

Start of final project

Notebook Setup

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

## Loading required package: quantmod

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

##
## ##### Warning from 'xts' package #####
## #
## # The dplyr lag() function breaks how base R's lag() function is supposed to #
## # work, which breaks lag(my_xts). Calls to lag(my_xts) that you type or #
## # source() into this session won't work correctly. #
## #
## # Use stats::lag() to make sure you're not using dplyr::lag(), or you can add #
## # conflictRules('dplyr', exclude = 'lag') to your .Rprofile to stop #
## # dplyr from breaking base R's lag() function. #
## #
## # Code in packages is not affected. It's protected by R's namespace mechanism #
## # Set 'options(xts.warn_dplyr_breaks_lag = FALSE)' to suppress this warning. #
## #
## #####
```

```

##
## Attaching package: 'xts'

## The following objects are masked from 'package:dplyr':
##
##     first, last

## Loading required package: TTR

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

## Loading required package: forecast

## Loading required package: fBasics

##
## Attaching package: 'fBasics'

## The following object is masked from 'package:TTR':
##
##     volatility

## Loading required package: CADFtest

## Loading required package: dynlm

## Loading required package: sandwich

## Loading required package: tseries

## Loading required package: urca

## Registered S3 methods overwritten by 'CADFtest':
##   method      from
##   bread.mlm    sandwich
##   estfun.mlm   sandwich

## Loading required package: lmtest

## Loading required package: nlme

##
## Attaching package: 'nlme'

## The following object is masked from 'package:forecast':
##
##     getResponse

```

```

## The following object is masked from 'package:dplyr':
##
## collapse

## Loading required package: MTS

##
## Attaching package: 'MTS'

## The following object is masked from 'package:TTR':
##
## VMA

## Loading required package: car

## Loading required package: carData

##
## Attaching package: 'car'

## The following object is masked from 'package:fBasics':
##
## densityPlot

## The following object is masked from 'package:dplyr':
##
## recode

## Loading required package: strucchange

## Warning: package 'strucchange' was built under R version 4.3.2

## Loading required package: vars

## Warning: package 'vars' was built under R version 4.3.2

## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
## select

##
## Attaching package: 'vars'

## The following object is masked from 'package:MTS':
##
## VAR

```

These results are really quite strange and I wouldn't entirely know how to include this in my final model correctly. So we are going to change the indexing of our final model. For my final project I have some snow data that I am going to compare these variables too. That data starts in 2008-12-31 and ends at 2017-03-30. So these will be our new start and end dates. I feel most of the issues that would arise from this model especially in relation to break points probably comes from what happened around covid as well so I feel this smaller section will be much better to work with.

```
startdate = "2009-12-01"
enddate = "2017-01-02"
```

calculate new first difference and returns

For our relationship calculations we are going to try to model the Vail resorts stock. response: mtn

predictors: cOil <- general economy and driving predictor snowfall <- average snow fall accross my multiple resorts T10YIE <- 10y breakeven inflation Rate

loading in snowfall data csvs

```
#have to keep these seprate intially as the dates don't match up
jackson <- read.csv("archive//Jackson Hole - Wyoming.csv")
snowbird <- read.csv("archive//Snowbird - Utah.csv")
telluride <- read.csv("archive//Telluride - Colorado.csv")
whistler <- read.csv("archive//Whistler Blackcomb - BC Canada.csv")
```

Were going to have to do alot of cleaning because snow dataset does not report days that there is 0 just days that there is snow. Snow depth is in cm as well includes cm in the name for some reason which is going to make it a bitch to read in.

```
#cutting out cm part of file
jackson$jacksonSnow <- as.numeric(gsub("[^0-9.]", "", jackson$X24.hr.New.Snow ))
snowbird$snowbirdSnow <- as.numeric(gsub("[^0-9.]", "", snowbird$X24.hr.New.Snow ))
telluride$tellurideSnow <- as.numeric(gsub("[^0-9.]", "", telluride$X24.hr.New.Snow ))
whistler$whistlerSnow <- as.numeric(gsub("[^0-9.]", "", whistler$X24.hr.New.Snow ))

#converting values to datetimes
jackson$Date <- as.POSIXct(jackson$Date, format = "%d-%b-%y")
snowbird$Date <- as.POSIXct(snowbird$Date, format = "%d-%b-%y")
telluride$Date <- as.POSIXct(telluride$Date, format = "%d-%b-%y")
whistler$Date <- as.POSIXct(whistler$Date, format = "%d-%b-%y")

#Combining Snowfalls into one dataset full join because want NA's where values are missing
snowfall <- jackson[c("Date", "jacksonSnow")] %>%
  full_join(snowbird[c("Date", "snowbirdSnow")], by = join_by(Date)) %>%
  full_join(telluride[c("Date", "tellurideSnow")], by = join_by(Date)) %>%
  full_join(whistler[c("Date", "whistlerSnow")], by = join_by(Date))

#replace NA's with 0's because that means it snowed 0 cm at these places
snowfall <- replace(snowfall, is.na(snowfall), 0)
snowfall$Dates <- snowfall$Date
snowfall$Date <- as.Date(snowfall$Date)
snowfall <- snowfall[order(snowfall$Date), ]
```

Now we need to find the range of values or months that this data is over.

```

startTemp <- as.Date(startdate)
endTemp <- as.Date(enddate)

#All dates between start and end
dateBetween <- seq(startTemp, endTemp, by = "1 day")

#overlapping dates
temp <- data.frame(Date = dateBetween, jargon = 0)
snowfallFull <- temp %>%
  full_join(snowfall, by = join_by(Date))

#remove extra col
snowfallFull <- snowfallFull[, !(names(snowfallFull) %in% c("jargon"))]
snowfallFull$allSnow <- (snowfallFull$jacksonSnow + snowfallFull$snowbirdSnow + snowfallFull$tellurideSnow)

plotData <- snowfallFull
#filling in NA's with 0's
snowfallFull <- replace(snowfallFull, is.na(snowfallFull), 0)

```

Loading stock and Commodities Data

```

getSymbols("T10YIE",src="FRED") #10y breakeven inflation 2003-01-02

```

```
## [1] "T10YIE"
```

```

getSymbols("MTN") #vail resorts Data

```

```
## [1] "MTN"
```

```

getSymbols("DCOILWTICO", src = "FRED") #Domestic Crude Oil

```

```
## [1] "DCOILWTICO"
```

```

#T10YIE doesn't need to be logged
MTN <- na.omit(window(MTN, start = startdate, end = enddate))
DCOILWTICO <- na.omit(window(DCOILWTICO, start = startdate, end = enddate))
T10YIE <- na.omit(window(T10YIE, start = startdate, end = enddate))#don't need to log

mtn <- merge.xts(log(MTN$MTN.Adjusted), log(DCOILWTICO),T10YIE)

colnames(mtn) <- c("mtn","cOil","T10YIE")

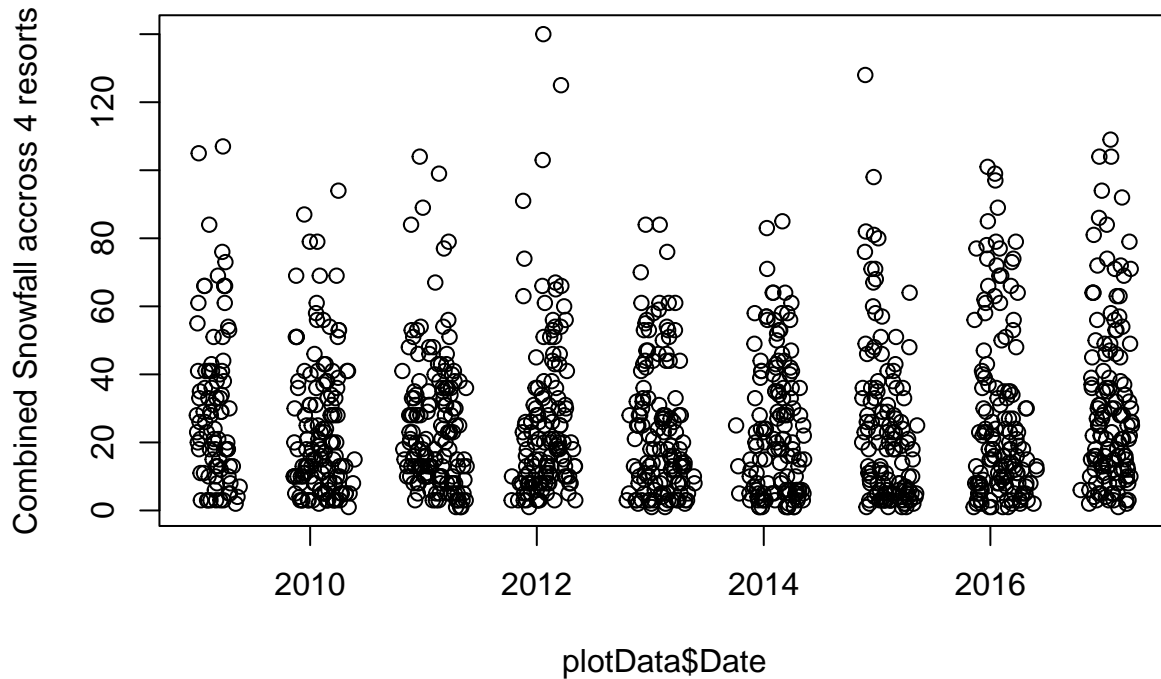
```

Basic Idea

The basic Idea that I am going to try to implement is that because the way the seasonality works for the snow fall data. The summers are completely 0 and isn't effected by snowfall. However, I can't just remove the summers completely from the data and test the complete dataset. So I am going to split the data set and test each winter individually.

We have info on 9 separate winters.

```
plot(plotData$allSnow ~ plotData$Date, ylab = "Combined Snowfall accross 4 resorts")
```



Going to run each year starting on November 20th which is Thanksgiving weekend and normally the week ski resorts open. Then last week is going to be the end of April.

splitting the variables into 8 separate dataframes for each year.

```
start <- 2009#date of first year
winters <- vector(mode='list', length=8)
# Loop through each year
for (i in 1:8) {
  # Define the start and end dates for each time series
  start_date <- as.Date(paste(as.character(start + i - 1), "-11-20", sep = ""))
  end_date <- as.Date(paste(as.character(start + i), "-05-01", sep = ""))

  # Subset the original data for the current time series
  current_time_series <- subset(snowfallFull, snowfallFull$Date >= start_date & snowfallFull$Date <= end_date)

