In [3]:
```
ffdata <- read.delim("ffdata.txt", header = FALSE, sep = "")
```

In [4]:
```
secdata <- read.delim("secdata.txt", header = FALSE, sep = "")
```

In [5]:
```
retdata <- read.delim("retdate.txt", header = FALSE)
```

In [6]:
```
ticker <- read.delim("ticker.txt", header = FALSE)
```

In [359]:
```
stock_returns <- matrix(secdata[,2], nrow = 1511, ncol = 1877)
```

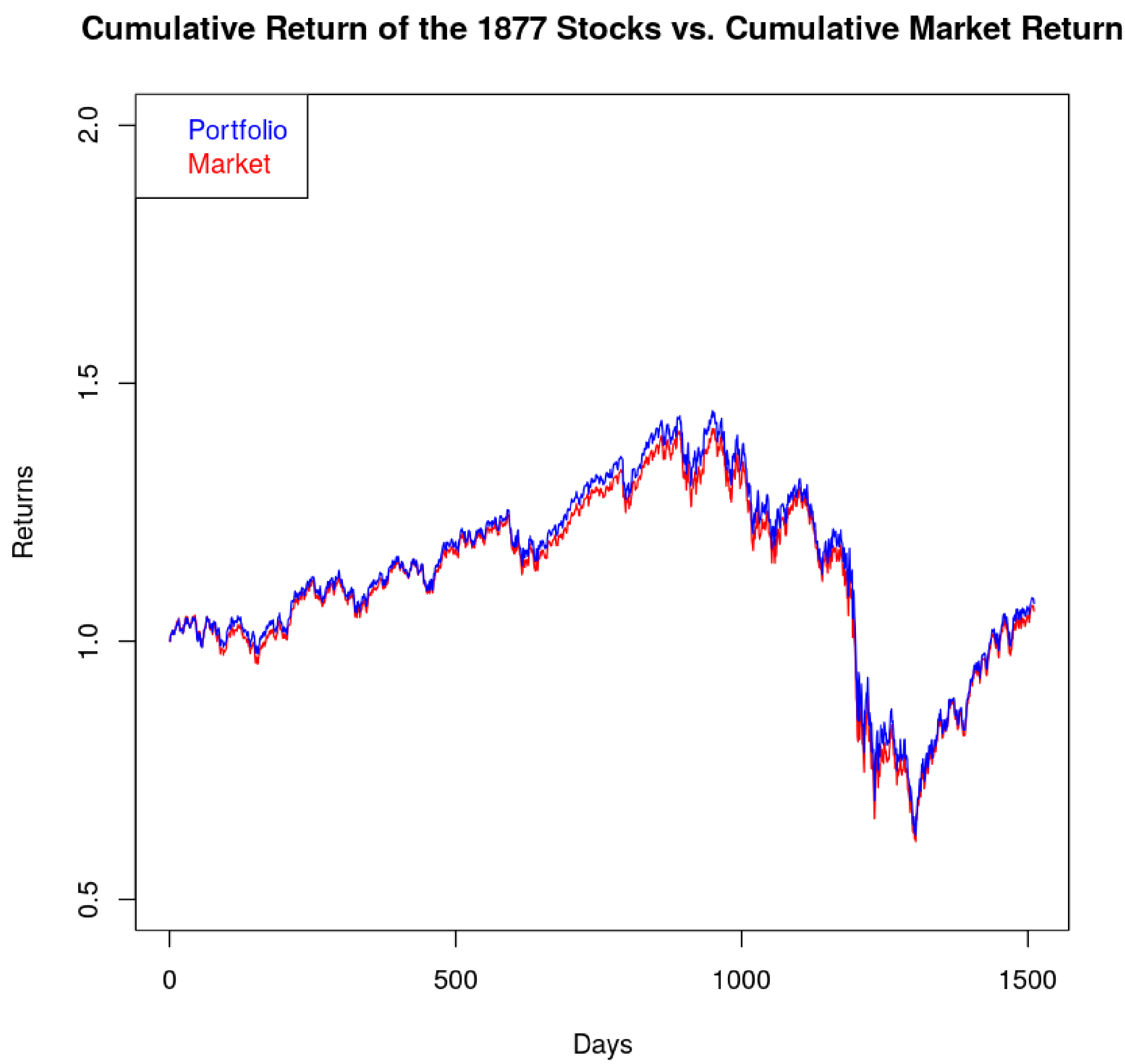
In [8]:
```
market_cap <- matrix(secdata[,3], nrow = 1511, ncol = 1877)
```

Question 1 Part a)

In [37]:
```
net_returns <- c(rep(1,1511))
for (i in 2:1511) {
    net_returns[i] <- sum(market_cap[i,])/sum(market_cap[i-1,])
}
cum_net_returns <- c(rep(0,1511))
for (i in 1:1511) {
    cum_net_returns[i] <- prod(net_returns[1:i])
}
```

In [38]:
```
ff_returns <- ffdata[,1] + 1
cum_ff_returns <- c(rep(0,1511))
for (i in 1:1511) {
    cum_ff_returns[i] <- prod(ff_returns[1:i])
}
```

In [39]:
```
plot(cum_ff_returns, type = "l", ylim = c(0.5,2), col = "red", main = "Cumulative Return of the 1877 Stocks vs. Cumulative Market Return", xlab = "Days", ylab = "Returns")
legend("topleft", text.col = c("blue","red"), c("Portfolio", "Market"))
lines(cum_net_returns, col = "blue")
```




We observe that the cumulative returns of the 1877 stocks and the cumulative returns of the market are overlapping, which suggests that the 1877 stocks we chose are a good tracker for market returns.

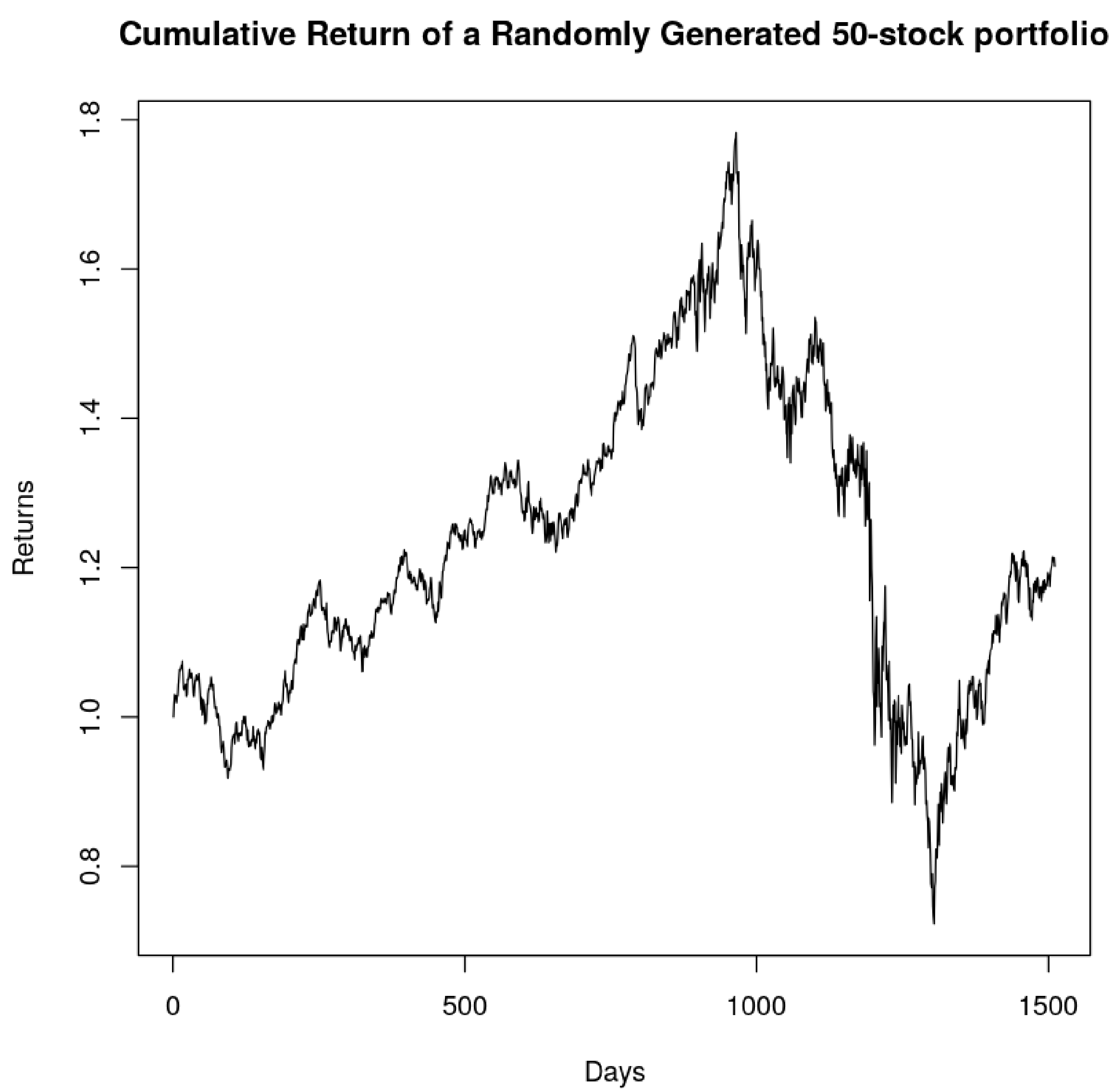
Question 1 Part b)

We will pick 50 stocks by randomly selecting 50 stocks from the first 800 stocks (alphabetically). We will first find and plot the cumulative returns of these randomly selected stocks. We will also find the RMSE

In [109]:
```
set.seed(100)
rnd_stocks <- c(sample(1:800,50,replace=F))
rnd_stocks_return <- stock_returns[,rnd_stocks]
rnd_stocks_market_cap <- market_cap[,rnd_stocks]
```

In [110]:
```
rnd_stock_net_returns <- c(rep(1,1511))
for (i in 2:1511) {
    rnd_stock_net_returns[i] <- sum(rnd_stocks_market_cap[i,])/sum(rnd_s
tocks_market_cap[i-1,])
}
cum_rnd_stock_net_returns <- c(rep(0,1511))
for (i in 1:1511) {
    cum_rnd_stock_net_returns[i] <- prod(rnd_stock_net_returns[1:i])
}
```

In [111]:
```
plot(cum_rnd_stock_net_returns, type = "l",main = "Cumulative Return of
 a Randomly Generated 50-stock portfolio", xlab = "Days", ylab = "Return
s" )
```



We will now find the RMSE of this stock portfolio compared to the market return based on 1-day simple return of the market.

