Time series forecasting for Brooklyn, NY rental prices using SARIMA and Holt-Winters methods

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1. Introduction

Brooklyn, NY has become an increasingly popular rental area over the past decade. Rents in some Brooklyn neighborhoods are nearing or exceeding those in Manhattan [1]. Rising rents impact families and low-income New Yorkers. StreetEasy, a New York City real estate site, has produced a number of studies on affordability of housing in New York. Rents for NYC listed on StreetEasy have increased by 31% overall between January 2010 and January 2018 [2] with some Brooklyn neighborhoods growing over 40% [3]. Without considering the implications of COVID-19, I've generated two models, seasonal ARIMA and seasonal Holt-Winters, to forecast the median rental prices in Brooklyn, NY into the first half of 2021.

2. Data set

StreetEasy captured the median rental prices in NYC from January 2010 to March 2020 [4]. Initially, I included all rental types and boroughs in the data set. After taking steps to clean the data (see Appendix.1), I narrowed the analysis to two bedrooms in Brooklyn. Fig.1 gives a sense for the raw and cleaned data.

Fig.1 (a) raw data all rental types and boroughs from StreetEasy

RentalType <chr>	areaName <fctr>	Borough <fctr>	areaType <fctr>	X2010.01 <dbl>	X2010.02 <dbl>	X2010.03 <dbl>	X2010.04 <dbl>	X2010.05 <dbl>	X2010.06 <dbl>
Studio	Brooklyn Heights	Brooklyn	neighborhood	1925	1900	1700	1725	1675	1675
OneBd	Brooklyn Heights	Brooklyn	neighborhood	2000	1950	1850	1863	2200	2200
TwoBd	Brooklyn Heights	Brooklyn	neighborhood	3850	3900	5500	4000	4000	4400
ThreePlusBd	Brooklyn Heights	Brooklyn	neighborhood	NA	NA	6250	NA	NA	6250
OneBd	Brookville	Queens	neighborhood	NA	NA	NA	NA	NA	NA
Studio	Brookville	Queens	neighborhood	NA	NA	NA	NA	NA	NA
ThreePlusBd	Brookville	Queens	neighborhood	NA	NA	NA	NA	NA	NA
TwoBd	Brookville	Queens	neighborhood	NA	NA	NA	NA	NA	NA
TwoBd	Brownsville	Brooklyn	neighborhood	NA	NA	NA	NA	NA	NA
OneBd	Brownsville	Brooklyn	neighborhood	NA	NA	NA	NA	NA	NA

Fig.1 (b) cleaned data 2bd Brooklyn data

Rental_Value <dbl>	date <date>
2544	2010-01-01
2539	2010-02-01
2520	2010-03-01
2459	2010-04-01
2538	2010-05-01
2600	2010-06-01

3. Results

3.1 Visualize, evaluate pattern of the data

From the plot of the time series data (see Fig. 2), the data does not appear stationary. There is a logarithmic trend with an upward swing around 2018 and potential seasonality. To confirm trend and seasonality, I plotted a classical decomposition chart (see Fig. 3) and performed a Dickey-Fuller test (see Appendix.2) to check for a drift in the mean of the data (unit root). From the classical decomposition, there is a clear trend and seasonal pattern to the data and because the data is monthly the seasonal period is 12. The Dickey-Fuller test produced a p-value of 0.5892, so I did not reject the null hypothesis that the time series is non-stationary.

