MGT 6203 Group Project Final Report

Effects of COVID-19 in Singapore’s Private Properties Rental Market

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Part I - Project Overview

Introduction

Housing rental prices are one of the proxies for the stability of the economy of a society. During the recent COVID-19 pandemic, we could observe a volatility in rental prices. In a Bloomberg article by Cadman et al. (2021), apartment rents plummeted in major cities such as Singapore, Sydney, Hong Kong, London, and New York during the pandemic. It was an exceptional situation due to the COVID-19 measures to prevent infections such as quarantine and remote work as well as the fear of economic downturn, especially in a big city where the rental prices had exhibited an increasing trend in recent years. However, the trend has reversed as the regulations to prevent and control the spread of COVID-19 are lifted. For example, in Singapore the housing rental market has heated up with a surge of about 21% in the first nine months of 2022. According to a Bloomberg article by De Wei (2023), the trend will continue with another 10-15% increase in 2023.

While the investment in the housing market is turning back to normal with optimism, consumer behaviors in the post-pandemic housing market can be different from before. COVID-19 has changed the way people live and work – a wide adoption of work from home and digitalization is likely to remain as a long-term outcome. Therefore, to be better prepared for the dynamics in the housing market after COVID-19, it is essential to understand the impacts of COVID-19 to the demand of the people.

Literature Review

In the previous research, factors such as the age of the apartments, the floor areas of the apartments, distance to the nearest park, the distance to the Central Business District (CBD), the distance to the nearest Mass Rapid Transit (MRT) were found to be particularly significant to the price in Singapore before COVID-19 (Cao et al., 2018). However, COVID-19 changed the preference in choosing the residence globally. A study of Boesel et al. (2021) illustrates that the pandemic increased consumer demand for more residential space and motivated them to move to lower-density suburban areas from high-rise urban cities. For Singapore, Lee & Lee(2022) analyzed the keywords for the transaction of the resale public housing from online listings and discovered that after COVID-19, proximity to CBD or MRT was not as preferred as before and even led to lower prices. According to the research, open air space at home, a higher floor with better view, and having more than three rooms to keep separate space for the house members had increasing demand.

The research gap that we found is that the two previous studies in Singapore were conducted using the data from public housing. In Singapore, the housing market is divided into public housing by the Housing Development Board (HDB) and the private sectors (Deng et al., 2019), where 74.1% of the residences are HDB flats. As the homeownership rate exceeds 90% in Singapore and housing is a major asset of the households, for stability's sake, the government regulates the transactions in the housing market (Deng et al., 2019). For this reason, in our research, the team will focus on the rental market of the private sector. It is more flexible and more likely to reflect the shift of the demands to the price faster.

Problem Statement & Hypothesis
The aim of this research is to analyze how the rental prices of Singapore's private properties changed over the course of COVID-19 pandemic. In particular, the team will focus on how people's preferences on different housing characteristics changed by analyzing the rental prices, how the trend has been developed and how it is likely to be in the near future. The problem statement can be translated into two initial research questions:

- How did the impact of housing characteristics on rental prices of Singapore private properties change before, during, and after COVID-19 pandemic?
- What is the expected change in Singapore private properties rental prices for the next one or two years?

The research will consist of two analyses. First, the team will attempt to discover the different attributes of a housing's relationship to the rental price. The team can employ a regression model, or depending on the data's attributes, decision tree or PCA. Second, the team will forecast the future rental prices in different areas in Singapore based on the 5 years of rental prices, using a time series model e.g., ARIMA(p,d,q) model. From the literature reviews and anecdotal evidence, the team set three hypotheses on the predicting variables, which will be compared to the result of our analysis.

- Compared to the pre-COVID-19 era, during COVID-19...
  - Importance of living in a larger apartment is more important
  - Proximity to shopping malls and public transportations is less important
  - Proximity to the city center is less important
  - Consumer preferences for different property types did not change
- Rental prices of private properties will constantly increase after COVID-19 across all areas of Singapore

Part II - Data Overview

Data Preparation
Three different datasets were combined for a comprehensive analysis. Each of them were acquired from different public sources and prepared using Python.

