The Effect of COVID-19 on the Airbnb Market — Comparing November 2019 to December 2020

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This article addresses the effect of the coronavirus pandemic on the temporary housing market of Airbnb in New York City from 2019 to 2020, with the context of the gig economy and gentrification in the city via postal code extrapolation. Our analysis identified that price per night after the pandemic decreased compared to before, which lines up with the economic recession as a result of stay-at-home orders and shutdowns, and that the minimum number of nights to stay had fewer offerings for a small number of nights compared to pre-pandemic, but more over 30 minimum night stays due to new Airbnb policy enacted in December 2019. Additionally, the pandemic has caused many inequities to be exacerbated, and in the Airbnb market, we found that hosts generally profited from the pandemic regardless of where their listings were located, rich or poor postal codes. We also found that the number of available days for listings in poor neighborhoods and rich neighborhoods were significantly different from before to after the pandemic. These findings are useful in further investigation into the continuation of the current pandemic in the near future and can aid Airbnb in extrapolating this relatively small-scale study to larger locales.

I. INTRODUCTION

The following paper addresses the question of how the COVID-19 pandemic has changed the Airbnb market in New York City in the space of one year, from the end of November 2019 to beginning of December 2020. The COVID-19 pandemic became a worldwide phenomenon in March 2020, but was identified in December 2020, and its effects on public health and safety resulted in a complete overhaul of hygienic practices and social life. Most people in the U.S. and other countries were governmentally mandated to abide by shelter-in-place restrictions and social distancing, which led to virtual learning and work, the continuation of the work week into the weekend, and stay-at-home vacations rather than urban tourism and globe-trotting adventures. It is logical then, to assume that, as a result of these restrictions, the number of people globally who would travel to New York City and rent an Airbnb for a certain number of days would be reduced from pre-pandemic levels. Does this mean that hosts, or people who list their properties for rent on Airbnb, would charge different prices due to the economic recession? Would they offer fewer listings or change the minimum number of nights to stay? And, during a pandemic, is it possible that Airbnb rentals could have become more gentrified such that only the rich or medically fortunate would have the luxury of renting a vacation residence in an economically and socially unstable period?

The long-term impact of these questions is undeniably crucial to how Airbnb will operate in the future. This study is a good microcosm of how the COVID-19 pandemic has impacted a relatively small market of a large urban area, which can be extrapolated to larger markets all over the world.

II. BACKGROUND

Since the start of the widespread recognition of the Covid-19 pandemic around March 2020, much research and discussion has been centered on its impact. We review literature on tourism, hotels, and gig-work in the Covid era, as each of these topics are somehow related to Airbnb and its business model.

It was not unexpected by researchers that a global pandemic would reduce tourism and upend the industry of hotels and hotel-style housing. As international flights were rapidly cancelled and tourist attractions shut down, tourism came to a standstill. Hotels were predicted in March 2020 to "be the first property type to be affected by the coronavirus due to reduced tourism and travel, and a slowdown in economic activity," with the virus expected to "exacerbate hotel cash flow declines and rising expenses from wages and real estate taxes" (Jiang et al. 2020). Since, like hotels, Airbnb offers a form of temporary housing, also used often by tourists, we asked if the company would be similarly affected in one of the most famous tourist destinations in the world: New York, New York.

Like on-demand transportation or delivery service companies like Uber, Lyft, or Doordash; Airbnb fulfils its brand of supplying vacation housing through gig workers: temporary, un-benefited independent contractors who often use their own property to provide the service. One study from August 2020 on the effect of Covid-19 on the gig economy concluded that "there is no long-term relationship between Covid-19 incidence and Gig economy," (Umar et al., 2020) even stating that "platform economy has been affected positively by Covid-19 in the short run". This implies, in contradiction to many other studies on the topic, that the numbers of listings may not change before and after the pandemic.

A different study found that "the global panic associated with COVID-19 may have enduring consequences on travel" that will require extreme measures to counteract, which somewhat contradicts the conclusion of the aforementioned study by assessing the impact of Covid on travel to be negative in the short and long term.

So, by employing gig workers as well as being driven by travel and tourism, it appears that Airbnb should be, respectively, positively and negatively affected by the pandemic. Through our own analysis of Airbnb's listing data in NYC, which we will take to be a microcosm of its service in cities around the world, we hope to understand the true impact of the Coronavirus on Airbnb—whether positive or negative.

III. DESCRIPTIVE ANALYSIS

A. Data Cleaning

After acquiring the listing data supplied by Airbnb for 2019 and 2020, we restrict and restructure the data for reasonable analysis. First, we perform minor cleaning by dropping those features present in one dataset but not the other, removing listings marked as hidden by Airbnb, and formatting numeric variables into numbers.

To the end of having the most up-to date data possible, we restrict to only listings that have been reviewed in the year on which the sample was taken: 2019 and 2020, respectively, for the 2019 and 2020 datasets. This way, listings that have not been reviewed for several years, and that might be inactive, are removed. As the data contains several outliers, skewed high in terms of price, we also remove any listings that have nightly prices greater than $1000.

Using Python's Geopy package, we perform reverse geolocation on the latitude and longitude values provided for each listing to extract the postcode and the borough of New York City in which they are located. We then scrape the richest postcodes from the Internal Revenue Service through zipdatamaps.com and label the listings as rich or not rich.

B. Data Cleaning

After cleaning, our variables are limited to:

- id, a unique, numeric identifier for each listing
- name, a string containing the name and description of the listing
- host_id, a unique numeric identifier for each host. This is not unique to listings, as multiple properties can be attributed to a single host
- host_name, the name of the host
- neighbourhood, the neighbourhood in which the listing is located
- latitude, the latitude element of the listing's geographic coordinates
- longitude, the longitude element
- room_type, type of room: either 'Entire home/apt', 'Private room', or 'Shared room'. The Post-Pandemic dataset has the additional category of 'Hotel room'
- price, price per night limited to less than $1000
- minimum_nights, minimum number of nights the host requires an occupant to rent a listing
- number_of_reviews, total number of reviews for each listing
- last_review, most recent date a listing was reviewed, restricted to the year in question
- reviews_per_month, average reviews per month for a listing
- calculated_host_listings_count, number of total listings in the dataset for the host of the current listing

- availability_365, number of days in the year during which the listing is available to rent. After cleaning, most zero availability listings are occupied rather than inactive
- postcode, postal code, extracted via reverse geolocation from latitude and longitude
- rich, indicator of whether or not the postcode in which the listing is located falls into a set of 'rich' postal codes as defined by the zipdatamap.com through the IRS
- borough, the borough of New York City in which the listings is located, or the suburb if the listing is not located in NYC. Also extracted via reverse geolocation

IV. EXPLORATORY DATA ANALYSIS

As our question of interest regards how the Airbnb landscape looks before and after the pandemic, we generate various plots of the different features using pre- and post- pandemic data in order to see if there is a visual difference between the years.

We are additionally interested in the difference in these differences when wealth is concerned: whether the listings are in a wealthy neighborhood or not; as well as the means of the host, which we approximate by the number of properties they have posted.

A. Listing Locations and Availability Before and After the Pandemic

1. Nonzero availability lost and new listings by wealth

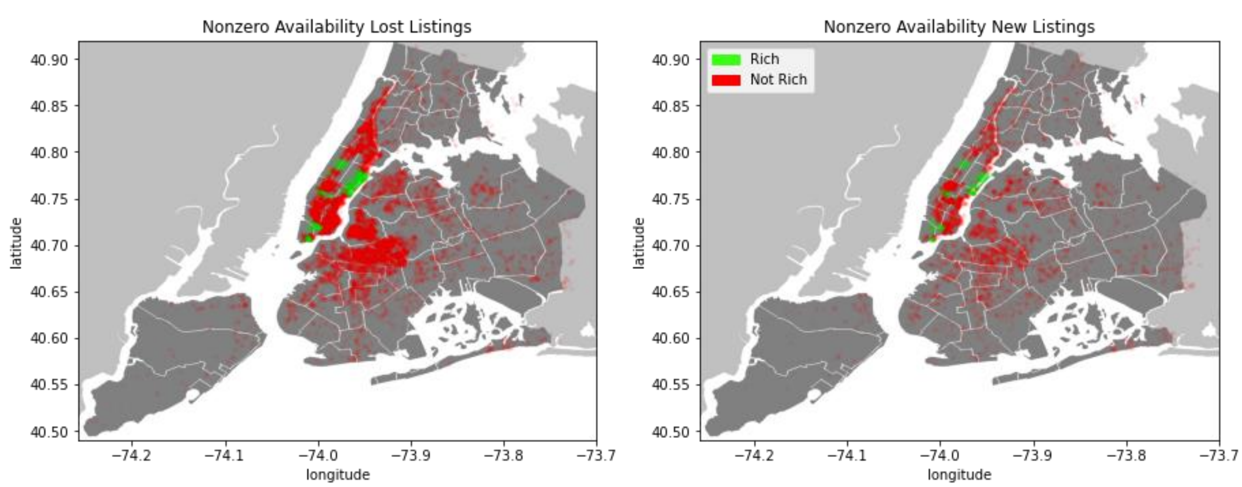


FIG. 1. A map of lost (present only in 2019, before the pandemic) and New (only in 2020, during the pandemic) nonzero availability listings, colored by whether they are located in a wealthy postal code.

