NASDAQ

Cisco Systems, Inc. (CSCO)

I chose Cisco Systems, Inc. (CSCO) from NASDAQ. This analysis focuses on close price and volume. The data was downloaded from http://finance.yahoo.com/q/hp?s=CSCO+Historical+Prices on January 31, 2016.

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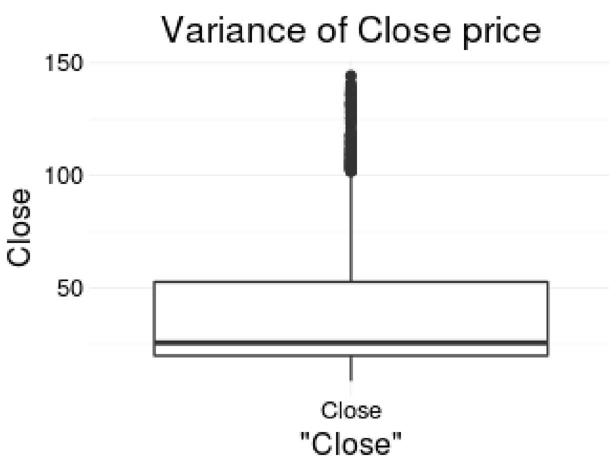
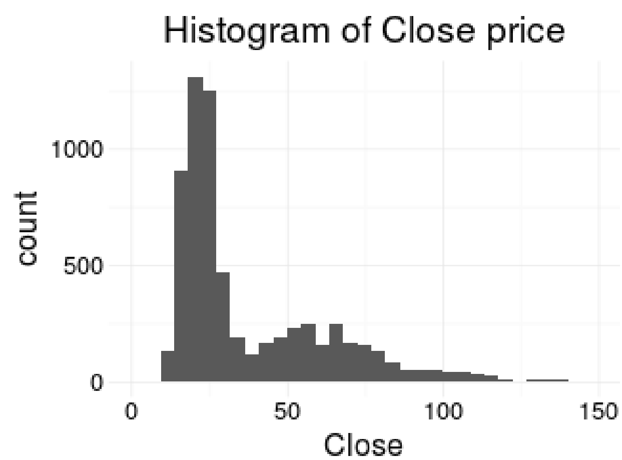
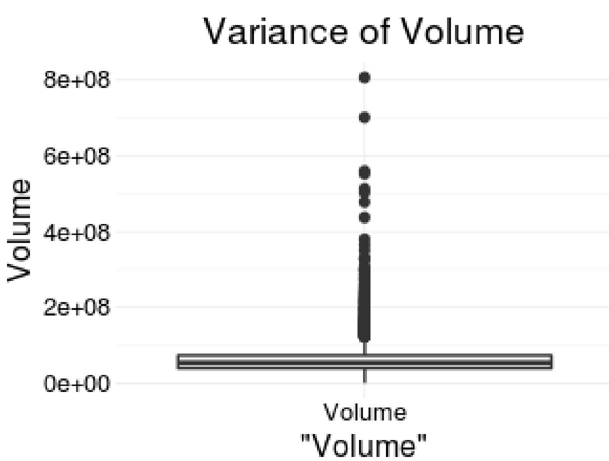
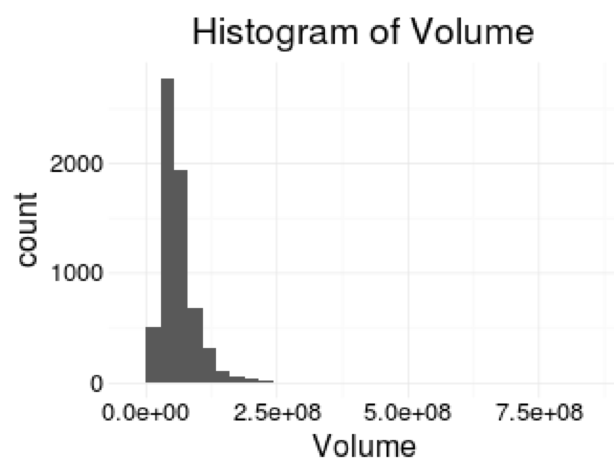
DATA