1. **Rental Contracts of Private Residential Properties**

This dataset was downloaded using API from Singapore Urban Redevelopment Authority (URA). URA publishes an API for public use and one of its offerings includes Private Residential Properties Rental Contract data. We retrieved data from the first quarter of

2019 to February 2023 to cover the pre-COVID-19, during-COVID-19, and post-COVID-19 times.

2. Distance of the Nearest Amenities from Residential Properties

Three datasets were combined to create the distance dataset. The team used coordinates data of Singapore residential properties, of the shopping malls and of the Metro Rail Transit (MRT) from Kaggle. The Haversine Distance Equation were used to find the closest location match based on distance for two files which have latitude and longitude. After identifying the closest shopping mall or MRT station from a residential property, distance between two given locations (in km) were calculated.

3. Timeline of Singapore's Covid-19 Restrictions

Main challenge in the data preparation was creating timeline data of Singapore's COVID-19 restrictions. The Singapore Ministry of Health implemented multiple restrictions to limit the spread of COVID-19 over the past three years. There was not any time series data readily available which recorded different phases and related measures. Hence, the team decided to create our own time series data based on going through the Singapore Ministry of Health's website. The data covers from the very first date of COVID-19 Control Order implementation and until the date when COVID-19 was established as endemic. The date format of the Rental Contracts were matched to that of Private Residential Properties which only records date in year and month. If there were more than one COVID-19 Control Order imposed during a given month, the team chose the Order that lasted for the majority of the month. Seven different variables that explain the related Order were created as well.

Date	Covid-19 Control Order	Default WFH	Dine-in Allowed	Social Gathering Limit	Social Gathering Allowed	Social Gathering Max Num	Outdoor Mask Required	Indoor Mask Required
chr	char	char	char	char	char	num	char	char
date in yyyy-mm	Phases enforced by Singapore government	Yes or No	Yes or No	Yes or No	Yes or No	Max number of people allowed to gather	Yes or No	Yes or No

Table 1: Summary of COVID-19 Control Order in Singapore Time Series Data

Exploratory Data Analysis

After preparing the final set of data, the team examined the data to see if there is any significant insight or finding that may impact our analysis. The key variables to consider are the characteristics of the Private Residential Properties which include type of the property, size, number of bedrooms, location by district the property belongs to, and the monthly rental rate. These traits are the key driving forces of the property prices, and different types of properties in the Singapore market may inherit different traits.

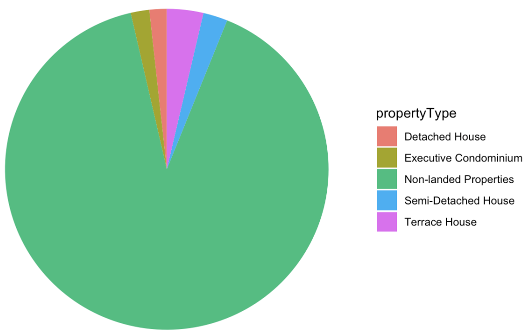


Figure 1: Types of Private Properties

There are five different types of private properties in Singapore: Non-landed property, Detached House, Executive Condominium, Semi-Detached House and Terrace House. 91% of the private properties are Non-Landed Properties and these properties are widely distributed across multiple districts. However, four other types of private properties can be found in different areas of Singapore.

While Detached Houses are mostly clustered in Central and Western Singapore, Executive Condominiums are more commonly found in Northern and Eastern districts. Terrace Houses and Semi-Detached Houses are widely distributed across Singapore. As the size of dots in the figure signifies the relative price of the property, it is observed that Detached Houses in purple are the most expensive, followed by Semi-Detached Houses in green.

