COVID-19 & Real Estate

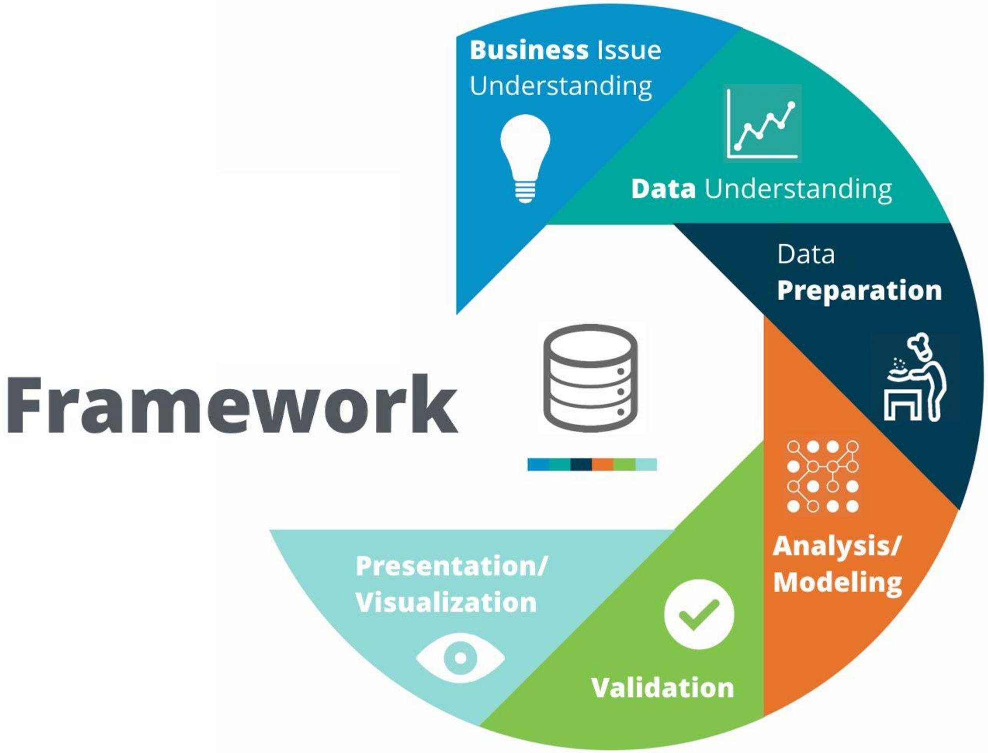
Exploring the implications of covid-19 on the real estate market and trying to predict rental/selling prices during the pandemic

Team members: Sindhuja Rao, Tomas Ortega

Agenda

- Phase 1: Business Understanding
- Phase 2: Data Collection
- Phase 3: Data Preparation
- Phase 4: Exploratory Data Analysis
- Time Series analysis
- Phase 5: Modelling
- Phase 6: Evaluation & Results
- Conclusion
- References

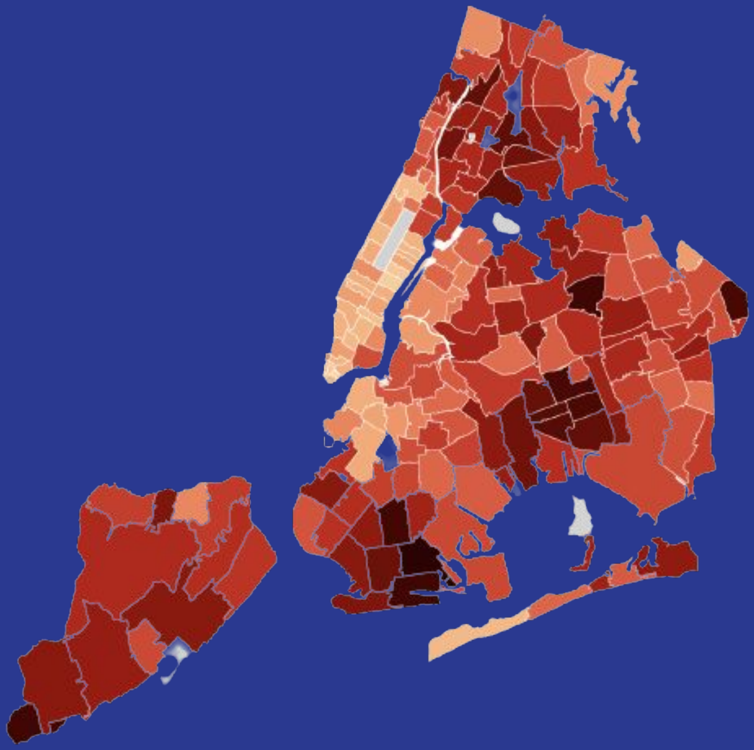
OVERVIEW : CRISP DM



Phase 1:
Business Understanding

Objectives

Explore the correlation between the number of COVID-19 cases and residential Real Estate Prices in New York



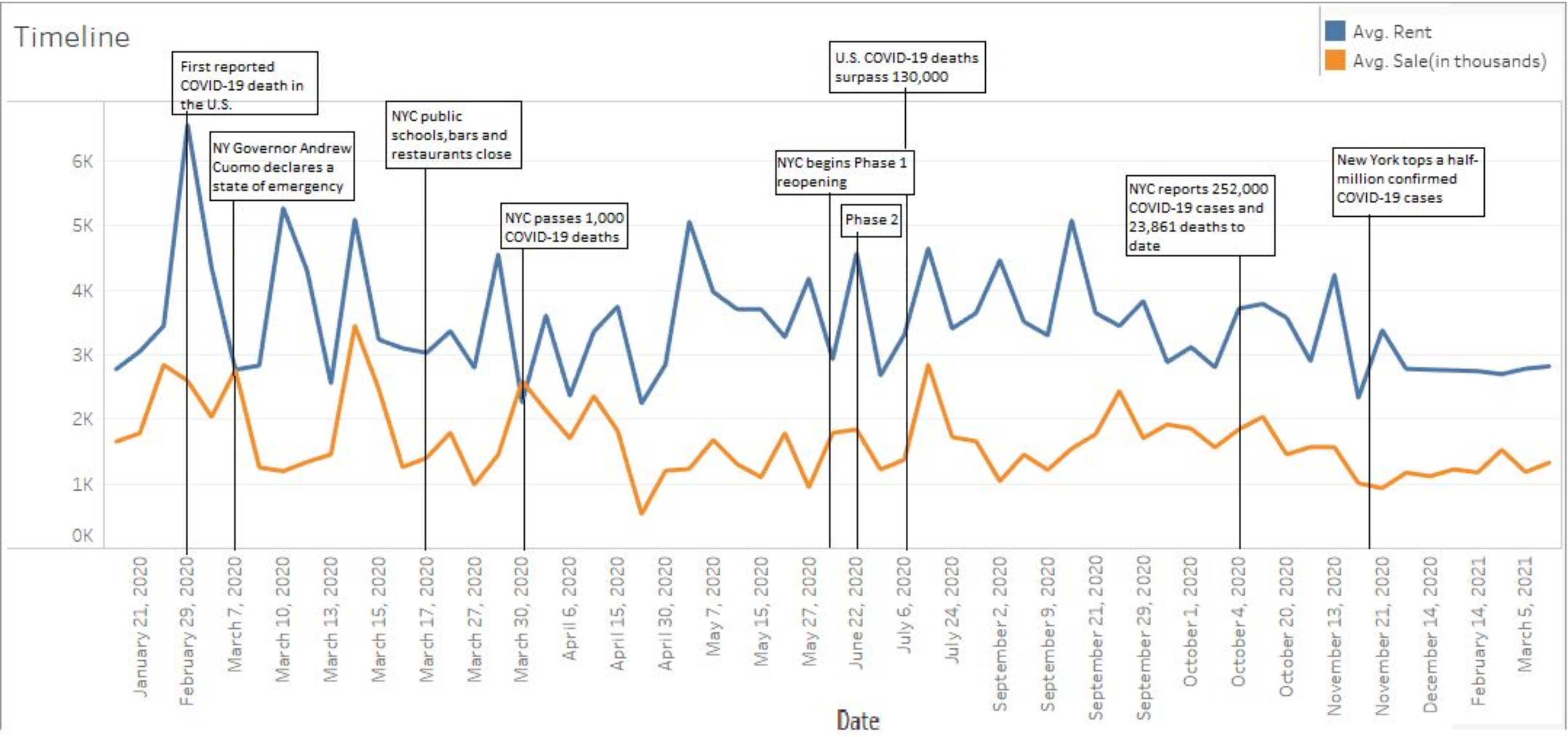
Background Information

- It’s been more than **a year since the official declaration of the COVID-19 pandemic.** (March 11th, 2020).
- The COVID-19 pandemic caused a dramatic **reduction in consumption**, with a further drop in prices and a decrease in workers’ per capita income.
- The acceptance of **remote work** is growing rapidly and it seems that it might stay relevant for the foreseeable future which might bring changes to the renting prices in the cities.

More Background Information

- According to “Hire a Helper” a company that helps people find local movers and moving companies, approximately 13% to 15% of people that moved at the beginning of 2020 moved because of reasons related to the pandemic. By the end of the year, this figure reached 25% of the total moving population.
- They also released other surprising statistics such as:
    - “68% more people left New York City in 2020 than moved into it.”
    - “28% moved because they started working from home and no longer had to live close to work”
    - “31% moved to either shelter-in-place with family or to take care of family members”

Covid Timeline on Real Estate



Literature Review

How Does COVID-19 Affect the Real Estate Market in Italy

Time Series Analysis of COVID-19 Data to Study the Effect of Lockdown and Unlock in India

Phase 2:
Data Collection

Data - Real Estate & COVID-19

- Selling and Rental prices of house listings in New York for the year 2020 and 2021. This includes 5 boroughs Manhattan, Brooklyn, Bronx, Queens and Staten Island.

- Our Covid data comes from the CDC and consists of the number of cases, the case rates, death counts, death rates etc. for the same time period for the above locations, 2020 to 2021.
    a. The data contains daily count and rate per 100,000 people of confirmed COVID-19 cases, deaths, and tests performed.
    b. The frequency of the data is daily, and is presented as a 7-day moving average

Data Scraping

We collected data from the listings website zillow.com using a scraper that we built specifically for this task.

Using python and libraries such as BeautifulSoup, Requests, and Selenium, we were able to scrape information from 343,600 properties including rent prices, date of price changes, selling price, and other physical characteristics of residential properties.

Some of the difficulties we encountered while scraping the data from zillow include:

- Dealing with Captcha pages
- Using multithreading to increase the rate of data collection
- Dealing with different page layouts for rentals, for sale and sold properties

Data Scraping

ZillowQuery

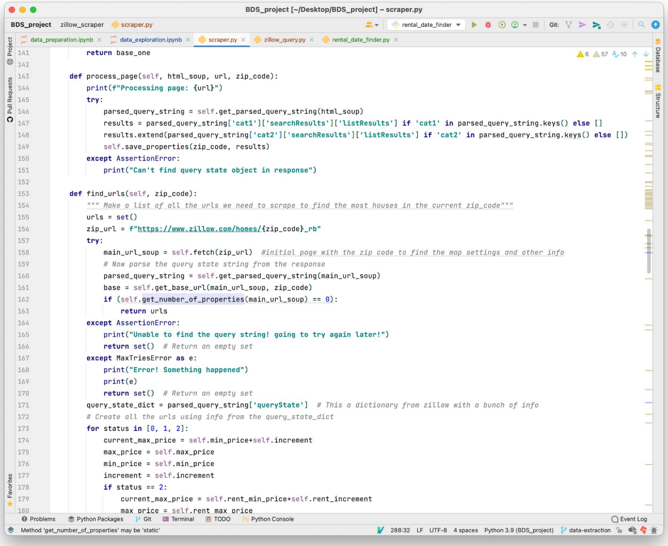
+ pagination: bool
+ base_url: string
+ handle_map_params: dict
+ min_price: int

+ get_frst_page(): void
+ get_urls(): list
+ url_to_query(): void
+ get_page(page_num: int): void

Scraper

+ domain: string
+ zip_codes: list
+ max_price: int
+min_price: int

+ get_headers(): dict
+ is_captcha(soup: bs4 obj): void
+ parse_cookie(): void
+ get_parsed_query_string: dict
+ save_properties(properties: dict): void
+ process_page(soup: bs4 obj, url, zip_code): dict
+ fint_urls(zip_code: string): void
+ fetch(url: string): bs4 obj
+ run_scraper(zip_codes: list): void



Phase 3:
Data Preparation

Data Preparation (Real Estate)

- We removed the values larger than the 95th percentile to remove spikes and avoid problems with regression models.
- We also had to deal with missing values. To do this we had to select among different alternatives.
  a. Imputation: where we fill missing data based on observations about the entire dataset
  b. Interpolation: where we use neighboring data points to estimate missing values.

- In this project we tested multiple methods and decided to use interpolation with a spline curve.

