al., 2013). Higher disagreement on a product or service increases its post-purchase reviewer percentage (Dellarocas & Narayan, 2006). These situations alter the composition of the reviews (Moe & Schweidel, 2012). Therefore, online reviews are polarized and usually reveal a J-shaped distribution with more positive reviews than negative reviews (Hu et al., 2009; Moon et al., 2014). Park and Nicolau (2015) found that consumer perceives these extreme positive and negative reviews more useful and enjoyable than neutral reviews.

### 2.1.4 Opinion Leaders

Online reviewers' intention to contribute to eWOM is related to building a reputation, gaining an enhanced image in a platform, influencing merchant/service providers, feeling a sense of belonging and a content from helping other customers (Cheung & Lee, 2012; Tong et al., 2013). These users are considered opinion leaders for potential customers. When reviewers are submitting their entry, they observe online reviews of other "opinion leaders." Therefore, online reviewers can be considered as a member of the social group and influenced by reviews and ratings of others in the platform (Sridhar & Srinivasan, 2012). A reviewer's reputation on the social platform helps to reduce the potential uncertainty of customers (Park & Nicolau, 2015). Individuals who consider themselves intelligent and expert in these social groups try to differentiate themselves by posting more negative reviews (Schlosser, 2005). According to Gan and Yu (2015), a reviewer who posts more reviews tends to provide, on average, lower ratings.

In the context of the restaurant industry, Jeong and Jang (2011) suggest that eWOM opinion leaders are likely to have good computer skills, and they are likely to be involved in restaurant-related professions. Opinion leaders in the restaurant industry may be more enthusiastic about sharing their knowledge and disseminate more eWOM than non-leaders (Jeong & Jang, 2011). They are willing to evaluate more on their dining experiences to be viewed as an expert by the other consumers in the platform (Cheung & Lee, 2012). First-time restaurant customers differ from frequent customers. When regular customers encounter high-quality service interactions in a restaurant, they are more inclined to exhibit positive word-of-mouth for that restaurant (Bardwell et al., 2018). Therefore, building a frequent customer base is vital for restaurants.

## 2.2 Hypotheses Development

The literature review helps us to formulate hypotheses to test. As studies suggest, all four dining attributes may be essential for customer satisfaction. Although food offerings are an essential component of restaurants (Namkung & Jang, 2007; Pantelidis, 2010), service has a powerful influence over meal experience (Zhang et al., 2014) and it may substantially impact customer evaluations. Thus, we hypothesize the followings:

$H_1$: Dining experience attributes, food, service, ambience, and price, have significant effects on customer satisfaction levels for fast-food restaurants.

$H_2$: Among all four attributes, service is the most important indicator of customer satisfaction.

Google Reviews provide an open-ended textual review as an option for quantitative star-rating. Our study only analyzes entries with contextual information from both small business and chain restaurants. According to Luca (2011), consumer reviews are less influential for chain restaurants as they already established their reputation through marketing and branding tools. Therefore, customers may use online review platforms as a tool to share their complaints on chain restaurants, whereas, for small businesses, they may prefer to share both positive and negative experiences. Due to the importance of eWOM content and its credibility for small businesses, and customers' intention to be "opinion leaders," we hypothesize:

$H_3$: Customer reviews on small business restaurants are less polarized compared to chain restaurants.

CHAPTER 3

# DATA

Before starting the data collection to answer the three hypotheses, we chose the criteria for data collection. We decided on a specific business type, certain food offerings, and a region to focus on. Taking these criteria into account, we created a list of restaurants to collect data. After that, we chose a customer review platform for these restaurants and started to collect the data. Therefore, this chapter provides background information on how we determined our criteria, why we preferred to use Google Reviews platform, and how the platform works. The chapter also presents details on the data collection and variables of demographic data.

## 3.1 Data Collection Criteria

According to the most recent data of the Statistics of U.S. Businesses (SUSB) published by the U.S. Census Bureau, restaurants and other eating places made 8.38% of employment in the United States in 2017. Two subcategories, full-service and limited-service restaurants, dominate the category. As customer expectations differ between two groups, focusing on one subcategory minimizes variation for attributes. Since 2000, customer demand shifted from full-service restaurants to limited-service restaurants, and they experienced strong sales growth (Saksena et al., 2018). SMEs provided 61.58% of employment within the limited-service restaurant group, which is 30.76% higher than the total contribution of SMEs to overall employment. Hence, small businesses are one of the major players within the category and essential for maintaining employment opportunities.

The study aims to revitalize economies in stagnant regions by building recommendations for small businesses. Thus, we decided to focus on a specific area with declining job opportunities. Upstate New York suffered from decreasing economic growth, investment, and employment opportunities in the past decade. After the financial crisis in 2008, major banks limited their lending to small businesses in Upstate NY. From 2010 to 2017, total private sector employment in the region grew only 0.9%, whereas, in the downstate (New York City, Long Island, and Westchester County), it grew by 18.2% (Wasylenko, 2020). Although focusing on Upstate NY limits the size of our dataset, it minimizes regional variations in tastes and eating habits (Saksena et al., 2018). Metropolitan areas are densely populated areas that demonstrate demographic differences. Thus, collecting data from urban areas enables to assess the effects of demographics on customer satisfaction levels and customer preferences. Therefore, we decided to focus on four major cities in Upstate New York region: Albany, Buffalo, Rochester, and Syracuse.

As the four main menu categories, burger, pizza, sandwiches, and Mexican, made 78.0% of limited-service restaurant sales in 2014 (Saksena et al., 2018), we decided to focus on these restaurants and restaurants specialized in chicken. We preferred the lowest price-range group to minimize discrepancies while comparing chain restaurants to small businesses. The data collection process for the research consists of two main stages. Firstly, we collected a list of restaurants in Albany, Buffalo, Rochester, and Syracuse and differentiated national chains from non-chain restaurants. In the second stage, we chose which fast-food restaurants to focus on from the dataset and collected their customer reviews from Google Maps. To have consistency among the choices of the restaurants, we only selected fast-food restaurants that (1) do not offer full table service and (2) serve pizza, sandwiches, chicken, and foods from American and Mexican cuisine (3) at the lowest price range.

## 3.2 The List of Restaurants

The New York State Department of Health inspects all licensed retail food establishments in the state. They publish the online data under the name of ”Food Service Establishment Inspection Data of New York State (NYS)” and update the document monthly (NYSDOH, 2020). The data provides names, locations, and inspection results of actively operating food service establishments in NYS counties except for New York City, Suffolk County, Orange County, and Erie County. As Buffalo is in Erie County, we used its regional inspection data called ”General inspections” from Open Data Buffalo, NY. Buffalo City publishes the inspection data in a similar format as the New York State Department of Health (NYSDOH). Merging two datasets produces the full list of food establishments in the four cities. After filtering the data to ”Food Service Establishment – Restaurant,” we were left with restaurants in these four cities to analyze. However, the list provided both full-service and limited-service restaurants. It did not provide any additional information to differentiate between these two establishment types.

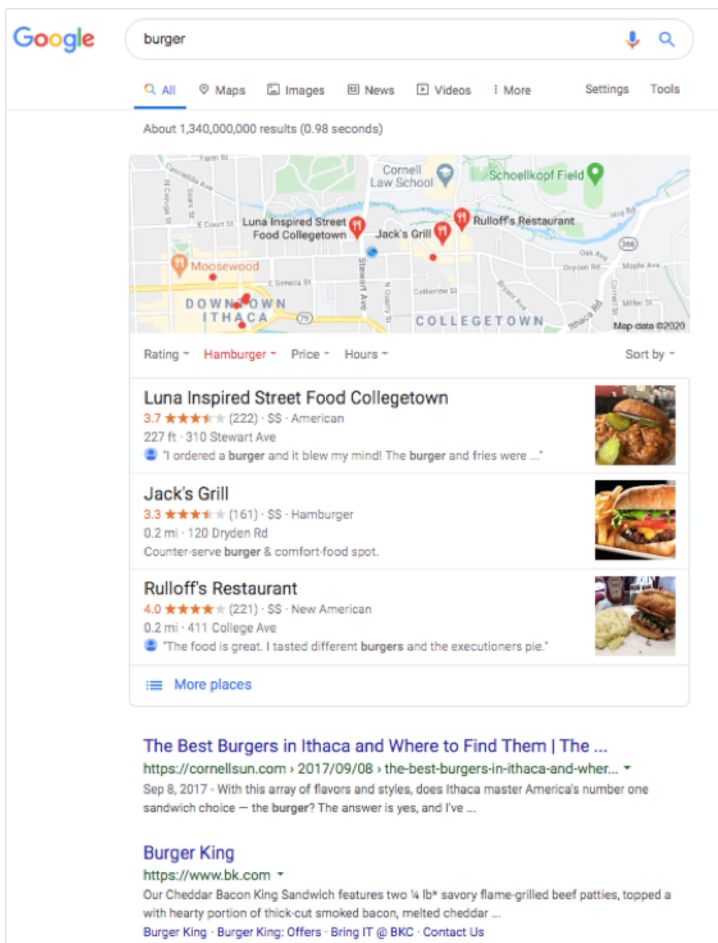
The second step was to differentiate the national restaurant chains (McDonald’s, Pizza Hut, etc.) from independent restaurants. Department of Health and Mental Hygiene (DOHMH) provides an interactive online database of nutrition and menu information of top national restaurant chains on a website called MenuStat.org. Among 96 chain restaurants listed in the database, limited-service fast-food restaurants were our focus. Matching the list of restaurant chains to the overall restaurant lists presented the names and locations of only 20 fast-food brands in these four cities (Table A.1). To create a distinction between chains and independent restaurants, we created a binary variable called ”Chain” and flagged all chain restaurants in the dataset.

## 3.3 Choice of a Review Platform: Information on Google Reviews

Google is a leading search engine around the world. It accounts for 62.5% of the U.S. desktop search queries and also accounts for over 93% of the mobile search market as of October 2019 (Clement, 2020). Before making a purchasing decision or choosing a service provider, customers search for product or service related information online. Therefore, search engines like Google become crucial for customers to reach these contents conveniently (Zhao et al., 2016). The indisputable impact of Google on customers' decisions strengthens its importance for small restaurant businesses. When a user searches a food-related word on the website, the search engine provides the results for the closest local restaurants at the top of the results page (Figure 3.1).

With the ”More Places” button, users have an option to view all local restaurants in the region on Google Maps platform. It lists each relevant restaurant in the area, shows their location, and indicates their average star ratings. Google Reviews is an integrated feature of Google Maps. It allows customers to post a review publicly and rate a business. These ratings form an average score for each entity and appear on the platform. This convenient transition between the search engine and Google Reviews increases its reach and usage during the customer decision-making process. The integration of Maps and Reviews helps customers to conveniently access the location of restaurants as they are reading the reviews. The transition between these Google platforms creates a competitive advantage for Google Reviews among its biggest competitor Yelp.com. Yelp is a stand-alone mediated reputation system that connects people and local businesses. The revenue of the platform relies on local and brand advertising. Its revenue stream creates a challenge for Yelp to maintain credibility while providing returns to the advertisers (Friedman, 2017). This situation also generates concern for customers in assessing the platforms' reliability. Besides, unless customers are regular users of Yelp, they probably prefer to use a search engine for their needs (Hall, 2013). Hence, Google Reviews is a credible and effective platform for restaurants to reach their potential customers. As Google Reviews is globally available, the platform is also likely to influence the choices of people from all around the world (Shah et al., 2019).

Figure 3.1: Google search engine desktop view for “Burger” search query




All internet users have access to read reviews on the platform. However, only Google users can rate and write a review. The platform uses the star rating system on a scale of five, five being very satisfied, and one being very dissatisfied. It provides an open-ended textual review option along with a quantitative star-rating. After the submission of a textual review, the platform automatically checks it to detect inappropriate content like fake reviews and spam. If the content is accepted for external publication, it becomes publicly available to anyone who accesses the platform. Google has a right to take down a review that does not comply with the company's policies and legal obligations. They also provide an option for users to flag and report inappropriate reviews (Google, 2020). Integrating these monitoring tools, Google aims to build the credibility of the platform for the users.

In brief, the integration of Google Reviews to Google Maps and Google search engine decreases friction for customers and maintains its convenient access. These aspects of Google Reviews appeal to a wide range of demographics and increases its usage among customers. Due to its perceived credibility, we preferred to investigate Google Reviews data to analyze customer preferences.

## 3.4 Collection of the Reviews

Google Places API allows developers to access up-to five reviews per location and uses AJAX (Asynchronous JavaScript + XML) interface that limits more straightforward access to details of each place (Google, 2020). Although some researchers preferred to restrict their research to five reviews (Mowery et al., 2016), some preferred to use web crawlers (Ban et al., 2019) and a private script (Lee & Yu, 2018) on Python.

The created list of the restaurants included names and addresses of all restaurants in four cities. To only collect data of limited-service restaurants, we needed to examine photos and information of these establishments on Google Maps during the data collection process. Scraping the data with JavaScript code provided us an ability to assess whether they were limited-service restaurants. It also eased the data collection process from a particular restaurant. We only gathered data from limited-service restaurants that were actively operating and serving pizza, sandwiches, chicken, and foods from American and Mexican cuisine at a one-dollar ($) price range on Google Maps.

Integration of the code to Google API Console for each restaurant provided a result in a JSON format. We collected information on an average rating of a restaurant, a total number of reviews it received, information on each review including the name of the reviewers, star value of the evaluation, review itself, and posting date of the entry. The posting date does not specify the exact day; it restricts information to phrases like ”one-month ago,” ”two-years ago.” Due to the limited information provided, the final dataset only presents the posting year of each review. It limits our opportunity to investigate seasonal differences for customer reviews. As Google Maps integrated review function to each business in June 2007 (Rasmussen, 2017), the oldest review entry dates back to 2008. Table 3.1 demonstrates the sample data collected from Google Maps.

Table 3.1: A sample of data collected

| **Restaurant ID** | **Year** | **Avg. Rating** | **Total No. Reviews** | **Star** | **Review** |
|---|---|---|---|---|---|
| 464 | 2018 | 3.7 | 341 | 4 | A great neighborhood pizzeria. Great food at decent prices. Don’t forget to tip your delivery driver! Been eating there for 35 years. |

Even though the dataset was sufficient to produce valuable information, we categorized restaurants according to the food type to have more insights during the data analysis on customer preferences. The categorization resulted in five different binary variables dedicated to groups of food: Pizza, Sandwich, Burger, Chicken, and Mexican (Table 3.2). As some small businesses prefer to sell multiple food options, they are part of two or three different cuisines in the dataset. This situation obstructs us from having a mutually exclusive dataset on the restaurant types.