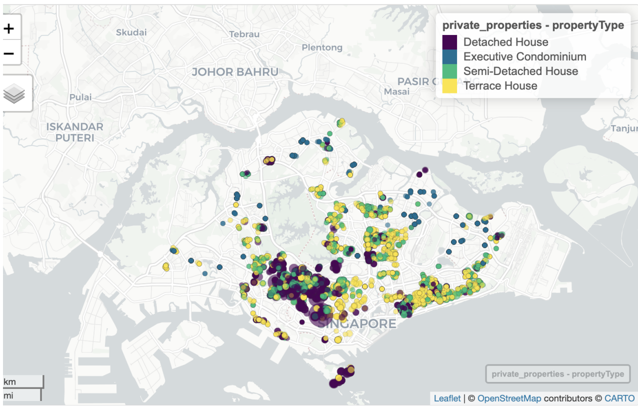
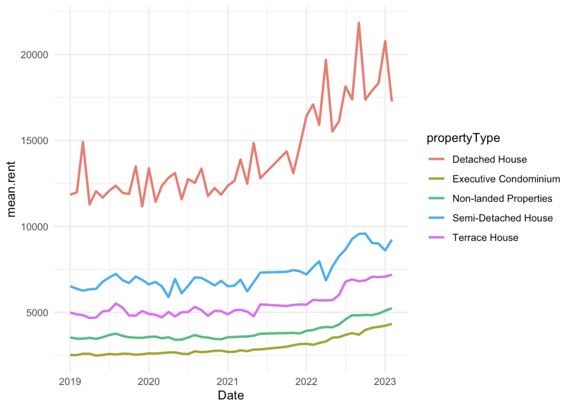


Figure 2: Distribution of Private Properties



Were all types of private properties impacted by Covid-19 over the past three years? Looking at the changes of the rental prices of these properties in the past three years, there is an increasing trend in prices for all five types of private properties. Especially from 2021 onwards, the slope of all five lines got steeper than the previous years. The team will examine the trend further to determine whether COVID-19 contributed to such change.

Figure 3: Rent trend by Property Type in the past three years

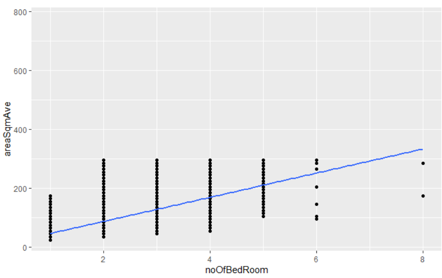
Part III - Data Modeling

Model 1 - Assess Variable Importance with Log-Linear Regression

The team used a linear regression model to identify the weight of each housing attribute's effect on the rental price. First, a linear regression model was built using all housing attributes and a variance inflation factor (VIF) function was used to verify if any of the predictors had an autocorrelation issue. VIF values on the table to the right show that while none were above 5, the number of bedrooms and apartment area may be correlated.

	vif(model)
noOfBedRoom	3.14747572
distance_mall	1.33488056
distance_mrt	1.27346355
NonLandProp	1.05727478
areaSqmAve	3.28552287
area_City	1.23344817
area_East	1.5919381
area_North	1.41996413
area_South	1.26606914
area_West	1.34945013F

Table 1: VIFs of independent variables



For further verification, a correlation plot between the two attributes was created. It was decided that it would be simpler to continue the rest of the data modelling without the number of bedrooms, as there is a strong relationship between the number of bedrooms and area.

Figure 4: Correlation plot between areaSqmAve and noOfBedRoom

After the attributes were narrowed down, the data was split into three different subsets with each representing different time periods identified by the Singaporian Government COVID-19 regulations dataset. Next, a separate linear regression model was built for each time period, and the model performance was observed.

As seen in the plots below, the model did not produce a strong Normal Q-Q plot or Residuals vs Fitted plot. The Residuals vs Fitted plot displayed heteroscedasticity, and the Normal Q-Q plot had very large tails. This was common across all three time periods.