In [112]:
```
(sum((rnd_stock_net_returns - ff_returns)^2)/1511)^(1/2)
```

0.00629367147361637

We can certainly reduce the RMSE by choosing a different portfolio of 50 stocks. To show this, let's now select another 50 stocks by randomly sampling from the last 800 stocks (alphabetically). This gives us the following RMSE

In [106]:
```
set.seed(100)
rnd_stocks_2 <- c(sample(1077:1877,50,replace=F))
rnd_stocks_return_2 <- stock_returns[,rnd_stocks_2]
rnd_stocks_market_cap_2 <- market_cap[,rnd_stocks_2]
```

In [107]:
```
rnd_stock_net_returns_2 <- c(rep(1,1511))
for (i in 2:1511) {
    rnd_stock_net_returns_2[i] <- sum(rnd_stocks_market_cap_2[i,])/sum(r
nd_stocks_market_cap_2[i-1,])
}
```

In [108]:
```
(sum((rnd_stock_net_returns_2 - ff_returns)^2)/1511)^(1/2)
```

0.00591688424400269

We see here that the RMSE has decreased slightly from 0.00629 to 0.00592. Hence, choosing a different portfolio of 50 stocks can reduce RMSE.

Question 1 part c)

25 10-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [105]:
```
set.seed(100)
rnd_stock_10 <- matrix(rep(0,250), nrow =25, ncol = 10) #generates the i
ndices for 25 10-stock portfolios
for (i in 1:25) {
    rnd_stock_10[i,] <- c(sample(1:1877,10,replace=F))
}
RMSE_10 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_10[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_10[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_10) #Finds the average of the RMSEs
```

0.0125078924822289

25 20-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [104]:
```
set.seed(100)
rnd_stock_20 <- matrix(rep(0,250), nrow =25, ncol = 20) #generates the i
ndices for 25 20-stock portfolios
for (i in 1:25) {
    rnd_stock_20[i,] <- c(sample(1:1877,20,replace=F))
}
RMSE_20 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_20[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_20[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_20) #Finds the average of the RMSEs
```

0.00988778984007995

25 30-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [103]:
```
set.seed(100)
rnd_stock_30 <- matrix(rep(0,250), nrow =25, ncol = 30) #generates the i
ndices for 25 30-stock portfolios
for (i in 1:25) {
    rnd_stock_30[i,] <- c(sample(1:1877,30,replace=F))
}
RMSE_30 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_30[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_30[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_30) #Finds the average of the RMSEs
```

0.00837869963367009

25 40-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [102]:
```
set.seed(100)
rnd_stock_40 <- matrix(rep(0,250), nrow =25, ncol = 40) #generates the i
ndices for 25 40-stock portfolios
for (i in 1:25) {
    rnd_stock_40[i,] <- c(sample(1:1877,40,replace=F))
}
RMSE_40 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_40[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_40[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_40) #Finds the average of the RMSEs
```

0.00755033712457847

25 50-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [101]:
```
set.seed(100)
rnd_stock_50 <- matrix(rep(0,250), nrow =25, ncol = 50) #generates the i
ndices for 25 50-stock portfolios
for (i in 1:25) {
    rnd_stock_50[i,] <- c(sample(1:1877,50,replace=F))
}
RMSE_50 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_50[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_50[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_50) #Finds the average of the RMSEs
```

0.00724531884293953

25 60-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [100]:
```
set.seed(100)
rnd_stock_60 <- matrix(rep(0,250), nrow =25, ncol = 60) #generates the i
ndices for 25 60-stock portfolios
for (i in 1:25) {
    rnd_stock_60[i,] <- c(sample(1:1877,60,replace=F))
}
RMSE_60 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_60[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_60[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_60) #Finds the average of the RMSEs
```

0.00602947940929144

25 70-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [99]:
```
set.seed(100)
rnd_stock_70 <- matrix(rep(0,250), nrow =25, ncol = 70) #generates the i
ndices for 25 70-stock portfolios
for (i in 1:25) {
    rnd_stock_70[i,] <- c(sample(1:1877,70,replace=F))
}
RMSE_70 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_70[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_70[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_70) #Finds the average of the RMSEs
```

0.0060808373798493

25 80-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [98]:
```
set.seed(100)
rnd_stock_80 <- matrix(rep(0,250), nrow =25, ncol = 80) #generates the i
ndices for 25 80-stock portfolios
for (i in 1:25) {
    rnd_stock_80[i,] <- c(sample(1:1877,80,replace=F))
}
RMSE_80 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_80[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_80[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_80) #Finds the average of the RMSEs
```

0.00596200750032389

25 90-stock portfolios of randomly chosen stocks and corresponding mean RMSE:

In [132]:
```
set.seed(100)
rnd_stock_90 <- matrix(rep(0,250), nrow =25, ncol = 90) #generates the i
ndices for 25 90-stock portfolios
for (i in 1:25) {
    rnd_stock_90[i,] <- c(sample(1:1877,90,replace=F))
}
RMSE_90 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_90[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_90[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511
)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 25
RMSEs
mean(RMSE_90) #Finds the average of the RMSEs
```

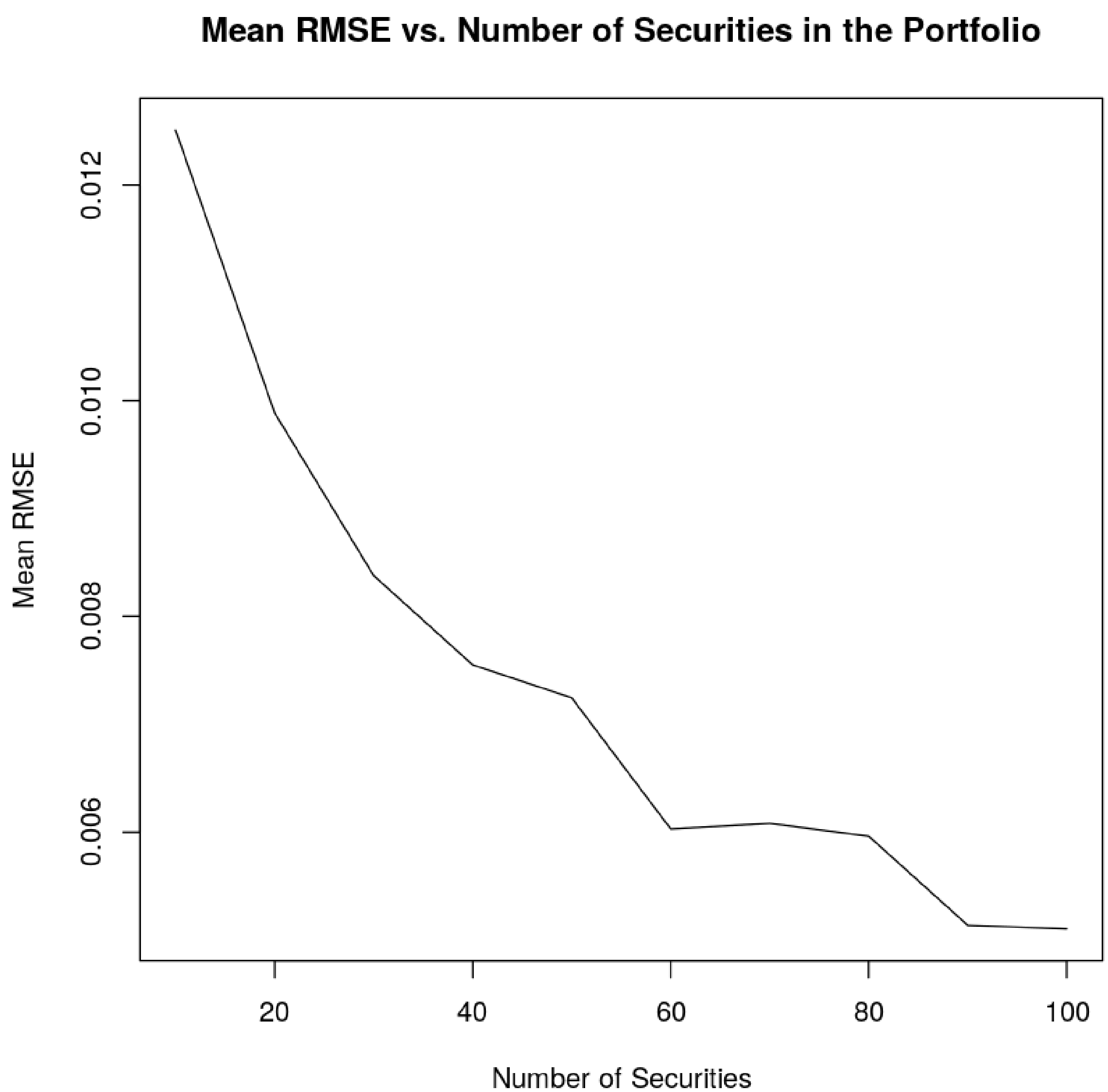
0.00513585463999323

25 100-stock portfolios of randomly chosen stocks:

In [114]:
```
set.seed(100)
rnd_stock_100 <- matrix(rep(0,250), nrow =25, ncol = 100) #generates the
indices for 25 100-stock portfolios
for (i in 1:25) {
    rnd_stock_100[i,] <- c(sample(1:1877,100,replace=F))
}
RMSE_100 <- c(rep(0,25))
for (i in 1:25){
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_100[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    RMSE_100[i] <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/151
1)^(1/2)} #calculates RMSE and stores it in a vector that compiles all 2
5 RMSEs
mean(RMSE_100) #Finds the average of the RMSEs
```

0.00510300091498504

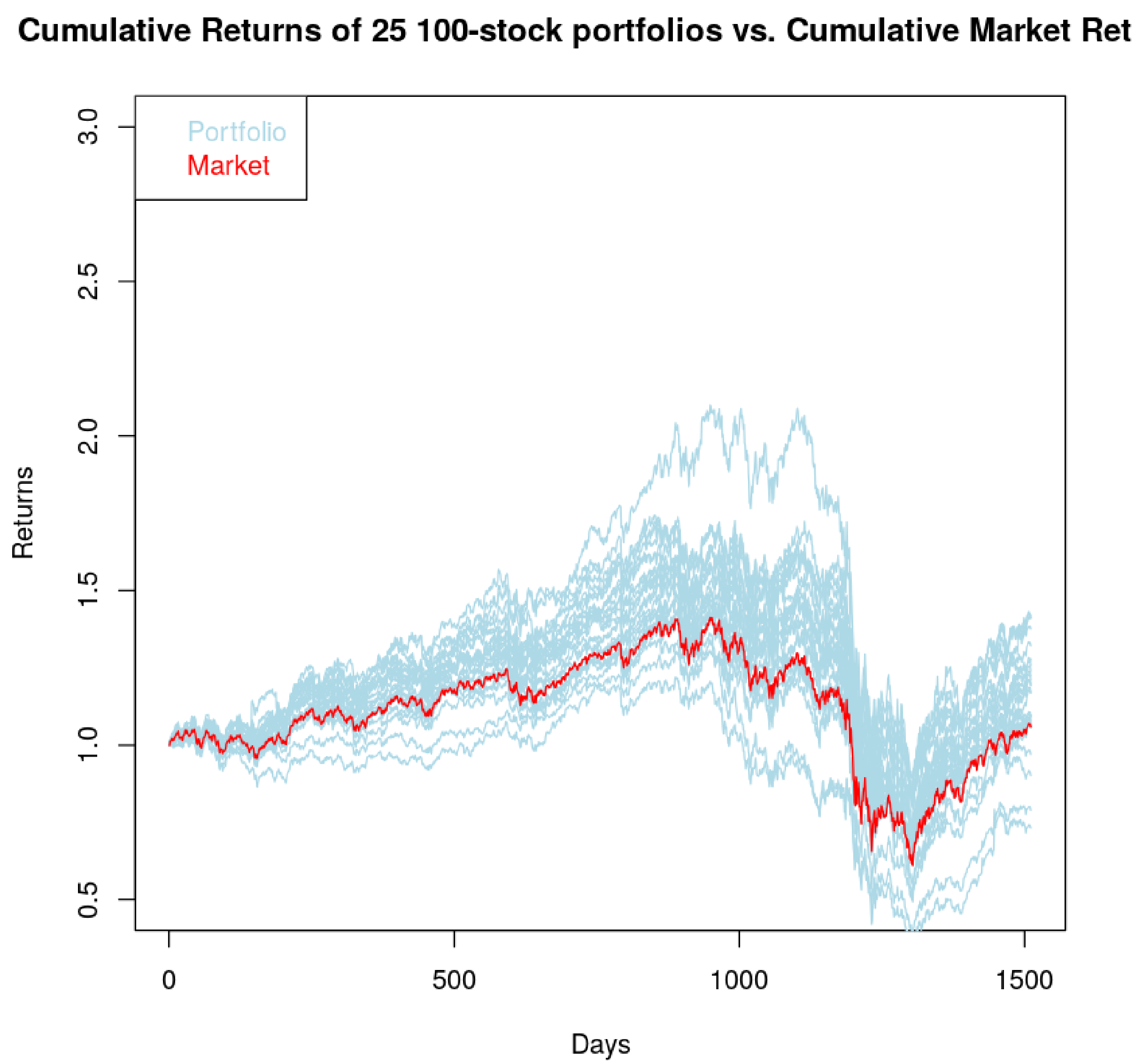
In [115]:
```
RMSEs <- c(mean(RMSE_10), mean(RMSE_20), mean(RMSE_30), mean(RMSE_40), m
ean(RMSE_50), mean(RMSE_60), mean(RMSE_70), mean(RMSE_80), mean(RMSE_90
), mean(RMSE_100))
number_securities <- c(10,20,30,40,50,60,70,80,90,100)
plot(number_securities, RMSEs, type = "l", main = "Mean RMSE vs. Number
 of Securities in the Portfolio", xlab = "Number of Securities", ylab =
"Mean RMSE")
```




We observe in this graph that mean RMSE steadily decreases as the number of securities increase. This is within expectation as more securities means larger sample size, thus lower variance. We will now select n=100 and plot the cumulative returns of all 25 portfolios, and to the market, as follow.

In [121]:
```
returns_of_25_portfolio <- matrix(rep(0,377750), nrow =25, ncol = 1511)
for (i in 1:25){
    rnd_stocks_return_dummy <- stock_returns[,rnd_stock_100[i,]]
    rnd_stocks_market_cap_dummy <- market_cap[,rnd_stock_100[i,]]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
    cum_rnd_stock_net_returns_dummy <- c(rep(0,1511))
    for (k in 1:1511) {
        cum_rnd_stock_net_returns_dummy[k] <- prod(rnd_stock_net_returns
_dummy[1:k])
    }
    returns_of_25_portfolio[i,] <-  cum_rnd_stock_net_returns_dummy
    }
```

In [122]:
```
plot(cum_ff_returns, type = "l", ylim = c(0.5,3), col = "red", main = "C
umulative Returns of 25 100-stock portfolios vs. Cumulative Market Retur
n", xlab = "Days", ylab = "Returns")
for (i in 1:25) {
lines(returns_of_25_portfolio[i,], col = "light blue")
    }
lines(cum_ff_returns, col = "red")
legend("topleft", text.col = c("light blue","red"), c("Portfolio", "Mark
et"))
```




Question 1 Part d)

One heuristic that we can use is comparing each individual stock's returns with the market return and include the n stocks with the lowest RMSE in our n-stock portfolio.

In [137]:
```
RMSE_individual_stocks <- c(rep(0,1877))
for (i in 1:1877) {
    rnd_stocks_market_cap_dummy <- market_cap[,i]
    rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- rnd_stocks_market_cap_dummy[j]
/rnd_stocks_market_cap_dummy[j-1]
    }
    RMSE_individual_stocks[i] <- (sum((rnd_stock_net_returns_dummy- ff_r
eturns)^2)/1511)^(1/2)
}
```

In [140]:
```
sorted_RMSE <- sort(RMSE_individual_stocks, index.return=TRUE, decreasin
g=FALSE) #sorts RMSE from smallest to largest
```

10-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [145]:
```
set.seed(100)
top_stock_10 <- head(sorted_RMSE$ix,10) #generates the indices for top 1
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_10]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top10 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top10
```

0.00648820572220311

20-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [146]:
```
set.seed(100)
top_stock_20 <- head(sorted_RMSE$ix,20) #generates the indices for top 2
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_20]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top20 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top20
```

0.00616154394654657

30-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [147]:
```
set.seed(100)
top_stock_30 <- head(sorted_RMSE$ix,30) #generates the indices for top 3
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_30]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top30 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top30
```

0.00607242031279169

40-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [148]:
```
set.seed(100)
top_stock_40 <- head(sorted_RMSE$ix,40) #generates the indices for top 4
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_40]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top40 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top40
```

0.00599365353022826

50-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [149]:
```
set.seed(100)
top_stock_50 <- head(sorted_RMSE$ix,50) #generates the indices for top 5
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_50]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top50 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top50
```

0.00555104258853075

60-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [150]:
```
set.seed(100)
top_stock_60 <- head(sorted_RMSE$ix,60) #generates the indices for top 6
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_60]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top60 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top60
```

0.00552924208433045

70-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [151]:
```
set.seed(100)
top_stock_70 <- head(sorted_RMSE$ix,70) #generates the indices for top 7
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_70]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top70 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top70
```

0.00554712520067994

80-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [152]:
```
set.seed(100)
top_stock_80 <- head(sorted_RMSE$ix,80) #generates the indices for top 8
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_80]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top80 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top80
```

0.00543141458304822

90-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [153]:
```
set.seed(100)
top_stock_90 <- head(sorted_RMSE$ix,90) #generates the indices for top 9
0-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_90]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top90 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(1
/2) #calculates RMSE
RMSE_top90
```

