ESSAYS ON FIRM QUALITY AND COMPETITION

by

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Economics

Middle Tennessee State University
December 2019

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To my father, Khosro Movahed, and mother, Javaher Alirezaei

ACKNOWLEDGEMENTS

Throughout the writing of this dissertation I have received a great deal of support and assistance. I will do my best not to leave anyone out. First and foremost, I would like to thank my supervisor, Dr Michael Roach and my committee Dr. Keith Gamble and Dr. Anton Eff, for their advice and guidance throughout this process

I want to thank my peers, Elvedin Bijelic, ATM Sayfuddin, and Amanda Dunaway for their wonderful collaboration. The time we spent together preparing for courses and reviewing materials was crucial to my success in this program. Thank you, to my close friends, Max Deaton and Ashkan Bahrani, who aided me more times than I can count on various aspects of the graduation process.

I would also like to acknowledge the excellent professors whose supervision helped shape this body of work. Thank you, Joachim Zietz, Stuart Fowler, Charles Baum, Mamit Deme, Mark Owen, Jason DeBacker and Ghasem Homaifar. I am particularly thankful to my advisor, Dr. Adam Rennhoff for his excellent cooperation whose expertise was invaluable in the formulating of the research.

Finally, I want to thank my family, without you I would not be where I am today. I would like to thank them for their wise counsel and sympathetic ear. You are always there for me.

ABSTRACT

This dissertation is composed of three separate empirical analyses. Each analysis is a separate article.

According to the quality competition theory, an increase in competitors' quality, all else equal, can force a business to raise its quality. The objective of this paper is to examine the theory through an assessment of a longitudinal dataset of restaurant quality as measured by restaurants customer satisfaction. Customer review ratings of a restaurant are utilized as a proxy of quality. To achieve the objective mentioned above, this research uses the average customer review ratings from 7,610 restaurants in the Phoenix metropolitan area. Ratings were collected from Yelp.com from the end of each month from 2014 to the end of 2017 to investigate the effect of competition on restaurant quality. A fixed effect panel regression model with a spatial distance band weight matrix is used to evaluate the effect that changes in competing restaurants' quality have on a restaurant. The results indicate that restaurants predominantly compete, and therefore are influenced, by their competitors and rivals within the same category and price range. The findings show that the rivals' customer rating has a much more significant impact on high-price restaurants than on lower-price restaurants. This paper also is the first to note that high-rating entrants have a positive effect on the review ratings of other restaurants.

Restaurants confront a dilemma to stay in the market or exit it as the market becomes more competitive. This research clarifies that the restaurant exit decision is established by the competitors' quality as well as competition intensity in the market. Taking advantage of the probit panel regression model, in this study I verify there is a

1.12 percentage point increase in restaurant exit probability if the difference between the average review of competitors and the review of restaurants increases by one star in the previous period. Furthermore, restaurant exit probability rise by 1.82 percentage points if the review rating of competitor within one mile with the same cuisine type increases. Also, one additional restaurant in the market enhances the probability of exit for a restaurant by 0.49 percentage points.

The final study investigates the financial implications of brand affiliation for businesses. Using a sample of hotels in Texas that had a change of ownership between 2014 and 2017, we explore how a change in brand affiliation that coincides with ownership change is associated with hotel revenue. Based on fixed-effects regressions, our results suggest brand affiliation is positively associated with hotel revenue. For the sample of hotels included in this study, we find after an independent hotel obtains brand affiliation, its monthly revenue per available room (RevPAR) increases by 28.8% on average; however, we do not find any statistically significant improvement of monthly revenue per available room for hotels that give up their affiliation status and become independent hotels. Our results support previous findings that brand affiliation boosts the financial performance of a business.

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CHAPTER I

Quality Competition in the Restaurant Industry:

How Restaurants Respond to Competitors' Consumer Reviews

1 Introduction

How does a firm respond to competition? In many businesses quality and price are the two major components of spatial competition. According to Chioveanu (2012) in price and quality competition, high quality is associated with high prices and low quality with low prices. Since low-quality businesses can eventually shift into a higher quality, a higher price business with a higher quality may need to raise quality to maximize profits. Also, when a new firm enters the market, nearby incumbent firms may increase their quality up to a higher level to retain their customers. This quality competition procedure is an intriguing research area for industrial organization economists as well as urban economics researchers.

An owner can attract more customers by either lowering prices or increasing quality. As the demand for restaurants increases, quality has become one of the most critical factors in evaluating customer satisfaction. Quality, therefore, is endogenously chosen by restaurants. If two restaurants have the same price, higher quality can make one restaurant successful if it is in the same location as a rival. In this way being aware of the satisfaction expected by the customers gives the restaurant an advantage in the highly competitive market. The most likely scenario is that shifting the customer satisfaction of

competitors would affect demand for the restaurant, and, as a result, they may adjust the quality based on the quality of competing restaurants.

It is difficult to measure the customer satisfaction of restaurants. I argue, however, that online customer reviews can serve as a proxy for the customer satisfaction of restaurants. In recent years reviews have become a vital key to the success of restaurants. That is why restaurant owners need to be aware of the influence of review websites such as Yelp and the role that they play in popularity and profitability of their restaurants.

Berry and Waldfogel (2010) showed that in the restaurant industry increasing competition will enhance the quality of firms that compete in the market. Jin and Leslie (2003) show consumer satisfaction increases when restaurants enhance their quality. This evidence of competition based on quality among restaurants leads me to investigate this relationship further. In light of recent evidence, the present research outlines the impact of competition on the quality of firms in the restaurant market by utilizing the customers' review ratings on Yelp as a proxy for restaurant quality. In this study I present empirical evidence regarding the dynamic spatial effect of competition on customer satisfaction among restaurants. This paper improves present empirical research of quality competition by focusing on the dynamic quality competition between restaurants. Using a panel dataset of 7,610 restaurants in the Phoenix Metropolitan Area, this paper looks to address whether a shift in the customer satisfaction of rivals influence a restaurant's customer satisfaction; whether restaurants with the same category and price have a higher effect on each other; and whether high-review entrants have effects on the incumbents' decision to increase their quality.

In this research I use longitudinal data of all restaurants listed on Yelp in the Phoenix Metropolitan Area. Yelp had 141 million unique visitors and 148 million reviews by the end of 2017. As a result, Yelp has become the primary source for consumer review ratings in the United States for the restaurant industry. I use a panel dataset that covers nearly all restaurants' reviews in the Phoenix metropolitan area from 2014 to 2017. This dataset includes the geographic location, cuisine category and average review rating of restaurants in each month. Furthermore, this dataset includes the price range of each restaurant in three categories: economy, midrange, and luxury. Since restaurants offer different cuisine type and prices for various services, researchers are able to examine product heterogeneity more accurately compared to other industries. Restaurants attract more customers during different seasons, especially summer which is the boom season for the businesses. The panel nature of the dataset allows me to deal with this seasonality problem that affects the restaurant industry.

The results indicate that restaurants at similar price levels have a strong effect on each other. An increase in the average competing restaurant's customer satisfaction also increases the customer satisfaction of restaurants that serve the same cuisine in a one-mile radius by 0.0522 unit of rating during the next month. This value means that a unit increase in the quality of the same cuisine competitors can increase the quality of restaurants by 3%. The theoretical model of Cellini, Siciliani, and Straume (2105) suggests that high-price restaurants, which tend to have more elastic demand, should care more about the changes in rival customer satisfaction because their consumers are less concerned about with price and more concerned with quality. Additional results illustrate that high-price restaurants are more responsive when competitors make a change in

quality. A one-star change in the average of competitors' ratings can increase the review rating of luxury restaurants in a one-mile radius by 0.2826 after one month.

I find that location features increase the customer satisfaction for the restaurants. A one standard deviation increase in location density increases the customer satisfaction by 0.0373 rating points. Similarly, this paper finds that high-rating entrants have an impact on competing restaurant quality. The restaurant's customer review rating increases by 0.002 if the proportion of high-rating restaurants increases by 10%.

In section 2 of this paper, I review some previous literature. I discuss the data in section 3. I suggest an empirical econometric model in section 4. Section 5 outlines the empirical results which complement the theoretical predictions. Finally, section 6 concludes.

2 Literature Review

Many researchers have studied the subject of quality competitors and developed models to analyse it. Cellini, Siciliani, and Straume (2105) suggested a new theory using quality competition with an endogenous price in the Hotelling linear city model, implying dynamic interaction of firms over time. They found that further quality and price competition motivate firms to increase their quality or reduce their price. Cellini, Siciliani, and Straume (2015) mentioned that profit-oriented businesses compete on quality as a way to attract customers when they do not intend to change the price. Their theory proposed that in a Hoteling model, where price do not change, more competition increases the quality of the firm. It can be concluded that with more competition,

consumers are reacting positively to quality. This response causes firms to improve their quality in order to raise their profit. Unlike quality price is not continuous number that can easily change.

Biscegliay, Cellini, and Grillix (2018) added to the previous research on the spatial quality competition by looking at government-regulated markets. They find that firms increase their quality to attract customers. Chioveanu (2012) proposed a simultaneous price and quality competition in an oligopolistic market. He emphasized the tradeoff between quality and price, and how profits change when some consumers consume the high-quality product and others spend less money to consume a lower quality product.

Existing studies have analyzed the influence of reviews on firm profits. Luca (2016) investigated the causal impact of online consumer reviews on restaurant revenues by using Yelp. He has found that one-star improvement in the Yelp ratings increases restaurant revenues by 5 to 9 percent. He indicated that consumers only use some of the information that is visible to them. Additionally, he noted that reviews do not impact restaurants with chain affiliation. Cabral and Hortacsu (2010) found that negative reviews drop the weekly sales rate of a seller from positive 5% to negative 8%. Also, with a duration model, they show that the seller's probability of exit after low review rating is very high, and it receives more negative reviews than its lifetime average just before exiting. The problem of low quality is a crucial indicator that often results in exiting the market.

Some research studied the effect of location on the competition. Berry and Waldfogel (2010) investigated the relationship between market size and quality in the

restaurant industry. They find if quality is associated with a variable cost, market size enhances the quality that the restaurants offer. The reason is that the broader market size has the smaller the market share. In other words, when there are more firms in the market, the number of customers that each firm can service is less.

3 Data

Yelp is a platform where reviewers write reviews about local businesses. In the fourth quarter of 2017 alone, Yelp had over 140 million visitors (based on unique IP addresses). On the Yelp website customers can write or read about restaurants after registering for a free account. The rating system includes discrete numbers between 1 to 5 with increments of 0.5. Reviews are accessible to everyone for free, and customers can discern the quality of restaurants quickly based on these ratings.

A unique panel dataset on the average review rating for each month for all restaurants in the Phoenix metropolitan area was collected from the Yelp website. Data are collected for each restaurant from January 2014 to December 2017. Table 1.1 presents summary statistics for the restaurants.

The data covers more than 96% of existing restaurants in the Phoenix area based on the Bureau of Labor Statistics data in the food service section. Specifically, the dataset has 9,611 unique restaurants properties. However, information needed for this research is available only for 7,610 of the restaurants. The address and price range which is required to analysis the model is missing for 2,001 restaurants. During the period from 2014 to 2017, 2,905 new restaurants entered the market, and 3,181 restaurants exited the market.

Figure 1.1 shows the numbers of entry and exit for each month. The latitude and longitude coordinates, price range, number of reviews in each month, an average rating of reviews, and food category are collected for each restaurant. Figure 1.2 shows the time trend of the average review rating between the different price ranges. Each restaurant is classified in three price range categories: economy, mid-price, and luxury. Table 1.2 and 1.3 contain the number of observations for the price ranges and different cuisine categories.

Based on Zhang, Li, and Hong (2016) and Karamshuk, et al. (2013), I can control location characteristics by setting three dynamic geographic features: location density, competitiveness, and homogeneity. Summary statistics of characteristics for restaurants in 48 months are presented in table 1.4.

