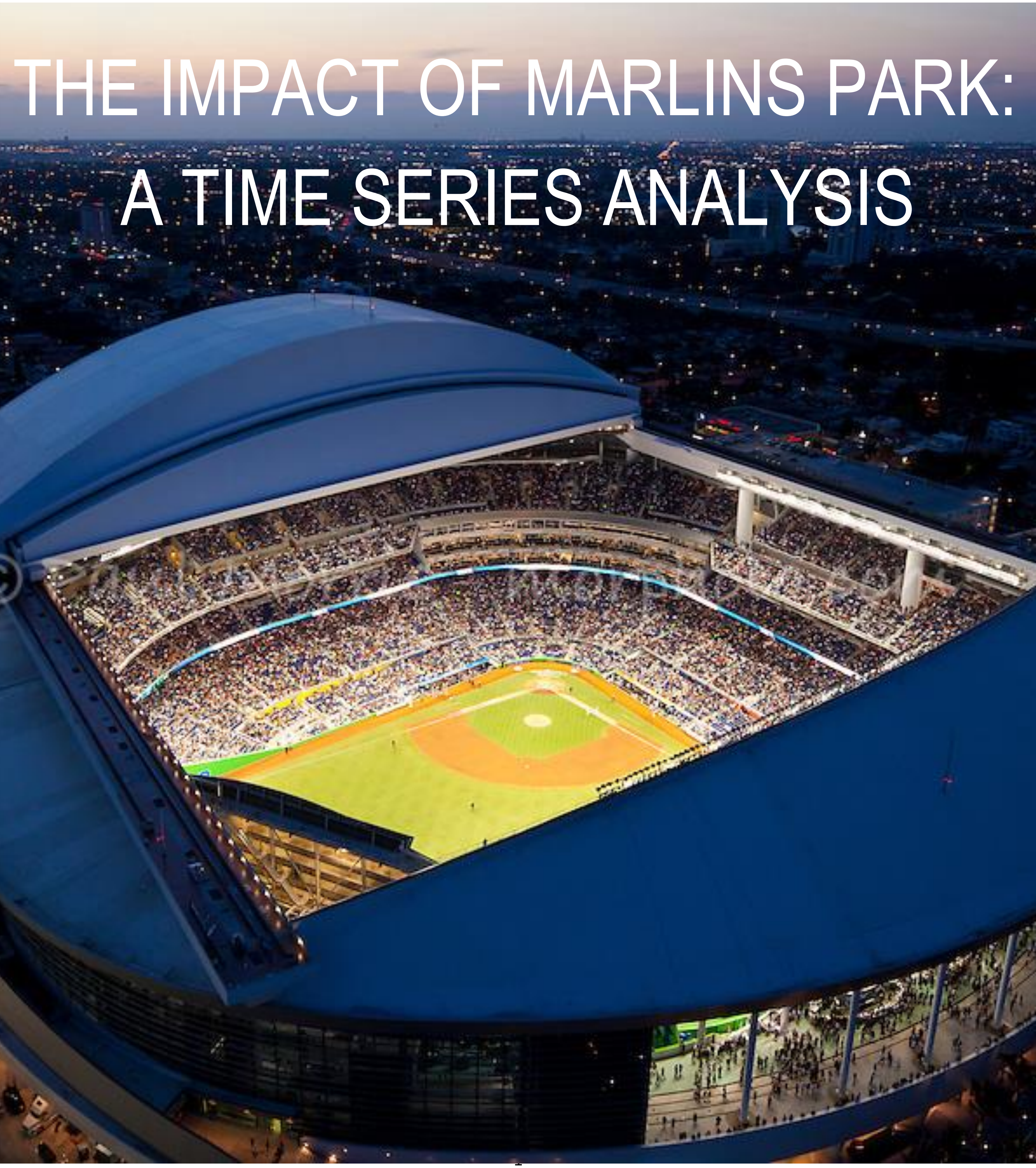
THE IMPACT OF MARLINS PARK: A TIME SERIES ANALYSIS



Abstract

This research investigates the impact of new stadium construction on local real estate prices. This case study will use the intervention of Marlins Park construction in Miami, FL on real estate prices in the immediate area surrounding the stadium and the city at large. The objective of the research is to better understand how cities can leverage ballpark planning, construction, and operations as anchor investments for redevelopment. Ballparks can be catalysts for ancillary development in the areas adjacent to the stadium, including commercial and retail properties. The outcome of this study is to uncover the highest and best use of the surrounding land. The next step would be to arrive at best building program for the development around Marlins Park based on market-driven insight. Ultimately, this method of research can be replicated and used to estimate the impact of similar construction projects, regardless of location or era.

EXECUTIVE SUMMARY

Preface

The purpose of this study is to quantify the impact of the one-time construction and long-term operation of a stadium, arena, or ballpark on the economic well-being of its' surrounding community. As part of an overall cost-benefit analysis, this study helps identify areas of opportunity for a team owner, ownership group, or municipality interested in a new venue. Venues can act as catalysts for development within a given region. They can anchor a community with regular visitors and inject energy and enthusiasm into areas that need it most.

Stadiums, arenas, and ballparks provide an overall social net benefit to the local community by offering entertainment and quality-of-life improvements for residents and visitors alike. When a venue's construction is included into diligent city/municipal planning, they can have remarkable economic benefits to the region by supporting many industries with additional jobs and increased earnings. The economic benefits can be categorized into impacts during construction and impacts resulting from the venue's continued operation. Stadium construction offers a large injection of spending to a region immediately while stadium operations have the potential to impact the region over time.

The objective of this analysis will be to inform a potential developer of the highest and best usage of the land surrounding a venue based on market-driven demand for leasable space. The results of this case study can be utilized in a final recommendation to achieve the optimal building program of the stadium's ancillary development. To uncover the optimal building program, the outcomes must align with the true mission and purpose driving a developer to invest in the land surrounding the stadium.