  # Store the current time series in the list
  winters[[i]] <- current_time_series
}
#test
winters[[1]]
```

```
##           Date jacksonSnow snowbirdSnow tellurideSnow whistlerSnow
## 1    2009-12-01           0           0           0           8
```

## 2	2009-12-02	10	0	0	0
## 3	2009-12-03	0	0	0	0
## 4	2009-12-04	0	0	0	0
## 5	2009-12-05	0	0	0	0
## 6	2009-12-06	0	3	0	0
## 7	2009-12-07	0	3	0	0
## 8	2009-12-08	10	0	3	0
## 9	2009-12-09	0	5	5	0
## 10	2009-12-10	3	5	3	0
## 11	2009-12-11	0	0	0	0
## 12	2009-12-12	8	0	3	0
## 13	2009-12-13	36	41	10	0
## 14	2009-12-14	18	0	23	0
## 15	2009-12-15	15	3	0	10
## 16	2009-12-16	0	0	0	0
## 17	2009-12-17	8	3	0	0
## 18	2009-12-18	8	0	0	5
## 19	2009-12-19	0	8	0	5
## 20	2009-12-20	3	0	0	15
## 21	2009-12-21	5	0	0	20
## 22	2009-12-22	3	0	0	18
## 23	2009-12-23	3	13	5	0
## 24	2009-12-24	5	3	5	0
## 25	2009-12-25	0	3	0	0
## 26	2009-12-26	0	0	0	0
## 27	2009-12-27	0	3	0	0
## 28	2009-12-28	0	0	0	0
## 29	2009-12-29	0	0	0	0
## 30	2009-12-30	8	0	20	3
## 31	2009-12-31	13	43	23	0
## 32	2010-01-01	23	0	0	8
## 33	2010-01-02	25	5	0	10
## 34	2010-01-03	8	5	0	3
## 35	2010-01-04	5	0	0	5
## 36	2010-01-05	8	0	0	5
## 37	2010-01-06	25	0	0	0
## 38	2010-01-07	3	15	0	0
## 39	2010-01-08	0	0	0	0
## 40	2010-01-09	0	0	0	0
## 41	2010-01-10	0	0	0	3
## 42	2010-01-11	0	0	0	15
## 43	2010-01-12	0	0	0	0
## 44	2010-01-13	3	0	0	5
## 45	2010-01-14	0	0	0	0
## 46	2010-01-15	0	0	0	46
## 47	2010-01-16	0	0	0	0
## 48	2010-01-17	0	0	0	8
## 49	2010-01-18	0	0	0	15
## 50	2010-01-19	10	0	3	18
## 51	2010-01-20	5	33	10	10
## 52	2010-01-21	8	20	5	3
## 53	2010-01-22	15	13	33	0
## 54	2010-01-23	43	0	13	0
## 55	2010-01-24	51	0	28	0

## 56	2010-01-25	15	18	0	8
## 57	2010-01-26	10	0	0	15
## 58	2010-01-27	13	0	3	3
## 59	2010-01-28	8	8	5	0
## 60	2010-01-29	0	0	0	2
## 61	2010-01-30	0	0	0	0
## 62	2010-01-31	3	13	0	3
## 63	2010-02-01	46	23	0	0
## 64	2010-02-02	3	0	0	3
## 65	2010-02-03	3	0	0	3
## 66	2010-02-04	13	5	5	0
## 67	2010-02-05	13	0	0	3
## 68	2010-02-06	18	0	0	0
## 69	2010-02-07	0	0	8	3
## 70	2010-02-08	0	0	15	0
## 71	2010-02-09	0	0	5	0
## 72	2010-02-10	0	0	0	0
## 73	2010-02-11	15	3	3	3
## 74	2010-02-12	13	18	0	25
## 75	2010-02-13	25	0	0	12
## 76	2010-02-14	0	10	15	18
## 77	2010-02-15	3	0	0	10
## 78	2010-02-16	5	13	5	0
## 79	2010-02-17	0	0	0	17
## 80	2010-02-18	0	5	0	0
## 81	2010-02-19	0	0	5	0
## 82	2010-02-20	10	0	33	0
## 83	2010-02-21	3	8	13	0
## 84	2010-02-22	0	10	28	0
## 85	2010-02-23	0	0	3	0
## 86	2010-02-24	0	0	0	3
## 87	2010-02-25	23	0	8	7
## 88	2010-02-26	3	25	3	2
## 89	2010-02-27	0	0	0	12
## 90	2010-02-28	0	0	0	3
## 91	2010-03-01	0	3	3	0
## 92	2010-03-02	0	0	0	0
## 93	2010-03-03	3	3	0	3
## 94	2010-03-04	3	5	0	0
## 95	2010-03-05	3	48	3	0
## 96	2010-03-06	0	0	0	0
## 97	2010-03-07	0	0	0	0
## 98	2010-03-08	5	5	10	8
## 99	2010-03-09	0	0	20	0
## 100	2010-03-10	3	23	5	3
## 101	2010-03-11	0	8	23	0
## 102	2010-03-12	0	0	0	28
## 103	2010-03-13	0	0	0	0
## 104	2010-03-14	5	28	8	0
## 105	2010-03-15	0	0	10	10
## 106	2010-03-16	0	0	0	3
## 107	2010-03-17	0	0	0	15
## 108	2010-03-18	0	0	0	0
## 109	2010-03-19	0	3	0	0

## 110	2010-03-20	0	0	28	0
## 111	2010-03-21	0	0	0	8
## 112	2010-03-22	0	0	0	8
## 113	2010-03-23	15	10	0	8
## 114	2010-03-24	0	8	8	0
## 115	2010-03-25	0	0	3	0
## 116	2010-03-26	15	3	0	2
## 117	2010-03-27	13	0	56	0
## 118	2010-03-28	0	0	0	10
## 119	2010-03-29	0	0	0	36
## 120	2010-03-30	0	0	0	28
## 121	2010-03-31	41	3	0	7
## 122	2010-04-01	3	33	3	0
## 123	2010-04-02	25	46	23	0
## 124	2010-04-03	18	0	10	25
## 125	2010-04-04	20	30	0	3
## 126	2010-04-05	0	13	0	0
## 127	2010-04-06	0	0	0	10
## 128	2010-04-07	0	0	0	3
## 129	2010-04-08	0	0	0	0
## 130	2010-04-09	0	0	0	5
## 131	2010-04-10	0	0	0	0
## 132	2010-04-11	0	0	0	0
## 133	2010-04-12	0	0	0	0
## 134	2010-04-13	0	0	0	5
## 135	2010-04-14	0	13	0	0
## 136	2010-04-15	0	0	0	0
## 137	2010-04-16	0	0	0	0
## 138	2010-04-17	0	0	0	0
## 139	2010-04-18	0	0	0	0
## 140	2010-04-19	0	0	0	0
## 141	2010-04-20	0	0	0	0
## 142	2010-04-21	0	0	0	0
## 143	2010-04-22	0	0	0	0
## 144	2010-04-23	0	0	0	0
## 145	2010-04-24	0	5	0	8
## 146	2010-04-25	0	5	0	0
## 147	2010-04-26	0	5	0	0
## 148	2010-04-27	0	0	0	0
## 149	2010-04-28	0	0	0	0
## 150	2010-04-29	0	0	0	0
## 151	2010-04-30	0	41	0	0
## 152	2010-05-01	0	0	0	0
## 2692	2009-11-21	0	0	0	10
## 2693	2009-11-22	0	0	0	18
## 2694	2009-11-23	0	23	10	3
## 2695	2009-11-24	25	5	0	8
## 2696	2009-11-28	0	0	0	4
## 2697	2009-11-30	0	0	0	3
##		Dates	allSnow		
## 1	2009-12-01 00:00:00		8		
## 2	2009-12-02 00:00:00		10		
## 3	1969-12-31 17:00:00		0		
## 4	1969-12-31 17:00:00		0		

## 5	1969-12-31 17:00:00	0
## 6	2009-12-06 00:00:00	3
## 7	2009-12-07 00:00:00	3
## 8	2009-12-08 00:00:00	13
## 9	2009-12-09 00:00:00	10
## 10	2009-12-10 00:00:00	11
## 11	1969-12-31 17:00:00	0
## 12	2009-12-12 00:00:00	11
## 13	2009-12-13 00:00:00	87
## 14	2009-12-14 00:00:00	41
## 15	2009-12-15 00:00:00	28
## 16	1969-12-31 17:00:00	0
## 17	2009-12-17 00:00:00	11
## 18	2009-12-18 00:00:00	13
## 19	2009-12-19 00:00:00	13
## 20	2009-12-20 00:00:00	18
## 21	2009-12-21 00:00:00	25
## 22	2009-12-22 00:00:00	21
## 23	2009-12-23 00:00:00	21
## 24	2009-12-24 00:00:00	13
## 25	2009-12-25 00:00:00	3
## 26	1969-12-31 17:00:00	0
## 27	2009-12-27 00:00:00	3
## 28	1969-12-31 17:00:00	0
## 29	1969-12-31 17:00:00	0
## 30	2009-12-30 00:00:00	31
## 31	2009-12-31 00:00:00	79
## 32	2010-01-01 00:00:00	31
## 33	2010-01-02 00:00:00	40
## 34	2010-01-03 00:00:00	16
## 35	2010-01-04 00:00:00	10
## 36	2010-01-05 00:00:00	13
## 37	2010-01-06 00:00:00	25
## 38	2010-01-07 00:00:00	18
## 39	1969-12-31 17:00:00	0
## 40	1969-12-31 17:00:00	0
## 41	2010-01-10 00:00:00	3
## 42	2010-01-11 00:00:00	15
## 43	1969-12-31 17:00:00	0
## 44	2010-01-13 00:00:00	8
## 45	1969-12-31 17:00:00	0
## 46	2010-01-15 00:00:00	46
## 47	1969-12-31 17:00:00	0
## 48	2010-01-17 00:00:00	8
## 49	2010-01-18 00:00:00	15
## 50	2010-01-19 00:00:00	31
## 51	2010-01-20 00:00:00	58
## 52	2010-01-21 00:00:00	36
## 53	2010-01-22 00:00:00	61
## 54	2010-01-23 00:00:00	56
## 55	2010-01-24 00:00:00	79
## 56	2010-01-25 00:00:00	41
## 57	2010-01-26 00:00:00	25
## 58	2010-01-27 00:00:00	19

## 59	2010-01-28 00:00:00	21
## 60	2010-01-29 00:00:00	2
## 61	1969-12-31 17:00:00	0
## 62	2010-01-31 00:00:00	19
## 63	2010-02-01 00:00:00	69
## 64	2010-02-02 00:00:00	6
## 65	2010-02-03 00:00:00	6
## 66	2010-02-04 00:00:00	23
## 67	2010-02-05 00:00:00	16
## 68	2010-02-06 00:00:00	18
## 69	2010-02-07 00:00:00	11
## 70	2010-02-08 00:00:00	15
## 71	2010-02-09 00:00:00	5
## 72	1969-12-31 17:00:00	0
## 73	2010-02-11 00:00:00	24
## 74	2010-02-12 00:00:00	56
## 75	2010-02-13 00:00:00	37
## 76	2010-02-14 00:00:00	43
## 77	2010-02-15 00:00:00	13
## 78	2010-02-16 00:00:00	23
## 79	2010-02-17 00:00:00	17
## 80	2010-02-18 00:00:00	5
## 81	2010-02-19 00:00:00	5
## 82	2010-02-20 00:00:00	43
## 83	2010-02-21 00:00:00	24
## 84	2010-02-22 00:00:00	38
## 85	2010-02-23 00:00:00	3
## 86	2010-02-24 00:00:00	3
## 87	2010-02-25 00:00:00	38
## 88	2010-02-26 00:00:00	33
## 89	2010-02-27 00:00:00	12
## 90	2010-02-28 00:00:00	3
## 91	2010-03-01 00:00:00	6
## 92	1969-12-31 17:00:00	0
## 93	2010-03-03 00:00:00	9
## 94	2010-03-04 00:00:00	8
## 95	2010-03-05 00:00:00	54
## 96	1969-12-31 17:00:00	0
## 97	1969-12-31 17:00:00	0
## 98	2010-03-08 00:00:00	28
## 99	2010-03-09 00:00:00	20
## 100	2010-03-10 00:00:00	34
## 101	2010-03-11 00:00:00	31
## 102	2010-03-12 00:00:00	28
## 103	1969-12-31 17:00:00	0
## 104	2010-03-14 00:00:00	41
## 105	2010-03-15 00:00:00	20
## 106	2010-03-16 00:00:00	3
## 107	2010-03-17 00:00:00	15
## 108	1969-12-31 17:00:00	0
## 109	2010-03-19 00:00:00	3
## 110	2010-03-20 00:00:00	28
## 111	2010-03-21 00:00:00	8
## 112	2010-03-22 00:00:00	8

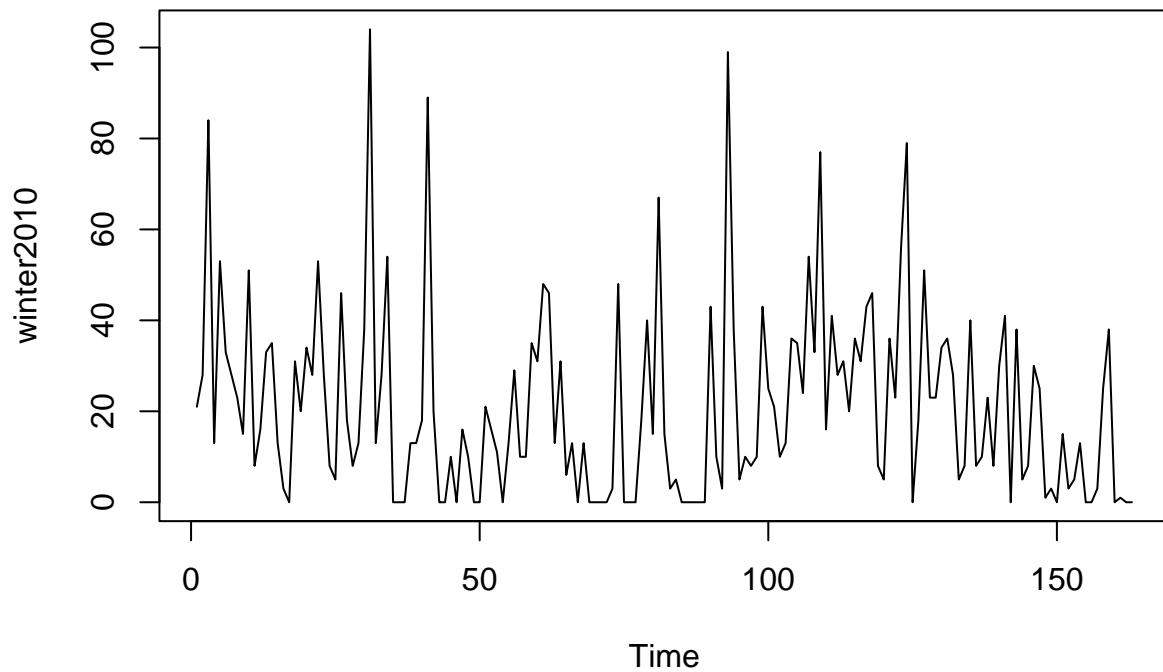
```
## 113 2010-03-23 00:00:00 33
## 114 2010-03-24 00:00:00 16
## 115 2010-03-25 00:00:00 3
## 116 2010-03-26 00:00:00 20
## 117 2010-03-27 00:00:00 69
## 118 2010-03-28 00:00:00 10
## 119 2010-03-29 00:00:00 36
## 120 2010-03-30 00:00:00 28
## 121 2010-03-31 00:00:00 51
## 122 2010-04-01 00:00:00 39
## 123 2010-04-02 00:00:00 94
## 124 2010-04-03 00:00:00 53
## 125 2010-04-04 00:00:00 53
## 126 2010-04-05 00:00:00 13
## 127 2010-04-06 00:00:00 10
## 128 2010-04-07 00:00:00 3
## 129 1969-12-31 17:00:00 0
## 130 2010-04-09 00:00:00 5
## 131 1969-12-31 17:00:00 0
## 132 1969-12-31 17:00:00 0
## 133 1969-12-31 17:00:00 0
## 134 2010-04-13 00:00:00 5
## 135 2010-04-14 00:00:00 13
## 136 1969-12-31 17:00:00 0
## 137 1969-12-31 17:00:00 0
## 138 1969-12-31 17:00:00 0
## 139 1969-12-31 17:00:00 0
## 140 1969-12-31 17:00:00 0
## 141 1969-12-31 17:00:00 0
## 142 1969-12-31 17:00:00 0
## 143 1969-12-31 17:00:00 0
## 144 1969-12-31 17:00:00 0
## 145 2010-04-24 00:00:00 13
## 146 2010-04-25 00:00:00 5
## 147 2010-04-26 00:00:00 5
## 148 1969-12-31 17:00:00 0
## 149 1969-12-31 17:00:00 0
## 150 1969-12-31 17:00:00 0
## 151 2010-04-30 00:00:00 41
## 152 1969-12-31 17:00:00 0
## 2692 2009-11-21 00:00:00 10
## 2693 2009-11-22 00:00:00 18
## 2694 2009-11-23 00:00:00 36
## 2695 2009-11-24 00:00:00 38
## 2696 2009-11-28 00:00:00 4
## 2697 2009-11-30 00:00:00 3
```