We use the unique IDs of the listings to identify which are lost and which are new. Nonzero availability means that the listings are available to rent for at least 1 day.

The new listings are visibly sparser in the plot for both rich and not rich postcodes, indicating that more listings were removed than added during the pandemic for both categories.

2. Nonzero availability total listings by wealth

TABLE I. Summary statistics of mean nonzero availability in days pre and Post-Pandemic, by listings in rich versus not rich postal codes.

	Rich Postal Code	Not Rich Postal Code
Pre-Pandemic	182.6621	165.5433
Post-Pandemic	226.9327	211.0596

Our summary statistics show that, both before and after the pandemic, the average non-zero availability in rich postal codes is greater than that in non-rich postal codes. And, contrary to what might have been expected, the average number of non-zero listings increases both after the pandemic. This may be indicative of more listings being posted but going unoccupied.

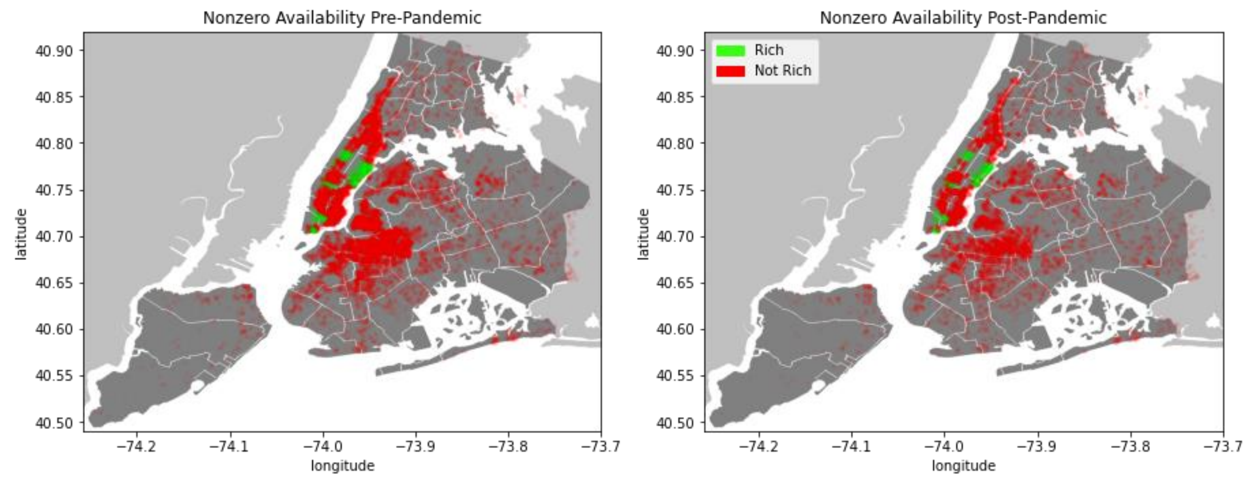


FIG. 2. A map of total nonzero availability before and during the pandemic. As in the previous plot, the post listings are much fewer in all locations, with the starkest difference visible in Manhattan and Brooklyn.

3. Zero Availability

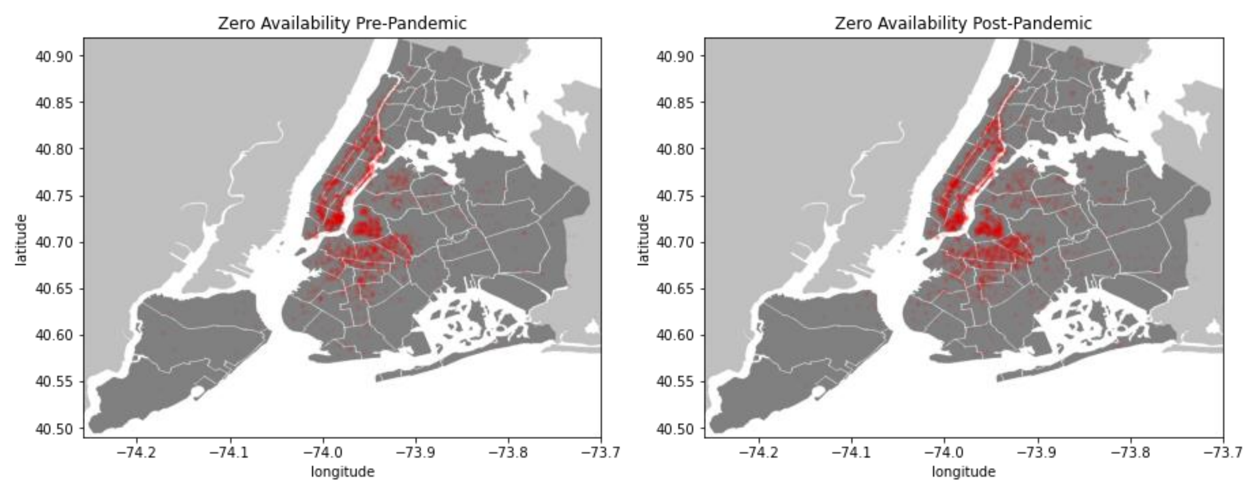


FIG. 3. We now plot the zero availability listings, which have availability set to zero because they are either occupied or disabled. Since we are only considering listings that had been reviewed in the last year at the time they were sampled, we suppose that the majority of these are occupied rather than inactive.

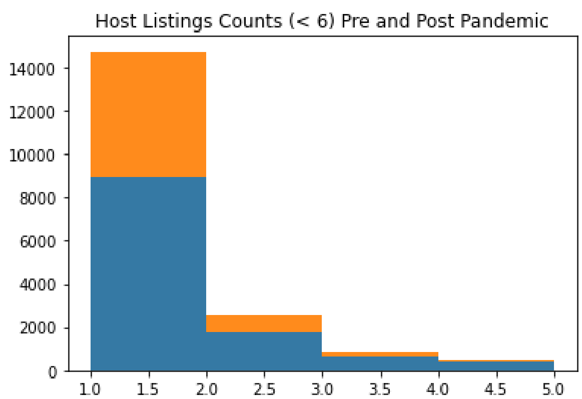
B. Host Listing Counts Before and After the Pandemic

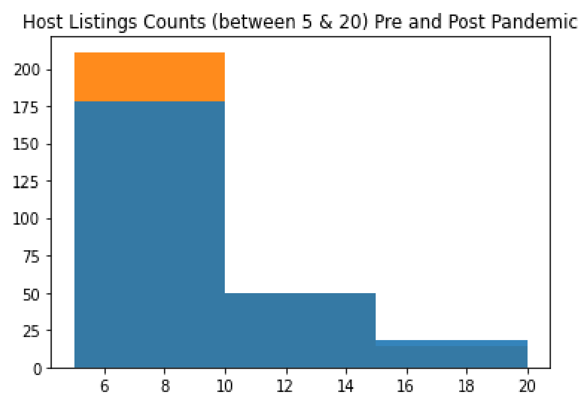
1. Host listings counts by number of listings

TABLE II. Summary statistics of mean days of nonzero availability pre- and post-pandemic, by listings in rich versus not rich postal codes.

	< 5 Listings Per Host	Between 5 & 20 Listings Per Host	> 20 Listings Per Host
Pre-Pandemic	1.2822	1.4164	59.6944
Post-Pandemic	1.3267	1.5182	55.8864

This table shows that the mean listings per host increases for hosts with fewer than 20 listings but decreases for hosts with more than 20 listings. This difference is not only mitigated, but starkly reversed when one considers the fact that hosts with more than 20 listings to their ID have over 50 listings on average, where hosts with fewer than 20 have at most two on average.





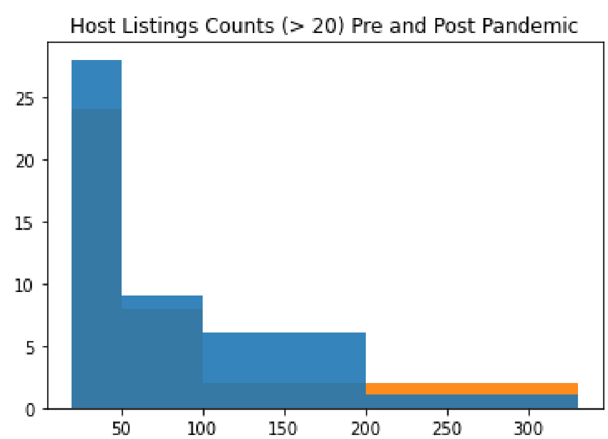


FIG. 4. This figure set of nonzero host listings counts gives more nuance to the contents of Table II, which implies that the mean listings for hosts with less than 20 listings increased overall, while the opposite is true for hosts with greater than 20 listings. Here, we see that, for host with less than 10 listings or greater than 200 listings, the orange pre-pandemic values are greater than the blue post-pandemic values.

