Analysis of Concert Ticket Pricing Strategy

in China Online Secondary Market

by

Jiayun Qu

An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business Honors Program

NYU Shanghai

May 2019

Professor Marti G. Subrahmanyam Professor Yuxin Chen

Professor Yiqing Lu

Professor Shuang Zhang

Faculty Advisers Thesis Adviser

Table of Contents

[Abstract 3](#_Toc8070204)

[Introduction 4](#_Toc8070205)

[Research Background 5](#_Toc8070206)

[Research Purpose 7](#_Toc8070207)

[Literature Review 8](#_Toc8070208)

[Research Methodology 11](#_Toc8070209)

[Hypothesis 11](#_Toc8070210)

[Data Selection 12](#_Toc8070211)

[Model 13](#_Toc8070212)

[Results & Analysis 17](#_Toc8070213)

[Conclusion & Discussion 18](#_Toc8070214)

[Difficulties and Future Expectations 21](#_Toc8070215)

[References 23](#_Toc8070216)

[Tables 25](#_Toc8070217)

# Abstract

 In this research, I planned to target at China online secondary market for concert tickets, aiming to study how different factors, such as days until concert, singer’s profile, venue location, can have an impact on the resell prices. I started from the hypothesis that the following 7 factors could make a difference on the final price, including location (city

& venue), timing, seasonality, seat location, competition among sellers, singer profile and the singer’s popularity. Due to the lack in established database as well as the difficulty in scraping the online data, the data set of this research was manually collected from Xishiqu.com, Baidu Index and QQ Music, serving as the three main data sources. Data within 7 days before the actual performance were collected for every singer that was to hold concerts from November 2018 to February 2019. By generating the potential factors, with time and location as control variables, I used the data of 28 concerts, and 1171 useful observations to build the regression model. To compare the price difference between the primary market and the secondary market, the percentage difference is used as the dependent variable. And I conclude that venue capacity, days until concert, number of fans, years of debut, Baidu Search Index, Baidu Media Index, total transactions, number of followers, and ticket surplus have significant impact on the price difference.

*Keywords: Concert Ticket Price, China Online Secondary Market, Pricing Strategy,*

*Linear Regression Model, Prediction Model*

# Introduction

This honors thesis will mainly focus on the research question of “***How are different factors influencing the price of concert tickets in the online secondary market in China?***” Here, “concert” refers to pop or rock concerts held by singers that are listed on the online ticket resell websites. “Secondary market” refers to the online ticketing websites where people resell their concert tickets after they have been purchased from the primary market (e.g. official ticketing websites, box office, etc.).

My initial hypothesis was that as time approaching the concert date, the concert ticket price in the secondary online market would surge up, and factors such as seat locations, day of the concert and singer popularity would have great impact on the price.

# Research Background

With the increase of per-capita income in China, there has been a gradual growth in the expenditure ratio in recreation and entertainment among the public. Especially in these two years when various idol production TV shows are emerging, more young idols are brought up in front of the public, while at the same time boosting the development of the music-related industry. Although China’s performing market has been rapidly growing thanks to the economic and entertaining environment, the concert ticket price still remains high compared to that of other countries.

In Mainland China, the average concert ticket price takes up 17.24% of the monthly GDP per capita, while it’s 1.81% in the United States, 3.11% in Japan and 2.87% in U.K. The average ticket price is around 600RMB while it’s 200RMB in developed countries like Japan and the U.S. (“Who is Driving the China Concert Price to the Globally Highest?”, 2015) Back to 2016, when the price of a single ticket of Faye Wong was raised to more than 10,000RMB (“Why Did the Grand Occasion of Faye Wong’s Sky-High Concert Ticket Price Crash Again Instantly?”, 2016), it caused a great disturbance in the ticketing market and aroused the public attention of the concert pricing, especially in the secondary market.

Movie industry, which shares the same feature of concerts in that movie tickets are perishable, also performs similarly. Recently, the biggest hit: Avengers 4: The End Game has just been on. The average ticket price for the premieres at the midnight of April 24 was 65.6RMB and 54.9RMB for the day, which is around 70% higher than the regular average ticket price of 35RMB. There were even tickets sold at 300-400RMB. (“What is More Terrible than the High Price at Cinema is that Consumers Have No Choice”, 2019) One reason that might account for this situation is that capacity for audience is low and demand for movies in China is much bigger that the supply because of the huge population, and this could be applied to the concert industry as well. In 2017, China became the top in the number of movie screens, with the number of 50,776 (“Number of cinema screens in China from 2009 to 2019”, 2019) while the United States only has 40,394. (“Number of Movie Screens in The United States from 2008 to 2018, by Format.”, 2018). According to China Times, movie screen coverage rate in Europe is 13,000 person/piece and 6,500 person/piece in the United States. If China were to reach the European level by 2020, the number of movie screens should reach 64,000, which is a 25% growth. If China were to reach the U.S standard, then the screen number should exceed 120,000. (“Behind the Rapid Growth: The Number of People Watching Movies and The Growth Rate of Box Office Are Difficult to Mutually Support”, 2018). We can see that the capacity level of China’s entertainment industry, with cinema as an example, is way lower compared to the developed countries.

