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**Statistical Approach to Stock Market
Overreaction and Seasonality**

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Science in Statistics

by

YuYan Hu

2012

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2012

ABSTRACT OF THE THESIS

Statistical Approach to Stock Market Overreaction and Seasonality

by

YuYan Hu

Master of Science in Statistics

University of California, Los Angeles, 2012

Professor Rick Paik Schoenberg, Chair

In their study “Does the Stock Market Overreact?”, Debondt and Thaler proposed the overreaction hypothesis, which states that if a stock experiences significant price movement, then a subsequent price movement in the opposite direction is likely to follow. Moreover, the level of extremeness is positively correlated between the initial and the following price movement. In this study we would adopt the similar algorithm, using the data of recent three decades to test the overreaction hypothesis. Besides, the study of overreaction has shed light to the research of “January Effect” in stock market. A linear regression model will be used to test the existence of “January Effect”, by analyzing the stocks with greater losses during a 5-year period.

The thesis of YuYan Hu is approved.

Nicolas Christou

YingNian Wu

Rick Paik Schoenberg, Committee Chair

University of California, Los Angeles

2012

To my beloved parents

TABLE OF CONTENTS

1	Background Introduction	1
1.1	Market Efficiency Theory	1
1.2	Stock Market Overreaction	3
2	Empirical Test	5
2.1	Main Algorithm	5
2.2	Formation Period	7
2.3	“Good Performance” and “Poor Performance” Portfolios	10
2.4	Test Period	14
2.5	t-Test	15
3	January Effect	17
3.1	Background	17
3.2	January Effect	17
3.3	Linear Regression Analysis	18
4	Conclusion and recommendations	22
5	Appendix: part of the R codes	23
	References	30

LIST OF FIGURES

Figure 1: Monthly stock return in formation period 1	9
Figure 2: Stock returns in “Good Performance” portfolio	12
Figure 3: Stock returns in “Poor Performance” portfolio	13

LIST OF TABLES

Table 1: Sample Monthly Stock Returns	8
Table 2: Sorted cumulative average stock returns	11
Table 3: t-statistics results	16
Table 4: fitted monthly parameters in linear regression	20

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CHAPTER 1

Background Introduction

1.1 Market Efficiency Theory

The market efficiency theory states that, “one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis, given the information available at the time the investment is made.”[1]

There are three major forms of market efficiency hypothesis: “Weak”, “Semi-strong” and “Strong”. The semi-strong form of market efficiency implies that, once there is publicly available new information, the share prices will be rapidly adjusted to reflect the information. As a result, no arbitrage can be attained based on that information. Also, no technical analysis will be able to predict the share prices to generate excess returns. In this study, we will mainly look at the “semi-strong” form of market efficiency as stated above.

However, various phenomena suggest that the real financial market does not conform to the market efficiency hypothesis, or at least the strong form of market efficiency. The reasons include human irrationalities, such as overconfidence and overreaction of investors, so that they may sell winning stocks and hold on to losing stocks. There are other non-human-related errors, such as unfair distribution of information. For stock market particularly, Dreman and Berry found that, stocks with low P/E, which refers to price earning ratio, earn greater risk-adjusted returns than high P/E stocks.[2] For the price earning ratio anomaly, one of the explanations based on investor overreaction is that, companies with very low P/Es

are thought to be “undervalued”, since investors are pessimistic after a series of bad news, such as poor earning reports. The investor overreaction would further drive the stock price down. Once future earnings turn better, the price would be adjusted accordingly to more reasonably reflect the company’s value. Similarly, the companies with high P/Es are “overvalued”, and the price would be driven down. To specifically look into the behavior of investor overreaction, Debondt and Thaler, in their study “Does the Stock Market Overreact?”, suggested that people tend to overreact to unexpected and dramatic events. [3]

In this thesis, an empirical method will be used to test the hypothesis of investor overreaction in stock market during recent decades. Monthly returns of stocks in S&P 500 are downloaded from “Yahoo Finance”. Then the cumulative average returns of stocks with extreme high returns and stocks with low returns are calculated. Finally, we will use t-test to analyze the existence of market overreaction.