```
##Data exploration /ARIMA models
```

```
#snowfall
```

```
winter2010 <- ts(winters[[2]]$allSnow, start = 1)
plot(winter2010, type = "l", main = "total snowfall in cm for winter 2010")
```

total snowfall in cm for winter 2010

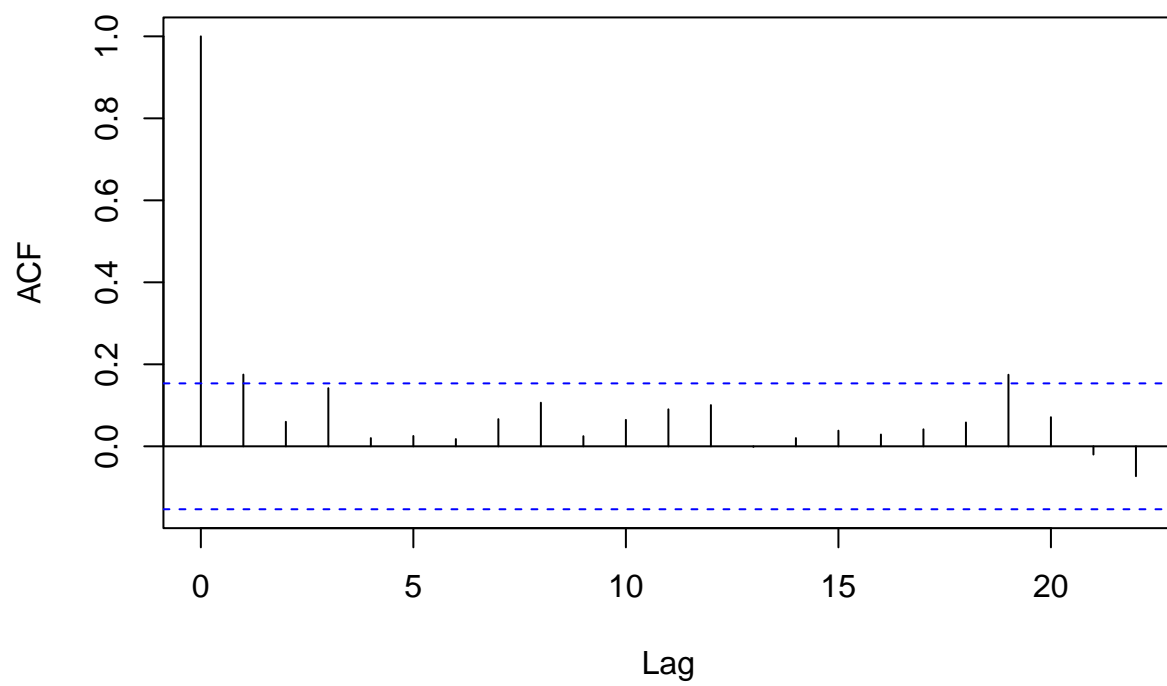


seeing if there is auto cor. Assume there will be.

Honestly there isn't really as much as I thought

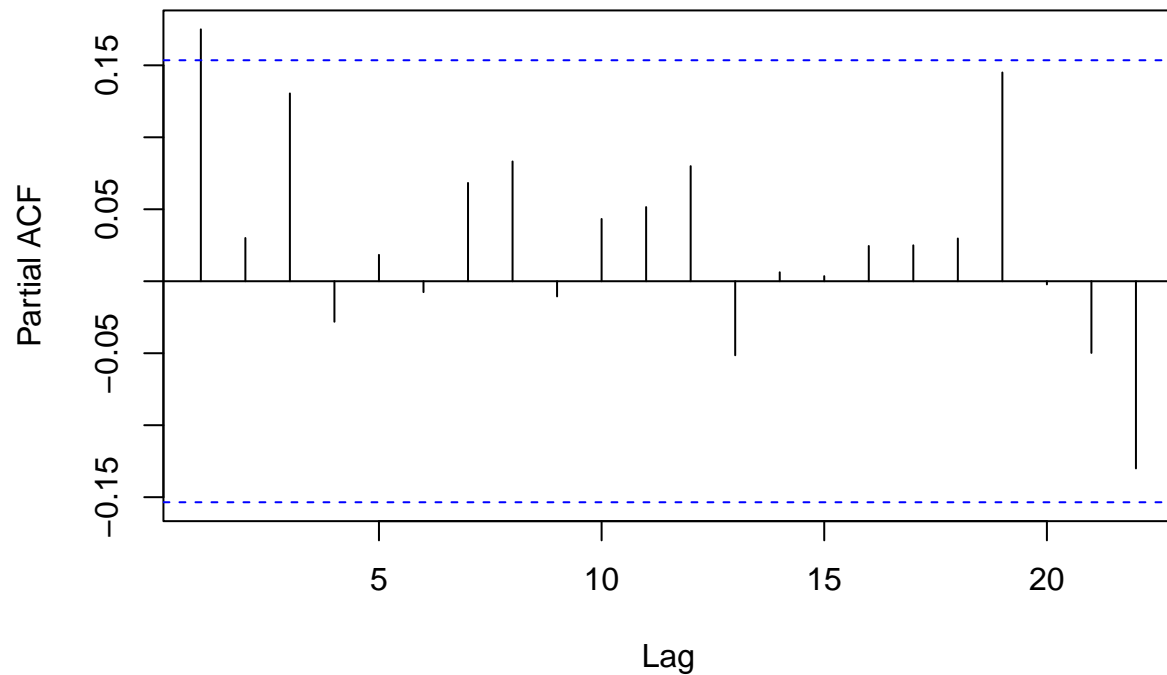
```
acf(winter2010)
```

Series winter2010



```
pacf(winter2010)
```

Series winter2010



Simple MA(1) - moving average model

```
auto.arima(winter2010)
```

```
## Series: winter2010
## ARIMA(0,0,1) with non-zero mean
##
## Coefficients:
##          ma1      mean
##          0.1714  21.0249
## s.e.  0.0779   1.8823
##
## sigma^2 = 426.9:  log likelihood = -723.9
## AIC=1453.8   AICc=1453.95   BIC=1463.08
```

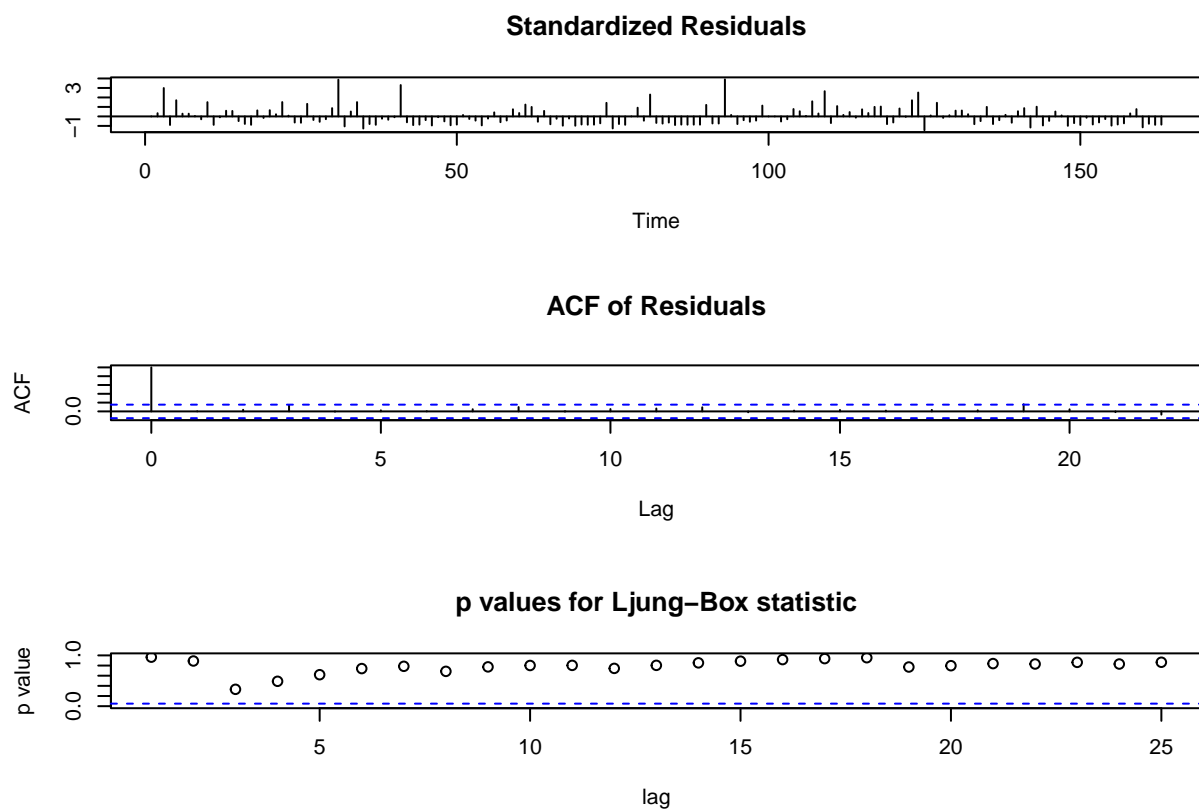
```
winter2010Model <- Arima(winter2010, order = c(0,0,1))
summary(winter2010Model)
```

```
## Series: winter2010
## ARIMA(0,0,1) with non-zero mean
##
## Coefficients:
##          ma1      mean
##          0.1714  21.0249
## s.e.  0.0779   1.8823
```

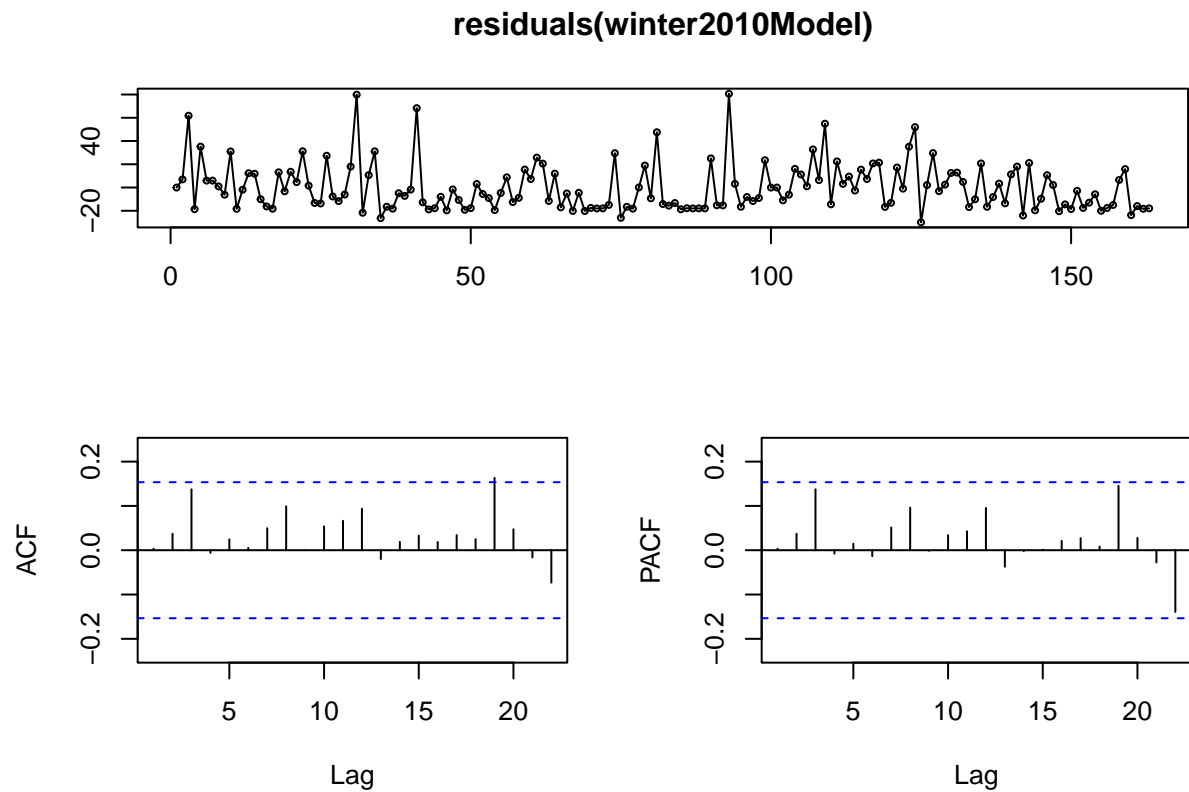
```
##
## sigma^2 = 426.9: log likelihood = -723.9
## AIC=1453.8 AICc=1453.95 BIC=1463.08
##
## Training set error measures:
##           ME      RMSE      MAE  MPE  MAPE      MASE      ACF1
## Training set -0.0006303049 20.53395 15.87137 -Inf  Inf  0.8499709 0.003365764
```

I feel that this is a pretty good model for this as well as it shows this data can be stationary and useful. No real need to difference or log.