Besides the above observations from the overall industry, there’s a common phenomenon in China that concert tickets are always sold at a limited number and quickly sold out in the primary market. The remaining tickets will be then re-distributed by the concert organizers or the individual sellers in the secondary market where the tickets are usually re-priced at a higher level. However, there isn’t any set government regulation regarding pricing of concert tickets in China, let alone the much freer secondary market where all the decisions are left to the brokers or scalpers, engendering more vagueness in the concert pricing. With such information asymmetry, the concert ticket consumers, including myself, are always confused about how the price is set and when to purchase the cheapest tickets. Therefore, I decided to look into the concert industry in China and study how different factors can influence the price of concert tickets on the online secondary market.

# Research Purpose

As one of the consumers of concert tickets, I find the ticket price on online secondary market is hard to predict and friends around me also share the similar confusion. With this initial question, this paper is aiming to fulfill the following two purposes.

Firstly, this paper can offer consumers and sellers insights on concert ticket pricing. There have always been questions regarding tickets before concerts, for example, when is the best time to purchase the cheapest ticket? Shall I go for primary market or secondary market? How did the organizer set the ticket price that made it so high? After the model is set, consumers will have a better understanding of the most significant factors that determine the ticket price and when there is an upcoming concert, consumers can see the predicted ticket price if they have the data for specific variables. In this way, the prediction model can help the consumers make better purchasing decisions and understand the constituents of a concert ticket price. Besides, it can offer the ticket resellers insights on setting their pricing range when they put their tickets on the secondary market so as to attract more buyers.

Secondly, this paper hopefully can serve as a supplement of the current blank literature field regarding Chinese concert ticket pricing and a starting point for the future studies. There is a lack of research or study about the pricing strategy of concert tickets in China, and even in the international literatures, there’s not a sufficient number of related topics. This research will develop a framework to estimate the ticket price based on various factors and evaluate their significance.

# Literature Review

The current situation regarding my research field is that there isn’t any established data base for the secondary market concert pricing, nor any literature directly related to my topic. From the Chinese and English literatures that I’ve read through, I found 3 of them most relevant to my thesis and would provide inspiring insights for my research. The reason why I intended to look at some Chinese literature is that I wanted to find something unique about the Chinese secondary market and see if there’s any possible case or data that I can use to support my own research.

The first literature is “*An Economic Guide to Ticket Pricing in The Entertainment Industry”* by Pascal Courty from the Department of Economics, London Business School. There is no single data in this paper, but it serves as a very informative and comprehensive empirical guide to give theoretical analysis of factors influencing the ticket pricing. It also offers me insights of how economic theories and different factors can cause the price variations, such as seat locations, dates, venues, bundling, etc. Therefore, this paper can not only help me gain ideas of what other factors can supplement to the current model, but also support some of the assumptions that I have made.

The second literature is “*Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets”* by Andrew Sweeting from Duke University and National Bureau of Economic Research. This paper mainly tested the effect of Dynamic Pricing (DP) strategies on the price changes of perishable goods, using baseball tickets as an example, which specifies the effect of time approaching the event and the customer demand. Dynamic Pricing is a very relevant issue related with concert tickets as I assume that for popular concerts that have a high consumer demand, the ticket price should be raised higher when the concert is approaching, and vice versa. Also, even baseball game is not directly relevant to the concert market that I’m focusing on, it still shares the similar characteristics in that they are both perishable goods.

The third literature is “*Resale and Rent-Seeking: An Application to Ticket Markets*” by Phillip Leslie from NBER and Anderson School of Management, UCLA, and Alan Sorensen from NBER and Department of Economics, University of Wisconsin, Madison. This paper explored on the interdependence of primary and secondary market and serves as the first one to analyze data from both markets in parallel. It also simulates the market outcomes under various market changes (seat quality, utility and arrival cost, etc.). This paper applies economic models that help connect the primary and secondary market together and study closely on the different market features, which helps me dwell on the relationship between the face value (primary market) and the value set on the secondary market. In addition, the ticket market it studies is quite similar to my thesis research field.