Data Preparation (Real Estate)

After collecting the raw data from zillow.com, we decided to maintain the data in a csv file in order to use it in different programs.

date	event_description	price	address_city	zip_code	area	status_type	home_type	beds	baths	living_area	lot_area	BOROUGH
2021-03-16	No price history	2425	Brooklyn	11201.0	850	FOR_RENT	MULTI_FAMILY	2.0	1.0	850.0	None	brooklyn
2021-04-21	Price change	2500	Brooklyn	11232.0	None	FOR_RENT	MULTI_FAMILY	3.0	2.0	None	None	brooklyn
2021-02-20	Listed for rent	1600	Bronx	10459.0	None	FOR_RENT	MULTI_FAMILY	None	1.0	None	None	bronx
2021-04-16	Price change	1699	Brooklyn	11230.0	800	FOR_RENT	MULTI_FAMILY	2.0	1.0	800.0	None	brooklyn
2021-03-26	No price history	1799	New York	10034.0	750	FOR_RENT	MULTI_FAMILY	1.0	1.0	750.0	None	manhattan

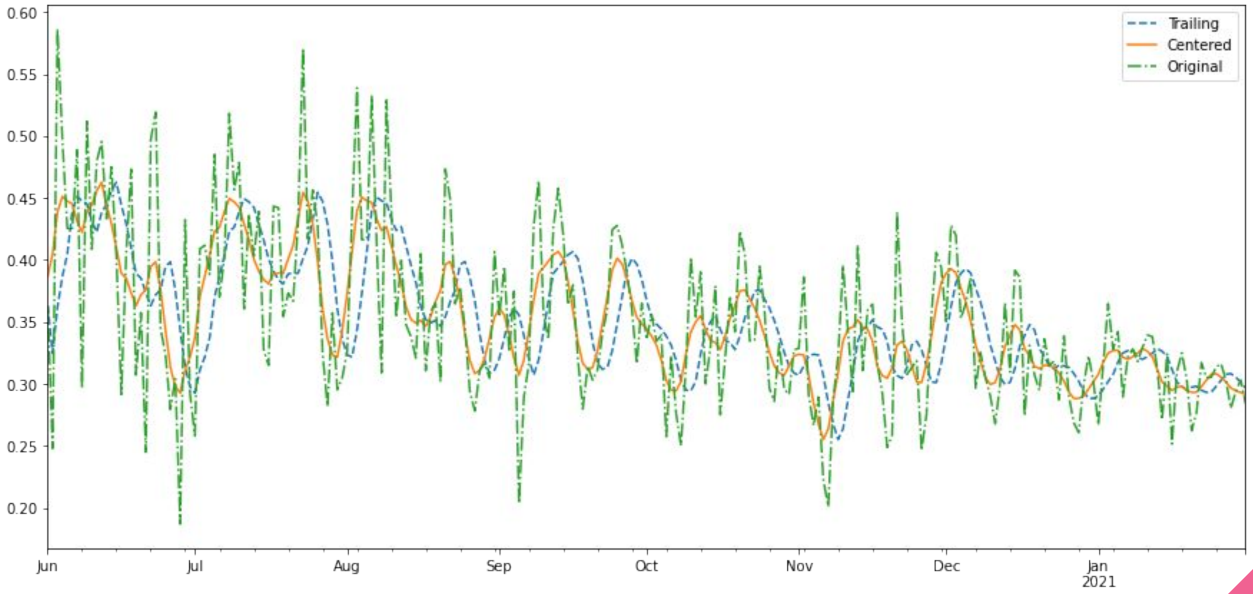
Data Preparation

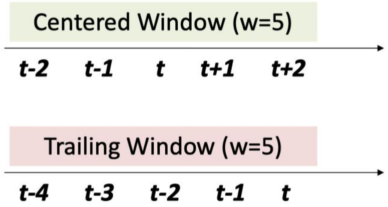
To use the data from zillow for time series analysis, we aggregated the data by date and applied different statistical functions like mean, median and the count.

	mean_rent_price	rent_count	median_rent_price	mean_selling_price	sales_count	median_selling_price
2019-06-01	3200.000000	1.000000	3200.000000	7.097500e+05	4.000000	6.795000e+05
2019-06-02	4633.203214	1.466596	4558.891459	1.414969e+06	56.707867	1.312222e+06
2019-06-03	4247.500000	2.000000	4247.500000	1.576849e+06	73.000000	1.300000e+06
2019-06-04	2800.000000	1.000000	2800.000000	1.321397e+06	58.000000	8.495000e+05
2019-06-05	3721.000000	3.000000	2850.000000	1.410283e+06	52.000000	1.075000e+06

Data Preparation (Real Estate)

We also had to smooth the data using a rolling window of size 7. Here are the results of using different window parameters.





Data Preparation (Covid-19)

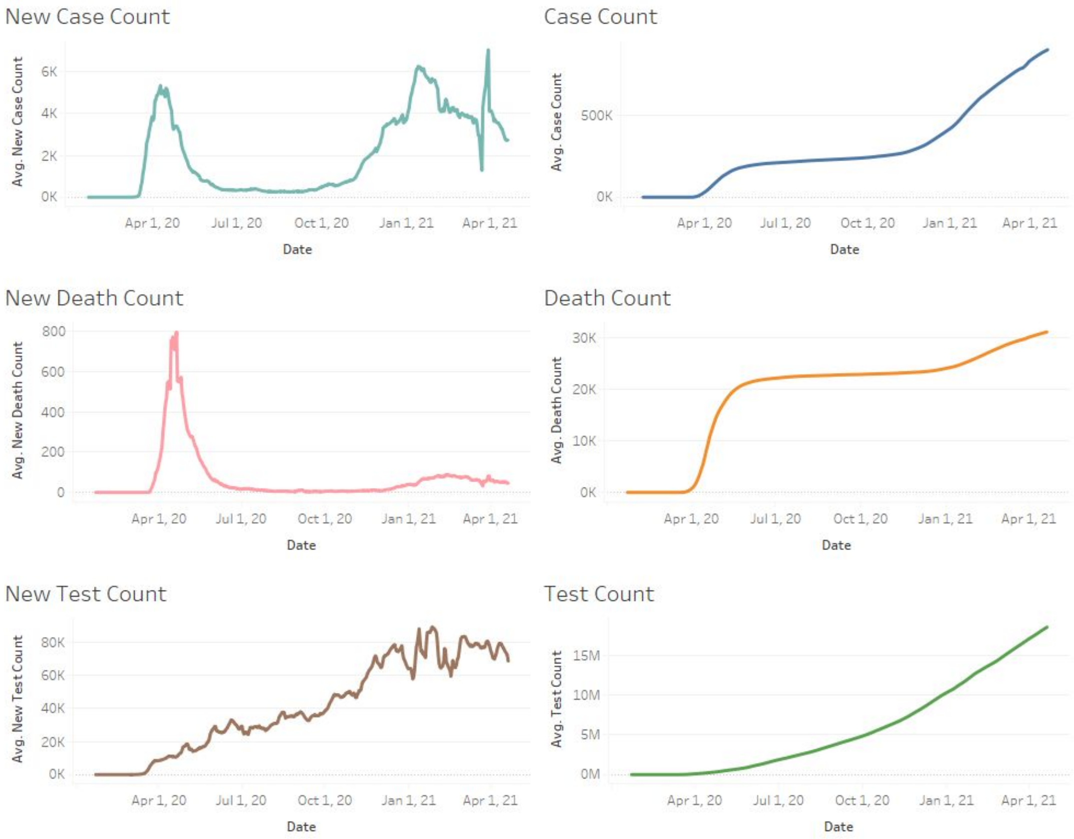
- Spline interpolation for missing values
- Scaled using minmax scaler, smoothed using rolling window

	new_case_count_covid	new_death_count_covid	new_test_count_covid	new_case_rate_covid	new_death_rate_covid	...	case_rate_covid	death_count_covid	death_rate_covid	test_count_covid	test_rate_covid
date											
2020-05-01	0.389527	0.421384	0.207793	0.389349	0.420776	...	0.194397	0.532031	0.533333	0.026640	0.026642
2020-05-02	0.349510	0.386164	0.206680	0.349112	0.386149	...	0.197388	0.542248	0.541667	0.027713	0.027712
2020-05-03	0.325812	0.377358	0.195198	0.325444	0.377754	...	0.200080	0.552265	0.552778	0.028726	0.028724
2020-05-04	0.307365	0.362264	0.170604	0.307692	0.362015	...	0.202672	0.561816	0.563889	0.029611	0.029610
2020-05-05	0.294735	0.348428	0.172426	0.294675	0.349423	...	0.205164	0.571067	0.572222	0.030506	0.030505

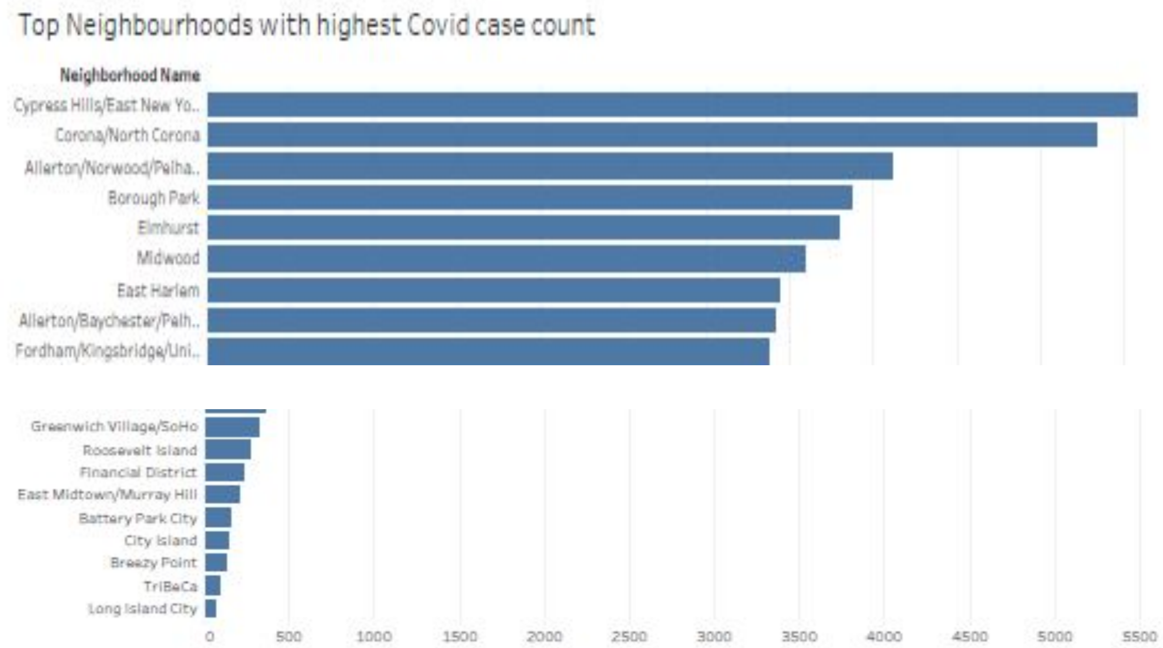
Phase 4:

Exploratory Data Analysis

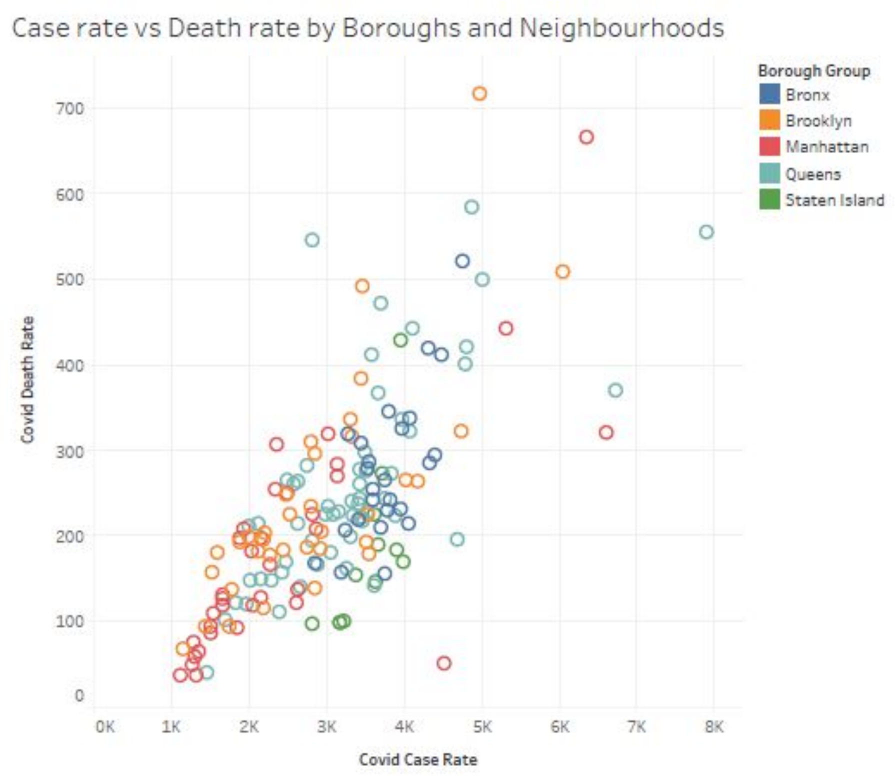
Stats on COVID-19 in NYC



Covid in different neighbourhoods

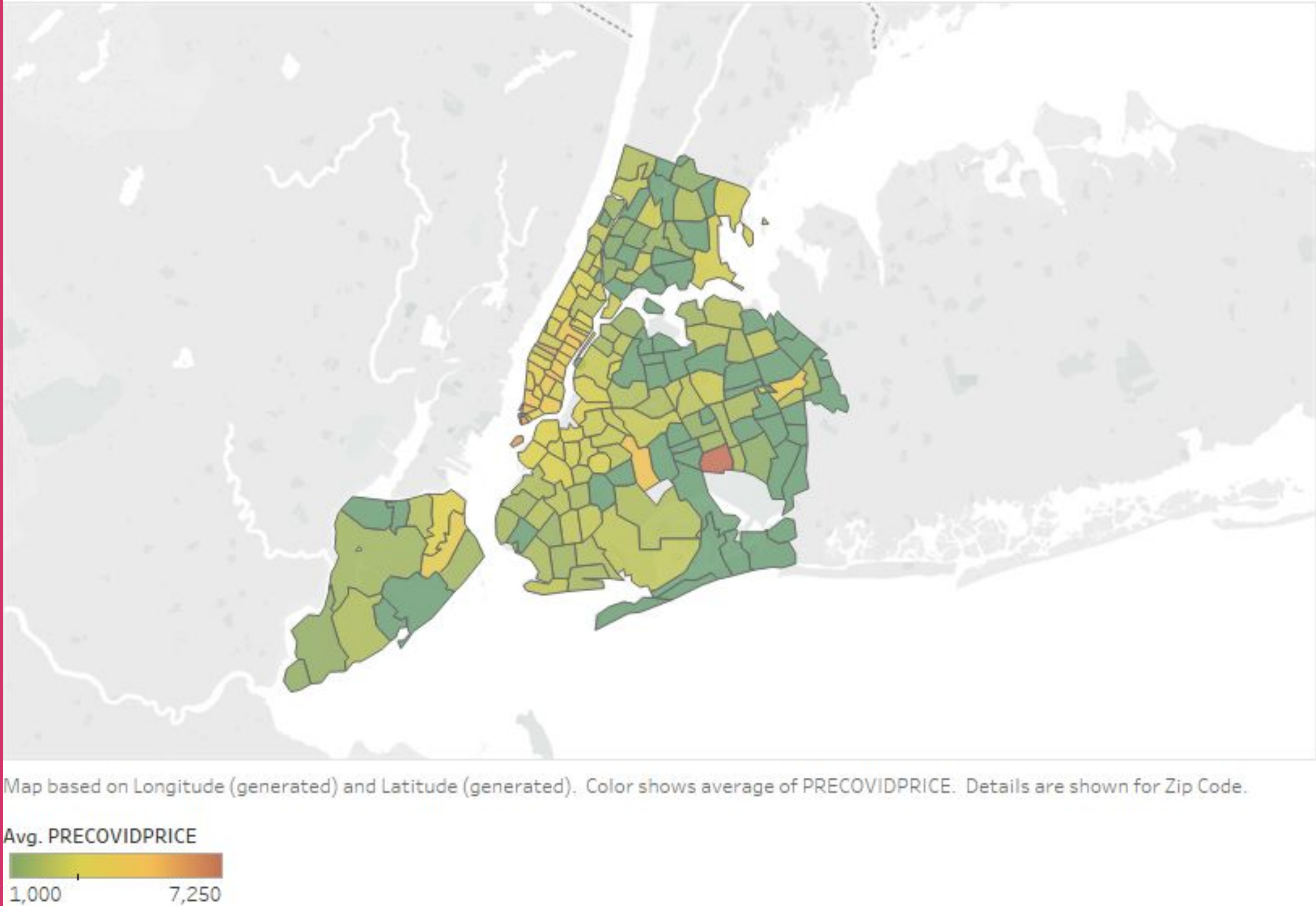


Rates By Boroughs & Neighbourhoods



Pre Covid Rental prices heatmap

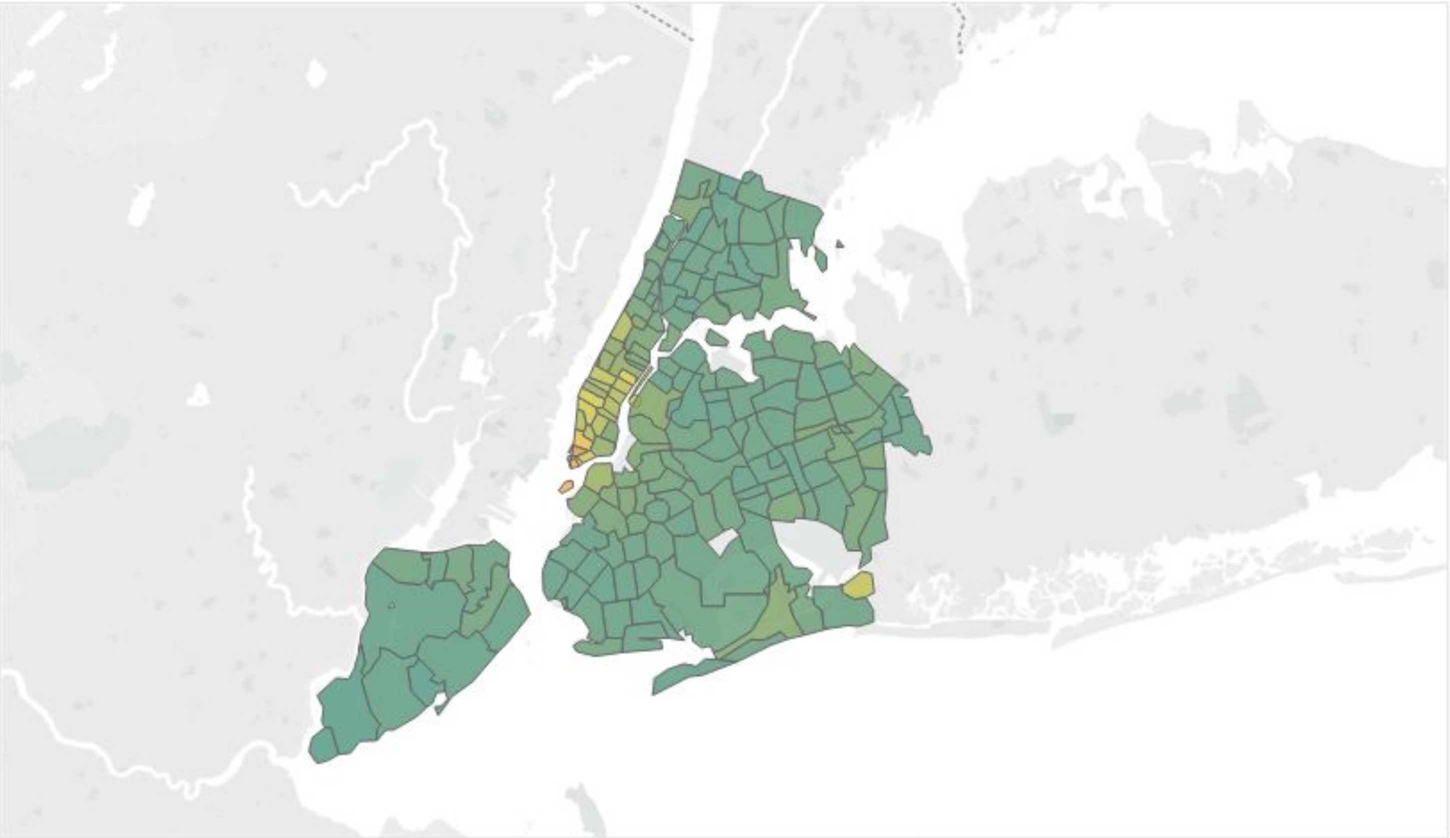
Pre Covid Rent



Map based on Longitude (generated) and Latitude (generated). Color shows average of PRECOVIDPRICE. Details are shown for Zip Code.

Covid Rental prices heatmap

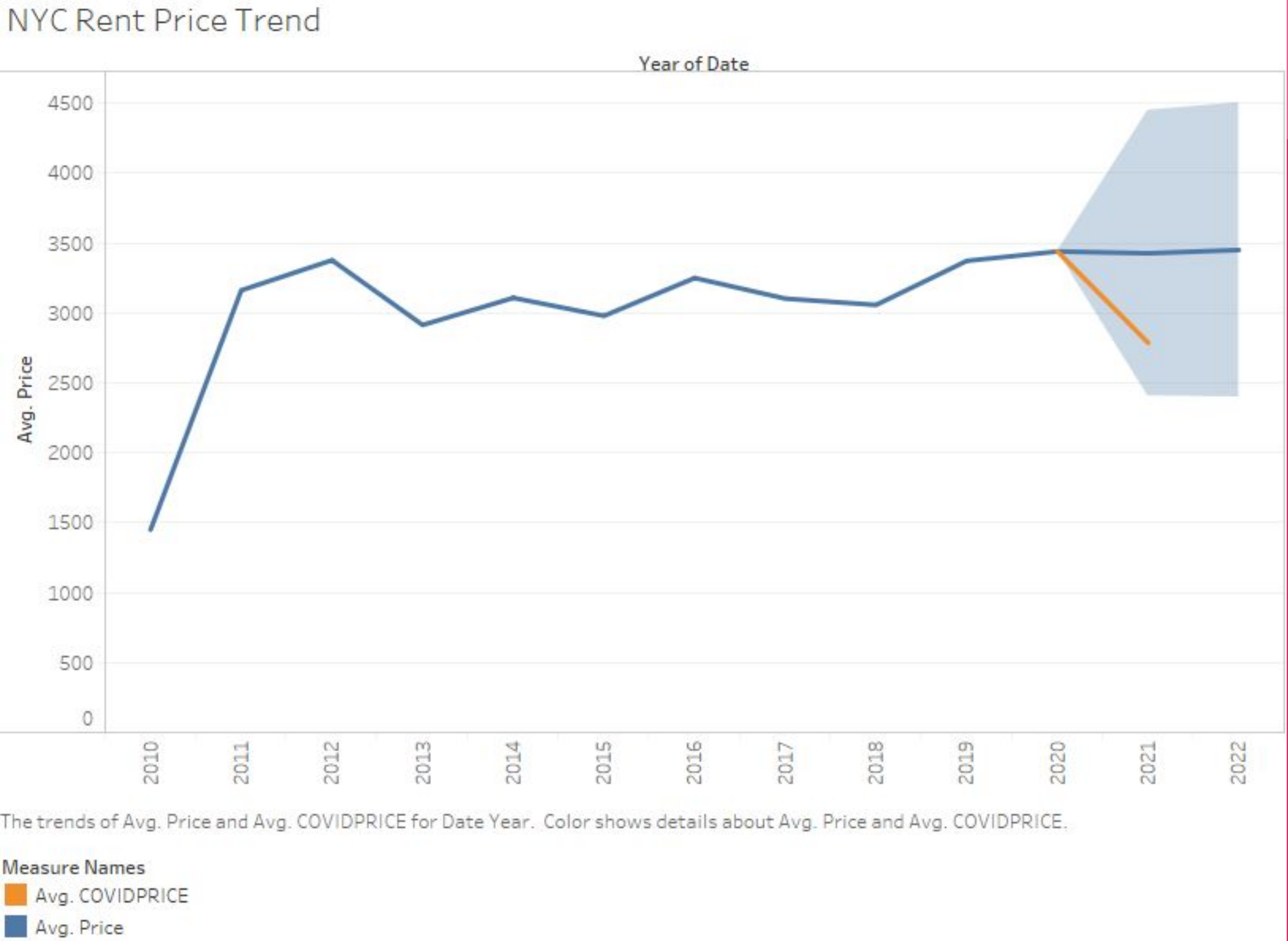
Covid Rent



Map based on Longitude (generated) and Latitude (generated). Color shows average of COVIDPRICE. Details are shown for Zip Code.

Avg. COVIDPRICE

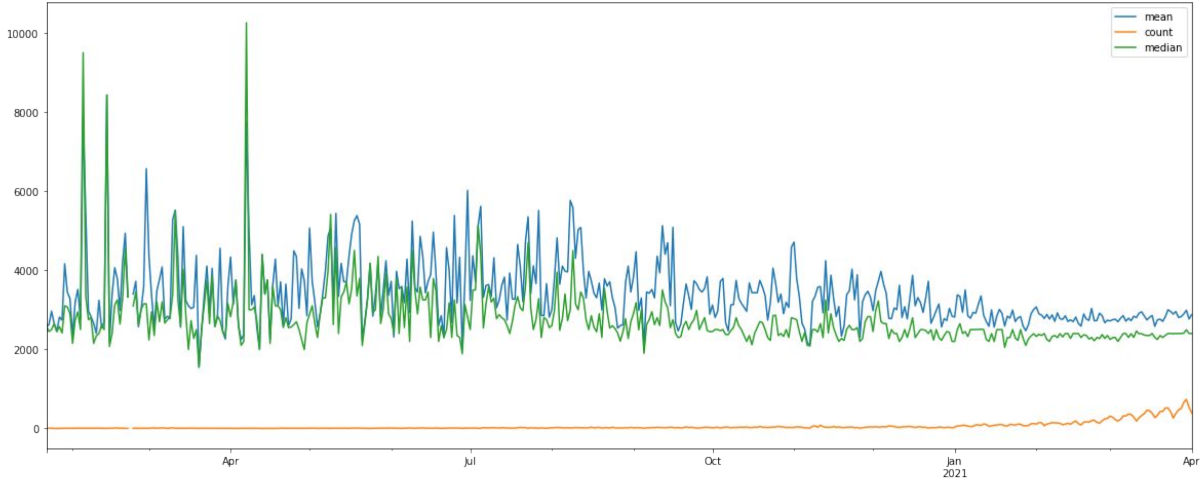
1,708 6,719



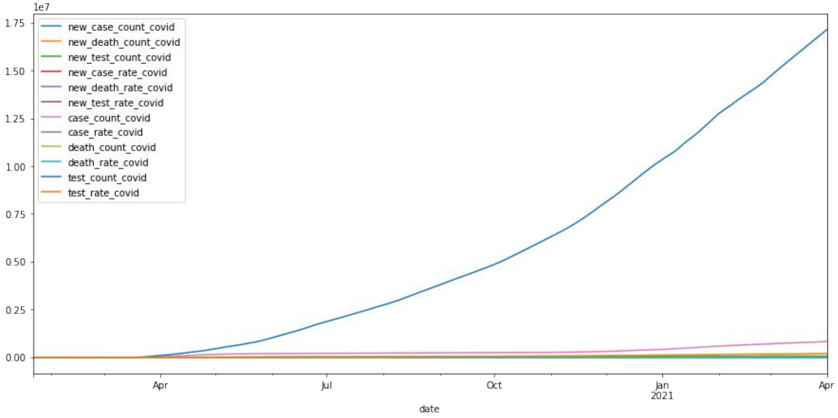
Rent Projections vs Actuals during Covid

Time Series Analysis

Raw Data:

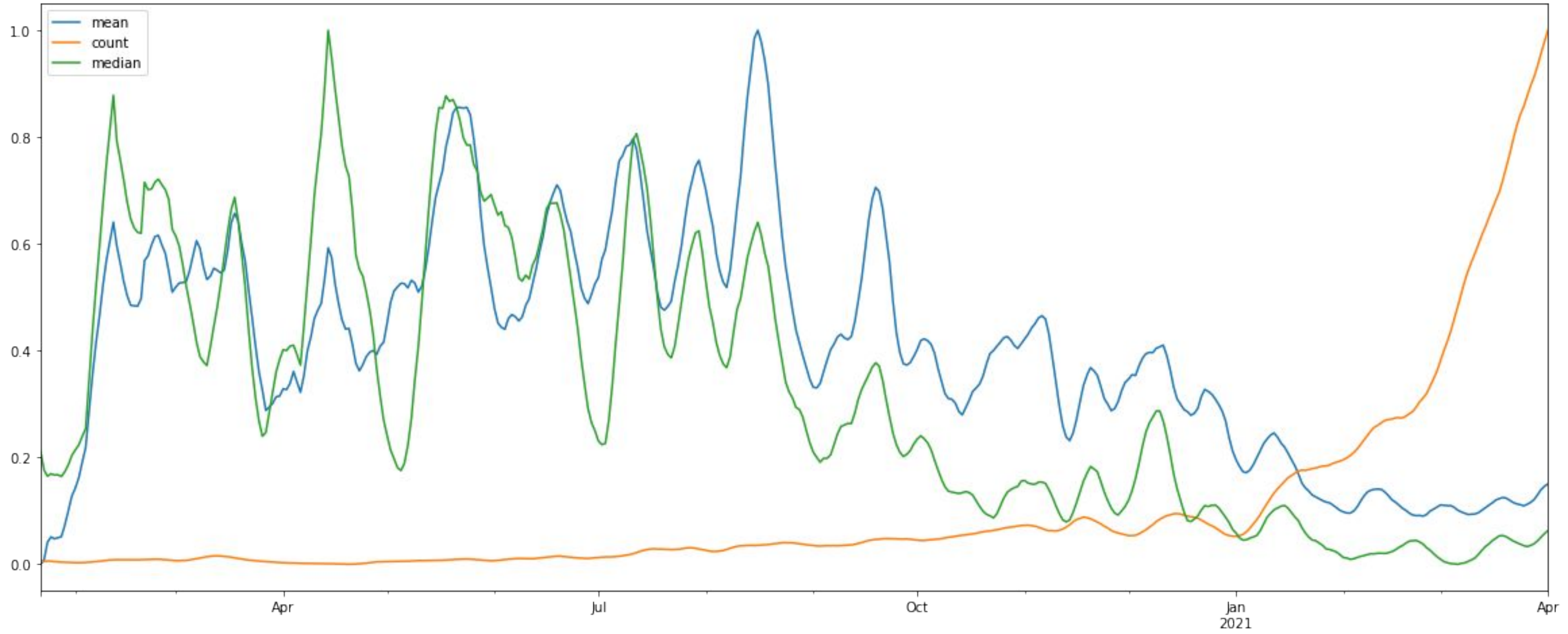


mean
count
median
10000
8000
6000
4000
2000
0
Apr
Jul
Oct
Jan
2021
Apr

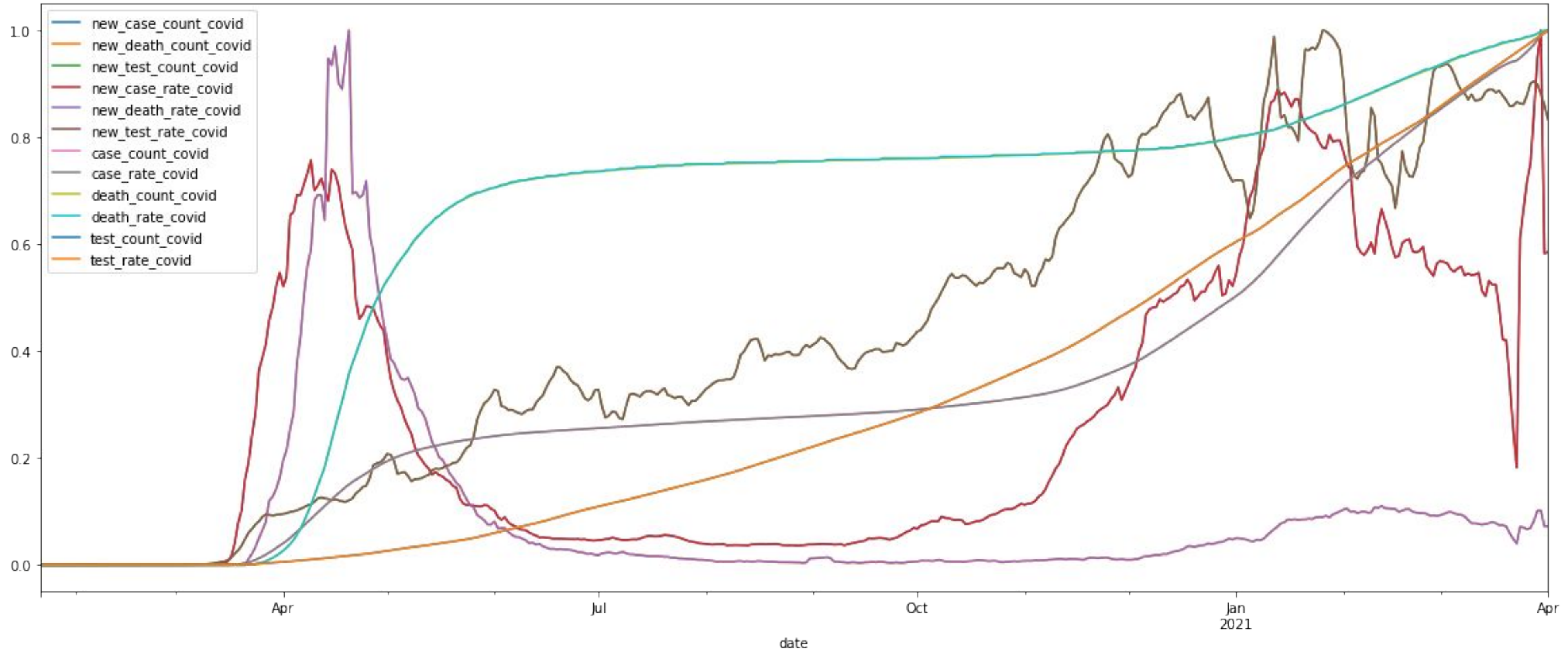


1e7
new_case_count_covid
new_death_count_covid
new_test_count_covid
new_case_rate_covid
new_death_rate_covid
new_test_rate_covid
case_count_covid
case_rate_covid
death_count_covid
death_rate_covid
test_count_covid
test_rate_covid
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Apr
Jul
Oct
Jan
2021
Apr
date

After data prep & transformations: Rent



After data prep & transformations: Covid



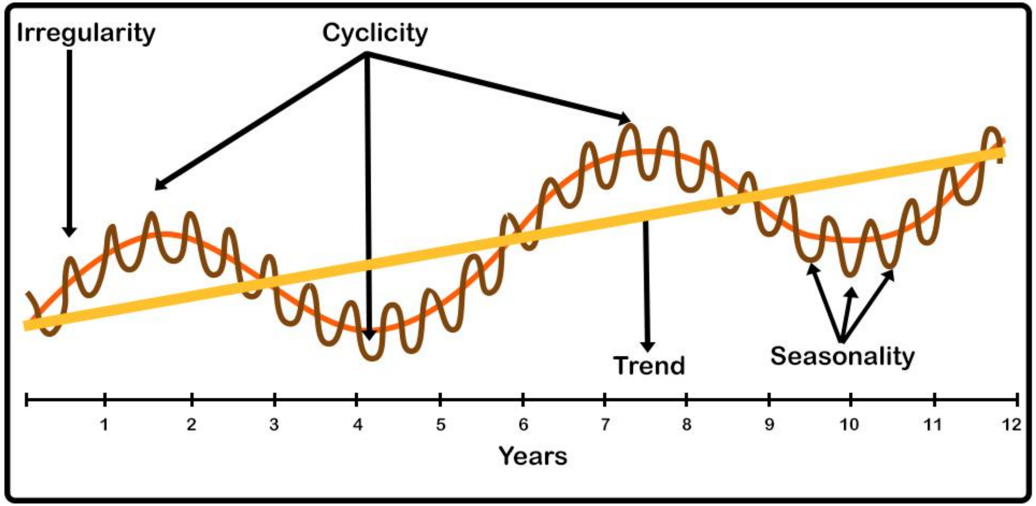
Dealing with stationarity & seasonality in Time series

A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time.

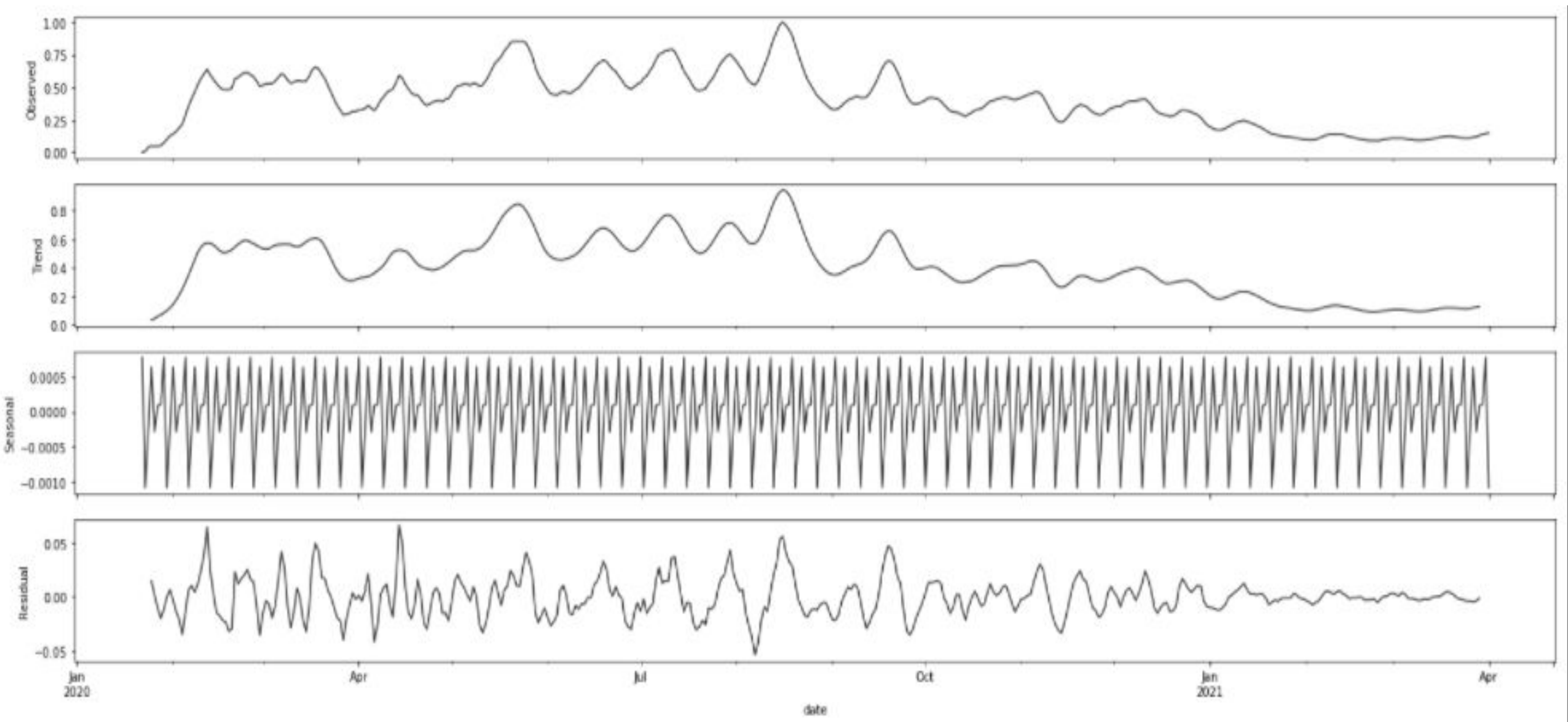
Most statistical tests and models rely on data being stationary.

Time Series Decomposition

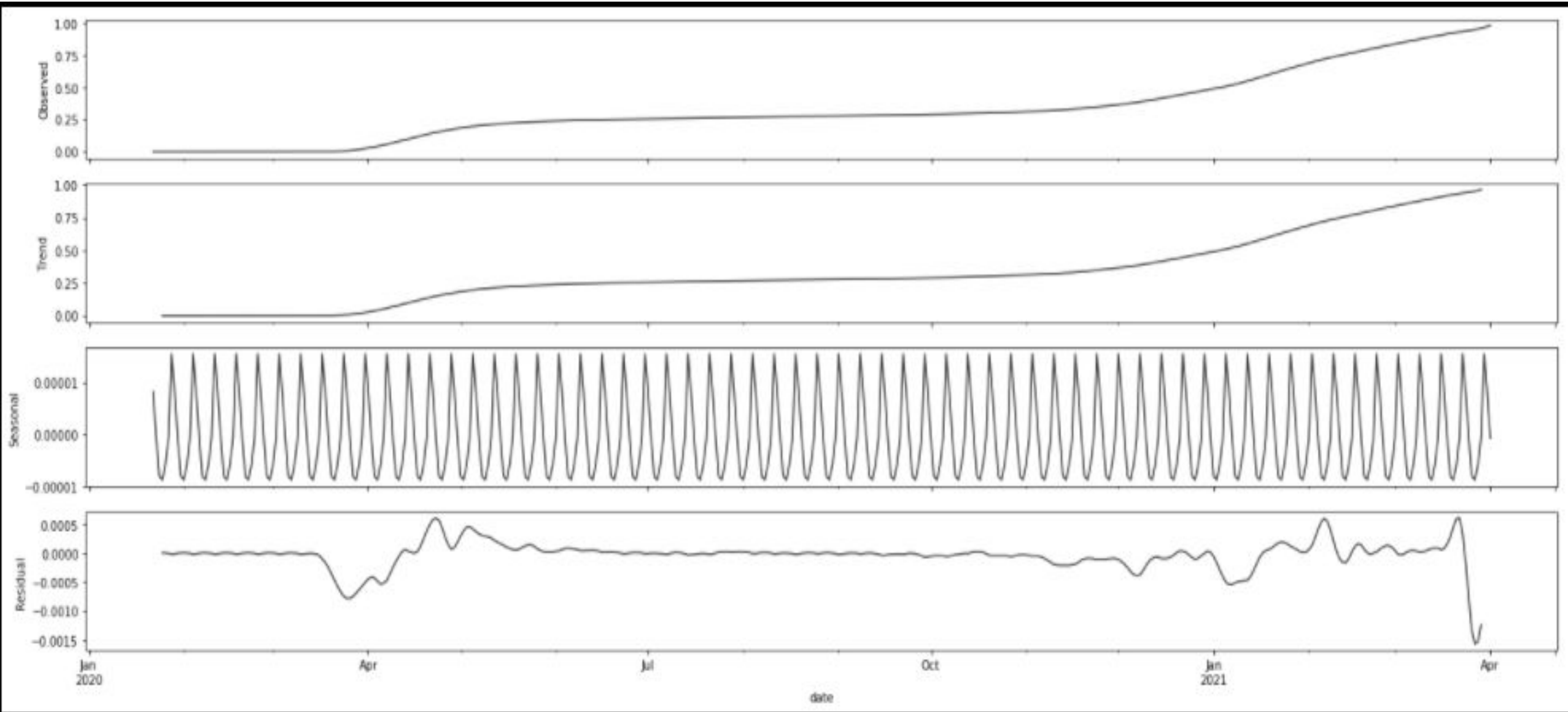
Time series decomposition involves thinking of a series as a combination of level, trend, seasonality, and noise components