2. Host listings counts by wealth of postal code

TABLE III. Mean listings per host, before and after the pandemic, separated by listings in rich versus not rich postal codes.

	Not Rich Postal Code	Rich Postal Code
Pre-Pandemic	1.6553	1.5192
Post-Pandemic	2.2323	1.6864

When separating by postal code rather than host listings count, the difference between the categories of listings is far less apparent. Still, rich postal codes have more average listings per host; and again, the average listings per host increases after the pandemic. This time, the value for rich postal codes increases considerably more than that for non-rich postal codes.

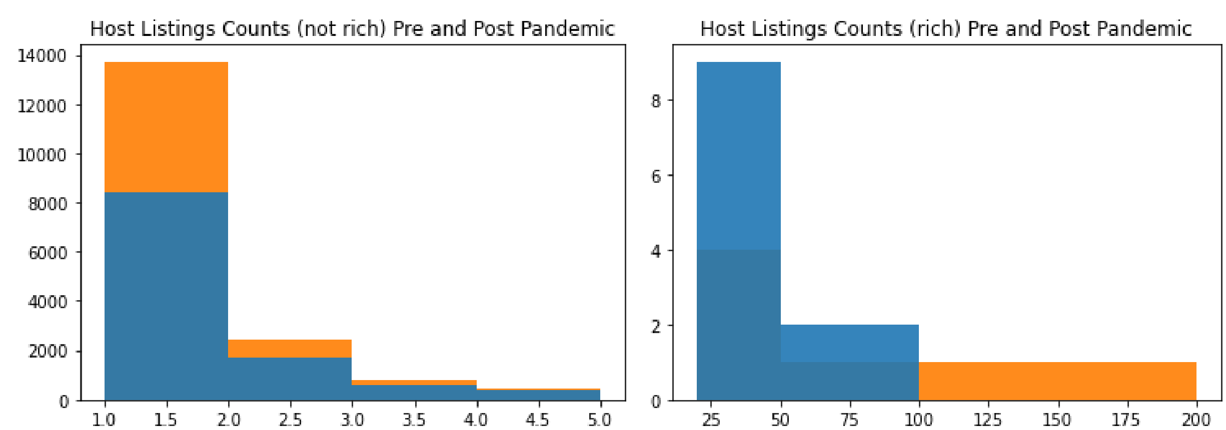


FIG. 5. This figure of host listing counts pre- and post- pandemic, by rich and not-rich postal code, adds context to the contents of Table III. Before-pandemic values are again shown in orange. We see that, for non-rich postal codes, the pre-pandemic values are consistently higher than post-pandemic ones, indicating that the mean listings per host in these areas decreased. For rich postal codes, while the post-pandemic value is similarly lower for hosts with over 100 listings, it is sharply higher between 25 and 100 listings. We also see that hosts in rich neighborhoods have at least 25 listings each, while in poor neighborhoods they do not have more than 5.

C. Other Notable Data Visualizations: Price Per Night, Minimum Nights, & Room Types Before and After the Pandemic

1. Price per night pre- and post-pandemic

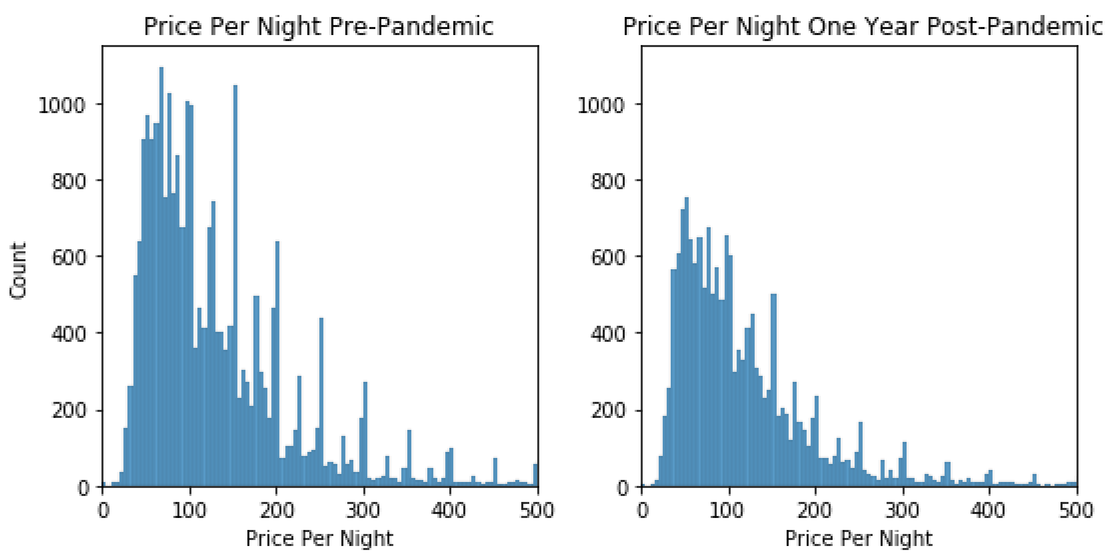


FIG. 6. This side-by-side plot of the distributions of price per night, instituted by host, before and after the pandemic (one year from Nov. 2019 to Dec. 2020), visibly demonstrates the decrease in prices per night one year into the pandemic. The distribution shapes are nearly the same, but the highest price drops from over $1000 to just under $800, a dramatic drop of 200 dollars per night, which would otherwise be unlikely to occur under normal circumstances.

2. Minimum nights frequency, by room type: joinplot and heatmap

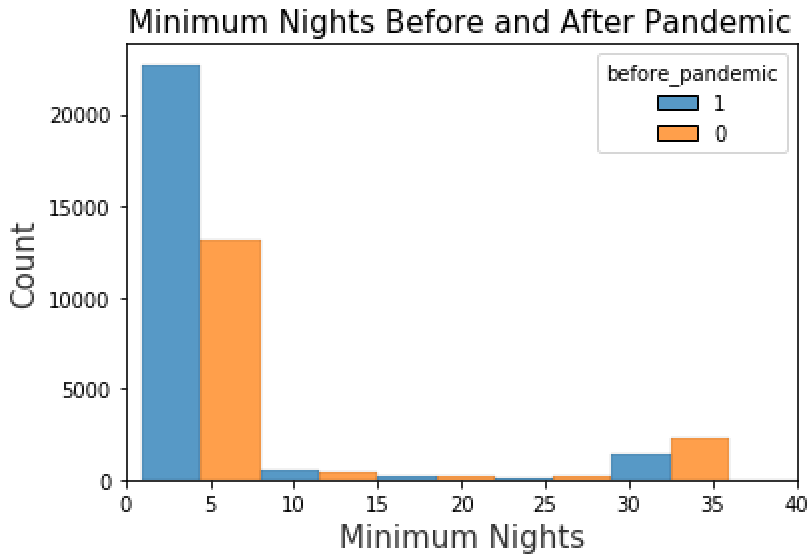


FIG. 7. The figure of minimum nights before and after the pandemic (1 indicates that before_pandemic is true, and 0 indicates that post-pandemic is true) reveals that a small number (0-8) of minimum nights, set in advance by hosts, is far more frequently listed before than after the pandemic. The count in the pre-pandemic decreases by nearly 10,000 listings for the small number of minimum nights. On the other hand, the number of minimum nights on the larger end of the scale grew by a small amount for minimum nights greater than or equal to 30. There could be several factors as to why this would be the case, such as less tourism due to the pandemic and thus fewer hosts who offer listings with low number of minimum nights, and who instead offer minimum nights over 30, or due to Airbnb policy changes, stay-at-home mandates, and more.