In summary, the above literatures offer me insights of what indicators I could include in my research model and what factors can have an impact on the pricing. They also give me a general idea of how the perishable good markets, including airline tickets, basketball game tickets, etc. share the similar features with the concert tickets. Besides, the existing literature provides me with a starting point to synthesize the important industry characteristics of the ticketing business. For example, some of the insights that I have gained are as followings:

1. The fixed capacity of the concert tickets: only certain amount of people can be admitted to the concert due to the capacity of the venue and fixed amount of the sellable seats.
2. Perishable: the tickets will lose its entire value after the concert starts, which means that the value of a concert ticket (or other perishable event tickets) only keep its value till the official start of the concerts.
3. Seat location: one of the biggest differentiations of price lies in the difference between seat locations, which is also related with issues like the distance to the stage, how central the seat is, etc. Customers tend to have different demand and preference on different seats as well. There’s a paper that specifically studies the relationship between the seat location and the ticket pricing, which I will look more deeply into and include in my final literature review.
4. Advanced selling: the concert tickets are usually sold 2 weeks to 1 month before the concert actually starts, therefore there must be a trend in the pricing of the tickets within the amount of time ahead due to various unpredictable issues.

Therefore, combined with the above findings, I believe that my own research could add value to the existing literature as a supplement of the lack in the Chinese online secondary market studies. Granted that there are still some limitations to my study, for example, the number of concerts and the pricing entries are much fewer compared to those literatures using the U.S. secondary online market concert data as the data base, I believe the data set that I’ve built could serve as a starting point for people that are interested in understanding or studying the Chinese online resale market in the future as it is much more complicated compared with the U.S. market.

# Research Methodology

## Hypothesis

Based on the empirical investigation of my personal experience of buying concert tickets, and a preliminary market research of the industry, the initial hypothesis is that the following factors might influence the pricing of concert tickets in the secondary market:

1. ***Location***: Location includes the city and the venue where the concert is held. As the population of consumer base and capacity vary, the rental costs change according to the venues, and the concert organizer can set higher prices in cities with a higher demand.
2. ***Timing***: The timing includes the date, the day in a week and the actual time when the concert is held. The number of days left before the concert can also affect the pricing. The ticket price usually becomes higher for popular singers when the concert is approaching since there are fewer remaining tickets while a relatively higher number of people will make up their minds to go to the concert.
3. ***Seasonality***: Seasonality is also a factor depending on the timing of the concert. I assume that summer and winter will be the peak seasons for the concerts as students will have their holidays and have more time to go to concerts. Therefore, the sellers might charge higher prices during winter break (Jan-Feb) than regular school months (Oct-Nov).
4. ***Seat location***: In the official primary market, the farther the seat location is, the cheaper the ticket will be, but the price stays the same for the seats in one specific seating area. However, in the secondary market, the price varies from seats within the same area. I assume that the shorter the straight-line distance is from the seat to the center of the stage, the higher the price will be.
5. ***Competition among sellers***: There are many individual sellers and scalpers in the secondary market, and each will set their own price for the tickets. If there are a large number of sellers for one concert, it indicates that the concert is popular, and the ticket price tends to be higher. The total sales by the day can also be an indicator.
6. ***Singer profile***: We should look at different indicators of the singer’s performance, including the years of debut, number of albums and fans, since their past experience can affect the box-office of the concert, as well as the ticket price. For example, if the singer has many years of experience and has already enjoyed great reputation, it’s highly possible that the concert tickets will sell good even at a high price.
7. ***The popularity of the celebrities***: The popularity of the singers is definitely an important factor in deciding the ticket price. Empirically, the more popular the singer is, the higher the ticket price will be.

## Data Selection

1. **Data Range**

There isn’t an established database for the concert industry right now in China; therefore, I decided to manually collect the data from multiple online resources. I will mainly look at the pop/rock concerts that take place from November 2018 to February 2019 in the three main cities: Shanghai, Beijing and Guangzhou. And the data collection period will be one week before the actual concert date. At last, my data set contains the information of 28 concerts (Table 1), around 1400 price entries and 1200 were used. The variables are divided into 4 categories: concert information, singer’s profile, dynamic data (singer’s popularity) and pricing information (Table 2).

1. **Data Source**

For this research, I will limit the concert ticket secondary market to the website: <http://www.xishiqu.com/>. Xishiqu is one of the largest online ticket resell platforms, which enables free competition and price comparison for all the consumers and sellers. Because of its comprehensiveness and extensiveness in the concert variety and consumer coverage, it is suitable for data collection and is considered as the primary data source. From Xishiqu, I mainly gathered the data of all the basic information of the upcoming concerts, including the concert location, timing, seat location of different tickets, the total sales, the seller competition scale, the popularity index of the concerts on the website, etc. as the independent variables. The pricing range of each ticket on sale is stated clearly on the website as well as the original face value of the tickets. To compare the difference between the prices in the primary and secondary market, I set the percentage difference in price as the dependent variable. For the singer profile, I gathered the data from QQ Music and desktop research as these indicators are all clearly documented. As for the popularity of the celebrities, unlike all the previous static data, this decision factor is more dynamic demonstrating a trend. I looked at Baidu Index to document the patterns of the daily discussion rate, search frequency and information heat rate.