```
tsdiag(winter2010Model, gof = 25)
```



```
tsdisplay(residuals(winter2010Model))
```

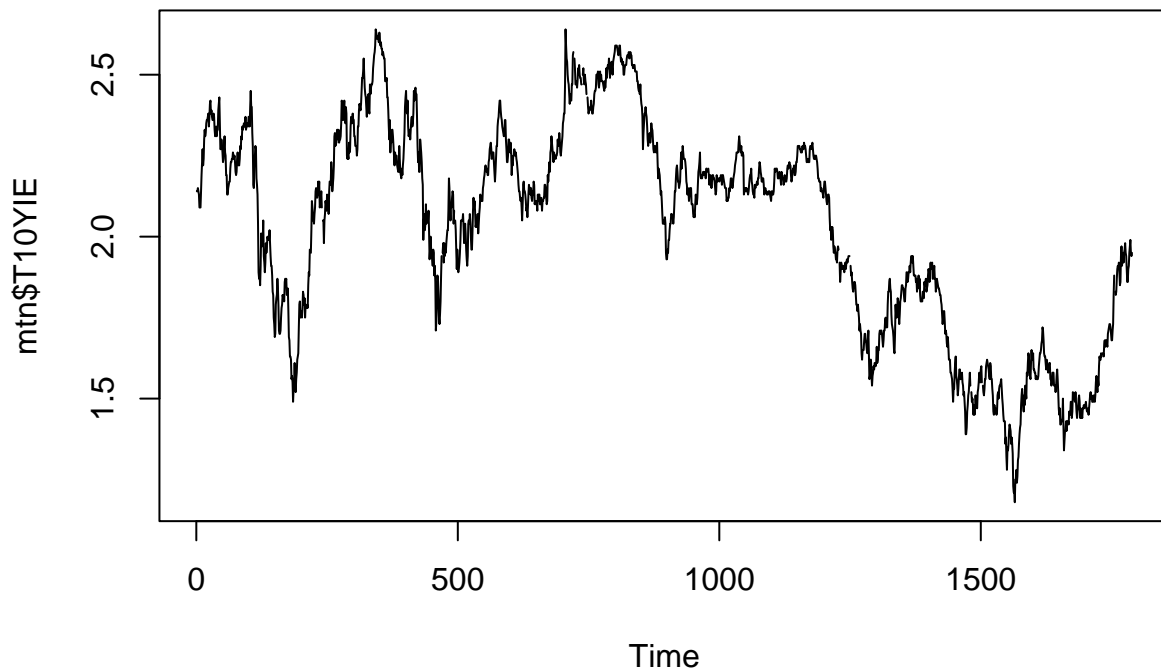



#other predictors

```
#Converting to ts object of returns
dmtn <- ts(na.omit(diff(mtn)),freq=252, start = 2009)#so they stay the same size remove columns out cor
```

going to explore the 10year inflation rate.

```
ts.plot(mtn$T10YIE)
```



Realized I forgot to do use my differenced. However it is then just an AR(3) model which is good.

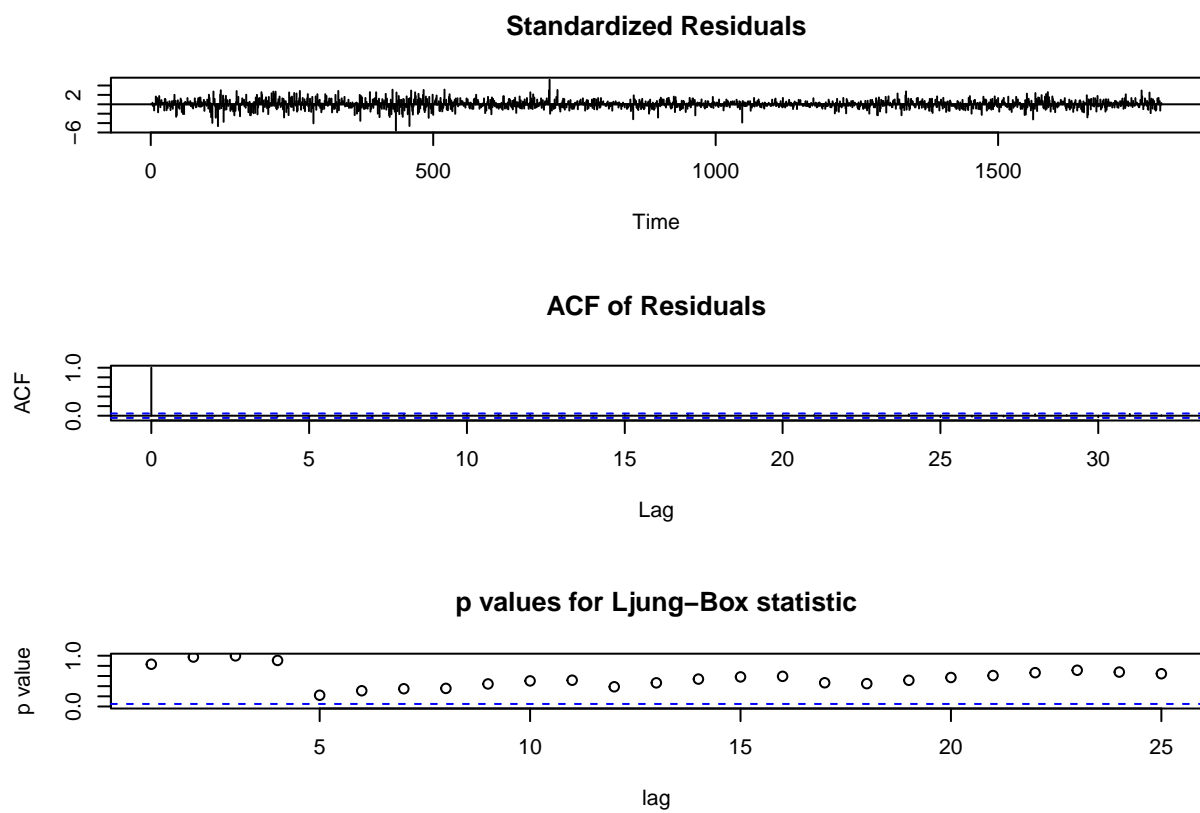
```
T10YIEarima <- auto.arima(mtn$T10YIE)
summary(T10YIEarima)
```

```
## Series: mtn$T10YIE
## ARIMA(3,1,0)
##
## Coefficients:
##      ar1      ar2      ar3
##      0.1019 -0.0692  0.0174
## s.e.  0.0238  0.0240  0.0242
##
## sigma^2 = 0.0009411: log likelihood = 3657.19
## AIC=-7306.37  AICc=-7306.35  BIC=-7284.42
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -6.945994e-05 0.03064247 0.02287666 -0.01525869 1.169321 0.9986881
##              ACF1
## Training set 0.005029832
```

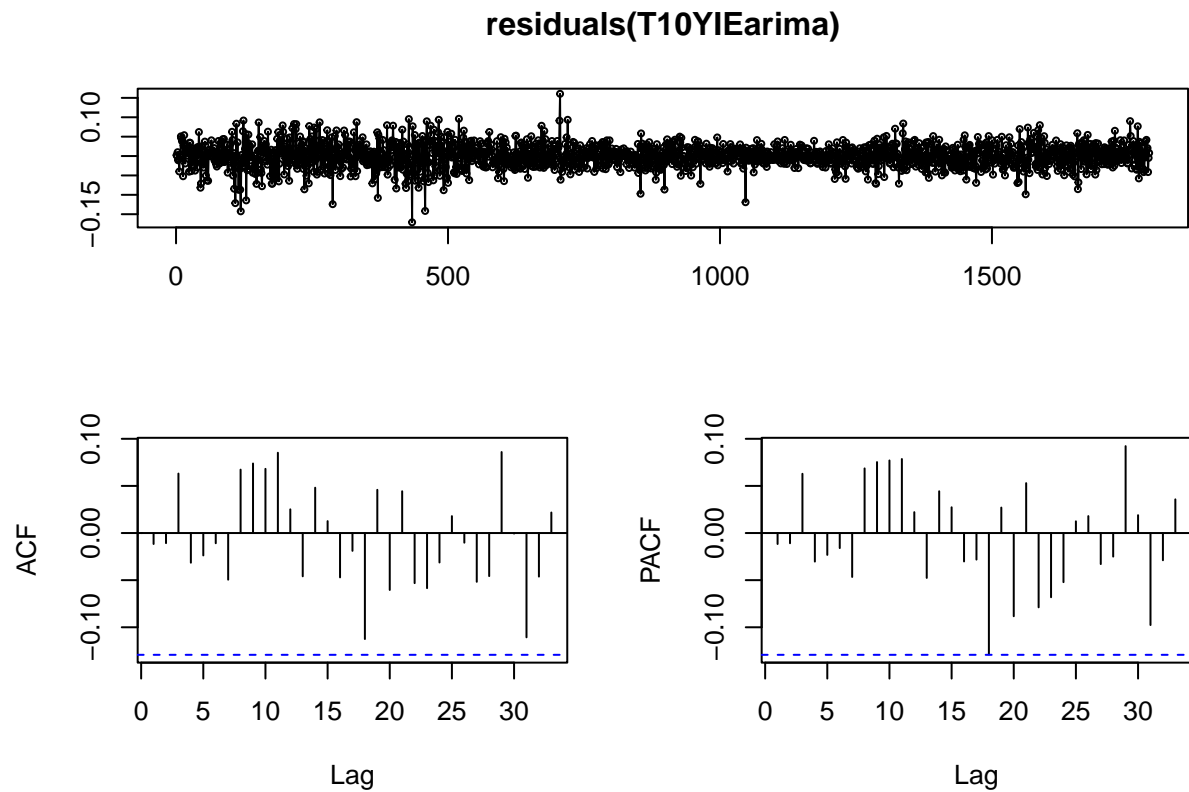
checking autocor

based on the plots bellow feeling pretty good about the autocorrelation. The arima (3,1,0) will work as a final model

```
tsdiag(T10YIEarima, gof = 25)
```

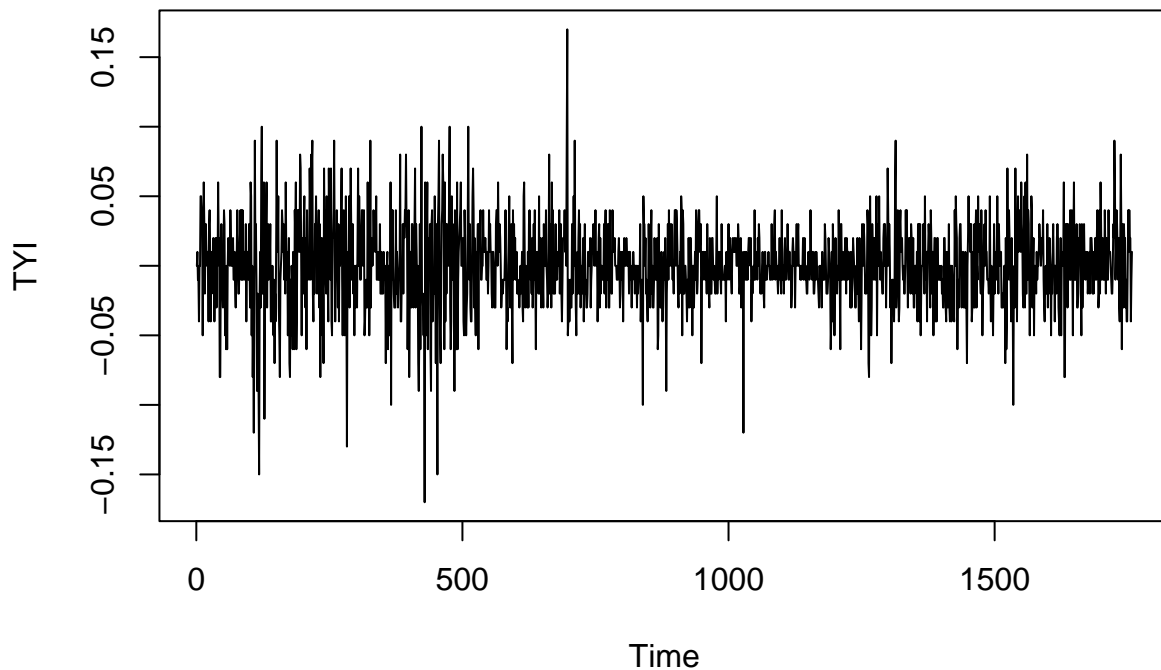


```
tsdisplay(residuals(T10YIEarima))
```



because there is a 1 in the differenced term we are going to difference it one more time then test for stationarity.