Table 3.2: Distribution of restaurant types

| **Restaurants** | **Chain** | **Small Businesses** |
|---|---|---|
| Total Restaurants | 237 | 387 |
| Pizza | 29 | 181 |
| Burger | 106 | 59 |
| Sandwiches/Wraps | 59 | 67 |
| Chicken | 20 | 30 |
| Mexican | 21 | 13 |
| Others | | 22 |
| Two Cuisines | | 13 |
| Three Cuisines | | 2 |

For multinomial models, combining adjacent categories would not change the results much (Rodriguez, 2007), and it would make interpretation of results easier. Therefore, for qualitative models, we grouped star ratings into three main groups. According to researchers, 3-star reflects a moderate view and mostly seen as a midpoint rating. They have neither strong positive or strong negative recommendations (Forman et al., 2008; Lei, 2017; Mudambi & Schuff, 2010). Therefore, 3-star symbolizes the sufficiency for customers in their restaurant choice (Lei, 2017). While 4 and 5-star ratings are clearly positive, 1 and 2-star ratings share negative opinions of customers. This aggregation of positive (4 and 5-stars) and negative (1 and 2-stars) reviews is widely used in the literature (Forman et al., 2008; Ganu, 2009; Liu, 2012; Park & Nicolau, 2015). Thus, we formed three groups of star ratings: Low-rated reviews (1 and 2-star reviews), moderate reviews (3-star reviews), and high-rated reviews (4 and 5-star reviews). As a result, we formed two different star rating variables. While we interpreted the ordinal star variable with five categories during qualitative analysis, we used star rating groups with three classes in our quantitative models.

## 3.5 Demographic Information

Google does not publicly share any personal information. Although some reviewers prefer to use their names and photos, most of them use aliases to be anonymous. Thus, it is not possible to gather information on each reviewer to analyze the demographics. The United States Census Bureau conducts a nationwide American Community Survey (ACS) that is designed to provide reliable social, economic, and demographic data (U.S. Census Bureau, 2019). The Census Bureau publishes 5-year demographic data at ”2013-2017 American Community Survey 5-Year Estimates.” Block groups are the smallest accessible unit that demographic information stored. However, our dataset lacks information on geographic identifiers (GEOIDs) on block groups to link demographic information to the location of restaurants. ”NYS GIS Dataset Inventory” publishes geospatial information on New York State. We looked at GEOIDs of each restaurant by using Google Earth Pro and recorded it to the dataset. We also collected variables on the current land area (ALAND) to calculate population density for these census tracts by merely dividing the population to the land area. We decided to use the following demographic variables: total population, median household income, income per capita, population density, education level variable (percentage of Bachelor degree or higher), and racial diversity variable (percentage of only white people in the population) (Table 4.3).

CHAPTER 4

# METHODS

Customer reviews grant essential insights on customer preferences. A combination of qualitative analysis and quantitative analysis on these reviews can reveal which attributes customers value the most. We used text analysis methods to categorize reviews into dining experience attributes according to their content. This categorization prepared the data for quantitative models. In addition to these, we created variables related to both sentiment scores and dining attributes to evaluate their connection and assess their impact on customer satisfaction levels. Using these variables, we determined our econometric model to test three hypotheses.

## 4.1 Text Analysis

The text mining and sentiment analysis approach gained popularity in the past decades due to the increasing availability of large datasets and advancements of methods in language processing. There are two main methods of text analysis: a lexicon-based approach and a machine learning approach (Drus & Khalid, 2019). Lexical features are vital in text and sentiment analysis (Riloff et al., 2006). It is a process of connecting each word to its corresponding label in a dictionary (Daud et al., 2010). However, words might have more than one meaning, which creates challenges to have an accurate analysis. Unigram tagger is one of the simplest methods to overcome this problem. It is commonly used in traditional topic-based text classifications. At the unigram statistical algorithm, each word is linked to the most frequently used meaning (Daud et al., 2010). Assigning a score to each word in a review creates its average score, tends to cluster it in the center (Dave et al., 2003) and provides consistently better performance (Pang et al., 2002). Machine learning is a supervised learning method and requires training data to process. It utilizes algorithms and complex models to detect themes, categories, and sentiments from the data. The literature review of Drus and Khalid (2019) suggests that a combination of both methods improves the quality and accuracy of the outcomes. Therefore, in our study, we preferred to combine both methods.

Many commercial software applications became available with a user-friendly interface and made the text analysis procedure easier for researchers. We preferred QDA Miner with Wordstat extensions for topic extraction and frequency analysis. This program automatizes a machine learning approach to understand and to construct common themes embedded in our dataset. While we used machine learning to categorize our dataset, we leveraged the lexicon-based approach to form our dining experience attributes. Quenteda package in R was a helpful tool to use the unigram method and code the data accordingly. Unigram provided us flexibility and ease during the coding procedure for both sentiment and text analysis. However, in a situation where the customer is discussing ”Burger King,” the unigram method counts ”burger” as a part of frequency. We eliminated and corrected these situations by considering the name of the entities.

The analysis of word counts and frequencies provides information on the dataset. It helps to construct attribute groups and a list of words to include each variable. Therefore, we used Nvivo, the qualitative analysis software, to prepare a word-cloud of most frequently used one hundred words in the dataset (Figure 4.1). According to the analysis, most frequent words are ”food,” ”good,” ”great,” ”pizza,” and ”service.”

Figure 4.1: Most frequently used terms in customer reviews


Although these terms suggest the importance of food and service for customers, they do not indicate how star ratings are affected by these attributes. The analysis of word-clouds and frequencies becomes informative when contextual data is examined under different categorizations. Thus, building categories for the data can provide more insights. Table 4.1 shows the result of the topic extraction using the Factor Analysis method. As the literature review suggested, extracted topics are related to four fundamental dining experience attributes: food, service, ambience, and price. The analysis confirmed that our dataset has similarities to the previous studies on online restaurant reviews and validated our idea of focusing on four fundamental attributes.

Table 4.1: Category suggestions of Wordstat

| Topic | Related Attribute |
|---|---|
| Great food, great service | Food & Service |
| Good food, fast service | Food & Service |
| Quick bite, great place | Food |
| Onion rings, hot sauce, hot dogs | Food |
| Good pizza, good price | Food & Price |
| Love this place; Staff is friendly | Service |
| Terrible service, order wrong | Service |
| Fast food, parking lot | Food & Ambience |
| Service was great; food was delicious | Service & Food |
| Delicious food, great prices | Food & Price |

Figure 4.1 and Table 4.1 also suggest that customers are frequently choosing words and phrases related to their feelings and attitudes towards certain restaurants. Collecting these words into one group called ”feeling” can provide insights on how the occurrence of these words affects star ratings. As words like ”love” and ”hate” are both included in one variable and weighted equally, the variable is neutral in its creation. It consists of positive and negative words used within our dataset. It creates a new perspective for us to understand customers' tendency to convey their ”feelings” and how this usage differentiates from sentiment scores. Therefore, we decided to create the fifth attribute group called ”feeling.”

The word-cloud presented limited information to understand the relationship between customer ratings and each attribute. Therefore, we decided to analyze the most frequently used ten phrases for each star rating to capture qualitative patterns (Figure 4.2). In the table, we colored phrases according to their related dining experience attributes.

Figure 4.2: Most frequently used ten phrases for each star rating
(colored according to a related dining experience attribute)

| **Color Legend for Attributes** | *Food* | *Service* | *Ambience* | *Price* | *Feeling* |
|---|---|---|---|---|---|

| **1-Star** | **2-Star** | **3-Star** | **4-Star** | **5-Star** |
|---|---|---|---|---|
| *Customer Service* | *Customer Service* | *Good Food* | *Good Food* | *Great Food* |
| *Slow Service* | *Slow Service* | *Customer Service* | *Good Pizza* | *Great Service* |
| *Horrible Service* | *Good Food* | *Slow Service* | *Fast Service* | *Great Pizza* |
| *Food Was Cold* | *Order Wrong* | *Pretty Good* | *Good Service* | *Fast Service* |
| *Waited Minutes* | *Long Wait* | *Good Pizza* | *Friendly Staff* | *Friendly Staff* |
| *Order Wrong* | *Poor Service* | *Good Service* | *Pretty Good* | *Love This Place* |
| *Chicken Sandwich* | *French Fries* | *Long Wait* | *Customer Service* | *Customer Service* |
| *Parking Lot* | *Chicken Sandwich* | *Fast Service* | *Great Place* | *Highly Recommend* |
| *Bad Experience* | *Pretty Good* | *Friendly Staff* | *Good Price* | *Great Prices* |
| *French Fries* | *Parking Lot* | *Order Wrong* | *Quick Bite* | *Pizza and Wings* |

For the analysis in Figure 4.2, we preferred to keep unique phrases. If ”great food” ranked higher than ”good food,” we added only ”great food” to the list vice versa. Therefore, the table presents unique phrases and lays out the patterns for star ratings. Although these phrases do not provide information on the significance of the attributes, it reveals customer reviews’ content and information related to five variables. The table demonstrates that 4-star and 5-star reviews, and 1-star and 2-star reviews have similar phrases and attributes. It justifies combining response categories into three groups. The dominance of the service attribute in the table is striking and suggests a possible significant relationship between star rating and service attribute. As star values are increasing, we also see the emergence of different phrases and qualities. The phrases at high rated reviews imply that customers prefer restaurants that serve delicious food with fast and friendly service at low prices. While lacking a parking lot may result in having a lower score, having a reasonable price may promote a high star rating. It also supports the need for the fifth attribute ”feeling” as customer opinions and sentiments mostly appear in each star group. These qualitative relationships provide insights into our quantitative model to understand the significance and direction of the association between the attributes and star ratings.

By using the word frequency list and leveraging literature (Medeiros, 2013; Namkung & Jang, 2007; Pantelidis, 2010; Ryu & Han, 2010), we created a comprehensive and mutually exclusive list of words linked to each attribute (Table A.3). We nearly included all of the attribute related words appearing in our dataset to minimize errors. Although emojis can be used to classify the emotional content of texts accurately (Felbo et al., 2017) and they are widely preferred in online reviews, our data analysis tools did not manage to integrate them as a part of the ”feelings” attribute. This situation created a limitation for the variable to have a complete capture of customers' feelings. We created two different variables: an occurrence-based binary variable and a frequency-based variable for each attribute.

For instance, for the following review, the occurrence of food attribute is one while the frequency of food-related words is six:

”This place is awesome!!! **Fresh toppings**, **dough** and **sauce**. The **chicken wings** are the best in town! This place does it right!!!”

While food-related words mentioned repetitively in each review, the same did not apply to the attributes of ambience and price (Table 4.2). Therefore, as using the frequency could underestimate the presence of these attributes, we preferred to keep them as binary variables. The creation of binary variables eliminated the risk associated with the dominance of one quality.

Table 4.2: Occurrence and frequency of dining experience attributes in the dataset

| Attributes | Occurrence | Frequency | Percentage Increase |
|---|---|---|---|
| Food | 69.75% | 151.00% | 116.47% |
| Service | 45.44% | 93.32% | 105.37% |
| Ambience | 15.60% | 21.97% | 40.85% |
| Price | 12.57% | 15.93% | 26.72% |
| Feeling | 73.90% | 126.25% | 70.85% |

For each dining experience attribute, we performed a pairwise comparison of the means (Tukey's test) to rating groups. This analysis captured the pattern of mean differences between response categories for each attribute. It evaluated the significance of differences between pairs of means for response categories. Except for differences between low-rated reviews (1 and 2-star), and moderate reviews (3-star) for price variable ($t = -2.19$ and $P > | t | = 0.072$), all rating groups have significant differences for each dining experience attribute ($P > | t | = 0$). Hence, our data and variables are suitable to investigate the relationship between customer satisfaction levels and dining experience attributes.

### 4.1.1 Sentiment Analysis

Sentiment analysis is the field of study that analyzes individuals' opinions, sentiments, emotions, evaluations, and attitudes towards entities such as a product, service, and organization (Liu, 2012). Improvements in technology enable us to identify and categorize a piece of text to determine whether a writer's attitude towards a particular topic is negative, positive, or neutral (Oxford, 2020). Nasukawa and Yi

(2003) are one of the first researchers to use the term ”sentiment analysis” (Liu, 2012). According to them, there are three essential interrelated steps in sentiment analysis. Researchers need to (1) identify how sentiments are expressed in texts, (2) assess polarity and strength of the expression, and (3) understand its relationship to the subject (Nasukawa & Yi, 2003). Since the year 2000, sentiment analysis has become one of the most popular areas in Natural Language Processing (NLP). Most of the studies on sentiment analysis started to appear after 2004 (Liu, 2012). With the emergence of social media and recommendation platforms, articles on the topic became more common (Drus & Khalid, 2019). When the relationship of sentiment analysis to the subject is determined, sentiment analysis provides valuable insights on a wide range of topics, including business, politics, and health policy. Especially feedback of customers plays a tremendous role in its application as it can assist companies in making wise decisions (Drus & Khalid, 2019). The abundance of publicly available customer opinions on products and services made surveys, opinion polls, and focus groups unnecessary (Liu, 2012). Besides this real-life application, researchers published application-oriented research papers like predicting sales performance, stock markets, and election results. Due to these useful applications, sentiment analysis spread from computer science to management science (Liu, 2012).

For our study, sentiment analysis provides a capability to evaluate star ratings of Google Reviews and understand the interaction between customer sentiments and dining experience attributes. Sentiment analysis scores would be insightful to assess customers' negativity and positivity towards each quality. Hence, for each review, we calculate sentiment scores related to four main dining experience attributes.

Tidytext package on R programming software uses unigram taggers to assign sentiment scores to data. The R package gave access to three different lexicons: AFINN, Bing, and Loughran. All of these lexicons are publicly available and have different scales to assign positive and negative scores to the data. The AFINN lexicon is made of 2477 words, including Internet slang and obscene words, and assigns scores between -5 and 5 (Lee & Yu, 2018; Naldi, 2019). Bing is made of 6789 words, 2006 being positive, 4783 being negative, and it assigns positive (1) or negative (-1) values to each word in the data. Loughran is a finance-specific dictionary and contains positive, negative, and uncertain words (Naldi, 2019).

Google Maps collects each textual review along with a quantitative star-rating. This availability of data enables us to assess the credibility of each lexicon. Therefore, we decided to evaluate the consistency between the sentiments scores for each dictionary and their associated star ratings. For determining a dictionary that fits better with the reviews, we analyzed small fast-food businesses dataset with these three dictionaries. We regressed sentiment results over star ratings and evaluated R-squared values. Although Bing was the best-fit dictionary ($R^2 = 0.82$) to our dataset, AFINN ($R^2 = 0.79$) also performed well. We eliminated the Loughran from our choices due to its finance specific nature and compared the other two dictionaries. Bing provided sentiment scores for 73.83% of the entries, whereas AFINN analyzed 3726 fewer observations and captured 69.32% of the reviews. As Bing has greater coverage and fits better to our dataset, we chose Bing for sentiment analysis. This package linked negative, neutral, and positive words to each review in the dataset and provided final sentiment score. The following examples are extreme cases of positive and negative comments.