## Model

After gathering the data, regression model is applied to test the relationships between the percentage difference in price of primary market and secondary market (y – dependent variable) and the above-mentioned potential decision factors (x – independent variable). In order to control the error and make the model for significant, I set city and time as control variables. The other unquantifiable variables, including day and ticket surplus, are converted into dummy variables. For example, 1 means the concert is held on the weekend while 0 means the concert is held on weekdays. Eventually, after correlation test is conducted, there are 12 independent variables. The meanings and summary statistics of the variables are listed below. (Table 4)

|  |
| --- |
| **Table 4. Summary Statistics** |
| Variables | Meaning | mean | sdv. | max | min |
| Price difference |  | 139.27 | 54.75 | 388.47 | 57.74 |
| D1 | Weekday | 0.75 | 0.44 | 1 | 0 |
| D2 | Ticket\_Surplus | 0.27 | 0.45 | 1 | 0 |
| X1 | Venue\_Capacity | 1.78 | 1.49 | 6.40 | 0.10 |
| X2 | Days\_Until\_Concert | 3.79 | 1.98 | 7 | 0 |
| X3 | Num\_Album | 48.24 | 37.56 | 138 | 2 |
| X5 | Num\_Fans (10k) | 70.27 | 86.58 | 357.20 | 0.10 |
| X6 | Years\_Debut | 22.51 | 16.26 | 54 | 1 |
| X7 | Baidu\_Search\_Index | 2,903.84 | 2,592.02 | 16,888 | 303 |
| X9 | Baidu\_Media\_Index | 0.89 | 1.33 | 7 | 0 |
| X10 | Total\_Transactions | 1,137.36 | 1,760.04 | 8,328 | 99 |
| X11 | Followers | 945.53 | 775.84 | 4133 | 45 |
| X12 | Num\_Competitors | 4.76 | 2.60 | 13 | 1 |

From the above table, price difference indicates the percentage premium or discount of the ticket price in the secondary market. We can see that on average price in the secondary market is 40% higher compared to that in the primary market. D1 shows if the concert is held on a weekday or on weekend. D2 indicates if the ticket surplus is sufficient. On the Xishiqu website, it only displays the number of tickets when the surplus is or lower than 6, therefore I decided to set a dummy variable here based on whether the surplus is sufficient or not. X1 is the venue capacity, the indicator to show how many people the venue can hold. X2 indicates the days until concert, ranging from 7 to 1. X3, X5 and X6 all serve as the indicators of the singers’ profile, showing the number of albums, the followers hey have and the years they have been on stage. X7 and X9 are from Baidu Index. X7 is the Baidu Search Index, showing the degree of public interests in the keyword and the continuous trend. X9 is the Baidu Media Index, reflecting the media attention and the number of news releases of the keyword. Both data are kept in the time range of a week ahead of the concert. X10 is the number of the total transaction of the tickets, X11 is the number of followers of the concert and X12 is the number of competitor sellers, all of which are captured from Xishiqu.com.

Correlation test (Table 5) was conducted with the above 12 variables and all values are lower than 0.6, which shows that there’s no great correlation between the selected variables and there is a minor chance of linear collinearity.

It’s also worth mentioning here that some of the initial variables were removed because the correlations are high and might increase the error of the model. The removed variables are X4: Num\_Singles, X8: Baidu\_Info\_Index and D8: Indoor. X4 (Number of Singles) is highly correlated with X3 (Number of Albums) and X6 (Years of Debut) with correlation values at around 0.8. Therefore, it was removed because I believe the other two variables can already well represent the singer’s performance experience. Similarly, I removed X8 (Baidu Info Index) because it has a high correlation with X7 (Baidu Search Index) and indicates similar information of media interests as X9 (Baidu Media Index). And lastly, the dummy variable of whether the venue is indoor or outdoor was added to test if it has an impact on the month when the concert is held and the related ticket price. However, more than 90% of the concerts in the dataset were held indoors and this variable has a correlation with X5 (number of fans) at around 0.77. The singer who has the greatest number of fans held his concert outdoors, while the rest, ranging from low fan base to high fan base all held their concerts indoors. Hence, this variable was removed because it doesn’t have a significant variance and might cause collinearity because of the high correlation.

