

Price-Book Ratio to Annual Return

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Below is some analysis conducted determining the effect of Price-Book value to subsequent 10 year returns.
Data gathered from Thompson Reuters' Eikon.

```
x <- read.csv(file="C:/Users/Sef/Desktop/Stats Project ASE/totPBret.csv", header=TRUE, sep=",")  
library(ggplot2)  
library('xts')  
library('tidyverse')  
library('broom')  
library('descriptr')  
library('olsrr')  
library('fitdistrplus')  
library('logspline')  
library('MASS')  
library('robustbase')  
library('Hmisc')  
library('lmtest')  
  
head(x)  
  
##   X     PB      Return  
## 1 1  2.63  0.11918479  
## 2 2  0.81  0.03100583  
## 3 3  3.53  0.12898107  
## 4 4  5.15  0.17560184  
## 5 5  1.40  0.14687995  
## 6 6  1.15  0.11419013
```

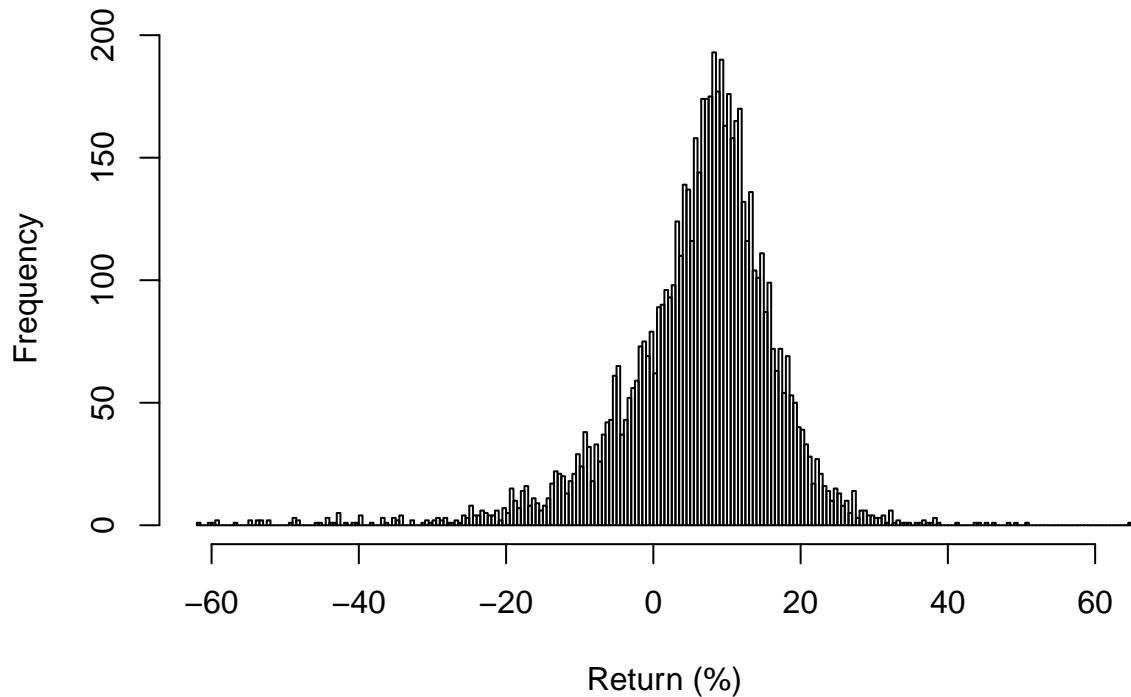
Data has been re-shaped into the following format: Stock #, Price-Book Value, Subsequent 10 Year Return

```
x<- x[,2:3] y<- data.frame(x[,1], (100*x[,2])) names(y)<-c("PB", "Return")  
x<- x[,2:3]  
y<- data.frame(x[,1], (100*x[,2]))  
names(y)<-c("PB", "Return")
```

Splitting the Data into positive, negative, and ‘low’ (<5) Price-Book Values

```
ypos<- y[ which(y$PB > 0) ,]  
ylow<-ypos[which(ypos$PB<5),]  
yhigh<-ypos[which(ypos$PB>5),]  
  
hist(y$Return, breaks= 200, main="10 Year Annualized Returns, 1990-2018", xlab="Return (%)")
```

