

# Group Project Representation

Group 10



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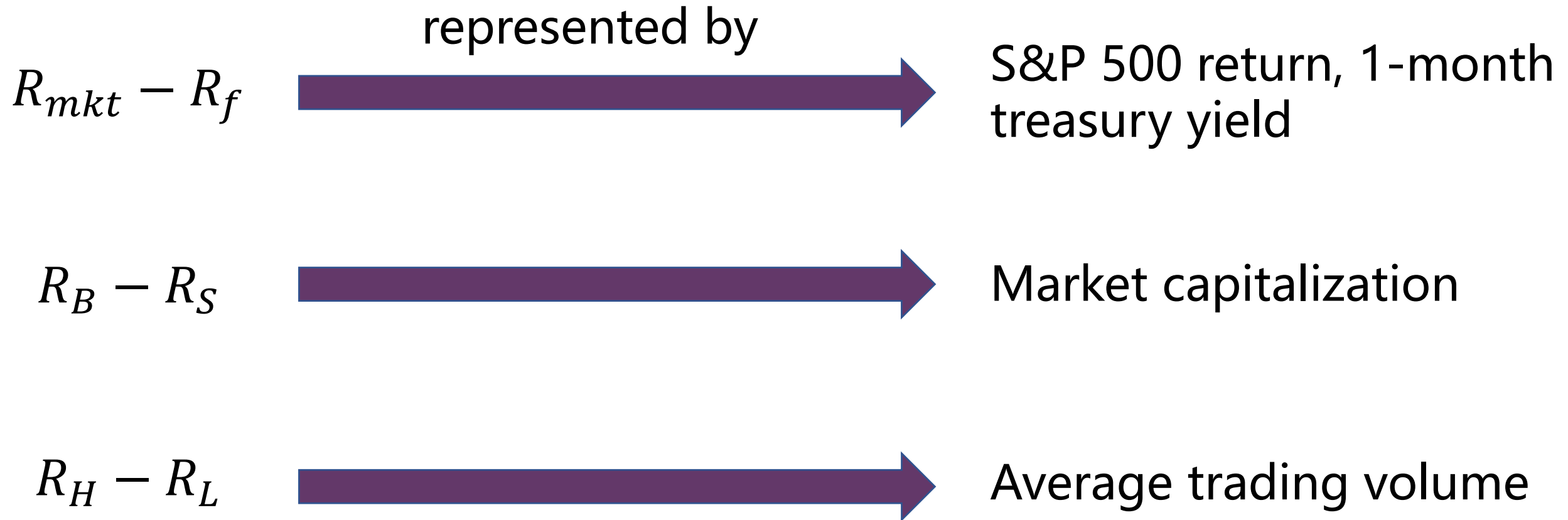
# Part 1 - Model Introduction

$$R_i - R_f = \alpha_i + \beta_i(R_{mkt} - R_f) + \beta_i^{SMB}(R_B - R_S) + \beta_i^{HML}(R_H - R_L)$$

- Explained variable
  - Security premium
- Explanatory variables
  - Market premium
  - Scale difference between corporations
  - Liquidity difference between securities
- Goal
  - Figure out  $\alpha_i, \beta_i, \beta_i^{SMB}, \beta_i^{HML}$  for each security with Multiple Linear Regression



# Part 1 - Model Introduction



# Part 2 - Data Scraping and Processing

*SlickCharts*



Symbol of companies  
in S&P 500

**YAHOO!**  
FINANCE



Adjusted close price,  
volume

U.S. DEPARTMENT OF THE TREASURY



1-month treasury yield



# Part 2 - Data Scraping and Processing

```
def SP500_cap_range_list():  
    #web has already sorted by cap  
    stocks_pool_url = 'https://www.slickcharts.com/sp500'  
    stocks_pool_page = requests.get(stocks_pool_url).text  
    stocks_pool_DataFrame = pd.read_html(stocks_pool_page)[0]  
  
    #construct the target list and list_for_test  
    stocks_pool_DataFrame_test = stocks_pool_DataFrame[31:61]['Symbol']  
    stocks_pool_DataFrame = stocks_pool_DataFrame[0:31]['Symbol']  
    security_list_test = stocks_pool_DataFrame_test.tolist()  
    security_list = stocks_pool_DataFrame.tolist()  
    # security_list_test是回归方程等式右边, security_list是等式左边  
    return security_list_test, security_list
```

- Extract the symbols of top 60 securities from S&P 500, equally divided into two lists
- Securities have been sorted by their market capitalization



# Part 2 - Data Scraping and Processing

```
# Establish connection to Yahoo Finance
yahoo_finance_url = 'https://au.finance.yahoo.com/quote/%s/history?period1=%s&period2=%s&interval=1d&filter=history&frequency=1d'
# July 1, 2018 starting_date = '1530403200'
# June 30, 2019 ending_day = '1561939199'
timestamp = ['1530403200', '1536710400', '1543017600', '1549324800', '1555632000', '1561939199']
# timestamp = [2018.7.31, 2018.9.12, 2018.11.24, 2019.2.5, 2019.4.19, 2019.6.30]

def fetch_Yahoo_Finance(security, timestamp):
    All_DataFrame = None
    for starting in range(0, len(timestamp)-1):
        each_DataFrame = fetch_Yahoo_Finance_part(security, timestamp[starting], timestamp[starting+1])
        All_DataFrame = pd.concat([All_DataFrame, each_DataFrame], axis = 0)
    return All_DataFrame
```

- To get daily adjusted close price
- Yahoo Finance allows only 100 rows to be scraped one time, so we divide the time interval into 5 parts



# Part 2 - Data Scraping and Processing

```
# Add security and daily stock return to the DataFrame  
yahoo_hist_price_DataFrame['%s Ri'% security] = yahoo_hist_price_DataFrame['Adj. close**'].pct_change( periods=1)
```