1.2 Stock Market Overreaction

The Bayes rule states that

BAYES'S RULE

$$P(A|B) = \frac{P(A_i) \cdot P(B|A_i)}{\sum [P(A_i) \cdot P(B|A_i)]}$$

where A_1, \dots, A_n is an all-inclusive set of possible outcomes given B .

One condition of rational investor behaviors is that they use Bayes Rule to form new belief as new information becomes available. Each time period new information signals are added to the information set. The investors can correctly use the new information set to update their expectations and thus determine the value of companies. Consequently, stock prices will accurately reflect fundamental values of the companies. And when there is unexpected positive or negative news, the prices will move up and down accordingly. However in real world, most investors are irrational when making decisions. Investors tend to give more weight of consideration to recent information or new data, and give less weight of consideration to historical data. [4] For instance, if a stock price drops, most irrational investors will have an incentive to buy in the stocks. Similarly, they are likely to sell the stock if stock price drops. And they will pay little attention to the long term paying power such as dividends. The price earning ratio(P/E) anomaly, as stated earlier in this paper, describes an observation that stocks with low P/E returns earn greater risk-adjusted returns than high P/E stocks. [5]

Based on those observations, DeBondt suggested two hypothesis: if a stock

experiences significant price movement, then a subsequent price movement in the opposite direction is likely to follow. Moreover, the level of extremeness is positively correlated between the initial and the following price movement. [6]

To test the hypothesis, DeBondt proposed an empirical test method, using the data of monthly stock returns from 1930s to 1970s. In this thesis we will adopt the similar algorithm, using the data from 1980s to 2010, to test whether the latest stock market still conforms with the “overreaction” hypothesis.

CHAPTER 2

Empirical Test

2.1 Main Algorithm

To test whether the market conforms to semi-strong market efficiency hypothesis: In the formation period, some news that will affect the stock prices, such as acquisition announcement, is released. If later on, the residual returns statistically differ from 0, then this serves as evidence of semi-strong form of market inefficiency.

To mathematically express the argument above, we write [7]:

$$E(R_{jt} - E_m(R_{jt}|F_{t-1}^m)|F_{t-1}) = E(u_{jt}|F_{t-1}) = 0$$

Where F_{t-1} represents the complete set of information which is available at time $t-1$. R_{jt} is the return on stock j at time t . u_{jt} is the residual return of stock j at time t , calculated by $u_{jt} = R_{jt} - R_{mt}$, which subtracts the market return from stock return. And $E_m(R_{jt}|F_{t-1}^m)$ is the expectation of R_{jt} , conditional on the information available at time $t-1$. If the market conforms to efficiency market hypothesis, then it implies that $E(u_{Gt}|F_{t-1}) = E(u_{Pt}|F_{t-1}) = 0$, where $E(u_{Gt}|F_{t-1})$ is the expected value of “Good Performance” portfolio and $E(u_{Pt}|F_{t-1})$ is the expected value of “Poor Performance” portfolio. Otherwise, if the overreaction hypothesis holds, the expected value of “Good Performance” will be less than 0 and the expected value of “Poor Performance” portfolio will be greater than 0, since the investors overreaction would drive the stock prices to the opposite direction.

We first look at the monthly returns of stocks in the formation period, 24 months in this study. Then based on the performance of the stocks, we take the stocks with highest cumulative residual returns to form the “Good Performance” portfolio. And we take the stocks with lowest cumulative residual returns to form the “Poor Performance” portfolio. After we get the portfolios, we look at the average residual returns in test period.

2.2 Formation Period

The monthly return data of all stocks in S&P 500 are used in this study. The initial date is January 1986. The ending date is December 2009. The monthly return data is downloaded from “Yahoo Finance” with the use of R package “stockPortfolio”.

The data available from “Yahoo Finance” does not necessarily starts from the stocks IPO date, so in the first step we choose the stocks with monthly return data available starting from January 1986. We obtain the monthly return data of the stock in a 24-month period, from January 1986 to December 1987. The 24-month period is the formation period, which determines the formation of “good performance” and “bad performance” portfolios in later step. In this step we select only the stocks with monthly return data available prior to 1986. Then we obtain the monthly return data of the stocks in a 24-month period, from January 1988 to December 1989. From January 1986 to December 2009, there are 11 non-overlapping formation periods. As we repeat the process, more and more stocks begin to have data available and are added into our portfolio.