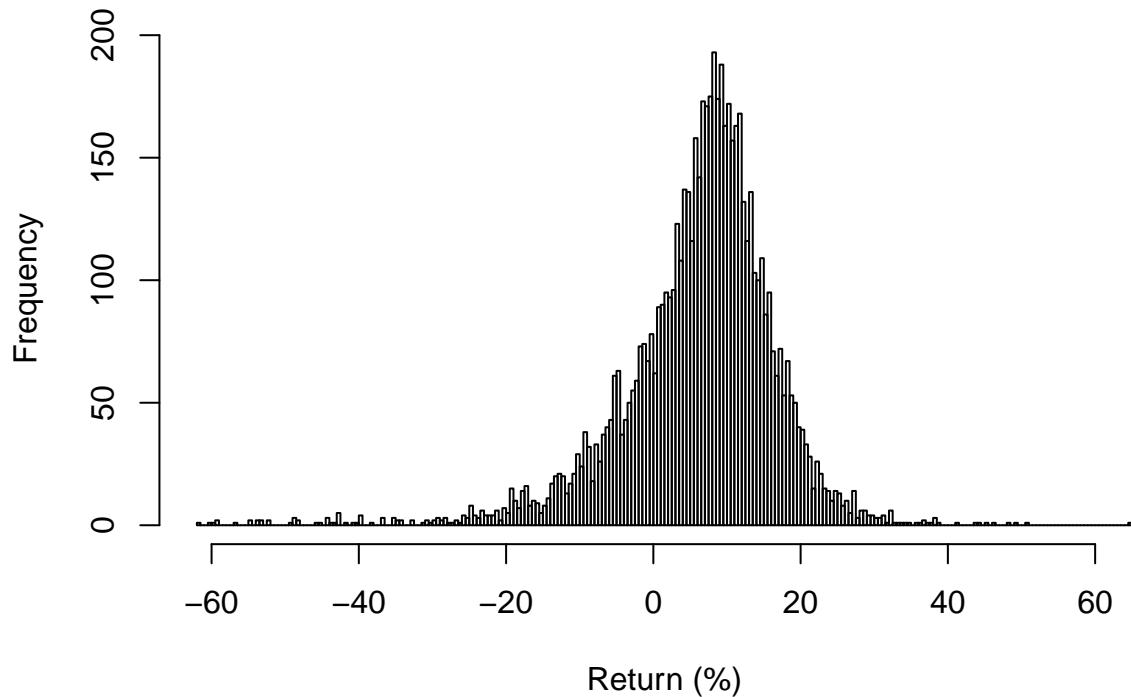
10 Year Annualized Returns, 1990–2018



Above are returns plotted for the complete data set and below is the same for the section of the data that had a positive Price-Book Value

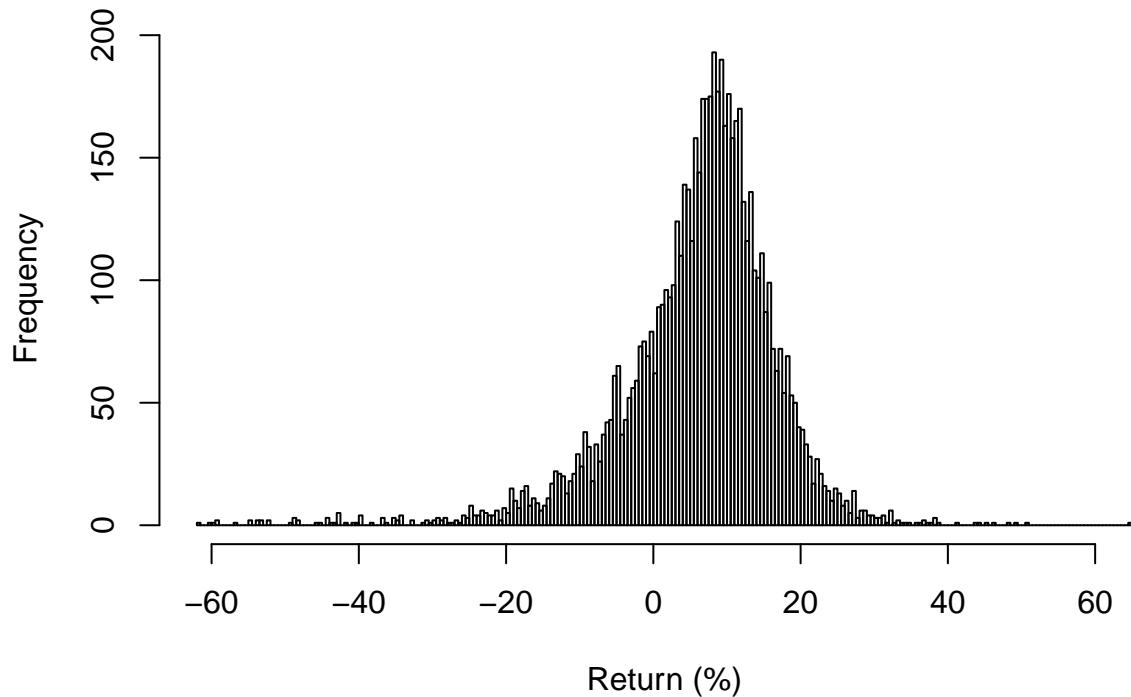
```
hist(ypos$Return, breaks= 200, main="10 Year Annualized Returns, 1990-2018", xlab="Return (%)")
```