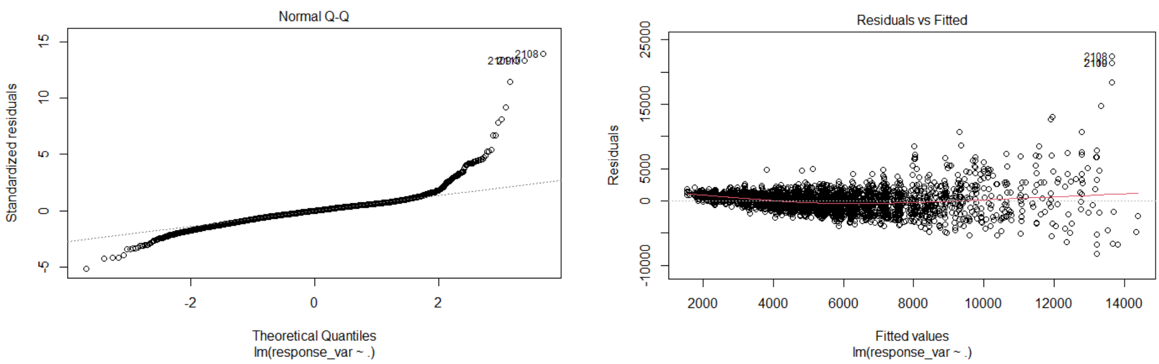


Figure 5: Linear regression Q-Q plot and Residual vs Fitted plot

In an attempt to improve performance of the regression model, the team changed the approach to using a log-lin model rather than using a lin-lin model. The new plots below show a significant reduction of the tails in the Normal Q-Q plot, and the Residuals vs Fitted plot no longer shows a cone-like pattern.

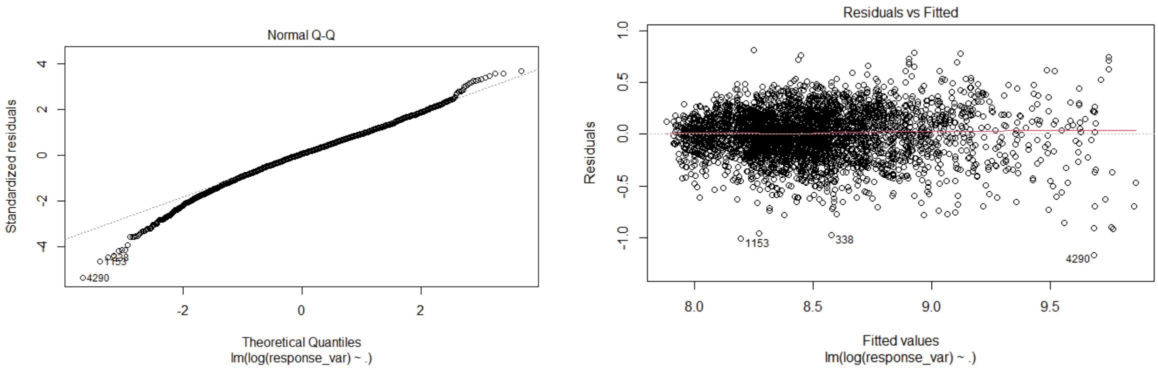


Figure 6: Log-Linear regression Q-Q plot and Residual vs Fitted plot

Finally, the models were in proper shape and ready to have their coefficients analysed. The intercept represents the variable states: area_Central = 1, LandedProperty = 1, NonLandedProperty = 0, distance_mall = 0, distance_mrt = 0, areaSqmAve = 0, areaCity = 0, area_East = 0, area_North= 0, area_South = 0, and area_West = 0. The table to the left lists the price of an apartment pre, during, and post pandemic, which represents the variable state previously described as the intercept. It also portrays the percent change each attribute has on the rental price per one unit change in the variable.

	model_pre	model_during	model_post
(Intercept)	$1695.03	$1919.74	$2632.53
distance_mall	-2.64121956%	-2.273874263%	-2.741485871%
distance_mrt	-4.08463513%%	-0.152915035%	-1.792436217%
NonLandProp	19.57737343%	28.98047182%	22.50668165%
areaSqmAve (10s)	6.890672679%	5.2035012%	5.705617837%
area_City	17.01520153%	11.45150327%	12.19750425%
area_East	-23.249483%	-22.99338666%	-20.22040292%
area_North	-28.2886734%	-26.04041285%	-24.07617081%
area_South	11.18919544%	11.80372882%	11.73573991%
area_West	-24.4158031%	-22.61964929%	-20.67432512%

Table 2: Coefficients of log-linear regression

For example, the effect of increasing the distance to the nearest mall pre, during, and post pandemic would decrease the price by about 2.64%, 2,27%, and 2.74% respectively.