Sample of the monthly stock returns:

An example of distribution of monthly stock returns:

Ticker	Symbols	Industry	IPO
A	'A'	Health Care	1999
AA	'AA'	Materials	1962
AAPL	'AAPL'	Information Technology	1984
ABC	'ABC'	Health Care	1995
ABT	'ABT'	Health Care	1983
ACE	'ACE'	Financials	1993
ACN	'ACN'	Information Technology	2001
ADBE	'ADBE'	Information Technology	1986
ADI	'ADI'	Information Technology	1984
ADM	'ADM'	Consumer Staples	1983
ADP	'ADP'	Information Technology	1983
ADSK	'ADSK'	Information Technology	1985
AEE	'AEE'	Utilities	1998
AEP	'AEP'	Utilities	1970
AES	'AES'	Utilities	1991
AET	'AET'	Health Care	1977
AFL	'AFL'	Financials	1984
AGN	'AGN'	Health Care	1989
AIG	'AIG'	Financials	1984

Table 1

**monthly
return distribution for formation period 1**

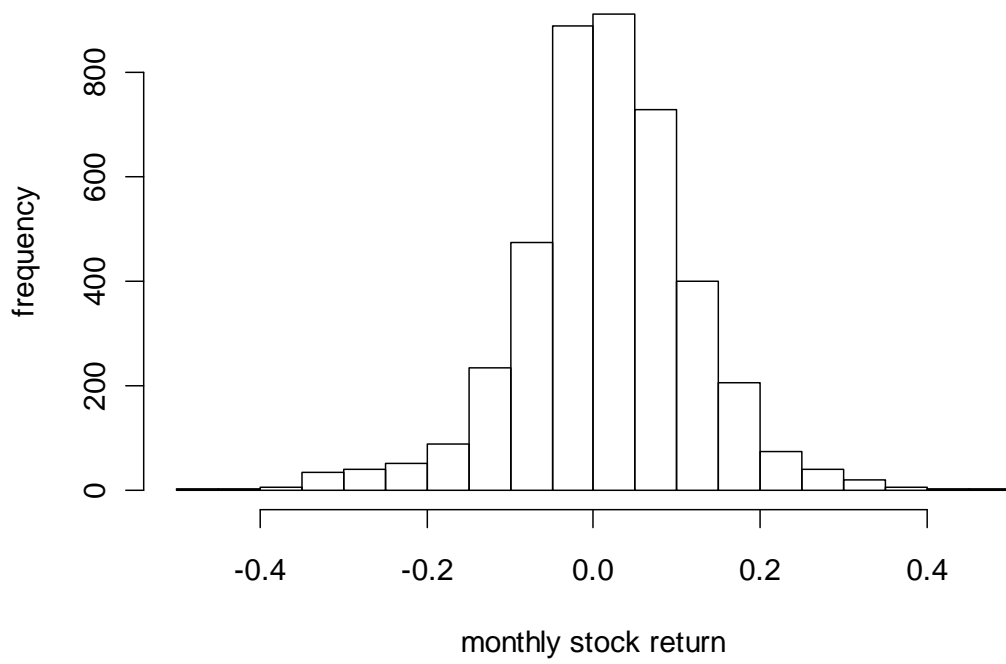


Figure 1

2.3 “Good Performance” and “Poor Performance” Portfolios

In the first formation period January 1986 to December 1987, after the monthly return data are obtained, we compute the cumulative excess returns

$$CU_j = \sum_{t=1}^{t=24} u_{jt}$$

where u_{jt} is the market adjusted excess return, $u_{jt} = R_{jt} - R_{mt}$. The CU s are ranked and approximately the top 10% of stocks are categorized as “Good Performance” portfolio. Similarly, the bottom 10% of stocks are categorized as “Poor Performance” portfolio.