Developing the right mix of real estate includes properties that garner higher lease rates and therefore can achieve the quickest return on investment. Higher lease rates are attractive to developers because they positively affect their debt capacity, or their capacity to borrow funds for project. Retiring the debt service at a quicker rate allows a developer to maximize their return on investment and move onto their next project.

This case study will provide insight into the long-run impacts of stadium construction and operations on retail and office lease rates in the immediate area surrounding the stadium compared to impacts to the city of Miami.

Introduction

The case study of Marlins Park in Miami Florida…

The Florida Marlins were a Major League Baseball expansion team in 1993. When they first began play, they were named the Florida Marlins and they originally shared their stadium with the Miami Dolphins of the National Football League. After sharing their stadium for almost a decade they decided to renovate the Orange Bowl stadium in downtown Miami and later became the "Miami Marlins". The Marlins and the city of Miami agreed to develop the stadium together with the City funding $500 Million and the team contributing $134 million. After demolishing the old Orange Bowl stadium, the city broke ground on the new Marlins Park in July of 2009. Construction of Marlins Park took 32 months and Marlins Park opened in March of 2012, just in time for Opening Day 2012. The Marlins report the construction of ballpark cost $634 Million (in 2012 dollars)

One of the major features of the ballpark is the retractable roof. Not only adding to the stadium's aesthetics but also providing a covered option during inclement weather. Figure 1 below shows several images of the ballpark's features, aesthetics, and game-day operations while Table 1.0 provides general project details.

Figure 1: Marlins Park interior, exterior, and design considerations

Table 1.0 Marlins Park Details

	Construction		Cost	Funding / Financing	
	Broke Ground	Opened	($MM)	Public	Private
Marlins Park	July, 2009	March, 2012	$634	$500	$134

Table 1: Aerial view of Miami including Marlins Park

METHODOLOGY

In order to quantify the impacts of Marlins Park on retail and office lease rates in both the surrounding area and Miami in general, the scope of the analysis must be defined. The two defined areas for this study will be city limits of Miami, FL and a 1-mile radius ring surrounding Marlins Park. The impact effect on lease rates for the 1-mile radius and the City of Miami will be quantified using time series analysis techniques to evaluate historical retail and office lease rate values ranging from 1999 – 2018.

Site Analysis

The first step in understanding the ballpark’s potential impacts is to generally inspect its location. Figure 1 is an aerial image of Miami including Marlins Park. The ballpark is bounded by the River and Highway ## to the north limiting access to foot traffic. It is located far away from the downtown development of Miami and separated by Interstate 95; therefore, rendering Marlins Park inaccessible to foot traffic from the downtown area. From the image, the location appears to be in a predominantly residential community.

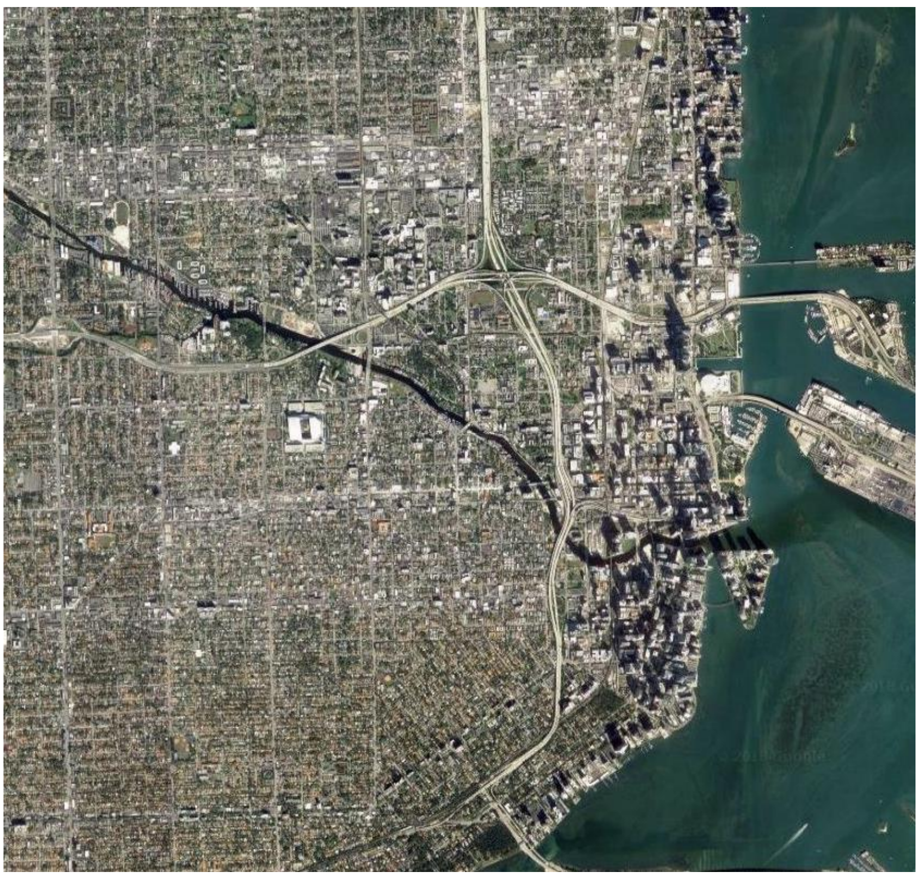


Figure 2: Aerial view of Miami including Marlins Park

1-Mile Radius Ring

The 1-mile radius ring is used as a catchment area for ballpark activity. Economic activity outside the stadium is measured in levels of spending before and after events and is a typical walking-distance for Marlins Park patrons, regardless of whether it is spent on food and beverage, lodging, merchandise, or parking. The objective of using the 1-mile radius ring is to compare any changes in lease rates between the catchment area of the stadium with changes in lease rates across the city of Miami. Since the 1-mile radius is the catchment area for ballpark activity any results captured within the radius can be attributed to the presence of the ballpark and its operation.