```
TYI <- na.omit(diff(mtn$T10YIE))  
  
ts.plot(TYI)
```



rejecting the null hypothesis good sign going to do the ur.df test now.

```
summary(CADFtest(TYI, type="drift"))
```

```
## Augmented DF test
##                                ADF test
## t-test statistic:             -2.994990e+01
## p-value:                     4.233707e-41
## Max lag of the diff. dependent variable: 1.000000e+00
##
## Call:
## dynlm(formula = formula(model), start = obs.1, end = obs.T)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.171082 -0.018096 -0.000208  0.018522  0.160357
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.673e-07  7.346e-04   0.000  0.99960
## L(y, 1)      -9.574e-01  3.197e-02 -29.950 < 2e-16 ***
## L(d(y), 1)    6.450e-02  2.384e-02   2.706  0.00688 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03078 on 1753 degrees of freedom
```

```
## Multiple R-squared:  0.452, Adjusted R-squared:  0.4513
## F-statistic:      NA on NA and NA DF,  p-value: NA
```

We confirm now that we have a stationary dataset.

```
TYI_df <- ur.df(TYI, type = "drift", lags = 1)
summary(TYI_df)
```

```
##
## #####
## # Augmented Dickey-Fuller Test Unit Root Test #
## #####
##
## Test regression drift
##
##
## Call:
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.171082 -0.018096 -0.000208  0.018522  0.160357
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.673e-07  7.346e-04   0.000  0.99960
## z.lag.1      -9.574e-01  3.197e-02 -29.950 < 2e-16 ***
## z.diff.lag    6.450e-02  2.384e-02   2.706  0.00688 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03078 on 1753 degrees of freedom
## Multiple R-squared:  0.452, Adjusted R-squared:  0.4513
## F-statistic: 722.9 on 2 and 1753 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -29.9499 448.4984
##
## Critical values for test statistics:
##      1pct  5pct 10pct
## tau2 -3.43 -2.86 -2.57
## phi1  6.43  4.59  3.78
```

##Snow Exploration

going to plot all snow falls onto the same plot. 8 different winters. I got a little lazy and didn't want to figure out how to change the xlabs so its just going to be that for now

```
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

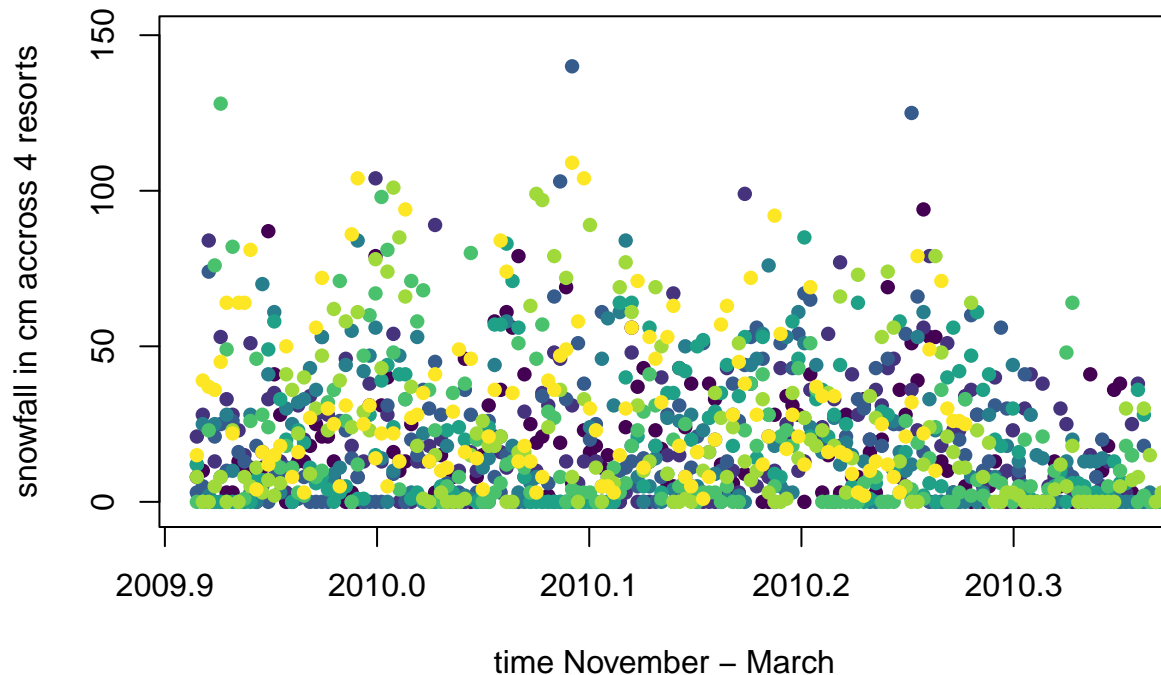
```
## The following objects are masked from 'package:base':
##
##   date, intersect, setdiff, union
```

```
library(viridis)
```

```
## Loading required package: viridisLite
```

```
temp <- as.Date(startdate)
plot(ts(winters[[1]]$allSnow, start = decimal_date(temp), frequency = 356.25), type = "p", pch = 16, col = "green")
for( i in 2:8){
  points(ts(winters[[i]]$allSnow, start = decimal_date(temp), frequency = 356.25), col = viridis(8)[i],
}
```

Daily Snowfall for years(2009–2017)



```
#return to this because this is annoying me
# plot(winters[[1]]$allSnow ~ winters[[1]]$Date, type = "p", pch = 16, col = viridis(8)[1], ylim = range
```

going to fit an arima with snowfall including all resorts to see if any have a significant relationship or if 1 resort is more significant than the others.

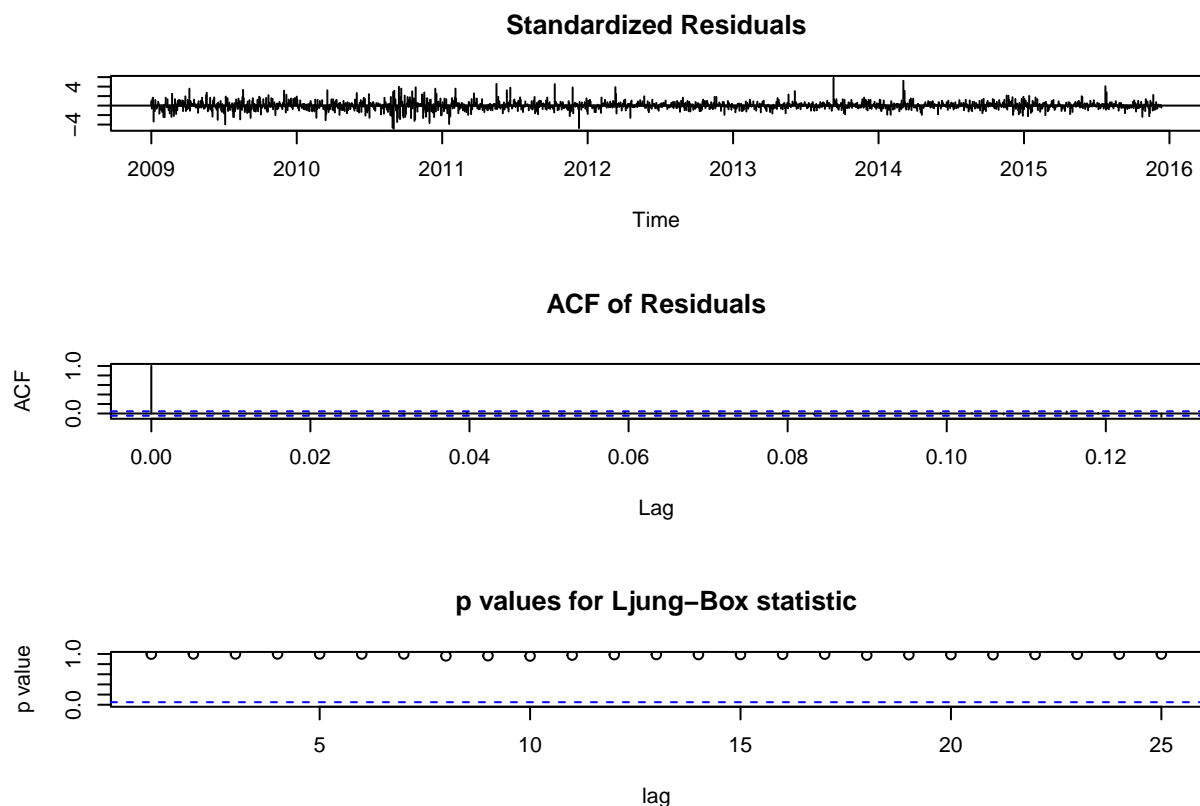
initial arima model for mtn including our non snowfall variables spanned across the entire time.

```
nonSnowModel <- auto.arima(dmtn[,1], xreg = cbind(dmtn[,2], dmtn[,3]))
summary(nonSnowModel)
```

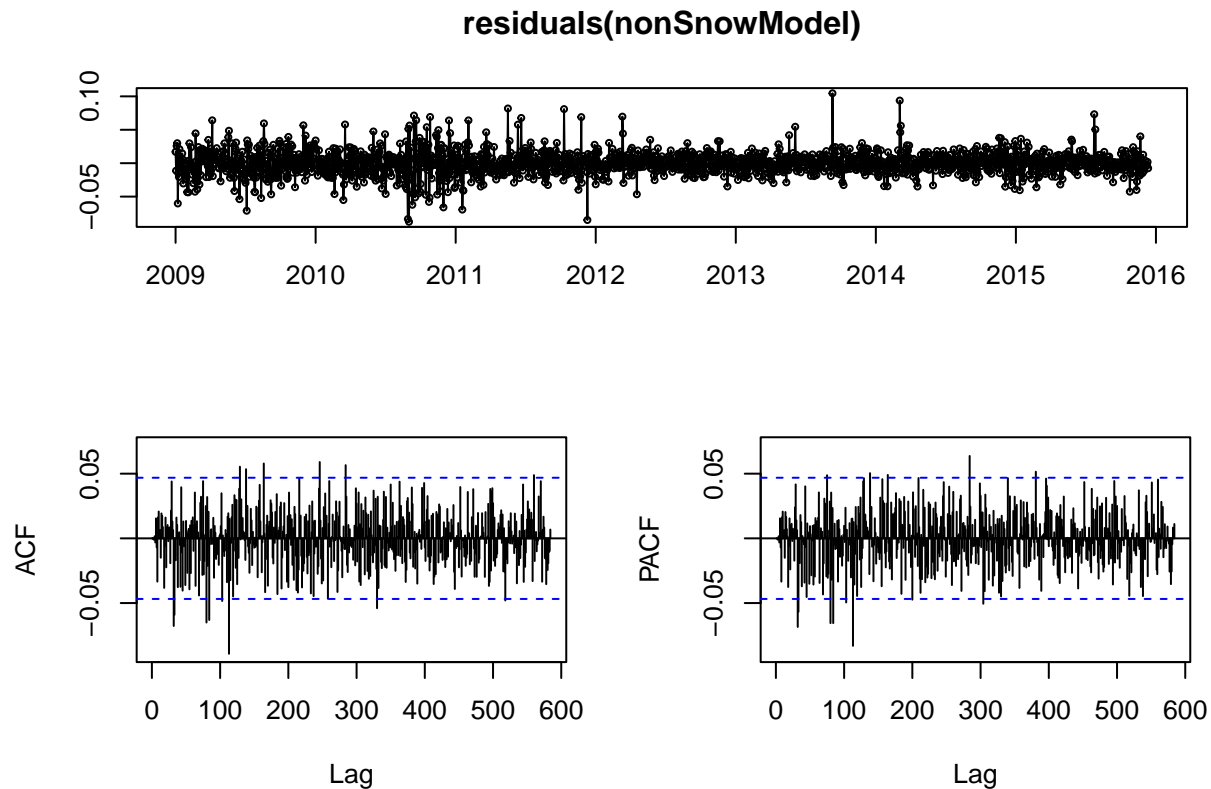
```
## Series: dmtn[, 1]
## Regression with ARIMA(5,0,1) errors
##
## Coefficients:
##          ar1      ar2      ar3      ar4      ar5      ma1  intercept  dmtn[, 2]
##          0.5754 -0.0749  0.0273 -0.0096 -0.0337 -0.6265      8e-04    0.0519
## s.e.    0.1992  0.0293  0.0349  0.0284  0.0285  0.1985      3e-04    0.0215
##          dmtn[, 3]
##          0.1611
## s.e.    0.0150
##
## sigma^2 = 0.0003232: log likelihood = 4556.48
## AIC=-9092.97  AICc=-9092.84  BIC=-9038.29
##
## Training set error measures:
##              ME      RMSE      MAE  MPE  MAPE      MASE
## Training set -4.594139e-06 0.01793196 0.01272391 NaN  Inf  0.6610151
##              ACF1
## Training set 0.0001221241
```