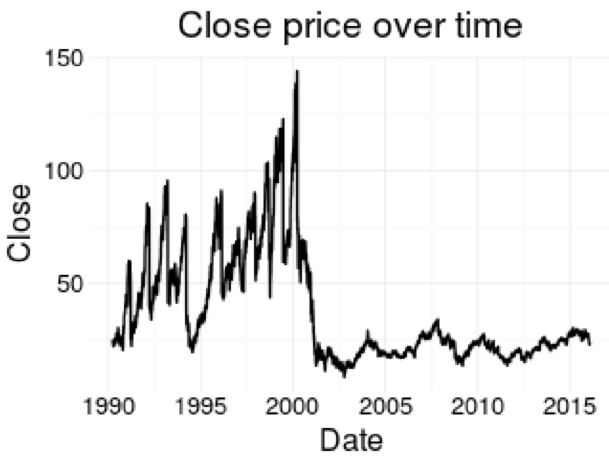
DATE	CLOSE	VOLUME
Min. :1990-03-26	Min. : 8.60	Min. : 806400
1st Qu.:1996-08-31	1st Qu.: 19.86	1st Qu.: 39292675
Median :2003-02-22	Median : 25.57	Median : 53373750
Mean :2003-02-20	Mean : 37.23	Mean : 62217983
3rd Qu.:2009-08-10	3rd Qu.: 52.63	3rd Qu.: 73021550
Max. :2016-01-29	Max. :144.38	Max. :806732800

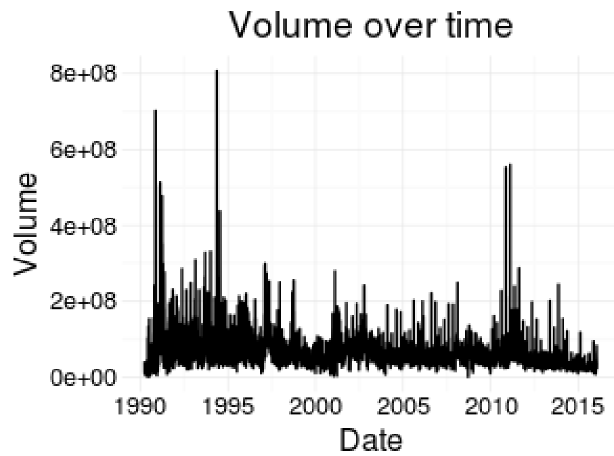









Close price over time
150
100
50
Close
1990
1995
2000
2005
2010
2015
Date


Volume over time
8e+08
6e+08
4e+08
2e+08
0e+00
Volume
1990
1995
2000
2005
2010
2015
Date

CLOSE PRICE

STATIONARITY

The "Close price over time" charts seems to show the characteristics of a random walk. But the Phillips-Perron test rejects the hypothesis that it has a unit root with a high confidence.

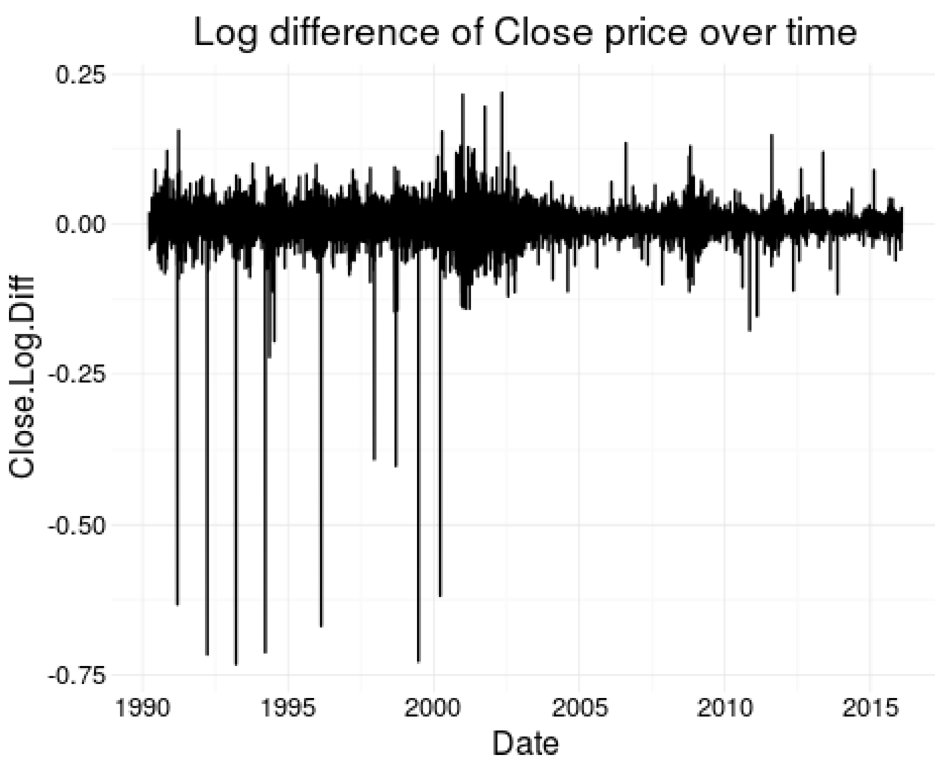
TEST STATISTIC	TRUNCATION LAG PARAMETER	P VALUE
-4.025	11	0.01 * *

Phillips-Perron Unit Root Test: ***Close price***

Although the original series can be accepted as stationary with high confidence, further improvements can be achieved via transforming the close price: taking the log difference results in a "more" stationary model.