The variation in attribute weight is better displayed in the coefficients plot below.

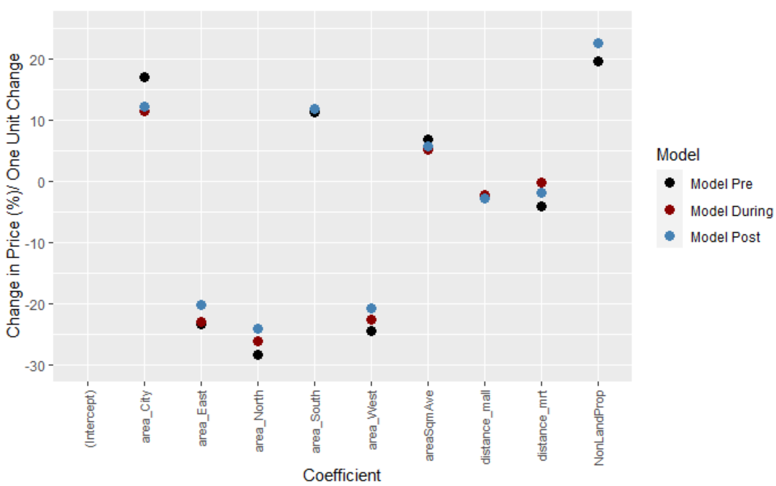


Figure 5. Attribute Coefficient Plot

The resulting coefficients reveal how the importance of each attribute have varied throughout the past years pre, during, and post pandemic. It is interesting to note that the importance of living in the city took a dip during COVID-19, and despite a slight recovery it has remained lower in importance than before the pandemic. The idea that people are able to continue working in a remote environment or simply prefer a less expensive area to live is further supported by the observed increase in the demand for non-central areas (East, North, South, and West areas). Another significant observation is that the size of the apartment actually decreased in its importance during the pandemic and has since recovered a bit, but has not yet returned to the relevance observed pre-COVID-19.

While the proximity to shopping malls did not change in its relevance very much, distance to the public transportation showed to have been more important during the pandemic than before and after the pandemic. One possible explanation is that shopping malls in Singapore do not only have retail shops but always have a giant supermarket or grocery stores within. Hence, shopping malls are not seen as desirable or useful places but an essential part of the Singaporean neighbourhood. An increased importance to the proximity of public transportation can be explained by the fact that people started to prefer non-central areas more during COVID-19. As people move to more suburban areas, they would prefer to make sure public transportation is nearby so the inconvenience of staying far from the city center does not get exacerbated.

Lastly, it appears that non-landed properties have become more popular following the pandemic. This follows the literature review and general perception that people would prefer to stay in condominiums with different amenities available such as swimming pools, gyms, and private gardens.

Model 2 - Time Series Forecasting with ARIMA

The team conducted time series forecasting to estimate the trend of rental prices in different areas. The data was grouped into different areas (Central, City, East, West, South, North) to further analyze changes in consumer preferences which were reflected in the regression coefficients. The North, which is traditionally a less preferred area, showed a smaller difference in the average rent price compared to Central, and the rent price of the City demonstrated a smaller difference to Central during and after COVID-19.

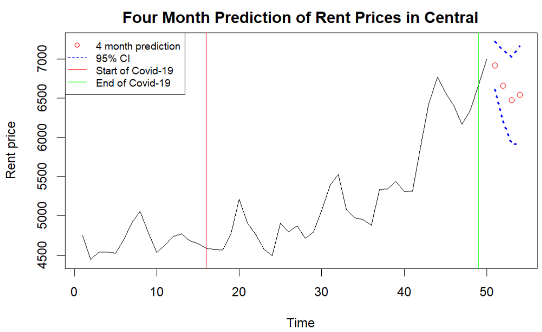
The time series data of all the areas had an increasing trend, which suggests that the data are not stationary. Therefore, as the first step to choose the appropriate model, the team checked if there was still autocorrelation between the time lags after removing the trend and differencing the data. The Augmented Dickey-Fuller (ADF) tests and the AutoCorrelation Function (ACF) plots of the differenced data demonstrated weak stationarity in all areas except for South and City. However, the lags were within the confidence bands in both cases. As differentiation is needed to reach stationarity in the time series, the team decided on using ARIMA for modelling and forecasting. Also, as the ARIMA model is not adequate for long-term prediction, contrary to the initial plan of making one or two year prediction, the team decided to conduct a near-future forecasting of four months to ensure the prediction accuracy.