Location density is defined as the popularity of location by utilizing number (*N*) of nearby restaurants *j* in the distance d_{ij} with *l* mile radius around restaurant *i* at time *t*. Location density is simply a number of restaurants in *l* mile radius. The location density is defined as:

$$Loc\_Den_{it} = \sum j \in (d_{ij} < l) \quad (1)$$

Competitiveness is defined as the ratio of nearby restaurants with similar category type with the total number of restaurants within the same area for the restaurant *i* at time t with category type *c*. For example, Indian restaurants could be situated close to each other which results to competition becoming higher for this type of cuisine. The value of this feature is between 0 to 1.

$$Competitiveness_{it} = \frac{N_{cjt}(i,l)}{N_{jt}(i,l)} \quad (2)$$

Homogeneity is the Herfindahl-Hirschman index (HHI) of different cuisine type in the market. The HHI Index is a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in a market and then summing the resulting numbers, and it can range from close to zero to one. To calculate homogeneity, I have used HHI index with finding market share of each cuisine type in the area. For example, if most restaurants around restaurant *i* are Indian type restaurants, the Homogeneity value is very high. However, a neighborhood that includes all types of restaurants has a lower Homogeneity value. Each restaurant has its cuisine type, c. N_c, signifies the number of nearby restaurants for cuisine type c with l mile radius where $c \in C$, and C is a set of all cuisine type.

$$Homogeneity_{it} = \sum_{c \in C} \left(\frac{N_{ct}(i,l)}{N_t(i,l)}\right)^2 \quad (3)$$

Inter-restaurant distance is a good estimate of the geographic interaction of restaurants. I use the haversine function on latitude and longitude points of restaurants to estimate the distance between them. The haversine function finds the circle distance between two points on a sphere with their longitudes and latitudes. In my dataset the distance between two restaurants ranges from less than a foot to more than 90 miles. Figures 1.3, 1.4 and 1.5 are the comparisons between average review ratings and location components of competing restaurants in a one-mile radius. Figure 1.3 shows that when the number of competitors increases around a given restaurant, the rating of that restaurant increases. In other words, competition and the quality of restaurants have positive relationship. Figure 1.4 and Figure 1.5 showcase the relationship between competitiveness and homogeneity with customer review rating, respectively. Even though they have a positive correlation

with the review rating of restaurants, the two figures are very noisy. I believe the noise is because restaurants do not just compete among their category type and price range, they also compete with other restaurants based on distance.

4 Empirical Strategy

The hypothesis of this paper suggests that a shift in an average of customer rating of rivals affects a restaurant's choice of quality. This effect is higher for restaurants with the same category and price. Economic theory also suggests that high-quality entrants have effects on the incumbents' decision to increase their quality. In order to test the hypothesis in this study, I have taken advantage of the panel fixed effect regression model to test the hypothesis of this paper related to quality competition theory.

I have applied a panel regression approach to analyze if a shift in the average rating of competitors has a causal impact on the change of the rating of restaurants. In this research, I have decided to remove all restaurants with less than ten reviews overall from my data analysis. These restaurants are removed because the customer rating of these restaurants changes a lot with each review in a month if they have a low number of reviews. The regression equation for model 1 can be written as follows:

$$R_{it} = \alpha_i + \beta_k \sum_{i \neq j,} W_{(ij)} R_{j(t-k)} + \gamma_n x_{itn} + \vartheta_m + \mu_y + \in_{it}, \qquad (4)$$

where, R_{it}, is the rating of review between time *t* and time *t-1* for restaurant i. $R_{j(t-k)}$, are competitor review ratings with lags subscript *k* determines the monthly lags for the ratings of the competitors. *W* is a distance band weighting matrix between restaurant *I* and its competitor *j*. In this weight matrix, the value of competitors that are located within

a certain geographic distance is set equal to one, and the rest are set equal to zero. Next, the matrix is row normalized to show the average value of review rating of competitors. x_{itn} is location features for restaurants, namely number of reviews, location density, competitiveness, and homogeneity. This regression includes month and year dummy variables. β_k are coefficients of interest that inform us of the effect that the change in restaurants' quality may have on one another.

For one specification I exclude all fast food to observe the effect of competition on independent restaurants in equation four. I analyze an alternative specification to observe the change in reviews of restaurants by including interaction terms between competition components and the average review of restaurants. The coefficient on interaction would capture the value of the change in both location features and the average review rating of rival restaurants. In the next step I analyze the effect of changes in the customer satisfaction of restaurants in the same category on each other by splitting restaurants into two categories. One category group is the same cuisine if both restaurants serve same service in a one-mile radius, and the second category groups are restaurants that serve different cuisines and compete with the given restaurant. Since all restaurants are in one of three price range. I also categorize restaurants in their price range for separate identification of the first model. This generates the estimate for the change in the restaurant's review rating associated with the change in a similarly priced competitor's average customer rating.

Finally, I estimate the effect of new high-rating entrants on the customer review rating of the incumbent restaurants in the market within a certain radius. I consider the

day in which the first review has been posted as the entrance day of a restaurant into a given market. This model 2 can be specified as:

$$R_{it} = \alpha_i + \beta \sum_{i \neq j,} W_{(ij)} enhq_{j(t-1)} + \gamma_n x_{itn} + \vartheta_m + \mu_y + \in_{it,} \quad (5)$$

Where $W_{(ij)}$ is the distance band weight matrix from equation four. Variable $enhq_{j(t-1)}$ is the number of high-rating entrants divided by the number of all restaurants in a one-mile radius around the restaurant. The coefficient of interest is β which identifies the effect of high-rating entry on the customer review rating of the incumbent. I consider restaurants that have an average of four or more reviews of at least four-star rating in the first month as a high-rating entrant. I analyze the model with the entry of all new restaurants without considering the customer reviews of them.

5 Results

In all tables panel A utilizes the model with all restaurants in the market and panel B shows the results when fast-food restaurants are excluded from the model. Table 1.5 shows the effect of competition on review rating of restaurants. The main dependent variables and the coefficients of interest are the average review of competitors with one and two lags**.** The other dependent variables of the regression are *Number of Reviews*, *Location Density*, *Competitiveness*, and *Homogeneity*.

I find on Table 1.5 that most of the coefficients of interest are not significant. However, the average change in the review rating of competitors at a two-mile radius is significant at a 10 percent level in panel A and 5 percent level in panel B. An estimate of 0.19 in panel A indicates that a restaurant's review rating changes by 0.19 if the average

customer review rating of competitors in two miles changes by one star. The result indicates evidence of the effect of the average review rating of competitors on the changing of the review rating of a given restaurant. One reason why more significant effects are estimated for a two mile radius is because more restaurants are included in this distance, and a change in average customer satisfaction would impact more restaurants. For two miles distance, review rating with two lag is insignificant which suggest immediate adjustment in quality.

By observing the results of Table 1.5, it is clear that the location component impacts the customer review rating of restaurants. In other words, customer satisfaction increases when the competition in the location becomes more intense. Regarding location density, restaurant rating increases by 0.04 if the number of restaurants in a one-mile distance increases by one standard deviation. One standard deviation in competitiveness (which is equal to 0.11) is estimated to increase the review rating of restaurants by 0.01. A one unit increase in standard deviation of homogeneity of location (which is equal to 0.19) also improves the customer review of restaurants by 0.01 in a one-mile distance. As the entry of new restaurants is correlated with location features, these results suggest that entry of new restaurants might increase the review rating of restaurants.

It is helpful to capture the effect of competition on the customer review rating of restaurants where both the location characteristic and the average review rating of competitors become more competitive. Table 1.6 shows the result of model1 with the interaction terms between average review rating of rivals and all location components. The coefficients for this interaction term are always significant, between 0.21 for restaurants within one half-mile to 0.49 for restaurants within 2 miles of their

competitors. The coefficients for the interaction between review rating and competitiveness are also found to be significant between 0.11 to 0.22 for different distances between competitors.

I expect to find that the average changing of the review rating of competitors affects the customer satisfaction of restaurants with the same cuisine category. Table 1.7 shows the results of a change in the customer satisfaction of restaurants compared to other restaurants in the same category and different category with varying distances. The results of column 5 and 6 for non-fast-food restaurants in the Phoenix metropolitan area are statistically significant. This means that restaurants respond to shifting the quality of same cuisine type restaurants. Review ratings change between 0.05 and 0.08 after one month within a one-mile distance and a two-mile distance, respectively, if the average review rating of the same category restaurants increases by one star. Average review ratings of restaurants with different categories does not have any effect on competitors.

The most important finding is that an increase in the rating of competitors with the same price is associated with an increase in competing restaurants review ratings in the following two months. These results show that differentiated product has greater impact on each other. Table 1.8 presents the results of changes in review ratings with restaurants differentiated by their price range. The spillover effect on luxury restaurants is considerably higher than for low-price restaurants. I believe the reason for this difference is that high-price restaurants compete in quality more than low-price restaurants. For low-price restaurants, theory suggests that competition to a large extent revolves around price. A one-star increase in average customer reviews of competing luxury restaurants can increase the rating of other luxury restaurants within a one-mile radius by 0.28 after one

month. However, economy restaurants and medium-price restaurants are affected by similar, competing restaurants by 0.17 and 0.08, respectively. Higher coefficient values for larger market radius in table 1.9 is likely due to the larger number of restaurants that are affected, which means that more absolute quality improvement is occurring.

Coefficients for location characteristics are more significant for lower-price restaurants compared to luxury restaurants in table 1.8. Increasing one value of location density can improve the review rating of economy restaurants by 0.05 and mid-range restaurants by 0.02. However, location density does not have a statistically significant effect on luxury restaurants. This means lower price restaurants shift the quality if the number of their competitors or the variety of restaurants in their market change. It can be concluded that luxury restaurants, whose customers are quality sensitive, respond to changes in the quality of their high price rivals more than other types of restaurants. For the economy restaurants with price-sensitive customers, on the other hand, the coefficients for average review rating of customers are getting smaller. As a result, lower-priced restaurants are affected more by the location in which they compete than the reviews of their rivals.

To investigate the effect of new high-rating entrants on responding to incumbents, I run the fixed effect panel model in the second model. In Table 1.10, panel A reports coefficients of all the restaurants in the market. Panel B estimates the regression when fast foods are excluded from the model. The results clearly indicate that restaurants respond to their incumbents in panel B. Although the new high-rating entrants do not have a significant effect in for the improvement of the customer satisfaction of restaurants in the market, they cause incumbent restaurants to increase customer rating by

0.02 if fast food restaurants are excluded from the model. This means that a one percent increase in the number of high-rating restaurants around a given restaurant results in an increase in customer satisfaction by a value of 0.0002.

6 Conclusion

Understanding the competition pattern of business behavior in the market, especially how businesses respond to each other's quality from the economics perspective, helps business owners proactively recover their loss and improve their profits. Theoretical analyses conclude that owners' profits are affected by quality shifting of other firms.

Using panel data on customer review ratings from Yelp in the Phoenix metropolitan area, my research highlights the quality competition in a two-stage format, where profit-oriented business providers set price in the first stage and then shift quality in the next stage based on their rivals' quality. Results indicate that elements of location change the customer review ratings of restaurants. The value of the customer review rating is estimated to rise by 0.0373 stars for a one standard deviation increase in location density. The level of competitiveness was found to increase the review rating by 0.0077 stars within a one-mile distance. Homogeneity is estimated to increase the review rating of restaurants by 0.0066 stars. Review ratings are found to be more critical for luxury restaurants, whose customers are less price sensitive. On average a one-star review rating increase by competing restaurant can increase a restaurant's review rating by 0.2826 stars after one month. Also, as theory predicts, the restaurants with same cuisine type, have an

effect on the customer satisfaction of each other. A one value change in the review rating of restaurants with same cuisine types without considering fast foods in the market can shift the customer satisfaction of competing restaurants by 0.0522 stars and 0.0787 stars in one mile and two-mile distances, respectively. Finally, an increase in the proportion of high-rating restaurants increases the customer review ratings of all restaurants by 0.0002.

Overall, the findings of this research show that restaurant competition affects customer satisfaction. This paper also presents evidence that online customer reviews of restaurants influence each other. An increase in a competing restaurant's quality makes the market more competitive, which in turn causes restaurants to increase their own quality. The impact of quality competition is more substantial in luxury and high-price restaurants. The model presented in this paper provides a guide for analyzing quality competition in other markets. The evidence of this paper also has the potential for future research on urban agglomeration and regional economics.