TEST STATISTIC	TRUNCATION LAG PARAMETER	P VALUE
-82.09	11	0.01 * *

Phillips-Perron Unit Root Test: ***Log difference of Close price***



OLS MODEL WITH NEWEY-WEST SE USING 2 LAGS

Based on OLS with Newey-West SE using 2 lags the returns can not be predicted. It is an evidence of Efficient Market Hypotheses.

	(INTERCEPT)	RETURN LAG 1	RETURN LAG 2
COEFFICIENTS	-4.905e-06	-0.01676	-0.03996
NEWEY-WEST SE	0.0004441	0.01343	0.01395

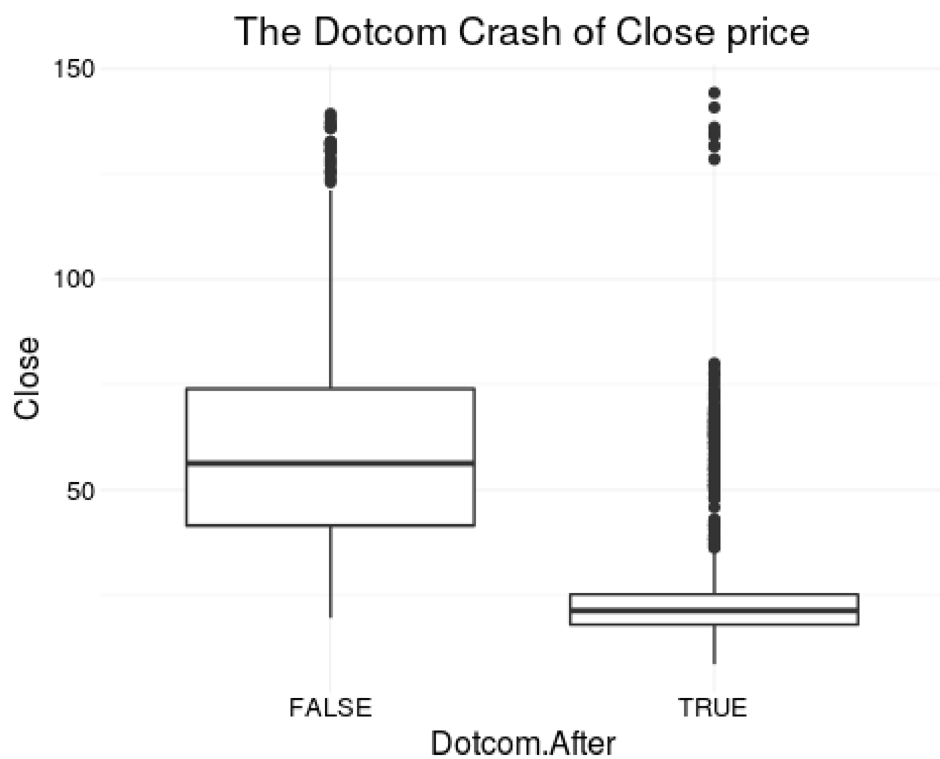
MONDAY EFFECT

Based on OLS with Newey-West SE using Monday dummy variable there is no evidence for Monday effect when considering the close prices between 1990 and 2016.

	(INTERCEPT)	MONDAY
COEFFICIENTS	0.0003848	-0.00205
NEWEY-WEST SE	0.0004306	0.001422

TIME PERIODS

Based on the "Close price over time" chart there is a significant difference in close price before and after March, 2000. According to Market Crashes: The Dotcom Crash article, The Nasdaq Composite lost 78% of its value as it fell from 5046.86 to 1114.11.



VOLUME

STATIONARITY

The "Volume over time" charts seems to be stationary. Also, the Phillips-Perron test rejects the hypothesis that it has a unit root with a high confidence.