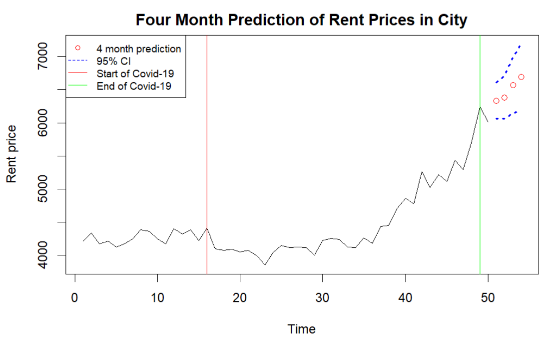
The dataset into training and test sets, sparing the 10% of the data for testing. Using the training dataset, the team conducted interaction with Auto Regressive (AR) and Moving Average (MA) order from 0 to 8 and a differencing order from 1 and 2 to select the order for ARIMA (p,d,q) models using the training dataset. The p, d, q values for each time series of the areas were chosen based on the lowest AIC scores. After selecting the p, d, q values, rental prices for the next four months were predicted using the chosen ARIMA models. Forecasted values were then compared with the actual observation of the test dataset.

Area	ARIMA(p,d,q) order	Mean Absolute Percentage Error	Precision Measure	Number of observation outside the prediction band
Central	(2,1,2)	0.0263172	0.3206667	0
City	(1,2,1)	0.04967412	1.059836	1
East	(1,2,2)	0.009506897	0.1727913	0
West	(0,2,1)	0.01089114	0.3764751	0
South	(1,2,2)	0.08007504	4.870781	2
North	(0,2,1)	0.04336779	2.966685	0

Table 3. ARIMA (p,d,q) orders, MAPE, PM and no. of observation outside the prediction band for each area

As shown in the table, in general, the model performed well in terms of prediction accuracy. However, for the South and the North, the prediction showed high volatility: the South was 4.87 times more varying in the prediction than the observed data, and 2.97 times more compared to the North. Residuals of the ARIMA models were assessed with ACF plot, Partial ACF plot and histogram. For all models, lags were within the confidence band in the ACF and PACF plots. However, the histograms of the residuals did not seem symmetric, suggesting that the residuals are not holding normality, except for City.