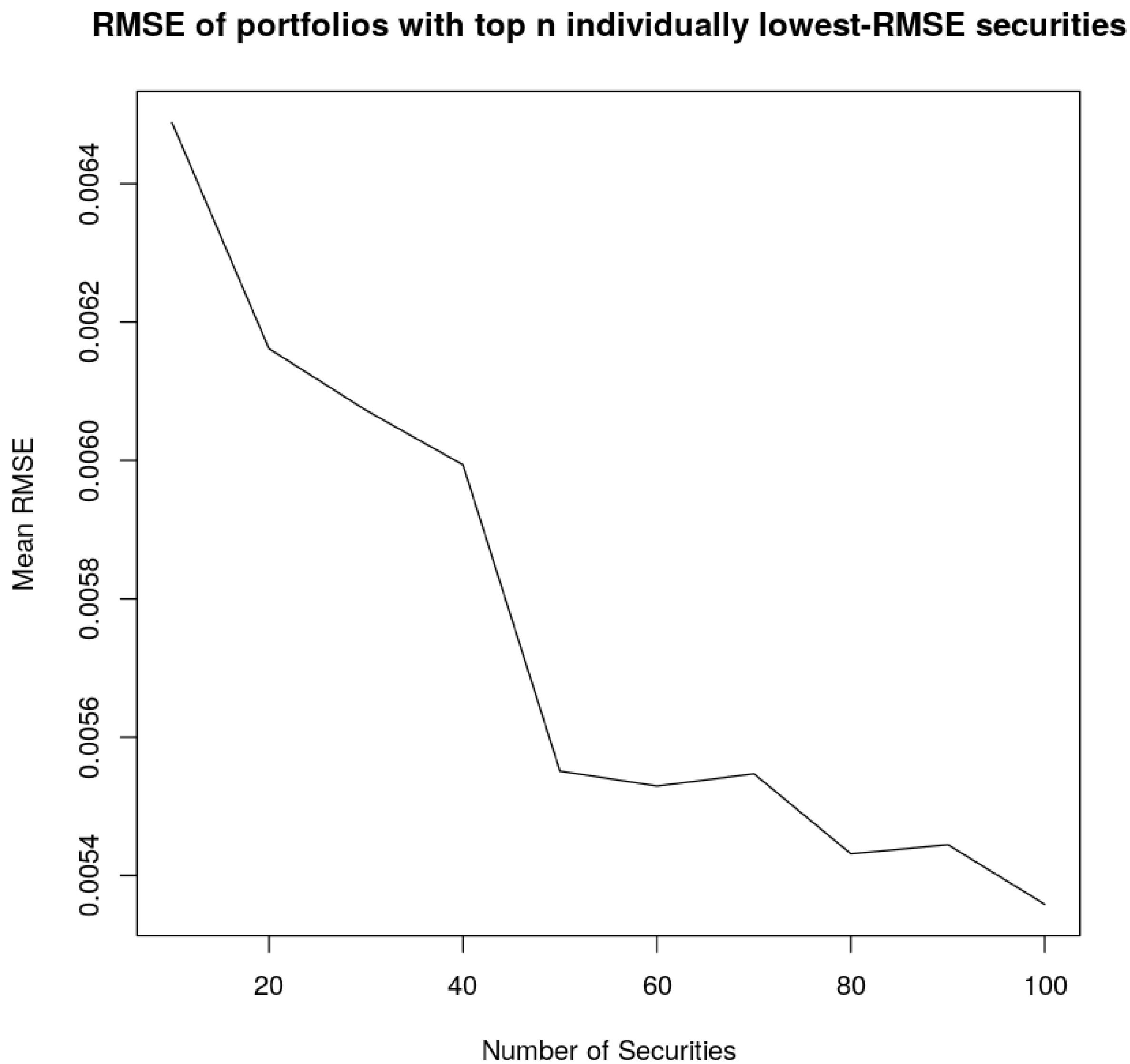
0.00544453970022969

100-stock portfolios of stocks that have the lowest individual RMSEs with the market and the corresponding RMSE of the portfolio

In [154]:
```
set.seed(100)
top_stock_100 <- head(sorted_RMSE$ix,100) #generates the indices for top
100-stock portfolios
rnd_stocks_market_cap_dummy <- market_cap[,top_stock_100]
rnd_stock_net_returns_dummy <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_dummy[j] <- sum(rnd_stocks_market_cap_dumm
y[j,])/sum(rnd_stocks_market_cap_dummy[j-1,])
    }
RMSE_top100 <- (sum((rnd_stock_net_returns_dummy- ff_returns)^2)/1511)^(
1/2) #calculates RMSE
RMSE_top100
```

0.0053583577677806

In [155]:
```
RMSEs <- c(RMSE_top10, RMSE_top20, RMSE_top30, RMSE_top40, RMSE_top50, R
MSE_top60, RMSE_top70, RMSE_top80, RMSE_top90, RMSE_top100)
number_securities <- c(10,20,30,40,50,60,70,80,90,100)
plot(number_securities, RMSEs, type = "l", main = "RMSE of portfolios wi
th top n individually lowest-RMSE securities", xlab = "Number of Securit
ies", ylab = "Mean RMSE")
```

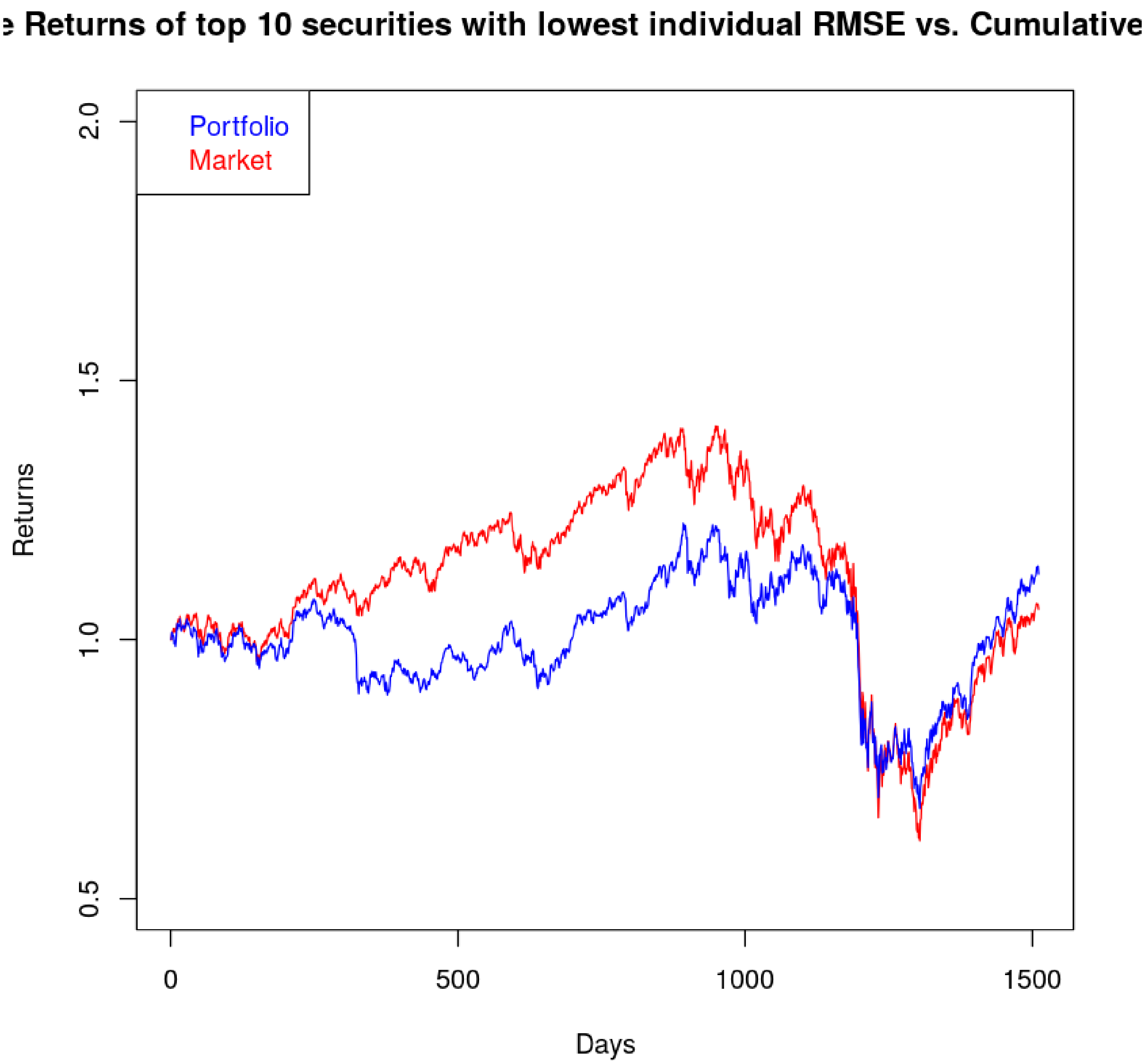



We observe that by constructing portfolios with n securities that have the n-lowest individual RMSE, we were able to drastically improve our RMSE for portfolios with lower numbers of securities. We were able to achieve an RMSE of 0.0065 with only 10 securities using this new method security selection. When we were using random security selection. the mean RMSE of 10 securities was 0.0125. Hence, this new method has cut the RMSE of portfolios with 10 securities by half. For larger numbers of securities, we see that the RMSE of this new method is pretty much the same as the RMSE of the old method where we randomly select securities. The value of this heuristic lies in the fact that we can minimize the number of securities that we put into our portfolio (to 10) without sacrificing as much RMSE as before.

Since n=10 yielded the most interesting results, we will plot the cumulative returns of n=10.

