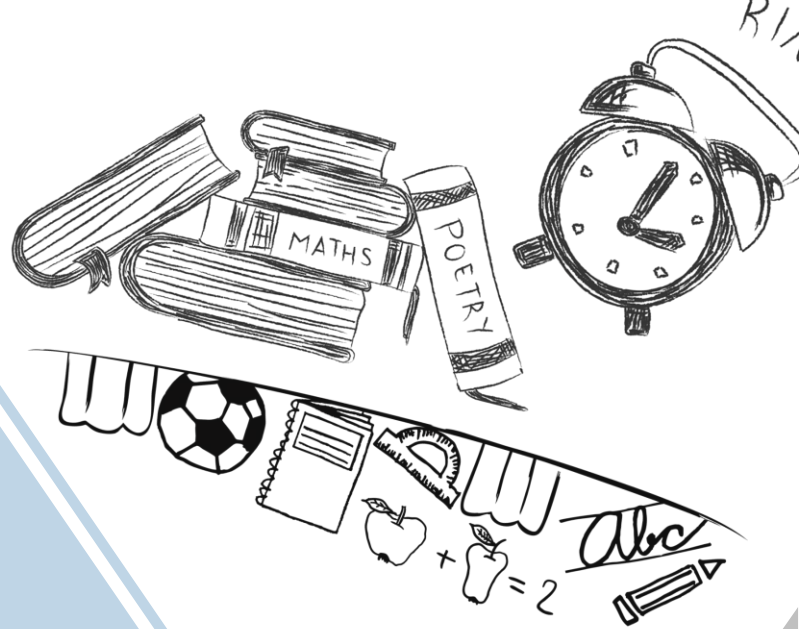


Airbnb's Demand in NYC: An Econometric Analysis on an Airbnb's popularity

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Introduction

BIG IDEA: How can we boost the Airbnb popularity in NYC and optimize the potential tourist?

Motivation:

- Boost the Airbnb reviews helps to attract more potential consumer
- Provide pre-insights for travelers
- Measure the customers' and providers' behavior and performance on the platform

Possible considerations:

- The popularity of Airbnb in the NYC is not consistent with other cities
- We cannot predict the case during the COVID-19 time



Research Question

This research aims to find the factors that will influence the prosperity of house sharing economics in NYC, especially for the price of Airbnbs in the year of 2019.

Why asking:

- Provide information for Airbnb hosts to maximize their surplus and help the government to better track and manage tourism resources.

Why Airbnbs? Why the year of 2019?

- The Rise of “Sharing Economics”
- Emit the impact of the pandemic.



Outline

1. **Literature Review:** Literature Review: Inspiration from Sung and Lee's work in 2018, they introduced a new economic model called "sharing economy" and aims to encourage people to make extra profit by sharing their unused properties with another person.
2. **Data Resources:**
 - New York City Airbnb Open Data in Kaggle for 2019 and each Airbnb's specific demographics like room type, reviews per month, price (in USD), borough group, etc.
 - RentHop New York Two Bedroom Median Rent Affordability from the NY Curbed website
3. **Descriptive statistics:** Basic summary for dependent variable and covariates.
4. **Methodology:** Use two stage least square method with instrumental variable 'income per rent'



Literature Review

Interested in Sharing economics (Airbnb market)

- Sung, E., Kim, H., & Lee, D. (2018). Why Do People Consume and Provide Sharing Economy Accommodation? —A Sustainability Perspective
- The word “sharing” indicates the activities that people maximize the utilization of unused by sharing the good or services with others.

Existent Research

- Voltes-Dorta, A., & Sánchez-Medina, A. (2020). Drivers of Airbnb prices according to property/room type, season and location: A regression approach. Journal of Hospitality and Tourism Management
- Dudás, G., Vida, G., Kovalcsik, T., & Boros, L. (2017). A socio-economic analysis of Airbnb in New York City
- Aim to build the demand model that can be used to estimate a reasonable price based on the quantity demand of Airbnb in New York City. Researchers indicates that price of Airbnb is related with its location, neighborhood group and room type.