Negative review with one-star rating: “Rude people, dirty place, greasy food, slow service, corporate office doesn’t care if they’re workers are rude, the food is greasy or the service is slow because they NEVER CONTACT YOU BACK! They probably get 1,000 complaints per hour!”

Positive review with five-star rating: "Best Example of a Fast Food Restaurant! Awesome location. Fast friendly service. Always clean. Easy in and easy out. Outside seating is great. Prices are good and food is so fresh. I am definitely going to come back here again"

The Google star ratings consist of positive (4 & 5) and negative reviews (1 & 2) (Park & Nicolau, 2015). Customers with extreme opinions are more inclined to post their experiences online than other customers (Dellarocas & Narayan, 2006; Moe & Schweidel, 2012). According to Schoenmüller et al. (2019), when customers' experiences exceed their predetermined expectations from a restaurant, they are more likely to rate the restaurant. These customer habits create a J-distribution response curve for online reviews (Hu et al., 2009; Moon et al., 2014), and it is also evident in our dataset (Figure 4.3). High ratings (4 & 5 stars) dominate the reviews by making 67.90% of all customer reviews, whereas low ratings ((1 & 2 stars) account for 21.15%. Moreover, small businesses have a higher percentage of positive reviews than chain restaurants (Figure 4.4).

Figure 4.3: Distribution of star ratings for the full dataset

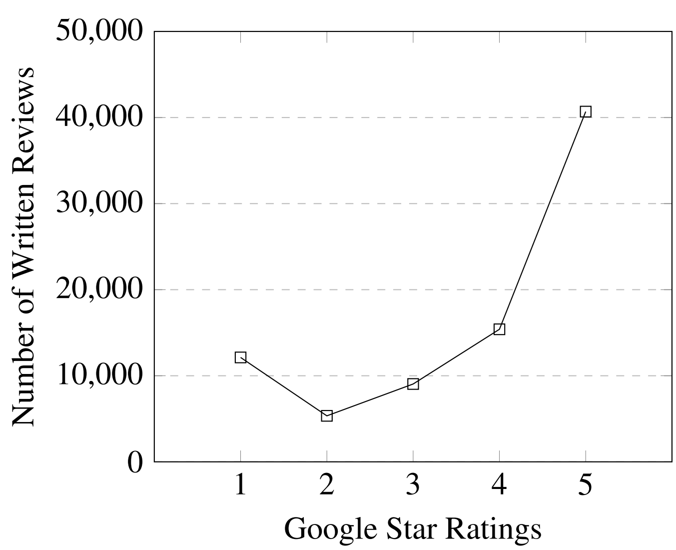
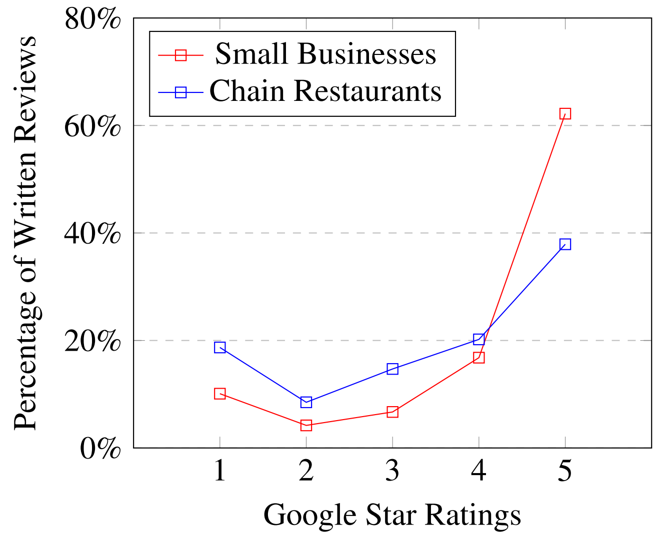


Figure 4.4: Distribution of star ratings for small and chain restaurants




Furthermore, star ratings correlate with calculated sentiment scores with a Pearson correlation coefficient of 0.52 and statistically significant at the 0.05 level. Although the overall relationship is clear, the spread of sentiment scores is quite large (Figure 4.5). For small businesses, sentiment score distribution has higher variance and positive skewness (Figure 4.6). The lower variance of the low-rating group (1&2-star) for chains suggests that customers mostly prefer to use negatively connotated phrases in this group of reviews.

Figure 4.5: Distribution of sentiment scores

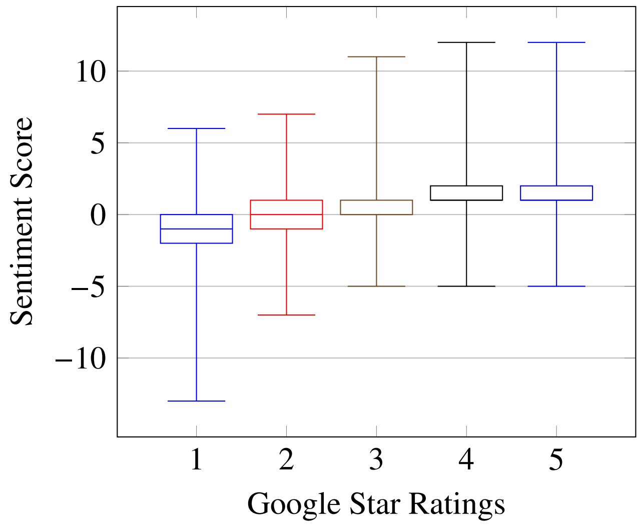
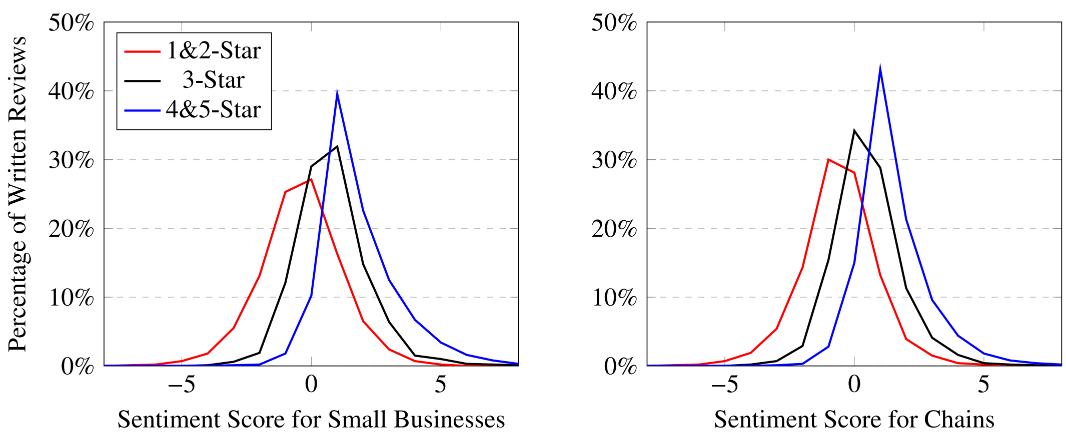



Figure 4.6: Distribution of sentiment scores for small business and chain restaurants




According to the sentiment analysis, while 59.39% of posts only have positive words, 10.87% of them only have negative, and 18.87% have both positive and negative sentiments. This strong positive skewness in both star ratings and sentiment analysis is consistent with the other studies analyzing online reviews (Jurafsky, 2014; Potts, 2011). According to Jurafsky (2014), there is a bias towards positivity in languages, resulting in positive skewness in online reviews.

Figure 4.7: Distribution of positive and negative sentiment scores

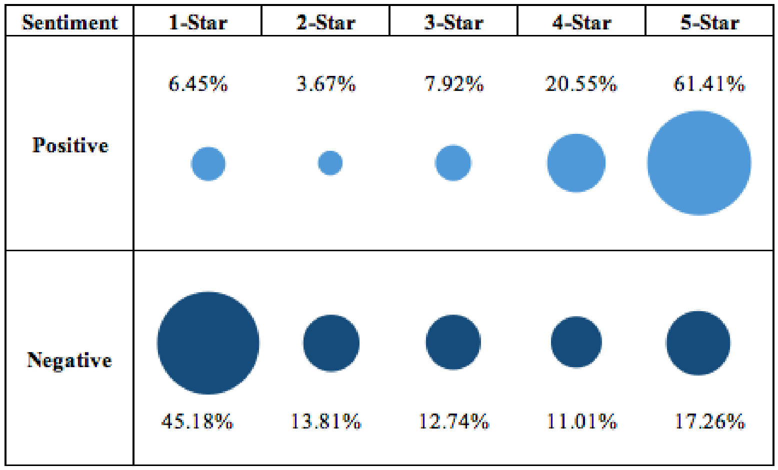



Figure 4.7 demonstrates the distribution and spread of negative and positive sentiment scores over star ratings. The majority of positive sentiments appear at 5-star reviews as they are associated with higher enjoyment (Park & Nicolau, 2015). Surprisingly, negative sentiment scores are spread over ratings and also highly present at 5-star ratings. Negative experiences elicit the emotion of disappointment towards the service provider and drive customers to share their negative experiences openly at online platforms (Verhagen et al., 2013). As a part of this, some reviewers compare their experiences to other restaurants and use negative and positive words in the same review. In addition to this, although their overall evaluation might be positive, they might still mention their negative experiences about the restaurant in their entry. These mixed reviews introduce significant noise to the sentiment scores (Dave et al., 2003). The following 5-star review embeds both positive and negative opinions of the customer:

”Fast friendly and inexpensive. But the rash of lazy customers parking illegally, in front of the restaurant is a safety hazard AND is inconvenient.”

Moreover, R programming software calculates sentiment scores of reviews based on each word in the Bing dictionary. The calculation does not account for complex nature of English language like extreme expressions (e.g., ”...they have mad good food”), negations (e.g., ”you won’t be disappointed”) and sarcasm (e.g., ”good luck getting the correct order”) (Lee & Yu, 2018.) While Google star ratings correlate with sentiment scores, this complexity of the language and psychological components of writing a review generate errors in quantitative models and also alters the distribution in both Figure 4.5 and Figure 4.7.

### Calculation Methods for Sentiment Scores of Attributes

In reference to the three-stage process that Nasukawa and Yi (2013) suggested, we leveraged technological tools to perform the first two stages. However, the third stage requires understanding the relationship between the context of a review and its sentiment. Both lexicon-based and machine learning approaches are applicable to a document or a sentence. Although it is practical to use a document-level classification rather than a sentence-level; an entry mostly contains multiple views, and a sentence usually conveys an individual thought (Liu, 2012). While one of the sentences in a review might share a positive experience in service quality, the other might discuss high prices. Therefore, the sentence-based approach would be more accurate to evaluate both sentiments and dining attributes. To minimize discrepancies, we accepted sentences after ”but” as a new sentence to investigate. We created binary variables for each attribute at a sentence level. Bing package in R calculated the sentiment score of each sentence. Then, we multiplied the score with a weighted average for each attribute. Their summation formed our final variables that capture the relationship between sentiment scores and dining experience attributes.

**Sentiment Scores of Attributes:**

$$SentimentScore_{ijk(n)} = SentimentScore_{ij(n)} * \frac{OccurrenceofAttribute_{ijk(n)}}{\sum_k^4 OccurrenceofAttribute_{ijk(n)}} \quad (4.1)$$

$$SentimentScore_{ijk} = \sum_{n=1}^{N} SentimentScore_{ijk(n)} \quad (4.2)$$

$$n = 1, 2, ...n^{th}\ sentence$$

$$k = Food, Service, Ambience, Price$$

$$i = 1, 2, ...i^{th}\ review$$

$$j = 1, 2, ...j^{th}\ restaurant$$

Example review: “**Slow service** and **cold food**. **Manager** said, they **lack staff** but few **employees** doing nothing!”

The first sentence, ”Slow service and cold food,” has sentiment score of -2, and it is related to both service and food. So, both attributes have -1 as a sentiment score of this sentence. The second sentence, ”Manager said, they lack staff”, has -1 as a sentiment score. As it is related to service attribute, the service attribute has -1 sentiment score from this sentence. The third sentence, ”...but few employees doing nothing”, does not have a sentiment score as ”nothing” is sentiment neutral word. Thus, for this review, food has a sentiment score of -1, and service has -2. The sentiment analysis procedure added four interaction variables to the dataset: sentiment$_{food}$, sentiment$_{service}$, sentiment$_{ambience}$, sentiment$_{price}$.

Table 4.3: Descriptive statistics of all variables in the full dataset

**Descriptive Statistics of Review Level Data**

| Variable Name | Mean/Freq | Std. Dev. | Min | Max | Observations |
|---|---|---|---|---|---|
| Star Rating | 3.81 | 1.47 | 1.00 | 5.00 | 82,598 |
| Sentiment Score | 1.08 | 1.72 | -13.00 | 12.00 | 82,598 |
| Positive Sentiment Score | 1.54 | 1.42 | 0 | 12.00 | 82,598 |
| Negative Sentiment Score | 0.46 | 0.86 | 0 | 13.00 | 82,598 |
| Food | 69.75% | | | | 82,598 |
| Service | 45.44% | | | | 82,598 |
| Ambience | 15.60% | | | | 82,598 |
| Price | 12.57% | | | | 82,598 |
| Feeling | 73.90% | | | | 82,598 |
| $\text{Sentiment}_{food}$ Score | 0.58 | 0.98 | -6.00 | 9.00 | 82,598 |
| $\text{Sentiment}_{service}$ Score | 0.24 | 0.81 | -13.00 | 9.00 | 82,598 |
| $\text{Sentiment}_{ambience}$ Score | 0.06 | 0.41 | -6.00 | 7.50 | 82,598 |
| $\text{Sentiment}_{price}$ Score | 0.04 | 0.30 | -3.67 | 4.00 | 82,598 |

**Descriptive Statistics of Restaurant Level Data**

| Variable Name | Mean/Freq | Std. Dev. | Min | Max | Observations |
|---|---|---|---|---|---|
| Avg. rating of a restaurant | 4.04 | 0.45 | 1.80 | 5.00 | 622 |
| Number of reviews | 249.39 | 271.78 | 1.00 | 2151 | 622 |
| Chain Restaurant | 37.78% | | | | 622 |
| Pizza Restaurant | 35.37% | | | | 622 |
| Burger Restaurant | 27.65% | | | | 622 |
| Sandwich/Sub Restaurant | 21.38% | | | | 622 |
| Chicken Restaurant | 9.00% | | | | 622 |
| Mexican Restaurant | 5.79% | | | | 622 |

**Descriptive Statistics of Block Group Level Demographic Data**

| Variable Name | Mean/Freq | Std. Dev. | Min | Max | Observations |
|---|---|---|---|---|---|
| Total Population | 1,210 | 725 | 213 | 6,180 | 333 |
| Median Household Income | 45,300 | 22,569 | 4,167 | 125,625 | 324 |
| Income per Capita | 26,725 | 13,087 | 3,095 | 81,959 | 332 |
| Population Density | 2,667 | 2,212 | 35 | 12,848 | 333 |
| Bachelor & higher (%) | 0.29 | 0.20 | 0 | 0.85 | 333 |
| Racial Diversity (White %) | 0.63 | 0.29 | 0 | 1.00 | 333 |
| Income per Capita (ln) | 10.07 | 0.52 | 8.04 | 11.31 | 332 |
| Population Density (ln) | 7.52 | 0.95 | 3.55 | 9.46 | 333 |

## 4.2 Quantitative Analysis

The full dataset presents opportunities to combine elements of both qualitative and quantitative research approaches to build depth understanding of customer preferences. Therefore, we performed a qualitative analysis of our dataset by using sentiment analysis and text analysis methods. The contextual analysis presented findings for us to consider during the quantitative analysis of the data. Besides these, the qualitative analysis shaped the dataset and added variables related to dining attributes and customer sentiments. By leveraging our findings from these, the next stage is determining correct models to test our three hypotheses.