AYY no auto cor issues where just gonna rip this and we can also conclude that both cOil and T10YIE are significant which is cash money.

```
tsdiag(nonSnowModel, gof = 25)
```




```
tsdisplay(residuals(nonSnowModel))
```



Now we need to join the snow data onto this data and we are going to do a partial join because we are just going to drop the weekends from the snow data as there is no trading over the weekends. It would probably be better to put all of the weekend snow into either friday or monday however I have a deadline and that will take to long for me to do so we are just going to drop them with a partial join

```
#need to put predictors in a non TS variable so there easier to index
tempPredictors <- na.omit(diff(mtn))
```

```
#converting to a df to make easier to work with and attaching the dates
tempPredictors <- data.frame(index(tempPredictors), tempPredictors)
```

```
#changing col names
colnames(tempPredictors) <- c("Date", "mtn", "cOil", "T10YIE")
```

```
#doing left join because we only want to left_join the weekday variables so we want to drop the weekend
full_data <- tempPredictors %>%
  left_join(snowfallFull, by = join_by(Date))
```

out final dataset that we are going to use to split and fit all of our snow models on.

```
#NICE
full_data <- full_data[, !names(full_data) %in% "Dates"]
summary(full_data)
```

```
##      Date          mtn          cOil
## Min.   :2009-12-02  Min.   :-0.0906078  Min.   :-1.113e-01
## 1st Qu.:2011-09-04  1st Qu.: -0.0083645  1st Qu.: -1.164e-02
## Median :2013-06-18  Median : 0.0006699  Median : 9.643e-05
## Mean   :2013-06-16  Mean   : 0.0008352  Mean   :-1.463e-04
## 3rd Qu.:2015-03-25  3rd Qu.: 0.0100179  3rd Qu.: 1.079e-02
## Max.   :2016-12-30  Max.   : 0.1106224  Max.   : 1.129e-01
##      T10YIE      jacksonSnow      snowbirdSnow      tellurideSnow
## Min.   :-1.700e-01  Min.   : 0.000  Min.   : 0.000  Min.   : 0.000
## 1st Qu.: -2.000e-02  1st Qu.: 0.000  1st Qu.: 0.000  1st Qu.: 0.000
## Median : 0.000e+00  Median : 0.000  Median : 0.000  Median : 0.000
## Mean   :-1.142e-05  Mean   : 2.916  Mean   : 2.827  Mean   : 1.325
## 3rd Qu.: 2.000e-02  3rd Qu.: 0.000  3rd Qu.: 0.000  3rd Qu.: 0.000
## Max.   : 1.700e-01  Max.   :86.000  Max.   :64.000  Max.   :48.000
##      whistlerSnow      allSnow
## Min.   : 0.000  Min.   : 0.000
## 1st Qu.: 0.000  1st Qu.: 0.000
## Median : 0.000  Median : 0.000
## Mean   : 2.306  Mean   : 9.374
## 3rd Qu.: 0.000  3rd Qu.: 11.000
## Max.   :71.000  Max.   :128.000
```

so going forward we can say these variables are significant and we can justifying adding them for snow.

Splitting the predictors into year sections

```
start <- 2009#date of first year
mtnSections <- vector(mode='list', length=8)
# Loop through each year
for (i in 1:8) {
  # Define the start and end dates for each time series
  start_date <- as.Date(paste(as.character(start + i - 1), "-11-20", sep = ""))
  end_date <- as.Date(paste(as.character(start + i), "-05-01", sep = ""))

  # Subset the original data for the current time series
  current_time_series <- subset(full_data, full_data$Date >= start_date & full_data$Date <= end_date)

  # Store the current time series in the list
  mtnSections[[i]] <- current_time_series
}
#test
mtnSections[[1]]
```

```
##      Date          mtn          cOil T10YIE jacksonSnow snowbirdSnow
## 1  2009-12-02  0.0167809966 -0.0228382289  0.00          10          0
## 2  2009-12-03 -0.0096269894 -0.0026136973  0.01           0          0
## 3  2009-12-04  0.0231510171 -0.0133045498 -0.01           0          0
## 4  2009-12-07  0.0277215690 -0.0203623914 -0.01           0          3
## 5  2009-12-08 -0.0709302844 -0.0177503295 -0.04          10          0
## 6  2009-12-09 -0.0170266984 -0.0268060166  0.00           0          5
## 7  2009-12-10 -0.0141017608 -0.0018412299  0.00           3          5
## 8  2009-12-11  0.0321670708 -0.0096866854  0.05           0          0
```

## 9	2009-12-14	0.0074966525	-0.0054542980	0.05	18	0
## 10	2009-12-15	-0.0030952983	0.0162744491	0.04	15	3
## 11	2009-12-16	0.0038674057	0.0282023438	0.04	0	0
## 12	2009-12-17	-0.0012871133	-0.0008263325	-0.05	8	3
## 13	2009-12-18	0.0198984956	0.0098712071	0.02	8	0
## 14	2009-12-21	0.0150414824	-0.0080816822	0.06	5	0
## 15	2009-12-22	-0.0254518539	0.0105343337	0.03	3	0
## 16	2009-12-23	-0.0020440034	0.0341147389	-0.02	3	13
## 17	2009-12-24	0.0053567732	0.0104671896	0.01	5	3
## 18	2009-12-28	-0.0086868588	0.0236666995	0.03	0	0
## 19	2009-12-29	-0.0149952613	0.0025390391	0.01	0	0
## 20	2009-12-30	-0.0191983034	0.0060675196	0.00	8	0
## 21	2009-12-31	0.0037101114	0.0005039688	0.01	13	43
## 22	2010-01-04	-0.0358188765	0.0264759732	0.01	5	0
## 23	2010-01-05	0.0019178117	0.0026950892	-0.04	8	0
## 24	2010-01-06	-0.0308488918	0.0167418687	0.03	25	0
## 25	2010-01-07	0.0156821631	-0.0062756663	0.04	3	15
## 26	2010-01-08	0.0381623361	0.0016934805	0.01	0	0
## 27	2010-01-11	-0.0032150972	-0.0024201367	-0.04	0	0
## 28	2010-01-12	-0.0067300578	-0.0214298288	0.01	0	0
## 29	2010-01-13	0.0221730741	-0.0140856177	-0.02	3	0
## 30	2010-01-14	-0.0079583021	-0.0038991308	-0.01	0	0
## 31	2010-01-15	-0.0204471285	-0.0176725723	0.00	0	0
## 32	2010-01-19	-0.0032668770	0.0129987812	0.02	10	0
## 33	2010-01-20	-0.0298945500	-0.0199495107	-0.01	5	33
## 34	2010-01-21	-0.0095986568	-0.0206192872	-0.04	8	20
## 35	2010-01-22	-0.0068321275	-0.0211880803	-0.02	15	13
## 36	2010-01-25	-0.0354687425	0.0087161128	0.02	15	18
## 37	2010-01-26	0.0513374840	-0.0030754855	0.01	10	0
## 38	2010-01-27	0.0025270896	-0.0138900487	-0.03	13	0
## 39	2010-01-28	-0.0186816451	-0.0002716284	0.02	8	8
## 40	2010-01-29	-0.0378500582	-0.0105141953	0.00	0	0
## 41	2010-02-01	-0.0050571902	0.0211878088	0.06	46	23
## 42	2010-02-02	0.0348752384	0.0369386409	0.02	3	0
## 43	2010-02-03	0.0157169546	-0.0032431760	0.02	3	0
## 44	2010-02-04	-0.0476143091	-0.0510471271	-0.08	13	5
## 45	2010-02-05	-0.0095607005	-0.0274483547	-0.08	13	0
## 46	2010-02-08	-0.0117776942	0.0100686069	0.00	0	0
## 47	2010-02-09	0.0263806585	0.0252795437	0.03	0	0
## 48	2010-02-10	0.0017734237	0.0103921578	-0.02	0	0
## 49	2010-02-11	0.0193048730	0.0100194546	-0.02	15	3
## 50	2010-02-12	0.0106612886	-0.0149996116	-0.03	13	18
## 51	2010-02-16	0.0045753460	0.0379951719	0.01	5	13
## 52	2010-02-17	0.0239615498	0.0037601341	0.04	0	0
## 53	2010-02-18	0.0108049665	0.0217622516	0.03	0	5
## 54	2010-02-19	0.0000000000	0.0100794604	-0.05	0	0
## 55	2010-02-22	0.0150420857	0.0033790158	-0.01	0	10
## 56	2010-02-23	-0.0339578296	-0.0180275919	-0.06	0	0
## 57	2010-02-24	0.0161565722	0.0143978239	0.00	0	0
## 58	2010-02-25	0.0002764170	-0.0223161283	-0.06	23	0
## 59	2010-02-26	-0.0052625629	0.0219398820	0.00	3	25
## 60	2010-03-01	0.0362683602	-0.0127502832	0.02	0	3
## 61	2010-03-02	-0.0191978460	0.0114951054	0.01	0	0
## 62	2010-03-03	-0.0093251966	0.0160721082	0.01	3	3

## 63	2010-03-04	-0.0121987603	-0.0086892304	0.00	3	5
## 64	2010-03-05	0.0315744020	0.0159548249	0.04	3	48
## 65	2010-03-08	-0.0070517476	0.0042852836	0.02	5	5
## 66	2010-03-09	0.0148592745	-0.0042852836	0.00	0	0
## 67	2010-03-10	0.0676513192	0.0069695214	0.01	3	23
## 68	2010-03-11	-0.0225587393	0.0003654748	0.00	0	8
## 69	2010-03-12	0.0140006354	-0.0102841259	0.02	0	0
## 70	2010-03-15	0.0073038789	-0.0182557072	-0.01	0	0
## 71	2010-03-16	0.0040070070	0.0242676265	-0.01	0	0
## 72	2010-03-17	0.0049861619	0.0143310687	0.01	0	0
## 73	2010-03-18	-0.0057360683	-0.0093283128	-0.02	0	0
## 74	2010-03-19	-0.0017527146	-0.0194180859	-0.03	0	3
## 75	2010-03-22	0.0208289289	0.0084034108	-0.01	0	0
## 76	2010-03-23	0.0097683629	0.0051552833	0.01	15	10
## 77	2010-03-24	0.0050898705	-0.0171640937	0.04	0	8
## 78	2010-03-25	-0.0043610381	-0.0004983182	0.02	0	0
## 79	2010-03-26	-0.0112340250	-0.0062500203	-0.02	15	3
## 80	2010-03-29	0.0007368297	0.0268464196	-0.02	0	0
## 81	2010-03-30	0.0066038962	0.0026819472	0.00	0	0
## 82	2010-03-31	-0.0229324591	0.0158225416	0.02	41	3
## 83	2010-04-01	0.0253675618	0.0128588508	0.04	3	33
## 84	2010-04-06	0.0018955152	0.0020821292	-0.01	0	0
## 85	2010-04-07	-0.0016584671	-0.0104542711	0.04	0	0
## 86	2010-04-08	0.0000000000	-0.0055032046	-0.01	0	0
## 87	2010-04-09	0.0218089326	-0.0067149925	0.01	0	0
## 88	2010-04-12	-0.0058162719	-0.0062844815	0.01	0	0
## 89	2010-04-13	0.0271595967	-0.0032167777	-0.01	0	0
## 90	2010-04-14	0.0155457896	0.0214858932	0.00	0	13
## 91	2010-04-15	0.0071290990	-0.0043307846	0.03	0	0
## 92	2010-04-16	-0.0224480169	-0.0271090195	-0.04	0	0
## 93	2010-04-19	-0.0040944020	-0.0176307078	0.01	0	0
## 94	2010-04-20	-0.0052565969	0.0177512260	0.01	0	0
## 95	2010-04-21	0.0032026970	-0.0024131286	0.00	0	0
## 96	2010-04-22	0.0385353615	0.0013279413	-0.01	0	0
## 97	2010-04-23	0.0534886578	0.0173418207	0.03	0	0
## 98	2010-04-26	-0.0100503109	-0.0016613271	0.00	0	5
## 99	2010-04-27	-0.0322920975	-0.0212454729	-0.03	0	0
## 100	2010-04-28	-0.0065414404	0.0095382552	0.06	0	0
## 101	2010-04-29	0.0147668957	0.0231615556	0.05	0	0
## 102	2010-04-30	-0.0162991885	0.0105116595	-0.05	0	41
##	tellurideSnow whistlerSnow allSnow					
## 1		0	0	10		
## 2		0	0	0		
## 3		0	0	0		
## 4		0	0	3		
## 5		3	0	13		
## 6		5	0	10		
## 7		3	0	11		
## 8		0	0	0		
## 9	23		0	41		
## 10		0	10	28		
## 11		0	0	0		
## 12		0	0	11		
## 13		0	5	13		