In [157]:
```
top_stock_10 <- head(sorted_RMSE$ix,10) #generates the indices for top 1
0-stock portfolios
rnd_stocks_market_cap_top10 <- market_cap[,top_stock_10]
rnd_stock_net_returns_top10 <- c(rep(1,1511))
    for (j in 2:1511) {
        rnd_stock_net_returns_top10[j] <- sum(rnd_stocks_market_cap_top1
0[j,])/sum(rnd_stocks_market_cap_top10[j-1,])
    }
cum_rnd_stock_net_returns_top10 <- c(rep(0,1511))
    for (k in 1:1511) {
        cum_rnd_stock_net_returns_top10[k] <- prod(rnd_stock_net_returns
_top10[1:k])
    }
```

In [158]:
```
plot(cum_ff_returns, type = "l", ylim = c(0.5,2), col = "red", main = "C
umulative Returns of top 10 securities with lowest individual RMSE vs. C
umulative Market Return", xlab = "Days", ylab = "Returns")
lines(cum_rnd_stock_net_returns_top10, col = "blue")
legend("topleft", text.col = c("blue","red"), c("Portfolio", "Market"))
```




Question 4 Part a) i) For 504 windows

In [441]:
```
set.seed(100)
rnd_stocks_ff <- c(1:10)
```

In [467]:
```
beta_storage <- matrix(rep(0,30210), nrow = 30, ncol = 1007) #For storin
g betas. Every three rows represents the rolling betas for a given secur
ity
for (j in 0:99) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1007))
    beta_SMB <- c(rep(0,1007))
    beta_HML <- c(rep(0,1007))
    for (i in 1:1007) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+503)] ~ rm_minus_rf[i:(i+503)] + SMB[
i:(i+503)] + HML[i:(i+503)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML
    }
```

Question 4 Part a) ii) For 504 windows

In [470]:
```
cov_matrix_storage <- list() #this part is for building fama-french cova
riance matrices
for (i in 1:1007) {
    A <- matrix(beta_storage[,i], nrow=100, ncol = 3, byrow = TRUE)
    cov_matrix_storage[[i]] <- cov(A)
    }
```

In [472]:
```
idio_var_storage <- matrix(rep(0,100700), nrow = 100, ncol = 1007) #For
 storing idiosyncratic variances
for (j in 0:99) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    var_residuals <- c(rep(0,1007))
    for (i in 1:1007) {
        ols <- lm(ri_minus_rf[i:(i+503)] ~ rm_minus_rf[i:(i+503)] + SMB[
i:(i+503)] + HML[i:(i+503)]) #perform OLS to obtain residuals
        var_residuals[i] <- var(ols$residuals) #find variance of residua
ls
    }
    idio_var_storage[j+1,] <- var_residuals
}
```

Question 4 Part a) iii) For 504 windows

In [473]:
```
variance_storage <- c(rep(0,1007)) #obtain the variances for all rolling windows
for (i in 1:1007) {
    beta <- matrix(beta_storage[,i], nrow=100, ncol = 3, byrow = TRUE)
    w <- matrix(market_cap[(i+503),rnd_stocks_ff] / sum(market_cap[(i+503),rnd_stocks_ff]))
    delta <- diag(idio_var_storage[,i])
    variance_storage  [i]   <-  t(w) %*% delta %*% w + t(w) %*% beta %*% cov_matrix_storage[[i]] %*% t(beta) %*% w
}
```

Question 4 Part a) iv) For 504 windows

In [463]:
```
one_day_ahead_storage <- c(rep(0,1007))#obtain one-day-ahead returns
for (i in 1:1007) {
    w <- market_cap[(i+504),rnd_stocks_ff ] / sum(market_cap[(i+504),rnd_stocks_ff])
    stock_returns_ahead <- stock_returns[(i+504),rnd_stocks_ff ]
    weighted_returns <- 0
    for (j in 1:100) {
        weighted_returns <- weighted_returns + w[j]* stock_returns_ahead[j]
    }
    one_day_ahead_storage[i] <- weighted_returns
}
```

Question 4 Part a) v) For 504 windows

In [594]:
```
standardized_outcome <- c(rep(0,1007))
for (i in 1:1007) {
    standardized_outcome[i] <- one_day_ahead_storage[i]/ (variance_storage[i])^(1/2)
}
```

In [595]:
```
var(standardized_outcome)^(1/2)
```

2.16216814281339

Question 4 Part a) i) For 252 windows

In [476]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1259) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:99) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1259))
    beta_SMB <- c(rep(0,1259))
    beta_HML <- c(rep(0,1259))
    for (i in 1:1259) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+251)] ~ rm_minus_rf[i:(i+251)] + SMB[
i:(i+251)] + HML[i:(i+251)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML
    }
```

Question 4 Part a) ii) For 252 windows

In [477]:
```
cov_matrix_storage <- list() #this part is for building fama-french cova
riance matrices
for (i in 1:1259) {
    A <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    cov_matrix_storage[[i]] <- cov(A)
    }
```

In [479]:
```
idio_var_storage <- matrix(rep(0), nrow = 10, ncol = 1259) #For storing
 idiosyncratic variances
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    var_residuals <- c(rep(0,1259))
    for (i in 1:1259) {
        ols <- lm(ri_minus_rf[i:(i+251)] ~ rm_minus_rf[i:(i+251)] + SMB[
i:(i+251)] + HML[i:(i+251)]) #perform OLS to obtain residuals
        var_residuals[i] <- var(ols$residuals) #find variance of residua
ls
    }
    idio_var_storage[j+1,] <- var_residuals
}
```

Question 4 Part a) iii) For 252 windows

In [481]:
```
variance_storage <- c(rep(0,1259)) #obtain the variances for all rolling windows
for (i in 1:1259) {
    beta <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    w <- matrix(market_cap[(i+251),rnd_stocks_ff] / sum(market_cap[(i+251),rnd_stocks_ff]))
    delta <- diag(idio_var_storage[,i])
    variance_storage [i]   <-        t(w) %*% delta %*% w + t(w) %*% beta %*% cov_matrix_storage[[i]] %*% t(beta) %*% w *0
}
```

Question 4 Part a) iv) For 252 windows

In [482]:
```
one_day_ahead_storage <- c(rep(0,1259))#obtain one-day-ahead returns
for (i in 1:1259) {
    w <- market_cap[(i+252),rnd_stocks_ff ] / sum(market_cap[(i+252),rnd_stocks_ff])
    stock_returns_ahead <- stock_returns[(i+252),rnd_stocks_ff ]
    weighted_returns <- 0
    for (j in 1:10) {
        weighted_returns <- weighted_returns + w[j]* stock_returns_ahead[j]
    }
    one_day_ahead_storage[i] <- weighted_returns
}
```

Question 4 Part a) v) For 252 windows

In [484]:
```
standardized_outcome <- c(rep(0,1259))
for (i in 1:1259) {
    standardized_outcome[i] <- one_day_ahead_storage[i]/ (variance_storage[i])^(1/2)
}
```

In [597]:
```
var(standardized_outcome)^(1/2)
```

1.80970289091147

Question 4 Part a) i) For 126 windows

In [489]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1385) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1385))
    beta_SMB <- c(rep(0,1385))
    beta_HML <- c(rep(0,1385))
    for (i in 1:1385) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+125)] ~ rm_minus_rf[i:(i+125)] + SMB[
i:(i+125)] + HML[i:(i+125)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML
    }
```

Question 4 Part a) ii) For 126 windows

In [495]:
```
cov_matrix_storage <- list() #this part is for building fama-french cova
riance matrices
for (i in 1:1385) {
    A <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    cov_matrix_storage[[i]] <- cov(A)
    }
```

In [496]:
```
idio_var_storage <- matrix(rep(0), nrow = 10, ncol = 1385) #For storing
 idiosyncratic variances
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    var_residuals <- c(rep(0,1385))
    for (i in 1:1385) {
        ols <- lm(ri_minus_rf[i:(i+125)] ~ rm_minus_rf[i:(i+125)] + SMB[
i:(i+125)] + HML[i:(i+125)]) #perform OLS to obtain residuals
        var_residuals[i] <- var(ols$residuals) #find variance of residua
ls
    }
    idio_var_storage[j+1,] <- var_residuals
}
```

Question 4 Part a) iii) For 126 windows

In [499]:
```
variance_storage <- c(rep(0,1385)) #obtain the variances for all rolling windows
for (i in 1:1385) {
    beta <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    w <- matrix(market_cap[(i+125),rnd_stocks_ff] / sum(market_cap[(i+125),rnd_stocks_ff]))
    delta <- diag(idio_var_storage[,i])
    variance_storage [i]   <-       t(w) %*% delta %*% w + t(w) %*% beta %*% cov_matrix_storage[[i]] %*% t(beta) %*% w *0
}
```

Question 4 Part a) iv) For 126 windows

In [504]:
```
one_day_ahead_storage <- c(rep(0,1385))#obtain one-day-ahead returns
for (i in 1:1385) {
    w <- market_cap[(i+126),rnd_stocks_ff ] / sum(market_cap[(i+126),rnd_stocks_ff])
    stock_returns_ahead <- stock_returns[(i+126),rnd_stocks_ff ]
    weighted_returns <- 0
    for (j in 1:10) {
        weighted_returns <- weighted_returns + w[j]* stock_returns_ahead[j]
    }
    one_day_ahead_storage[i] <- weighted_returns
}
```

Question 4 Part a) v) For 126 windows

In [518]:
```
standardized_outcome <- c(rep(0,1385))
for (i in 1:1385) {
    standardized_outcome[i] <- one_day_ahead_storage[i]/ (variance_storage[i])^(1/2)
}
```