Fig. 2

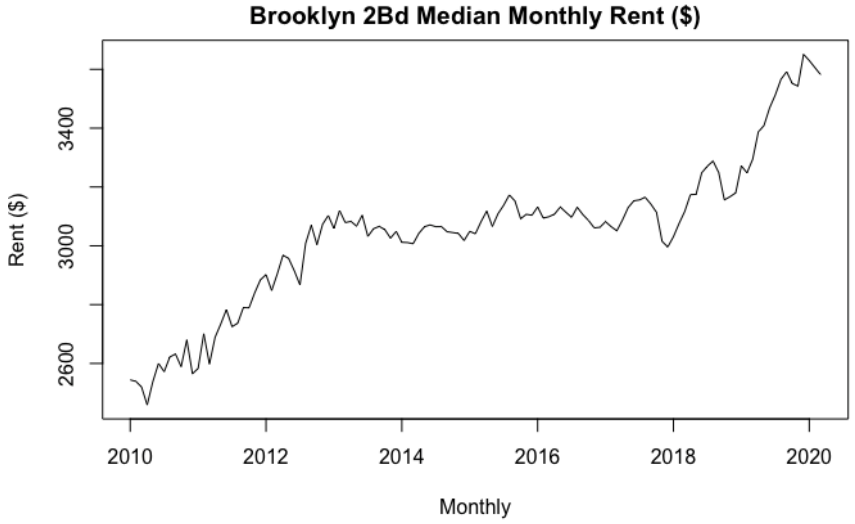
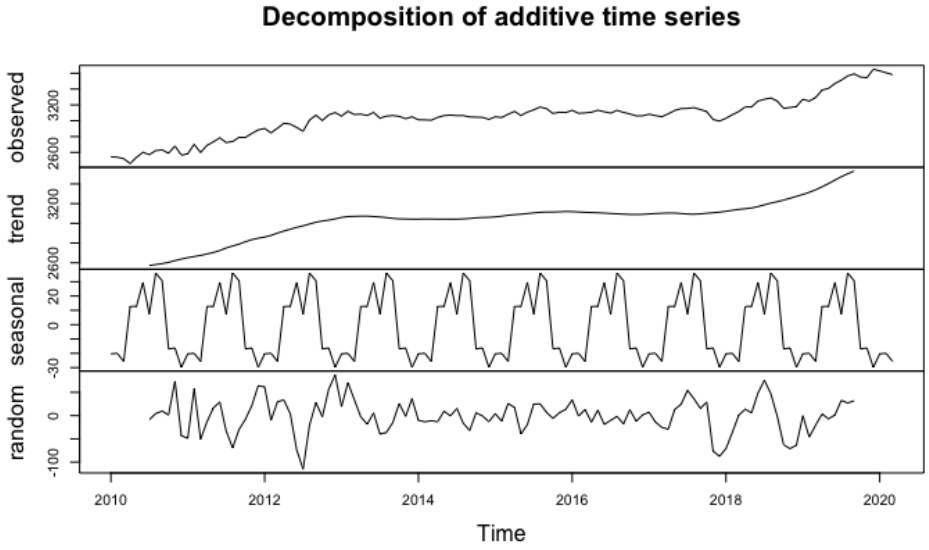


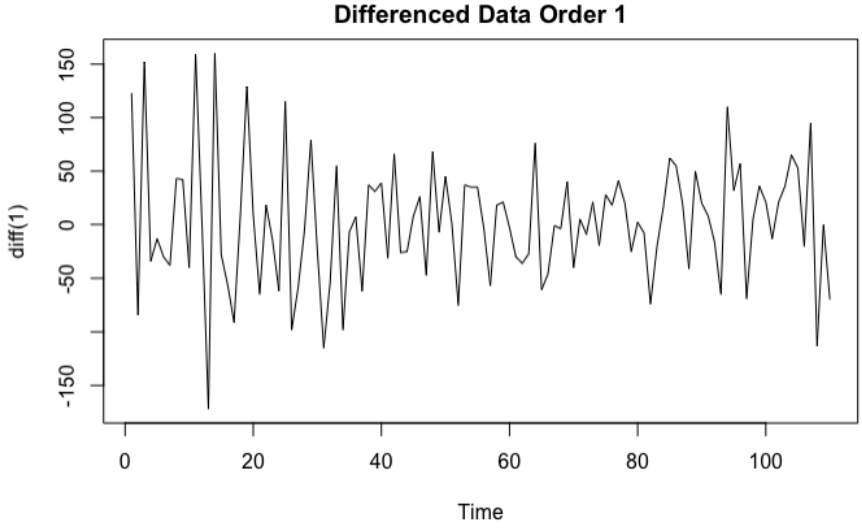
Fig. 3



3.2 Transformations

To correct for seasonality (deterministic part) and unit root, I applied a difference of order 1 and order 12 (see Fig. 4). A variance stabilizing transformation was not needed. The p-value after rerunning the Dickey-Fuller test was 0.01 indicating stationarity (see Appendix.3).