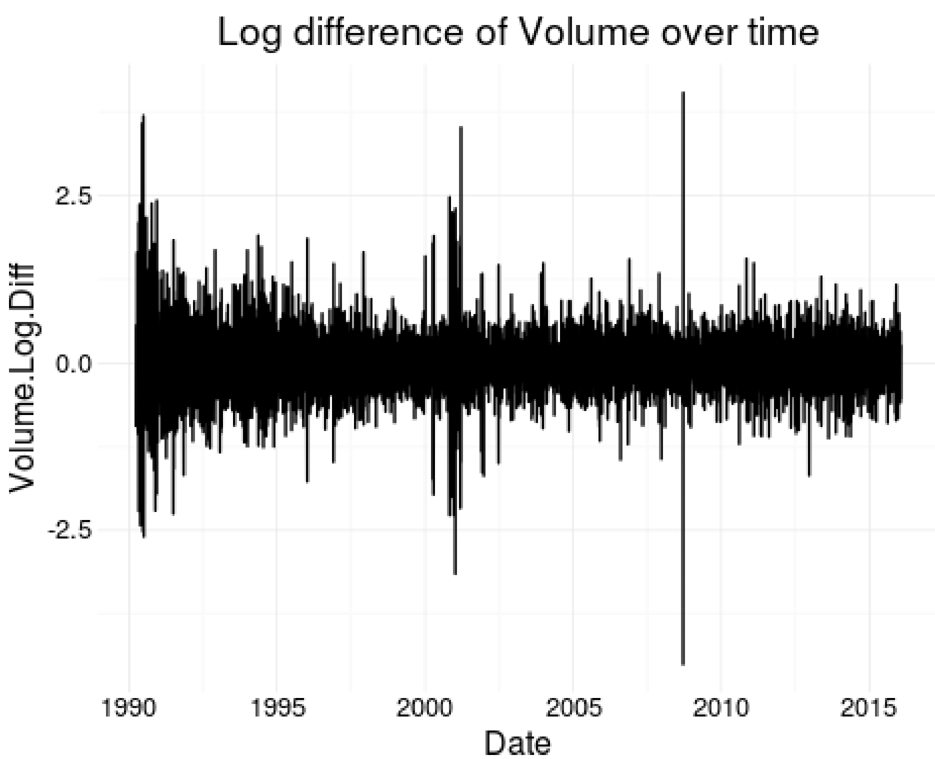
TEST STATISTIC	TRUNCATION LAG PARAMETER	P VALUE
-49.33	11	0.01 * *

*Phillips-Perron Unit Root Test: **Volume***

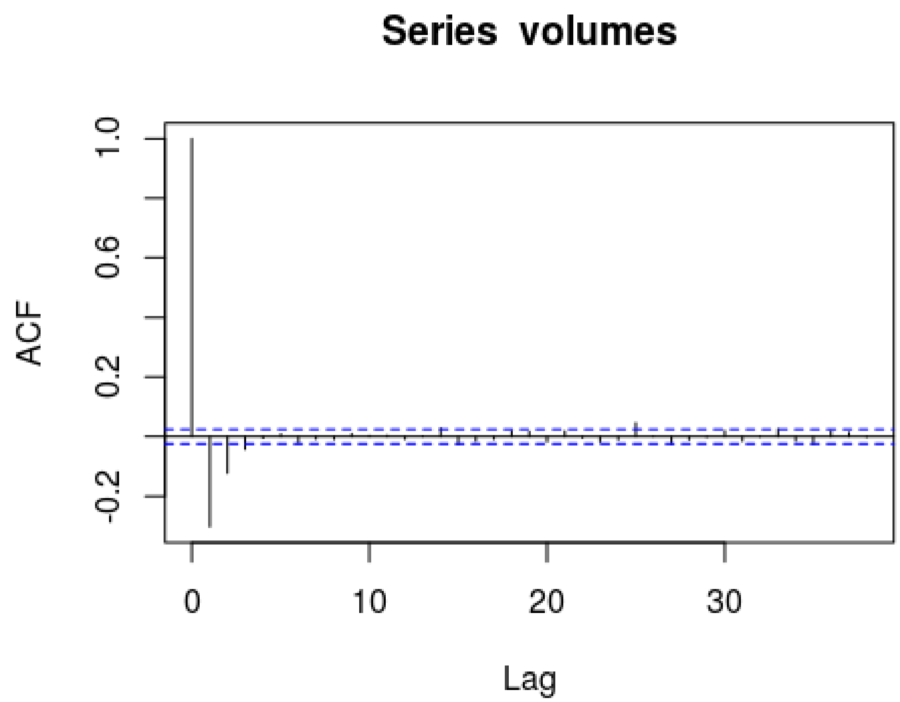
Although the original series can be accepted as stationary with high confidence, further improvements can be achieved via transforming the volume: taking the log difference results in a "more" stationary model.