Preliminary analysis-Data cleaning

- price \leq 500
- Merge with the table “*RentHop New York Two Bedroom Median Rent Affordability*”

RangeIndex: 14811 entries, 0 to 14810

Data columns (total 19 columns):

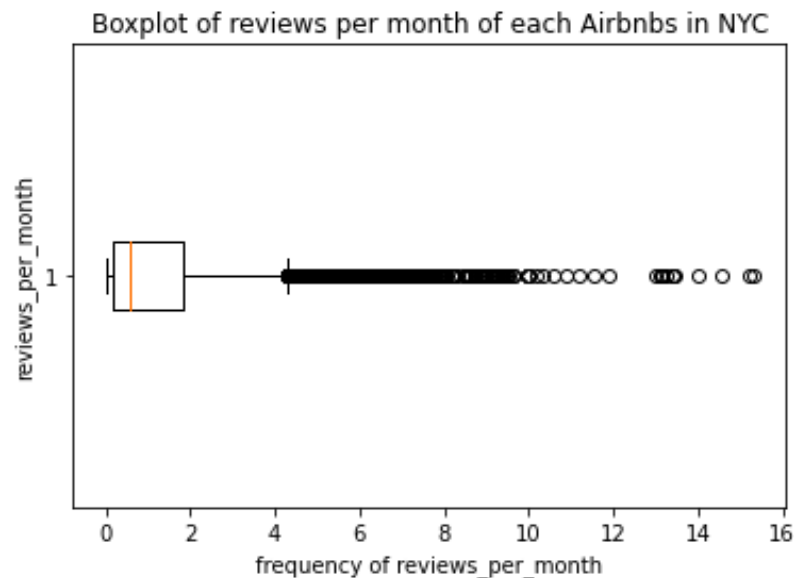
#	Column	Non-Null Count	Dtype
0	id	14811 non-null	int64
1	name	14810 non-null	object
2	host_id	14811 non-null	int64
3	host_name	14807 non-null	object
4	neighbourhood_group	14811 non-null	object
5	neighbourhood	14811 non-null	object
6	latitude	14811 non-null	float64
7	longitude	14811 non-null	float64
8	room_type	14811 non-null	object
9	price(in USD)	14811 non-null	int64
10	minimum_nights	14811 non-null	int64
11	advertisement	14811 non-null	int64
12	last_review	14811 non-null	object
13	reviews_per_month	14811 non-null	float64
14	calculated_host_listings_count	14811 non-null	int64
15	availability_365	14811 non-null	int64
16	Coordinates	14811 non-null	object
17	income_per_rent	14811 non-null	float64
18	per_rent_borough	14811 non-null	float64