10 Year Annualized Returns, 1990–2018



```
h<-hist(y$Return, breaks=200 , xlab="Return (%)", #Histogram  
main="Annualized Returns, 1990–2018")
```

Annualized Returns, 1990–2018



```
xfit<-seq(min(y$Return),max(y$Return),length=40)
yfit<-dnorm(xfit,mean=mean(y$Return),sd=sd(y$Return))
yfit <- yfit*diff(h$mids[1:2])*length(y$Return)
```

Average Return by examining mean return for whole data set and data set limited to positive PB values

```
summary(y)
```

```
##          PB             Return
##  Min.   :-2127.960   Min.   :-61.623
##  1st Qu.:    1.710   1st Qu.:  1.474
##  Median :    2.590   Median :  7.624
##  Mean   :    3.161   Mean   :  6.191
##  3rd Qu.:    4.140   3rd Qu.: 12.342
##  Max.   :  243.480   Max.   : 64.984
```

```
summary(ypos)
```

```
##          PB             Return
##  Min.   :  0.220   Min.   :-61.623
##  1st Qu.:  1.740   1st Qu.:  1.487
##  Median :  2.610   Median :  7.626
##  Mean   :  3.875   Mean   :  6.205
##  3rd Qu.:  4.162   3rd Qu.: 12.323
```

```

##  Max.    :243.480  Max.    : 64.984
cor(ypos$PB, ypos$Return)

## [1] -0.05872881

```

Visualising the Data

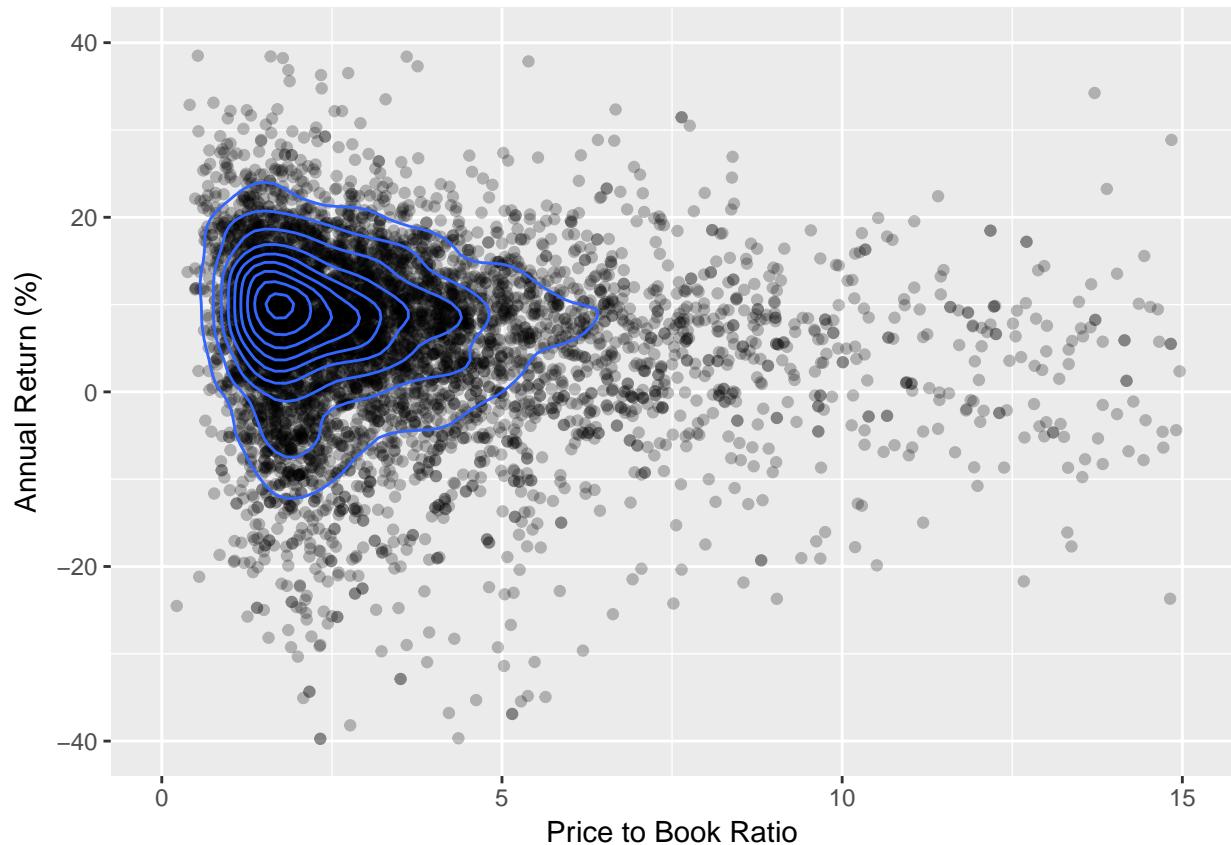
```

ggplot(ypos, aes(x=PB, y=Return)) + geom_point(alpha=0.25) + xlim(0,15) + geom_density2d() + ylim(-40, 40)

## Warning: Removed 161 rows containing non-finite values (stat_density2d).

## Warning: Removed 161 rows containing missing values (geom_point).