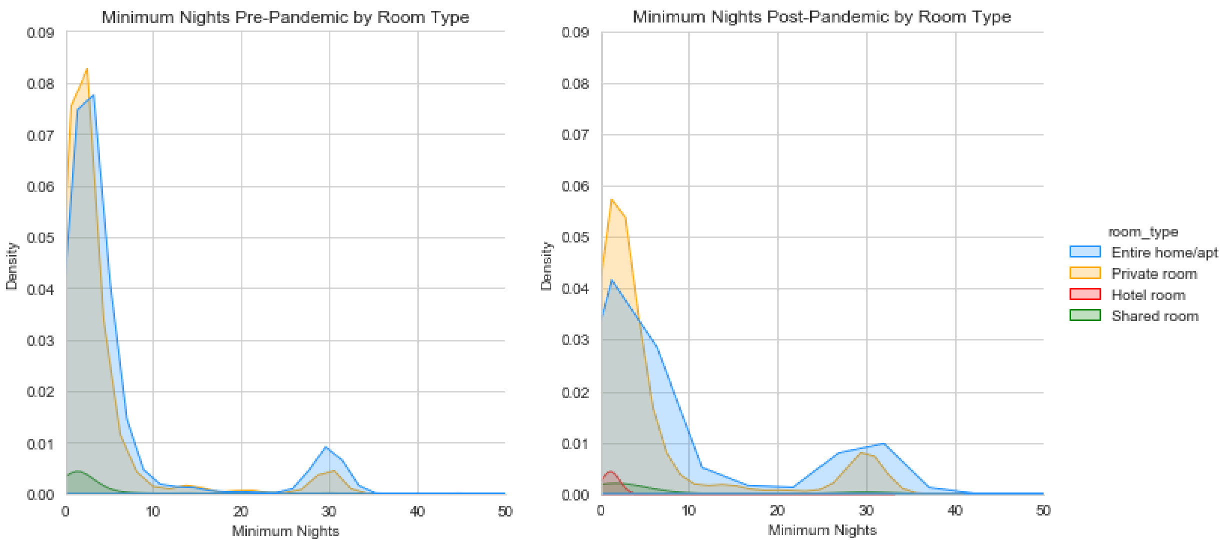


FIG. 8. This figure of a comparison between the minimum number of nights instituted by hosts, grouped by room type, shows a similar reduction in the number of minimum nights as in FIG. 7. For the pre-pandemic plot (left), the data extracted from Nov 2019 did not include the room type of hotel, while for post-pandemic, it was likely significant enough to be included by Airbnb. Minimum nights for entire homes or apartments decreased in density after the pandemic by around 0.02, and the gap between the density of entire home or apartment and private room increased after the pandemic. The green distribution of shared rooms flattened out and decreased, which makes sense post-pandemic, as it is risky to share a room with someone who might have the virus. While more hosts offered hotel rooms for a few nights, the red distribution is still not very large.

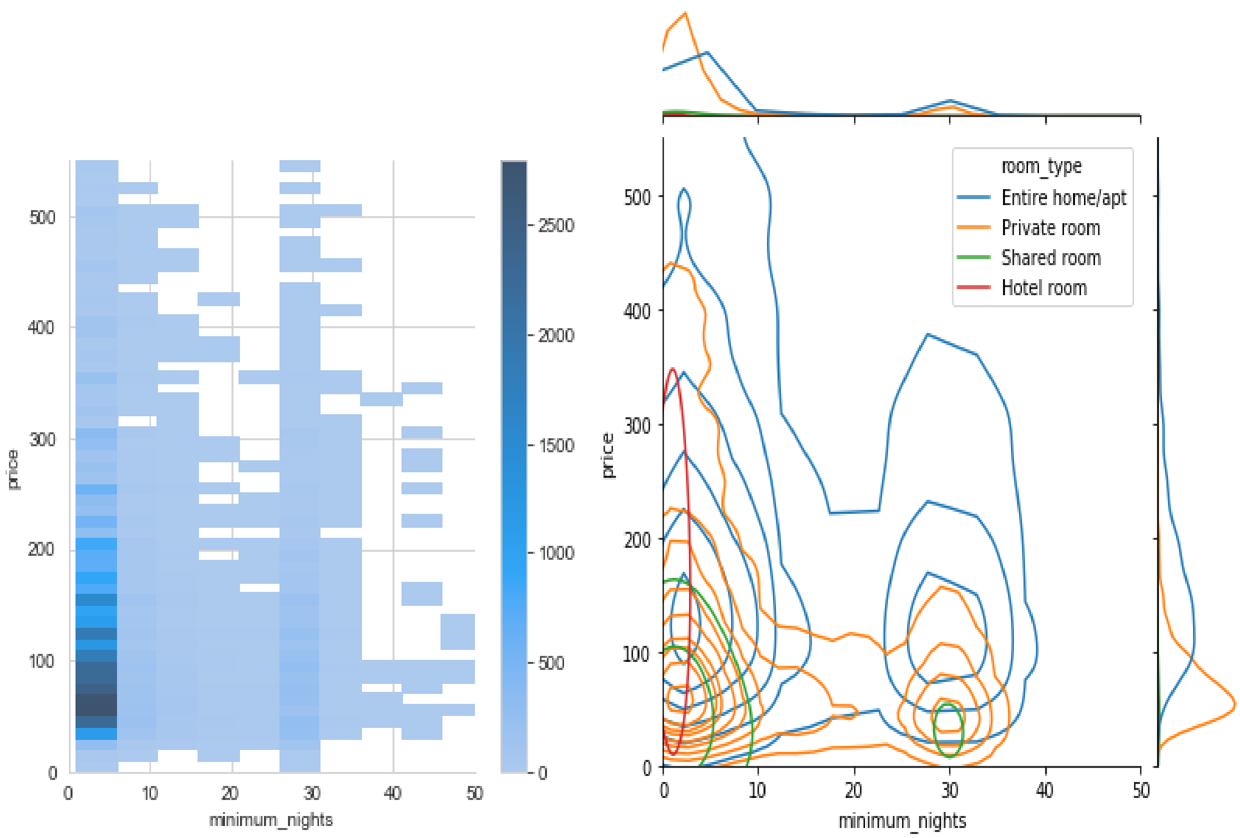


Fig 9. The two plots above show the relationship between minimum number of nights and price per night and includes listings from both before and after the pandemic: the left, emphasizing frequency, and the right, grouping by room type. The plot above and to the left is a heatmap of minimum nights against price and reveals that the most common bookings over the last two years are in the price range of approximately 300 to 200 dollars per night, with a minimum night stay of 5 nights. The joinplot above, right has the marginal distribution of the minimum number of nights on top of the graph, and the marginal distribution of price on the right side of the graph. The main plot in the center has oval and circular shaped figures that grow larger as the price increases. These oval and circular shapes indicate clusters of points that grow larger, more varied, and more stretched as price increases and the number of points in the area gets sparser. For example, private room (orange) is clustered at minimum nights near 0 and 30, with tighter ovals where there are more data values and less ovals and more white space between the orange curves as price grows.

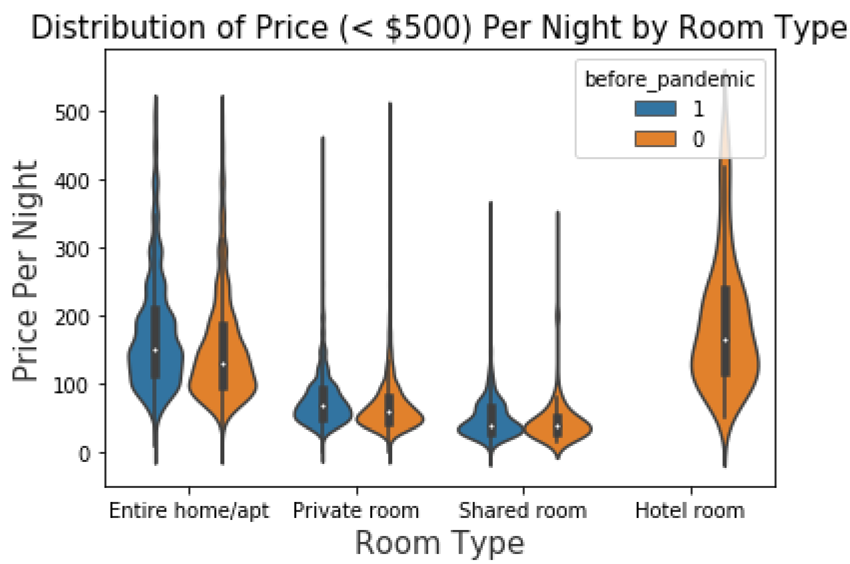


FIG. 10. This grouped violin plot of price less than 500 dollars per night for the room types before and after the pandemic (1, or blue color, indicates pre-pandemic prices; 2, or orange, indicates post-pandemic prices) shows the trend that the post-pandemic violins are smoother than their blue counterparts, and are slightly wider towards the end. The smoothness means that there are fewer minor clusters of the listings in a certain price range, and the wideness of the violin indicates that more listings are in the corresponding price range. This means that post-pandemic, the listings are a bit more evenly spread out than pre-pandemic, and that the price ranges set by hosts are more universal in New York City, likely due to the economic downturn: people being less likely to spend more than a reasonable amount per night. Private rooms have a slightly higher price per night than shared rooms; and hotel rooms, which are only available post-pandemic, have very high variability.

V. INFERENTIAL ANALYSIS

A. Before and After Pandemic: Mean Listings per Host

1. Before and after pandemic: mean listings per host

We would like to determine whether mean listings per host in rich neighborhoods were greater after the pandemic than before.

a. Hypothesis.

$$H_0: F_1(x) = F_2(x)$$

$$H_A: F_1(x) \geq F_2(x),$$

where $F_1(X)$ is the distribution for group 1: rich neighborhood mean listings per host pre-pandemic, and $F_2(x)$ is the distribution for group 2: rich neighborhood mean listings per host post-pandemic.

b. Assumptions. Let us test for assumptions of a parametric two sample test. From the below distribution (FIG. 11.) of the rich neighborhood calculated host listings (with no duplicate host ids), the data is not Normal in shape, is asymmetric, and has heavy tails. From the QQ-Plot below we see a very heavy tail which includes several outliers that appear influential.