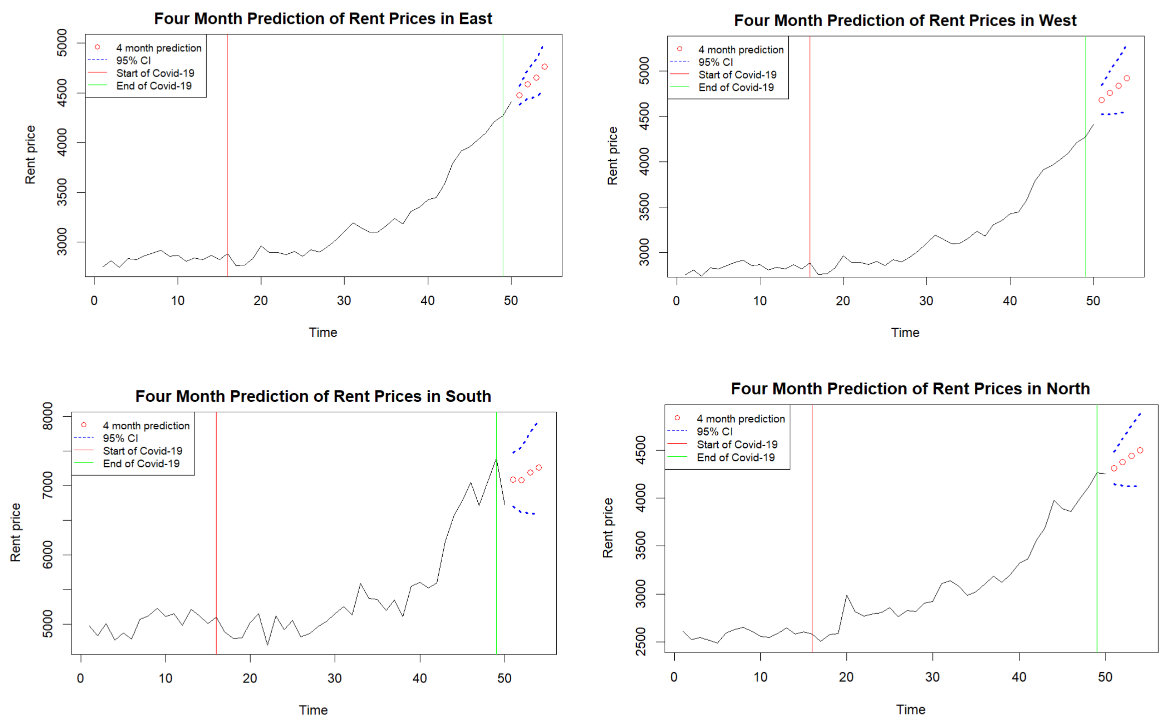


Figure 6. Time series plots of each area with four-month prediction

The time series plots show that the rental prices did not increase steeply during the COVID-19 periods. However, a slow increase started before the official lift of all COVID-19 restrictions and started skyrocketing after the time lag 40 (April, 2022) in all of the areas. We cannot say about causality, but the major changes from May 2022 was that the social gathering limit and the outdoor mask requirement ended. The increase is faster and more explicit in Central, City and South.

The four-month forecasts suggest that most of the areas in Singapore are likely to experience a steep increase in rental prices for the next four months, except for the Central. The Central area is likely to go through fluctuations with the rent prices decreasing and then starting to increase again after a quarter. The South, which historically has had the most expensive rentals price on average but recently had a decreasing trend, would experience an upward trend again.

This time series analysis shows that despite the changes in the consumer preferences observed in the Model 1, the Central and the City areas will still continue to be the most demanded area with the high prices in the post-COVID-19 Singapore.

Part IV - Conclusion

Limitation

The regression model showed that the impact of housing characteristics on rental prices indeed changed over COVID-19 eras but failed to validate all of the initial hypotheses set in the beginning.

Compared to the pre-COVID-19 era, during COVID-19...	
Initial Hypothesis	**Log-Lin Regression Result**
Importance of living in a larger apartment is more important	False: Size of the properties decreased in its importance
Proximity to shopping malls and public transportations is less important	False: Proximity to shopping malls did not change much in relevance while proximity to public transportations became more important
Proximity to the city center is less important	True: Importance of living in the city took a dip
Consumer preferences for different property types did not change	False: Non-landed properties became more popular

The most interesting yet perplexing observation is that the importance of living in a larger apartment did not change during the COVID-19 eras. In fact, Figure 5 shows that its relevance did not change very much over the time relative to other housing characteristics. Further research into varying consumer preferences over the pandemic or dividing the dataset into a more granular time period could reveal more insights about this.

The time series analysis with ARIMA was able to prove that rental prices of private properties will constantly increase after COVID-19 across all areas of Singapore. However, only a near-future forecast was possible as ARIMA model is not adequate for long-term prediction. The team could consider machine learning models for long-term forecasting and pattern recognition.

Key Takeaways

MSCI Real Estate Market Size Report 2021/22 reports that Singapore has the third-largest housing market in Asia, followed by China and Hong Kong. The Singapore market is the 13th largest globally with an estimated size of US$192.9 billion. This indicates multiple opportunities for real estate investment await in Singapore after the pandemic. Real estate developers have to understand and adjust to the shift in consumer demand due to COVID-19 which was clearly observed in the first model presented by the team.

Contrary to the new business opportunity presented to the Singapore real estate market, the Singapore government is now faced with extreme challenges in developing a welfare society and maintaining a stable market. The government has to make data-driven decisions to effectively support its citizens and control the tumultuous real estate market rising out of the pandemic.

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