```

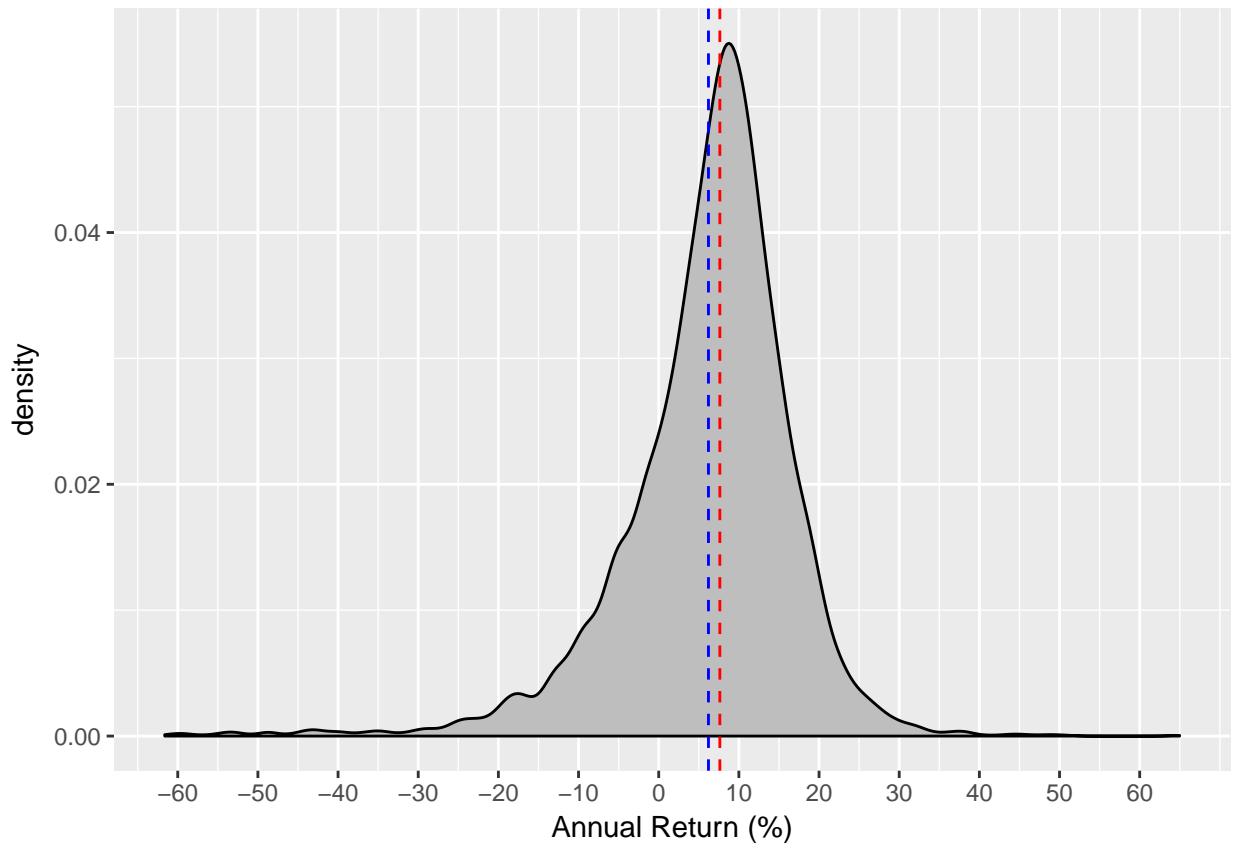


Density Plot with Mean and Median Return, Blue and Red respectively

```

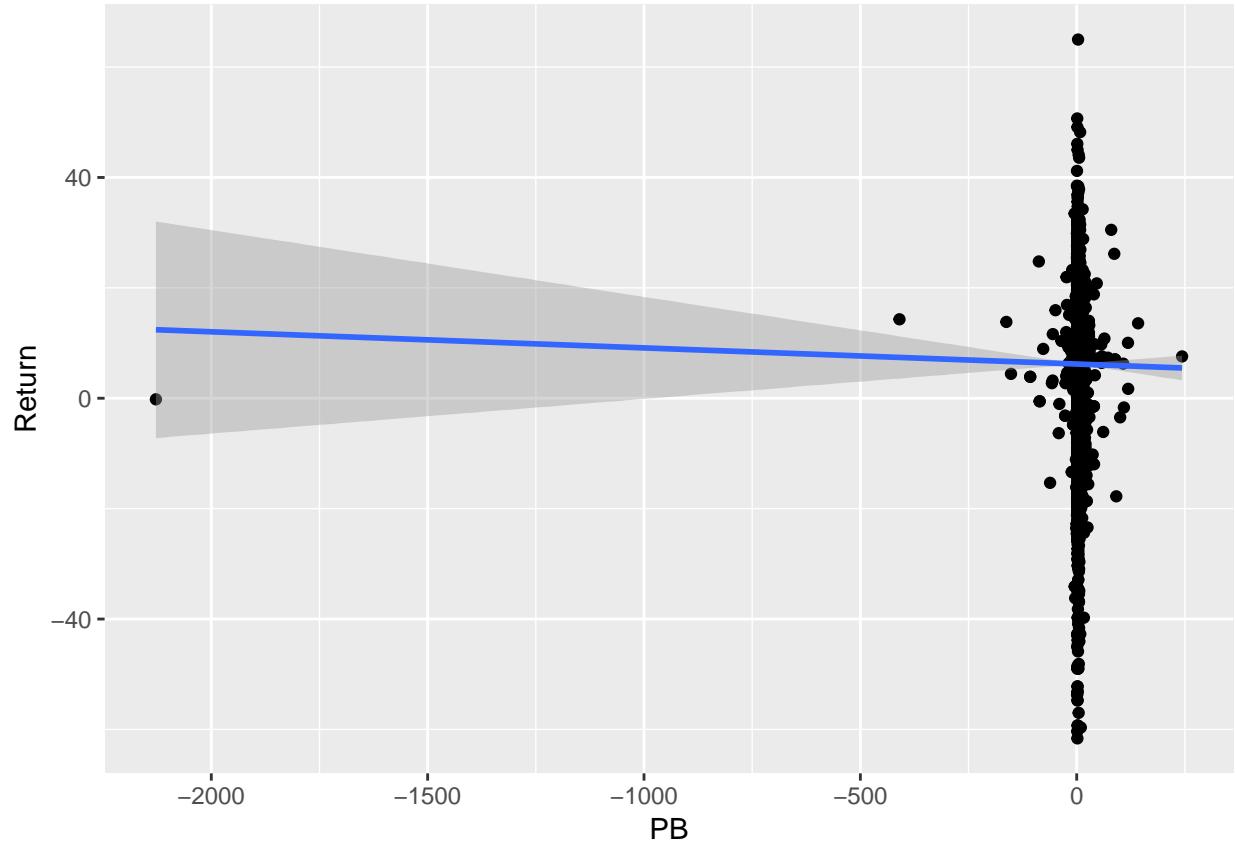