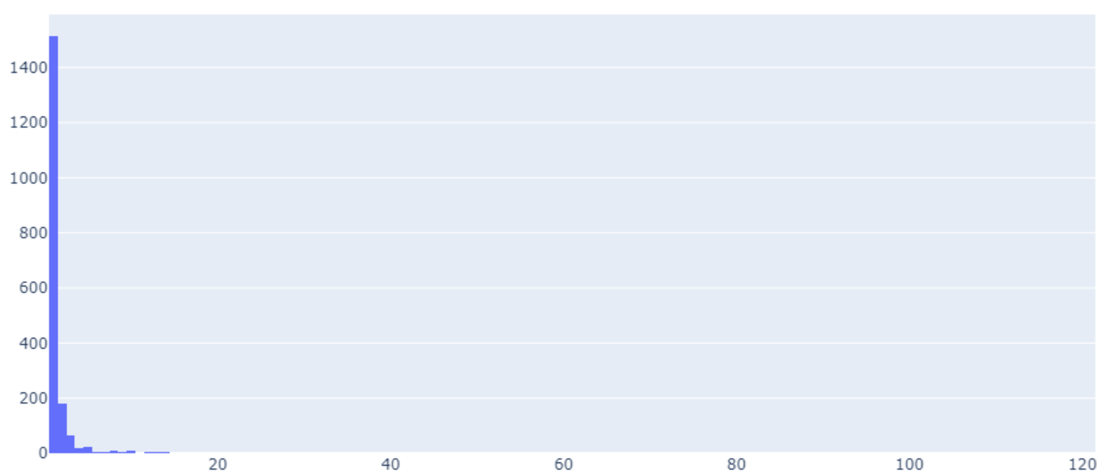


FIG. 11.

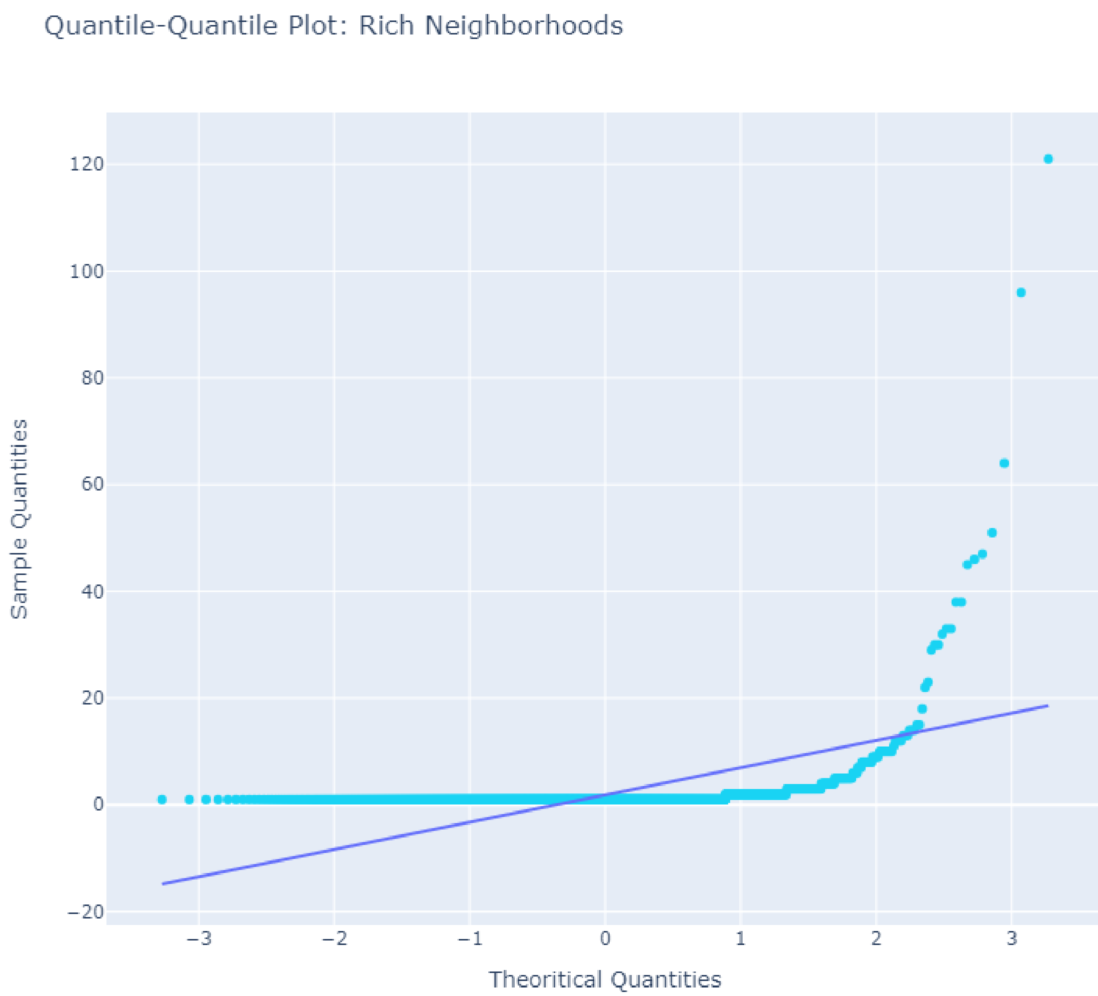


FIG. 12.

Let us now test for Normality using Shapiro-Wilks Test.

Test Statistic	p-value	Comments
0.14855217933654785	0.0	Sample does not look Gaussian (reject H0)

From the skewed distribution of the rich neighborhood hosts data, the QQ-plot, and the Shapiro-Wilks test, we conclude that our sample is not Normally distributed. Therefore, the assumptions for a parametric two-sample test are violated.

c. Wilcoxon Rank Sum Test. Let us now use the methodology of the nonparametric two-sample test. Because our distribution exhibited heavy tails and asymmetry (skewness) as well as clear outliers, we shall perform the Wilcoxon Rank Sum test for the mean calculated host listings for rich neighborhoods. We use this test because ranks tend to make inferences more robust to outliers, and from nonparametric methodology, the mean is a better measure of center with the distribution shape we have. The Wilcoxon Rank Sum Test tends to have higher power when the distribution is skewed, and outliers are present than the Permutation Test.

For the Wilcoxon rank sum test, we have the assumptions of independence of the samples and equal variance. Because the samples were sampled randomly from the population of Airbnb listings in New York City and that each sample was taken in a different year and filtered by whether the listings had been reviewed in that year alone, we can assume independence. The boxplot below of the samples show that both the pre- and post-pandemic data have a similar spread, so we can assume equal variance.

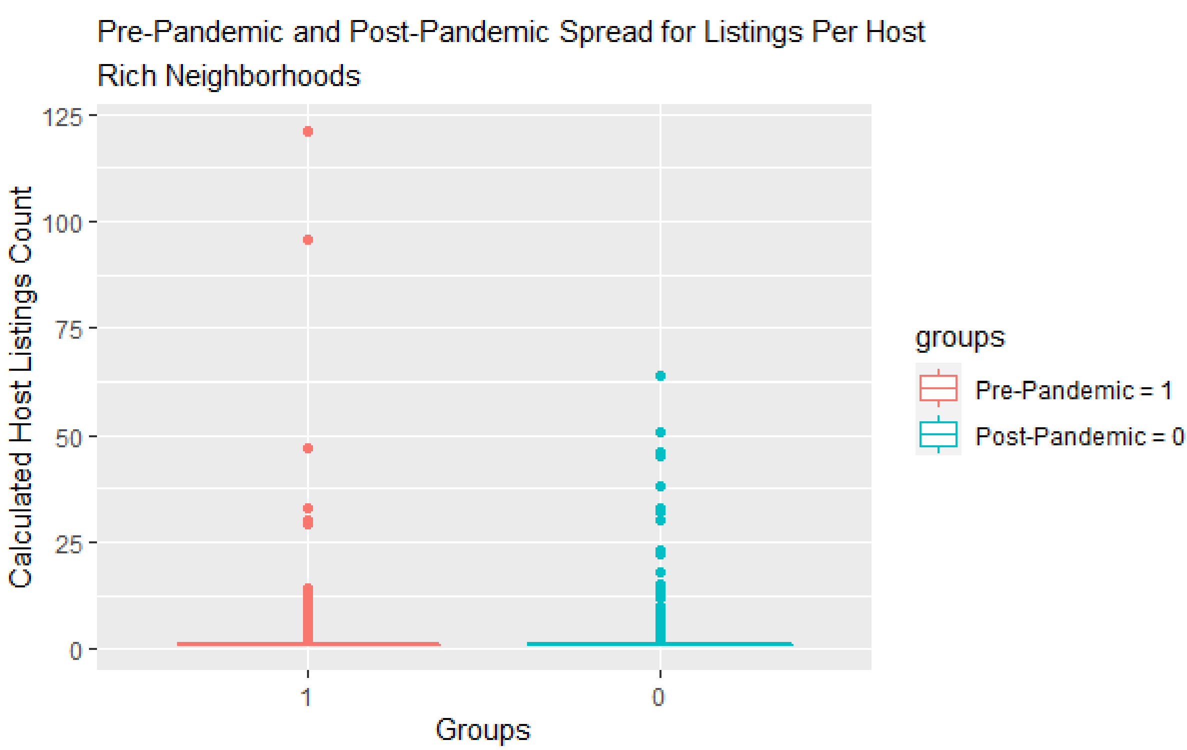


FIG. 13.