Time series decomposition : Rent



Time series decomposition : Case Count



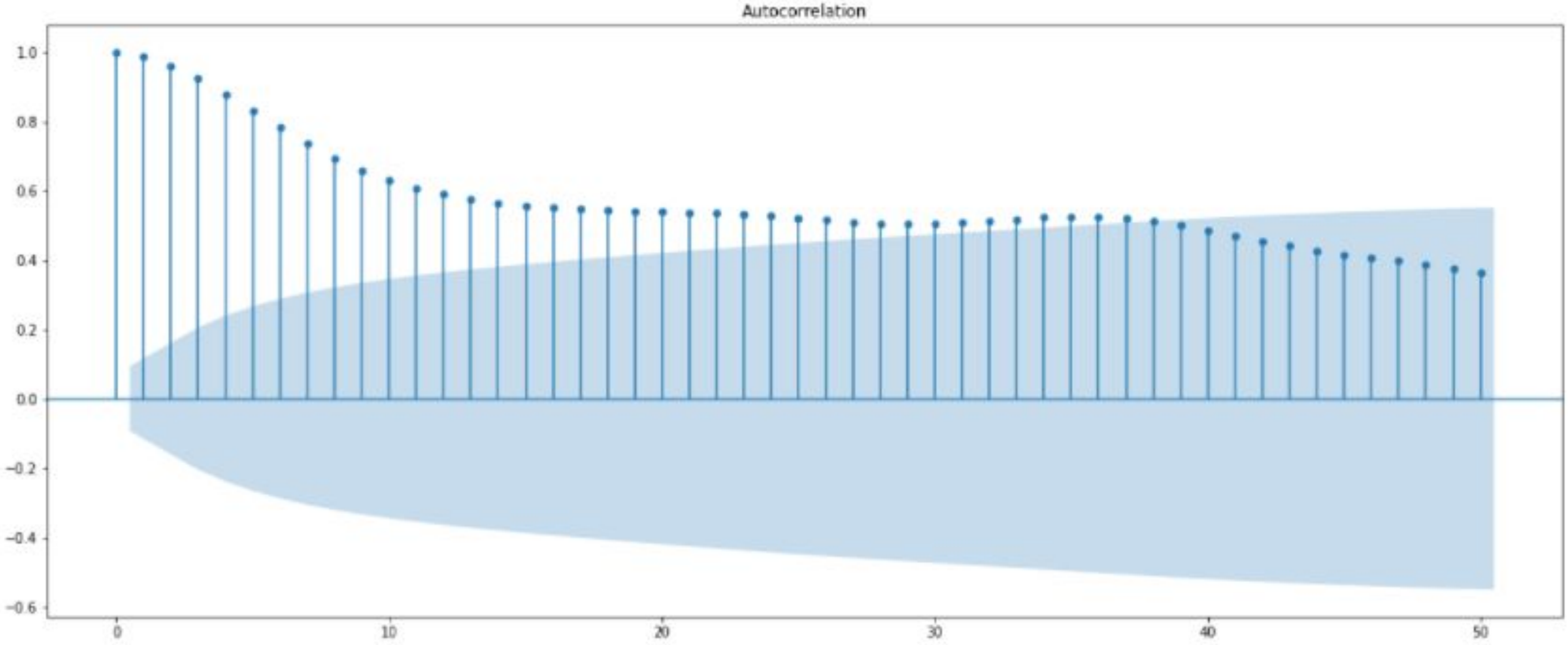
AutoCorrelation / ACF

Autocorrelation represents the degree of similarity between a given time series and a lagged version of itself over successive time intervals.

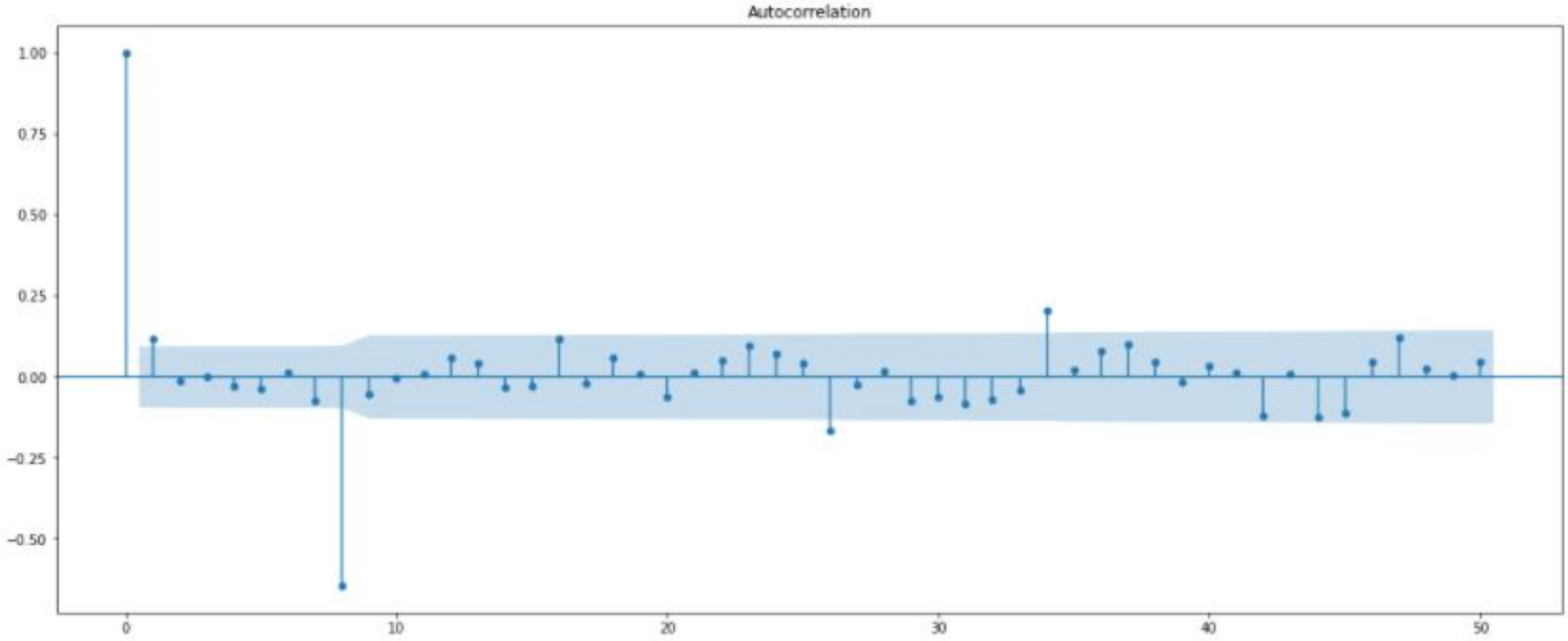
Autocorrelation measures the relationship between a variable’s current value and its past values.

An autocorrelation of +1 represents a perfect positive correlation, while an autocorrelation of negative 1 represents a perfect negative correlation.