Period1	Cumulative Average Return
AMD	-0.855246368
VLO	-0.852425792
LUV	-0.805398256
JPM	-0.726598693
ADI	-0.554020847
HON	-0.552952171
FDX	-0.547495237
HUM	-0.519230402
LOW	-0.4957297
NOC	-0.464380382
CI	-0.439355074
.....
AMAT	0.982549561
AMGN	0.986897417
FMC	1.000408846
ADSK	1.12832653
CA	1.337823584
AAPL	1.461911789

Table 2

Good Performance Portforlio

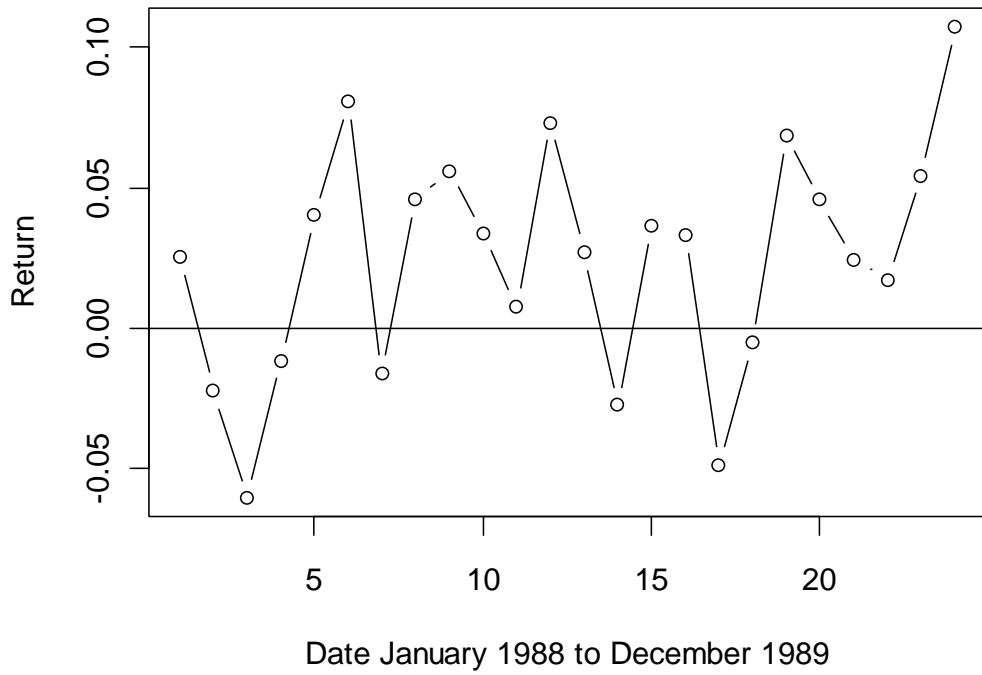


Figure 2

Bad Performance Portforlio

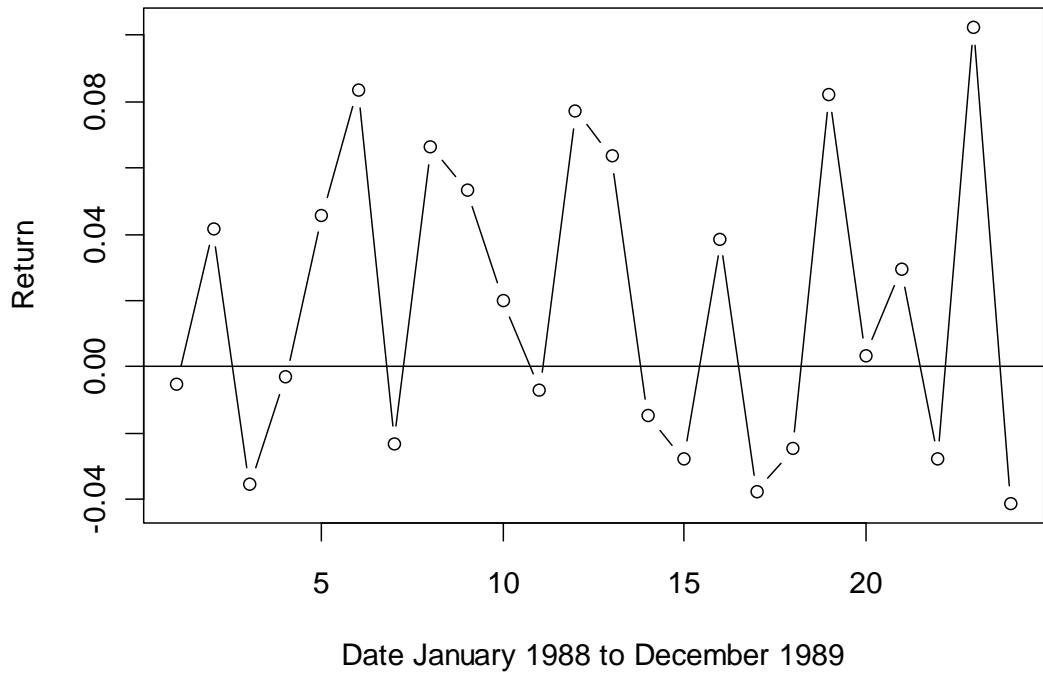


Figure 3

Then this process is repeated for 11 times in each non-overlapping 2-year formation periods. 11 “Good Performance” and 11 “Poor Performance” portfolios are generated.

2.4 Test Period

Now that the “Good Performance” and “Poor Performance” portfolios are formed, starting from January 1988 and up to December 1989, we compute the cumulative average residual returns for all stocks in the “Good Performance” portfolio, denoted by $CAR_{G,t}$. Similarly, the cumulative average residual returns for stocks in “Poor Performance” portfolio are calculated, denoted by $CAR_{P,t}$. The cumulative average residual return of “Good Performance” portfolio in test period 1 is:

$$CAR_{G,1} = \sum_{t=1}^{24} \bar{u}_t$$

Then we calculate the average $CARs$ for each of the 11 test periods, denoted by $ACAR_{G,t}$.

$$ACAR_{G,t} = \left(\sum_{n=1}^{11} CAR_{G,t} \right) / 11$$

2.5 t-Test

As we stated early, the overreaction hypothesis predicts that, if a stock experiences significant price movement, then a subsequent price movement in the opposite direction is likely to follow. Moreover, the level of extremeness is positively correlated between the initial and the following price movement. Mathematically, in the test period,

$$ACAR_{G,t} < 0 \text{ and } ACAR_{P,t} > 0, \text{ which implies that}$$
$$[ACAR_{P,t} - ACAR_{G,t}] > 0$$

We will use t-test for two samples with equal sample size, equal variance. Pooled estimate of the population variance in CAR_t :

$$S_t^2 = \left[\sum_{n=1}^N (CAR_{G,n,t} - ACAR_{G,t})^2 + \sum_{n=1}^N (CAR_{B,n,t} - ACAR_{B,t})^2 \right] / 2(N - 1)$$

Where $N = 11$ is the number of the non-overlapping 24-month testing periods. And the corresponding t-statistics is:

$$T_t = [ACAR_{G,t} - ACAR_{P,t}] / \sqrt{2S_t^2 / N}$$

t-statistic:

t statistics	Degree of Freedom	P-value
0.3118	18.094	0.7587

Table 3

Conclusion: the t-statistics is not significant, suggesting there is not a significant overreaction phenomenon. One possible reason for the non-significant p-value is that the study is based on only the stocks in S&P 500. A larger sample, which may include all the stock portfolio in NYSE or NASDAQ, should be analyzed given the access to the database. Another interpretation for the p-value is that, the stocks included in S&P 500 are large and actively traded companies, which show less volatile price fluctuations comparing to small-scale companies. Even if the stock price drops, investors are more optimistic in holding the stock for a longer period instead of selling the stocks immediately.

CHAPTER 3

January Effect

3.1 Background

Debondt suggested that the study of market overreaction hypothesis has shed light to the research of the so-called “January Effect”. He proposed that the “Poor Performance” stocks are likely to earn exceptionally large January returns, while the “Good Performance” stocks do not. Here we will propose a further study of the January Effect by analyzing the “Poor Performance” portfolio.

3.2 January Effect

Generally, stock price is believed to exhibit no seasonality factors. However, there is one phenomenon that has been constantly observed by investors and researchers, called “January Effect”. Wachtel was the first economist to examine this phenomenon. He used the Dow Jones Industrial Average data from 1927 to 1942. He observed that stock prices tend to increase from December to January in eleven of the fifteen years he studied. [8]

The most widely accepted explanation for January Effect is tax-induced selling: In December, the final month in a tax year, the individual investors who are tax-sensitive tend to sell the stocks that performed poorly during the year to claim capital losses. This action will further depress the prices of losing stocks. During January of next year, those investors would reinvest on those stocks, driving the

prices up. This phenomenon is called January Effect.