From our Wilcoxon Rank Sum test, we get a test statistic of Z = -4.2322 and p-value of 1.157e-05. If, in reality, the distribution of mean calculated host listings for rich neighborhoods before and after the pandemic were the same, we would observe our test statistic or more extreme with probability of 1.157e-05.

2. Poor neighborhoods

We would like to determine whether poor neighborhood mean listings per host were greater after the pandemic than before.

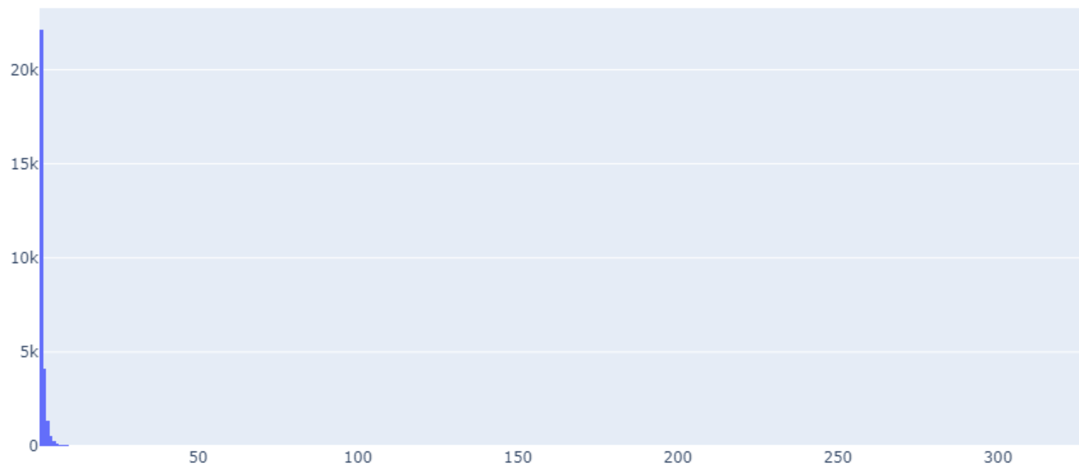
a. Hypotheses.

$$H_0: F_1(x) = F_2(x)$$

$$H_A: F_1(x) \geq F_2(x),$$

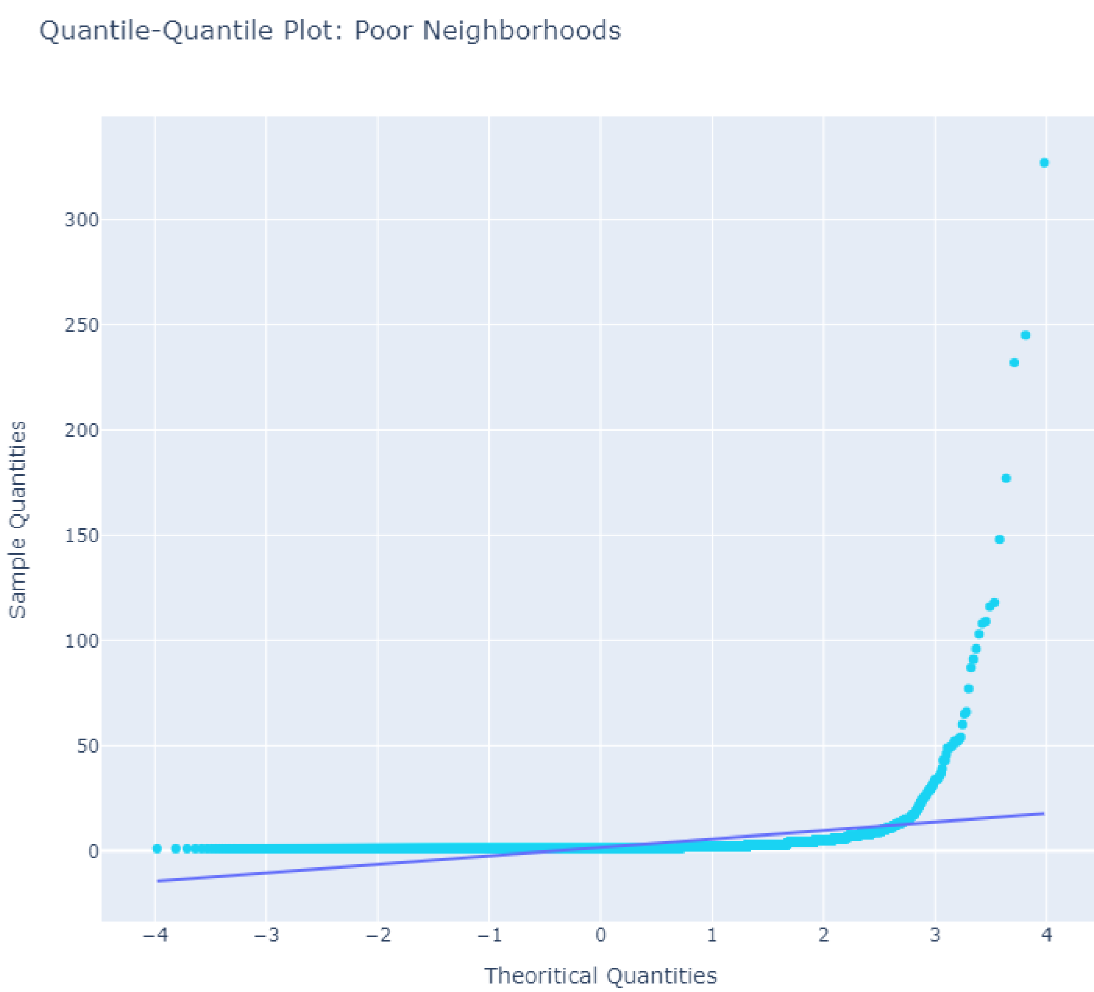
where $F_1(X)$ is the distribution for group 1: poor neighborhood mean listings per host pre-pandemic, and $F_2(x)$ is the distribution for group 2: poor neighborhood mean listings per host post-pandemic.

b. Assumptions. Let us again test for assumptions of a parametric two sample test. From the below distribution (FIG. 14.) of the poor neighborhood calculated host listings (with no duplicate host ids), the data is not Normal in shape, is asymmetric, and has heavy tails. From the QQ-Plot below we see a very heavy tail which includes several outliers that appear influential.



0
5k
10k
15k
20k
50
100
150
200
250
300

FIG. 14.



Quantile-Quantile Plot: Poor Neighborhoods
Sample Quantities
Theoritical Quantities
0
50
100
150
200
250
300
−4
−3
−2
−1
0
1
2
3
4

FIG. 15.

Let us now test for Normality using Shapiro-Wilks Test.

Test Statistic	p-value	Comments
0.08792716264724731	0.0	Sample does not look Gaussian (reject H0)

From the skewed distribution of the poor neighborhood hosts data, the QQ-plot, and the Shapiro-Wilkes test we conclude that our sample is not Normally distributed. Therefore, the assumptions for a parametric two-sample test are violated.

c. *Wilcoxon Rank Sum Test.* Let us now use once again the methodology of the nonparametric two-sample test. For similar reasons as for the Rich data, we shall perform the Wilcoxon Rank Sum test for the mean calculated host listings for poor neighborhoods. The data is again independent, and our boxplot below shows that pre- and post-pandemic have a similar spread, so we can assume equal variance.