ggplot(ypos, aes(x=Return)) + geom_density(fill="gray") + geom_vline(aes(xintercept=mean(Return)), linetype="solid", color="blue")

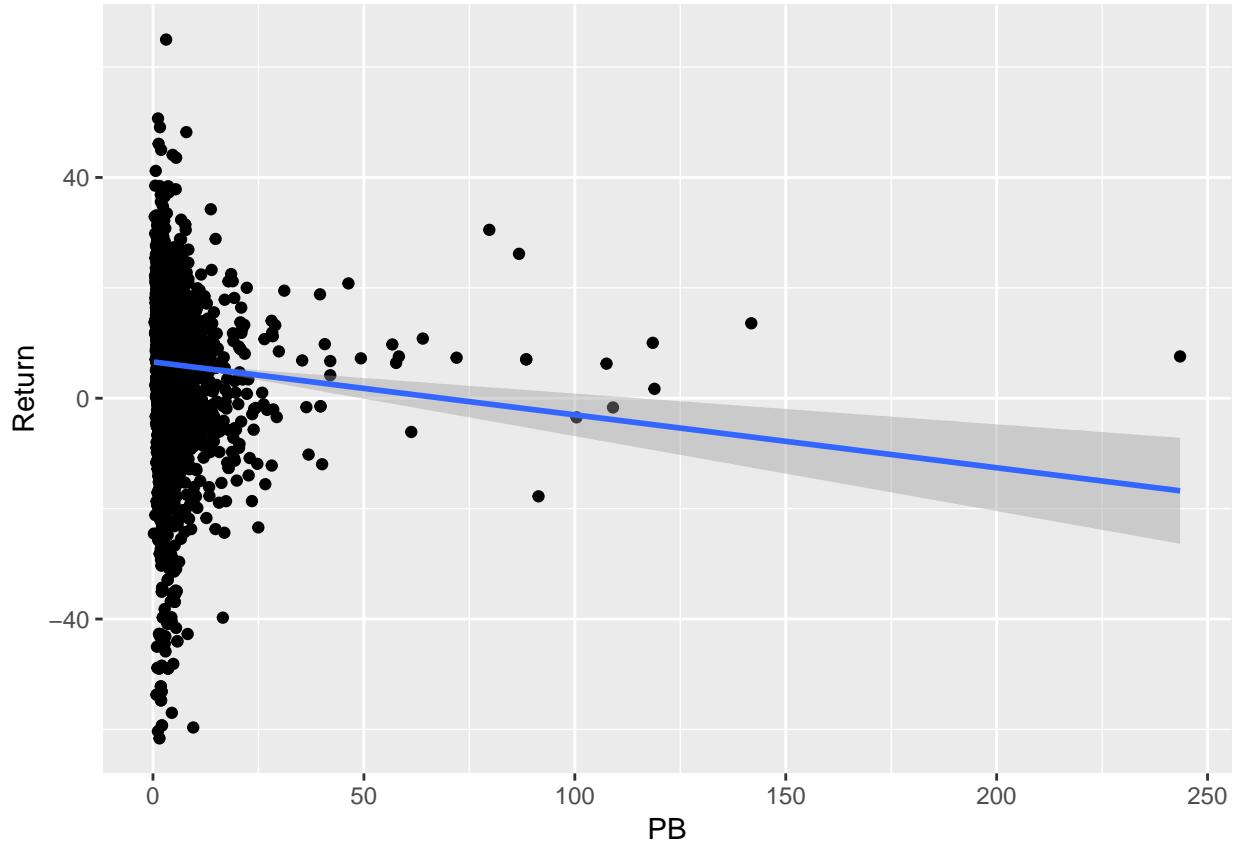
```