TEST STATISTIC	TRUNCATION LAG PARAMETER	P VALUE
-169.7	11	0.01 * *

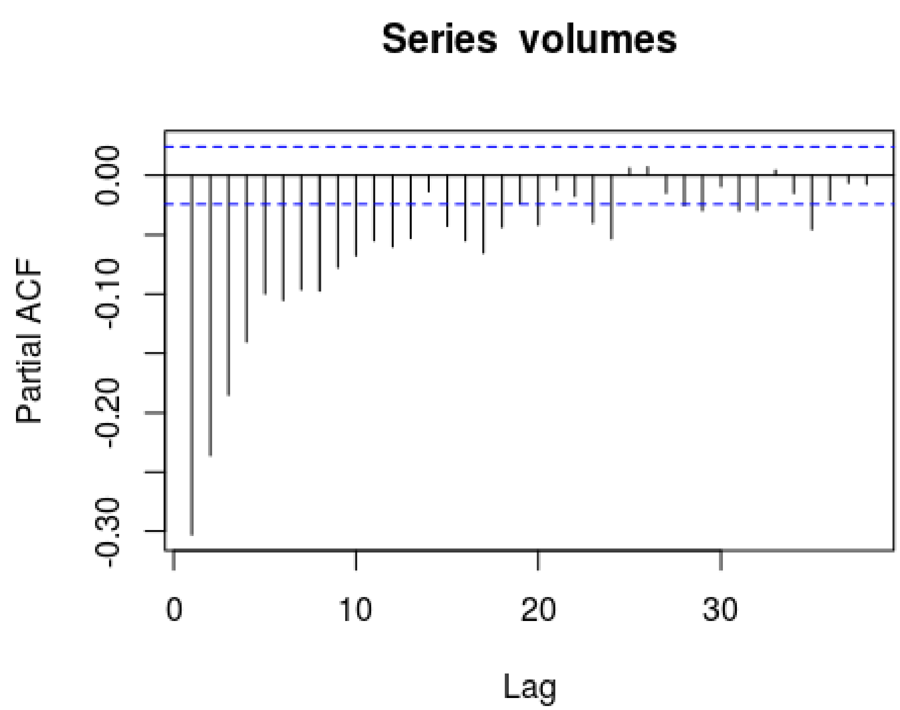
*Phillips-Perron Unit Root Test: **Log difference of Volume***



AUTOCORRELATION FUNCTION



PARTIAL AUTOCORRELATION FUNCTION



ARMA(2,2)

	AR1	AR2	MA1	MA2	INTERCEPT
	1.14	-0.2737	-1.679	0.6901	0.0001372
S.E.	0.07927	0.03856	0.07717	0.07356	0.0003834

CHANGE IN TREND

Similarly to the close price, the Dotcom Crash had an effect on daily volumes as well. But this effect is not as significant as on the close price.

REGRESSION

(1) $E[\ln RS_t|\ln RI_t] = \alpha + \beta * RI_t$

(2) $E[\ln RS_t|\ln RI_t] = \alpha + \beta * RI_t + \gamma * t + \mathrm{sum}(O_i * s_i)$

where RS is the return of your stock, RI is the return of nasdaq composite, s are seasonal dummies.

OLS MODEL WITH NEWEY-WEST SE USING 2 LAGS

VAR	COEFFICIENTS (1)	NEWEY-WEST SE (1)	COEFFICIENTS (2)	NEWEY-WEST SE (2)
(INTERCEPT)	-0.000479	0.0003666	0.001077	0.003505
NASDAQ RETURN	1.318	0.02648	1.318	0.02693
DATE	NA	NA	-9.496e-08	2.458e-07
MONDAY	NA	NA	-0.0008548	0.00127
BEFORE DOTCOM	NA	NA	-0.0006324	0.0015

B COEFFICIENT

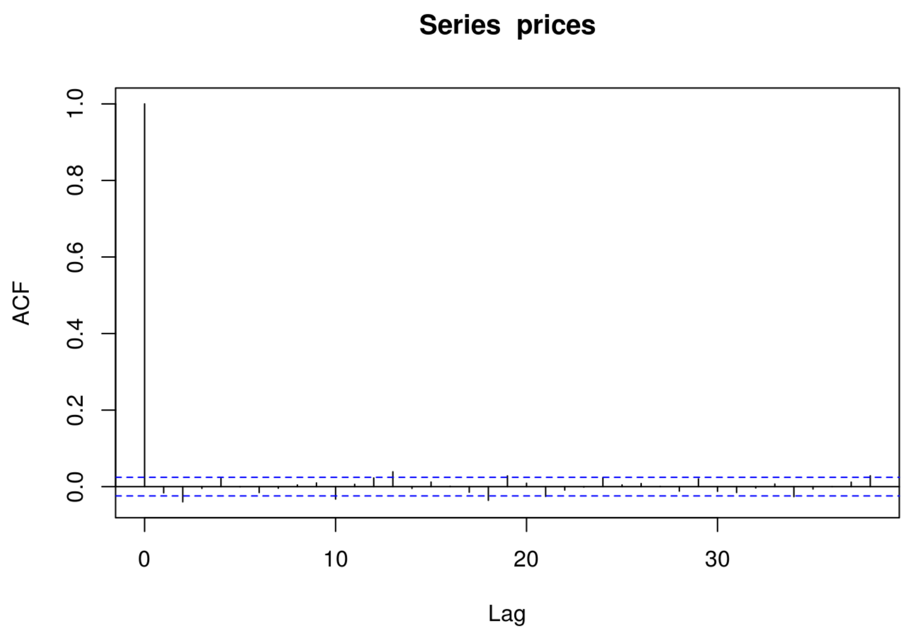
The contemporaneous log difference of NASDAQ composite index has a significant coefficient of 1.318 considering the standard error of 0.026. It means that one unit difference in the NASDAQ composite index is expected to result in 1.3 unit difference in the Cisco stock price. So whenever the NASDAQ composite index is 10 percentage points higher than the previous day, the Cisco is expected to close with 13 percentage point higher price.