### 4.2.1 Multilevel Model

Multilevel analysis is an appropriate approach for data with nested design. It allows a simultaneous examination of the effects of variables at different levels. It accounts for non-independence of observations within groups and provides variances within a group and between groups (Diez Roux, 2002). The multilevel model considers the individual group members as a unit of analysis and uses data structure to uncover the effects of being part of the group. The model adds variance components, called random effects, to parameterize the dependence among group members to estimate their correlation. (Feaster et al., 2011).

Ordinary least squares (OLS) models assume that each variable provides unique statistical information that is unrelated to other variables in the dataset. Statistical dependencies violate this assumption of OLS regression, lead to biased estimates of standard errors and incorrect conclusions (O'Dwyer & Parker, 2014). Contrary to this, multilevel models produce unbiased regression estimates of standard errors for nested datasets and include group characteristics into its models. It allows to partitioning variance and covariance components across levels and provides a within-group ($\delta_{ij}$) and between-group ($\xi_j$) component of the total variance (O'Dwyer & Parker, 2014). The model offers flexibility in forming different levels according to the data structure. Therefore, the multilevel model is suitable to apply to our hierarchical dataset.

### 4.2.2 Models for Categorical Data

Online platforms often use numerical ordinal data for customers to rank their experiences related to service or product. Google Review ratings are integers on a scale of 1 to 5. We organized this system into three ordinal categories: Low-rated reviews (1 and 2-star reviews), moderate reviews (3-star reviews), and high-rated reviews (4 and 5-star reviews). These groups indicate customers' satisfaction levels from their dining experience related to a specific contextual review. This ordinal rating system is essential for restaurants as individual star ratings make an average rating of a restaurant and affect the choices of prospective customers (Chevalier & Mayzlin, 2006; Senecal & Nantel, 2004). As we would like to understand the importance of dining experience attributes for customers, these rating groups are dependent variables for our model.

Ordinary Least Squares (OLS) regressions assume that a dependent variable is measured on a continuous, interval scale (Peel et al., 1998). It assumes normally distributed data and standardizes all variables to have a variance of 1. OLS might be suitable for the data that has a dependent variable with ten or more categories due to its continuous structure (Crouchley et al., 2009). Our dependent variable has three groups, and it violates the key assumption of OLS regressions. The analysis of Peel et al. (1998) suggests that the application of OLS methods to a model with ordinal dependent variables might lead to severe underestimates of the importance of independent variables, and it fails to predict categories for the dataset. Therefore, we can employ either ordered logit or ordered probit statistical models to our data. For probit and logit models, attain the standardization by scaling the variables and residuals to have residual variances of either 1 (for probit) or $\pi * 2/3$ (for logit) (Williams, 2009). Both methods use maximum likelihood functions to estimate model parameters, and they have similar statistical characteristics. They consider ceiling and floor effects on a dependent variable, while a linear model ignores the effects. These effects are strongest when the dependent variable is highly skewed (Winship & Mare, 1984). J-shaped of our dependent variable demonstrates both ceiling and floor effects and justifies its high variability. Therefore, for our data, ordered logit and probit models might be suitable.

However, assumptions of ordered logit models are easy to violate. In those cases, researchers either keep the model or switch to a multinomial logit model, which does not consider the ordering of the categories (Williams, 2016). Ordinal regression assumes that the effects of any explanatory variables are consistent across different thresholds and ignore variability across them. This assumption is often referred to as ”proportional odds” or ”parallel lines” assumptions (Williams, 2016). To decide between ordered logit and multinomial logit models, we structured an ordered logit model. To test whether any variable violates the parallel-lines assumption and to find variables violating the assumption, we used the globally preferred Brant Test (Williams, 2006). The result of the Brant Test ($\chi^2_5$=815.57, P> $\chi^2_5$=0) is highly significant and demonstrates the violation of the parallel lines assumption. The test suggests that underlying latent variables, a propensity to be more satisfied with a particular fast-food restaurant, may not be symmetric. The presence of dining attributes within a review is not proportional among different star categories. To avoid misleading results, we decided to use a nonordinal alternative, a multinomial logit regression. The model frees all variables from proportional odds constraint and generates more parameters compare to ordered logit regression (Williams, 2016).

### 4.2.3 Multilevel Multinomial Logit Models

The dataset satisfies the properties of both multilevel and multinomial logit models. Therefore, it requires using a multilevel model where the independent variable is categorical. Hence, we applied multilevel multinomial logit models to our dataset.

Variants of maximum likelihood are typically used to estimate multilevel multinomial logits. The process is usually more computationally demanding compared to the models with simpler outcomes (Hedeker, 2015). The integration of maximum likelihood performs better with a large number of clusters (Bauer & Sterba, 2011). Ali et al. (2016) recommend having a multilevel model with at least 100 groups and 30 observations per group to achieve accurate estimates. Structuring our model, we aimed to have at least one observation per star category within each restaurant group. In addition to this, for more accurate estimates, we filtered our data to have at least 30 observations per restaurant (Ali et al. 2016). Table 4.4 demonstrates the descriptive statistics of the final dataset used for the multilevel multinomial logit models.

Our dataset consists of 80,308 individual reviews associated with 484 unique fast-food restaurants located at 287 different block groups in 4 cities. All of 80,308 reviews are linked to one rating group among three categories: ”Low” being 1&2-Stars, ”Moderate” being 3-Star, and ”High” being 4&5 Stars.

Table 4.4: Descriptive statistics of the variables in multilevel multinomial logit models

| **Variable Name** | **Mean/Freq** | **Std. Dev.** | **Min** | **Max** | **Observations** |
|---|---|---|---|---|---|
| Star Groups | | | | | 80,308 |
| High - (4&5-Star) | 67.51% | | | | 54,212 |
| Moderate – (3-Star) | 11.12% | | | | 8,933 |
| Low - (1&2-Star) | 21.37% | | | | 17,163 |
| Food | 69.39% | | | | 80,308 |
| Service | 45.40% | | | | 80,308 |
| Ambience | 15.50% | | | | 80,308 |
| Price | 12.46% | | | | 80,308 |
| Feeling | 73.62% | | | | 80,308 |
| $\text{Sentiment}_{food}$ | 0.57 | 0.97 | -6.00 | 9.00 | 80,308 |
| $\text{Sentiment}_{service}$ | 0.23 | 0.81 | -13.00 | 9.00 | 80,308 |
| $\text{Sentiment}_{ambience}$ | 0.06 | 0.41 | -6.00 | 7.50 | 80,308 |
| $\text{Sentiment}_{price}$ | 0.04 | 0.30 | -3.67 | 4.00 | 80,308 |
| Restaurant Groups | | | | | 484 |
| Demographic Groups | | | | | 287 |

Contents of individual reviews are not entirely independent of each other. They tend to cluster within restaurants that they reviewed. Although fast-food chains are 54.23% of the dataset, even restaurants of the same brand are not identical and show variability in terms of dining experiences. As the research investigates customer preferences for fast-food restaurants, capturing variability between them is crucial to minimize errors during the assessment of attributes. Furthermore, individual fast-food restaurants are also nested within locations with different demographic variables such as different income levels, population density, racial diversity, and educational attainment. Due to this structure, both restaurants and block groups can be seen as a distinct layer of sources. Therefore, customer review data requires a hierarchical system where customer reviews are nested in restaurants that they evaluated.

As the lowest level (Level-1) is mostly defined by individuals (Hox et al., 2017), customer reviews are Level-1 for the model, and these reviews are nested in individual restaurants, which construct Level-2 of the model. These two levels are necessary to analyze our dataset. However, the dataset might also require creating a third level dedicated to block groups that restaurants are located. As demographics are an important factor in digital access (Pew Research, 2019), this might affect the choices of individuals and create a variance between each block group. User privacy and security limits the availability of information about reviewers' demographics. Therefore, we based our assumption that the demographics of the restaurant's location affect its performance and rating.

To evaluate the need for the third level, we examined the effects of demographics on aggregated star ratings of a block group. We calculated mean values of average restaurant ratings and number of reviews for each 332 block groups by using the full dataset (Table 4.3). To evaluate the relationship between star ratings and demographics, we constructed a multiple linear regression model (Table A.2). We regressed the average number of reviews, chain ratio, racial diversity, education level, logarithmic transformation of both income and population density on the mean star rating. Adjusted R-squared value (Adj. $R^2 = 0.262$) indicated that demographics were not explaining the variation of star ratings much. Most of the demographic variables were insignificant and not powerful to explain average star ratings. There is limited literature on demographics and customer reviews due to privacy restrictions. Bakshi et al. (2014) also used Census Data to conduct a study to examine the effects of demographics on customer ratings. According to their research, demographic variables, racial diversity, population, and education, have either an insignificant or a negligible effect on customer ratings. Rather than constructing a third level model for the full dataset, we decided to keep our model at two levels. The current multilevel multinomial logit models have two levels, reviews

(Level-1) nested within restaurants (Level-2).

The multinomial logit models are generalized logits that model different logits simultaneously due to multiple category responses (Pickery & Loosveldt, 2002). This generalized logit model has linear predictors and a multinomial logit link (Grilli and Rampichini, 2007). The response distribution usually assumed to be multivariate normal and defined conditionally on the random effects (Hartzel et al., 2001). Maximum Marginal Likelihood (MML) estimates the parameter of the model, and MML is approximated by Gauss-Hermite quadrature (Hedeker, 2003). According to Hedeker (2015), the most accurate approach is adaptive quadrature in the estimation procedure, and it performs well in a wide variety of situations. GLIMMIX procedure on SAS fits generalized linear mixed models (GLMMs), and the process approximates the marginal log-likelihood with an adaptive Gauss-Hermite quadrature rule (SAS, 2013).

The intraclass correlation coefficient (ICC) is a ratio of group-level error variance over total error variance. It calculates an unexplained portion of the variance in a dependent variable and helps to assess the addition of each independent variable. Higher ICC suggests that grouping of the data is significant, and a multilevel model is more suitable to the data than linear regression. Measuring available variance in a dependent variable requires constructing an empty multilevel multinomial logit model with a random group effect. This null-model gives information on whether there are significant differences between restaurants in star ratings or not. This simple model is a benchmark model to estimate an explanatory power of each variable, allows measuring a change in variance with the inclusion of independent variables. This variance component analysis process is informative to assess the importance of certain levels and their corresponding independent variables (Radojevic et al., 2017).

$$ICC^m = \frac{Var(\xi_j^m)}{Var(\xi_j^m) + Var(\delta_{ij}^m) + \pi^2/3} \tag{4.3}$$

Where m=1,. . . ,M is star category, j=1,. . . J is a cluster of a restaurant, and $i_j$ is a review in $j^{th}$ restaurant. $\xi_j$ is an unobserved heterogeneity at the cluster level (Level-2), and $\delta_{ij}$ is an unobserved heterogeneity at the subject level (Level-1).

## 4.3 Structuring the Models

In our model, dining attributes and sentiment analysis variables are independent variables. Customer star rating group ($y_{ij}$) is a dependent variable, representing the customer satisfaction level of $i^{th}$ review for $j^{th}$ restaurant. By building multiple models with different variables, we can assess how much variation dining attributions can explain. Therefore, we constructed and executed three multilevel multinomial logit models to provide insights on customer preferences. We applied all three models to four different datasets: (1) Full dataset suitable for multilevel analysis, (2) Only Small Businesses from the dataset, (3) Only chains from the dataset and (4) "Opinion Leaders" data (limits the entire dataset to reviewers with more than five reviews within the full data).

### 4.3.1 Information on the Multilevel Multinomial Logit Models

The multilevel multinomial logit models have linear predictors (4.4) and a multinomial logit link (4.5) (Grilli & Rampichini, 2007). The first equation has specific parameters ($\alpha^{(m)}$ and $\beta^{(m)}$) for each star group category (m). Star group category, $Y_{ij}$, is conditional on random effects ($\xi_j^{(m)}$ and $\beta_j^{(m)}$), takes a value of specific star category (m), and has a multinomial distribution. The reference category is m=1 (low-rated reviews) for all parameters, and the category has a random error of zero.

$$\eta_{ij}^{m} = \alpha^{(m)} + \beta^{(m)'} x_{ij} + \xi_j^{(m)} + \delta_{ij}^{(m)} \tag{4.4}$$

$$P(Y_{ij} = m | x_{ij} + \xi_j + \delta_{ij}) = \frac{exp(\eta_{ij}^{m})}{1 + \sum_{l=2}^{M} exp(\eta_{ij}^{l})} \tag{4.5}$$

$$where \quad \xi_j^{(')} = (\xi_j^{(2)} + ... + \xi_j^{(M)})' \sim iidN(0, \Sigma_\xi)$$

$$\delta_j^{(')} = (\delta_j^{(2)} + ... + \delta_j^{(M)})' \sim iidN(0, \Sigma_\delta)$$

$$m = 1, 2, ...M^{th} \ star \ category$$

$$i = 1, 2, ...\eta_j \ review$$

$$j = 1, 2, ...j^{th} \ restaurant$$

The parameters of the restaurant-level covariance matrix $\Sigma_\xi$ are all identified. In contrast, the parameters of the review-level covariance matrix $\Sigma_\delta$ are, in principle, identified but empirically not identified due to the convergence difficulties (Grilli & Rampichini, 2007). Therefore, the random errors $\delta_{ij}$ are omitted from the model.