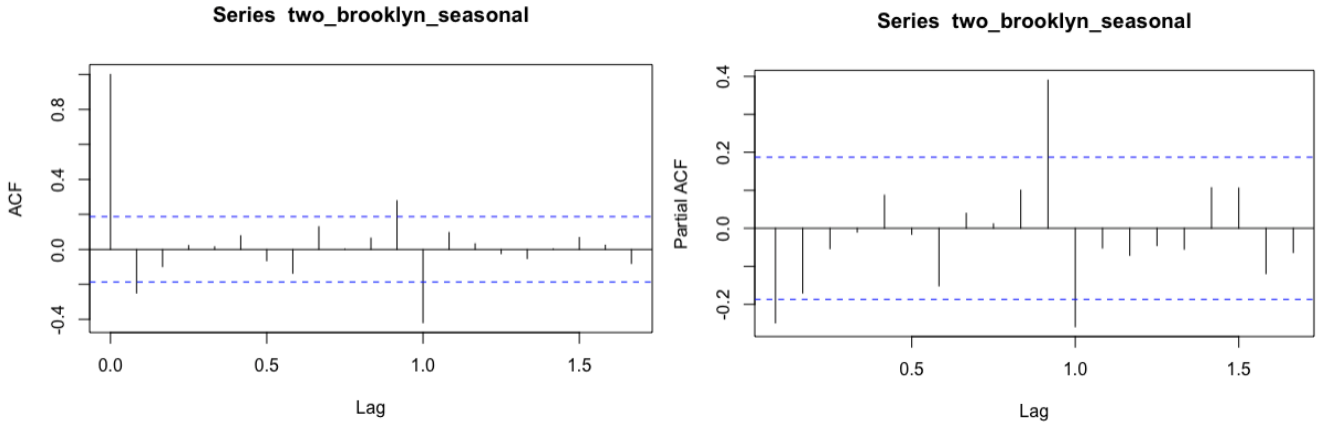
Fig. 4



3.3 Model-based Forecast: ARIMA

To forecast future values of the time series, I used a seasonal ARIMA model. The model-based approach fits an ARIMA model to data to then forecast. From the ACF and PACF plots (see Fig. 5), it seems reasonable to consider a low order ARMA model. The PACF cuts off near lag 2 decaying to 0 and the ACF cuts off after lag 2 decaying to 0. However, although there is an early cutoff, the lag significance returns around month 12 and this periodic pattern is a characteristic of seasonality with period 12 (stochastic part). This confirms what was observed in the seasonal component from Fig.3.

Fig. 5

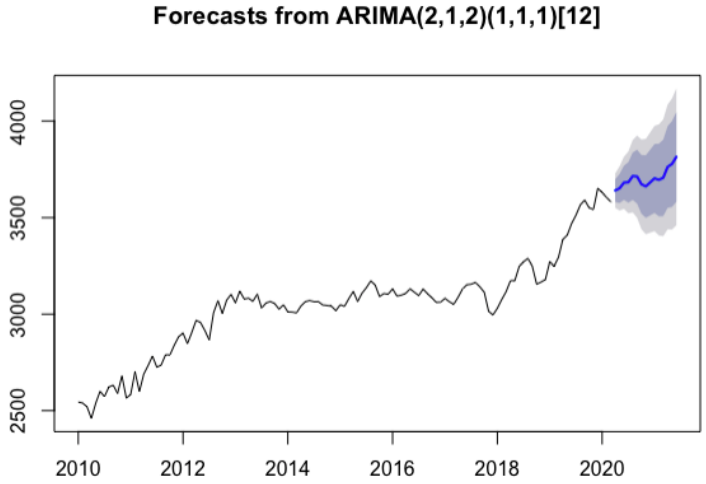


For the initial model, I chose an ARMA (2,1,2) x SARMA $(1,1,1)_{12}$ model. First, for the non-seasonal ARMA(p,d,q) model, there is a decaying pattern in the ACF and PACF. Second, for the seasonal ARMA(P,D,Q) model, there is strong autocorrelation and strong partial autocorrelation around lag 12 and both cutoff decaying to 0. Because there are multiple interpretations to take, I generated six additional variations and compared performance. Although the different models had roughly comparable AICc values (see Table.1), the initial model had the smallest and that was the model that was used for forecasting the time series (see Fig. 6).