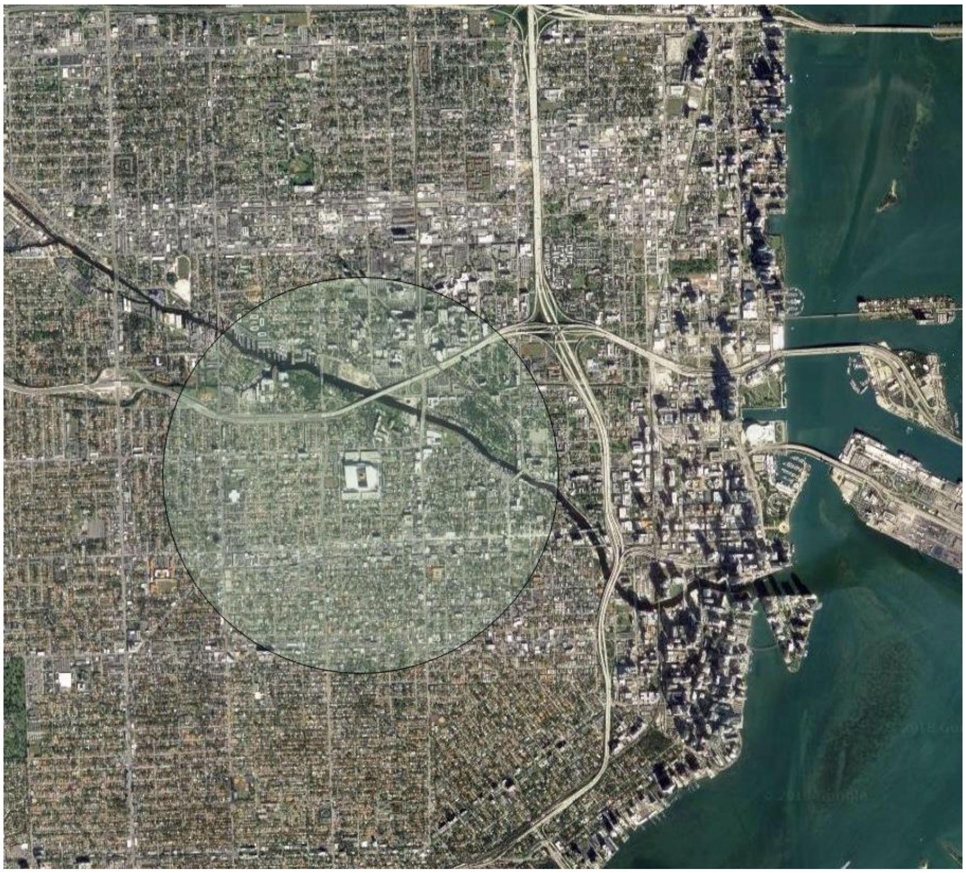


Figure 3: Aerial view of Miami including Marlins Park and a 1-mile radius ring

The Trade Area

In the case of Marlins Park, the trade will be limited to the city limits of Miami. Many patrons of Marlins Park will likely originate from locations outside Miami's city limits, but the value in the research will be to understand the effect nearest to the ballpark. Real estate prices in the Miami trade area will serve as a benchmark for comparison against the changes in real estate prices within the 1-mile radius.

Figure 4: Aerial view of Miami including Marlins Park, 1-mile radius ring, and Miami city limits

Per-Cap Spending

Spending per capita is used as a measure of economic activity both inside and outside the stadium. Per-Cap spending is used to generalize the amount of spending activity per person. Per-cap spending increases in the surrounding are outside the stadium based on the frequency and level of attendance. The average Major League Baseball per-cap is around $15, indicating on average, attendees of a Major League Baseball games are spending $15 beyond the value of their ticket. Spending includes food and beverage, lodging, parking, retail/merchandise as well as transportation.

The Data

The real estate data will be supplied by CoStar and can be divided into retail, office, or residential categories. Through CoStar, the user can gather real estate data by selecting specific areas from any given location in the United States. CoStar aggregates the data in to quarterly averages where observations represent the average value among all available properties in the predetermined area each quarter.

Quarter	Inventory Bldgs	Inventory SF	Vacant SF Direct	Vacant SF Sublet	Vacant SF Total	All Service Type Rent Overall	NNN Rent Direct	NNN Rent Sublet	NNN Rent Overall
QTD	501	3,007,148	131,922	0	131,922	$23.19	$22.12	-	$22.12
2018 Q2	501	3,007,148	113,406	0	113,406	$24.39	$24.60	-	$24.60
2018 Q1	501	3,007,148	132,344	0	132,344	$23.35	$23.96	-	$23.96
2017 Q4	501	3,007,148	98,674	0	98,674	$23.44	$24.36	-	$24.36
2017 Q3	501	3,007,148	91,319	2,500	93,819	$23.07	$23.71	$27.00	$23.78
2017 Q2	501	3,007,148	113,372	2,500	115,872	$22.59	$23.81	$27.00	$23.88
2017 Q1	501	3,007,148	115,211	2,500	117,711	$23.06	$24.57	$27.00	$24.63
2016 Q4	501	3,007,148	104,381	2,500	106,881	$23.46	$25.35	$27.00	$25.39
2016 Q3	501	3,007,148	93,859	2,500	96,359	$23.70	$25.06	$27.00	$25.10
2016 Q2	501	3,007,148	107,123	2,500	109,623	$23.85	$25.18	$27.00	$25.22
2016 Q1	501	3,007,148	110,071	0	110,071	$24.06	$24.86	-	$24.86
2015 Q4	501	3,007,148	136,403	0	136,403	$23.36	$23.84	-	$23.84
2015 Q3	501	3,007,148	127,362	0	127,362	$23.64	$23.97	-	$23.97
2015 Q2	501	3,007,148	115,393	0	115,393	$22.98	$23.73	-	$23.73
2015 Q1	501	3,007,148	124,071	0	124,071	$20.77	$20.56	-	$20.56
2014 Q4	499	2,963,681	86,971	0	86,971	$19.64	$19.25	-	$19.25
2014 Q3	499	2,963,681	94,521	0	94,521	$18.51	$18.01	-	$18.01
2014 Q2	499	2,963,681	102,821	0	102,821	$18.62	$18.75	-	$18.75
2014 Q1	498	2,955,281	113,270	0	113,270	$18.50	$18.57	-	$18.57
2013 Q4	497	2,952,381	112,378	0	112,378	$17.83	$17.88	-	$17.88
2013 Q3	497	2,952,381	136,203	0	136,203	$17.16	$17.88	-	$17.88
2013 Q2	497	2,952,381	127,560	0	127,560	$18.02	$19.11	-	$19.11
2013 Q1	496	2,900,077	125,277	0	125,277	$16.72	$16.62	-	$16.62