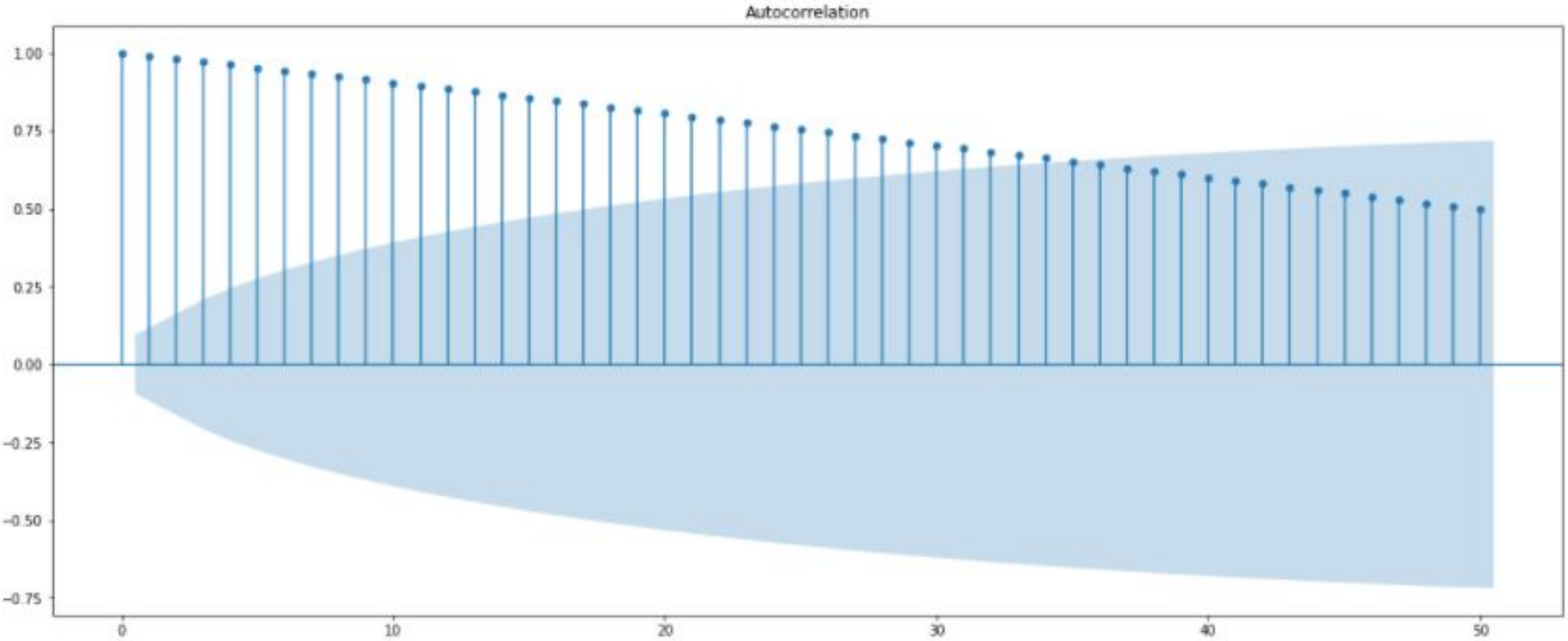
ACF Plots : Rent - Before stationarity



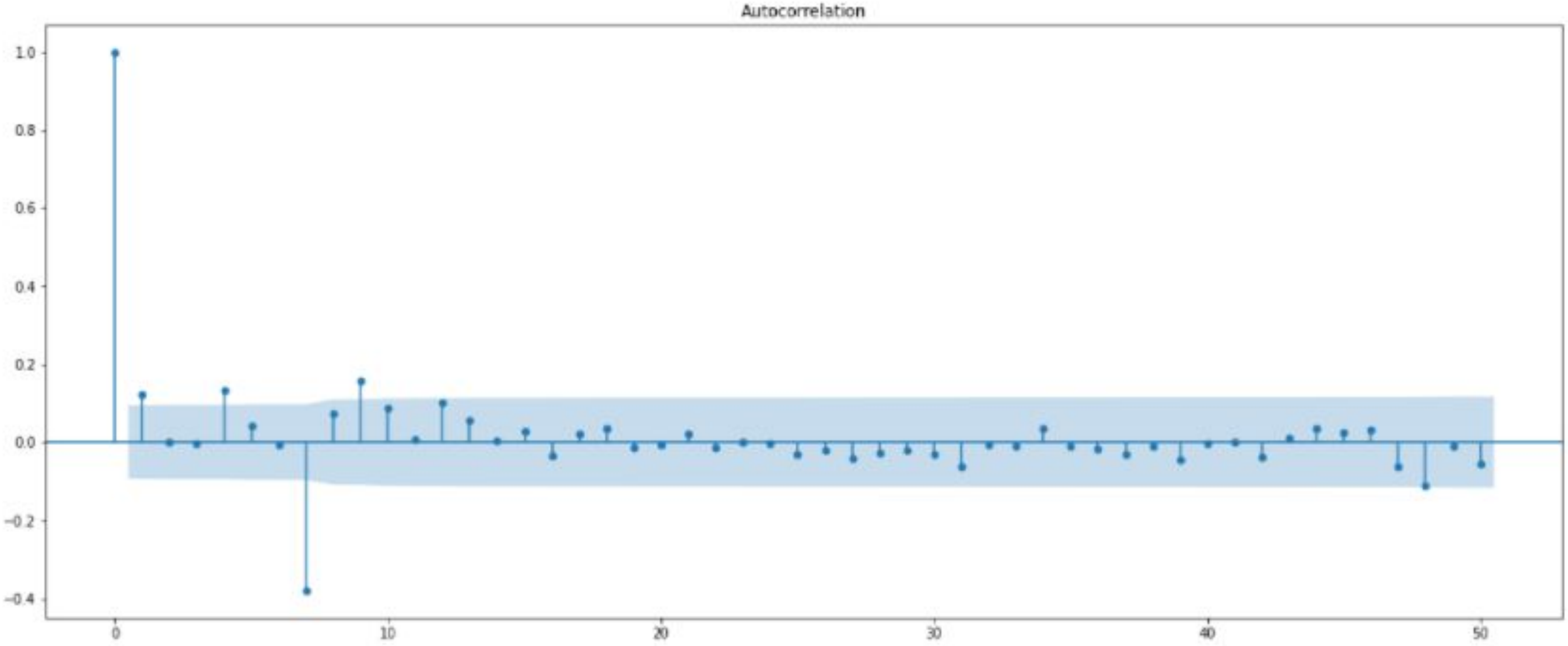
ACF Plots : Rent - After stationarity



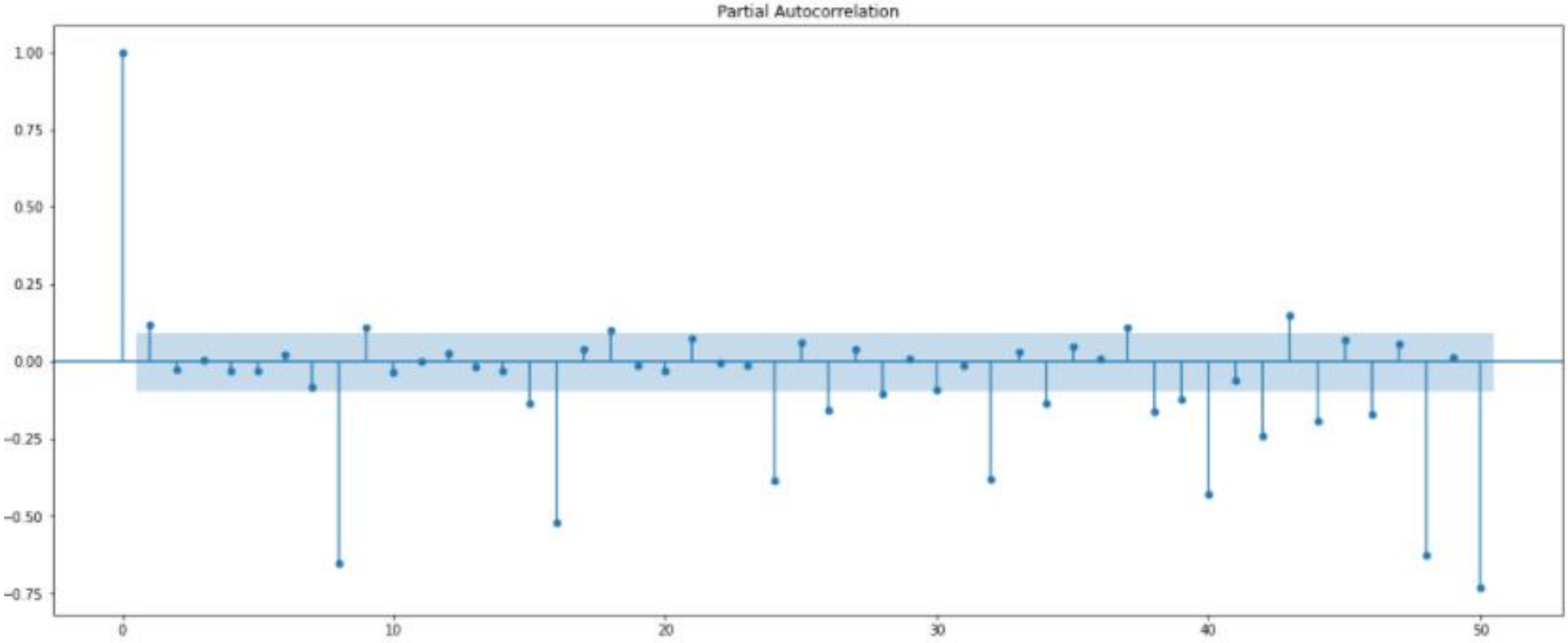
ACF Plots : Case Count - Before stationarity



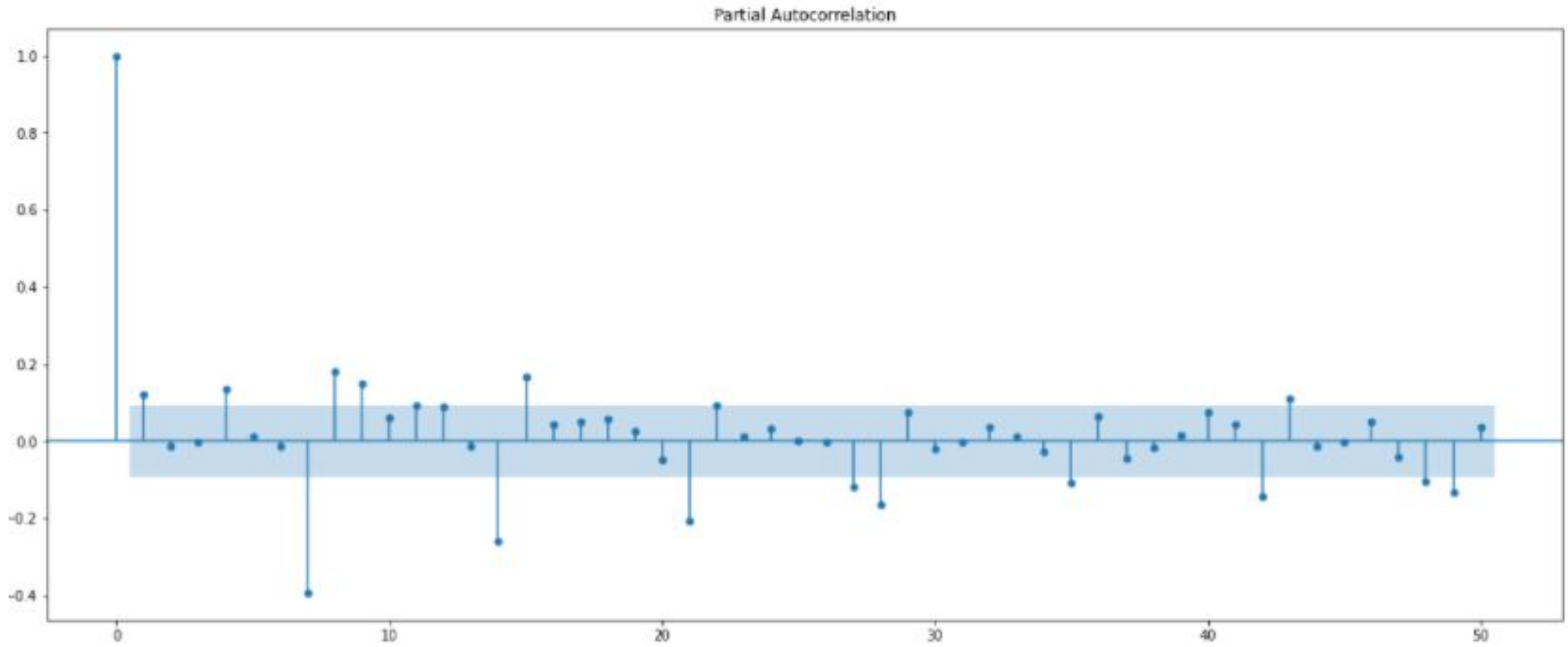
ACF Plots : Case Count - After stationarity



PACF Plots : Rent - After stationarity



PACF Plots : Case Count - After stationarity



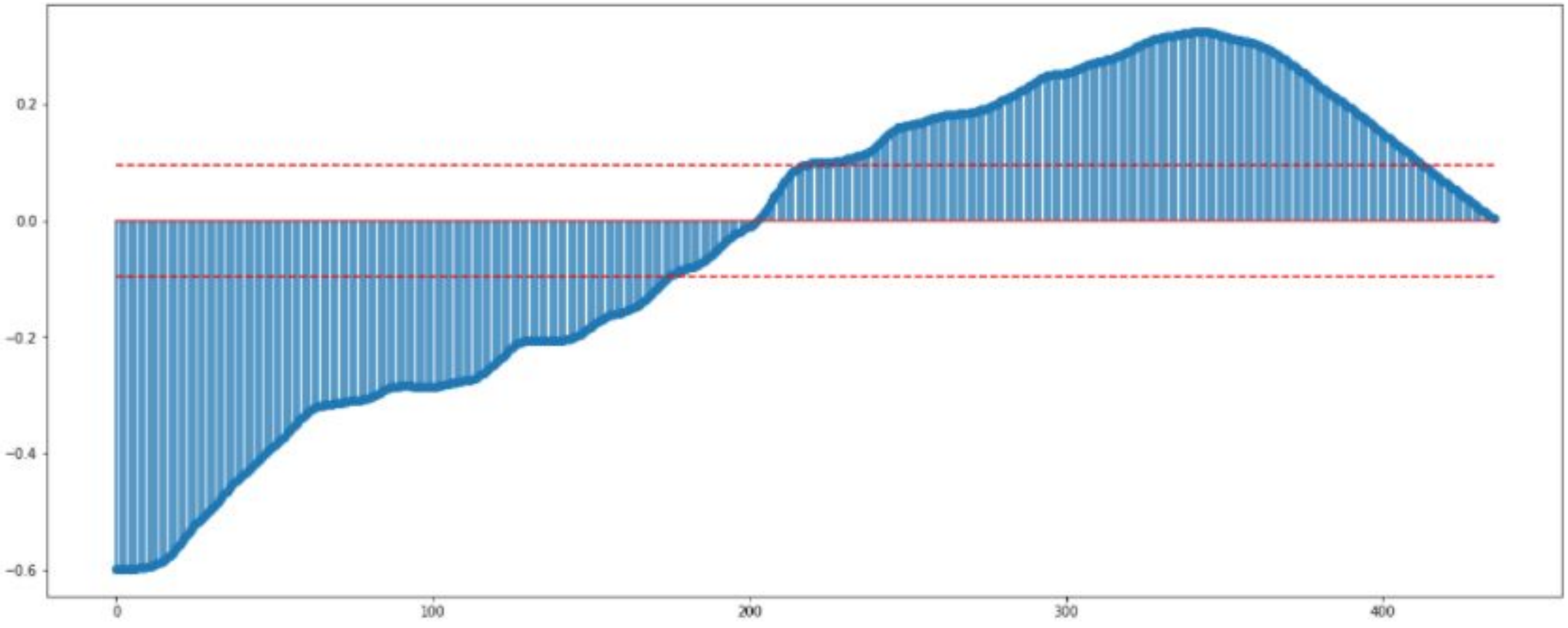
Cross Correlation / CCF

Cross-correlation is the degree of similarity between two time series in different times or space while lag can be considered when time is under investigation.

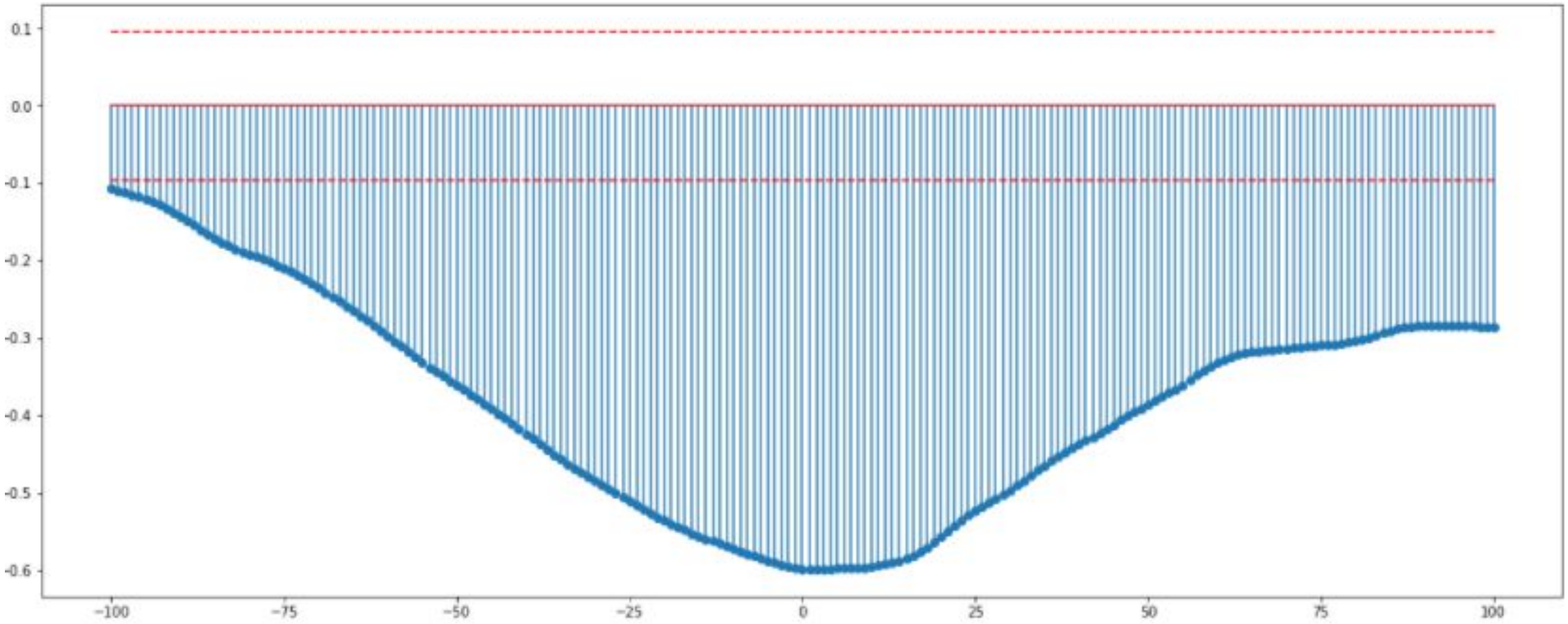
A negative value for h (lag) is a correlation between the x-variable at a time before t (the current time) and the y-variable at time t. if h = -2 then the ccf value would give the correlation between xt-2 and yt.

- When one or more x_{t+h} , with h *negative*, are predictors of y_t, it is sometimes said that ***x* leads *y***.
- When one or more x_{t+h}, with h *positive*, are predictors of y_t, it is sometimes said that ***x* lags *y***.