|  |
| --- |
| **Table 5. Correlation Test** |
| 　 | D1 | D2 | X1 | X2 | X3 | X5 | X6 | X7 | X9 | X10 | X11 | X12 |
| D1 | 1.00 |  |  |  |  |  |  |  |  |  |  |  |
| D2 | 0.15 | 1.00 |  |  |  |  |  |  |  |  |  |  |
| X1 | 0.28 | 0.13 | 1.00 |  |  |  |  |  |  |  |  |  |
| X2 | 0.11 | 0.09 | 0.03 | 1.00 |  |  |  |  |  |  |  |  |
| X3 | -0.02 | -0.04 | -0.05 | -0.04 | 1.00 |  |  |  |  |  |  |  |
| X5 | 0.23 | -0.10 | 0.17 | 0.00 | -0.08 | 1.00 |  |  |  |  |  |  |
| X6 | -0.35 | 0.12 | 0.16 | -0.12 | 0.57 | -0.06 | 1.00 |  |  |  |  |  |
| X7 | 0.22 | -0.20 | 0.18 | 0.03 | -0.08 | 0.43 | -0.18 | 1.00 |  |  |  |  |
| X9 | 0.14 | -0.22 | 0.17 | -0.08 | -0.24 | 0.35 | -0.28 | 0.43 | 1.00 |  |  |  |
| X10 | 0.09 | -0.08 | 0.06 | 0.30 | 0.30 | 0.20 | 0.30 | 0.23 | 0.09 | 1.00 |  |  |
| X11 | -0.13 | 0.17 | -0.11 | -0.05 | -0.01 | -0.11 | 0.29 | -0.22 | -0.33 | 0.13 | 1.00 |  |
| X12 | -0.15 | -0.13 | -0.04 | -0.39 | 0.14 | 0.01 | 0.19 | 0.03 | 0.05 | 0.21 | 0.15 | 1.00 |

Therefore, the regression model is set based on the 12 independent variables as below. C stands for the control variables: location (Shanghai, Beijing and Guangzhou) and time (November, December and January).

Price difference=$β\_{0}+β\_{1}D1+β\_{2}D2+β\_{3}X1+β\_{4}X2+β\_{5}X3+β\_{6}X5+β\_{7}X6+β\_{8}X7+β\_{9}X9+β\_{10}X10+β\_{11}X11+β\_{12}X12+γC$+$ε$

注程度及持续变化情况。

# Results & Analysis

The regression results are displayed in Table 6. After data cleaning, 1171 price entries are used for the model. The R-squared value is 0.4068, which has been improved due to correlation check and is satisfactory enough for this dataset. The P-values show that 75% of the variables have significant impact on the price difference, with only D1: day of concert, X3: number of albums and X12: number of competitors not having great influence.

|  |  |
| --- | --- |
|  | **Table 6. Regression Results** |
| Variables | Meaning | Price difference |
| D1 | Weekday (Dummy) | -0.0634 |
|  |  | (0.0540) |
| D2 | Ticket\_Surplus (Dummy) | -0.4329\*\*\* |
|  |  | (0.0331) |
| X1 | Venue\_Capacity | 0.0626\*\*\* |
|  |  | (0.0151) |
| X2 | Days\_Until\_Concert | 0.0255\*\*\* |
|  |  | (0.0081) |
| X3 | Num\_Album | -0.0000 |
|  |  | (0.0005) |
| X5 | Num\_Fans (10k) | -0.0011\*\*\* |
|  |  | (0.0002) |
| X6 | Years\_Debut | -0.0040\*\*\* |
|  |  | (0.0015) |
| X7 | Baidu\_Search\_Index | 0.0001\*\*\* |
|  |  | (0.0000) |
| X9 | Baidu\_Media\_Index | 0.0324\*\*\* |
|  |  | (0.0122) |
| X10 | Total\_Transactions | -0.0000\*\*\* |
|  |  | (0.0000) |
| X11 | Followers | 0.0001\*\*\* |
|  |  | (0.0000) |
| X12 | Num\_Competitors | -0.0070 |
|  |  | (0.0091) |
| Constant |  | 1.5450\*\*\* |
|  |  | (0.0874) |
| Date (Month) |  | Control |
| Location (City) |  | Control  |
| Observations |  | 1,171 |
| R-squared |  | 0.4068 |
|  | Standard errors in parentheses |
|  | \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 |

# Conclusion & Discussion

 It is interesting to find out that 9 out of the 12 variables have significant impact on the concert ticket price in the online resell market, and most of my hypotheses are proved to be right. But the ones that do not have strong influence do make sense as well. This section will discuss the rationale behind the relationship between the variables and the price difference.