Figure 5: Sample of CoStar data for retail with the 1-mile radius of Marlins Park

TIME SERIES THEORY AND RESEARCH

The time series analysis used when researching the impact of ballpark construction quantifies the relationship between current lease rates and their past values. When analyzing real estate lease rates around Marlins Park and Miami uses the intervention method for comparing pre-construction and post-construction rates. The timing of the intervention coincides with the opening of Marlins Park and it tests the one-way effect of stadium construction on changes in lease rates.

The intervention analysis requires an ARIMA model to be fit to each set of lease rates in the study, with a unique ARIMA (*p,d,q*) sequence describing a different series. The general solution for the intervention analysis includes an intercept term and an a1 parameter. The a1 parameter describes the relationship between current lease rates and their past values. The c0 parameter is used to estimate the effect of the intervention, where the intervention is represented as Z. In this case, Z represents a dummy variable that is assigned (0,1) values depending on the time period. For time periods before the opening of Marlins Park Z = 0, while time periods after the opening Z=1.

$$\boldsymbol{Lease\ Rate_{Time} = a_0 + a_1 Lease\ Rate_{Time-1} + c_0 Z_{Time} + w_{Time}}$$

Using R software, the above regression is used to estimate each parameter. After the software has calculated the values, the parameters are used to interpret the pre-intervention average price for lease rates as well as the estimated long-run effect of the treatment. The three equations listed above are used to evaluate the results of the regression.

$$\boldsymbol{Pre-Intervention\ Mean:\ \frac{a_0}{(1-a_1)}}$$

$$\boldsymbol{Post-Intervention\ Mean:\ \frac{c_0}{(1-a_1)}}$$

$$\boldsymbol{Long-Run\ Effect:\ \frac{a_0+c_0}{(1-a_1)} - \frac{a_0}{(1-a_1)} = \frac{c_0}{(1-a_1)}}$$

The steps in the intervention analysis include the following

Intervention Analysis

- View ACF of original series.
- Difference each series to obtain stationarity.
- View ACF of differenced series. *(See Appendix)*
- Test for stationarity and unit roots:
- Use the significant lags to fit a model.
- Confirm using get.best arima
- Use ARIMA and a dummy variable to estimate long-run impact

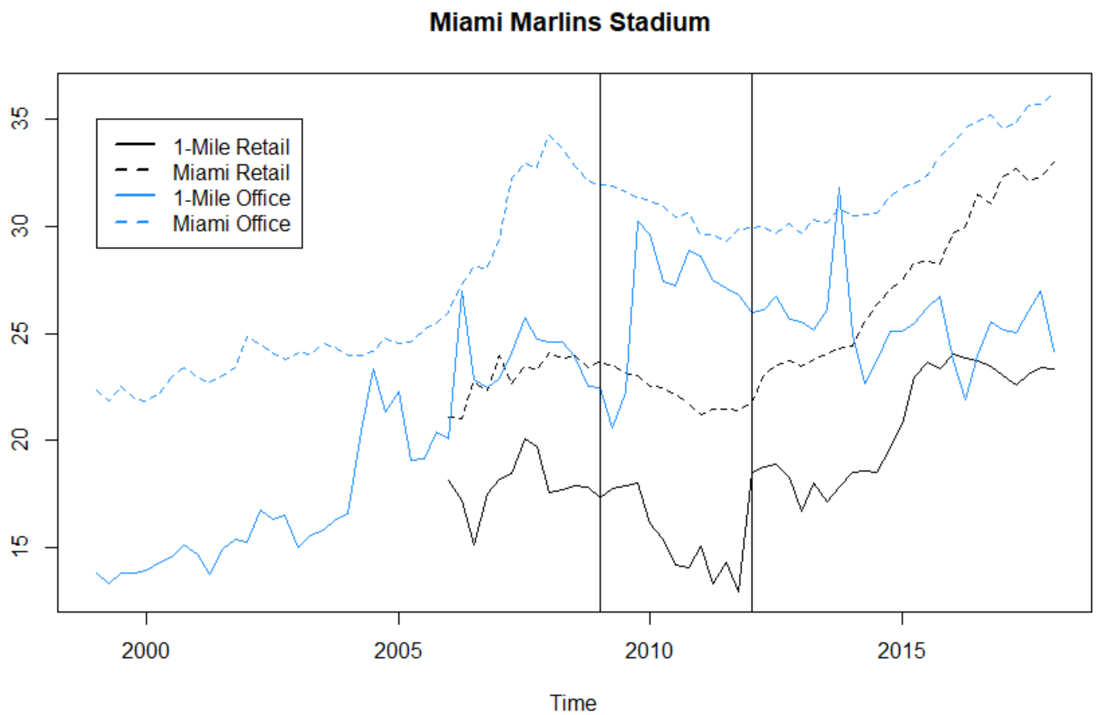


Figure 6: Office and Retail lease rates for Miami and 1-mile radius

Area (Differenced)	Dickey-Fuller (p-value)	ARIMA	AIC
1-Mile Retail	.01	(0,1,2) (2,1,1)	164.85
1-Mile Office	.01	(2,0,2) (2,1,1)	332.7979
Miami Retail	.01	(1,0,2) (1,2,0)	107.6237
Miami Office	.01	(1,2,1) (2,0,0)	141.7016