Linear Regression (grey shading is standard error) - for both Positive PB and whole Data Set

```
ggplot(data=y, aes(x=PB, y=Return)) + geom_point() + geom_smooth(method="lm")
```





Regression Model

```
mod <- lm(Return ~ PB, data=ypos)
coef_lmbeta <- mod$coefficients[2]
```

Regression Summary Statistics

```
coef(mod)

## (Intercept)          PB
##  6.57675701 -0.09585723

summary(mod)

##
## Call:
## lm(formula = Return ~ PB, data = ypos)
##
## Residuals:
##    Min     1Q   Median     3Q    Max 
## -68.052 -4.701   1.416   6.050  58.706 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 6.57676   0.09586  69.22   <2e-16 ***
## PB          -0.09586  0.00000 -95.93   <2e-16 ***
```

```

## (Intercept) 6.57676    0.15421  42.649 < 2e-16 ***
## PB          -0.09586   0.02042  -4.694 2.74e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 10.56 on 6366 degrees of freedom
## Multiple R-squared:  0.003449, Adjusted R-squared:  0.003293
## F-statistic: 22.03 on 1 and 6366 DF, p-value: 2.736e-06

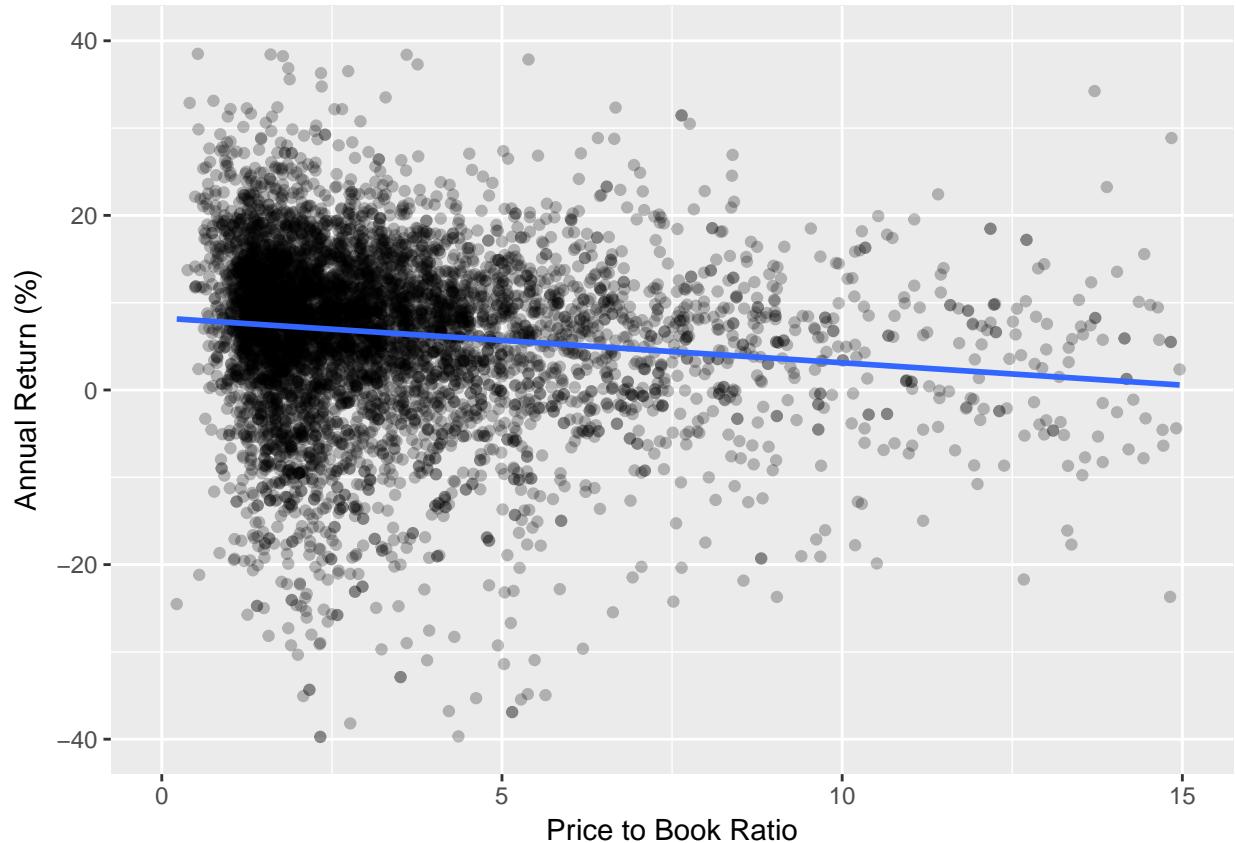
```