 D2 stands for the ticket surplus. From hypothesis, I assume that the fewer tickets are left, the higher the price will be, since it shows that the demand is high for this concert and the price will become higher accordingly. The constant for D2 is in fact negative, which can prove that the price difference will be lower when the ticket surplus is sufficient, implying that the ticket price in the secondary market is higher with an insufficient number of tickets.

 X1 and X2 both fall in the category of concert basic conditions. X1 stands for the venue capacity and X2 represents the days left until the concert. When the venue is bigger, the rent tends to be higher and it can show that the singer is popular enough to attract the large number of audiences. In this way, it will cause the ticket price to become higher. Even though the days until concert here do have an impact on the price. It is in fact contrary to the hypothesis that the change in price follows the dynamic pricing pattern, which is that the price will become higher when the event is approaching. Here, the positive constant indicates that the price difference will become smaller as days go by. This might be due to the low demand of the concert, which will force the seller to lower the price so as to sell more tickets before the concert starts. Therefore, dynamic pricing strategy is not always applicable and indeed depends on other factors of the concerts. This might also indicate that the concert ticket secondary market in China is very concentrated with few sellers controlling the ticket sources so that the ticket price could be easily adjusted.

 X5 (number of fans) and X6 (years of debut) are the indicators of the singer profile, which accords to the common sense to have an influence on the concert price setting. The years of debut has a strong impact in that consumers would like to see singers that have many years of past experience and the opportunities for these singers to hold concerts are actually rarer and therefore more precious than the newly debuted stars. On the other hand, the number of fans does have a great influence as well and is not directly correlated with the years of debut. For example, according to the dataset, the male idol group NEXT which has just debuted for one year already has three times as many fans as Scorpions, the classic rock band that has debuted for more than 50 years. The factors together can show how the price changes with the singers’ experience and popularity.

 X7 and X9 represent Baidu Search Index and Baidu Media Index and can show the popularity of the singers during the concert period. The more the online users search the singers’ name, the more exposure the singers will get during the time, which helps deliver the message of the upcoming concert and can attract more people to convert the online search into actual purchase. So does the Baidu Media Index, showing how many news are discussing about the singer, serving as a way to increase the singer exposure to the public.

 And lastly, X10 stands for the amount of total transactions and X11 stands for the number of people following the concert price change. Both of the factors indicate the level of attention of the concert on the ticket resell website, with a significant but minor impact.

The rest of the variables, which are D1: day of concert, X3: number of albums and X12: number of competitors do not have significant impact on the ticket price compared to the above variables.

Firstly, in terms of day of concert, even though I assume that concerts that are held on the weekends have higher ticket price than the ones held on the weekdays. In fact, it is not always the case, which accounts for the reason why it does not have a direct impact on the price difference. Indeed, from the dataset, the concert that has the highest ticket price (Fan Weiqi, Shanghai, Feb 14th) took place on Thursday, which is a weekday.

It makes sense that the number of albums doesn’t impact the price as much as the other variables in the category of singer profile such as number of fans and years of debut. The number of singles can outweigh the number of albums and the popularity of the singer is not directly related with how many albums the signer has released. As for the number of competitor sellers, it can to some extent indicate the popularity of the concerts, but not as directly as the number of followers, which are the ones that perform the real interests in going to the concerts.

The regression model can also serve as a prediction model for the ticket prices in the future. Knowing the values of each indicator, both buyers and consumers can insert the numbers and get the predicted concert price and make a comparison to see if the price is set too high or too low in the secondary market. In this way, guidelines could be given to the consumers to purchase the tickets in a reasonable price range.

However, this model does have its limitations, which would be discussed in the next section. Consumers can use this as a reference but definitely not the official price guidelines.

# Difficulties and Future Expectations

There have been several difficulties in this research. First and foremost is the data collection. Unlike established database or data that can be scraped, the website data for my research are mainly imbedded in another webpage and prevents scraping. It also took time to figure out what variables would be useful and whether it would be collectable.

Besides, my database was fully manually collected and it’s hard to keep the consistency of all the data in that not all the data was collected at the same time. Manual collection would cause the different collection time due to various situations, which might make the results less accurate. Another difficulty that is closely related with the first is the missing data. During the first few days of collection, it was still in the exploration and testing process to see what indicators were valuable and when to collect them. There was also time when the best collection time for certain data passed and the data no longer existed, for example, the pricing information on the day of the concert and some artists were not part of the Baidu Index. Because of these situations, some of the concerts are missing the complete data set, which would lead to model inaccuracy.