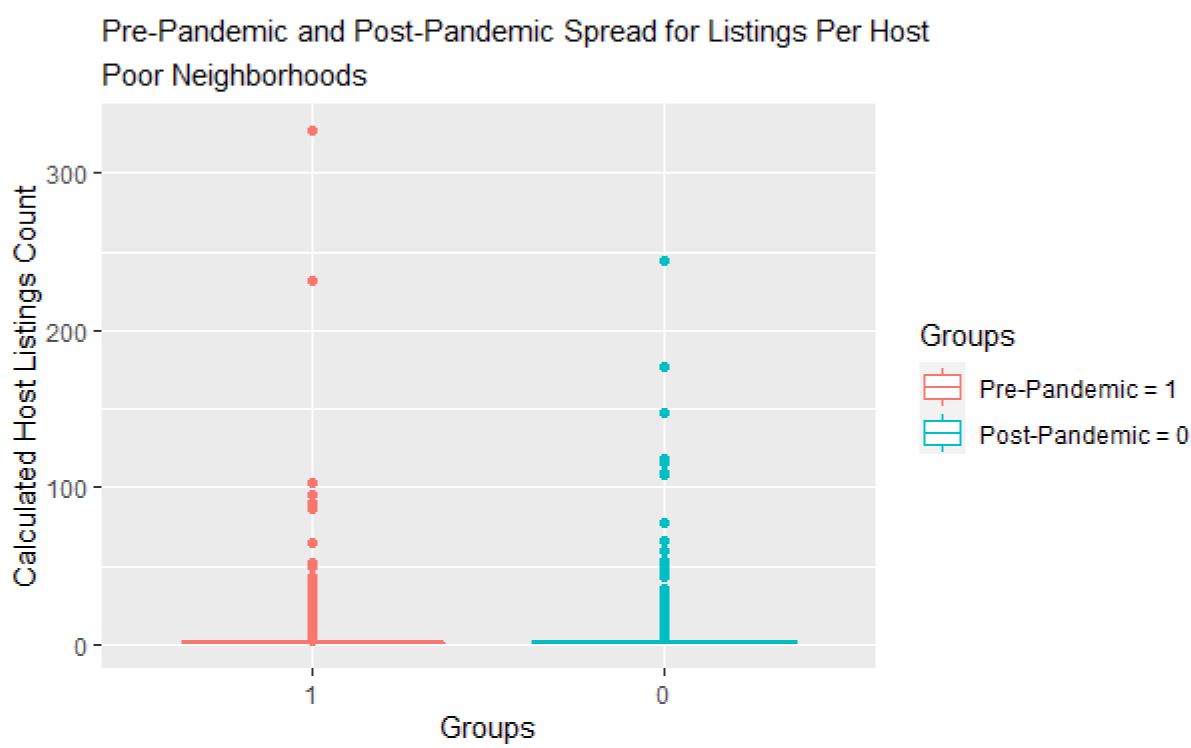


FIG. 16.

From our Wilcoxon Rank Sum test, we get a test statistic of Z = -6.565 and a p-value of 2.602e-11. If, in reality, the distribution of mean calculated host listings for poor neighborhoods before and after the pandemic were the same, we would observe our test statistic or more extreme with probability 2.602e-11.

Because the p-value = $2.602e-11 \leq \alpha = 0.05$, we reject the H_0. Therefore, at the 5% level, we conclude that the mean listings per host in poor neighborhoods post pandemic is greater than the mean listings per host in poor neighborhoods pre pandemic.

B. Before and After Pandemic: Mean Days of Nonzero Availability

1. Rich neighborhoods

We would like to determine whether mean days of nonzero availability in rich neighborhoods have changed after the pandemic compared to before. We think this claim may be true because after the pandemic hit in December 2019, Airbnb increased the minimum number of nights people should stay at the same place, in order to "[crack] down on the availability of illegal short-term rentals" (Shared Economy Tax, 2019) and data sharing laws, so hosts would have to offer their listings for a longer period of time. It's possible, however, that hosts did not heed this policy because they could only offer listings for a smaller number of days, because of fear of COVID-19 transmission in their homes, or because they were conducting illegal activities in short-term rental Airbnbs. There could be many factors that we cannot account for. Thus, we test for a significant difference in the mean days of nonzero availability for rich neighborhoods.

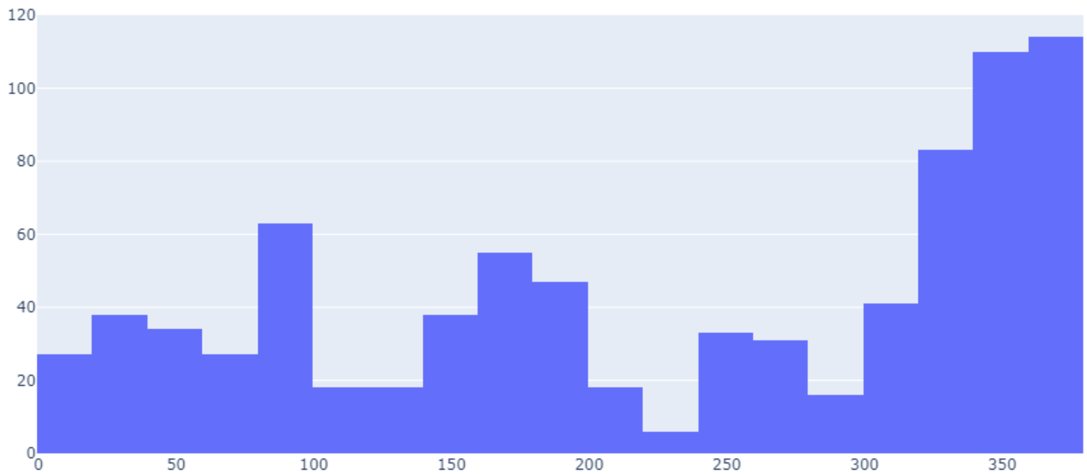
a. Hypotheses.

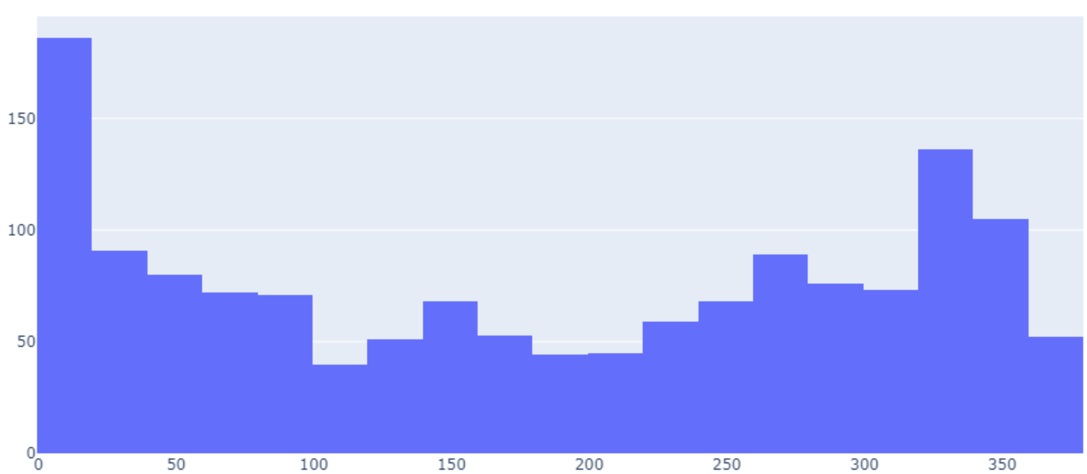
$$H_0: F_1(x) = F_2(x)$$

$$H_A: F_1(x) \geq F_2(x), F_1(x) \leq F_2(x),$$

where $F_1(X)$ is the distribution for group 1: rich neighborhood mean days of nonzero availability pre-pandemic, and $F_2(x)$ is the distribution for group 2: rich neighborhood mean days of nonzero availability post-pandemic.

b. Assumptions of Normality. From the below distributions of the rich neighborhood nonzero availability (number of days available greater than 0), the distributions for both pre- and post-pandemic, respectfully, are not Normal in shape. The first distribution, for pre-pandemic rich neighborhoods, is skewed right and has two peaks. The second distribution, for post-pandemic rich neighborhoods, is more skewed to the left, and has a heavy tail. The distributions do not look the same.





c. Kolmogorov Smirnov Test. Because these two distributions appear to be different, we will test to see if the two samples are from the same distribution. We will use the Kolmogorov-Smirnov Test to determine if there is a difference in mean days of nonzero availability in rich neighborhoods before and after the pandemic. Under the assumption that the samples are from the same distribution, the samples have been independently sampled in different years, with only listings with reviews in the same year as sampled included in each sample; we have that the assumptions for the Kolmogorov-Smirnov Test have been met.

From our K-S test, we get a test statistic of 0.21494 and p-value of 1.2212453270876722e-15. If the distribution of mean days of nonzero availability for rich neighborhoods before and after the pandemic were the same, we would observe our test statistic or more extreme with probability of almost 0.

Because our p-value= $1.2212453270876722e-15 \leq \alpha = 0.05$, we reject the H_0. At the 5% level, we conclude that there is a significant difference in mean days of nonzero availability in rich neighborhoods before and after the pandemic.