Table.1 AICc values per ARIMA model

Model	AICc
(2,1,2) x (1,1,1)[12]	1170.18 **
(2,1,2) x (0,1,1)[12]	1173.43
(2,1,1) x (0,1,1)[12]	1171.84
(2,1,0) x (0,1,1)[12]	1170.62
(1,1,0) x (1,1,1)[12]	1172.49
(2,1,1) x (1,1,1)[12]	1174.23
(1,1,1) x (0,1,1)[12]	1171.8

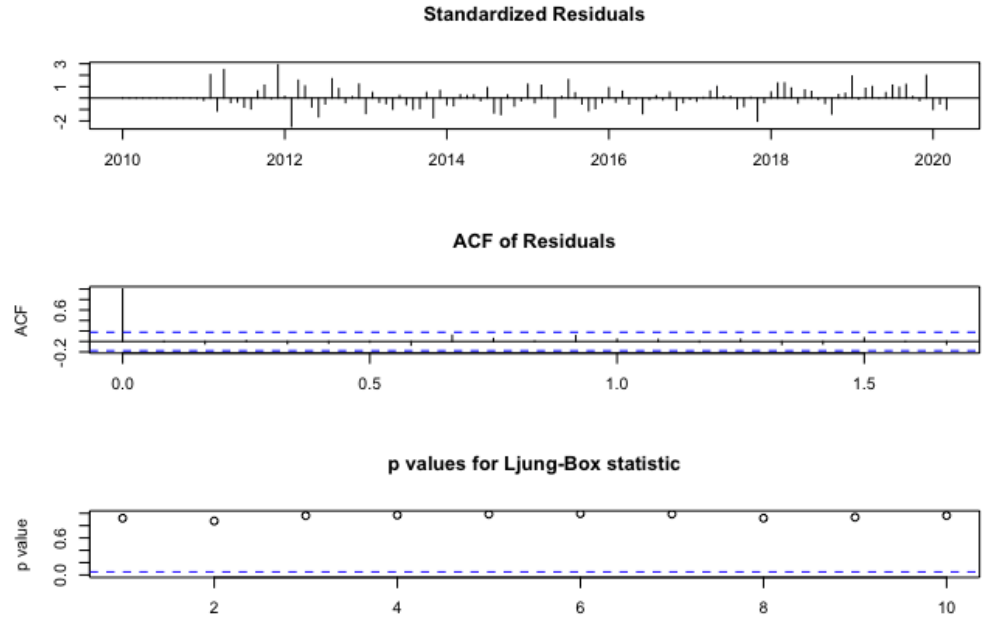
Fig.6



3.4 Model Diagnostics

The ARMA (2,1,2) x SARMA $(1,1,1)_{12}$ model had the lowest AICc value, the Q-Q plot shows that the data is coming from a normal population (see Appendix.4), and diagnostic plots indicate that the ACF of the residuals and p-values are not significant, so the model is adequate (see Fig. 7).