## 14	0	20	25
## 15	0	18	21
## 16	5	0	21
## 17	5	0	13
## 18	0	0	0
## 19	0	0	0
## 20	20	3	31
## 21	23	0	79
## 22	0	5	10
## 23	0	5	13
## 24	0	0	25
## 25	0	0	18
## 26	0	0	0
## 27	0	15	15
## 28	0	0	0
## 29	0	5	8
## 30	0	0	0
## 31	0	46	46
## 32	3	18	31
## 33	10	10	58
## 34	5	3	36
## 35	33	0	61
## 36	0	8	41
## 37	0	15	25
## 38	3	3	19
## 39	5	0	21
## 40	0	2	2
## 41	0	0	69
## 42	0	3	6
## 43	0	3	6
## 44	5	0	23
## 45	0	3	16
## 46	15	0	15
## 47	5	0	5
## 48	0	0	0
## 49	3	3	24
## 50	0	25	56
## 51	5	0	23
## 52	0	17	17
## 53	0	0	5
## 54	5	0	5
## 55	28	0	38
## 56	3	0	3
## 57	0	3	3
## 58	8	7	38
## 59	3	2	33
## 60	3	0	6
## 61	0	0	0
## 62	0	3	9
## 63	0	0	8
## 64	3	0	54
## 65	10	8	28
## 66	20	0	20
## 67	5	3	34

## 68	23	0	31
## 69	0	28	28
## 70	10	10	20
## 71	0	3	3
## 72	0	15	15
## 73	0	0	0
## 74	0	0	3
## 75	0	8	8
## 76	0	8	33
## 77	8	0	16
## 78	3	0	3
## 79	0	2	20
## 80	0	36	36
## 81	0	28	28
## 82	0	7	51
## 83	3	0	39
## 84	0	10	10
## 85	0	3	3
## 86	0	0	0
## 87	0	5	5
## 88	0	0	0
## 89	0	5	5
## 90	0	0	13
## 91	0	0	0
## 92	0	0	0
## 93	0	0	0
## 94	0	0	0
## 95	0	0	0
## 96	0	0	0
## 97	0	0	0
## 98	0	0	5
## 99	0	0	0
## 100	0	0	0
## 101	0	0	0
## 102	0	0	41

Now here we can sort of go two ways. I can fit an arima for each section of the snow data and view each separately which is the better way to go but this will take a while so I might just do the arima fit for around 2 and then do the var on every object.

none of our snows are significant which honestly isn't that surprising I didn't really think any would be but still cool. Jackson is the most significant which is surprising as it isn't even an epic resort.

```
predictors1allResorts <- ts(na.omit(mtnSections[[1]][, c("cOil", "T10YIE", "jacksonSnow", "snowbirdSnow", "tellurideSnow", "whistlerSnow")]), freq=252, start = 2009)
mtn1 <- ts(na.omit(mtnSections[[1]][, c("mtn")]), freq=252, start = 2009)
```

```
snowArima <- auto.arima(mtn1, xreg = predictors1allResorts)
summary(snowArima)
```

```
## Series: mtn1
## Regression with ARIMA(0,0,0) errors
##
## Coefficients:
##          cOil  T10YIE  jacksonSnow  snowbirdSnow  tellurideSnow  whistlerSnow
```

```
##      0.1175  0.2026      -5e-04      2e-04      0e+00      2e-04
## s.e.  0.1379  0.0759      3e-04      2e-04      3e-04      2e-04
##
## sigma^2 = 0.0004303:  log likelihood = 253.67
## AIC=-493.33  AICc=-492.14  BIC=-474.96
##
## Training set error measures:
##              ME      RMSE      MAE MPE MAPE MASE      ACF1
## Training set 0.001370938 0.02012382 0.01553192 Inf  Inf  NaN -0.02941515
```

Now I am going to test it with all of the snow data combined.

The result is that the predicted value is equal to 0. So all together they don't really have any effect.

```
predictors1resortsCombined <- ts(na.omit(mtnSections[[1]][, c("cOil", "T10YIE", "allSnow")]),freq=252,
snowArima <- auto.arima(mtn1, xreg = predictors1resortsCombined)
summary(snowArima)
```

```
## Series: mtn1
## Regression with ARIMA(0,0,0) errors
##
## Coefficients:
##      cOil  T10YIE  allSnow
##      0.1296  0.2014    0e+00
## s.e.  0.1389  0.0775    1e-04
##
## sigma^2 = 0.0004353:  log likelihood = 251.51
## AIC=-495.01  AICc=-494.6  BIC=-484.51
##
## Training set error measures:
##              ME      RMSE      MAE MPE MAPE MASE      ACF1
## Training set 0.001356747 0.02055441 0.01592116 Inf  Inf  NaN -0.04554121
```

Due to the poor showing on the part of snow in the initial response I am going to create a for loop that is going to fit an ARIMA(2,0,0) on all of the winters. An ARIMA(2,0,0) was choose as it is what was significant without the snowfall. AutoArima isn't going to be used as it is having errors most likely due to the large number of 0's in the snowfall data.

```
#number of models
n <- length(mtnSections)
snow_models <- vector("list", length = n)

coefs <- matrix(NA, nrow = n, ncol = 12)
for( i in 1:n){
  #retrieving the data and converting to ts object
  predictors <- ts(na.omit(mtnSections[[1]][, c("cOil", "T10YIE", "allSnow")]),freq=252, start = 2009)
  response <- ts(na.omit(mtnSections[[1]][, c("mtn")]),freq=252, start = 2009)

  #fitting model
  model <- Arima(response, order = c(2,0,0), xreg = predictors)
  snow_models[[i]] <- model
```

```

#saving SE from coefs
coefs[i,] <- diag(sqrt(diag(coef(model))))
}

```

```

## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced
## Warning in sqrt(diag(coef(model))): NaNs produced

```

So basically none of the snow variables converged so we cannot conclude anything about there fits really

```
coefs
```

```

##      [,1] [,2]      [,3]      [,4]      [,5] [,6] [,7] [,8]      [,9]
## [1,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [2,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [3,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [4,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [5,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [6,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [7,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
## [8,]  NaN  NaN  0.05326618  0.3219664  0.446595  NaN  NaN  NaN  0.05326618
##      [,10]      [,11] [,12]
## [1,]  0.3219664  0.446595  NaN
## [2,]  0.3219664  0.446595  NaN
## [3,]  0.3219664  0.446595  NaN
## [4,]  0.3219664  0.446595  NaN
## [5,]  0.3219664  0.446595  NaN
## [6,]  0.3219664  0.446595  NaN
## [7,]  0.3219664  0.446595  NaN
## [8,]  0.3219664  0.446595  NaN

```

lets print out all of there summaries just to be safe

```

for(i in 1:n){
  print(summary(snow_models[[i]]))
}

```

```

## Series: response
## Regression with ARIMA(2,0,0) errors
##

```



```

## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994  -1e-04
## s.e.   0.1038   0.1017    0.0025  0.1456  0.0796   2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994  -1e-04
## s.e.   0.1038   0.1017    0.0025  0.1456  0.0796   2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994  -1e-04
## s.e.   0.1038   0.1017    0.0025  0.1456  0.0796   2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994  -1e-04
## s.e.   0.1038   0.1017    0.0025  0.1456  0.0796   2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response

```

```

## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994   -1e-04
## s.e.    0.1038    0.1017    0.0025  0.1456  0.0796    2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994   -1e-04
## s.e.    0.1038    0.1017    0.0025  0.1456  0.0796    2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994   -1e-04
## s.e.    0.1038    0.1017    0.0025  0.1456  0.0796    2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1
## Training set 1.226634e-05 0.02029829 0.01573076 NaN  Inf  NaN -0.003924798
## Series: response
## Regression with ARIMA(2,0,0) errors
##
## Coefficients:
##      ar1      ar2  intercept    cOil  T10YIE  allSnow
##      -0.0597 -0.1175    0.0028  0.1037  0.1994   -1e-04
## s.e.    0.1038    0.1017    0.0025  0.1456  0.0796    2e-04
##
## sigma^2 = 0.0004378: log likelihood = 252.77
## AIC=-491.54  AICc=-490.35  BIC=-473.16
##
## Training set error measures:
##              ME          RMSE          MAE MPE MAPE MASE          ACF1

```

```
## Training set 1.226634e-05 0.02029829 0.01573076 NaN Inf NaN -0.003924798
```

Yeah we cannot conclude that there is any relationship between snowfall and Vail resorts stock price.

Going forwards

Although we didn't get the result that we were looking for we still definitely learned some stuff. I am really happy with how cOil and Inflation fit to the Vail resorts data and it is definitely worth looking more into that. These makes sense as skiing is extra. People aren't going skiing if they don't have any money so both of these can be used to model how the average person is really doing so it makes sense that there is a relationship. I feel the biggest problem with this model and my process really is the response variable. We are trying to model MTN or vail resorts stock. The problem with doing this is stocks are much more speculative and the information can be reflected in stocks much more randomly. That is why we got a random walk when looking at the vail resorts data. As well there is alot more going on in the vail resorts stock than just skiing. They most likely reinvest there money in the summer trying to turn revenue there. As well people are buying stock on speculation. They are honestly not really overly concerned about the snow especially on a particular day. I was basically trying to see if maybe a big snow would jolt stock investors and more so act as a reminder to buy the stock they already wanted to buy. This is a big stretch by any means. However, if I could get my hands on daily skiers at certain resorts or potential car traffic on a highway like I70. I feel like there would be a good chance of significance. However stock price is just too resilient to be effect by something small like daily snowfall. I feel as though it could be effected by like say a 5 year terrible snow stretch. I do not have examples of this occurring however and some clever macro economic modeling will be required to prove this.

Fitting the Var

I'm still going to fit a var for just the non snowfall data just for gigs. I really doubt that there is going to any underlying causal relationships

```
require(vars)
```

going to go with 1 lag.

```
mtn <- na.omit(mtn)
VARselect(mtn, lag.max = 15, type = "none")
```

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      3      1      1      3
##
## $criteria
##           1           2           3           4           5
## AIC(n) -2.280142e+01 -2.281110e+01 -2.281996e+01 -2.281752e+01 -2.281191e+01
## HQ(n)  -2.279105e+01 -2.279036e+01 -2.278885e+01 -2.277604e+01 -2.276007e+01
## SC(n)  -2.277337e+01 -2.275499e+01 -2.273580e+01 -2.270531e+01 -2.267165e+01
## FPE(n)  1.251607e-10  1.239554e-10  1.228619e-10  1.231626e-10  1.238547e-10
##           6           7           8           9          10
## AIC(n) -2.280882e+01 -2.280259e+01 -2.279373e+01 -2.278749e+01 -2.278001e+01
## HQ(n)  -2.274661e+01 -2.273001e+01 -2.271078e+01 -2.269417e+01 -2.267632e+01
## SC(n)  -2.264051e+01 -2.260622e+01 -2.256931e+01 -2.253502e+01 -2.249948e+01
## FPE(n)  1.242382e-10  1.250154e-10  1.261284e-10  1.269175e-10  1.278715e-10
```

```
##              11              12              13              14              15
## AIC(n) -2.277694e+01 -2.277137e+01 -2.276789e+01 -2.276081e+01 -2.275411e+01
## HQ(n) -2.266289e+01 -2.264695e+01 -2.263310e+01 -2.261565e+01 -2.259858e+01
## SC(n) -2.246836e+01 -2.243474e+01 -2.240321e+01 -2.236808e+01 -2.233332e+01
## FPE(n) 1.282644e-10 1.289817e-10 1.294313e-10 1.303518e-10 1.312295e-10
```