Lastly, compared to literatures studying ticket pricing, this data set is rather small and might lack comprehensiveness. The independent variables that I selected are mostly based on empirical investigation and might miss out some of the important decision factors. Due to the time and resource limitation, in this research, I am not able to include other ticket resell websites like Motianlun or Taobao, and to incorporate some of the unique Chinese ticketing models like company complimentary ticket or fans’ group purchase tickets. Also, because of the limited time, this dataset only covers the data from November 2018 to February 2019. With 4 months of data, it is not enough to explain the situation across the year, which makes it hard to see the impact of factors such as seasonality. Similarly, for the ease of collection, the location of the concerts is limited to Shanghai, Beijing and Guangzhou as the major representative cities across China. A more comprehensive dataset should be able to indicate the characteristics of ticket prices, no matter when and where the concert is held.

For the future research, it would be ideal to figure out ways to capture the data of the online ticket secondary markets instead of manual collection, which would make the analysis more efficient and models more complex. Studying one target online ticket selling website: Xishiqu this time has helped establish the foundation to study other platforms in the future. Rolling out the similar model to other Chinese ticket resell markets can cover more concerts and help discover the industry characteristics with larger datasets. The dataset right now is also limited in the number of variables. In the future, in addition to these existing ones, adding more quantifiable data, such as the seat location, would incorporate and prove the practical relevance of such foreign theories in the Chinese market as the demand associated with the distance between seats and the stage. It would also add value if more Chinese specific laws or regulations would be taken into consideration as one of the decision factors, differentiating China from other markets in the ticket pricing policy.

# References

Courty, P. (2000). An economic guide to ticket pricing in the entertainment industry*. Recherches Économiques De Louvain / Louvain Economic Review, 66(2)*, 167-192. Retrieved from <http://www.jstor.org/stable/40724285>

LESLIE, P., & SORENSEN, A. (2014). Resale and Rent-Seeking: An Application to Ticket Markets*.* *The Review of Economic Studies, 81(1 (286)),* 266-300. Retrieved from <http://www.jstor.org/stable/43551672>

MPAA. (n.d.). Number of movie screens in the United States from 2008 to 2018, by format. In *Statista - The Statistics Portal*. Retrieved May 6, 2019, from https://www.statista.com/statistics/255355/number-of-cinema-screens-in-the-us-by-format/.

SARFT (China), & AskCI Consulting. (n.d.). Number of cinema screens in China from 2009 to 2019. In *Statista - The Statistics Portal*. Retrieved May 6, 2019, from <https://www.statista.com/statistics/279111/number-of-cinema-screens-in-china/>.

Sweeting, A. (2012). Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets*.* *Journal of Political Economy, 120(6)*, 1133-1172. doi:10.1086/669254

2020年电影银幕总数将达8万块 高速增长背后：人均观影次数和票房增速难支(“The Number of Movie Screens Will Reach 80,000 in 2020. Behind the Rapid Growth: The Number of People Watching Movies and The Growth Rate of Box Office Are Difficult to Mutually Support”*).* (2018, December 14). Retrieved April 24, 2019, from https://baijiahao.baidu.com/s?id=1619837640686136140&wfr=spider&for=pc

是谁把中国演唱会票价推到全球最高? (“Who is Driving the China Concert Price to the Globally Highest?”*).* (2015, August 10). Retrieved April 8, 2019, from http://www.xinhuanet.com/ent/2015-08/10/c\_128112689.htm

王菲演唱会的天价票"盛况"为何再次瞬间崩盘? (“Why Did the Grand Occasion of Faye Wong’s Sky-High Concert Ticket Price Crash Again Instantly?”). (2016, December 22). Retrieved April 8, 2019, from http://news.ifeng.com/a/20161222/50458717\_0.shtml