### 4.3.2 Constructing the Models

**Model-1:**

Model-1 is an empty model, the simplest possible multilevel multinomial logit model with no Level-1 and Level-2 predictors. It only has intercept variables as parameters. It provides a baseline for calculations and building more complex models.

$$\eta_{ij}^{m} = \alpha^{(m)} + \xi_j^{(m)} \tag{4.6}$$

$$P(Y_{ij} = m|\xi_j) = \frac{exp(\eta_{ij}^{m})}{1 + \sum_{l=2}^{M} exp(\eta_{ij}^{l})} \tag{4.7}$$

$$where \quad \xi_j^{(')} = (\xi_j^{(2)} + ... + \xi_j^{(M)})' \sim iidN(0, \Sigma_\xi)$$

$$m = 1, 2, ...M^{th}\ star\ category$$

$$i = 1, 2, ...\eta_j\ review$$

$$j = 1, 2, ...j^{th}\ restaurant$$

StarGroup$_{ij}$ is the categorical dependent variable that demonstrates a star group of a particular review for a particular restaurant. $\alpha^{(m)}$ is the intercept parameter for a particular category of star rating and fixed effect component of the equation. Restaurant specific intercept $\xi_j^{(m)}$ is random effects with variance var($\xi_j^{(m)}$).

**Model-2:**

Model-2 introduces explanatory variables to the equation and adds five independent dining experience attribute variables to Model-1.

$$\eta_{ij}^{m} = \alpha^{(m)} + \beta^{(m)}x_1Food_{ij} + \beta^{(m)}x_2Service_{ij} + \beta^{(m)}x_3Ambience_{ij} + \beta^{(m)}x_4Price_{ij} + \beta^{(m)}x_5Feeling_{ij} + \xi_j^{(m)} \tag{4.8}$$

$$P(StarGroup_{ij} = m|x_{ij}, \xi_j) = \frac{exp(\eta_{ij}^{m})}{1 + \sum_{l=2}^{M} exp(\eta_{ij}^{l})} \tag{4.9}$$

$$where \quad \xi_j^{(')} = (\xi_j^{(2)} + ... + \xi_j^{(M)})' \sim iidN(0, \Sigma_\xi)$$

$$m = 1, 2, 3 \ star\ category$$

$$i = 1, 2, ...\eta_j \ review$$

$$j = 1, 2, ...j^{th} \ restaurant$$

StarGroup$_{ij}$ is again the star rating group of a particular review for a specific restaurant. $\xi_j^{(m)}$ is a random portion of the model, whereas the intercept ($\alpha^{(m)}$) and all variables (x$_{ij}$) are fixed effects of the model. As we included other variables to Model-1, we expect the unexplained portion of the variance, ICC, to decrease.

**Model-3:**

Model-3 introduces sentiment scores of dining attributes. The model has four variables all related to each contextual customer review.

$$\eta_{ij}^{m} = \alpha^{(m)} + \beta^{(m)} x_1 sentiment_{food(ij)} + \beta^{(m)} x_2 sentiment_{service(ij)} + \quad (4.10)$$

$$\beta^{(m)} x_3 sentiment_{ambience(ij)} + \beta^{(m)} x_4 sentiment_{price(ij)} + \xi_j^{(m)}$$

$$P(StarGroup_{ij} = m | x_{ij}, \xi_j) = \frac{exp(\eta_{ij}^{m})}{1 + \sum_{l=2}^{M} exp(\eta_{ij}^{l})} \quad (4.11)$$

$$where \quad \xi_j^{(')} = (\xi_j^{(2)} + ... + \xi_j^{(M)})' \sim iidN(0, \Sigma_\xi)$$

$$m = 1, 2, 3 \ star \ category$$

$$i = 1, 2, ...\eta_j \ review$$

$$j = 1, 2, ...j^{th} \ restaurant$$

StarGroup$_i j$ is a categorical dependent variable. $\xi_j^{(m)}$ is a random portion of the model, whereas the intercept ($\alpha^{(m)}$ and all variables (x$_{ij}$) are fixed effects of the model.

### 4.3.3 Multiple Linear Regression Models

Multilevel models investigate all customer reviews to provide insights on consumer preferences. They can capture specific information from the full dataset. However, for having a more comprehensive picture of consumer preferences, we can leverage the capabilities of multiple linear regression models (MR). Multiple linear regression allows us to understand the roles of various independent variables on a single dependent variable (Nathans et al., 2012). To investigate the roles of dining experience attributes, restaurant types, and demographics, we built multiple linear regression models. As we discussed earlier, our data has a restaurant level and a Census block group level information. For investigating the effect of attributes at the restaurant level, we calculated the group means of each variable at the restaurant level, and this calculation resulted in data of 622 unique restaurants. Secondly, the group means of variables for block groups in this dataset also gave us 332 block groups to analyze. As a result of these aggregated datasets, we conducted two linear regression models for each restaurant-level analysis and block group level analysis.

**Restaurant-Level Analysis**

**Model-4:**

Multiple linear regression model based on attributes are applied to three datasets, (1) all restaurants, (2) chains, and (3) small businesses data separately:

$$AvgStar_i = \beta_0 + \beta_1 Food_i + \beta_2 Service_i + \beta_3 Ambience_i + \tag{4.12}$$
$$\beta_4 Price_i + \beta_5 Feeling_i + \beta_6 TotalReview_i + \beta_7 Chain_i +$$
$$\beta_8 Pizza_i + \beta_9 Burger_i + \beta_{10} Sub_i + \beta_{11} Chicken_i + \beta_{12} Mexican_i + e_i$$
$$i = 1, 2, ...i^{th}\ restaurant$$

At Model-4, we control for a chain restaurant, an average number of reviews, average restaurant attribute occurrences, and types of food through four binary variables: pizza, burger, sandwich, and Mexican.

**Model-5:**

Multiple linear regression model based on sentiment scores are applied to (1) all restaurants, (2) chains, and (3) small businesses data separately:

$$AvgStar_i = \beta_0 + \beta_1 sentiment_{food(i)} + \beta_2 sentiment_{service(i)} + \tag{4.13}$$
$$\beta_3 sentiment_{ambience(i)} + \beta_4 sentiment_{price(i)} + \beta_5 TotalReview_i + \beta_6 Chain_i +$$
$$\beta_7 Pizza_i + \beta_8 Burger_i + \beta_9 Sub_i + \beta_{10} Chicken_i + \beta_{11} Mexican_i + e_i$$
$$i = 1, 2, ...i^{th}\ restaurant$$

At Model-5, for restaurant-level analysis, we control for a chain restaurant, and an average number of reviews, average sentiment scores related to each attribute, and types of food through four binary variables: pizza, burger, sandwich, and Mexican.

**Block Group Level Analysis**

**Model-6:**

Multiple linear regression model based on attributes are applied to aggregated block group dataset:

$$\begin{gathered}
AvgStar_i = \beta_0 + \beta_1 Food_i + \beta_2 Service_i + \beta_3 Ambience_i + \\
\beta_4 Price_i + \beta_5 Feeling_i + \beta_6 TotalReview_i + \beta_7 ChainRatio_i + \\
\beta_8 PopulationDensity_i + \beta_9 IncomePerCapita_i + \\
\beta_{10} RacialDiversity_i + \beta_{11} BachelorsDegree_i + e_i \\
i = 1, 2, ...i^{th}\ Census\ Block\ Group
\end{gathered} \tag{4.14}$$

At Model-6, we control for a chain ratio, average number of reviews, average restaurant attribute occurrences, population density, income per capita, racial diversity, and educational level.

**Model-7:**

Multiple linear regression model based on sentiment scores are applied to aggregated block group dataset:

$$AvgStar_i = \beta_0 + \beta_1 sentiment_{food(i)} + \beta_2 sentiment_{service(i)} + \tag{4.15}$$

$$\beta_3 sentiment_{ambience(i)} + \beta_4 sentiment_{price(i)} + \beta_5 TotalReview_i + \beta_6 ChainRatio_i +$$

$$\beta_7 PopulationDensity_i + \beta_8 IncomePerCapita_i +$$

$$\beta_9 RacialDiversity_i + \beta_{10} BachelorsDegree_i + e_i$$

$$i = 1, 2, ...i^{th}\ Census\ Block\ Group$$

At Model-7, we control for a chain ratio, average number of reviews, average sentiment scores related to each attribute, population density, income per capita, racial diversity, and educational level. Creating these two models helps to determine the key variable among dining experience attributes.

CHAPTER 5

# RESULTS

## 5.1 Results of Multilevel Multinomial Logit Models

Table 5.1 shows odds ratios for the estimates of fixed and random parameters of the multinomial logit models. Intraclass correlation coefficients (ICC) of null models for high ratings and moderate ratings are 15.4% and 4.3%, respectively. According to the findings of Vajargah and Masoomehnikbakht (2015), multilevel models improve the results of variables for models with ICC scores higher than 10%. As high-rating reviews make up 67.5% of our data, the multilevel model was a suitable choice to capture variability between restaurants.

At Model-2, the addition of the five binary attributes decreases the variability of the model by 16.3% for high ratings and by 8.9% for the moderate ratings. The explanatory power of the third model is higher for the high-rating group, and the variability decreased by 32.4% for high ratings and 0.3% for moderate ratings.

Goodness-of-fit statistics for the models, –2 log-likelihood (-2LL) values, are used to compare the fit of nested models. The likelihood ratio test for Model-1 and Model-2 ($\Delta$-2LL= 5,597) is considerably higher than the critical chi-square value with five degrees of freedom. The difference between Model-1 and Model-3 ($\Delta$-2LL= 20,347) is also significantly greater than the chi-square value with four degrees of freedom. The substantial difference between the null model and Model-3 suggests a better fit for the data. Both ICC and log-likelihood ratios prove that including sentiment interaction scores generate a better fit model.

Table 5.1: Results for Full Dataset with 484 Clusters - Odds Ratios (SE)

| **Variable Name** | **Star Category** | **Model-1 Null** | **Model-2 Attribute** | **Model-3 Sentiment** |
|---|---|---|---|---|
| Intercept | High | 1.349*** (0.037) | 1.200*** (0.041) | 0.722*** (0.032) |
| Intercept | Moderate | -0.699*** (0.025) | -0.180*** (0.037) | -0.786*** (0.026) |
| Food | High | | 1.004 (0.022) | |
| Food | Moderate | | 0.953 (0.028) | |
| Service | High | | 0.474*** (0.009) | |
| Service | Moderate | | 0.543*** (0.015) | |
| Ambience | High | | 0.572*** (0.014) | |
| Ambience | Moderate | | 0.775*** (0.027) | |
| Price | High | | 0.584*** (0.016) | |
| Price | Moderate | | 0.955 (0.037) | |
| Feeling | High | | 2.533*** (0.054) | |
| Feeling | Moderate | | 0.842*** (0.023) | |
| $Sentiment_{food}$ | High | | | 3.481*** (0.061) |
| $Sentiment_{food}$ | Moderate | | | 2.131*** (0.045) |
| $Sentiment_{service}$ | High | | | 3.750*** (0.076) |
| $Sentiment_{service}$ | Moderate | | | 2.077*** (0.047) |
| $Sentiment_{ambience}$ | High | | | 2.861*** (0.107) |
| $Sentiment_{ambience}$ | Moderate | | | 1.887*** (0.082) |
| $Sentiment_{price}$ | High | | | 2.244*** (0.106) |
| $Sentiment_{price}$ | Moderate | | | 1.237*** (0.073) |
| -2Log Likelihood | | 126,112 | 120,515 | 105,765 |
| Observations | | 80,308 | 80,308 | 80,308 |
| Observations | High | 54,212 | 54,212 | 54,212 |
| | Moderate | 8,933 | 8,933 | 8,933 |
| | Low-Base | 17,163 | 17,163 | 17,163 |
| ICC | High | 15.4% | 12.9% | 10.4% |
| ICC | Moderate | 4.3% | 3.9% | 4.3% |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

The ICC values lower than 5% for the moderate rating group suggest that variability between restaurants does not create high discrepancies for this response group. It proposes that 3-star reviews may not be sufficient to evaluate a particular restaurant. They may not provide differentiating information related to the dining experience.

Although the overall fit of Model-3 is better than Model-2, it does not apply to the moderate ratings. Sentiment variables create higher variability for the group. This situation suggests that 3-star reviews are not strictly composed of positive sentiments. A ”feeling” variable is a collection of both positive and negative opinions, and it generates an opportunity to understand the usage of sentiment related words for each response group. Model-2 demonstrates that the moderate group has a fewer occurrence of a feeling attribute, and an increase in the variable causes a 15.8% decrease of a review to be rated at a moderate level compared to the base group. At Model-3, odd ratios greater than 1 for each attribute suggest that 3-star symbolizes a better customer experience than the low rating group. However, as the odds ratios of the moderate group are smaller than the top rating group, the moderate responses have fewer positive sentiments compared to them. Our results confirm the findings of other studies (Forman et al., 2008; Lei, 2017; Mudambi & Schuff, 2010). 3-star ratings demonstrate a satisfactory level and contain fewer words related to extreme feelings compared to other groups.

Model-2 partially proves Hypothesis 1. It proposes that three dining attributes, service, ambience and price, have significant effects on customer satisfaction levels for fast-food restaurants, especially for the high rating group. Among three qualities, discussing service attributes has the highest impact and decreases the chance of a review to be in a top star group by 52.6%. Commenting on ambience and price attributes decrease the chance of getting high ratings by 42.8% and 41.6%, respectively. As the presence of service and ambience have similar effects on the moderate ratings, discussing ambience and service attributes increases the likelihood for a customer review to have a low score.

According to Model-3, reviews that reflect feelings of customers on service attributes have the greatest impact on high star ratings; it increases chances to get a high rating by 2.75 times. The change in the direction of service attribute between two models describes that service is crucial to impact the sentiment of reviewers. According to this finding, while customers are sharing their experiences on service-related qualities, they are more inclined to form sentences that include extreme negative or positive words. This effect of service on sentiments supports Hypothesis 2. It confirms that service is crucial to impact customer satisfaction levels.

### 5.1.1 Models for Small Business and Chain Restaurants

We created three models for both small businesses and restaurant chains (Table 5.2, Table 5.3). One of the most striking findings is a change in the intraclass correlation coefficients between Model-1 and Model-3 for restaurant chains. Adding sentiment variables to its model decreases its variability dramatically by 36.2% and 27.9% for the high rating and moderate rating group, respectively. However, for small businesses, the change in variability was smaller. In addition to these, feelings variable is significant for all categories of chain restaurants, whereas for small businesses the variable is not significant at the moderate level. For chain restaurants, an occurrence of the feeling variable increases the probability of a review to be at a high rating group by 117.6% and decreases its likelihood of being at the moderate group by 22.3%. Both of these findings suggest that customer sentiments have a higher impact on chain restaurants, and polarized opinions of customers potentially affect these businesses more.