2. Poor Neighborhoods

We would like to determine whether poor neighborhood mean days of nonzero availability have changed after the pandemic compared to before the pandemic. For the same reasons as for rich neighborhoods, namely the new policy by the city of New York and Airbnb that requires longer stays by occupants of a listing to prevent illegal activity in short term rentals, but also other factors that we cannot control for, we test for a significant difference rather than increase or decrease in the mean days of nonzero availability for poor neighborhoods.

a. Hypotheses

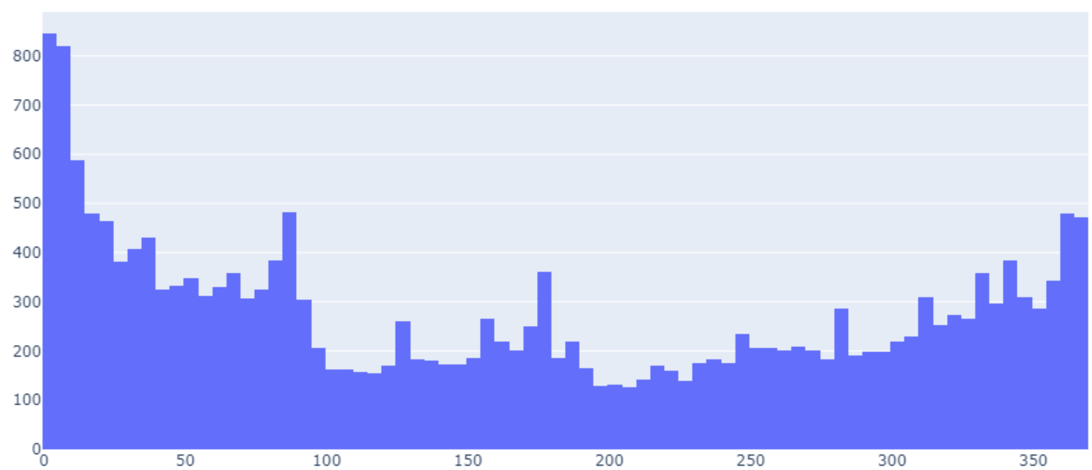
$$H_0: F_1(x) = F_2(x)$$

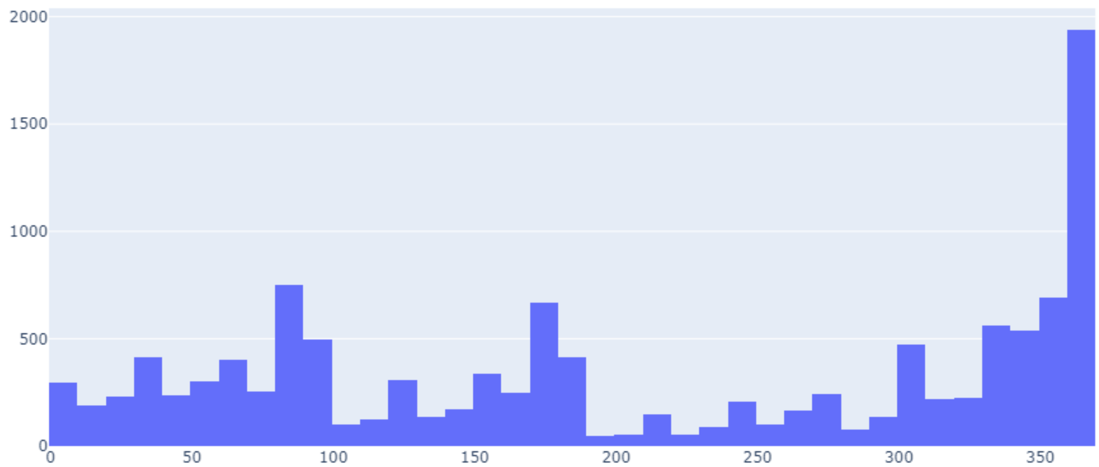
$$H_A: F_1(x) \geq F_2(x), F_1(x) \leq F_2(x),$$

where $F_1(x)$ is the distribution for group 1: poor neighborhood mean days of nonzero availability pre-pandemic, and $F_2(x)$ is the distribution for group 2: poor neighborhood mean days of nonzero availability post-pandemic.

b. Assumptions of Normality

From the below distributions of the poor neighborhood nonzero availability (number of days available greater than 0), the data for both pre- and post-pandemic, respectively, are not Normal in shape. The first distribution, for pre-pandemic poor neighborhoods, is skewed right, and has a heavy tail with a relatively large peak. The second distribution, for post-pandemic poor neighborhoods, is skewed strongly to the left, and has a heavy tail with two much smaller peaks. The assumption of Normality has not been met, so we cannot use the parametric two sample test. The distributions do not look the same.





c. Kolmogorov Smirnov Test. Because these two distributions for poor neighborhoods also appear to be different like the rich neighborhoods, we will test to see if the two samples are from the same distribution. We again use the Kolmogorov-Smirnov Test, this time to find if there is a difference in mean days of nonzero availability in poor neighborhoods before and after the pandemic. Under the same assumptions as the previous test, we have that the assumptions for the Kolmogorov-Smirnov Test have been met.

From our K-S test, we get a test statistic of 0.17175 and p-value of 1.1866766660863536e-194. If the distribution of mean days of nonzero availability before and after the pandemic for poor neighborhoods were the same, we would observe our test statistic or more extreme with probability of almost 0.

Because our p-value= $1.1866766660863536e-194 \leq \alpha = 0.05$, we reject the H_0. At the 5% level, we conclude that there is a significant difference in mean days of nonzero availability in poor neighborhoods before and after the pandemic.

VI. CONCLUSION

The goal of this paper was to determine some of the myriad ways in which the COVID-19 pandemic has significantly affected the Airbnb market in New York City by comparing data from

November 2019 to December 2020, a timespan of approximately one year. During this relatively short of time, one of the major events in our lifetimes occurred, upending the economy, public health and safety, social activities, and every part of people's daily lives. One would be hard-pressed to find even a single person who has not been impacted by the pandemic, so for the largest city in the US and arguably the most famous city in the world, the results have been transformative.

In a small sector of the temporary housing market is the Airbnb marketplace, which has suffered the loss of tourists to New York City, real estate price devaluation, and hosts moving to warmer and less infected locales like Miami or the Midwest. Thus, the main customers who would rent Airbnbs in NYC have been greatly depreciated, and any influx from those who would ordinarily rent an Airbnb from out-of-town, or country would hesitate to visit such a famous location in the circumstances of the pandemic.

Earlier, we questioned if this would mean that hosts would charge different prices due to the economic recession, or if they would offer less listings or change the minimum number of nights to stay. Through data visualizations and summary statistics we discovered that in fact, the price per night hosts charged fell dramatically after the pandemic, which is likely due to the economic downturn and hosts offering cheaper prices to get back tourists and those who are unconcerned about the pandemic. Additionally, the number of lost listings was higher than the ones gained after the pandemic, and for hosts who had between 20 and 200 listings, the average listings per host increased.

Another interesting find that we developed from data visualizations and confirmed through hypothesis testing was that after the pandemic, both poor and rich neighborhoods had average mean listings per host that were higher than before, and that the average non-zero availability in rich postal codes is greater than that in non-rich postal codes. It seems likely as a result that only hosts who could survive medical (through expensive treatments, healthcare, and access to good doctors) and financial hardships could continue to profit from Airbnb rentals, which would become more gentrified.

We deduced that a possible reason for why both rich and poor neighborhoods had growth in the mean listings per host, which means that hosts listed more properties rather than less one year after the start of the pandemic, is that despite having listings in either or both poor and rich neighborhoods, the hosts themselves are almost certainly not poor. To be able to offer even one listing post pandemic may be expensive enough to maintain, let alone more than one. Many hosts may even have listings in both poor and rich neighborhoods and may have profited from low real estate prices in New York City due to people moving out of the city after the pandemic hit. This also supports the referenced study on the effects of the pandemic on the gig economy, which concluded that the pandemic would cause businesses that run on the gig or platform economy to flourish.

Our four hypothesis tests, using the nonparametric techniques of Wilcoxon Rank Sum and Kolmogorov-Smirnov Test, sought to determine whether rich neighborhoods had significant differences in mean listings per host and mean number of nonzero available days pre and post pandemic, and whether poor neighborhoods had significant differences in mean listings per host and mean number of nonzero available days pre and post pandemic. We found that the mean listings per host post-pandemic for both rich and poor neighborhoods were significantly larger than before the pandemic, and this is supported by our summary statistics for these categories. We also found that there was a significant difference for both rich and poor neighborhoods pre and post pandemic, but we would need more hypothesis testing and a rigorous method to account for the various factors associated with the new policy by Airbnb and the fallout from the coronavirus pandemic.

The results of our study have far reaching implications on the impact of the pandemic for Airbnb rentals in New York City as well as other gig economies, as it is likely that the pandemic will continue to influence our daily lives, two, five, and even ten years into the future. Understanding how hosts, who determine how customers will interact with the market in rich and poor neighborhoods, will set prices, minimum nights to stay, number of days available out of 365, and other factors, in conjunction with city and Airbnb policy will allow us to gain a better sense of what may occur in the future under similar circumstances. Having this microcosm of a study would allow for extrapolation into larger markets than New York, such as Tokyo, Delhi, or Shanghai Airbnb or other gig marketplaces.

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