Regression Plot

```

ggplot(data=ypos, aes(x=PB, y=Return)) + geom_point(alpha=0.25) + geom_smooth(method="lm", se=FALSE) + xlab("Price to Book Ratio") + ylab("Annual Return (%)")
## Warning: Removed 161 rows containing non-finite values (stat_smooth).
## Warning: Removed 161 rows containing missing values (geom_point).

```

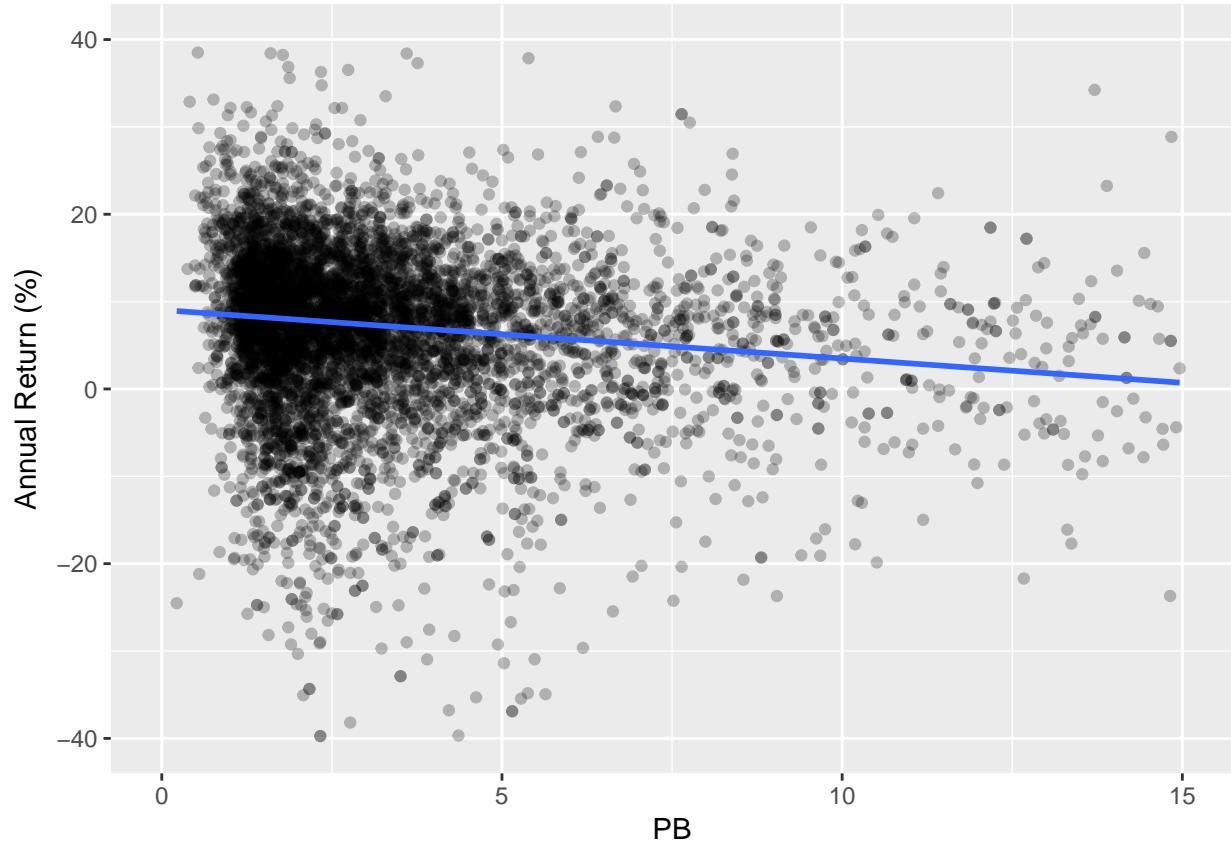


Regression Plot with RLM

```

ggplot(data=ypos, aes(x=PB, y=Return)) + geom_point(alpha=0.25) + geom_smooth(method="rlm", se=FALSE) + xlab("Price to Book Ratio") + ylab("Annual Return (%)")
## Warning: Removed 161 rows containing non-finite values (stat_smooth).
## Warning: Removed 161 rows containing missing values (geom_point).

```



```
#Test for Heteroskedasticity
bptest(mod)

##
## studentized Breusch-Pagan test
##
## data: mod
## BP = 2.8539, df = 1, p-value = 0.09115
ds_kurtosis(ypos$Return)

## [1] 5.102515
ds_skewness(ypos$Return)

## [1] -1.236622
cor.test(ypos$PB, ypos$Return)

##
## Pearson's product-moment correlation
##
## data: ypos$PB and ypos$Return
## t = -4.6939, df = 6366, p-value = 2.736e-06
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.08317071 -0.03421629
## sample estimates:
```

```
##           cor
## -0.05872881
```

Sorting by Cook's distance

```
mod %>%
  augment() %>%
  arrange(desc(.cooksdi)) %>%
  head()

##   .rownames     Return      PB    .fitted   .se.fit   .resid      .hat
## 1      3638  7.575727 243.48 -16.762561 4.894910 24.33829 0.21478934
## 2      6409 13.580324 141.83 -7.018674 2.820370 20.59900 0.07130756
## 3      5320 30.506626  79.73 -1.065940 1.554724 31.57257 0.02166857
## 4      419   26.166137  86.77 -1.740775 1.698015 27.90691 0.02584677
## 5      4731 10.038719 118.48 -4.780407 2.344158 14.81913 0.04926029
## 6      3490 -17.771589  91.39 -2.183635 1.792091 -15.58795 0.02879011
##   .sigma   .cooksdi .std.resid
## 1 10.55703 0.92494043   2.600511
## 2 10.55924 0.15724515   2.023820
## 3 10.55506 0.10115126   3.022237
## 4 10.55669 0.09507551   2.677071
## 5 10.56092 0.05364290   1.438976
## 6 10.56078 0.03324212  -1.497595
```