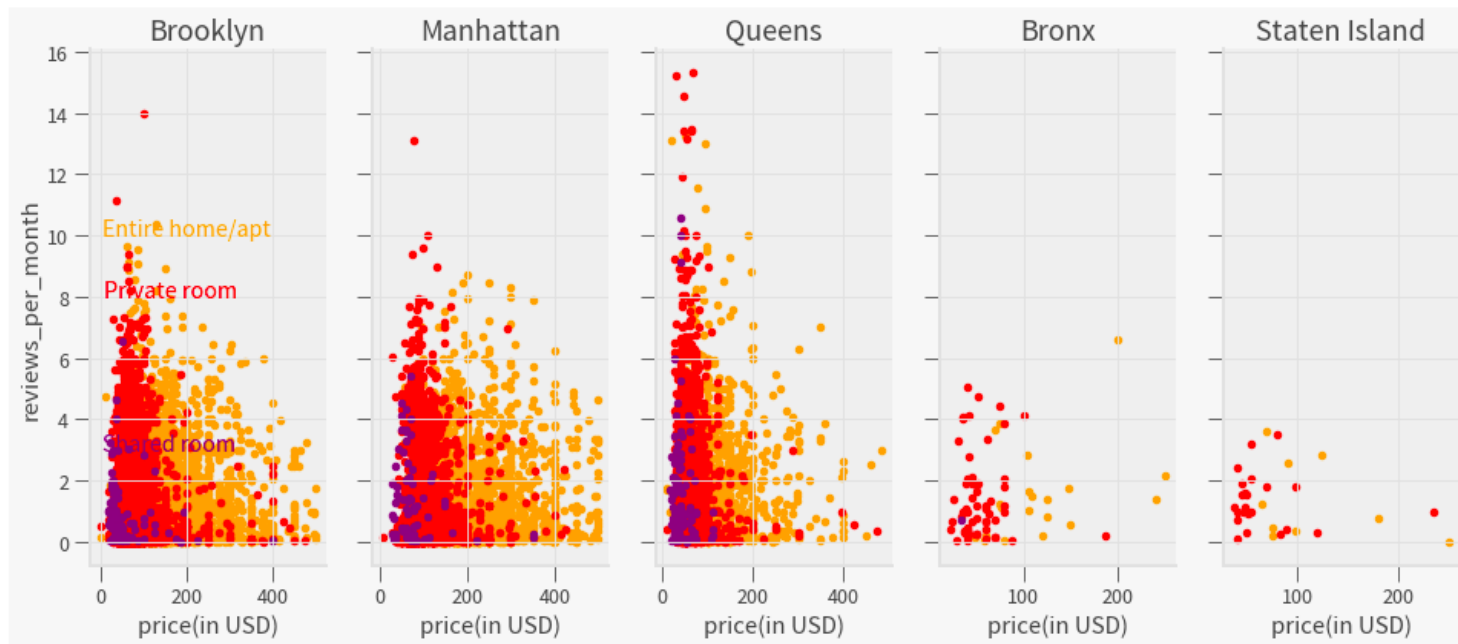
dtypes: float64(5), int64(7), object(7)



Descriptive Statistics - Dependent Variable

count	14811
mean	1.25
std	1.56
min	0.01
25%	0.16
50%	0.59
75%	1.82
max	15.32







Methodology - OLS

Why use OLS

- Building the OLS model with Airbnb's monthly review frequency and price and then gradually add other factors to view the changing coefficient significance.
- Whether all variables are significant and whether there are some potential problems such as endogenous
- We selected the model with the highest R-square

Controls include:

review_per_month: Average daily review in each month in 2019

price: Price in US dollarneighbourhood_group: location in NYC

room_type: listing space type

advertisement: number of reviews cause by web-recommendation

availability_365: number of days when listing is available for booking

minimum_nights: amount of nights minimum for booking



OLS Regression Model

$$\text{Model1: } \widehat{\text{reviews_per_month}}_i = \beta_0 + \beta_1 \times \text{price(in USD)}_i$$

$$\text{Model2: } \widehat{\text{reviews_per_month}}_i = \beta_0 + \beta_1 \times \text{price(in USD)}_i + \beta_{2j} \times \text{neighbourhood_group}_{ij}$$

$$\text{Model3: } \widehat{\text{reviews_per_month}}_i = \beta_0 + \beta_1 \times \text{price(in USD)}_i + \beta_{2j} \times \text{neighbourhood_group}_{ij} + \beta_{3j} \times \text{room_type}_{ij}$$

$$\text{Model4: } \widehat{\text{reviews_per_month}}_i = \beta_0 + \beta_1 \times \text{price(in USD)}_i + \beta_{2j} \times \text{neighbourhood_group}_{ij} + \beta_{3j} \times \text{room_type}_{ij} + \beta_4 \times \text{advertisement}_i$$

$$\text{Model5: } \widehat{\text{reviews_per_month}}_i = \beta_0 + \beta_1 \times \text{price(in USD)}_i + \beta_{2j} \times \text{neighbourhood_group}_{ij} + \beta_{3j} \times \text{room_type}_{ij} + \beta_4 \times \text{advertisement}_i + \beta_5 \times \text{availability_365}_i + \beta_6 \times \text{minimum_nights}_i$$