3.3 Linear Regression Analysis

Ddebondt proposed that the “Poor Performance” stocks are likely to earn exceptionally large January returns, while the “Good Performance” stocks do not. We will conduct a further study on only the stocks in the “Poor Performance” portfolio by fitting a linear regression model. The stocks with lowest cumulative average returns in year 2005 to 2010 are selected.

- Regression Formula

$$R_t = a_1 + a_2D_{2t} + a_3D_{3t} + \cdots + a_{12}D_{12t} + e_t$$

Where

R_t :the monthly return data

a_1 :the intercept. It indicates mean return in the month of January.

$a_2, a_3 \cdots a_{12}$:the average differences in return between January and other month.

e_t :the white noise error term.

- Hypothesis:

$$H_0 : a_2 = a_3 = \cdots = a_{12} = 0$$

$$H_1 : a_2 \neq a_3 \neq \cdots \neq a_{12} \neq 0$$

- Assumptions with Multiple Regression [9]
 - The relationship between the dependent variable, Y , and the independent variables, X_1, X_2, \cdots, X_k , is linear.
 - There is no exact linear relation exists between two or more of the independent variables.

- The conditional distribution of the independent variables, has an expected value of 0: $E(e_t|X_1, X_2, \dots, X_k) = 0$.
- For all observations, the variance of the error term is the same.
- The error term is uncorrelated across observations
- The error term is normally distributed.

In this study we will assume that the stock price is linearly associated with the month variables, which is supported by most empirical studies. Moreover, the residuals we obtained from the model follows approximately normal distribution with constant variance, suggesting the assumptions are reasonable in this model.

Fitted parameters of multiple regression:

	Estimate	Standard Error	t Value	Pr>(t)
(intercept)	0.023337	0.029009	0.804	0.4251
Month2	-0.054742	0.041025	-1.334	0.1884
Month3	-0.073271	0.041025	-1.786	0.0804
Month4	-0.005271	0.041025	-0.128	0.8983
Month5	-0.018220	0.041025	-0.444	0.6590
Month6	0.003485	0.041025	0.085	0.9326
Month7	-0.070009	0.041025	-1.706	0.0944
Month8	-0.027785	0.041025	-0.677	0.5015
Month9	0.024857	0.041025	0.606	0.5474
Month10	0.018427	0.041025	0.449	0.6553
Month11	-0.056151	0.041025	-1.369	0.1775
Month12	-0.039243	0.041025	-0.957	0.3436

Table 3

Interpretation: The average return in the benchmark month of January is 2.33 percent. Except for the month of June, September and October, returns are lower for all months as compared to the benchmark month of January. The relatively lowest return occurs in the month of July, which is in consistent with the recent findings of a negative July Effect hypothesis.

CHAPTER 4

Conclusion and recommendations

One interpretation of the t-test is that during recent decades, there is no statistically significant existence of market overreaction. Another interpretation is that, it could also be caused by the non-sufficient sample size which covers only the stocks in S&P 500. A larger sample should be used, such as all the stocks in NYSE or NASDAQ, given the access to the database. An alternative reason for the non-significant p-value is that, the stocks included in S&P 500 are large and actively traded companies, which show less volatile price fluctuations comparing to small-scale companies. Even if the stock price drops, investors are more optimistic in holding the stock for a longer period instead of selling the stocks immediately. Another noticeable observation is that, the cumulative average returns of stocks in “Poor Performance” portfolio are significantly greater than 0, with a mean of 0.2607416. In the 11 formation periods of $CAR_{B,n,t}$, 6 out of 11 of them have outperformed the stocks in “Good Performance” portfolio. This observation is in consistent with the explanation that investors tend to be more optimistic in large companies. They are likely to hold the stock for longer time even the stock price drops.

For the “January Effect” study, the fitted values provide evidence for a significant January Effect. Except for the month of June, September and October, Returns are lower for all months as compared to the benchmark month of January.