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APPENDIX A: CHAPTER I TABLES

Table 1.1: *Restaurant Summary Statistics*

Variable	Mean	Std. Err	Min	Max
Economy Restaurants	0.505	0.499	0	1
Midrange Restaurants	0.470	0.497	0	1
Luxury Restaurants	0.025	0.157	0	1
Average stars	3.413	0.807	1	5
Number of reviews per restaurant	86.624	143.224	3	2035
Number of Restaurants		9611		

Table 1.2: *Summary of Restaurants by Price Level*

Price level	Counts	% Not Omitted	% Sample
Economy Restaurants	3751	74.321	49.290
Midrange Restaurants	3639	84.944	47.819
Luxury Restaurants	220	78.853	2.891

Table1.3: *Counts of each restaurants type*

Cuisine type	Counts	Cuisine type	Counts	Cuisine type	Counts
Fast Food	1530	*Mexican*	825	*Sandwiches*	574
Burgers	402	*American (New)*	345	*Breakfast/Brunch*	344
Chinese	344	*Italian*	264	*Chicken Wings*	182
Seafood	150	*Cafes*	150	*Salad*	134
Delis	127	*Sushi Bars*	123	*Japanese*	120
Barbeque	109	*Coffee & Tea*	98	*Event Planning*	97
Thai	96	*Buffets*	89	*Asian Fusion*	78
Greek	76	*Steakhouses*	76	*Diners*	75
Vegetarian/Vegan	73	*Bakeries*	71	*Vietnamese*	68
Hot Dogs	66	*Indian*	65	*Juice Bar & Smoothies*	60
Middle Eastern	50	*Ice Cream*	48	*Specialty Food*	44
Gluten-Free	41	*Korean*	36	*Food Trucks*	33
Latin American	33	*Beer*	32	*Arts & Entertainment*	30
French	29	*Cheesesteaks*	27	*Food Delivery Services*	27
Hawaiian	24	*Comfort Food*	23	*Grocery*	22
Southern	20	*Others*	2274		

Table 1.4: *Dynamic Summary Statistics of Restaurants*

Variable	Mean	Std. Err	Min	Max
Economy Restaurants	0.497	0.499	0	1
Midrange Restaurants	0.473	0.497	0	1
Luxury Restaurants	0.029	0.151	0	1
Review Change	-0.004	0.148	-3	3.5
Average Number of Cuisine Type	7.836	18.016	0	38
Number of Reviews	3.091	3.877	0	62
Location Density	53.604	53.257	0	298
Competitiveness	0.103	0.111	0	1
Homogeneity	1.02	0.192	0	1.337
Time Competing in the Market	39.719	9.13	4	48
Number of Observations	302262			

Notes: Excluded restaurants with missing price and address and with less than ten customer reviews. Distance for competition characteristic is one mile.

Table 1.5: *Effect of competition on review rating of restaurants*

	Panel A			Panel B		
Independent Variables	0.5 mile	1 mile	2 mile	0.5 mile	1 mile	2 mile
$Rating_{j(t-1)}$	0.0386	0.0666	0.1934*	0.0080	0.0454	0.1995 **
	(0.0522)	(0.0817)	(0.0583)	(0.0352)	(0.0753)	(0.0476)
$Rating_{j(t-2)}$	-0.0109	0.0252	0.1068	-0.0073	0.0438	0.1245
	(0.0522)	(0.0885)	(0.1349)	(0.0491)	(0.0631)	(0.1234)
Number of Reviews	0.0161***	0.0156***	0.0156***	0.0196***	0.0194***	0.0194***
	(0.0012)	(0.0014)	(0.0014)	(0.0012)	(0.0014)	(0.0014)
Location Density	0.0369***	0.0373***	0.0375***	0.0446***	0.0446***	0.0448***
	(0.0064)	(0.0042)	(0.0043)	(0.0088)	(0.0082)	(0.0082)
Competitiveness	0.0075**	0.0077*	0.0131*	0.0081**	0.0094**	0.0153*
	(0.0034)	(0.0047)	(0.0086)	(0.0023)	(0.0029)	(0.0056)
Homogeneity	0.0074***	0.0066***	0.0025	0.0089***	0.0080***	0.0071***
	(0.0026)	(0.0024)	(0.0020)	(0.0026)	(0.0025)	(0.0023)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 1.6: *Effect of competition on review rating of restaurants with interaction terms*

	Panel A			Panel B		
Independent Variables	0.5 mile	1 mile	2 mile	0.5 mile	1 mile	2 mile
$Rating_{j(t-1)}$	0.1279**	0.0343	0.0632	0.0946	0.0458	0.0867
	(0.0471)	(0.1086)	(0.1805)	(0.0675)	(0.0975)	(0.2273)
$Rating_{j(t-1)}$ * *Location Density*	0.2140***	0.2822***	0.4735***	0.2245***	0.3087***	0.4859***
	(0.0450)	(0.0469)	(0.0573)	(0.0411)	(0.0410)	(0.0518)
$Rating_{j(t-1)}$ * *Competitiveness*	0.1052***	0.1587**	0.2101*	0.1379***	0.1716**	0.2183**
	(0.0315)	(0.0644)	(0.1293)	(0.0311)	(0.0623)	(0.1167)
$Rating_{j(t-1)}$ * *Homogeneity*	0.0056	-0.0003	-0.0128	-0.0003	-0.0006	-0.0069
	(0.0227)	(0.0264)	(0.0230)	(0.0285)	(0.0292)	(0.0314)
Numbers of review	0.0137***	0.0137***	0.0113***	0.0186***	0.0185***	0.0184***
	(0.0011)	(0.0013)	(0.0012)	(0.0012)	(0.0014)	(0.0014)
Location Density	0.0684**	0.0807***	0.0927***	0.9574***	0.1006***	0.1504***
	(0.0275)	(0.0108)	(0.0142)	(0.0198)	(0.0134)	(0.0163)
Competitiveness	0.0287***	0.0480**	0.0506	0.0303***	0.0496***	0.0522
	(0.0079)	(0.0170)	(0.0340)	(0.0076)	(0.0117)	(0.0302)
Homogeneity	0.0018	0.0056	0.0059	0.0036	0.0108	0.0112*
	(0.0045)	(0.0061)	(0.0043)	(0.0044)	(0.0067)	(0.0049)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 1.7: *Effect of competition on review rating of restaurants with cuisine category differentiation*

	Panel A			Panel B		
Independent Variables	0.5 mile	1 mile	2 miles	0.5 mile	1 mile	2 miles
Same cuisine $Rating_{j(t-1)}$	0.0475	0.0285	0.0554	0.0511	0.0522**	0.0787**
	(0.0468)	(0.0683)	(0.1165)	(0.0373)	(0.0175)	(0.0187)
Same cuisine $Rating_{j(t-2)}$	0.0283	0.0266	0.100	0.0194	0.0168	0.02954
	(0.0448)	(0.0708)	(0.124)	(0.0189)	(0.0185)	(0.0298)
Different cuisine $Rating_{j(t-1)}$	-0.0104	0.0069	-0.015	0.0053	0.0037	-0.0059
	(0.0306)	(0.0320)	(0.035)	(0.0280)	(0.0808)	(0.0473)
Different cuisine $Rating_{j(t-2)}$	-0.0287	-0.0044	0.017	-0.0094	0.0049	0.0059
	(0.0324)	(0.0308)	(0.034)	(0.0495)	(0.0428)	(0.0280)
Number of Reviews	0.0161***	0.0156***	0.0156***	0.0195***	0.0195***	0.0195***
	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Location Density	0.0295***	0.0373***	0.0374***	0.0446***	0.0446***	0.0448***
	(0.0065)	(0.0042)	(0.0043)	(0.0088)	(0.0082)	(0.0082)
Competitiveness	0.0074**	0.0079	0.0131*	0.0081**	0.0095**	0.0157**
	(0.0034)	(0.0052)	(0.0086)	(0.0024)	(0.0029)	(0.0042)
Homogeneity	0.0066***	0.0032	0.0024	0.0089***	0.0080***	0.0071***
	(0.0024)	(0.0022)	(0.0020)	(0.0028)	(0.0026)	(0.0024)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 1.8: *Effect of competition on review rating of restaurants with price differentiation in a one-mile distance*

	Panel A			Panel B		
Independent Variables	Economy Restaurants	Midrange Restaurants	Luxury Restaurants	Economy Restaurants	Midrange Restaurants	Luxury Restaurants
$Rating_{j(t-1)e}$	0.1665*	0.0145	0.0890	0.2793***	0.0773	0.1167
	(0.0917)	(0.0827)	(0.1801)	(0.0478)	(0.0487)	(0.9323)
$Rating_{j(t-2)e}$	0.0333	0.0873	-0.0273	0.0635	0.1191*	-0.0057
	(0.0929)	(0.0767)	(0.0975)	(0.0589)	(0.0443)	(0.0847)
$Rating_{j(t-1)m}$	0.0605	0.0253	0.1179	0.1184	0.0459	0.2085*
	(0.0710)	(0.0772)	(0.1562)	(0.0635)	(0.0571)	(0.0838)
$Rating_{j(t-2)m}$	0.1293	0.0792*	0.1383*	0.1749*	0.1247*	0.2268***
	(0.0694)	(0.0397)	(0.0797)	(0.0639)	(0.0487)	(0.0586)
$Rating_{j(t-1)l}$	-0.0218	-0.0292	0.2826**	0.0191	0.0387	0.3067***
	(0.0365)	(0.0311)	(0.0723)	(0.0269)	(0.0295)	(0.0680)
$Rating_{j(t-2)l}$	0.0295	0.0367	0.1074	0.0312	0.0056	0.1198 *
	(0.0342)	(0.0290)	(0.0612)	(0.0368)	(0.0471)	(0.0558)
Number of Reviews	0.0232***	0.0077***	0.0059***	0.0378***	0.0093***	0.0060***
	(0.0028)	(0.0015)	(0.0005)	(0.0028)	(0.0013)	(0.0005)
Location Density	0.0529***	0.0153***	0.0059	0.0858***	0.0212***	0.0094
	(0.0085)	(0.0049)	(0.0146)	(0.0062)	(0.0034)	(0.0097)
Competitiveness	0.0095	0.0095	0.0032*	0.0086	0.0082	0.0024*
	(0.0084)	(0.0066)	(0.0012)	(0.0076)	(0.0062)	(0.0010)
Homogeneity	0.0063*	0.0064*	0.0043*	0.0061**	0.0061**	0.0043*
	(0.0036)	(0.0033)	(0.0025)	(0.0028)	(0.0026)	(0.0021)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 1.9: *Effect of competition on review rating of restaurants with price differentiation in for different radius*

	0.5 mile			2 mile		
Independent Variables	Economy Restaurants	Midrange Restaurants	Luxury Restaurants	Economy Restaurants	Midrange Restaurants	Luxury Restaurants
$Rating_{j(t-1)l}$	0.0152	0.0633	0.0700	0.3044**	0.0723	0.1614
	(0.0612)	(0.0584)	(0.1353)	(0.1255)	(0.1327)	(0.3198)
$Rating_{j(t-2)l}$	0.0013	0.0024	-0.2672	0.0305	0.0634	0.3706
	(0.0707)	(0.0574)	(0.1945)	(0.0818)	(0.0774)	(0.3184)
$Rating_{j(t-1)m}$	0.0703	0.0046	-0.0637	-0.0186	0.0645	0.4552
	(0.0507)	(0.0496)	(0.1786)	(0.1332)	(0.1281)	(0.3768)
$Rating_{j(t-2)m}$	0.0208	0.0723*	0.0565*	-0.0425	0.1007*	0.1493
	(0.0503)	(0.0374)	(0.0206)	(0.0663)	(0.0504)	(0.1623)
$Rating_{j(t-1)h}$	-0.0293	0.0297	0.0784*	0.0046	-0.0070	0.2838**
	(0.0562)	(0.0416)	(0.0363)	(0.0329)	(0.0286)	(0.1474)
$Rating_{j(t-2)h}$	0.0230	0.0149	0.0105	0.0090	0.0384	0.1079*
	(0.0496)	(0.0374)	(0.1136)	(0.0175)	(0.0193)	(0.0602)
Number of Reviews	0.0217***	0.0072***	0.0109***	0.0233***	0.0078***	0.0050***
	(0.0021)	(0.0015)	(0.0034)	(0.0028)	(0.0015)	(0.0005)
Location Density	0.0317	0.0113	0.0213	0.0532***	0.0156***	0.0039
	(0.0279)	(0.0214)	(0.0412)	(0.0085)	(0.0049)	(0.0147)
Competitiveness	0.0171**	0.0023	0.0044	0.0201	0.0042	0.0107
	(0.0062)	(0.0042)	(0.0091)	(0.0143)	(0.0096)	(0.0255)
Homogeneity	0.0018*	0.0047 *	0.0096 *	0.0024	0.0049 *	0.0098**
	(0.0044)	(0.0019)	(0.0042)	(0.0027)	(0.0032)	(0.0047)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 1.10: *Effect of new entrants on review rating of restaurants in a one-mile radius*