In [598]:
```
var(standardized_outcome)^ (1/2)
```

1.57396040336633

Question 4 Part a) i) For 63 windows

In [508]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1448) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1448))
    beta_SMB <- c(rep(0,1448))
    beta_HML <- c(rep(0,1448))
    for (i in 1:1448) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML
    }
```

Question 4 Part a) ii) For 63 windows

In [513]:
```
cov_matrix_storage <- list() #this part is for building fama-french cova
riance matrices
for (i in 1:1448) {
    A <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    cov_matrix_storage[[i]] <- cov(A)
    }
```

In [514]:
```
idio_var_storage <- matrix(rep(0), nrow = 10, ncol = 1448) #For storing
 idiosyncratic variances
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,rnd_stocks_ff][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    var_residuals <- c(rep(0,1448))
    for (i in 1:1448) {
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #perform OLS to obtain residuals
        var_residuals[i] <- var(ols$residuals) #find variance of residua
ls
    }
    idio_var_storage[j+1,] <- var_residuals
}
```

Question 4 Part a) iii) For 63 windows

In [515]:
```
variance_storage <- c(rep(0,1448)) #obtain the variances for all rolling
windows
for (i in 1:1448) {
    beta <- matrix(beta_storage[,i], nrow=10, ncol = 3, byrow = TRUE)
    w <- matrix(market_cap[(i+62),rnd_stocks_ff] / sum(market_cap[(i+62
),rnd_stocks_ff]))
    delta <- diag(idio_var_storage[,i])
    variance_storage  [i]   <-       t(w) %*% delta %*% w + t(w) %*% bet
a %*% cov_matrix_storage[[i]] %*% t(beta) %*% w *0
}
```

Question 4 Part a) iv) For 63 windows

In [516]:
```
one_day_ahead_storage <- c(rep(0,1448))#obtain one-day-ahead returns
for (i in 1:1448) {
    w <- market_cap[(i+62),rnd_stocks_ff ] / sum(market_cap[(i+62),rnd_s
tocks_ff])
    stock_returns_ahead <- stock_returns[(i+62),rnd_stocks_ff ]
    weighted_returns <- 0
    for (j in 1:10) {
        weighted_returns <- weighted_returns + w[j]* stock_returns_ahead
[j]
    }
    one_day_ahead_storage[i] <- weighted_returns
}
```

Question 4 Part a) v) For 63 windows

In [521]:
```
standardized_outcome <- c(rep(0,1448))
for (i in 1:1448) {
    standardized_outcome[i] <- one_day_ahead_storage[i]/ (variance_stora
ge[i])^(1/2)
}
```

In [528]:
```
var(standardized_outcome) ^ 1/(2)
```

1.45611471984054

Question 5 part 1

In [559]:
```
random_stocks <- matrix(0, nrow = 50, ncol = 10)
for (i in 1:50) {
    random_stocks[i,] <- c(sample(1:1877,10,replace=F))
}
```

In [560]:
```
weighted_market_cap_1005 <- market_cap[1005,random_stocks[1,]]/sum(marke
t_cap[1005,random_stocks[1,]])
```

In [562]:
```
weighted_market_cap_503 <- market_cap[503,random_stocks[1,]]/sum(market_
cap[503,random_stocks[1,]])
```

In [561]:
```
weighted_market_cap_1510 <- market_cap[1510,random_stocks[1,]]/sum(marke
t_cap[1510,random_stocks[1,]])
```

In [569]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1448) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,random_stocks][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1448))
    beta_SMB <- c(rep(0,1448))
    beta_HML <- c(rep(0,1448))
    for (i in 1:1448) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML}



beta_storage_503 <- beta_storage[,439:503]
```

In [565]:
```
for (i in 1:64){
    beta <- weighted_market_cap_503 %*% matrix(beta_storage_503[,1], nro
w = 10, ncol =3, byrow = TRUE)
}
```

A matrix: 1 × 3 of type dbl

| | | |
|---|---|---|
| 1.197618 | 0.3981891 | -0.7618308 |

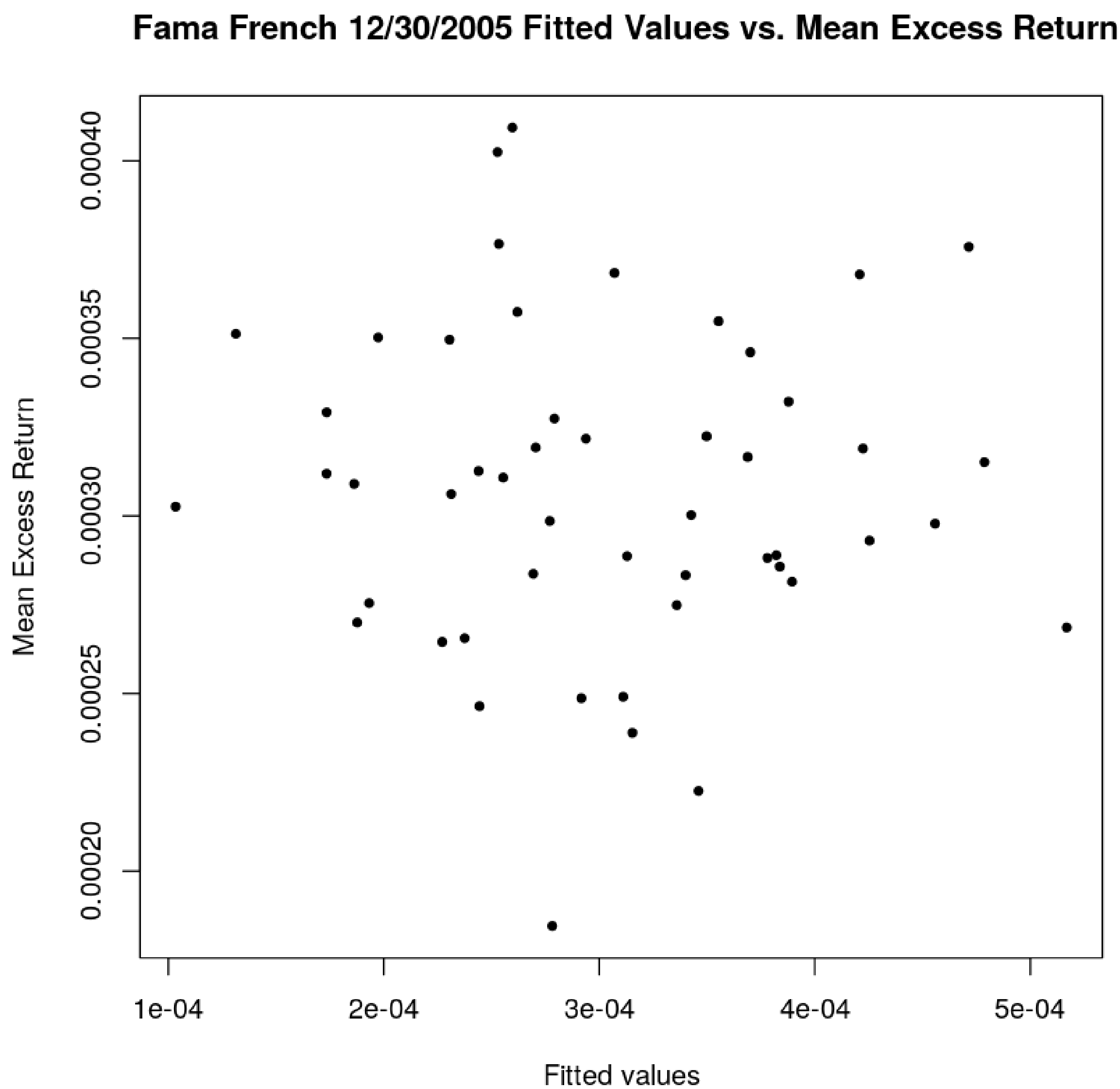
In [566]:

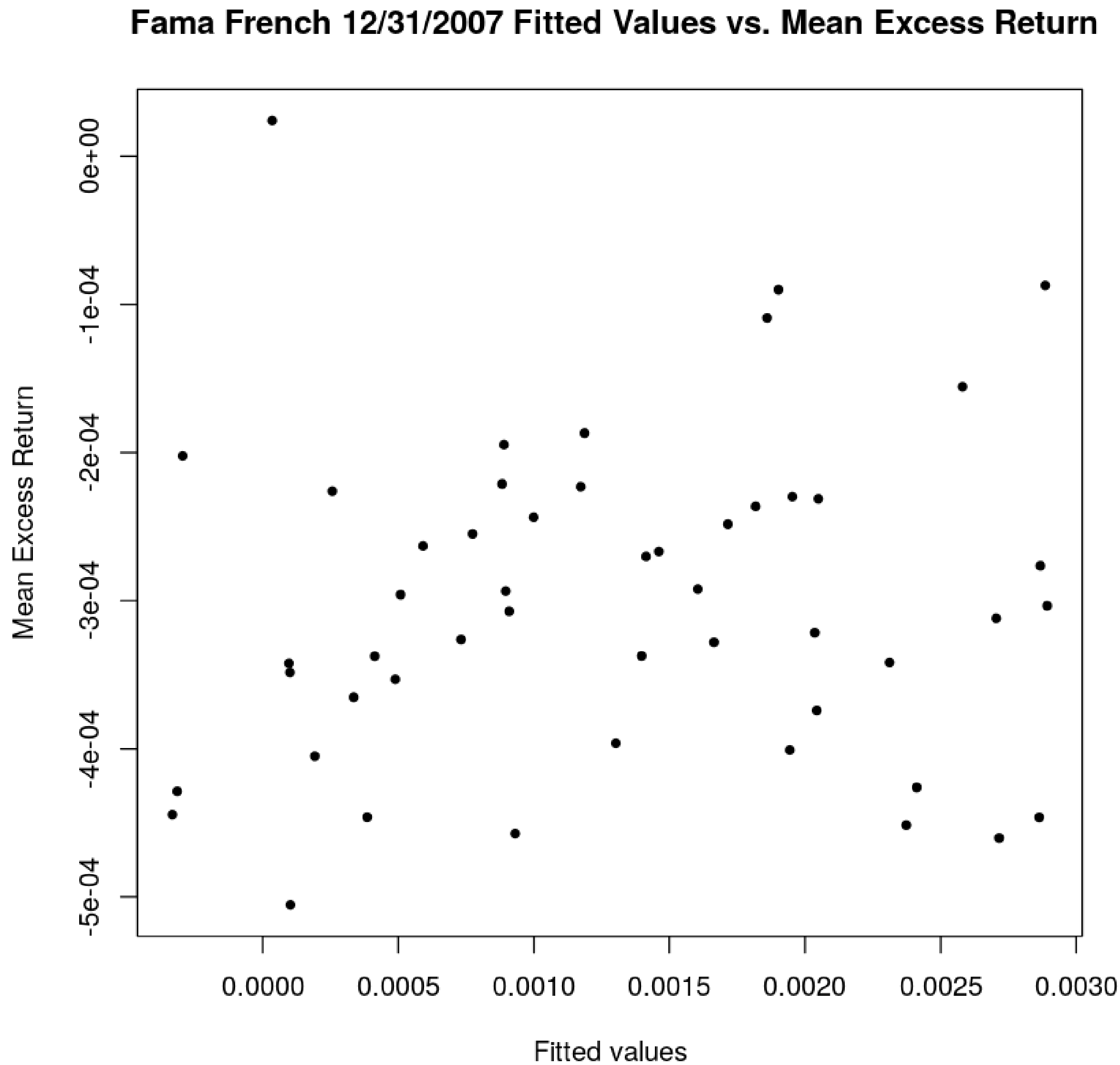
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1448) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,random_stocks][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1448))
    beta_SMB <- c(rep(0,1448))
    beta_HML <- c(rep(0,1448))
    for (i in 1:1448) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML}
```

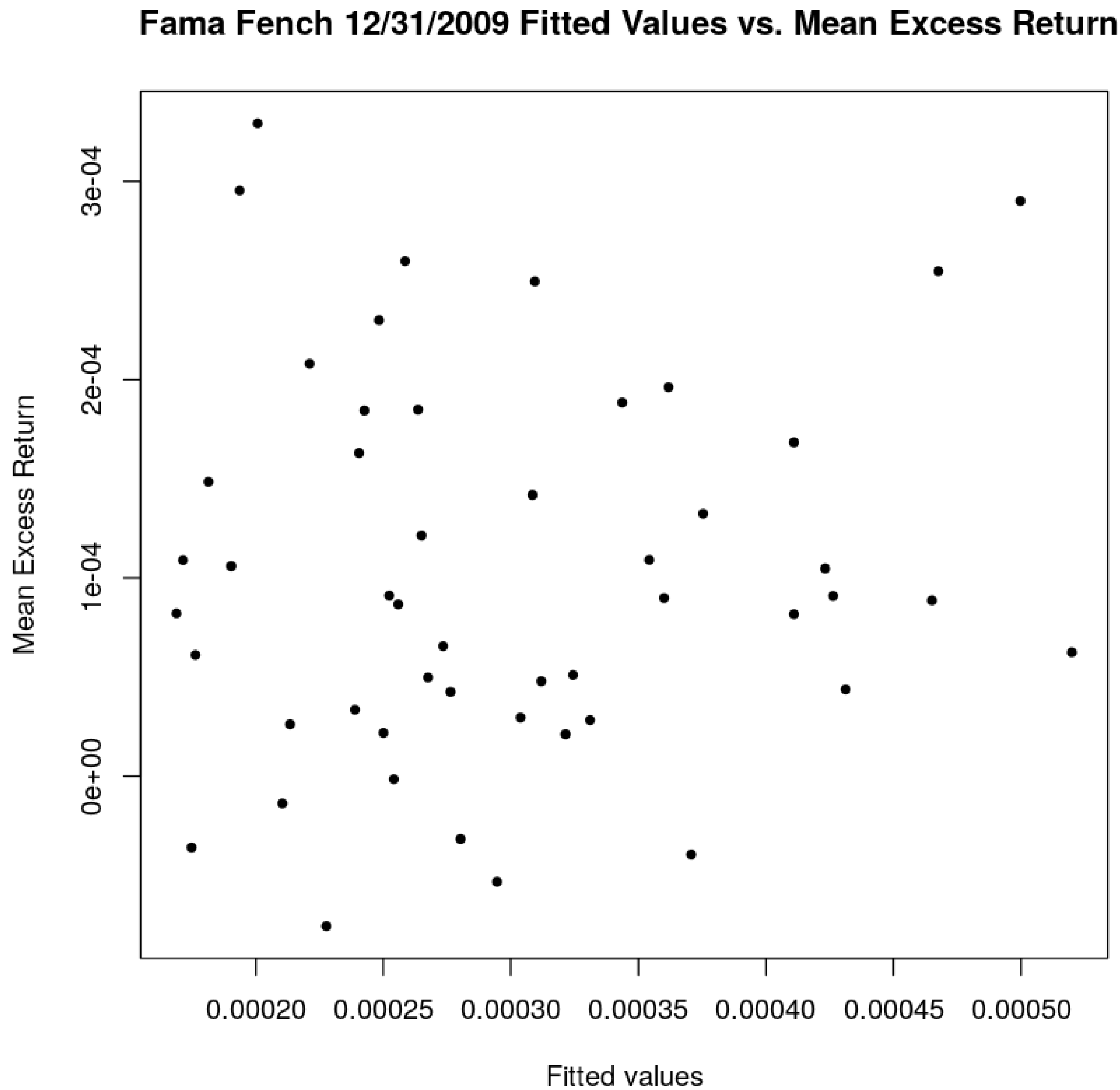
A data.frame: 1 × 4

| | V1 | V2 | V3 | V4 |
|---|---|---|---|---|
| | <dbl> | <dbl> | <dbl> | <dbl> |
| **503** | -0.0025 | 0 | 0.0023 | 0.00015 |

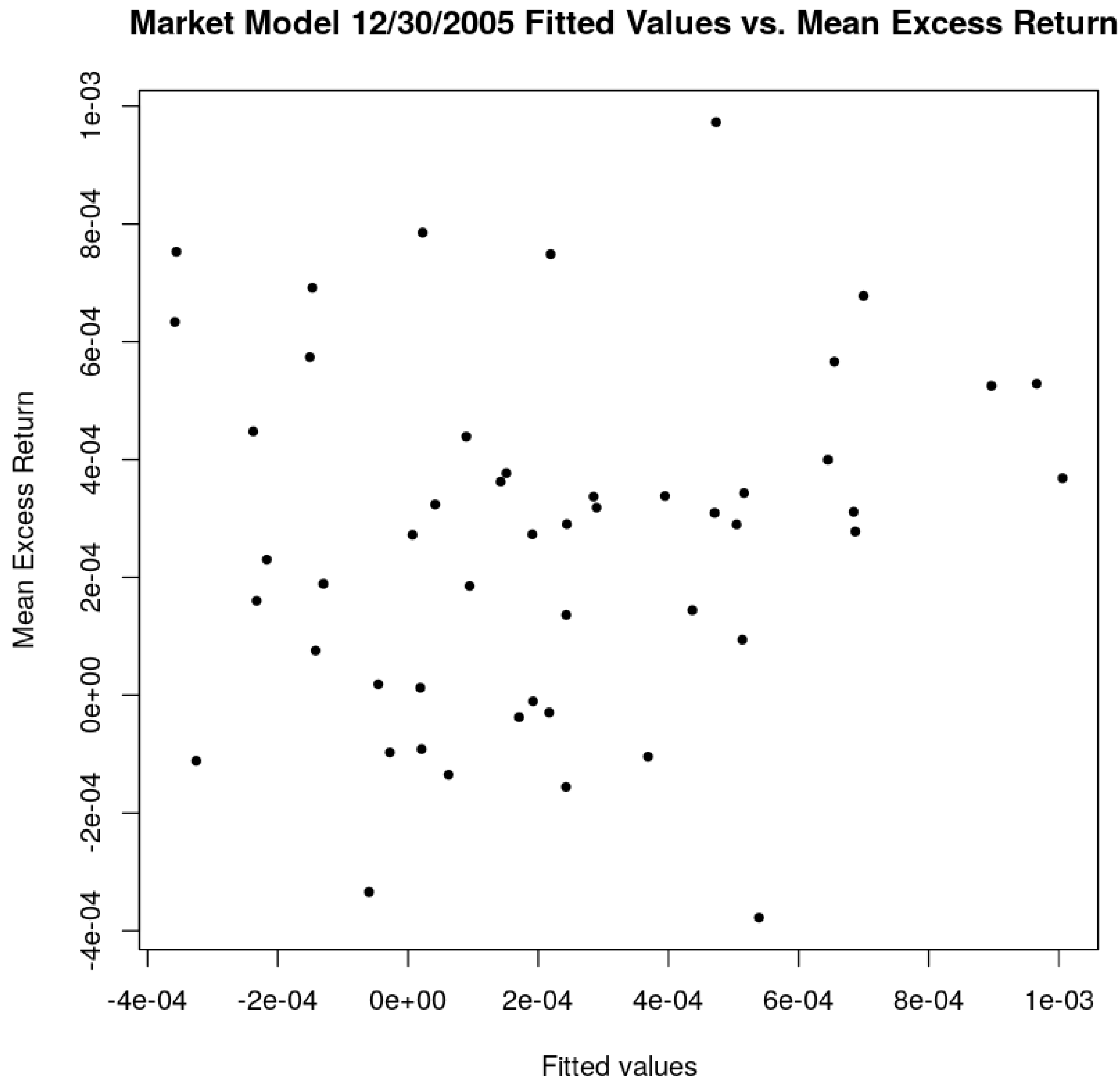
In [604]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1448) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,random_stocks][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1448))
    beta_SMB <- c(rep(0,1448))
    beta_HML <- c(rep(0,1448))
    for (i in 1:1448) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML}
```