# Tables

**Table 1: Concert Information**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **No.** | **City** | **Artist** | **Date** | **Data Collection Date** | **Location** |
| 1 | Beijing | Scorpians | 2018/11/17 | 2018/11/10 | 国家奥体中心体育馆 |
| 2 | Beijing | Xin Xiaoqi | 2018/11/17 | 2018/11/10 | 工人体育馆 |
| 3 | Guangzhou | Li Jian | 2018/11/17 | 2018/11/10 | 宝能国际体育演艺中心 |
| 4 | Shanghai | Scorpians | 2018/11/21 | 2018/11/14 | 上海梅赛德斯奔驰 |
| 5 | Shanghai | Wang Xiaokun | 2018/11/23 | 2018/11/16 | 大观舞台 |
| 6 | Shanghai | Li Yugang | 2018/11/24 | 2018/11/17 | 国家会展中心(上海)虹馆EH |
| 7 | Beijing | Donglihuoche | 2018/11/24 | 2018/11/17 | 工人体育馆 |
| 8 | Guangzhou | A-Lin | 2018/11/24 | 2018/11/17 | 广州体育馆 |
| 9 | Guangzhou | Guo Fucheng | 2018/11/24 | 2018/11/17 | 宝能国际体育演艺中心 |
| 10 | Guangzhou | Pan Weibo | 2018/12/1 | 2018/11/24 | 宝能国际体育演艺中心 |
| 11 | Shanghai | 乃木坂46 | 2018/12/1 | 2018/11/24 | 上海梅赛德斯奔驰 |
| 12 | Shanghai | Chen Jia | 2018/12/3 | 2018/11/26 | 兰心大戏院 |
| 13 | Guangzhou | 许冠杰 谭咏麟 | 2018/12/15 | 2018/12/8 | 广州天河区海心沙 |
| 14 | Shanghai | 乐华七子 | 2018/12/15 | 2018/12/8 | 上海梅赛德斯奔驰 |
| 15 | Shanghai | Donglihuoche | 2018/12/22 | 2018/12/15 | 国家会展中心(上海)虹馆EH |
| 16 | Beijing | Li Jian | 2018/12/22 | 2018/11/30 | 工人体育馆 |
| 17 | Beijing | 小野丽莎 | 2018/12/25 | 2018/12/18 | 北京展览馆剧场 |
| 18 | Guangzhou | 小野丽莎 | 2019/1/2 | 2018/12/26 | 星海音乐厅 |
| 19 | Guangzhou | 中岛美嘉 | 2019/1/4 | 2018/12/3 | 广州中山纪念堂 |
| 20 | Beijing | 鹿先生乐队 | 2019/1/5 | 2018/12/28 | 工人体育馆 |
| 21 | Guangzhou | Zhou Bohao | 2019/1/6 | 2018/12/30 | 宝能国际体育演艺中心 |
| 22 | Shanghai | 中岛美嘉 | 2019/1/6 | 2018/12/30 | 新静安体育中心 |
| 23 | Guangzhou | Wang Lihong | 2019/1/12 | 2019/1/5 | 海心沙亚运公园 |
| 24 | Shanghai | 火箭少女 | 2019/1/12 | 2019/1/5 | 上海梅赛德斯奔驰 |
| 25 | Shanghai | Tan Yonglin | 2019/1/19 | 2019/1/12 | 东方体育中心 |
| 26 | Beijing | Xie Chunhua | 2019/1/25 | 209/1/18 | 北京展览馆剧场 |
| 27 | Shanghai | 小野丽莎 | 2019/2/14 | 2019/2/7 | 新静安体育中心 |
| 28 | Shanghai | 范玮琪 | 2019/2/14 | 2019/2/7 | 上海梅赛德斯奔驰 |

|  |
| --- |
| **Concert Info** |
| Artist | City | Venue | Indoor |  Outdoor | Venue\_Capacity (10k) | Date | Day | Day\_Until\_Concert |
| Scorpians | Beijing | 国家奥体中心体育馆 | 1 | 0 | 4 | 2018/11/17 | Saturday | 7 |
| Scorpians | Beijing | 国家奥体中心体育馆 | 1 | 0 | 4 | 2018/11/17 | Saturday | 7 |

 **Table 2: Data Categories**

|  |
| --- |
| **Singer Profile (QQ Music)** |
| Num\_Album | Num\_Single | Num\_Fans(10k) | Years\_Debut |
| 68 | 516 | 4.20 | 54 |
| 68 | 516 | 4.20 | 54 |

|  |
| --- |
| **Dynamic Index** |
| Baidu\_Search\_Index | Baidu\_Info\_Index | Baidu\_Media\_Index | Xishiqu\_Index |
| 931 | 113 | 0 | 99.0 |
| 931 | 113 | 0 | 99.0 |

|  |
| --- |
| **Pricing Info** |
| Total Transaction | Followers | Num\_Competitors | Price | Face\_Value | Price Difference | Ticket\_Surplus |
| 300 | 1033 | 2 | 650 | 180 | 3.61 | 4 |
| 300 | 1033 | 2 | 780 | 580 | 1.34 | sufficient |

**Table 3: Variables Used in Model**

|  |  |
| --- | --- |
| Variables | Meaning |
| Price difference | Discount Difference between price & value |
| D1 | Day (Dummy) |
| D2 | Ticket\_Surplus (Dummy) |
| X1 | Venue\_Capacity (10k) |
| X2 | Day\_Until\_Concert |
| X3 | Num\_Album |
| X5 | Num\_Fans(10k) |
| X6 | Years\_Debut |
| X7 | Baidu\_Search\_Index |
| X9 | Baidu\_Media\_Index |
| X10 | Total\_Transaction |
| X11 | Followers |
| X12 | Num\_Competitors |