	Panel A			Panel B		
Independent Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
$enhq_{j(t-1)}$	0.0200	0.0200*	0.0201*	0.0240	0.0244*	0.0245**
	(0.0149)	(0.0112)	(0.0104)	(0.0148)	(0.0113)	(0.0106)
$en_{j(t-1)}$	0.0368	-	0.0306	0.0370	-	0.0331
	(0.0352)		(0.0292)	(0.0358)		(0.0338)
Number of Reviews	-	0.0159***	0.0158***	-	0.0198***	0.0198***
		(0.0013)	(0.0013)		(0.0014)	(0.0014)
Location Density	-	0.0373***	0.0293**	-	0.0328*	0.0287*
		(0.0022)	(0.0098)		(0.0109)	(0.0124)
Competitiveness	-	0.0077	0.0077	-	0.0094*	0.0094*
		(0.0047)	(0.0046)		(0.0044)	(0.0044)
Homogeneity	-	0.0062**	0.0062**	-	0.0083***	0.0083***
		(0.0022)	(0.0022)		(0.0023)	(0.0023)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

APPENDIX B: CHAPTER I FIGURES

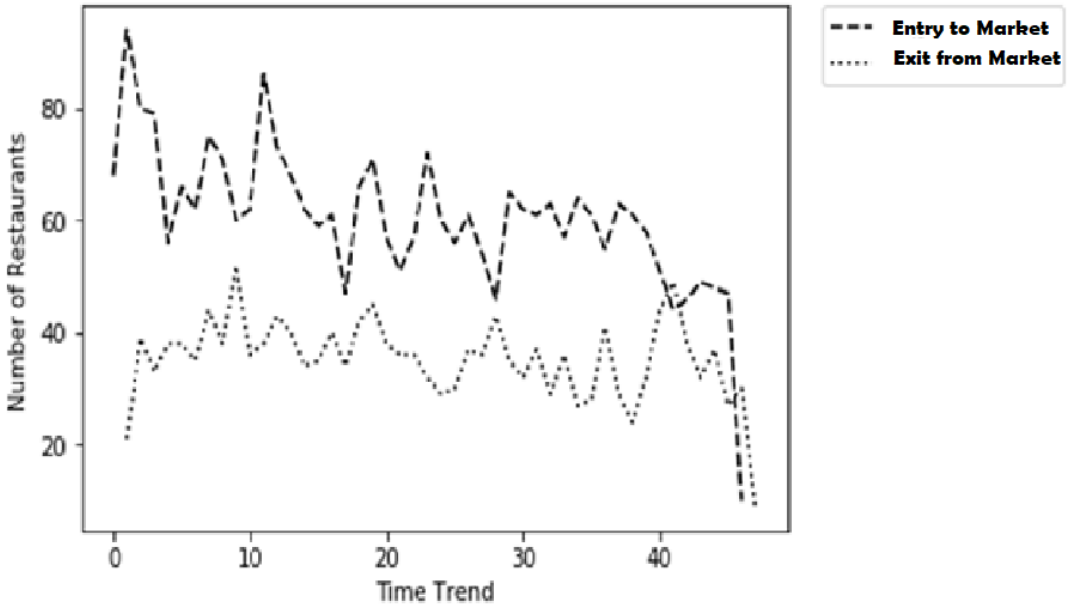

Figure1.1: *Count of entry and exit in each month*

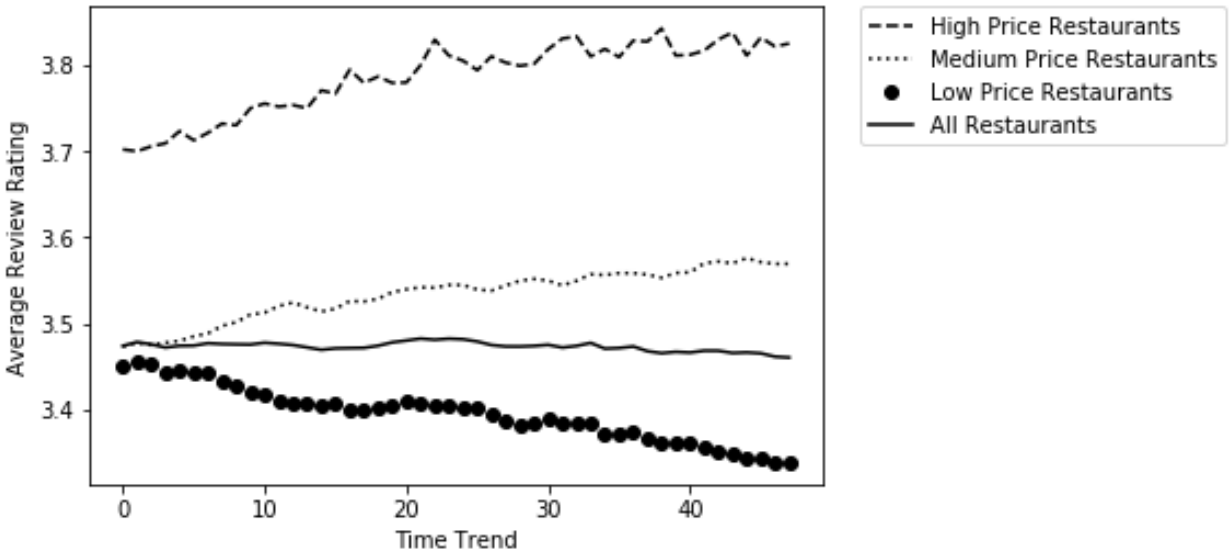

Figure 1.2: *Average review rating for the different price range for every month*

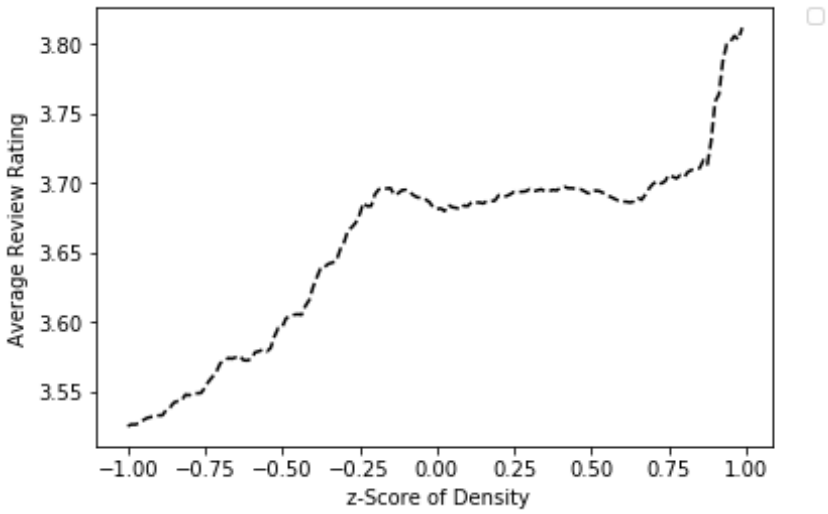

Figure 1.3: *Z score of density in one mile compared to average review*

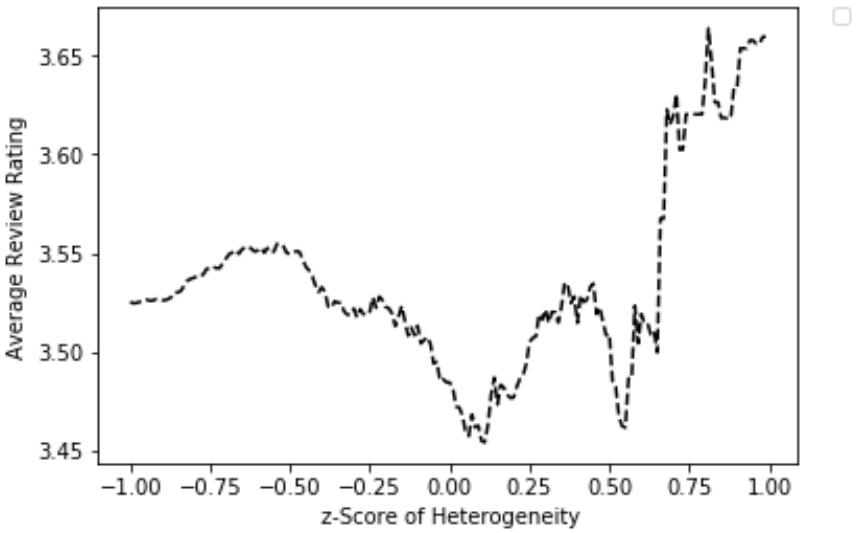

Figure 1.4: *Z score of Homogeneity in one mile compared to average review*

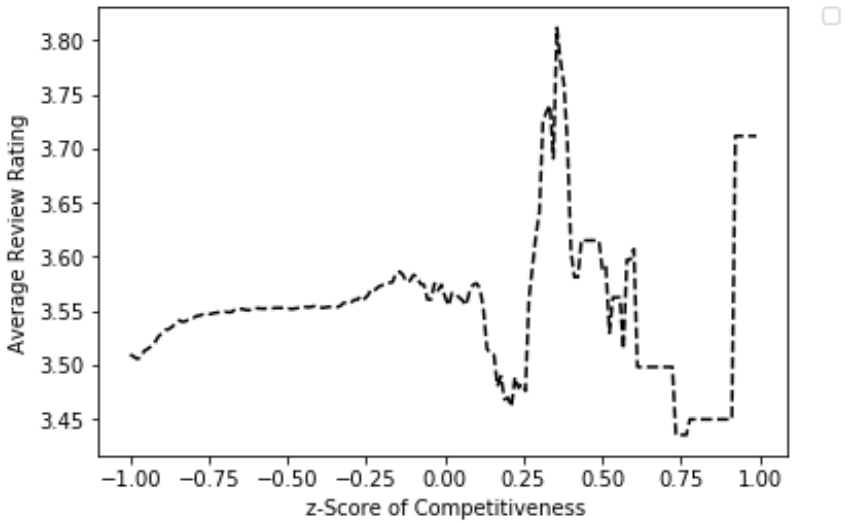

Figure 1.5: *Z score competitiveness in one mile compared to average review*

CHAPTER II

The Empirical Analysis of Customer Satisfaction and the Exit Decision in the Restaurant Industry

1 Introduction

It has been reported that 19% of restaurant customers use Yelp reviews and rating before visiting a place. Yelp had an overall 141 million unique visitors and 148 million reviews by the end of 2017. For this reason, restaurant owners need to be aware of the influence of review websites such as Yelp and the role that they can play in the popularity and profitability of their restaurants.

In economic theory competition can reduce prices, increase quality, or both. If we assume that there is a situation where the price does not change, quality should improve as the competition increases. However, if firms cannot enhance their quality, they will not be successful in the market which causes them to exit from the market.

In this paper I examine the effect of customer satisfaction of rivals on the decision of restaurants to exit from the market in the Phoenix metropolitan area by utilizing longitudinal data for all restaurants from the Yelp Website. I find that restaurant customer reviews have an impact on each other. I examine the exit decision when a restaurant faces increases in quality from its competitors. By way of explanation, the restaurant decides to exit from the market if the average rival quality increases compared to the quality of the restaurants in the prior month. I also study the exit decision for heterogeneous

competitors. Usually, heterogenous competition means individuals with different characteristics compete with each other differently based on the characteristics of their consumers (different cuisine type and price range of restaurants have a different effect on a particular restaurant). Since restaurants offer various cuisine types and price ranges, I can account for the product heterogeneity.

In my empirical research, I use a unique panel data set that covers nearly all restaurants reviews in the Phoenix metropolitan area from 2014 to 2018. Yelp has information for over 10,000 restaurants in Phoenix alone, which covers more than 97% of restaurants. The panel nature of data helps me to deal with seasonality problems that may exist in the market. This data includes the first review, geographic location, as well as the timing of exit for restaurants during the four years covered by the dataset. Also, this data provides a price range of each restaurant in three categories: low price restaurants, medium price restaurants and high price restaurants. Therefore, this paper looks to address whether restaurants decide to exit from the market when they face increases in quality from its competitors, whether restaurants with the same category and price have an effect on exit decision of each other, and whether location characteristics have effect on exit decision of restaurants.

The results show that the probability of exit increases by 1.12 percentage points if the value of change in $RR_{i(t-1)}$ increases by one unit. On the other hand, I find that the number of restaurants has a statistically significant effect on the exit decision of restaurants from the market. One more restaurant in the market enhances the probability of exit by 0.49 percentage points. Additional analysis on the restaurants indicates that one

unit change in the relative rating of the same cuisine type for restaurants within a one-mile distance increase the probability of exit by 1.82 percentage points.