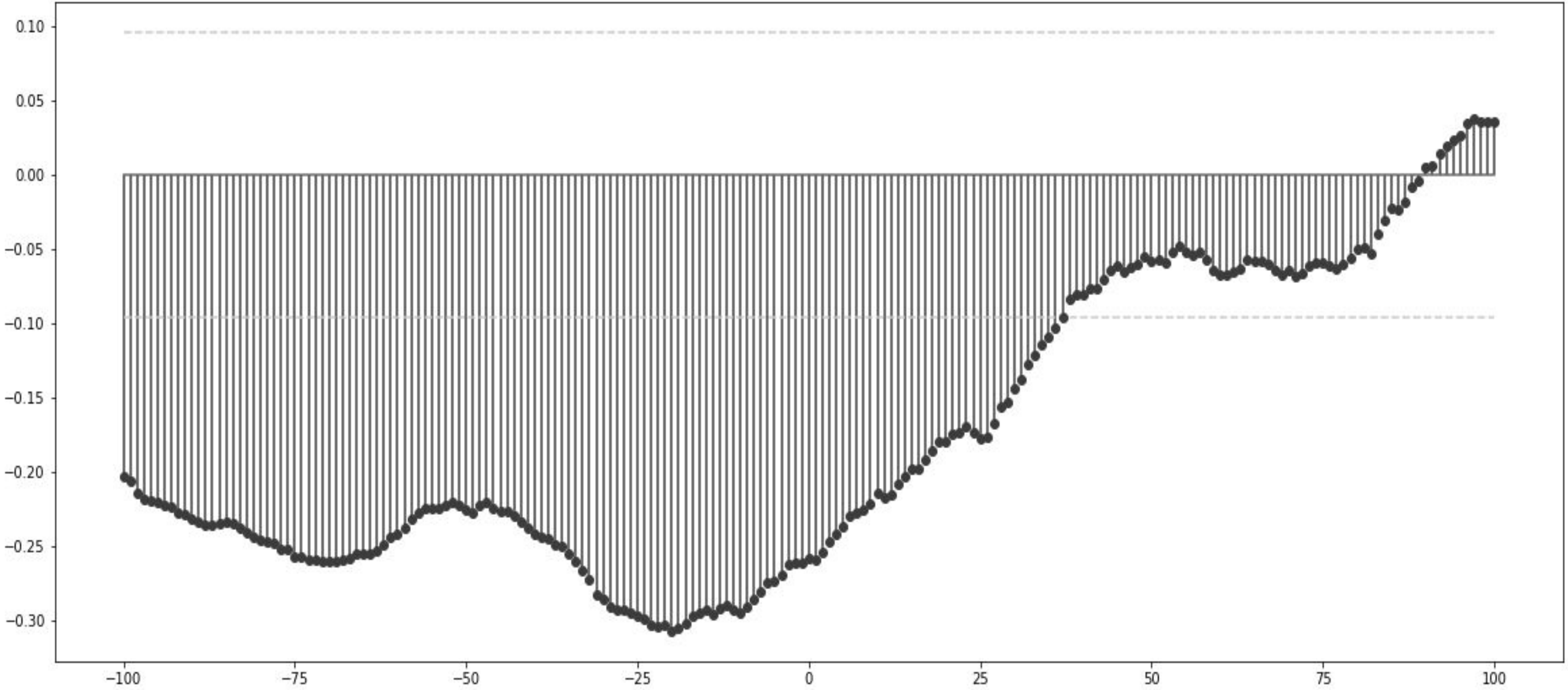
CCF Plots : Correlation of Rent Prices and Covid Cases



CCF Plots :With positive and negative lags



CCF Plots :With positive and negative lags- Case rate



Weird Correlations?- Can Rent prices cause Covid?

This is a key factor in understanding why correlations do not imply causation.

NYC average rents have been falling for a couple of years now and the pandemic's advent has only worsened this scenario.

Hence Statistically while there is correlation between them causation hasn't been proven yet.

NYC RENTAL MARKET REPORTS

NYC rental market's 'slow grind' keeps prices down

As long as luxury inventory stays high, prices are likely to continue dropping

By **Emily Nonko** | Jul 12, 2018, 9:21am EDT

Rents Are Down in Manhattan, But Up in Neighborhoods Hit Hardest by COVID-19

Yes, it's a good time to get a deal in Manhattan. But in areas hardest-hit by COVID-19, rents are actually going up.

By **Caroline Spivack** | Sep 11, 2020, 11:02am EDT

NYC Rents and Home Prices Continue to Fall, With No End in Sight

By Emily McDonald
Feb. 19, 2021

Stationarity checks

Differencing can help stabilize the mean of the time series by removing changes in the level of a time series, and so eliminating (or reducing) trend and seasonality.

Second order differencing was required to make both series stationary.

(a)Augmented Dickey Fuller test

The augmented Dickey-Fuller (ADF) test is a notable and plausible statistical test for stationary checking.

It can be utilized to decide on the existence of the unit root in a domain of the series, and in addition, it helps us to understand whether the time series is stationary.

P-value > 0.05 — **Fail to reject the null hypothesis(H0)**

- It indicate that data has unique roots and **time series is non-stationary.**

P-Value <= 0.05 — **Reject the null hypothesis(H0)**

- It indicates that data does not have unique roots and **time series is Stationary.**

(a)Augmented Dickey Fuller test - Before differencing

```
Results of Dickey-Fuller Test for column: Rent
Test Statistic                 -1.614051
p-value                         0.475849
No Lags Used                   18.000000
Number of Observations Used   417.000000
Critical Value (1%)            -3.446129
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
Data is non-stationary
Test Statistic                 -1.614051
p-value                         0.475849
No Lags Used                   18.000000
Number of Observations Used   417.000000
Critical Value (1%)            -3.446129
Critical Value (5%)            -2.868496
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
Data is non-stationary
Test Statistic                 -1.614051
p-value                         0.475849
No Lags Used                   18.000000
Number of Observations Used   417.000000
Critical Value (1%)            -3.446129
Critical Value (5%)            -2.868496
Critical Value (10%)           -2.570475
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
```

```
Results of Dickey-Fuller Test for column: case_count
Test Statistic                  1.627808
p-value                         0.997939
No Lags Used                   16.000000
Number of Observations Used   419.000000
Critical Value (1%)            -3.446054
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
Data is non-stationary
Test Statistic                  1.627808
p-value                         0.997939
No Lags Used                   16.000000
Number of Observations Used   419.000000
Critical Value (1%)            -3.446054
Critical Value (5%)            -2.868463
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
Data is non-stationary
Test Statistic                  1.627808
p-value                         0.997939
No Lags Used                   16.000000
Number of Observations Used   419.000000
Critical Value (1%)            -3.446054
Critical Value (5%)            -2.868463
Critical Value (10%)           -2.570458
dtype: float64
Conclusion:====>
Fail to reject the null hypothesis
```

(a)Augmented Dickey Fuller test - After differencing

```
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
Critical Value (5%)             -2.868463
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
Critical Value (5%)             -2.868463
Critical Value (10%)            -2.570458
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
```

```
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
Critical Value (5%)             -2.868463
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
Test Statistic                  -3.856129
p-value                          0.002383
No Lags Used                    14.000000
Number of Observations Used    419.000000
Critical Value (1%)             -3.446054
Critical Value (5%)             -2.868463
Critical Value (10%)            -2.570458
dtype: float64
Conclusion:====>
Reject the null hypothesis
Data is stationary
```

(b)KPSS test

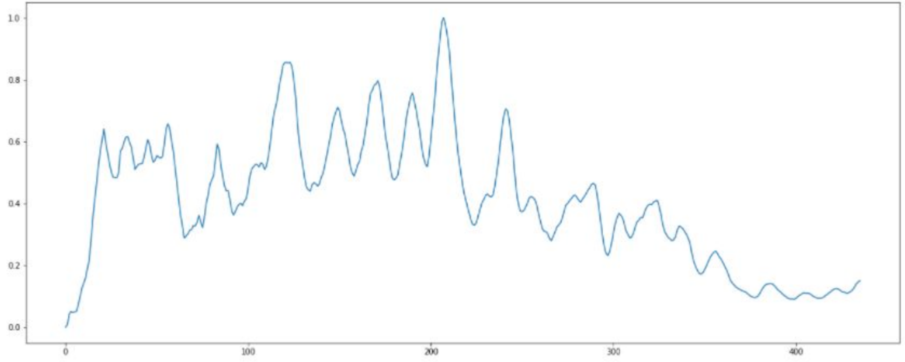
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are utilized to examine the null hypothesis that the time series is stationary around a conclusive trend (i.e., trend stationary) compared to the alternative of a unit root.

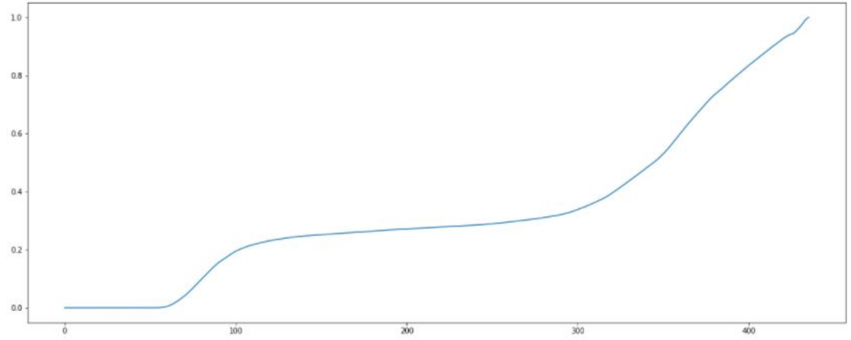
(b)KPSS test - Before & After differencing

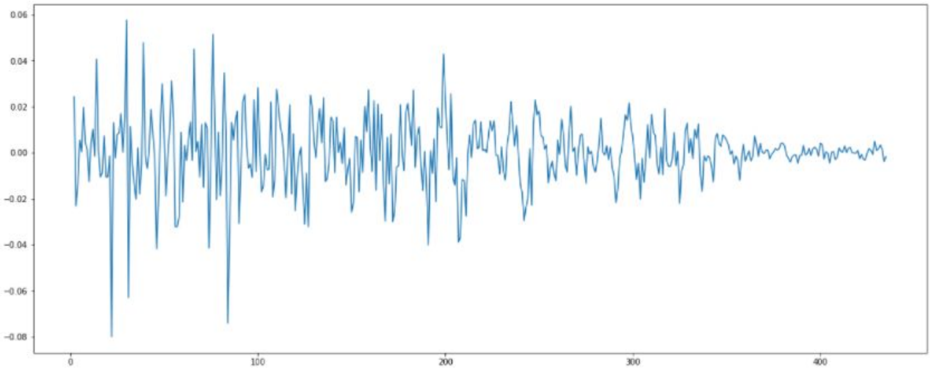
```
KPSS Statistic: 1.219741529479865
p-value: 0.01
num lags: 18
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is not stationary
KPSS Statistic: 2.025603182610288
p-value: 0.01
num lags: 18
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is not stationary
```

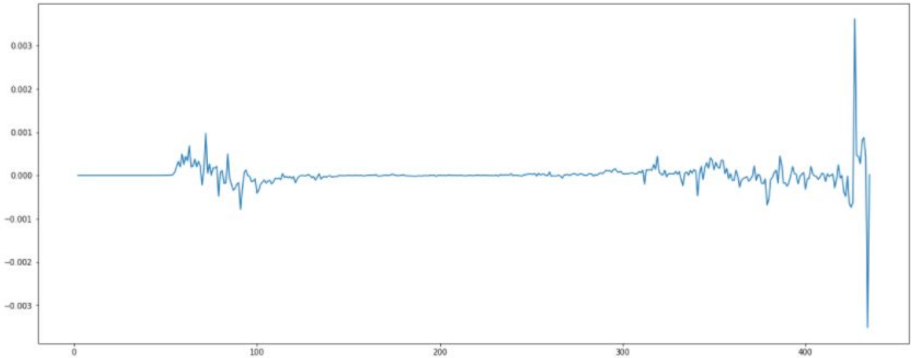
```
KPSS Statistic: 0.02376221234137097
p-value: 0.1
num lags: 18
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
KPSS Statistic: 0.06633185645150017
p-value: 0.1
num lags: 18
Critial Values:
   10% : 0.347
   5% : 0.463
   2.5% : 0.574
   1% : 0.739
Result: The series is stationary
```