OLS Regression Model Comparison

OLS Regressions Summaries for Model 1-5

	Model1	Model2	Model3	Model4	Model5
R-squared	0.003	0.031	0.032	0.339	0.350
	0.003	0.031	0.032	0.339	0.350
Intercept	1.375***	1.467***	1.355***	0.823***	0.809***
	(0.024)	(0.172)	(0.174)	(0.144)	(0.144)
price	-0.001***	-0.000	0.000*	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
C(neighbourhood_group)[T.Brooklyn]		-0.333*	-0.324*	-0.281**	-0.213
		(0.173)	(0.172)	(0.143)	(0.142)
C(neighbourhood_group)[T.Manhattan]		-0.386**	-0.379**	-0.335**	-0.240*
		(0.173)	(0.173)	(0.143)	(0.142)
C(neighbourhood_group)[T.Queens]		0.345**	0.353**	0.308**	0.314**
		(0.174)	(0.174)	(0.144)	(0.142)
C(neighbourhood_group)[T.Staten Island]		-0.145	-0.145	-0.187	-0.229
		(0.318)	(0.318)	(0.263)	(0.261)
C(room_type)[T.Private room]			0.116***	0.089***	0.037
			(0.032)	(0.026)	(0.026)
C(room_type)[T.Shared room]			0.001	0.114	-0.001
			(0.096)	(0.079)	(0.079)
advertisement				0.018***	0.017***
				(0.000)	(0.000)
availability_365					0.001***
					(0.000)
minimum_nights					-0.009***
					(0.001)
R-squared	0.00	0.03	0.03	0.34	0.35
No. observations	14811	14811	14811	14811	14811

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01



Methodology-2SLS

Why choose 2SLS:

- Endogenous between independent variable and dependent variable

Controls include:

- Income_per_rent: the instrument variable represent the percent of income spend and income required in a neighborhood
- Almost the same with OLS, since these variables are informative for the estimation
- Except for Location which cause is collinear with the instrument variable

Endogeneity of price ~ reviews_per_month

```

=====
                        OLS Regression Results
=====
Dep. Variable:          price      R-squared:                0.003
Model:                  OLS        Adj. R-squared:             0.003
Method:                 Least Squares   F-statistic:              38.66
Date:                  Sun, 04 Apr 2021   Prob (F-statistic):       5.19e-10
Time:                  23:20:25         Log-Likelihood:           -85964.
No. Observations:      14811          AIC:                     1.719e+05
Df Residuals:          14809          BIC:                     1.719e+05
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	133.6183	0.843	158.562	0.000	131.966	135.270
reviews_per_month	-2.6190	0.421	-6.218	0.000	-3.445	-1.793

```

=====
Omnibus:                 3735.111   Durbin-Watson:           1.943
Prob(Omnibus):            0.000     Jarque-Bera (JB):        8616.569
Skew:                     1.427     Prob(JB):                 0.00
Kurtosis:                 5.411     Cond. No.                 2.84
=====

```









Instrument Variable

- It shows the percent of income spent and income required in neighborhoods with sufficient data

RentHop New York Two Bedroom Median Rent Affordability

Search:

Neighborhood 	Borough 	Two-Bedroom Median Rent 	Median Household Income 	Income % for Median Rent 	Income Required to Lease (40X Rule) 
Queensbridge-Ravenswood-Long Island City	Queens	\$3,300.00	\$28,378	139.54%	\$132,000
Williamsburg	Brooklyn	\$2,499.00	\$21,502	139.47%	\$99,960
Lower East Side	Manhattan	\$3,495.00	\$31,273	134.11%	\$139,800
Mott Haven-Port Morris	Bronx	\$2,200.00	\$20,334	129.83%	\$88,000
East Harlem North	Manhattan	\$2,495.00	\$26,099	114.72%	\$99,800



- Z independent with Y

Dep. Variable:	price	R-squared:	0.001			
Model:	OLS	Adj. R-squared:	0.001			
Method:	Least Squares	F-statistic:	10.98			
Date:	Sun, 04 Apr 2021	Prob (F-statistic):	0.000923			
Time:	23:18:57	Log-Likelihood:	-85978.			
No. Observations:	14811	AIC:	1.720e+05			
Df Residuals:	14809	BIC:	1.720e+05			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	125.7441	1.540	81.629	0.000	122.725	128.764
income_per_rent	0.0584	0.018	3.314	0.001	0.024	0.093
Omnibus:	3708.375	Durbin-Watson:	1.940			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	8476.456			
Skew:	1.422	Prob(JB):	0.00			
Kurtosis:	5.376	Cond. No.	204.			



IV limitation - Collinearity with location factor

IV-2SLS Estimation Summary