This paper is organized as follows. Section 2 reviews the literature. Section 3 outlines the data and reviews the data collection process. Section 4 elaborates on the empirical model of this research. Section 5 discusses the results, and section 6 is the conclusion of this paper.

2 Literature Review

Prior research on customer satisfaction has looked at firm responses, financial performance, firm marketing strategy, and sale and pricing strategy. Chen and Xie (2005) analyze how firms adopt a marketing strategy to respond to customer reviews. They indicated that firms should not change their prices to respond to the reviews. However, firms with low rating should have a new strategy to ensure that they can still compete with other firms in the market. Williams and Neumann (2011) improved on prior works by utilizing a longitudinal coordinate of panel data for five years. They find a strong link between customer reviews and the stock prices of firms. Luca (2016) also investigates the causal impact of online consumer reviews on restaurants demand by using the Yelp website. He finds that Yelp rating increases the revenue of restaurants. He also discovers that consumers use some of the information which is visible to them.

The influence of rival reviews on the exit decision of firms has been studied in a few papers in the economics literature. Cheung and Lee (2008) compare the effect of negative and positive online consumer reviews. They find out that negative reviews are

highly more impressive than positive ones. Cabral and Hortacsu (2010) also find that negative reviews cause a drop in the weekly sales rate of the sellers. They also discover that a seller's probability of exiting from the market as a result of a low reputation is very high, and reputation is lower than average before exit. On the other hand, McDevitt (2011) investigate the effect of a bad reputation on changing the brand name of the business. He shows that a low review rating cause business to change their name rather than exiting from the market. However, businesses in smaller market have more possibility to exit from the market compared to business in large markets. Freedman and Kosova (2011) investigate the relationship of entry and exit to market and product heterogeneity. They find that the pattern for exit decision in the hotel industry depends on the size of other hotels in the same location.

Mazzeo (2002) analyzes the effect of differentiation product of competitors on the market structure by using cross-sectional data. His result signifies that competition between same type product has higher impact on each other. Berry and Waldfogel (2006) investigate the relationship between market size and quality in the restaurant industry. They find that markets size enhances the quality that restaurants offer because bigger market size corresponds to smaller market shares. So, larger market on average have firms with smaller market share. Xie, So and Wang (2017) study the effect of online reviews on hotel performance. They find that when the average review rating increases, the management of the hotel provides a longer response to the review and therefore increase the profitability of the hotel.

This research adds to the previous literature by looking at the effect of competitor reviews on the performance of firms. Also, the panel structure of the data allows me to

identify the exit probability of restaurants in the market. Results of this paper on the firm responses to reviews combined with Mazzeo (2002) research about the same type competition clarify the reason behind the firm's exit decision from the market. Furthermore, this paper analyzes the impact of location characteristics on the restaurant's exit decision. The results show that increasing the number of rivals within a close distance causes firms with low customer ratings to exit from the market.

3 Data

Yelp is a review forum where reviewers can write reviews about local businesses. Yelp was founded in 2004 in San Francisco. It has received over 140 million unique visitors (based on unique IP address) on a monthly basis during the fourth quarter of 2017. On the Yelp website, customers can write and read about restaurants after registering for a free account. The rating is a discontinuous number of stars between one and five with an interval of 0.5. Reviews are accessible to everyone for free. From the reviews, customers can convey and observe the customer satisfaction of restaurants. Yelp chooses to round restaurants review average rating to the nearest half star value. Figure 2.1 shows the average review rating for all restaurants in each month. The trend over time shows that low-price restaurant reviews decrease over time while medium-price restaurant and high-price restaurant customer ratings increase over time.

The data for this paper is monthly panel data of average reviews for all restaurants in the Phoenix metropolitan area. This data has been collected from Yelp. Yelp provides the data for restaurants that exit from the market. Distance, based on longitudinal data,

can be a reasonable estimation of geographic interaction of restaurants with each other. In this data the distance between two restaurants ranges from less than a foot to more than 90 miles.

The dataset covers more than 97% of existing restaurants in the Phoenix area reported on the Bureau of Labor Statistics in the food service section. Specifically, the dataset has 10,434 unique restaurants properties. 9,253 of these restaurants were open at least for one month from 2014 to the end of 2017. During the sample period, 1,729 restaurants exit from the market. For each restaurant, the dataset provides latitude and longitude coordinate, price range, number of reviews and average rating of reviews, as well as a food type category. Each restaurant is classified in four price range categories in the Yelp platform from $ to $$$$. However, I organize restaurants in three different groups: low price, medium price, and high price. Due to a limited number of $$$ restaurants and $$$$ restaurants, I combine those groups. Price range information for 823 restaurants are missing, which I drop from my data. Table 2.1 summarizes the restaurant properties which I used in the model of this paper after dropping the missing observations. The new dataset covers 9,611 restaurants with 302,262 observations.

Every month, approximately 38 restaurants exit from the market. On average 16 of these restaurants are low-price restaurants, 19 mid-price restaurants and 3 high-price restaurants. Figure 2.2 shows the number of exits from the market for four years of the trend. Figure 2.3 also displays the number of different price restaurants that exit from the market for 48 months of the data.

Restaurant owners might decide to exit even after improving quality compared to their competitors. In this research competitors are defined as all the restaurants in one-

mile radius with the given restaurants. Restaurants are more likely to exit from the market, however, if there happens to be a decline in their quality whereas their competitors succeed to increase the quality during the same period. Tables 2.2, 2.3 and 2.4 display the likelihood of exit for restaurants facing different conditions. Table 2.2 illustrates the likelihood of exit based on restaurant reviews. A notable distinction between restaurants that are facing better reviews and the other restaurants can be observed. Table 2.3 demonstrates the likelihood of exit based on the average review of competitors. Finally, Table 2.4 shows the likelihood of exit based on relative rating which is a covariable defined in this paper. Relative rating is the differences between the average review of restaurant competitors and the review of a restaurant. Regarding competition, this table highlights that restaurants that receive a lower review than their rivals are more likely to exit the market.

4 Empirical Model

This research analyzes if the review rating of competitors affects the exit decision of competing restaurants. I estimate the probability of exit from the market for incumbent restaurants when the quality of a given restaurant's competitors increase in a close distance. By using panel probit regression, I calculate the probability of exiting the restaurants by observing the relative rating. The estimation presented calculates if the difference between competitors' average quality and the restaurant's quality increases in the market at time *t-1*, impacts the restaurant's probably of exit from the market at time t. Relative Rating is defined as:

$$RR_{it} = \frac{\sum_j R_{jt}}{N} - R_{it} \quad (1)$$

Variable RR_{it} , or relative rating, estimates the level of competition value between restaurant *i* at time *t* and its competitors *j* at the same time. Since the rating of a restaurant is between 1 to 5, the relative rating variable is between -4 to 4, and it is rounded to the nearest decimal place. Figure 2.4 shows the number of observations for all possible values of relative rating. This figure displays that RR_i is normally distributed around zero. Rising values over time indicate that the competitor's reviews are improving compared to the restaurant. On the other hand, if this value decreases over time, the trend determines that the customer satisfaction of the restaurant has been improving in comparison to its rivals.

In the next step, I analyze the model with ΔRR_{it} to evaluate the effect of change in the level of competition on the exit decision. Change in relative rating estimates the difference between restaurant reviews at time *t* and its competitors' reviews over the same period.

In an alternative specification I estimate the exit decision probability with a second and third time lag to observe if it takes more than one period for incumbents to respond to competition. With the marginal effect I can find the percentage point change in exit probability when the average customer rating of competitors increases compared to the restaurant's customer rating. In other words, the marginal effects of each explanatory variable display the partial effect of the variable on the probability that restaurants decide to exit. I also run a probit model by categorizing the data into price

ranges and the different cuisine categories. The following regression is the main regression of this analysis:

$$exit_{it} = \beta_1 RR_{i(t-1)} + \beta_2(N - Review)_{it} + \beta_3(Density)_{it} + \beta_4(Competitiveness)_{it} + \beta_5(Heterogeneity)_{it} + \sum_{m=1}^{11}\beta_m month_m + \sum_{y=1}^{3}\beta_y year_y + \in_{it} \quad (2)$$

The outcome variable $exit_{it}$ is the binary value of exiting for the restaurant *i* at time *t*. The coefficient of interest β_1 is estimating the probability of exit if the difference between the average review of competitors and the review of restaurant increase.

Based on the research done by Zhang, Li, and Hong (2016) and Karamshuk, et al. (2013), I can control for location characteristics by setting three dynamic geographic features: location density, competitiveness, and homogeneity.

Location density is defined as the popularity of location by utilizing number (*N*) of nearby restaurants *j* in the distance d_{ij} with *l* mile radius around restaurant *i* at time *t*. Location density is simply a number of restaurants in *l* mile radius. This value ranges between 3 to 131 in the data. The probability of exiting from the market rising if the number of competitors increases around the given restaurant. Table 2.5 shows the percentage of restaurants that exit from the market for a different set of competitors. This table demonstrates that there is a strong, direct connection between the rise in number of competitors, on the one hand, and the rise in the likelihood of exit especially when the number of competitors exceeds 60. The Location density is formulated as:

$$Loc\_Den_{it} = \sum j \in (d_{ij} < l) \quad (3)$$

Competitiveness is defined as the ratio of nearby restaurants with similar cuisine type and the total number of restaurants within the same area for the restaurant *i* at time *t* with cuisine type *c*. For example, Indian restaurants could be situated close to each other, which results in competition becoming higher for this type of cuisine. The value of this measure is between 0 to 1, and it can be represented through the following equation.

$$Competitiveness_{it} = \frac{N_{cjt}(i,l)}{N_{jt}(i,l)} \quad (4)$$

Homogeneity is the HHI (Herfindahl-Hirschman index) of different cuisine type in the market. The HHI is a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in a market and then summing the resulting numbers, and It can range from close to zero to one. I use the HHI index by finding a market share of each cuisine type in the area. For example, if most restaurants around restaurant *i* are Indian type restaurants, the homogeneity value is very high. However, a neighborhood that includes all types of restaurants has a lower homogeneity value. Each restaurant has its cuisine type, *c*. N_c, signifies the number of nearby restaurants for cuisine type *c* with *l* mile radius where $c \in C$, and *C* is a set of all cuisine type. The homogeneity equation can be represented in the following equation.

$$Homogeneity_{it} = \sum_{c \in C} \left(\frac{N_{ct}(i,l)}{N_t(i,l)}\right)^2 \quad (5)$$

5 Results

Table 2.6 reports the marginal effects of the probability of exit for restaurants within one mile when restaurants observe the review of their competitors in the market for the

last three months. This table shows that relative rating does not have a statistically significant effect on the exit decision of restaurants. Results of Table 2.7 also show that relative rating in different level of competition distances does not have an impact on the exit decision of restaurants. Furthermore, location density coefficients reveal that the number of restaurants in the market affects the probability of exit of restaurants from the market. One more restaurant in the market enhances the probability of exit by 0.49 percentage points.

Table 2.8 presents the probability of exit by observing the change in the difference between the review of restaurants and its competitors over time. Column one of Table 2.8 declares that a one unit change in relative rating increases the probability of exit by 1.12 percentage points for the one-mile distance. The result indicates that a one value increase in the difference of customer rating of competitors results in a 1.12 percentage point higher chance that restaurants exit from the market after a month. Results in column 2 and 3 also show that change in the level of competition with a second and third lag affects the exit decision of a restaurant, but these values are smaller. The probability of exit increases by 0.68 and 0.46 percentage point with a one value increase in second and third lag relative rating respectively. It also can be noticed that location density and heterogeneity of location enhance the exit probability of restaurants. One more additional restaurant in the market increases the probability of exit by 0.46 percentage points. Moreover, a one value increase in the HHI index of different cuisine type in the market increases the probability of exit by 0.21 percentage points.

Additionally, Table 2.9 indicates that $\Delta RR_{i(t-1)}$ has the same effect for a half of a mile competition distance, but the estimate is lower for a two-mile competition distance

in the second and third lag. The probability of exit is 1.12 percentage points for a one unit increase in relative rating for both half of a mile distance and two-mile competition distances. However, second lag relative rating increases the probability of exit by 0.65 percentage point for change in the level of competition within a half of a mile and 0.42 percentage point for the change in the level of competition in a two-mile distance. Also, the third lag relative rating enhances the probability of exit by 0.46 and 0.36 percentage point for the change in the level of competition within a half mile distance and two-mile distance, respectively.