Table 2: Results from model fitting

ANALYSIS & RESULTS

Figure 6 displays evidence of a negative affect on retail rates within the 1-mile radius during construction. Looking at the results on the graph and looking through the costar data, retail lease rates drop to $5 during construction. Office rates and retail rates within the 1-mile radius behave differently during and after construction. Retail rates in both the 1-mile radius and Miami behave similarly. Office rates behave differently within the 1-mile radius compared to Miami office rates.

Long-run effects of construction and operations of Marlins Park have the largest impact on retail rates 1-mile from the stadium. Before the intervention retail rates grow an average of ($ .8 56) while after the construction, retail rates average a growth of ($5.83)

Long-run effects of Marlins Park construction and operations are less significant on retail rates across the entire city of Miami.

When looking at the time series plot there appears to be a moment where both retail and office lease rates for all series start to decline at around 2007. Perhaps this coincides with the announcement of the stadium project before they broke ground.

SUMMARY Marlins Park Stadium Impact

	Pre-Intervention Mean	a1	Impact Effect (c0)	Long-Run Effect
1-Mile Retail	16.90	0.856	0.84	5.83
Miami Retail	22.64	0.605	0.93	2.35
1-Mile Office	20.50	0.464	-0.91	-1.70
Miami Office	26.92	0.074	0.98	1.06

Note:
The long run effect is calculated as c0 / (1-a1)

Table 3: Summary of Intervention Analysis Results

NET STEPS

The results of the time series analysis will be utilized in a larger effort to understand the residual land value of the land surrounding the ballpark. Understanding the potential lease rates after stadium construction will be valuable to property developers expecting a return on their investment. In order to arrive at a price for the land, assessors use forecasted lease rates to understand how well the cash flow (revenues – expenses) affect the debt capacity and the level of debt service. The level of lease rates collected after the property is built will affect the timing to fully retiring the debt used during construction.

Future & Additional Tests:

Future tests would include vector autoregression (VAR) to understand the two-way effect of shocks to real estate prices in both Miami and within the 1-mile radius. For example, the VAR model would help uncover the effect of a one-standard deviation shock to Miami real estate prices (office and retail) on the real estate prices within 1-mile of the ballpark. If the city is experiencing growth in the real estate market, does it effect prices local to the stadium? Do one standard deviation shocks to real estate prices within one mile of Marlins Park affect real estate prices throughout Miami?

RECOMMENDATION

The time series results are one component when measuring the cost and benefits of new stadium construction and operations on the surrounding area. The purpose of studying the long-run effect would aid in uncovering the economic benefits of stadium construction and operations. Using a comprehensive economic cost-benefit analysis the municipality (city of Miami), team owner, or developer can arrive at a well-though development agreement between all parties involved incorporating the measured economic benefits. The development agreement would include the recommended building program for the ballpark, the anticipated building financial performance, and the residual land value for the adjacent development.