Fig. 7 model diagnostics

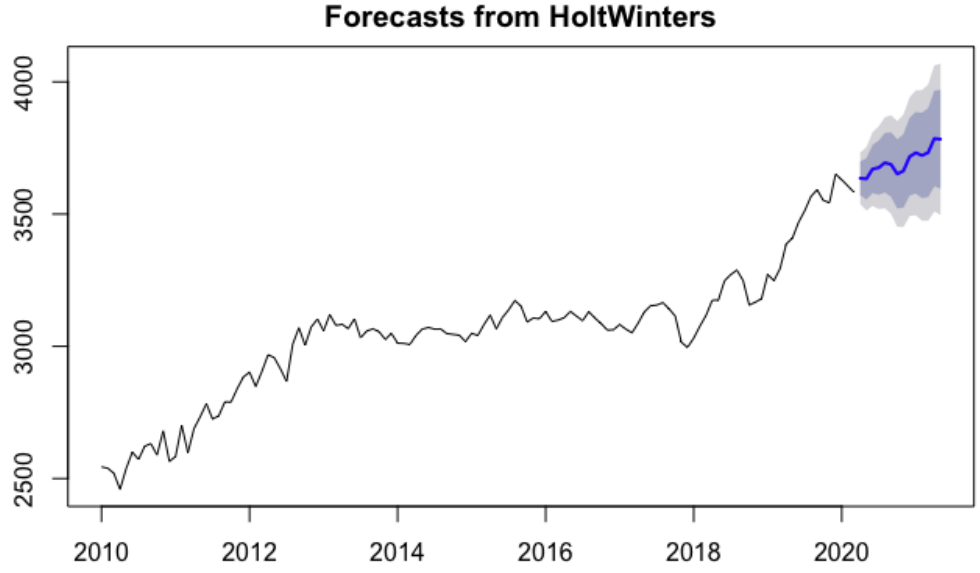


The majority of the model parameters were also significant. Of the 6 parameters in the model, 4 non-seasonal AR(2) MA(2) and 2 seasonal SAR (1) SMA(1), 4 seasonal parameters were significant while only the seasonal SMA(1) was significant (see Appendix.5). Taking out the non-significant SAR(1) parameter in the ARMA (2,2) x SARMA $(0,1)_{12}$ model did not improve the AICc value (see Table.1).

3.5 Smoothing-based Forecast: Holt-Winters

Another widely used and successful forecasting method is the seasonal Holt-Winters method. The smoothing-based method uses the pattern of the data to extrapolate the forecast using double exponential smoothing. I performed the additive version as the seasonal pattern remained roughly the same for the range of the data. The forecast looks reasonable (see Fig. 8).

Fig. 8 Holt-Winters forecast of 2bd Brooklyn



3.6 Evaluation of Forecast Accuracy

Both the seasonal ARIMA and seasonal Holt-Winters models look reasonable, but forecast accuracy is an important aspect in determining an appropriate model. To judge forecast accuracy, I used an out-of-sample forecast validation to compare the two methods. My validation sample size was about 11% of the total sample size or the 14 most recent observations. With seasonal data, it is important to hold back enough of the seasonality in the test sample.

I used the root mean square error (RMSE), Mean Absolute Error (MAE), and Mean absolute Percentage Error (MAPE) measures to evaluate the forecast. After running the metrics, the seasonal ARIMA model performed better than the seasonal Holt-Winters (see Table.2).

Table.2

	Holt-Winters	SARIMA (2,1,2) x (1,1,1)[12]
MAE	209.729741	192.759418
RMSE	232.326900	218.947107
MAPE	5.895694	5.609597

4. Conclusions

The purpose of this time series analysis was to forecast the rental prices of Brooklyn NY into the first half of 2021. I used the seasonal ARIMA and seasonal Holt-Winters models for forecasting rent from April 2020 to June 2021 (see Appendix.6). Then, I chose the suitable forecasting method by considering the AICc values among the ARIMA models and RMSE, MAE, and MAPE when comparing against the Holt-Winters method. The results showed that the seasonal ARIMA model can represent a suitable forecasting method for rental prices. This model can be extended to the other boroughs of New York City. For future analysis, it would also be interesting to include an intervention methodology anticipating some threshold of COVID-19 impact on NY rents as new rental listings fell 52% in the second half of March [5].