Table 2.10 estimates the restaurant's exit decision with cuisine category differentiation with the change in relative rating. One unit increases in the change of the relative rating of the same cuisine type restaurants increase the probability of exit by 1.82 percentage points for one-mile radius. This result signifies that the restaurants with the same cuisine type have more influence on the exit decision of each other.

Finally, Table 2.11 reports the probit regression result for restaurants with different prices. We can observe that change in the relative rating does not affect the exit decision of low-price and medium-price restaurants. However, improving the relative rating of different price range restaurants causes the probability of exit for high price restaurants rises by 0.24, 0.66 and 0.86 percentage point respectively. One additional low-price restaurant increases the exit probability of low-price restaurants by 0.46 percentage points, and one additional medium price restaurant increases the exit probability of medium-price restaurants by 0.54 percentage points. Finally, Table 2.12 demonstrates the probability of exit for different price restaurants within half of a mile distance and two-mile distance. The results of this table declare that there would be less competition for

restaurants with farther distance. Results for half mile distance competition is similar to the results of table 2.11.

6 Conclusion

This research analyzes the effect of competitor reviews on the exit decision of restaurants by investigating all restaurants in the Phoenix Metropolitan Area between 2014 and 2018. This study also examines the impact of dynamic geographic features on the exit decision of restaurants. By applying probit panel regression model, the results of this study suggest that by changing in the level of relative rating in a restaurant will lead to an increase in the probability of exit from the market not the relative rating.

While investigating the dataset, I find that the level of relative rating does not have any effect on the exit decision of restaurants. However, the probability of exit increases by 1.12 percentage points if the value of change in $RR_{i(t-1)}$ increases by one unit. On the other hand, I find that the number of restaurants has a statistically significant effect on the exit decision of restaurants from the market. One more restaurant in the market enhances the probability of exit by 0.49 percentage points.

Additional models on the restaurants support the idea that restaurants with the same cuisine type have a higher effect on each other. A one unit change in the relative rating of the same cuisine type for restaurants within a one-mile distance increase the probability of exit by 1.82 percentage points. This may suggest that competition is tenser among restaurants with the same cuisine type in a close distance. Impact of same price restaurants review on each other is less significant.

Overall, the results explain why restaurants decide to exit from the market with high competition. Particularly the review rating of restaurants with the same cuisine type has a higher effect on each other.

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APPENDIX C: CHAPTER II TABLE

Table 2.1: *Dynamic Summary Statistic of Restaurants within One Mile Distance*

Variable	Mean	Std. Err	Min	Max
Economy Restaurants	0.497	0.499	0	1
Midrange Restaurants	0.473	0.497	0	1
Luxury Restaurants	0.029	0.151	0	1
Reviews	3.474	0.888	1	5
Average Rivals Reviews	3.479	0.689	1	5
Review difference between restaurant and rivals	0.006	1.044	-2.6	3.9
Average Number of Cuisine Type	7.836	18.016	0	38
Number of Reviews	3.091	3.877	0	62
Location Density	53.604	53.257	0	298
Competitiveness	0.103	0.111	0	1
Homogeneity	1.02	0.192	0	1.337
Time Competing in the Market	39.719	9.13	4	48
Number of Observations	302262			

Notes: Excluded restaurants with missing price and address and with less than ten customer reviews. Distance for competition characteristic is one mile.

Table 2.2: *Likelihood of Exit based on Restaurant's Review (R_i)*

	Likelihood of Exit
Restaurants Facing Improved Review	0.02 %
Restaurants Facing Constant Review	0.73 %
Restaurants Facing Declining Review	0.94 %

Table 2.3: *Likelihood of Exit based on Competitor's Review* ($\frac{\sum R_j}{N}$)

	Likelihood of Exit
Restaurants Facing Improved Competitors Review	0.83 %
Restaurants Facing Constant Competitors Review	0.59 %
Restaurants Facing Declining Competitors Review	0.50 %

Table 2.4: *Likelihood of Exit based on Relative Rating (RR_i)*

	Likelihood of Exit
Restaurants Facing Improved Competition	1.09 %
Restaurants Facing Constant Competition	0.03 %
Restaurants Facing Declining Competition	0.12 %

Table 2.5: *likelihood of Exit based on Location Density within One Mile Distance*

Number of Competitors	Number of Observation	Number of Exit	Likelihood of Exit (%)
< 10	1181	1	0.084674
10-20	7811	15	0.192037
20-30	19531	42	0.215043
30-40	36920	84	0.227519
40-50	56034	122	0.217725
50-60	61918	400	0.646016
60-70	52880	351	0.663767
70-80	40161	330	0.821693
80-90	19456	251	1.29009
> 90	6370	133	2.087912

Table 2.6: *Probability of Exit from the Market within One Mile Distance*

	(1)	(2)	(3)	(4)
$RR_{i(t-1)}$	0.0112	-	-	0.0082
	(0.0303)			(0.0322)
$RR_{i(t-2)}$	-	0.0186	-	0.0113
		(0.0216)		(0.0199)
$RR_{i(t-3)}$	-	-	0.0198*	0.0185*
			(0.0128)	(0.0098)
Number of Reviews	0.0312	0.0425	0.0356	0.0480
	(0.0765)	(0.0779)	(0.0575)	(0.0892)
Location Density	0.0049***	0.0048***	0.0048***	0.0049***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Competitiveness	-0.0835	-0.0050	-0.0396	-0.0284
	(1.3000)	(1.0899)	(0.8034)	(0.8595)
Homogeneity	0.0021*	0.0022	0.0021	0.0020*
	(0.0018)	(0.0019)	(0.0022)	(0.0018)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 2.7: *Probability of Exit from the Market within 0.5 Mile and 2 Mile Distance*

	0.5 mile				2 mile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$RR_{i(t-1)}$	0.0148	-	-	0.0087	0.0042	-	-	0.0013
	(0.0289)			(0.0312)	(0.0342)			(0.0311)
$RR_{i(t-2)}$	-	0.0212	-	0.0195	-	0.0048	-	0.0020
		(0.0209)		(0.0290)		(0.0117)		(0.0284)
$RR_{i(t-3)}$	-	-	0.0318*	0.0296*	-	-	0.0056	0.0052
			(0.0192)	(0.0154)			(0.0181)	(0.0056)
Number of Reviews	0.0396	0.0428	0.0301	0.0409	0.0240	0.0338	0.0307	0.0312
	(0.0767)	(0.0705)	(0.0481)	(0.0775)	(0.0782)	(0.0801)	(0.0557)	(0.0882)
Location Density	0.0049***	0.0048***	0.0048***	0.0049***	0.0049***	0.0048***	0.0048***	0.0049***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Competitiveness	-0.1275	-0.0000	-0.0165	-0.0367	-0.0087	-0.0048	-0.0057	-0.0089
	(0.6591)	(0.6119)	(0.6782)	(0.6212)	(1.1342)	(1.0072)	(0.8559)	(0.8843)
Homogeneity	0.0021*	0.0022	0.0021	0.0020*	0.0021	0.0022	0.0021	0.0020
	(0.0017)	(0.0019)	(0.0022)	(0.0016)	(0.0020)	(0.0021)	(0.0023)	(0.0022)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 2.8: *Probability of Exit based on Change in Competition within One Mile Distance*

	(1)	(2)	(3)	(4)
$\Delta RR_{i(t-1)}$	0.0112***	-	-	0.0119***
	(0.0014)			(0.0014)
$\Delta RR_{i(t-2)}$	-	0.0068***	-	0.0069***
		(0.0013)		(0.0013)
$\Delta RR_{i(t-3)}$	-	-	0.0046***	0.0040***
			(0.0013)	(0.0010)
Number of Reviews	0.0224	0.0241	0.0176	0.0292
	(0.0623)	(0.0597)	(0.0405)	(0.0514)
Location Density	0.0046***	0.0045***	0.0046***	0.0046***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Competitiveness	-0.0754	-0.0746	-0.0197	-0.0394
	(1.0564)	(0.9943)	(0.6126)	(0.6250)
Homogeneity	0.0021*	0.0021*	0.0021*	0.0021*
	(0.0016)	(0.0017)	(0.0016)	(0.0017)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 2.9: *Probability of Exit based on Change in Competition within 0.5 Mile and 2 Miles Distance*

	0.5 mile				2 mile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\Delta RR_{i(t-1)}$	0.0112***	-	-	0.0118***	0.0112*	-	-	0.0118*
	(0.0013)			(0.0013)	((0.0048)			(0.0051)
$\Delta RR_{i(t-2)}$	-	0.0065***	-	0.0058***	-	0.0042*	-	0.0036
		(0.0011)		(0.0010)		(0.0032)		(0.0030)
$\Delta RR_{i(t-3)}$	-	-	0.0046***	0.0041***	-	-	0.0046**	0.0038**
			(0.0012)	(0.0010)			(0.0013)	(0.0011)
Number of Reviews	0.0267	0.0300	0.0212	0.0576	0.0310	0.0228	0.0212	0.0478
	(0.0884)	(0.0856)	(0.0664)	(0.0818)	(0.0926)	(0.0870)	(0.0592)	(0.0760)
Location Density	0.0046***	0.0046***	0.0046***	0.0047***	0.0038***	0.0038***	0.0038***	0.0038***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Competitiveness	-0.0702	-0.0428	-0.0210	-0.0909	-0.0090	-0.0339	-0.0293	-0.0172
	(0.9957)	(0.6910)	(0.2852)	(0.5646)	(1.0492)	(1.0042)	(0.5932)	(0.6888)
Homogeneity	0.0022*	0.0022*	0.0022*	0.0022*	0.0021*	0.0021*	0.0020	0.0020*
	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0018)	(0.0018)	(0.0016)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in parenthesis are robust at the group level*

Table 2.10: *Probability of Exit with Category Differentiation*

Exit Decision	0.5 mile	1 mile	2 mile
$\Delta RR_{i_{Same-Cuisine-Type}(t-1)}$	0.0182***	0.0182***	0.0127*
	(0.0016)	(0.0016)	(0.0080)
$\Delta RR_{i_{Different-Cuisine-Type}(t-1)}$	- 0.0001	0.0010	0.0078
	(0.0108)	(0.0104)	(0.0152)
Numbers of review	0.0218	0.0212	0.0255
	(0.0711)	(0.0708)	(0.0814)
Density	0.0046***	0.0046***	0.0037***
	(0.0000)	(0.0000)	(0.0000)
Competitiveness	-0.0670	-0.0756	-0.0764
	(0.6122)	(0.6544)	(0.3128)
Homogeneity	0.0021*	0.0021*	0.0020*
	(0.0016)	(0.0016)	(0.0016)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in Parenthesis are robust at the group level*

Table 2.11: *Probability of Exit with Price Differentiation within One Mile Distance*

	Low Price	Medium Price	High Price
$\Delta RR_{i_{Low-Price}(t-1)}$	- 0.0057	0.0029	0.0024*
	(0.0912)	(0.0854)	(0.0019)
$\Delta RR_{i_{Medium-Price}(t-1)}$	- 0.0094	0.0030	0.0066*
	(0.0842)	(0.0501)	(0.0020)
$\Delta RR_{i_{High-Price}(t-1)}$	- 0.0045	0.0012	0.0072*
	(0.0668)	(0.0715)	(0.0042)
Numbers of Reviews	0.0419	0.0097	-0.0188*
	(0.0621)	(0.0126)	(0.0090)
Location Density	0.0046***	0.0054***	0.0003
	(0.0000)	(0.0000)	(0.0003)
Competitiveness	-0.0018	-0.0068	-0.0012
	(0.8955)	(1.1232)	(1.0102)
Homogeneity	0.0021*	0.0021*	0.0021
	(0.0016)	(0.0015)	(0.0020)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in Parenthesis are robust at the group level*

Table 2.12: *Probability of Exit with Price Differentiation in 0.5 Mile and 2 Miles Distance*