The relative higher proportional increase of price could be explained by the relative strength of the Cisco stock. Cisco can be considered as a Blue-chip company.

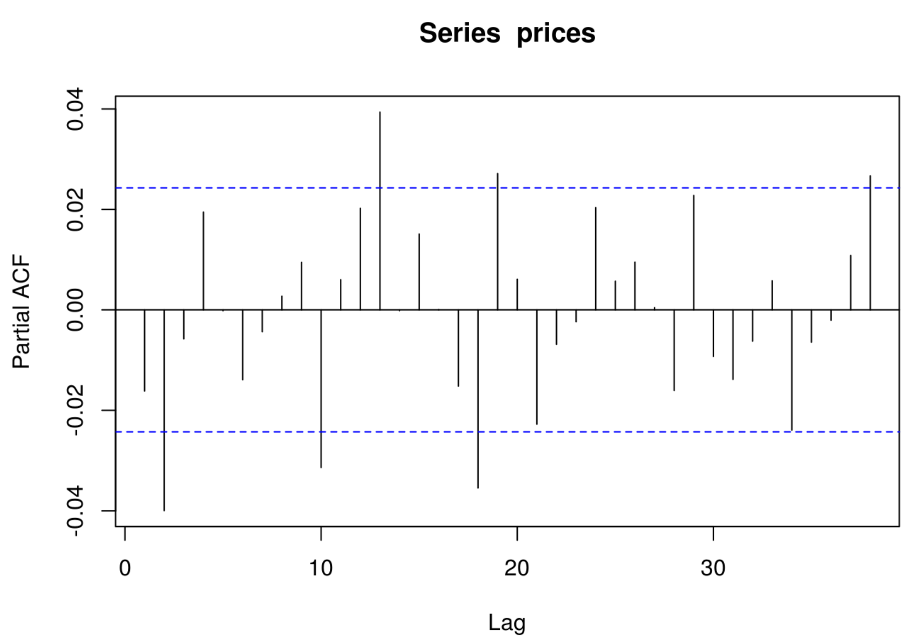
EXTRA CREDIT: ARMA (2,2)

The ARMA model is built on the time series of the Cisco stock price. The insignificance of the coefficients is the evidence of Efficient Market Hypotheses.

AUTOCORRELATION FUNCTION



PARTIAL AUTOCORRELATION FUNCTION



MODEL (1)

	AR1	AR2	MA1	MA2	INTERCEPT	NASDAQ RETURN
	0.5115	-0.8231	-0.5257	0.8028	-0.0004885	1.316
S.E.	0.09359	0.09306	0.09727	0.09922	0.000363	0.02504

MODEL (2)

	AR1	AR2	MA1	MA2	INTERCEPT	NASDAQ RETURN	MONDAY	BEFORE DOTCOM
	0.5118	-0.8276	-0.526	0.8077	-0.0002702	1.317	-0.0007374	-0.0001845
S.E.	0.09298	0.08757	0.09675	0.0935	0.0004999	0.02506	0.0009949	0.0007457

APPENDIX

```
---
title: "NASDAQ"
output: html_document
---

I chose Cisco Systems, Inc. (CSCO) from NASDAQ. This analysis focuses on close price and volume. The
data was downloaded from http://finance.yahoo.com/q/hp?s=CSCO+Historical+Prices on January 31, 2016.

```{r echo=FALSE, warning=FALSE, message=FALSE}
library(data.table)
library(ggplot2)
library(pander)
library(stats)
library(xts)
library(sandwich)

# Open
src = "http://real-
chart.finance.yahoo.com/table.csv?s=CSCO&d=0&e=31&f=2016&g=d&a=2&b=26&c=1990&ignore=.csv"
src = "csco.csv" # Comment this line in order to download the latest data from web
cisco <- read.csv(src, stringsAsFactors = FALSE)
# Clean and Transform
setDT(cisco)
setkey(cisco, Date)
cisco[, Date := as.Date(Date)]
cisco[, Open := NULL]
cisco[, High := NULL]
cisco[, Low := NULL]
cisco[, Adj.Close := NULL]
```

Data