Table 5.2: Results for Small Business Restaurants with 277 Clusters - Odds Ratios (SE)

| **Variable Name** | **Star Category** | **Model-1 Null** | **Model-2 Attribute** | **Model-3 Sentiment** |
|---|---|---|---|---|
| Intercept | High | 1.694*** (0.044) | 0.886*** (0.060) | 0.912*** (0.042) |
| Intercept | Moderate | -0.824*** (0.038) | -0.689*** (0.070) | -0.99*** (0.040) |
| Food | High | | 1.644*** (0.068) | |
| Food | Moderate | | 1.295*** (0.081) | |
| Service | High | | 0.410*** (0.014) | |
| Service | Moderate | | 0.468*** (0.024) | |
| Ambience | High | | 0.568*** (0.025) | |
| Ambience | Moderate | | 0.852* (0.058) | |
| Price | High | | 0.539*** (0.022) | |
| Price | Moderate | | 1.018 (0.062) | |
| Feeling | High | | 3.501*** (0.134) | |
| Feeling | Moderate | | 1.071 (0.059) | |
| $\text{Sentiment}_{food}$ | High | | | 3.720*** (0.094) |
| $\text{Sentiment}_{food}$ | Moderate | | | 2.192*** (0.071) |
| $\text{Sentiment}_{service}$ | High | | | 3.727*** (0.147) |
| $\text{Sentiment}_{service}$ | Moderate | | | 2.023*** (0.101) |
| $\text{Sentiment}_{ambience}$ | High | | | 2.563*** (0.178) |
| $\text{Sentiment}_{ambience}$ | Moderate | | | 1.781*** (0.186) |
| $\text{Sentiment}_{price}$ | High | | | 2.498*** (0.172) |
| $\text{Sentiment}_{price}$ | Moderate | | | 1.259** (0.113) |
| -2Log Likelihood | | 46,098 | 43,240 | 37,883 |
| Observations | | 36,758 | 36,758 | 36,758 |
| Observations | High | 28,918 | 28,918 | 28,918 |
| | Moderate | 2,523 | 2,523 | 2,523 |
| | Low-Base | 5,317 | 5,317 | 5,317 |
| ICC | High | 11.8% | 11.0% | 9.5% |
| ICC | Moderate | 4.8% | 4.1% | 4.2% |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

Table 5.3: Results for Chain Restaurants with 207 Clusters - Odds Ratios (SE)

| **Variable Name** | **Star Category** | **Model-1 Null** | **Model-2 Attribute** | **Model-3 Sentiment** |
|---|---|---|---|---|
| Intercept | High | 0.886*** (0.047) | 1.015*** (0.052) | 0.445*** (0.039) |
| Intercept | Moderate | -0.593*** (0.029) | 0.005 (0.041) | -0.600*** (0.027) |
| Food | High | | 0.839*** (0.021) | |
| Food | Moderate | | 0.890*** (0.029) | |
| Service | High | | 0.508*** (0.013) | |
| Service | Moderate | | 0.569*** (0.018) | |
| Ambience | High | | 0.578*** (0.017) | |
| Ambience | Moderate | | 0.746*** (0.030) | |
| Price | High | | 0.630*** (0.024) | |
| Price | Moderate | | 0.928 (0.047) | |
| Feeling | High | | 2.176*** (0.055) | |
| Feeling | Moderate | | 0.777*** (0.025) | |
| $Sentiment_{food}$ | High | | | 3.238*** (0.079) |
| $Sentiment_{food}$ | Moderate | | | 2.106*** (0.058) |
| $Sentiment_{service}$ | High | | | 3.777*** (0.089) |
| $Sentiment_{service}$ | Moderate | | | 2.092*** (0.054) |
| $Sentiment_{ambience}$ | High | | | 2.975*** (0.130) |
| $Sentiment_{ambience}$ | Moderate | | | 1.917*** (0.094) |
| $Sentiment_{price}$ | High | | | 2.012*** (0.131) |
| $Sentiment_{price}$ | Moderate | | | 1.204* (0.095) |
| -2Log Likelihood | | 79,842 | 76,766 | 67,676 |
| Observations | | 43,550 | 43,550 | 43,550 |
| Observations | High<br>Moderate<br>Low-Base | 25,294<br>6,410<br>11,846 | 25,294<br>6,410<br>11,846 | 25,294<br>6,410<br>11,846 |
| ICC | High | 11.0% | 10.4% | 7.0% |
| ICC | Moderate | 3.1% | 2.9% | 2.2% |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

Model-2 on the full dataset (Table 5.1) suggests that mentioning food attributes does not have a significant impact on customer satisfaction level. Differentiating the full data to small business and chain restaurants demonstrates that food attributes are significant for customer satisfaction. Discussing food attributes increases the chance of a review to be at a high rating group by 64.4% for small businesses whereas for chain restaurants it decreases likelihood of a review to be in a high rating group by 16.1%. It is a critical factor especially for small businesses to capture customers' attention and increase their online interaction with the restaurant. This finding proves Hypothesis 1: all four dining experience attributes have significant impact on customer satisfaction levels.

For chain restaurants, results for food attributes are close in magnitude. As they do not have the same variance, we calculated adjusted confidence intervals to compare both variables (Knol et al., 2011). According to these confidence intervals, the high rating group (CI 0.812-0.867) and the moderate rating group (CI 0.861-0.919 ) are overlapping, and they are not significantly different from each other. As restaurant chains serve the same food in all their franchises, there is a smaller variation between different locations. This effect reflects in customer reviews and discussing food attributes has less impact on customer satisfaction.

Model-3 for both business groups suggests the importance of service attributes. At Model-2, discussing service qualities is an indicator of getting a lower rating and decreases the probability of a review to be in the high rating group by 59.0% and 49.2% for small business and chain restaurants, respectively. Mentioning ambience attributes have similar impact on both groups; it decreases probabilities by 43.2% and 42.2% for small business and chain restaurants, respectively. With sentiment variables, service becomes a differentiating attribute and increases the likelihood of a review to be in a high rating group by 2.73 times and 2.78 times for small business and chain restaurants, respectively. These values confirm that for both groups, service is a critical factor that affects customers' attitudes.

### 5.1.2 Models for "Opinion Leaders"

To examine the preferences of "opinion leaders," we applied the same three models to a limited dataset that is composed of reviews from customers with five and more entries within our dataset. The limited dataset has a higher percentage (15.9%) of moderate ratings than the full dataset (11.1%). In addition to this, 72.6% of the data is related to chain restaurants and 57.82% of the users reviewed the same restaurant brand at least twice. Due to these aspects, the group knows what to expect from a quick-service restaurant. Therefore, we expect that 3-star ratings would be a satisfactory threshold for them.

The analysis (Table 5.4) demonstrates that food-related attributes do not increase or decrease ordinally. If a review comments on a food-related attribute, it has 11.7% less probability to be in the moderate rating group compared to the low rating group. Hence, this customer group who actively shares their opinion on the social platform mentions food attributes more at the extreme ratings. This finding suggests that decent food quality is the must for a satisfactory experience. For fast-food restaurants that fails to meet decency in food quality may get lower scores from frequent visitor. Moreover, the effect of food attributes is smaller compared to the service attributes. Discussing service attributes in a review decreases its likelihood to be in a high rating group by 45.2% compared to the base group. Therefore, the opinion leaders in our dataset are not food enthusiasts; they are frequent visitors. They expect restaurants to have decent food quality and they value service quality more.

Table 5.4: Results for Opinion Leaders with 210 Clusters - Odds Ratios (SE)

| **Variable Name** | **Star Category** | **Model-1 Null** | **Model-2 Attribute** | **Model-3 Sentiment** |
|---|---|---|---|---|
| Intercept | High | 1.563*** (0.053) | 1.342*** (0.067) | 1.05*** (0.047) |
| Intercept | Moderate | -0.004 (0.034) | 0.382*** (0.063) | -0.057 (0.034) |
| Food | High | | 0.972 (0.049) | |
| Food | Moderate | | 0.883* (0.053) | |
| Service | High | | 0.548** (0.026) | |
| Service | Moderate | | 0.625*** (0.036) | |
| Ambience | High | | 0.566*** (0.034) | |
| Ambience | Moderate | | 0.788** (0.058) | |
| Price | High | | 0.750*** (0.055) | |
| Price | Moderate | | 1.115 (0.098) | |
| Feeling | High | | 2.635*** (0.130) | |
| Feeling | Moderate | | 0.925 (0.054) | |
| $\text{Sentiment}_{food}$ | High | | | 3.154*** (0.134) |
| $\text{Sentiment}_{food}$ | Moderate | | | 1.961*** (0.092) |
| $\text{Sentiment}_{service}$ | High | | | 3.549*** (0.168) |
| $\text{Sentiment}_{service}$ | Moderate | | | 2.088*** (0.105) |
| $\text{Sentiment}_{ambience}$ | High | | | 3.030*** (0.259) |
| $\text{Sentiment}_{ambience}$ | Moderate | | | 2.034*** (0.188) |
| $\text{Sentiment}_{price}$ | High | | | 2.687*** (0.314) |
| $\text{Sentiment}_{price}$ | Moderate | | | 1.482** (0.194) |
| -2Log Likelihood | | 25,767 | 24,783 | 22,679 |
| Observations | | 15,650 | 15,650 | 15,650 |
| Observations | High | 10,622 | 10,622 | 10,622 |
| | Moderate | 2,495 | 2,495 | 2,495 |
| | Low-Base | 2,533 | 2,533 | 2,533 |
| ICC | High | 11.9% | 9.0% | 7.9% |
| ICC | Low-Base | 1.6% | 1.5% | 1.0% |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

## 5.2 Results of Multiple Linear Regressions

We conducted a restaurant-level analysis (Table 5.5), and a block group-level analysis (Table 5.6) and structured two models for each. At the restaurant level, we applied the models into three different datasets (1) all restaurants, (2) small businesses, and (3) chains (Table 5.5). For the block group-level, we used the data of all restaurants (Table 5.6).

Sentiment models create better fitting models for all three datasets at the restaurant-level analysis (Table 5.5). Adjusted R-squares values increase by 32.7%, 39.1%, and 166.8% for all restaurants, small businesses, and chains, respectively. This substantial change in data fit for chain restaurants supports the findings from the review-level analysis. Star ratings for chains heavily depend on customer sentiments. For small businesses, the feeling variable has a greater impact. If a restaurant has feeling related words in its all reviews, the restaurant's rating will increase by 2.315 stars. In addition to these, sentiment variables explain the variability between the chain and non-chain restaurants. Being a chain restaurant decreases the average rating of a restaurant by 0.251 stars for the sentiment model.

Model-4 demonstrates the importance of food and service attributes for fast-food restaurants. Model-5 exhibits that the sentiment score for all dining experience attributes except ambience has a significant impact on customer satisfaction. As sentiment scores have greater impact on chain restaurants, effects of its variables are greater than small business variables. Service quality is more important for chain restaurants compared to small businesses. A point increase in a service-related sentiment score can increase an average rating by 0.462 for a small business, 1.033 for a chain restaurant.

Model-5 suggests that the sentiment score of price is significant and it has a greater impact than the other attributes for chain restaurants. However, the magnitude of the variable is pretty small for all three datasets. For the full restaurant dataset, 82.4% of its data points reside within -0.1 and 0.1 and its median is 0.04. The median of $\text{sentiment}_{food}$ is 0.71 that is 17.80 times of $\text{sentiment}_{price}$. For chain restaurants, the magnitude of the price variable gets smaller and the median becomes 0.02. Therefore, although it is significant at Model-5, it has a negligible effect on the average ratings of restaurants.

Food types (pizza, burger, sub, chicken, and Mexican) have minor or no impact on average ratings of quick-service restaurants. When the effects of sentiment scores are considered, food offerings become insignificant to explain customer satisfaction levels. However, food quality is significant for both models and substantially increases the average score of a restaurant. This finding suggests that food types do not impact customer satisfaction levels.

Table 5.5: Restaurant Level Analysis - Results for Multiple Regressions

| | **Model-4 - Attribute Model** | | | **Model-5 - Sentiment Model** | | |
|---|---|---|---|---|---|---|
| **Variable Name** | **All** | **Small B.** | **Chains** | **All** | **Small B.** | **Chains** |
| Food | 0.860*** | 0.903*** | 0.968** | | | |
| | (0.198) | (0.258) | (0.320) | | | |
| Service | -0.520*** | -0.643*** | -0.778* | | | |
| | (0.137) | (0.159) | (0.306) | | | |
| Ambience | -0.309 | -0.512* | 0.223 | | | |
| | (0.205) | (0.235) | (0.417) | | | |
| Price | -0.117 | -0.097 | 0.110 | | | |
| | (0.195) | (0.211) | (0.525) | | | |
| Feeling | 1.742*** | 2.315*** | 0.857* | | | |
| | (0.218) | (0.276) | (0.377) | | | |
| $\text{Sentiment}_{food}$ | | | | 0.724*** | 0.687*** | 1.043*** |
| | | | | (0.054) | (0.066) | (0.091) |
| $\text{Sentiment}_{service}$ | | | | 0.699*** | 0.462*** | 1.033*** |
| | | | | (0.079) | (0.102) | (0.118) |
| $\text{Sentiment}_{ambience}$ | | | | 0.278 | 0.161 | 0.283 |
| | | | | (0.164) | (0.207) | (0.265) |
| $\text{Sentiment}_{price}$ | | | | 0.659*** | 0.720*** | 1.455** |
| | | | | (0.172) | (0.194) | (0.519) |
| Total Review | 0 | 0 | 0 | 0*** | 0** | 0 |
| | (0) | (0) | (0) | (0) | (0) | (0) |
| Chain | -0.107 | | | -0.251*** | | |
| | (0.058) | | | (0.041) | | |
| Pizza | -0.246*** | -0.258*** | 0.176 | -0.019 | -0.051 | -0.062 |
| | (0.066) | (0.066) | (0.129) | (0.055) | (0.060) | (0.079) |
| Burger | -0.125 | -0.128 | 0.186 | -0.024 | -0.008 | 0.011 |
| | (0.069) | (0.075) | (0.103) | (0.057) | (0.068) | (0.062) |
| Sub | 0.077 | 0.104 | 0.409*** | 0.097 | 0.078 | 0.096 |
| | (0.070) | (0.074) | (0.117) | (0.057) | (0.066) | (0.074) |
| Chicken | -0.269** | -0.228** | 0 | 0.018 | 0.007 | 0 |
| | (0.078) | (0.084) | (omitted) | (0.064) | (0.076) | (omitted) |
| Mexican | 0.067 | 0.015 | 0.458*** | 0.159* | 0.049 | 0.185* |
| | (0.090) | (0.116) | (0.129) | (0.073) | (0.102) | (0.079) |
| Constant | 2.356*** | 1.928*** | 2.433*** | 3.194*** | 3.313*** | 2.719*** |
| | (0.195) | (0.240) | (0.343) | (0.072) | (0.082) | (0.073) |
| Adj. R-Squared | 0.4973 | 0.3309 | 0.2723 | 0.6599 | 0.4604 | 0.7265 |
| Observations | 622 | 387 | 235 | 622 | 387 | 235 |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

Similar relationships can also be found in demographic analysis (Table 5.6). Food and service are significant attributes for Model-7. Comparing Model-6 and Model-7 shows that after introducing sentiment scores, the variable on the chain restaurant ratio becomes significant. According to Model-7, if a block group only consists of chain restaurants, an average rating of restaurants in the area decreases by 0.192.