	0.5 mile			2 miles		
	Low Price	Medium Price	High Price	Low Price	Medium Price	High Price
$\Delta RR_{i_{Low-Price}(t-1)}$	- 0.0035	0.0032	0.0024*	- 0.0075	0.0022	0.0012
	(0.0912)	(0.0855)	(0.0019)	(0.0573)	(0.0620)	(0.0046)
$\Delta RR_{i_{Medium-Price}(t-1)}$	- 0.0034	0.0020	0.0066*	- 0.0223	0.0029	0.0046
	(0.0901)	(0.0509)	(0.0021)	(0.1096)	(0.0391)	(0.0068)
$\Delta RR_{i_{High-Price}(t-1)}$	- 0.0030	0.0000	0.0072*	- 0.0040	0.0021	0.0047
	(0.0582)	(0.0710)	(0.0042)	(0.0652)	(0.0924)	(0.0098)
Number of Reviews	0.0366	0.0004	-0.0188*	0.0860	0.0936	-0.0188*
	(0.0447)	(0.0174)	(0.0096)	(0.1007)	(0.0939)	(0.0090)
Location Density	0.0046***	0.0054***	0.0003	0.0038***	0.0050***	0.0000
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0002)
Competitiveness	-0.0084	-0.0146	-0.0145	-0.0182	-0.0007	-0.0638
	(0.8610)	(1.9202)	(1.1900)	(0.9512)	(2.5301)	(0.9295)
Homogeneity	0.0021*	0.0021*	0.0021*	0.0021*	0.0021*	0.0021
	(0.0014)	(0.0014)	(0.0017)	(0.0016)	(0.0015)	(0.0023)

*Notes: *** p<0.01, ** p<0.05, * p<0.1, standard errors reported in Parenthesis are robust at the group level*

APPENDIX D: CHAPTER II FIGURES

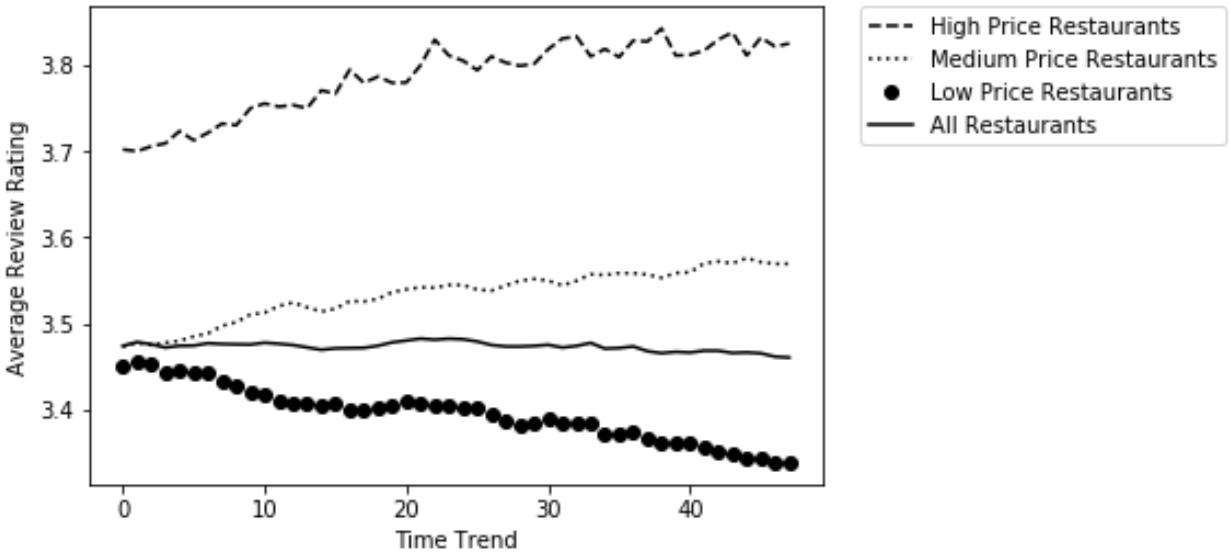

Figure 2.1: *Average review rating of restaurants in each month*

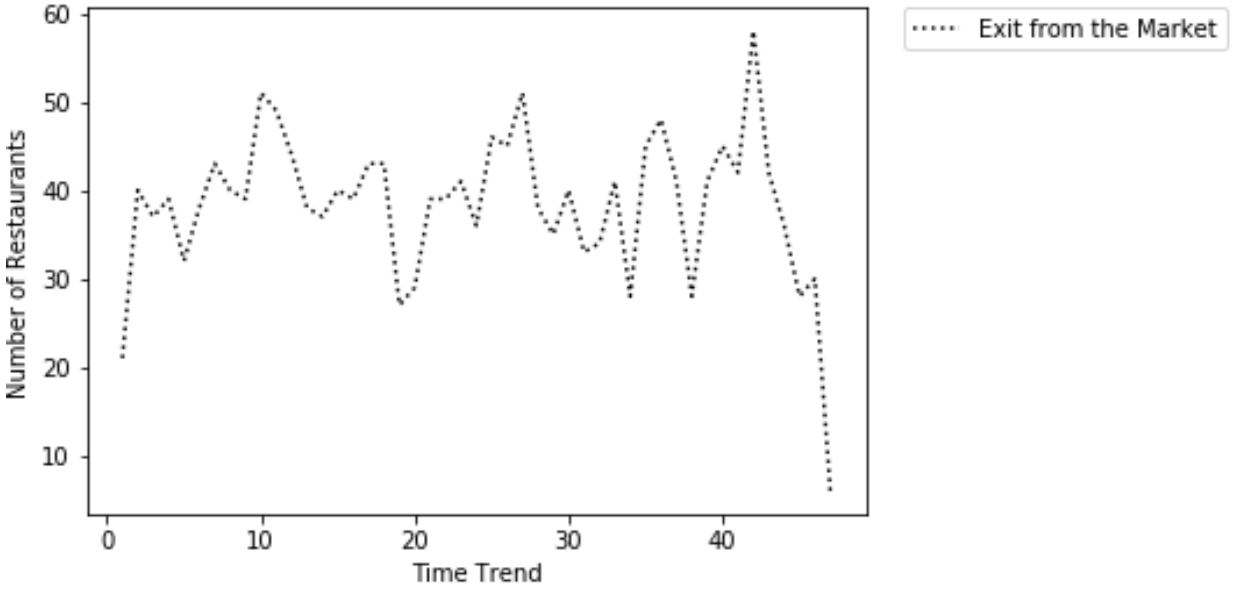

Figure 2.2: *Count of restaurants that exit from the market each month*

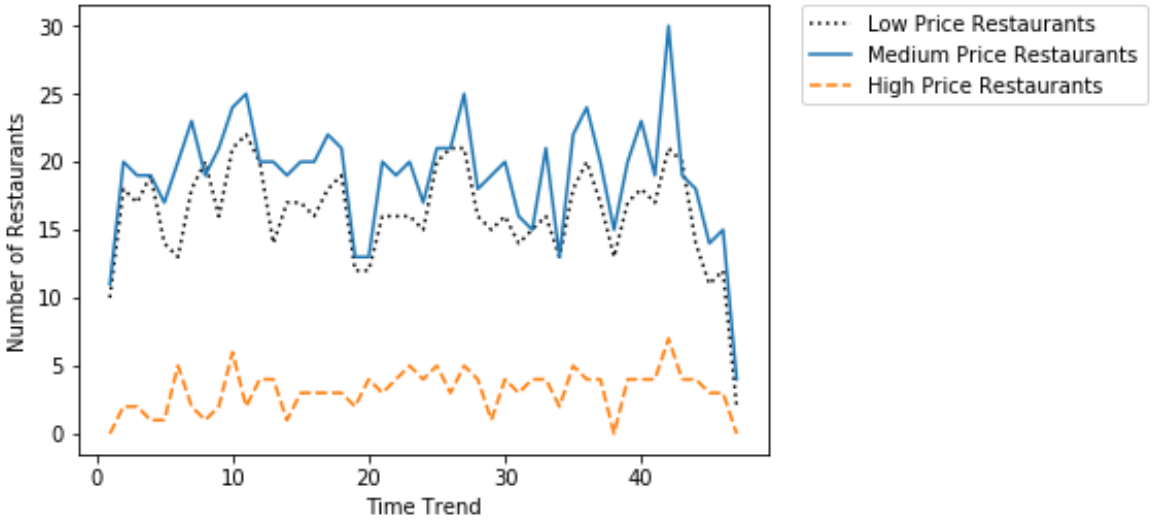

Figure 2.3: *Count of different price restaurants that exit from the market*

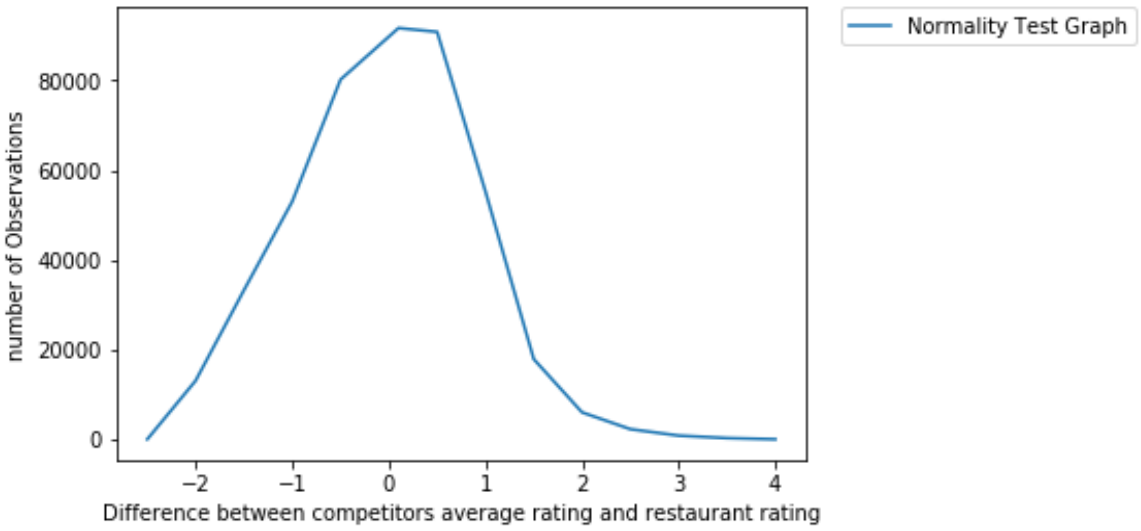

Figure 2.4: *Count of observations for different relative rating value*

CHAPTER III

The role of brand affiliation in business performance: An investigation into the hotel industry

(Coauthor with ATM Sayfuddin)

1 Introduction

The existing literature regarding the lodging industry suggests that the brand affiliation of a hotel property is one of the crucial factors in its financial performance. With the help of branding strategies, both the brand-owning hotel companies and individual hotel operators are able to run viable businesses and foster growth. Because brand affiliation is a form of strategic alliance, value creation is a vital element when it comes to being affiliated with a brand (O'Neill and Xiao, 2006; Carvell et al., 2016).

Previous studies have indicated popular brands provide consumers with a range of emotional and functional benefits, which positively impact consumer behavior and perceptions related to the brand. According to Keller (2002) research has also demonstrated that a brand can be an intangible asset, providing measurable financial values. Using the notion of brand equity, Aaker (1991), finds that both the brand-affiliated companies and consumers attach considerable value to brands. According to this view, brand equity facilitates product differentiation and offsets competition, which allows a brand-affiliated firm to maintain customer loyalty while charging a premium. Various studies have suggested the growth of the brand value is imperative in the

successful operation of a business (Kapferer, 1997; Keller, 1998; Aaker, 1991; Aaker, 1996). For instance, Prasad and Dev (2000) assert brand equity is a major determinant for success in the lodging industry. There is empirical evidence that supports their claim. Kim and Kim (2005), for example, have investigated luxury hotels and reported a significant positive association between sales and brand equity.

If brand affiliation provides value to hotels owners by means of reduced competition, increased prices, and loyal customers, all else equal, the brand affiliated hotel owners should observe a better financial return relative to their unaffiliated counterparts. Empirical findings in this regard, however, show mixed results. Ingram and Baum (1997) report that brand affiliated hotels tend to have a higher survival rate compared to unaffiliated hotels. According to Love et al. (2012), when unaffiliated hotels obtain affiliation, their revenue per available room (RevPAR) index improves. Hanson et al. (2009) suggest hotels rebranding to an upper market segment improves their performance. O'Neill and Carlback (2011) find that the occupancy rates of brand affiliated hotels are significantly higher, on average, compared to their unaffiliated counterparts. Conversely, research also shows unaffiliated hotels enjoy a considerably higher RevPAR and average daily room rates (ADR).

In the existing literature of brand affiliation and hotel performance, the wide-ranging ideas and contradictory findings warrant further investigation into the role of brand affiliation in hotel performance, particularly by comparing affiliated with unaffiliated hotels. In addition, we find the current literature mostly utilizes cross-sectional hotel data and the analysis mainly includes hypothesis testing and analysis of variance (ANOVA) to study the relationship between hotel brands and performance. Our

endeavor, therefore, is to contribute to the literature by using richer data (i.e., longitudinal data) and a more sophisticated empirical approach in order to present conclusive results.