APPENDIX

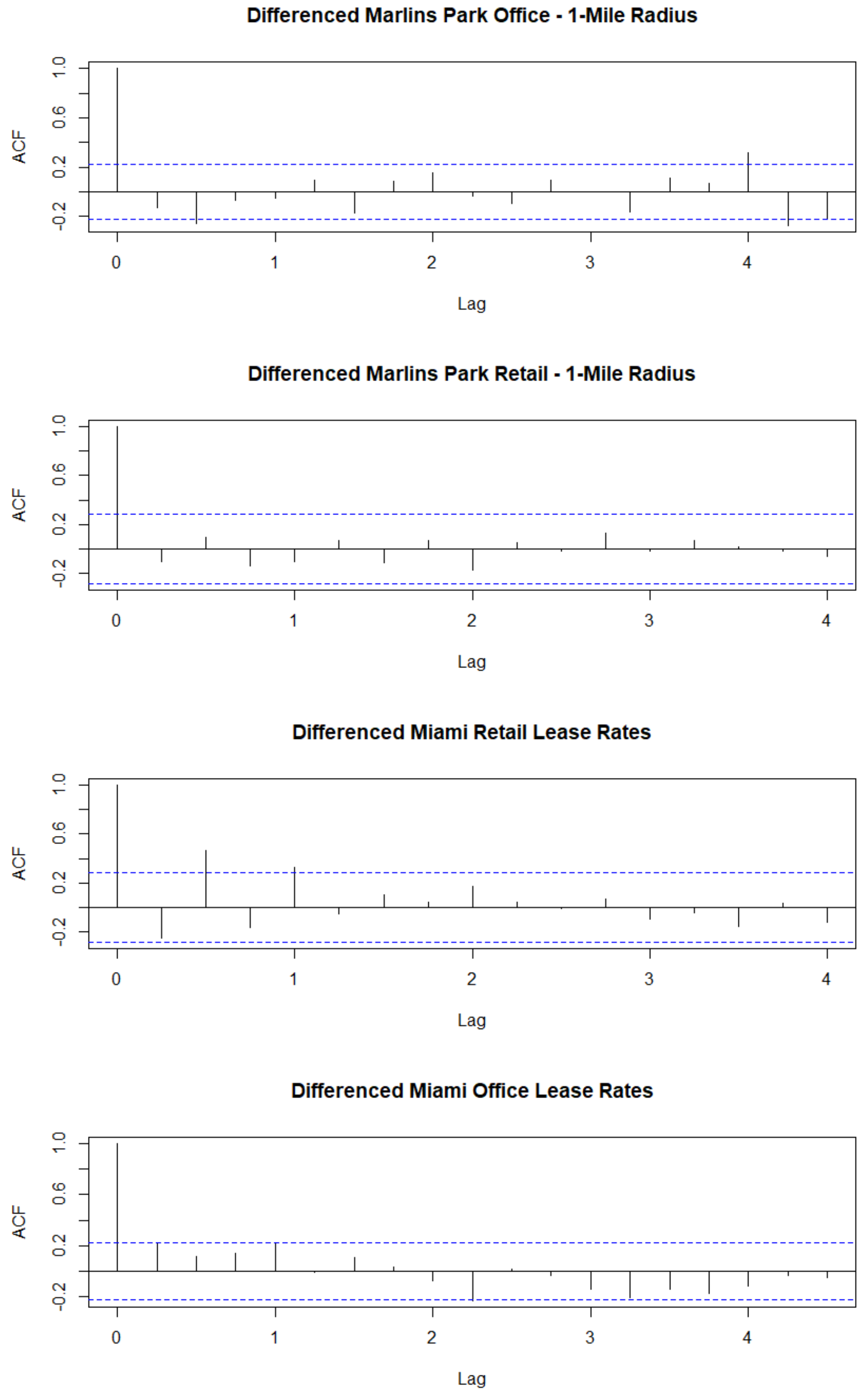


Figure 6: ACF tests of the differenced series

Log:

```
library(dplyr)
library(readr)
library(tseries)
library(scales)
library(ggplot2)

MarlinsPark <- Marlins_Park_1_mile_radius_retail %>% select(Quarter, `All Service Type Rent
Overall`)
Miami <- Miami_retail_historical_data %>% select(Quarter, `All Service Type Rent Overall`)
names(Miami) <- c("Quarter", "Miami Rent")
Miami <- cbind(MarlinsPark , Miami)
names(Miami) <- c("Quarter", "1-Mile Rent", "QTR" , "Miami Rent")
Miami <- Miami %>% select(Quarter, "1-Mile Rent", `Miami Rent`)

ts.Mile <- ts(rev(Miami$`1-Mile Rent`), start = 2006, end = 2018, frequency = 4)
ts.Rent <- ts(rev(Miami$`Miami Rent`), start = 2006, end = 2018, frequency = 4)

#Plot Marlins 1-Mile Retail and Miami Retail
ts.plot(ts.Mile, ts.Rent, lty=1:2, col = c("black", "dodger blue"), lwd=c(2,2), main = "Marlins Park
1-Mile Retail and Miami Retail 2006 - 2018")

##Miami Office:
Office <- Miami_office_historical_data %>% select(Quarter, `Office Gross Rent Overall`)
Marlins.Office <- Marlins_Park_1_mile_radius_office %>% select(Quarter, `Office Gross Rent
Overall`)
names(Marlins.Office) <- c("Quarter", "1-Mile Office")

ts.Office <- ts(rev(Office$`Office Gross Rent Overall`), start = 1999, end = 2018, frequency = 4)
ts.Marlins.Office <- ts(rev(Marlins.Office$`1-Mile Office`), start = 1999, end = 2018, frequency =
4)

ts.plot(ts.Office, ts.Marlins.Office, lty=1:2, col = c("red", "dodger blue"), lwd=c(2,2), main =
"Marlins Park 1-Mile Office and Miami Office 1999 - 2018")

##Plotting all together
ts.plot(ts.Mile, ts.Rent, ts.Marlins.Office, ts.Office, lty = c(1,2,1,2), col= c("black", "black",
"dodger blue", "dodger blue"), main = "Miami Marlins Stadium ")
legend(1999,35, c("1-Mile Retail","Miami Retail", "1-Mile Office", "Miami Office"),lty=c(1,2,1,2),
col=c("black", "black", "dodger blue" , "dodger blue") , lwd=c(2,2,2,2))
abline(v=c("2009" , "2012", col = c("green", "orange"), lty  = 1, lwt = 2))


#Difference
diff.1mile <- diff(ts.Mile)
diff.retail <- diff(ts.Rent)
diff.office <- diff(ts.Office)
diff.Marlins.office <- diff(ts.Marlins.Office)
```

```
plot((diff.1mile),type = "l", main = "Marlins Park: 1-Mile Retail DIFF")
plot((diff.retail), type = "l",main = "Miami Retail DIFF")
plot((diff.office), type = "l",main = "Miami Office DIFF")
plot((diff.Marlins.office), type = "l", main = "Marlins Park: 1-Mile Office DIFF")

##Second Difference Test:
diff2.1mile <- diff(diff(ts.Mile))
diff2.retail <- diff(diff(ts.Rent))
diff2.office <- diff(diff(ts.Office))
diff2.Marlins.office <- diff(diff(ts.Marlins.Office))

#ACF
acf(ts.Mile)
acf(ts.Rent)
acf(ts.Marlins.Office)
acf(ts.Office)

#ACF of difference
acf((diff.1mile), main = "Differenced Marlins Park Retail - 1-Mile Radius")
acf((diff.retail), main = "Differenced Miami Retail Lease Rates")
acf((diff.office), main = "Differenced Miami Office Lease Rates")
acf((diff.Marlins.office), main = "Differenced Marlins Park Office - 1-Mile Radius")
layout(1:4)

##ACF of second difference
acf(diff2.1mile)
acf(diff2.retail)
acf(diff2.office)
acf(diff2.Marlins.office)

##Need ot ensure each time series is stationary for the model results to hold. Use PP and ADF
tests for stationarity.
#Stationary Tests: All the differenced values are stationary according to Dickey-Fuller Test

#Marlins 1-Mile Retail
adf.test(ts.Mile, k=0)
#Non-stationary

adf.test(diff.1mile, k=0)
#Stationary

#Miami Retail Rent
adf.test(ts.Rent, k=0)
#Non-Stationary

adf.test(diff.retail, k=0)
#Stationary

#Marlins 1-Mile Office
```

```
adf.test(ts.Marlins.Office, k=0)
#Non-Stationary

adf.test(diff.Marlins.office, k=0)
#Stationary

#Miami Office
adf.test(ts.Office, k=0)
#Non-Stationary

adf.test(diff.office, k=0)