All analyses on restaurant chains and small businesses confirm Hypothesis 3. Customer sentiments have a greater impact on fast-food chains and customers share their attitudes and feelings more in their reviews on these restaurants. The average ratings of small business restaurants are higher and the distribution of reviews is more positively skewed. Thus, compared to chain restaurants, small businesses have less polarized customer reviews.

Table 5.6: Block Group Level Analysis - Results for Multiple Regressions

| **Variable Name** | **Model-6 Attribute Model** | **Model-7 Sentiment Model** |
|---|---|---|
| Food | 0.892** | |
| | (0.280) | |
| Service | -0.364 | |
| | (0.201) | |
| Ambience | 0.342 | |
| | (0.297) | |
| Price | -0.364 | |
| | (0.330) | |
| Feeling | 1.788*** | |
| | (0.305) | |
| $\text{Sentiment}_{food}$ | | 0.694*** |
| | | (0.077) |
| $\text{Sentiment}_{service}$ | | 1.003*** |
| | | (0.129) |
| $\text{Sentiment}_{ambience}$ | | 0.288 |
| | | (0.252) |
| $\text{Sentiment}_{price}$ | | 0.486 |
| | | (0.283) |
| Chain Ratio | -0.015 | -0.192*** |
| | (0.085) | (0.055) |
| Total Review | 0 | 0 |
| | (0) | (0) |
| Population density (ln) | 0.045 | 0.038* |
| | (0.023) | (0.018) |
| Income per Capita (ln) | 0.006 | 0.034 |
| | (0.045) | (0.035) |
| Racial Diversity (Only White %) | 0.059 | -0.035 |
| | (0.093) | (0.072) |
| Bachelor's Degree (%) | 0 | -0.110 |
| | (0) | (0.098) |
| Constant | 1.597** | 2.581*** |
| | (0.531) | (0.385) |
| Adj. R-Squared | 0.4347 | 0.6515 |
| Observations | 332 | 332 |

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

CHAPTER 6

# DISCUSSION

## 6.1 Discussion of the Results

In brief, the findings support all three hypotheses. According to the results of the models, all four dining experience attributes, food, service, ambience and price, are significant for customer satisfaction. Among all four attributes, service is the most important indicator of customer satisfaction. Customer reviews on small business restaurants are less polarized compared to restaurant chains.

According to our findings, discussing food in a review is an indicator of a high star rating for small businesses. As the food quality of fast-food chain restaurants has a lower variation between different locations of the same brand, it has less impact on customer satisfaction levels. Thus, to capture customers' attention, small business restaurants need to have delicious and high-quality food offerings. These offerings invite customers in, create an urge for them to share their experiences, and rate the restaurant highly. Although food is essential to get high ratings, it is not the primary driver of customer sentiments, and it may not be sufficient to have influential and persuasive customer recommendations.

A comparison between Model-2 and Model-3 for all datasets demonstrates that service quality impacts customers' sentiments, and this effect of service eventually results in changes at customer satisfaction levels. According to Zhang et al. (2014), service quality is an antecedent of consumer satisfaction, and perception of service quality is a predictor of positive eWOM. Our study also demonstrates that service has a powerful influence on customers' dining experience, and the context of reviews is highly dependent on service quality. High-quality service may elicit positive emotions in customers, and it may be reflected in the content of a review. On the other hand, unsatisfactory service experience may result in anger and disappointment and it may decrease customer evaluation. Due to this, when customers use a service-related word, it mostly indicates that they are sharing a bad experience, and a review has a high likelihood of being at a low-rating group. Therefore, service is a critical factor in improving review content and differentiate eWOM of restaurants from their competitors. However, customer satisfaction is not a predictor of service quality (Ryu & Han, 2010) and customers' experience can also be strengthened with other attributes.

Price is not a critical driver to write eWOM for restaurants (Hyun, 2010; Jeong & Jang, 2011; Zhang et al., 2014). However, as fast-food consumption is more price-sensitive compared to other healthy options (Afshin et al., 2017) , it could be seen as an essential factor for customer satisfaction (Medeiros, 2013). Small business and chain fast-food restaurants in our dataset are in a similar price range. Even though pricing has a significant effect on customer choice, when customers filter their choices to fast-food serving restaurants, price became less of a differentiating factor for them (Table 5.1). However, when we distinguish the data between small businesses (Table 5.2) and fast-food chains (Table 5.3), pricing has a higher impact on choosing a restaurant from the local options. As fast-food chains that have similar pricing at all their locations, pricing has less effect on their customers' satisfaction levels. One of the customers left a 5-star comment to a pizzeria in Rochester in 2018,

"Love it here! Food is great and decently priced compared to other places. Also, a very green place!"

As shown in the quote, prices of small businesses might affect customer satisfaction levels and their possible revisits. However, overall, it is not a powerful factor determining customers' ratings.

The quantitative models have empirical findings to support the positive skewness of the dataset that the text analysis has already proposed (Figure 4.5,Figure 4.7). A review that contains a feeling variable has a higher likelihood to be rated 4 or 5-star than 1 or 2-star (Table 5.1). At the restaurant-level model (Table 5.5), feeling variables increase average star ratings. So, positive words are more commonly used than expressions with negative connotations. However, the feeling variable has less impact on chain restaurants at the restaurant-level model, and reviews on small businesses mostly drive positive skewness in the dataset. Small restaurants have more positive words across all levels of ratings and the usage of feeling related words does not differ between 3-star reviews and 1 and 2-star reviews (Table 5.2). On the contrary to chain restaurants, small businesses have less polarized reviews and more positively connotated words, even in the low-rated reviews.

This positive skewness might be explained with customers' intentions while writing reviews for small businesses. For choosing a local restaurant, due to high uncertainty, consumers rely more on the experiences of other customers (Reimer & Benkenstein, 2016). If a review is based on a personal reason, readers may not consider it a reliable source (Sen & Lerman, 2007). Therefore, as online reviewers have intentions to contribute to eWOM and to be considered trustworthy (Cheung and Lee, 2012; Tong et al., 2013), they may be more careful and objective on their reviews concerning small businesses. Hence, reviews for small businesses may be more informative and less polarized compared to fast-food chains.

Customer reviews on fast-food chains are not as positively skewed as small businesses and their low rated reviews have more sentiment related words. Customers' expectations determine their satisfaction levels, and failure to meet a customer's expectation results in receiving a low-rated online score. As customers already have prior knowledge of fast-food chains, their expectations are already set. Moreover, due to the brand recognition of these restaurants, reviewers might not feel an urge to write objective reviews. In addition to these, when customers confront negative reviews of the others, they are more inclined to share their unpleasant experiences on the platform (Verhagen et al., 2013). Expectations from these brands and prior commentaries result in increased usage of opinion and emotion-related words to share disappointments and excitements. These websites provide a platform for dissatisfied customers to share their complaints. Thus, customers might share their experiences about a specific location of a fast-food chain to get attention from its corporate office. Therefore, chain restaurants have more personal and sentiment-related reviews compared to small businesses.

## 6.2 Managerial Implications

This study has implications for owners and managers of small fast-food businesses. Overall, the research findings suggest that restaurants need to provide fulfilling experience at all four attributes, food, service, ambience, and price. Among these four dining experience attributes food, and service are essentials for customer preferences and restaurants' ratings. These attributes have great importance in attracting customers at online platforms (Zhang et al., 2010).

Food is a primary attribute that invites customers in and urges them to share and rate their experiences at the online platforms for small businesses. According to the study of Huang et al. (2014), reviews that talk about the quality of food also tend to mention the quality of other dining experience attributes. Businesses need to improve and maintain food quality to increase positive eWOM. Furthermore, when customers are expressing their feelings and opinions, they do not favor any specific cuisines. Food attributes are the most important factor, regardless of the type of restaurants (Bardwell et al., 2018). Thus, small businesses do not need to focus on a particular food group to get more customers. Customers can be satisfied with food offerings as long as they are delicious and serve customers' tastes. According to Jeong and Jang (2011), new menu items with great taste may draw more opinion leaders and increase positive eWOM. Maru/Matchbox 2018 Customer Surveys highlights that 93% of customers think the ability to see an online menu is essential during their decision process. Small businesses can post photos of their full menus and high demanding menu items on review platforms to invite more customers in. Even though the food might initially attract customers, it does not guarantee their revisits (Bardwell et al., 2018).

Although food is essential for customer satisfaction levels, it is less effective in inducing positive and negative emotions. Due to positive skewness in average ratings of small businesses, when customers filter restaurants in a recommendation platform according to average scores, they may still have a high number of choices. Therefore, expression of feelings and opinions within a review becomes more crucial for differentiating between these local restaurants. Service quality elicits an emotional response that may result in a persuasive customer review content. Therefore, service may be a determining factor during the choice of a local fast-food restaurant. In addition to that, service is essential to create a good reputation in the service industry, and it increases customer retention (Ban, 2019). Hence, small businesses need to focus on improving aspects related to service.

Positive beliefs of customers towards fast-food businesses are mostly related to convenience (Dunn et al., 2008). According to the top ten unique phrases in the dataset (Figure 4.2), small businesses need to provide fast, convenient, and friendly service and to take orders correctly for maintaining high customer satisfaction. Most frequently used service-related words are fast, staff, friendly, slow, quick, employees, rude, and delivery. It demonstrates that both timely and friendly service are essential for customers. Service quality helps with building trust between a restaurant and its customers (Hyun, 2010). Restaurants can align their preparation times to customers' expectations and communicate these wait times with customers to increase satisfaction levels. Even though efficiency and convenience are the most critical component of fast-food restaurants, friendly service can induce positive emotions (Ha & Jang, 2012). As service is a driver of positive sentiments, friendly, polite, fast, and convenient service can promote positive feelings. An attitude of customer-facing employees is key to create a good reputation. If employers provide appropriate work environments for their employees, improvements in their satisfaction may result in better customer service. Building a personal relationship with customers produces positive sentiments and improves both the rating and content of a review. According to Min and Min (2011), the most frequently visited fast-food chains have high service quality. The following review for a restaurant in Buffalo exemplifies that excellent service promotes positive sentiments.

”Blown away by the friendly service! Super friendly, helpful, call you by name... possibly the best service I’ve ever received at ANY restaurant - and this is a fast-casual place! Food is also excellent and very reasonably priced for quality. Will be a regular!”

A low-price strategy might be less useful to draw customers’ attention (Zhang et al., 2010). Although models suggest that price has a significant impact on customer satisfaction level, it is one of the least important factors for customer satisfaction. As long as restaurants stay in the same price range, they can eliminate negative comments on the pricing. Hence, restaurants can be flexible in their prices. They can use this markup in purchasing high-quality ingredients or improving service quality.

People write more positively skewed reviews for small businesses. Although it has positive implications in general, as most of their competitors have high ratings, it becomes harder to differentiate a restaurant from the others. Due to high competition, a context of a review gets more critical for customers during their decision-making process. Good branding has a lasting impact on a customer’s loyalty to a particular restaurant (Min & Min, 2011). On contrary to fast-food chains, most of the customers do not have prior knowledge or expectations towards small business restaurants. Small businesses are required to build a good first impression on customers. Therefore, they can build a strategy to focus on a couple of aspects in their restaurants to build their reputation and brand. If they perform consistently good at one aspect, customers will eventually discuss that in their reviews. Frequently mentioned qualities of restaurants in these reviews might affect the decisions of potential customers. These points of differentiation will be in part of their brands. Therefore, sustaining high satisfaction results in customer loyalty and positive eWOM, which leads to repurchase intention and customer acquisition, respectively.

As most of the small businesses lack websites and corporate email addresses to ask for feedback from their customers, online reviews are a customer feedback platform for them. Negative comments are valuable, but sometimes they may be biased, and they may just depend on the experience of a single customer. However, if there is a particular trend or consensus between these reviews, analyzing them becomes more important to diagnose the problems at the operation. Managers can prioritize these issues and take corrective actions to improve customer satisfaction. They can also monitor the reviews and respond to their customers (Zhang et al., 2010). These online platforms create an opportunity for genuine interaction between restaurants and customers (Pantelidis, 2010). They can win back unsatisfied customers by providing an explanation or apologizing on the platform. Responding to both positive and negative reviews can build credibility and convey that they take customer service seriously.

## 6.3 Theoretical Implications

Online customer review data is widely used in academic research. However, their usage in small business literature is limited. Therefore, this research contributes to the literature in the following ways.

Firstly, this study compares online customer reviews from fast-food chains to small fast-food businesses. The only other comparative study done in the area quantifies the revenue impact of average ratings on Yelp for both chain and independent restaurants (Luca, 2011). Rather than only analyzing customer ratings, our study analyzes contextual reviews and categorizes reviews into dining experience attributes. This methodical structure proves the positive skewness of small businesses compared to chain restaurants. Our research empirically shows that customers use more positive words when they are sharing their experiences in small business restaurants.

Secondly, our study is unique as its recommendations are specific to limited-service restaurants, and the research is built on 82,598 customer reviews. There are several studies on fast-food chains and franchises (Hyun, 2010; Lee & Ulgado, 1997; Min & Min, 2011) and non-chain restaurants (Keller & Kostromitina, 2020). These studies focus on customer evaluations and investigate the drivers of customer satisfaction. However, among these studies, only a few researchers investigate online customer review data (Keller & Kostromitina, 2020), and none of the studies utilize Google Reviews during their analysis of dining experience satisfaction. In addition to this, our analysis focuses on a specific business type, limited-service restaurants, and our recommendations are tailored to small business restaurants for increasing their revenues. Thus, our study contributes to the strategy of small business restaurants.

Lastly, although sentiment analysis is widely used in academic research, our study was the first to introduce a ”feeling” variable that combines both positive and negative sentiments into one group. This independent variable assesses the relationship between the usage of opinion related words and customer satisfaction levels. It provides insights into evaluating the polarization of review content. For our research, the feeling variable exhibited empirical findings on the positive skewness of reviews on small businesses.

## 6.4 Limitations and Future Research

Our research has some limitations, and this promotes opportunities for future research. Firstly, our study mainly focuses on restaurants in the four biggest cities in Upstate New York. Even though it limits the variation in tastes and eating habits, the geographical limitation also raises questions on the applicability of the findings to the other regions within the U.S. Future research could examine data from multiple areas. Especially, collecting data from various economically stagnant cities within each state could provide insights into customer preferences in poor-performing cities.

Secondly, emojis were commonly used in our dataset. They could convey the emotional content of text accurately. However, we did not analyze the meanings of these emojis for sentiment scores and feeling variables. This situation limited our abilities to capture customers' attitudes towards dining attributes comprehensively. Thus, future studies could consider integrating emojis into their dataset during the calculation of sentiment scores.