In this paper we present a comparative analysis between brand affiliated and unaffiliated hotels by studying 450 hotels in Texas that had a change of ownership between 2014 and 2017. We examine whether a hotel had a statistically significant increase in its revenue following a change of ownership, which may or may not have coincided with a change of brand affiliation. This means ownership change can happen in one of the following four different ways: independent to independent (hence, remains unaffiliated), independent to affiliation, affiliation to independent, and affiliation to affiliation (which means the hotel either keeps or changes its original brand). In particular, we compare the financial implications of brand affiliation by inspecting all the four scenarios above. We also test if the impact of the change of ownership is higher for the budget and economy hotels. Notably, we ask two questions in this paper: Do new hotel owners generate higher revenues when they obtain brand affiliation for their previously unaffiliated hotels, and vice versa? Is this impact higher or lower for the budget and economy hotels?

This paper is organized as follows. Section 2 discusses the data sources and data collection procedure, section 3 outlines and explains the empirical approach, section 4 discusses the results, section 5 elaborates on the limitations of this study, and section 6 concludes.

2 Data

The data for this study are collected in two parts. We have collected revenue data from the Texas Comptroller of Public Accounts. This data set contains information on when, if any, each hotel had an ownership change, alongside other basic information, such as hotel name, address, and the number of rooms. For tax purposes, Texas law defines a hotel "to be any building in which members of the public rent sleeping accommodations for $15 or more per day." As a result, the Airbnb properties and any other vacation rentals that comply with the Texas tax code are also reported in the revenue data set. For this study, I only include hotel accommodations that had a change of ownership in the 2014-2017 period. The number of such hotels at this stage is 499.

We have also collected another data set from STR Inc. that includes information related to hotels' addresses, phone numbers, open dates, brand affiliation, market segment, price segment, and other hotel characteristics. Note that all variables in this additional data are time invariant.

After collecting both data sets, we combine them based on their property address. The final data set contains 450 hotels, as 49 of the hotels from revenue data were missing in the STR data set.

Table 1 reports summary statistics for the sample of hotels in our data. The average monthly RevPAR for a hotel is $1,346.08. Figure 3.1 shows the average revenue for 12 months before the change of ownership and 12 months after the change of ownership. We can observe the raising of the revenue after the transition of ownership. Table 3.1 also reports summary statistics for hotel categories based on their room price. STR categorizes

hotels into five classes based on their average room prices - also known as average daily rates (ADR) - compared to other hotels in the same market. These categories are:

- Luxury: Top 15% average room rates
- Upscale: Next 15% average room rates
- Mid-Price: Middle 30% average room rates
- Economy: Next 20% average room rates
- Budget: Lowest 20% average room rates

It can be observed in table one that the average monthly RevPAR for luxury hotels is $3,550.27, whereas the budget hotels' average monthly RevPAR is only $528.26.

3 Empirical Strategy

We begin with the following regression with hotel fixed effects to initially examine the impact of the change of ownership, regardless of brand affiliation status, on hotel revenue:

$$\ln(\text{RevPAR}_{it}) = \text{ownership}_{it} + \gamma_i + \delta_t + \epsilon_{it} \quad (1)$$

where $ln(RevPAR_{it})$ denotes log of *RevPAR* for hotel *i* in month *t*; $ownership_{it}$ is a dummy variable denoting a change of ownership for hotel *i* in month *t*; i denotes time-invariant hotel characteristics; and *t* denotes time-variant factors (i.e., year and month). The coefficient of interest in equation (1) is ownership, which, if positive and statistically significant, would indicate a change of ownership has a positive impact on hotel revenue. However, it is also possible that ownership change is correlated with other unobservable factors that are associated with hotel revenues. This empirical strategy, therefore, suffers

endogeneity bias, which we intend to address as we continue to collect more data for further investigation in the near future.

Next, we estimate the impact of brand affiliation on hotel revenue. In doing so we use the same empirical specification as above but with different subsets of hotels. For brand affiliated hotels we construct the following two samples: (a) hotels that do not change brand affiliation after an ownership change and (b) hotels that switch to independent or unaffiliated status following its ownership change. Likewise, for initially independent or unaffiliated hotels we construct the following samples of hotel: (c) hotels that maintain unaffiliated status followed by an ownership change and (d) hotels that obtain brand affiliation immediately after an ownership change. It is important to note here that in each of the four constructed samples above, all hotels undergo a change in ownership, which may or may not coincide with a change of their initial affiliation status. Finally, we evaluate the effect of price in the change of ownership. For this purpose we use the same regression but only for the budget and economy hotels. The coefficients of interest indicate if it is different between low-priced hotels and others.

4 Results

Table 3.2 reports regression results based on equation (1). Each column reports the same empirical specification estimated using different samples of hotels. Column 1 indicates regression results based on the total sample of hotels, but the results between column 2 and 4 are estimated using samples of hotels depending on how their affiliation changed followed by an ownership change. Column 2, 3, 4, and 5 report ownership

change from, respectively, affiliated hotels to affiliated hotels, affiliated hotels to independent hotels, independent hotels to independent hotels, and independent hotels to affiliated hotels. We find on average a hotel's RevPAR increases by 11.8% after its ownership change. Looking at the sample of hotels that remain affiliated, we find an ownership change increases their RevPAR by 15.5%**.** On average, the RevPAR increase is highest (28.8%) when an independent hotel becomes an affiliated hotel after its ownership change. In all of the above cases, the coefficients are statistically significant at 1% level.

For the economy and budget hotels, the result in table 3.3 shows the increasing of RevPAR 12.9%. The value is slightly bigger compared to the change of ownership for all hotels. The revenue increases by 25.1% for the budget and economy affiliated hotels change the ownership to another affiliated hotel. The RevPAR is 20.9% when an independent low-priced hotel becomes an affiliated hotel after its ownership change. Results indicate that the change of ownership has a higher effect on the economy and budget hotels that remain affiliated.

However, for hotels that remain independent (or unaffiliated) or convert from affiliated to independent status, a change of ownership does not have any statistically significant effect on their RevPAR. Overall, the results indicate brand affiliation does have a positive impact in the revenue of a hotel.

5 Limitations

Our results suffer endogeneity bias due to unobserved factors that lead to some hotels undergoing an ownership change as well as a change of affiliation status. We are continuously looking to improve this study by incorporating more sophisticated analysis and completing the existing data set with more data, such as review data. We believe review data may provide necessary insights related to how a hotels quality changes over time, including before and after an ownership change, and whether the hotel underwent a renovation during the ownership change. At this stage our results only indicate a positive association, not causation, between brand affiliation and hotel revenue.

6 Conclusion

Overall we have investigated 450 hotels in Texas that had a change of ownership between 2014 and 2017. Alongside the ownership change, some hotels changed their affiliation status, becoming an independent hotel, and vice versa. Other hotels maintained their original status- independent or affiliated - after their ownership change. This study investigated whether changes in affiliation during or after an ownership change has any impact on the hotels' revenue. By estimating fixed-effects regressions, our results suggest brand affiliation enhances hotel revenue. For instance, within our sample of hotels, we find when an independent hotel becomes an affiliated hotel after its ownership change, its monthly RevPAR increases by 28.8% on average. For economy and budget hotels, the average rising of RevPAR is 20.9%

On the other hand, we do not find any statistically significant improvement of monthly RevPAR for hotels that give up their affiliation status and become independent hotels. The results are similar for the low-priced hotels. Our results support previous findings that brand affiliation boosts the financial performance of a business. Although the empirical strategy used in this paper suffers endogeneity bias due to unobserved factors not being accounted for, the results indicate necessary insights to further the study and contribute to the existing literature. We plan to collect more data and incorporate more sophisticated empirical approach in order to address the limitations of this paper.

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APPENDIX E: CHAPTER III TABLES

Table 3.1: *Summary Statistics*

Hotel	Mean	Std. Dev	Min	Max	Hotels	N
All	1346.08	1195.59	0.27	19846.99	450	16884
Budget	528.26	416.54	0.27	5383.34	152	5808
Economy	1073.83	603.02	29.25	3573.20	106	2828
Midprice	1781.71	1192.55	129.37	19846.99	111	4080
Upscale	2234.60	713.45	169.25	5497.90	58	2256
Luxury	3550.27	1996.33	179.05	14722.94	23	912

Table 3.2: *Effect of Changing Ownership on the Revenue*

Dependent Variable = ln(RevPAR)					
Independent Variables	All Data (1)	Affiliation to Affiliation (2)	Affiliation to Independent (3)	Independent to Independent (4)	Independent to Affiliation (4)
Ownership	0.112*** (0.015)	0.144*** (0.018)	0.001 (0.029)	0.399 (0.264)	0.253*** (0.044)
Year Fixed Effect	*X*	*X*	*X*	*X*	*X*
Month Fixed Effect	*X*	*X*	*X*	*X*	*X*
No. of Hotels	450	269	105	7	75
N	16884	9780	4068	240	2568

Notes: *, **, ** indicate significance at 10%, 5%, and 1% level. Robust standard errors are reported in parenthesis.

Table 3.3: *Effect of Changing Ownership on the Revenue for Budget and Economy Hotels*

Dependent Variable = ln(RevPAR)

Independent Variables	All Data (1)	Affiliation to Affiliation (2)	Affiliation to Independent (3)	Independent to Independent (4)	Independent to Affiliation (4)
Ownership	0.122***	0.224***	-0.037	0.399	0.190***
	(0.026)	(0.028)	(0.475)	(0.264)	(0.025)
Year Fixed Effect	*X*	*X*	*X*	*X*	*X*
Month Fixed Effect	*X*	*X*	*X*	*X*	*X*
No. of Hotels	220	63	88	7	62
N	7932	2172	3420	240	2100

Notes: *, **, ** indicate significance at 10%, 5%, and 1% level. Robust standard errors are reported in parenthesis.

APPENDIX F: CHAPTER III FIGUERE

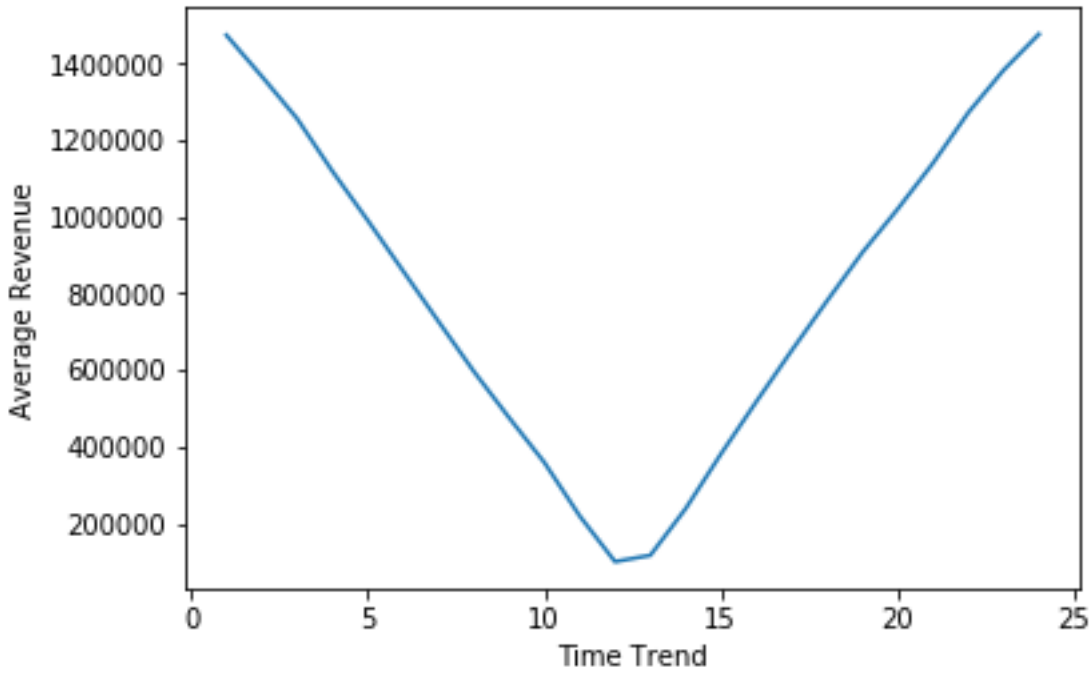

Figure 3.1: *Average revenue for hotels that change ownership for 12 months before changing and 12 months after changing*