```{r echo=FALSE, warning=FALSE, message=FALSE, fig.width=3.5, fig.height=2.6}
# Explore
pander(summary(cisco))
ggplot(cisco, aes(x = "Close", y = Close)) + geom_boxplot() + ggtitle("Variance of Close price") +
theme_minimal()
ggplot(cisco, aes(x = Close)) + geom_histogram() + ggtitle("Histogram of Close price") + theme_minimal()
ggplot(cisco, aes(x = "Volume", y = Volume)) + geom_boxplot() + ggtitle("Variance of Volume") +
theme_minimal()
ggplot(cisco, aes(x = Volume)) + geom_histogram() + ggtitle("Histogram of Volume") + theme_minimal()
ggplot(cisco, aes(x = Date, y = Close)) + geom_line() + ggtitle("Close price over time") +
theme_minimal()
ggplot(cisco, aes(x = Date, y = Volume)) + geom_line() + ggtitle("Volume over time") + theme_minimal()
```

Close Price
Stationarity
The "Close price over time" charts seems to show the characteristics of a random walk. But the Phillips-
Perron test rejects the hypothesis that it has a unit root with a high confidence.

```{r echo=FALSE, warning=FALSE}
pander(PP.test(cisco$Close))
```

Although the original series can be accepted as stationary with high confidence, further improvements
can be achieved via transforming the close price: taking the log difference results in a "more"
stationary model.

```{r echo=FALSE, warning=FALSE}
cisco[, Close.Log := log(Close)]
cisco[, Close.Log.Diff := Close.Log - shift(Close.Log, n=1, fill=NA, type="lag")]
ggplot(cisco, aes(x = Date, y = Close.Log.Diff)) + geom_line() +
  ggtitle("Log difference of Close price over time") + theme_minimal()
```
```{r echo=FALSE, warning=FALSE}
pander(PP.test(cisco$Close.Log.Diff[-1]))
```
```

````
```

## OLS model with Newey-West SE using 2 lags
Based on OLS with Newey-West SE using 2 lags the returns can not be predicted. It is an evidence of
Efficient Market Hypotheses.

```{r echo=FALSE, warning=FALSE}
cisco[, Close.Log.Diff.lag.1 := shift(Close.Log.Diff, n=1, fill=NA, type="lag")]
cisco[, Close.Log.Diff.lag.2 := shift(Close.Log.Diff, n=2, fill=NA, type="lag")]
fit <- lm(Close.Log.Diff ~ Close.Log.Diff.lag.1 + Close.Log.Diff.lag.2, data = cisco)
se <- sqrt(diag(NeweyWest(fit, lag = 2)))
df <- data.frame()
df <- rbind(df,fit$coefficients,se)
colnames(df) <- labels(fit$coefficients)
rownames(df) <- c("Coefficients", "Newey-West SE")
pander(df)
```

## Monday Effect
Based on OLS with Newey-West SE using Monday dummy variable there is no evidence for Monday effect when
considering the close prices between 1990 and 2016.

```{r echo=FALSE, warning=FALSE}
cisco[, Weekday := weekdays(Date)]
cisco[, Weekday.Monday := Weekday == "Monday"]
fit <- lm(Close.Log.Diff ~ Weekday.Monday, data = cisco)
se <- sqrt(diag(NeweyWest(fit, lag = 2)))
df <- data.frame()
df <- rbind(df,fit$coefficients,se)
colnames(df) <- labels(fit$coefficients)
rownames(df) <- c("Coefficients", "Newey-West SE")
pander(df)
```

## Time Periods
Based on the "Close price over time" chart there is a significant difference in close price before and
after March, 2000. According to [Market Crashes: The Dotcom Crash](the
http://www.investopedia.com/features/crashes/crashes8.asp) article, The Nasdaq Composite lost 78% of its
value as it fell from 5046.86 to 1114.11.

```{r echo=FALSE, warning=FALSE}
dotcom <- as.Date("2000-03-11")
cisco[, Dotcom.Before := Date <= dotcom ][,Dotcom.After := Date > dotcom]
ggplot(cisco, aes(x = Dotcom.After, y = Close)) + geom_boxplot()  + ggtitle("The Dotcom Crash of Close
price") + theme_minimal()
```

# Volume
## Stationarity
The "Volume over time" charts seems to be stationary. Also, the Phillips-Perron test rejects the
hypothesis that it has a unit root with a high confidence.

```{r echo=FALSE, warning=FALSE}
pander(PP.test(as.numeric(cisco$Volume)))
```

Although the original series can be accepted as stationary with high confidence, further improvements
can be achieved via transforming the volume: taking the log difference results in a "more" stationary
model.

```{r echo=FALSE, warning=FALSE}
cisco[, Volume.Log := log(Volume)]
cisco[, Volume.Log.Diff := Volume.Log - shift(Volume.Log, n=1, fill=NA, type="lag")]
ggplot(cisco, aes(x = Date, y = Volume.Log.Diff)) + geom_line() +
  ggtitle("Log difference of Volume over time") + theme_minimal()
```
```{r echo=FALSE, warning=FALSE}
pander(PP.test(cisco$Volume.Log.Diff[-1]))
```