Lastly, our study leverages text analysis tools to categorize reviews into attributes. The results of the categorization provided insights into quantitative models. Although we investigated the most frequently used words for the attributes, we did not quantify the importance of subcategories under each attribute. We could detect underlying patterns and evaluate the significance of the categories for each quality. To accomplish these, we could investigate each group with methods like multiple correspondence analysis and factor analysis. Hence, for future studies, these tools could be used to examine each category further.

CHAPTER 7

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APPENDIX A

# APPENDIX

Table A.1: List of fast-food chains in the dataset

| Restaurant Name |
|---|
| Arby’s Restaurant |
| Burger King |
| Chick-Fil-A |
| Chipotle Mexican Grill |
| DiBella’s Old Fashioned Submarines |
| Domino’s |
| Five Guys Burgers & Fries |
| Jimmy Johns |
| Kentucky Fried Chicken |
| Little Caesars |
| McDonald’s |
| Panera Bread |
| Papa John’s Pizza |
| Pizza Hut |
| Popeye’s Louisiana Kitchen |
| Sbarro |
| Sonic Drive-In |
| Subway |
| Taco Bell |
| Wendy’s |

Table A.2: Regression results on average rating of block groups

| **Multiple Linear Regression Model on Avg. Rating of Block Groups** | |
|---|---|
| Total Review | -0.000<br>(0.00) |
| Chain ratio | -0.433***<br>(0.050) |
| Racial Diversity (Only White %) | 0.180*<br>(0.086) |
| Bachelor's Degree (%) | 0.061<br>(0.117) |
| Income per capita (ln) | 0.046<br>(0.042) |
| Population Density (ln) | 0.027<br>(0.022) |
| Constant | 3.442***<br>(0.457) |
| Adj. R-squared | 0.262 |
| No. Observation | 332 |

Standard errors are reported in parentheses.

*, **, *** indicates significance at the 95% 99% and 99.99% level respectively.

Table A.3: List of the words used during the coding process

| **FOOD** |
|---|
| Burger, Cheese, Fries, Chicken, Wing, Philly, Turkey, Pizza, Mushroom, Cooked, Dressing, Sandwich, Cheesesteak, Cheesecake, Cheeseburger, Fry, Fried, McChicken, Deli, Tomato, Tomatoes, Overcooked, Crust, Steak, Meat, Salad, Sauce, Taco, Sub, Burrito, Sandwiches, Pita, Biscuit, Food, Eat, Yumm, Taste, Beef, Seasoning, Cajun, Calzone, Breakfast, Lunch, Dinner, Menu, Meal, Ingredients, Beverages, Fresh, Quality, Delicious, Tasty, Tastier, Bread, Drink, Coke, Cheddar, Mountain Dew, Spicy, Frost, Nugget, Soup, Chowder, Avocado, Coffee, Chili, Pretzel, Bacon, Tuna, Fry, Whopper, Hot Dog, Yummy, Yum, Hotdog, Salt, Crunchy, Dipping, Cookie, Greasy, Potato, Filling, Healthy, Plate, Vegan, Slice, Milk, Garlic, Pepper, Pie, Fried, Crispy, Dough, Grilled, Wrap, Hots, Onion, Bbq, Gluten, Sausage, Tummy, Guacamole, Soggy, Beer, Vegetarian, Veggie, Rice, Pickle, Chips, Topping, Gyro, Queso, Rolls, Frozen, Parmesan, Dish, Mozzarella, Custard, Butter, Tender, Mayo, Ham, Shrimp, Tea, Soda, Lettuce, Shake, Bun, Pancake, Pasta, Lemon, Chocolate, Strawberry, Alfredo, Whopper, Fish, Cream, Dogs, Delish, Baked, Lobster, Empanada, Poutine, Ribs, Flavor, Frosties, Ketchup, Spinach, Bagel, Banana, Pork, Eggplant, Lasagna, Dessert, Hamburger, Frappe, Mocha, Cake, Oil, Grease, Muffin, Burger, Cheese, Cheesecake, Steak, Biscuit, Breakfast, Frost, Bacon, Pretzel, Grilled, Parmesan, Dough, Beer, Tea, Shrimp, Strawberry, Empanada, Eggplant, Popper, Potatoes, Mustard, Lemonade, Mushroom, Tomatoes, Sandwiches, Seasoning, Queso, Cajun, Nut, Fries, Cheeseburger, Meat, Sandw, Soup, Fry, Nugget, Tuna, Dipping, Slice, Wrap, Veggie, Mcmuffin, Soda, Alfredo, Poutine, Lasagna, Milkshake, Meatless, Potato, Filet, Chicken, Fry, Salad, Chowder, Wopper, Cookie, Milk, Hots, Wing, Fried, Sauce, Bread, Avocado, Whopper, Garlic, Onion, Pickle, Float, Custard, Shake, Cream, Frosties, Hamburger, Fresh, Barbacoa, Egg, Sprite, Dressing, Pepperoni, Philly, Mcchicken, Taco, Drink, Coffee, Hot Dog, Potato, Pepper, Bbq, Turkey, Deli, Sub, Filling, Pie, Gluten, Topping, Tender, Pancake, Delish, Spinach, Cake, Bowl, Fruit, Cheddar, Guacamole, Pizza, Tomato, Burrito, Beef, Beverages, Coke, Fried, Sausage, Gyro, Mayo, Pasta, Baked, Lemon, Vegetable, Whopper, Ribs, Dessert, Dip, Frappe, Slider, Guac, Sugar, Sub's, Ketchup, Mocha, Tofu, Muffin, Sandwich, Bun, Dogs, Hash Brown, Peanut, Lettuce, Fish, Bagel, Oil, Whooper, Chips, Vegan, Vegetarian, Protein, Frozen, Ice Cream, Frosty, Butter, Rice, Mozzarella, Banana, Dinner, Lunch, Food, Eat, Menu, Meal, Ingredients, Taste, Appetite, Plate, Dish, Quality, Spicy, Salt, Crunchy, Juicy, Stale, Greasy, Cold, Grease, Cooked, Overcooked, Stomach, Tummy, Delicious, Tasty, Tastier, Flavor, Yumm, Yummm, Yummmy, Yummie, Yummy, Yum, Tastey, Tasting, Cheesey, Pounder, Texmex, Tex Mex, Quesadilla, Slushy,Slushie, Salty, Crunch, Smoothie, Chilli, Halal, Freshly, Tots, Tater Tot, Undercooked, Undercook, Ate, Eating, Reuben, Variety, Happy Hour, Curly, Jamoca, Oreo, Bite, Pound, Healthy, Fanta, Sourdough, Whoper, Morzellrella, Broiler, Water, Broil, Specials, Apple, Brunch, Chocolate, Tasted, Tasteless, Spaghetti, Crispy, Crust, Sour, Nutritional, Nutrition, Tasteful, Canned, Acai, Tastebud, Pita, Falafel, Lukewarm, Warmed, Hotdog, Hot Dog, Croissant, Crisp, Vanilla, Cinnamon, Breadstick, Drumstick, Sticks, Mozzerella, Frenchtoast, Toast, Homefries, Omelet, Mcfries, Fastfood, Craving, Diet, Sammiches, Broiled, Baconator, Slidder, Grill, Frites |

| SERVICE |
| --- |
| Manager, Cashier, People, Worker, Unfriendly, Employee, Server, Waiter, Waitress, Management, Friendly, Training, Lazy, Welcome, Lousy, Professional, Welcoming, Staff, Friendliest, Likeable, Rude, Kiosk, Accommodating, Cordial, Respectful, Friendly, Unprofessional, Pleasant, Owner, Staffed, Register, Attentive, Well Managed, Attitude, Ppl, Helpful, Polite, Crew, Customer, Listen, Phone, Courteous, Professionally, Professionalism, Handled, Trainee, Trained, Understaffing, Understaffed, Workforce, Patient, Driver, Yelling, Yelled, Yell, Personnel, In-Person, Helping, Girl, Woman, Pizza Man, Clerk,Treatment, Poeple, Busy, Busiest, Busier, Waited, Wait, Faster, Waiting Time, Hurry, Fastest, Speedy, Faster, Slowest, Slower, On Time, Minute, Min, Waited, Convenient, Conveniently, Slow, Quickly, Fast, Convenience, Slow., Quickest, Quick, Quicker, Efficiently, Efficient, Inefficiency, Inconvenience, Rush, Ready In, Wrong Order, Order Right, Accuracy Of Order, Mess Up, Messed, Check Your Order, Correct Order, Wrong Order, Orders, Online, Mix Up, Our Order, Separate Order, Order Wrong, Order Correct, My Order, Screwed Up, Screw Up, Take Out, Take-Out, Drivethru, Drive Through, Grub Hub, Grubhub, Drivethru, Drive Thru, Deliveries, Delivered, App, Drive-Thru, Deliver, Delivery, Delivering, To-Go, Takeout, Drive Though, Service, Convenent, Mixed Up, Close Early, Prompt, Teamwork, Was Wrong, Forget To Put, Organization, Cortegeous, Staaaaff, Right Order, Disrespectful, Long Time, Incompetent, 24/7, Open, Hour, Ladies, Lady, Grumpy, Young Man, Thoughtful,Ownership, Greet, Greeted |
| **AMBIENCE** |
| Mess, Cleanliness, Cleanest, Filthy, Trashy, Mess, Gross, Counter, Sanitary, Cleaner, Unclean, Filthy, Sterile, Cleaning, Glove, Dirty, Clean, Dirtiest, Cleaned, Bug, Roach, Roaches, Dust, Flies, Fly, Sticky, Feels Like Home, Home Made, Homemade, Homey, Home Cooked, Comfy, Cozy, Comfortable, Relaxing, Chill, Crowded, Noisy, Small, Ac, Spacious, Packed, Freezing, Quiet, Fun, Music, Entertainment, Loud, Play Area, Bar Area, Arcade, Interior, Play House, Eating Area, Waiting Area, Dinning Room, Dining Room, Play Area, Childrens Area, Toddler Area, Play Land, Playland, Outdoor, Indoor, Patio, Dining Area, Seating, Inside, Seats, Sitting, Kitchen Area, Environment, Floor, Doors, Store, Building, Parking, Restroom, Washroom, Toilet, Bathroom, Bathroom, Wifi, Plenty Of, Taproom, Tap Room, More Room, Much Room, Location, Locate, Ghetto Place, Ghetto,Getto, Security, Neighborhood, Bins, Unsafe, Atmosphere, Close To, Table, Bad Area, Disease, Updating, Remodeled, Mall, Unsanitary, Renovation, Renovated,Exterior, Remodeling, Remodel, Fireplace, Gnat, Lobby, Chair, Located, Kid Place, Messy, Modernization, Noise, Easy to Find |

| |
|---|
| **PRICE** |
| Affordable, Pricy, Overpriced, Cheap, Value, Expensive, Reasonable, Inexpensive, Pricey, Over Priced, Overcharged, Cheep, Rip, Costly, $$, $$$, Coupon, Discount, Deal, Buy One Get One, 50% Off, Charge, Buck, Pay, Money, Price, Paid, Priced, Dollar, $, Credit, Card, Penny, Fare, Dollar, Refund, Charged, Cost, Pricing, Math, Receipt, Prix, Cent, Dime, Size, Portion, Bucket, Combo, Serving, Upgrade, Theft, Bargain |
| **FEELINGS** |
| Good, Mad, Want, Absolutely, Loving, Perfect, Bomb, Exciting, Lovely, Worth It, Awesomeness, Great, Definitely, Feel, Love, Ever, Bueno, Lol, Yes, Legend, Loved, Fav, Nice, Thank, Wow, Smile, Yas, Impressed, Thank, Enjoyed, Best, Really, Cool, Like, Sweet, Honestly, Better, A+, Excelente, Excellence, Epic, Enjoyable, Fantastic, Omg, Beautiful, God, Rock, Die For, Greatest, Excite, Wonderful, Happy, Glad, Delightfull, Yup, Enjoy, Liked, Excited, Awesome, Please, Mmmm, Enjoyed, Favorite, Well, Super, Enjoy, Excellent, Star, Beat, Amazing, Haha, Addictive, Crazy, Recommended, Pleasure, Yeah, Solid, Incredible, Outstanding, Sensational, Recommend, Very Satisfying, Very Satisfied, Exceed, Never, Awful, Overrated, Eh, Bad, Nasty, Garbage, Unimpressed, Disgust, Sorry, Adequate, Disaster, Horrible, Disappointed, Disgusting, Shame, Terrible, Suck, Hate, Disappointing, Zero, Hated, Disappoint, Worse, Complaint, Yuck, Gross, Not Satisfy, Not Satisfied, Not Satisfying, Unsatisfying, Wasn't Satisfied, Worst |

Table A.4: Variables and their explanations

| **Variable** | **Explanation** |
|---|---|
| Star Rating | Star-rating of the review |
| Positive Sentiment Score | Number of positive words in the review |
| Negative Sentiment Score | Number of negative words in the review |
| Sentiment Score | Positive score minus negative score |
| Food | Food attribute (1 if a review has food-related words) |
| Service | Service attribute (1 if a review has service-related words) |
| Ambience | Ambience attribute<br>(1 if a review has ambience-related words) |
| Price | Price attribute (1 if a review has price-related words) |
| Feeling | Feeling attribute (1 if a review has feeling related words) |
| $\text{Sentiment}_{food}$ Score | Calculated sentiment score of food attribute |
| $\text{Sentiment}_{service}$ Score | Calculated sentiment score of service attribute |
| $\text{Sentiment}_{ambience}$ Score | Calculated sentiment score of ambience attribute |
| $\text{Sentiment}_{price}$ Score | Calculated sentiment score of price attribute |
| Avg. rating of a restaurant | Average rating of a restaurant |
| Number of reviews | Total comment received for a restaurant |
| Chain Restaurant | Chain Flag (1 if Chain) |
| Pizza Restaurant | Serving pizza primarily (1 if serving) |
| Burger Restaurant | Serving primarily American food (1 if serving) |
| Sandwich/Sub Restaurant | Serving primarily sandwiches (1 if serving) |
| Chicken Restaurant | Serving primarily chicken (1 if serving) |
| Mexican Restaurant | Serving primarily Mexican food (1 if serving) |
| Total Population | Total number of population |
| Median Household Income | Median household income in the past 12 months<br>(In 2017 inflation-adjusted dollars) |
| Income per Capita | Per capita income in the past 12 months<br>(in 2017 inflation-adjusted dollars) |
| Population Density | Total number of the population over a total land area in $km^2$ |
| Bachelor & higher (%) | Percentage of Bachelor degree or higher for<br>the population 25 years and over |
| Racial Diversity (White %) | Percentage of only white people in the population |
| Income per Capita (ln) | Natural log of income per capita |
| Population Density (ln) | Natural log of population density |