Sorting by Cook's distance colour="Red") + ylab("Annual Return (%)")

```
r1mmod <- rlm(Return ~ PB, data=ypos)
r1mmod <- lmrob(Return ~ PB, data=ypos)
summary(r1mmod)

##
## Call:
## lmrob(formula = Return ~ PB, data = ypos)
##   \--> method = "MM"
## Residuals:
##   Min     1Q   Median     3Q    Max
## -69.3539 -5.7075  0.3525  5.0245 57.5968
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 8.06712   0.29272 27.559 < 2e-16 ***
## PB          -0.21857   0.07805 -2.801  0.00512 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Robust residual standard error: 7.871
## Multiple R-squared:  0.01545,   Adjusted R-squared:  0.0153
## Convergence in 35 IRWLS iterations
## 
## Robustness weights:
```

```

## 68 observations c(163,229,345,416,564,599,857,876,890,969,1043,1153,1175,1187,1275,1349,1459,1481,1
##   are outliers with |weight| = 0 ( < 1.6e-05);
## 557 weights are ~= 1. The remaining 5743 ones are summarized as
##      Min.    1st Qu.    Median    Mean    3rd Qu.    Max.
## 0.0000879 0.8484000 0.9501000 0.8790000 0.9863000 0.9990000
## Algorithmic parameters:
##      tuning.chi          bb      tuning.psi      refine.tol
##      1.548e+00 5.000e-01 4.685e+00 1.000e-07
##      rel.tol      solve.tol  eps.outlier     eps.x
##      1.000e-07 1.000e-07 1.570e-05 4.429e-10
## warn.limit.reject warn.limit.meanrw
##      5.000e-01 5.000e-01
##      nResample      max.it      best.r.s      k.fast.s      k.max
##      500            50           2             1           200
##      maxit.scale      trace.lev      mts      compute.rd fast.s.large.n
##      200              0           1000            0           2000
##                  psi      subsampling      cov
##                  "bisquare"  "nonsingular" ".vcov.avar1"
## compute.outlier.stats
##                  "SM"
## seed : int(0)

```