#Stationary


## Try get best arima
#get.best.arima function----------
get.best.arima <- function(ts.Rent, maxord = c(1,1,1,1,1,1))
{
  best.aic <- 1e8
  n <- length(ts.Rent)
  for (p in 0:maxord[1]) for(d in 0:maxord[2]) for(q in 0:maxord[3])
    for (P in 0:maxord[4]) for(D in 0:maxord[5]) for(Q in 0:maxord[6])
    {
      fit <- arima(ts.Rent, order = c(p,d,q),
                   seas = list(order = c(P,D,Q),
                               frequency(ts.Rent)), method = "CSS")

      fit.aic <- -2 * fit$loglik + (log(n) + 1) * length(fit$coef)
      if (fit.aic < best.aic)
      {
        best.aic <- fit.aic
        best.fit <- fit
        best.model <- c(p,d,q,P,D,Q)  }  }

  list(best.aic, best.fit, best.model)
}

#Best ARIMA for Miami Office: Use ts.Office
get.best.MIA_Office <- get.best.arima((ts.Office), maxord=c(2,2,2,2,2,2))
best.fit.MIA_Office <- get.best.MIA_Office[[2]]
acf( resid(best.fit.MIA_Office))
get.best.MIA_Office[[3]]

#Best ARIMA for Marlins Office: Use ts.Marlins.Office
get.best.Marlins_Office <- get.best.arima((ts.Marlins.Office), maxord = c(2,2,2,2,2,2))
best.fit.Marlins_Office <- get.best.Marlins_Office[[2]]
acf( resid(best.fit.Marlins_Office))
get.best.Marlins_Office[[3]]

#Best ARIMA for Miami Retail: Use ts.Rent
```

```
get.best.Miami_Retail <- get.best.arima((ts.Rent), maxord = c(2,2,2,2,2,2))
best.fit.Miami_Retail <- get.best.Miami_Retail[[2]]
acf( resid(best.fit.Miami_Retail))
get.best.Miami_Retail[[3]]

#Best ARIMA for Marlins Retail 1-Mile: use ts.Mile
get.best.Marlins_Retail <- get.best.arima((ts.Mile), maxord = c(2,2,2,2,2,2))
best.fit.Marlins_Retail <- get.best.Marlins_Retail[[2]]
acf( resid(best.fit.Marlins_Retail))
get.best.Marlins_Retail[[3]]

##Fit models to data using the get.best ARIMA results:
arima.Miami.Office <- arima(ts.Office, order = c(1,1,1),include.mean = TRUE)
arima.Marlins.Office <- arima(ts.Marlins.Office, order = c(2,0,2),include.mean = TRUE)
arima.Miami.Retail <- arima(ts.Rent, order = c(1,0,2),include.mean = TRUE)
arima.Marlins.Retail <- arima(ts.Mile, order = c(0,1,2),include.mean = TRUE)

##AIC
AIC(arima.Miami.Office)
AIC(arima.Marlins.Office)
AIC(arima.Miami.Retail)
AIC(arima.Marlins.Retail)

##Model Coefficients:
coef(arima.Marlins.Office)
coef(arima.Marlins.Retail)
coef(arima.Miami.Office)
coef(arima.Miami.Retail)

##Square the residuals from the fitted ARIMA models for each, if the squared residuals look
volitile, then a GARCH is appropriate:
##Test for Quared Residuals:

#Marlins Office:
res.Marlins.Office <- resid(arima.Marlins.Office)
layout(1:2)
acf(res.Marlins.Office)
acf((res.Marlins.Office)^2)
##Result: Residuals are not volitile, variance is stationary

#Miami Office:
res.Miami.Office <- resid(arima.Miami.Office)
layout(1:2)
acf(res.Miami.Office)
acf((res.Miami.Office)^2)
#ACF of Miami Office residuals^2 looks volative, GARCH may be appropriate.

#Miami Office - GARCH
garch.Miami.Office <- garch(res.Miami.Office, trace = F)
t(confint(garch.Miami.Office))
```

```
garch.res.Miami.Office <- resid(garch.Miami.Office)[-1]
layout(1:2)
acf(garch.res.Miami.Office)
acf(garch.res.Miami.Office^2)

##ACF of Residuals^2 show significant lag @ 4

##Marlins Retail:
res.Marlins.Retail <- resid(arima.Marlins.Retail)
layout(1:2)
acf(res.Marlins.Retail)
acf((res.Marlins.Retail)^2)
#Residuals look stationary, variance is stationary

##Miami Retial:
res.Miami.Retail <- resid(arima.Miami.Retail)
layout(1:2)
acf(res.Miami.Retail)
acf((res.Miami.Retail)^2)
##Residuals look stationary

##Test treatment effect of stadium construction:
arima.Miami.Office <- arima(ts.Office, order = c(1,1,1))
arima.Marlins.Office <- arima(ts.Marlins.Office, order = c(2,0,2))
arima.Miami.Retail <- arima(ts.Rent, order = c(1,0,2))
arima.Marlins.Retail <- arima(ts.Mile, order = c(0,1,2))