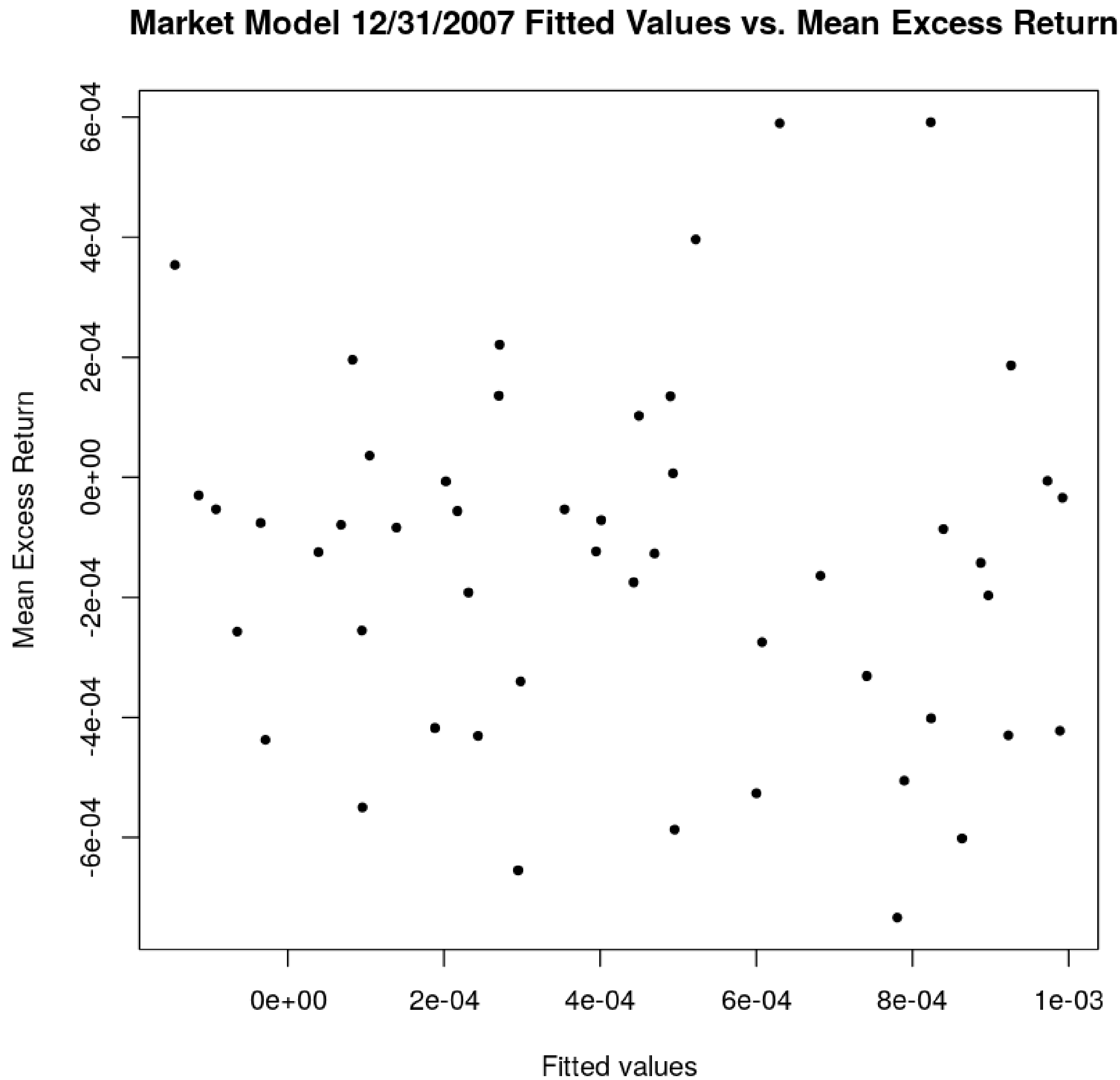

Fama French 12/30/2005 Fitted Values vs. Mean Excess Return
Mean Excess Return
0.00020
0.00025
0.00030
0.00035
0.00040
1e-04
2e-04
3e-04
4e-04
5e-04
Fitted values

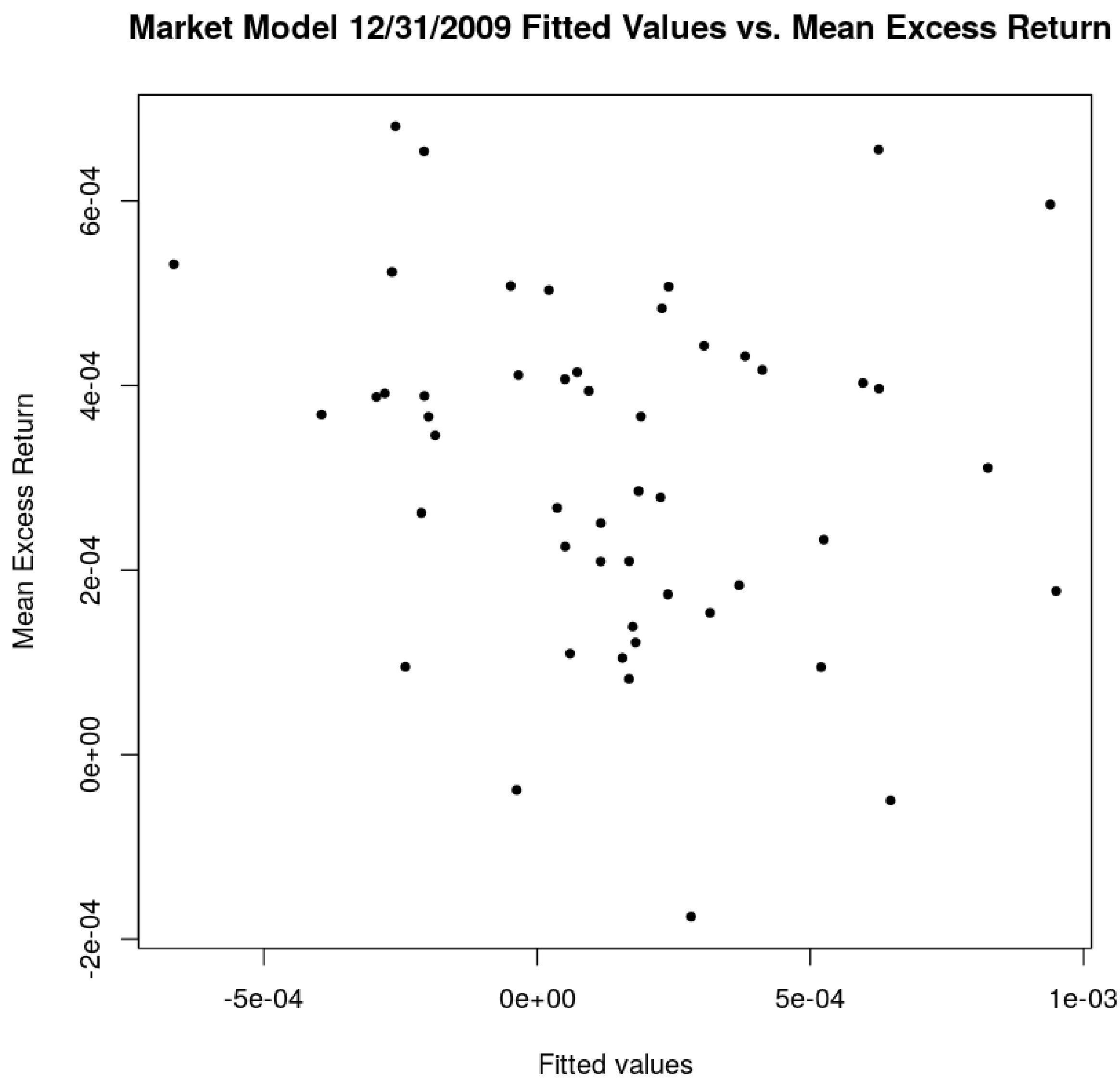

Fama French 12/31/2007 Fitted Values vs. Mean Excess Return
0e+00
-1e-04
-2e-04
-3e-04
-4e-04
-5e-04
Mean Excess Return
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
Fitted values


Fama Fench 12/31/2009 Fitted Values vs. Mean Excess Return
Mean Excess Return
0e+00
1e-04
2e-04
3e-04
0.00020
0.00025
0.00030
0.00035
0.00040
0.00045
0.00050
Fitted values

In [607]:
```
beta_storage <- matrix(rep(0), nrow = 30, ncol = 1448) #For storing beta
s. Every three rows represents the rolling betas for a given security
for (j in 0:9) {
    ri_minus_rf <- stock_returns[,random_stocks][,(j+1)] - ffdata[,4]
    rm_minus_rf <- ffdata[,1] - ffdata[,4]
    SMB <- ffdata[,2]
    HML <- ffdata[,3]
    beta_M <- c(rep(0,1448))
    beta_SMB <- c(rep(0,1448))
    beta_HML <- c(rep(0,1448))
    for (i in 1:1448) { #iterate through each rolling window
        ols <- lm(ri_minus_rf[i:(i+62)] ~ rm_minus_rf[i:(i+62)] + SMB[i:
(i+62)] + HML[i:(i+62)]) #OLS to find bets at each rolling window
        beta_M[i] <- ols$coefficients[2] # assign coefficients
        beta_SMB[i] <- ols$coefficients[3]
        beta_HML[i] <-ols$coefficients[4]
    }
    beta_storage [(3*j+1),] <- beta_M # assign coefficients to broader b
eta_storage
    beta_storage [(3*j+2),] <- beta_SMB
    beta_storage [(3*j+3),] <- beta_HML}
```


Market Model 12/30/2005 Fitted Values vs. Mean Excess Return
Mean Excess Return
-4e-04
-2e-04
0e+00
2e-04
4e-04
6e-04
8e-04
1e-03
Fitted values
-4e-04
-2e-04
0e+00
2e-04
4e-04
6e-04
8e-04
1e-03


Market Model 12/31/2007 Fitted Values vs. Mean Excess Return
Mean Excess Return
6e-04
4e-04
2e-04
0e+00
-2e-04
-4e-04
-6e-04
0e+00
2e-04
4e-04
6e-04
8e-04
1e-03
Fitted values


Market Model 12/31/2009 Fitted Values vs. Mean Excess Return
Mean Excess Return
6e-04
4e-04
2e-04
0e+00
-2e-04
-5e-04
0e+00
5e-04
1e-03
Fitted values

```
In [ ]:
```