CHAPTER 5

Appendix: part of the R codes

```
library (stockPortfolio)
## read in the stock tickers for formation period 1
P1=read.table(period1,header=FALSE, sep= ",")
##The stock returns for period 1
P1R=getReturns(P1,freq="month",start="1985-12-31", end
="1987-12-31")
##market returns of S&P 500 for period 1
P1MR=getReturns("^GSPC",freq="month",start="1985-12-31",
end="1987-12-31")
P1MRs=replicate(length(P1),P1MR$R)
## market-adjusted returns
P1AR=P1R$R-P1MRs
##cumulative excess return
P1sum=apply(P1AR,2,sum)
P1sum=sort(P1sum)
write.table(P1sum, "c:/Users/Yuyan Hu/Desktop/thesis/P1sum
.txt", sep="\t")

##The stock returns for period 2
P2=read.table(period2,header=FALSE, sep= ",")
P2R=getReturns(P2,freq="month",start="1987-12-31", end
```

```

    ="1989-12-31")
##market returns of S&P 500 for period 2
P2MR=getReturns("^GSPC",freq="month",start="1987-12-31",
    end="1989-12-31")
P2MRs=replicate(length(P2),P2MR$R)
## market-adjusted returns
P2AR=P2R$R-P2MRs
##cumulative excess return
P2sum=apply(P2AR,2,sum)
P2sum=sort(P2sum)
write.table(P2sum, "c:/Users/Yuyan Hu/Desktop/thesis/P2sum
    .txt", sep="\t")
##The stock returns for period 3
P3=read.table(period3,header=FALSE, sep=
    , )

P3R=getReturns(P3,freq="month",start="1989-10-31",end
    ="1991-12-31")
##market returns of S&P 500 for period 3
P3MR=getReturns("^GSPC",freq="month",start="1989-11-30",
    end="1991-11-30")
P3MRs=replicate(length(P3),P3MR$R)
## market-adjusted returns
P3AR=P3R$R-P3MRs
##cumulative excess return
P3sum=apply(P3AR,2,sum)
P3sum=sort(P3sum)
write.table(P3sum, "c:/Users/Yuyan Hu/Desktop/thesis/P3sum
    .txt", sep="\t")

```

```

## similar codes for formation period 4 through 11
##Test Period
##Test Period 1
##"Good Performance Portfolio"
G1=c(
  'AMD', 'VLO', 'LUV', 'JPM', 'ADI', 'HON', 'FDX', 'HUM', 'LOW', 'NOC
    ', 'CI', 'MAT', 'TGT', 'BA', 'LMT', 'IBM', 'BK', 'ETR', 'APA', 'GD
    ,
  )
G1R=getReturns(G1, freq="month", start="1987-12-31", end
  ="1989-12-31")
##market returns of "Good Performance" Portforlio for test
  period 1
G1MR=getReturns("^GSPC", freq="month", start="1987-12-31",
  end="1989-12-31")
G1AR=apply(G1R$R, 1, mean)
## cumulative market-adjusted returns (CAR)
G1CAR=sum(G1AR-G1MR$R)
## "Poor Performance Portfolio"
B1=c(
  'TXN', 'CNP', 'BEAM', 'IP', 'BMS', 'MO', 'IR', 'DIS', 'MDT', 'GT', '
    MRK', 'DOW', 'HD', 'AMAT', 'AMGN', 'FMC', 'ADSK', 'CA', 'AAPL', '
    NEM'
  )
B1R=getReturns(B1, freq="month", start="1987-12-31", end
  ="1989-12-31")
B1AR=apply(B1R$R, 1, mean)