```
varmtn <- VAR(mtn, lag.max = 13, type = "none", ic = "SC")
varmtn
```

```
##
## VAR Estimation Results:
## =====
##
## Estimated coefficients for equation mtn:
## =====
## Call:
## mtn = mtn.l1 + cOil.l1 + T10YIE.l1
##
##      mtn.l1      cOil.l1      T10YIE.l1
## 0.99953125 0.00283722 -0.00468887
##
##
## Estimated coefficients for equation cOil:
## =====
## Call:
## cOil = mtn.l1 + cOil.l1 + T10YIE.l1
##
##      mtn.l1      cOil.l1      T10YIE.l1
## 0.0001839469 0.9994520042 0.0006774723
##
##
## Estimated coefficients for equation T10YIE:
## =====
## Call:
## T10YIE = mtn.l1 + cOil.l1 + T10YIE.l1
##
##      mtn.l1      cOil.l1      T10YIE.l1
## -0.001494636 0.007153411 0.987679755
```

```
summary(varmtn)
```

```
##
## VAR Estimation Results:
## =====
## Endogenous variables: mtn, cOil, T10YIE
## Deterministic variables: none
## Sample size: 1769
## Log Likelihood: 12642.271
## Roots of the characteristic polynomial:
##      1 0.9998 0.9867
## Call:
## VAR(y = mtn, type = "none", lag.max = 13, ic = "SC")
##
```

```

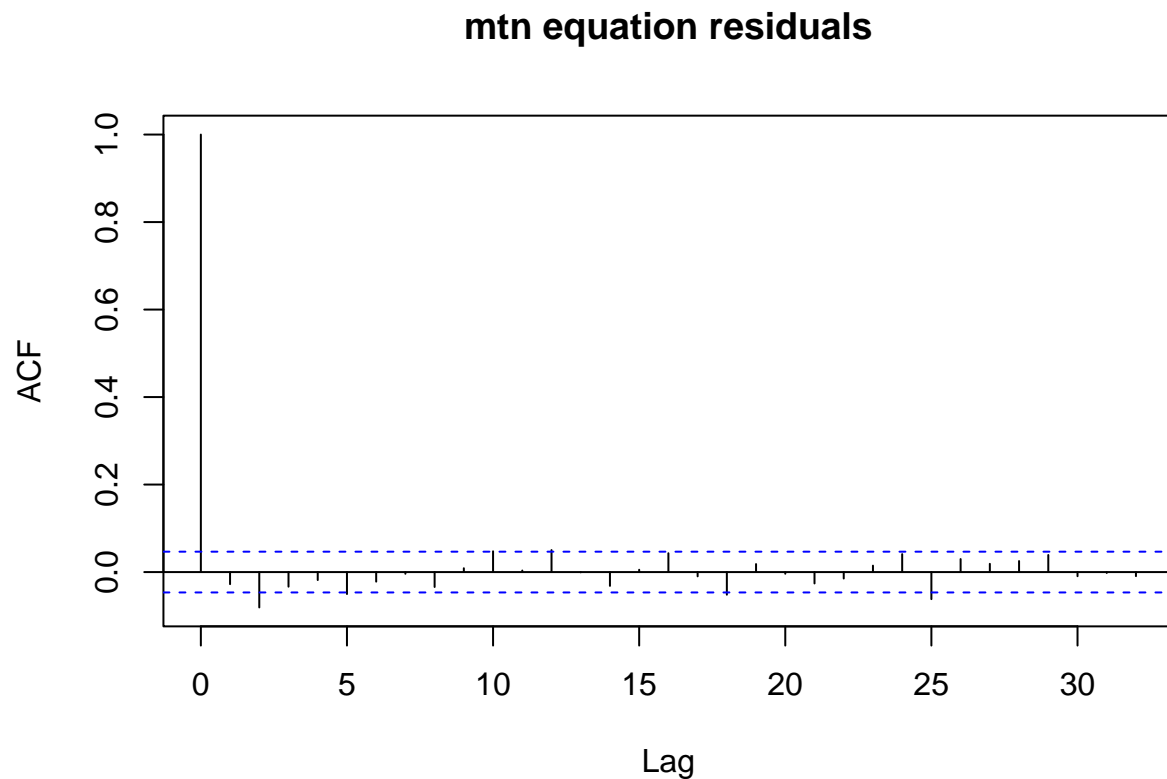
##
## Estimation results for equation mtn:
## =====
## mtn = mtn.l1 + cOil.l1 + T10YIE.l1
##
##           Estimate Std. Error  t value Pr(>|t|)
## mtn.l1      0.9995312  0.0007119 1404.108  <2e-16 ***
## cOil.l1      0.0028372  0.0016518   1.718   0.0860 .
## T10YIE.l1 -0.0046889  0.0025637  -1.829   0.0676 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01887 on 1766 degrees of freedom
## Multiple R-Squared: 1, Adjusted R-squared: 1
## F-statistic: 2.662e+07 on 3 and 1766 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation cOil:
## =====
## cOil = mtn.l1 + cOil.l1 + T10YIE.l1
##
##           Estimate Std. Error t value Pr(>|t|)
## mtn.l1      0.0001839  0.0008215   0.224   0.823
## cOil.l1      0.9994520  0.0019063 524.292  <2e-16 ***
## T10YIE.l1  0.0006775  0.0029586   0.229   0.819
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.02178 on 1766 degrees of freedom
## Multiple R-Squared: 1, Adjusted R-squared: 1
## F-statistic: 2.329e+07 on 3 and 1766 DF, p-value: < 2.2e-16
##
##
## Estimation results for equation T10YIE:
## =====
## T10YIE = mtn.l1 + cOil.l1 + T10YIE.l1
##
##           Estimate Std. Error t value Pr(>|t|)
## mtn.l1      -0.001495  0.001166  -1.282  0.20005
## cOil.l1      0.007153  0.002706   2.644  0.00827 **
## T10YIE.l1   0.987680  0.004199 235.210 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.03091 on 1766 degrees of freedom
## Multiple R-Squared: 0.9998, Adjusted R-squared: 0.9998
## F-statistic: 2.611e+06 on 3 and 1766 DF, p-value: < 2.2e-16
##
##
## Covariance matrix of residuals:

```

```
##           mtn      cOil    T10YIE
## mtn      3.560e-04 6.952e-05 0.0001654
## cOil      6.952e-05 4.742e-04 0.0002626
## T10YIE    1.654e-04 2.626e-04 0.0009551
##
## Correlation matrix of residuals:
##           mtn      cOil    T10YIE
## mtn      1.0000 0.1692 0.2836
## cOil      0.1692 1.0000 0.3903
## T10YIE    0.2836 0.3903 1.0000
```

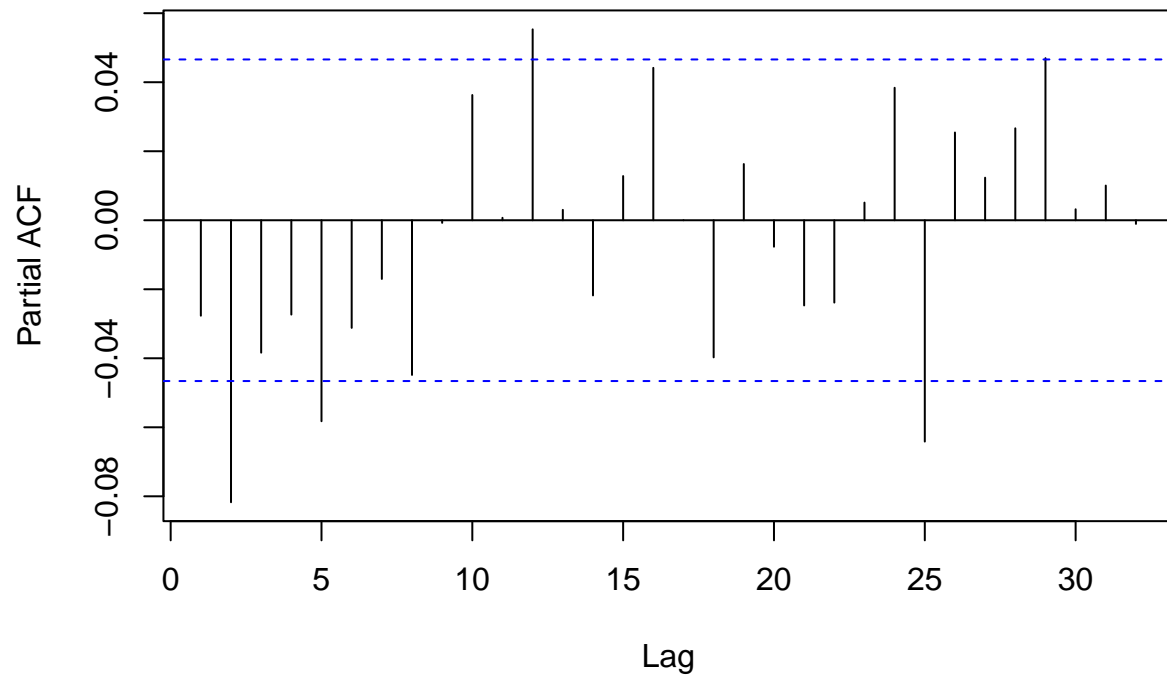
slight concerns with the pacf however I am not insanely worried

```
acf(varmtn$varresult$mtn$residuals,main="mtn equation residuals")
```



```
pacf(varmtn$varresult$mtn$residuals,main="mtn equation residuals")
```

mtn equation residuals



#Granger Causality

no real evidence of causality

```
roots(varmtn)
```

```
## [1] 1.0001432 0.9998244 0.9866955
```

```
causality(varmtn, cause="T10YIE")
```

```
## $Granger
```

```
##
```

```
## Granger causality H0: T10YIE do not Granger-cause mtn c0i1
```

```
##
```

```
## data: VAR object varmtn
```

```
## F-Test = 1.8217, df1 = 2, df2 = 5298, p-value = 0.1618
```

```
##
```

```
##
```

```
## $Instant
```

```
##
```

```
## H0: No instantaneous causality between: T10YIE and mtn c0i1
```

```
##
```

```
## data: VAR object varmtn
```

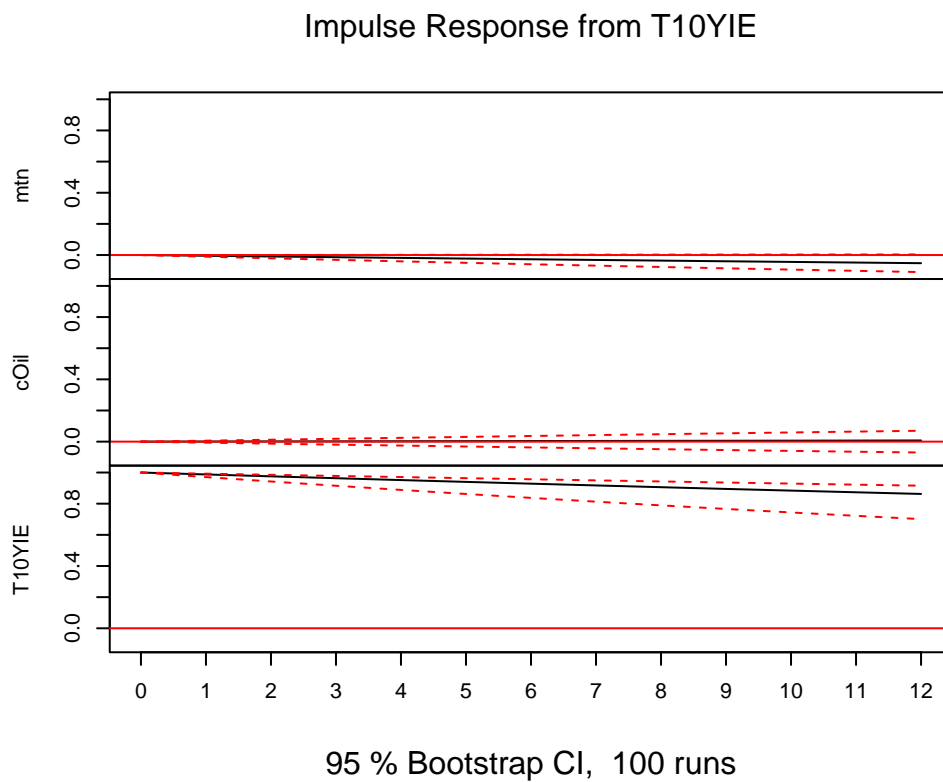
```
## Chi-squared = 296.12, df = 2, p-value < 2.2e-16
```

```
serial.test(varmtn, lags.pt = 16)
```

```
##  
## Portmanteau Test (asymptotic)  
##  
## data: Residuals of VAR object varmtn  
## Chi-squared = 179.39, df = 135, p-value = 0.006365
```

Yeah there is no causal relationships that we can find in our data. I feel as though this is mainly derived from Vail resorts being a stock. It is extremely hard to find causal relationships within stock. Due to people normally trade on these suspicions and that differences that out of the stock.

```
plot(irf(varmtn,n.ahead=12,ortho=F,impulse = "T10YIE"))
```



```
plot(irf(varmtn,n.ahead=12,ortho=T,impulse = "T10YIE"))
```