REFERENCES:

[1] https://streeteasy.com/blog/february-2020-market-reports/
[2] https://furmancenter.org/research/sonychan
[3] https://streeteasy.com/blog/nyc-rent-affordability-2018/#_ftn1
[4] https://streeteasy.com/blog/data-dashboard/
[5] https://streeteasy.com/blog/q1-2020-market-reports/

APPENDIX

[1] A few steps were taken to clean the raw data in Fig.1 for analysis.

a. Rows were removed where there were more than 3 consecutive NA values and remaining NAs replaced with last-observation-carried-forward method. This is a common approach when accounting for NAs.
b. In order to structure the data to perform time series analysis, I converted the column headers (example X2010.01) into date values. I then transformed the data into a single record per year per month by rental type and borough.

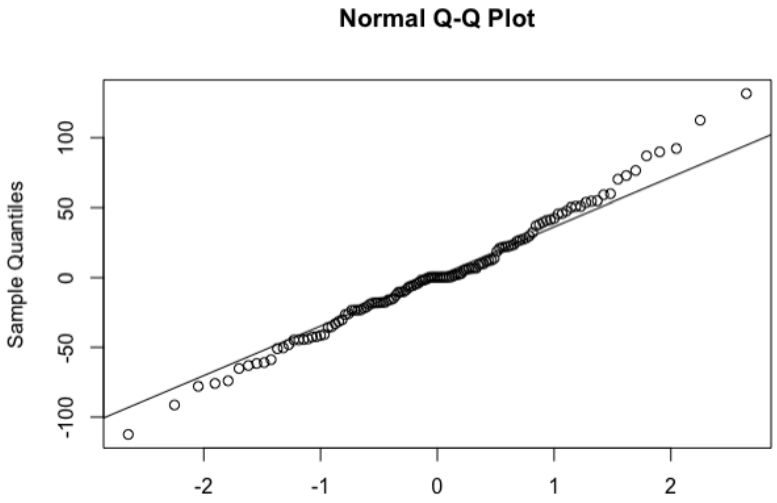
[2]

```
        Augmented Dickey-Fuller Test

data:  two_brooklyn
Dickey-Fuller = -1.9696, Lag order = 4, p-value = 0.5892
alternative hypothesis: stationary
```

[3]

```
        Augmented Dickey-Fuller Test

data:  two_brooklyn_diff
Dickey-Fuller = -4.914, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

[4]



[5] ARMA (2,1,2) x SARMA $(1,1,1)_{12}$ estimated parameter values

```
Series: two_brooklyn
ARIMA(2,1,2)(1,1,1)[12]

Coefficients:
         ar1      ar2      ma1     ma2     sar1     sma1
      0.9948  -0.7755  -1.1877  0.9678  -0.0523  -0.7166
s.e.  0.0924   0.0989   0.0518  0.0666   0.1643   0.1425

sigma^2 estimated as 2043:  log likelihood=-577.54
AIC=1169.09   AICc=1170.18   BIC=1187.99
```

[6] ARMA (2,1,2) x SARMA $(1,1,1)_{12}$ forecasted values

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
Apr 2020	3639.790	3581.821	3697.759	3551.134	3728.446
May 2020	3651.107	3576.590	3725.624	3537.143	3765.071
Jun 2020	3680.681	3592.674	3768.687	3546.087	3815.275
Jul 2020	3682.313	3578.286	3786.340	3523.217	3841.409
Aug 2020	3714.537	3592.362	3836.711	3527.687	3901.387
Sep 2020	3712.716	3573.890	3851.542	3500.399	3925.032
Oct 2020	3672.517	3520.841	3824.194	3440.548	3904.487
Nov 2020	3661.084	3499.792	3822.376	3414.410	3907.759
Dec 2020	3681.695	3512.108	3851.282	3422.334	3941.055
Jan 2021	3702.837	3524.625	3881.050	3430.285	3975.390
Feb 2021	3695.091	3507.347	3882.836	3407.961	3982.222
Mar 2021	3706.181	3508.629	3903.733	3404.052	4008.311
Apr 2021	3762.470	3551.525	3973.415	3439.857	4085.083
May 2021	3777.612	3555.794	3999.430	3438.371	4116.853
Jun 2021	3814.621	3583.038	4046.203	3460.446	4168.795