```
=====
Dep. Variable:    reviews_per_month    R-squared:                0.3413
Estimator:        IV-2SLS              Adj. R-squared:           0.3409
No. Observations: 14811                F-statistic:             1.487e+04
Date:             Thu, Apr 08 2021      P-value (F-stat)         0.0000
Time:             19:40:07              Distribution:            chi2(11)
Cov. Estimator:   robust
```

Parameter Estimates

```
=====
               Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
C(neighbourhood_group)[Bronx]      0.5117    0.2840    1.8017    0.0716    -0.0449    1.0683
C(neighbourhood_group)[Brooklyn]    0.2060    0.3140    0.6560    0.5118    -0.4095    0.8215
C(neighbourhood_group)[Manhattan]    0.1088    0.3692    0.2948    0.7682    -0.6148    0.8325
C(neighbourhood_group)[Queens]       0.7981    0.2625    3.0400    0.0024     0.2835    1.3126
C(neighbourhood_group)[Staten Island] 0.2766    0.2701    1.0240    0.3058    -0.2528    0.8060
C(room_type)[T.Private room]         0.2476    0.1700    1.4564    0.1453    -0.0856    0.5807
C(room_type)[T.Shared room]          0.2765    0.2377    1.1631    0.2448    -0.1894    0.7424
advertisement                       0.0175    0.0004   46.367    0.0000     0.0168    0.0183
availability_365                     0.0007    0.0002    4.1899    0.0000     0.0004    0.0011
minimum_nights                      -0.0085    0.0027   -3.0918    0.0020    -0.0139   -0.0031
price                               0.0025    0.0019    1.2831    0.1995    -0.0013    0.0062
=====
```

Endogenous: price
Instruments: income_per_rent
Robust Covariance (Heteroskedastic)
Debiased: False



Finalize regression

IV-2SLS Estimation Summary

```
=====
Dep. Variable:      reviews_per_month    R-squared:          0.2233
Estimator:          IV-2SLS              Adj. R-squared:     0.2230
No. Observations:   14811                F-statistic:        1.299e+04
Date:               Thu, Apr 08 2021      P-value (F-stat)    0.0000
Time:               19:40:15              Distribution:        chi2(7)
Cov. Estimator:     robust
```

Parameter Estimates

```
=====
               Parameter  Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
C(room_type)[Entire home/apt]  2.1653    0.3895    5.5597    0.0000    1.4019    2.9286
C(room_type)[Private room]    1.4223    0.1769    8.0384    0.0000    1.0755    1.7690
C(room_type)[Shared room]     1.1696    0.1367    8.5578    0.0000    0.9017    1.4375
advertisement                  0.0169    0.0004   43.571    0.0000    0.0162    0.0177
availability_365                0.0017    0.0002   10.704    0.0000    0.0014    0.0020
minimum_nights                 -0.0119    0.0037   -3.2000    0.0014   -0.0193   -0.0046
price                         -0.0088    0.0022   -3.9595    0.0001   -0.0132   -0.0045
=====
```

```
Endogenous: price
Instruments: income_per_rent
Robust Covariance (Heteroskedastic)
Debiased: False
```



Considerations in future

- Due to the limited information provided by dataset, we only measure 5 factors that will influence the dependent variable which makes the R^2 small

Possible solution:

1. Find more information from online resources like: 'whether the Airbnb is close to a tourist site' and merge them into our dataset; then refit the model
 2. We also have column 'name', if possible, we can do the text analysis; find out top used listings' name words and see how entitle the Airbnb influence the reviews.
- Our analysis is limited in NYC, which cannot represent the low-tier cities' Airbnb situation
 - Due to the local epidemic prevention policy, we cannot get the sample data for Airbnb 2020 which we fail to use the hedonic regression to measure the effect of time period.

Thanks for
Listening