Rent(left) & Cases(right)- Before & After stationarity

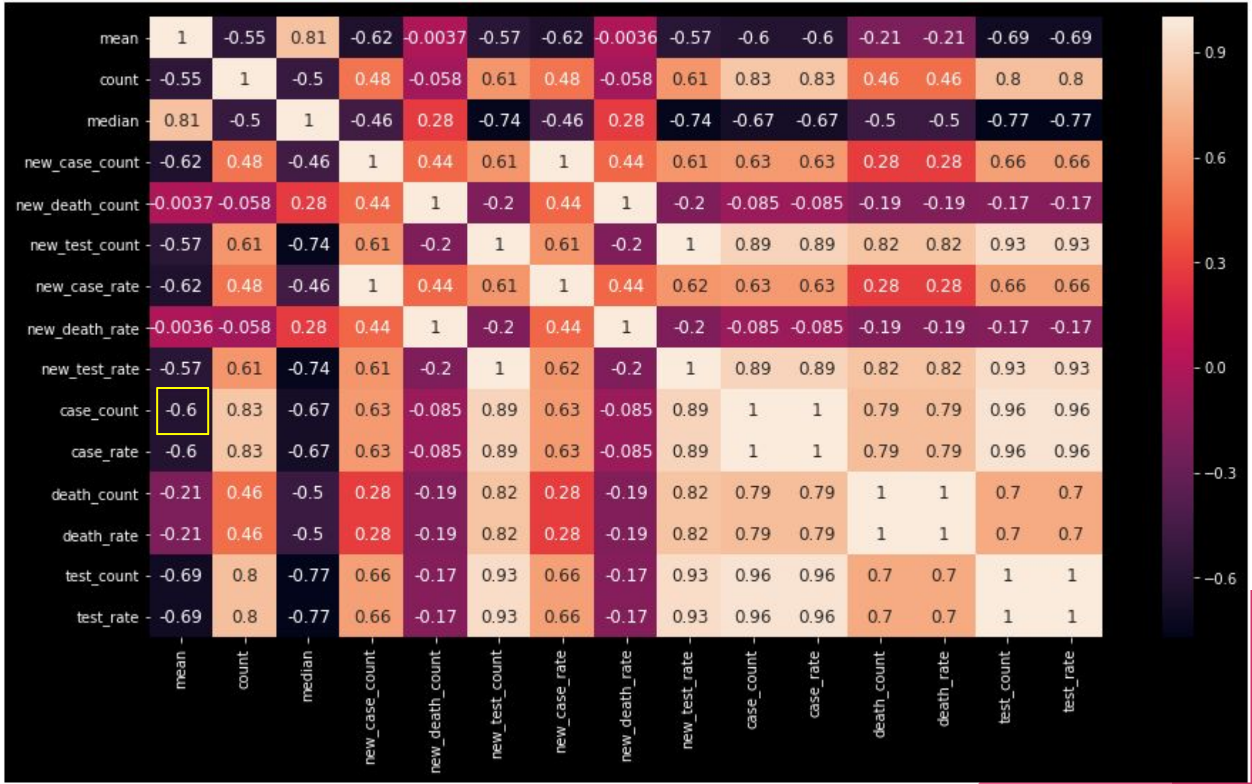








Pearson Correlation

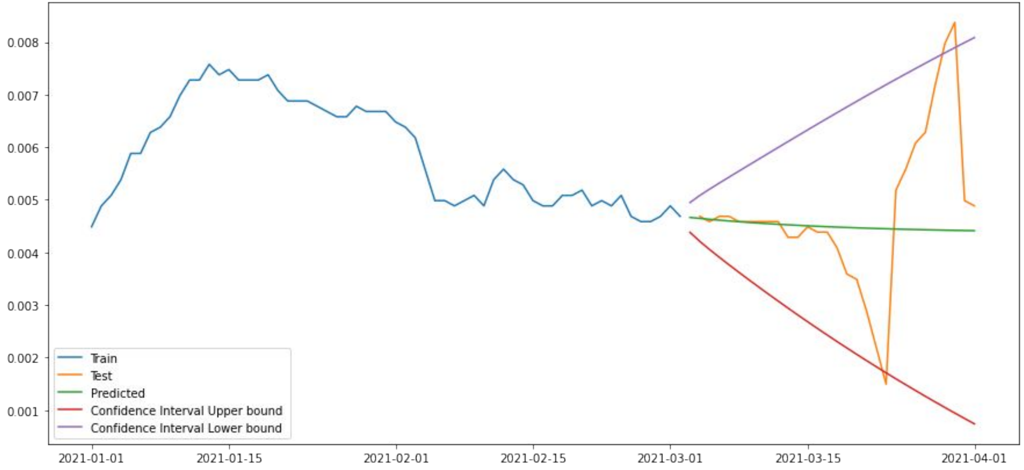


Phase 5: Modeling

Modeling Covid Case Rates using ARIMA

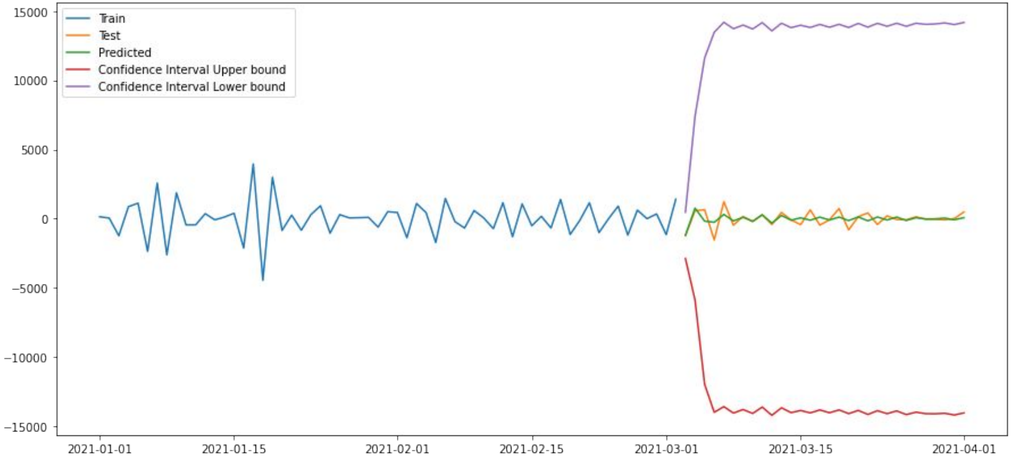
ARIMA stands for autoregressive integrated moving average and it is a statistical analysis model that uses time series data to better understand the data set or to predict future trends.

To model the rate of covid cases, we used the auto_arima model from the library pmdarima. This function allows us to optimize the parameters of ARIMA to minimize the AIC. In this case, the optimum parameters seems to ARIMA(1,1,2) which results in the following forecast:



Modeling Rent Prices using ARIMA

To model the movement of the mean rental prices in NYC, we used the auto_arima model again which in this case, the optimum parameters seems to ARIMA(20,0,0) which results in the following forecast:



Granger's causation

Granger causality it a statistical test for determining whether one time series can forecast another.

According to Granger causality, if a X1 "Granger-causes" (or "G-causes") a X2, then past values of X1 should contain information that helps predict X2 above and beyond the information contained in past values of X2 alone.

	mean_x	case_count_x
mean_y	1.0000	0.0065
case_count_y	0.0017	1.0000

Durbin Watson Statistic

Check for Serial Correlation of Residuals (Errors) using Durbin Watson Statistic
The value of this statistic can vary between 0 and 4.
The closer it is to the value 2, then there is no significant serial correlation.
The closer to 0, there is a positive serial correlation, and the closer it is to 4 implies negative serial correlation.

mean : 1.8
case_count : 2.12

Coint_johansen cointegration_test

A cointegration test is the co-movement among underlying variables over the long run. This long-run estimation feature distinguishes it from correlation. Two or more variables are cointegrated if and only if they share common trends.

```
Column Name > Test Stat > C(95%) => Signif
 ----------------------------------------
mean    >  113.73    > 12.3212   =>  True
case_count >  46.45     > 4.1296    =>  True
```

Vector Autoregressive Model (VAR)

Vector autoregression (VAR) is a statistical model used to capture the relationship between multiple quantities as they change over time.

VAR is a type of stochastic process model.

VAR models generalize the single-variable (univariate) autoregressive model by allowing for multivariate time series

Vector Autoregressive Model (VAR)

Choosing lag order using lowest AIC/BIC values
Metrics: AIC,BIC,FPE,HQIC

Why AIC?
The Akaike information criterion (AIC) is an estimator of prediction error and thereby relative quality of statistical models for a given set of data.Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection.

Lag Order = 9
AIC : -27.012106541998197
BIC : -26.630051642938422
FPE : 1.857185273229239e-12
HQIC: -26.86074812206476

Phase 6:
Evaluation & Results

Results of Running VAR on NYC data

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Tue, 04, May, 2021
Time:                     13:39:19
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                   -26.6301
Nobs:                     396.000    HQIC:                  -26.8607
Log likelihood:           4262.60    FPE:                1.85719e-12
AIC:                     -27.0121    Det(Omega_mle):     1.69102e-12
--------------------------------------------------------------------
```

```
Correlation matrix of residuals
                  mean  case_count
mean          1.000000   -0.042632
case_count   -0.042632    1.000000
```

```
Forecast accuracy of Rent
RMSE:   0.01
MAE:   0.11
```

```
Forecast accuracy of CASE_COUNT
RMSE:   0.85
MAE:   0.92
```

Results of Running VAR on Queens data

```
Forecast accuracy of case_count_covid
RMSE:  0.85
MAE:  0.92
```

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Wed, 05, May, 2021
Time:                     14:07:39
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                  -5.36230
Nobs:                     396.000    HQIC:                 -5.59299
Log likelihood:           51.5823    FPE:                0.00320128
AIC:                     -5.74435    Det(Omega_mle):     0.00291486
--------------------------------------------------------------------
```

Conclusion

Conclusion/Work going forward

We can safely predict the average rent prices in New york in tandem with the number of covid cases in the city. However going forward we have new variables such as vaccination rates which can interfere with the model.VAR allows us to even evaluate the relationship between all 3 when enough data is available for vaccination.

Also other models such as VECM or bleeding edge techniques like LSTMs could also be the way to go and thus more variables can be brought into the picture.

Alternatively we are also expanding upon the predictions boroughwise for New York which would give us more granular insights into the situation in each borough.

References

Del Giudice, V., De Paola, P., & Del Giudice, F. P. (2020). “*COVID-19 infects real Estate markets: Short And Mid-Run effects on housing prices in Campania Region (Italy)*”. *Social Sciences, 9*(7), 114.

Ling, Wang, Zhou., (2020). “*A First Look at the Impact of COVID-19 on Commercial Real Estate Prices: Asset-Level*”. *The Review of Asset Pricing Studies*, Volume 10, Issue 4, December 2020, Pages 669–704.

Blakeley, Grace., (January 2021).Financialization, Real Estate and COVID-19 in the UK. Community Development Journal Vol. 56, Iss. 1, 79-99.

“*Where are people moving to During COVID-19, in 2020 and beyond?*” (n.d.). Retrieved March 03, 2021, from https://www.hireahelper.com/moving-statistics/migration-report/

Appendix: VAR on NYC data

Results for equation mean

	coefficient	std. error	t-stat	prob
const	-0.000045	0.000803	-0.056	0.955
L1.mean	0.967966	0.043443	22.281	0.000
L1.case_count	-5.181653	4.956486	-1.045	0.296
L2.mean	-0.070850	0.057263	-1.237	0.216
L2.case_count	4.021303	8.199537	0.490	0.624
L3.mean	0.003125	0.057288	0.055	0.956
L3.case_count	-0.071264	7.898112	-0.009	0.993
L4.mean	-0.021027	0.056851	-0.370	0.711
L4.case_count	11.571922	7.863471	1.472	0.141
L5.mean	-0.014146	0.056935	-0.248	0.804
L5.case_count	-1.298983	7.826636	-0.166	0.868
L6.mean	0.028097	0.056899	0.494	0.621
L6.case_count	-18.417837	7.905096	-2.330	0.020
L7.mean	0.003356	0.056866	0.059	0.953
L7.case_count	13.266141	8.081841	1.641	0.101
L8.mean	-0.632071	0.056334	-11.220	0.000
L8.case_count	-14.390559	8.425666	-1.708	0.088
L9.mean	0.533365	0.042568	12.530	0.000
L9.case_count	10.526386	5.066653	2.078	0.038

Appendix: VAR on NYC data

Results for equation case_count

	coefficient	std. error	t-stat	prob
const	0.000015	0.000008	1.904	0.057
L1.mean	-0.000180	0.000428	-0.420	0.674
L1.case_count	1.461899	0.048850	29.926	0.000
L2.mean	0.000656	0.000564	1.162	0.245
L2.case_count	-0.522169	0.080813	-6.461	0.000
L3.mean	-0.001408	0.000565	-2.494	0.013
L3.case_count	0.254461	0.077842	3.269	0.001
L4.mean	0.000687	0.000560	1.226	0.220
L4.case_count	-0.084218	0.077501	-1.087	0.277
L5.mean	-0.000215	0.000561	-0.384	0.701
L5.case_count	-0.213434	0.077138	-2.767	0.006
L6.mean	0.000554	0.000561	0.988	0.323
L6.case_count	0.346831	0.077911	4.452	0.000
L7.mean	-0.000266	0.000560	-0.475	0.635
L7.case_count	-0.702033	0.079653	-8.814	0.000
L8.mean	0.000458	0.000555	0.825	0.409
L8.case_count	0.783270	0.083042	9.432	0.000
L9.mean	-0.000944	0.000420	-2.250	0.024
L9.case_count	-0.330135	0.049936	-6.611	0.000

Appendix: VAR on Queens data

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Wed, 05, May, 2021
Time:                     14:07:39
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                   -5.36230
Nobs:                     396.000    HQIC:                  -5.59299
Log likelihood:           51.5823    FPE:                 0.00320128
AIC:                     -5.74435    Det(Omega_mle):      0.00291486
--------------------------------------------------------------------
Results for equation y1
========================================================================
           coefficient       std. error           t-stat            prob
------------------------------------------------------------------------
const         0.000014         0.000008            1.707           0.088
L1.y1         1.467119         0.049146           29.852           0.000
L1.y2        -0.000000         0.000000           -0.257           0.797
L2.y1        -0.529580         0.081703           -6.482           0.000
L2.y2        -0.000000         0.000000           -0.491           0.624
L3.y1         0.265672         0.078380            3.390           0.001
L3.y2        -0.000000         0.000000           -0.808           0.419
L4.y1        -0.086693         0.077902           -1.113           0.266
L4.y2        -0.000000         0.000000           -0.697           0.486
L5.y1        -0.215655         0.077412           -2.786           0.005
L5.y2         0.000000         0.000000            0.261           0.794
L6.y1         0.356812         0.078302            4.557           0.000
L6.y2        -0.000000         0.000000           -0.456           0.648
L7.y1        -0.714599         0.079707           -8.965           0.000
L7.y2         0.000000         0.000000            1.165           0.244
L8.y1         0.755366         0.083218            9.077           0.000
L8.y2         0.000000         0.000000            0.021           0.983
L9.y1        -0.303376         0.050062           -6.060           0.000
L9.y2         0.000000         0.000000            0.331           0.740
========================================================================
```

```
Results for equation y2
========================================================================
             coefficient       std. error           t-stat            prob
------------------------------------------------------------------------
const           9.699571        32.751762            0.296           0.767
L1.y1        2916.552025    201464.994687            0.014           0.988
L1.y2          -0.260590         0.051514           -5.059           0.000
L2.y1      -81972.605594    334923.936818           -0.245           0.807
L2.y2          -0.438690         0.052859           -8.299           0.000
L3.y1      261894.415339    321302.433734            0.815           0.415
L3.y2          -0.284405         0.057132           -4.978           0.000
L4.y1      -63038.557361    319340.747439           -0.197           0.844
L4.y2          -0.344762         0.057884           -5.956           0.000
L5.y1     -105376.256593    317331.547892           -0.332           0.740
L5.y2          -0.285369         0.058629           -4.867           0.000
L6.y1      -30697.048586    320980.161701           -0.096           0.924
L6.y2          -0.219724         0.057724           -3.806           0.000
L7.y1     -189065.727826    326741.956506           -0.579           0.563
L7.y2          -0.109513         0.056684           -1.932           0.053
L8.y1      228205.791752    341134.446754            0.669           0.504
L8.y2          -0.113569         0.051885           -2.189           0.029
L9.y1      -25762.205689    205216.926834           -0.126           0.900
L9.y2          -0.007167         0.050322           -0.142           0.887
========================================================================

Correlation matrix of residuals
            y1        y2
y1    1.000000  0.018654
y2    0.018654  1.000000
```