## Autocorrelation Function
````
````

~~~~
```{r echo=FALSE, warning=FALSE}
volumes <- xts(cisco$Volume.Log.Diff[-1], cisco$Date[-1])
acf(volumes)
```

## Partial Autocorrelation Function
```{r echo=FALSE, warning=FALSE}
pacf(volumes)
```

## ARMA(2,2)
```{r echo=FALSE, warning=FALSE}
model <- arima(volumes, c(2,0,2))
pander(model)
```

## Change in Trend
Similarly to the close price, the Dotcom Crash had an effect on daily volumes as well. But this effect
is not as significant as on the close price.

```{r echo=FALSE, warning=FALSE}
ggplot(cisco, aes(x = Dotcom.After, y = Volume)) + geom_boxplot()  +
  ggtitle("The Dotcom Crash of Volume") + theme_minimal()
```

# Regression

(1) $E[ lnRS_{t} | lnRI_{t} ] = \alpha + \beta * RI_{t}$

(2) $E[ lnRS_{t} | lnRI_{t} ] = \alpha + \beta * RI_{t} + \gamma * t + sum ( O_{i} * s_{i} )$

where RS is the return of your stock, RI is the return of nasdaq composite, s are seasonal dummies.

```{r echo=FALSE, warning=FALSE}
# Download and calculate return on nasdaq composite
src = "http://real-
chart.finance.yahoo.com/table.csv?s=%5EIXIC&a=02&b=26&c=1990&d=00&e=29&f=2016&g=d&ignore=.csv"
src = "nasdaq.csv"
nasdaq <- read.csv(src, stringsAsFactors = FALSE)
# Clean and Transform
setDT(nasdaq)
setkey(nasdaq, Date)
cisco[, Nasdaq.Close := nasdaq$Close]
cisco[, Nasdaq.Close.Log := log(Nasdaq.Close)]
cisco[, Nasdaq.Close.Log.Diff := Nasdaq.Close.Log - shift(Nasdaq.Close.Log, n=1, fill=NA, type="lag")]
```

## OLS model with Newey-West SE using 2 lags
```{r echo=FALSE, warning=FALSE}
# Model 1
model <- lm(Close.Log.Diff ~ Nasdaq.Close.Log.Diff, data = cisco)
se <- sqrt(diag(NeweyWest(model, lag = 2)))
dt1 <- data.table(labels(model$coefficients))
dt1 <- cbind(1:2, dt1, model$coefficients, se)
colnames(dt1) <- c("i", "var", "Coefficients (1)", "Newey-West SE (1)")

model <- lm(Close.Log.Diff ~ Nasdaq.Close.Log.Diff +
               Date + Weekday.Monday + Dotcom.Before, data = cisco)
se <- sqrt(diag(NeweyWest(model, lag = 2)))
dt2 <- data.table(labels(model$coefficients))
dt2 <- cbind(1:5, dt2, model$coefficients, se)
colnames(dt2) <- c("i", "var", "Coefficients (2)", "Newey-West SE (2)")

dt <- merge(dt1, dt2, by = "var", all.y = TRUE)
setorder(dt, i.y)
dt[, i.x := NULL][, i.y := NULL]
pander(dt, split.table = Inf)
```

## β coefficient
~~~~

The contemporaneous log difference of NASDAQ composite index has a significant coefficient of 1.318 considering the standard error of 0.026. It means that one unit difference in the NASDAQ composite index is expected to result in 1.3 unit difference in the Cisco stock price. So whenever the NASDAQ composite index is 10 percentage points higher than the previous day, the Cisco is expected to close with 13 percentage points higher price.

The relative higher proportional increase of price could be explained by the relative strength of the Cisco stock. Cisco can be considered as a Blue-chip company.

Extra Credit: ARMA(2,2)
The ARMA model is built on the time series of the Cisco stock price. The insignificance of the coefficients is the evidence of Efficient Market Hypotheses.

Autocorrelation Function
```{r echo=FALSE, warning=FALSE}
prices <- xts(cisco$Close.Log.Diff[-1], cisco$Date[-1])
acf(prices)
```

Partial Autocorrelation Function
```{r echo=FALSE, warning=FALSE}
pacf(prices)
```

Model (1)
```{r echo=FALSE, warning=FALSE}

model <- arima(prices, c(2,0,2), xreg = cisco[-1,.(Nasdaq.Close.Log.Diff)])
pander(model)
```

Model (2)
```{r echo=FALSE, warning=FALSE}
model <- arima(prices, c(2,0,2), xreg = cisco[-1,.(Nasdaq.Close.Log.Diff, Weekday.Monday,
Dotcom.Before)])
pander(model)
```