```

```

## cumulative market-adjusted returns (CAR)
B1CAR=sum(B1AR-G1MR$R)
##Test Period 2
##"Good Performance Portfolio"
G2=c(
  'WDC', 'TXN', 'TER', 'GT', 'PH', 'HPQ', 'CA', 'BIG', 'HOT', 'R', '
    TSO', 'IBM', 'ADI', 'NOC', 'AAPL', 'AMD', 'USB', 'CAT', 'BBY', '
    GD', 'BLL', 'RTN', 'SNA'
)
G2R=getReturns(G2, freq="month", start="1989-12-31", end
  ="1992-1-31")
##market returns of "Good Performance" Portforlio for test
  period 2
G2MR=getReturns("^GSPC", freq="month", start="1989-12-31",
  end="1992-1-31")
G2AR=apply(G2R$R,1,mean)
## cumulative market-adjusted returns (CAR)
G2CAR=sum(G2AR-G2MR$R)
## "Poor Performance Portfolio"
B2=c(
  'TMK', 'APA', 'BEN', 'UNM', 'CMS', 'MAT', 'GPS', 'AVP', 'BAC', 'HD
    ', 'NI', 'OKE', 'NKE', 'MYL', 'ETR', 'VLO', 'NWL', 'HOG', 'TIF', '
    DTE', 'S', 'KR', 'ROST'
)
B2R=getReturns(B2, freq="month", start="1989-12-31", end
  ="1992-1-31")
B2AR=apply(B2R$R,1,mean)
## cumulative market-adjusted returns (CAR)

```

```

B2CAR=sum(B2AR-G2MR$R)
##Test Period 3
##"Good Performance Portfolio"
G3=c(
'LUV', 'CLF', 'NWL', 'HAS', 'STJ', 'WMT', 'PHM', 'PFE', 'HOG', 'PCL
', 'MDT', 'AMD', 'NKE', 'MSFT', 'SCHW', 'FDO', 'BIG', 'SYK', 'HD
', 'ADBE', 'ALTR', 'GPS', 'BBY', 'EMC', 'DELL', 'AMGN
)
G3R=getReturns(G3, freq="month", start="1991-12-31", end
="1993-12-31")
##market returns of "Good Performance" Portforlio for
period 1
G3MR=getReturns("^GSPC", freq="month", start="1991-12-31",
end="1993-12-31")
G3AR=apply(G3R$R, 1, mean)
## cumulative market-adjusted returns (CAR)
G3CAR=sum(G3AR-G3MR$R)
## "Poor Performance Portfolio"
B3=c(
'HOT', 'WDC', 'CMS', 'TSO', 'HAR', 'RDC', 'HP', 'APC', 'AXP', 'OXY
', 'TYC', 'HAL', 'CAT', 'EOG', 'DOW', 'S', 'SUN', 'VMC', 'AVY',
NBL', 'BHI', 'HST', 'FDX', 'NEM', 'L', 'MUR'
)
B3R=getReturns(B3, freq="month", start="1991-12-31", end
="1993-12-31")
B3AR=apply(B3R$R, 1, mean)
## cumulative market-adjusted returns (CAR)
B3CAR=sum(B3AR-G3MR$R)

```

```

## similar codes for test periods 4 through 11
## linear regression
loser=c(
'JDSU', 'C', 'TWX', 'SWY', 'ETFC', 'PFE', 'IPG', 'RF', 'FHN', 'LLY
', 'KEY', 'GE', 'EP', 'TYC', 'MU', 'S', 'MMC', 'LUV', 'BMY', 'MRK
', 'MS', 'DELL', 'BK', 'GCI', 'AMGN', 'MOLX', 'WPO', 'MDT', 'CTAS
', 'AA'
)
## t-test
y1
[1] 0.46783520 0.08635327 0.29636150 0.16926480
0.25229800 0.24357650
[7] 0.19201760 0.49634760 0.52998260 0.14728030
0.25235120
> y2
[1] 0.30200820 0.21234560 0.50951310 0.28349210
0.14961740 0.15868420
[7] 0.25378000 0.67914280 0.08858518 -0.10847180
0.33946100
>t.test(y1,y2)
loserR=getReturns(loser, freq="month", start="2005-12-31",
end="2010-12-31")
loserAR=apply(loserR$R, 1, mean)
loserAR=loserAR[2:61]
month=rep(1:12, 5)
month=as.factor(month)
f=lm(loserAR~month)
summary(f)

```

```
##plots
##plot of winner portfolio in test period 1
plot(G1AR,type="b",ylab="Return", xlab="Date January 1988
      to December 1989",main="Good Performance Portforlio")
abline(h=0)
plot(B1AR,type="b",ylab="Return", xlab="Date January 1988
      to December 1989",main="Bad Performance Portforlio")
abline(h=0)
```

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