#Subset each for before and after stadium construction.
Marlins$Dummy <- ifelse(Marlins$Quarter > "2012 Q2",1,0)
Marlins$PRE <- ifelse(Marlins$Quarter < "2012 Q3", 1,0)
Marlins$"Post Miami Office" <- Marlins$`Miami Office`*Marlins$Dummy
Marlins$"Post 1-Mile Office" <- Marlins$`1-Mile Office`*Marlins$Dummy
Marlins$"Post 1-Mile Rent" <- Marlins$`1-Mile Rent`*Marlins$Dummy
Marlins$"Post Miami Retail" <- Marlins$`Miami Rent`*Marlins$Dummy

Marlins$"PRE Miami Office" <- Marlins$`Miami Office`*Marlins$PRE
Marlins$"PRE 1-Mile Office" <- Marlins$`1-Mile Office`*Marlins$PRE
Marlins$"PRE 1-Mile Rent" <- Marlins$`1-Mile Rent`*Marlins$PRE
Marlins$"PRE Miami Retail" <- Marlins$`Miami Rent`*Marlins$PRE

Marlins <- Marlins[,c(1:6, 9:11, 13)]

##PRE Intervention:
ts.PRE_MIA_Office <- ts(rev(Marlins$`PRE Miami Office`),start = 1999, end = 2018, frequency
= 4)
ts.PRE.Marlins.Office <- ts(rev(Marlins$`PRE 1-Mile Office`), start = 1999, end = 2018,
frequency = 4)
ts.PRE.Marlins.Retail <- ts(rev(Marlins$`PRE 1-Mile Rent`), start = 2006, end = 2018, frequency
= 4)
```

```
ts.PRE.MIA.Retail <- ts(rev(Marlins$`PRE Miami Retail`), start = 2006, end = 2018, frequency =
4)

##PRE Intervention ARIMA:
PRE.MIA.Retail <- arima(ts.PRE.MIA.Retail, order = c(1,0,2), include.mean = TRUE)
PRE.Marlins.Office <- arima(ts.PRE.Marlins.Office, order = c(2,0,2), include.mean = TRUE)
PRE.Marlins.Retail <- arima(ts.PRE.Marlins.Retail, order = c(1,0,2), include.mean = TRUE)
PRE.MIA.Office <- arima(ts.PRE_MIA_Office, order = c(1,1,1), include.mean = TRUE)

##ARIMA Coeffiecients:
coef(PRE.MIA.Retail)
coef(PRE.Marlins.Office)
coef(PRE.Marlins.Retail)
coef(PRE.MIA.Office)


##Post Intervention
ts.Post_MIA_Office <- ts(rev(Marlins$`Post Miami Office`),start = 1999, end = 2018, frequency =
4)
ts.Post.Marlins.Office <- ts(rev(Marlins$`Post 1-Mile Office`), start = 1999, end = 2018,
frequency = 4)
ts.Post.Marlins.Retail <- ts(rev(Marlins$`Post 1-Mile Rent`), start = 2006, end = 2018, frequency
= 4)
ts.Post.MIA.Retail <- ts(rev(Marlins$`Post Miami Retail`), start = 2006, end = 2018, frequency =
4)

##Post Intervention ARIMA:
Post.MIA.Retail <- arima(ts.Post.MIA.Retail, order = c(1,0,2), include.mean = TRUE)
Post.Marlins.Office <- arima(ts.Post.Marlins.Office, order = c(2,0,2),include.mean = TRUE)
Post.Marlins.Retail <- arima(ts.Post.Marlins.Retail, order = c(1,0,2),  include.mean = TRUE)
Post.MIA.Office <- arima(ts.Post_MIA_Office, order = c(1,1,1), include.mean = TRUE)

##Model Coeficients
coef(Post.MIA.Retail)
coef(Post.Marlins.Office)
coef(Post.Marlins.Retail)
coef(Post.MIA.Office)


##New Data frames:

MarlinsRetailPRE <- (Marlins[c(26:51),c(14)])
MarlinsRetailPOST <- (Marlins[c(1:24),c(9)])
ts.MarlinsRetailPRE <- as.ts(Marlins[c(1:51),c(14)])
ts.MarlinsRetailPOST <- as.ts(Marlins[c(1:51),c(9)])
mean(MarlinsRetailPRE)
mean(MarlinsRetailPOST)

MarlinsOfficePRE <- (Marlins[c(26:51),c(13)])
MarlinsOfficePost <- (Marlins[c(1:24),c(8)])
```

```
mean(MarlinsOfficePRE)
mean(MarlinsOfficePost)

MiamiOfficePRE <- (Marlins[c(26:51),c(12)])
MiamiOfficePost <- (Marlins[c(1:24),c(7)])
mean(MiamiOfficePRE)
mean(MiamiOfficePost)

MiamiRetailPRE <- (Marlins[c(26:51),c(15)])
MiamiRetailPOST <- (Marlins[c(1:24),c(10)])
mean(MiamiRetailPRE)
mean(MiamiRetailPOST)


###

PRE.RetailARIMA <- arima(ts.MarlinsRetailPRE, order = c(1,0,2), include.mean = TRUE)

POST.RetailARIMA <- arima(ts.MarlinsRetailPOST, order = c(1,0,2),include.mean = TRUE)
ts.plot(ts.Mile, lty=1, col = c("black"), lwd=c(2,2), main = "Marlins Park 1-Mile Retail 2006 -
2018")
abline(v=c("2009" , "2012", col = c("green", "orange"), lty  = 1, lwt = 2))


Z <- MarlinsOfficePOST
PRE.OfficeARIMA <- arima(MarlinsOfficePRE, order = c(1,0,2),xreg = Z, include.mean = TRUE)
```