- To calculate daily return of securities
- Use DataFrame.pct\_change function on adjusted close price





# Part 2 – Data Scraping and Processing

```
US_treasury_URL = 'https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yieldYear&year=%s'  
year1 = '2018'  
year2 = '2019'  
US_treasury_hist_price_page1 = requests.get(US_treasury_URL % year1)  
US_treasury_hist_price_page2 = requests.get(US_treasury_URL % year2)  
  
#Read Table from the US Treasury webpage  
US_treasury_hist_price_DataFrame1 = pd.read_html(US_treasury_hist_price_page1.text)[1]  
US_treasury_hist_price_DataFrame2 = pd.read_html(US_treasury_hist_price_page2.text)[1]
```

- To get daily 1-month yield of US Treasury (risk-free rate)
- US Treasury website put the data of the same year in one page, so we scrape the data of 2018 and 2019 respectively



# Part 2 – Data Scrapping and Processing

```
def X1(Rm, Rf):  
    X1_DataFrame = pd.merge(Rm, Rf, on = 'Date')  
    X1_DataFrame['Rm_Rf'] = X1_DataFrame['^GSPC Rm'] - X1_DataFrame['1 mo']/100/365  
    temp = X1_DataFrame.loc[:, ['Date', 'Rm_Rf']]  
    return temp
```

- To establish the first explanatory variable  $R_{mkt} - R_f$ , we use S&P 500 daily return rate minus 1-month US Treasury yield
- To unify the scales, 1-month US Treasury yield should be divided by 100 and 365



# Part 2 – Data Scrapping and Processing

```
def X2(security_list, timestamp):  
    list1 = security_list[0:int(len(security_list)/2)]  
    list2 = security_list[int(len(security_list)/2):int(len(security_list))]  
    R1 = combine_Ri_DataFrame(list1, timestamp)  
    R1.rename(columns = {'Ri Average': 'R1 Ri Average'}, inplace = True)  
    R2 = combine_Ri_DataFrame(list2, timestamp)  
    R2.rename(columns = {'Ri Average': 'R2 Ri Average'}, inplace = True)  
    R = pd.merge(R1, R2, on = 'Date')  
    R['Weight'] = R['R1 Ri Average'] - R['R2 Ri Average']  
    temp = R.loc[:, ['Date', 'Weight']]  
    return temp
```

- To establish the second explanatory variable  $R_B - R_S$ , we
  - sort the 30 securities by market capitalization (done by SlickCharts)
  - calculate the average return of the first 15 securities and the last 15 securities respectively for every single day
  - calculate the difference between two average returns each day



# Part 2 – Data Scrapping and Processing

```
def X3(security_list, timestamp):  
    list1 = security_list[0:int(len(security_list)/2)]  
    list2 = security_list[int(len(security_list)/2):int(len(security_list))]  
    R1 = combine_Ri_DataFrame(list1, timestamp)  
    R1.rename(columns = {'Ri Average': 'R1 Ri Average'}, inplace = True)  
    R2 = combine_Ri_DataFrame(list2, timestamp)  
    R2.rename(columns = {'Ri Average': 'R2 Ri Average'}, inplace = True)  
    R = pd.merge(R1, R2, on = 'Date')  
    R['Volume'] = R['R1 Ri Average'] - R['R2 Ri Average']  
    temp = R.loc[:, ['Date', 'Volume']]  
    return temp
```

- To establish the third explanatory variable  $R_H - R_L$ , we
  - sort the 30 securities by up-to-date volume (done by function `fetch_vol`)
  - calculate the average return of the first 15 securities and the last 15 securities respectively for every single day
  - calculate the difference between two average returns each day



# Part 2 - Data Scraping and Processing

```
def Y(security_list, timestamp, Rf):  
    Ri = combine_Ri_DataFrame(security_list, timestamp)  
    Y_DataFrame = pd.merge(Ri, Rf, on = 'Date')  
    Y_DataFrame['Ri_Rf'] = Y_DataFrame['Ri Average'] - Y_DataFrame['1 mo']/100/365  
    temp = Y_DataFrame.loc[:, ['Date', 'Ri_Rf']]  
    return temp
```

- To establish the explained variable  $R_i - R_f$ , we
  - simply do subtraction on the data we've gotten
  - notice that risk-free rate (1-month US Treasury yield) should be divided by 100 and 365



# Part 3 – Regression and Result

## OLS Regression Results

Dep. Variable:	Ri_Rf	R-squared:	0.945			
Model:	OLS	Adj. R-squared:	0.945			
Method:	Least Squares	F-statistic:	4172.			
Date:	Tue, 20 Aug 2019	Prob (F-statistic):	5.15e-155			
Time:	18:44:05	Log-Likelihood:	1121.1			
No. Observations:	245	AIC:	-2238.			
Df Residuals:	243	BIC:	-2231.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0002	0.000	-1.119	0.264	-0.000	0.000
Rm_Rf	1.0550	0.016	64.592	0.000	1.023	1.087
=====						
Omnibus:	0.146	Durbin-Watson:	2.004			
Prob(Omnibus):	0.930	Jarque-Bera (JB):	0.026			
Skew:	-0.002	Prob(JB):	0.987			
Kurtosis:	3.050	Cond. No.	102.			

- Firstly, we only consider the factor  $R_{mkt} - R_f$
- Market premium has a positive influence on security return
- $R^2$  is 0.945, which means  $R_{mkt} - R_f$  explains the change in security return very well





# Part 3 – Regression and Result

## OLS Regression Results

=====						
Dep. Variable:	Ri_Rf	R-squared:		0.946		
Model:	OLS	Adj. R-squared:		0.946		
Method:	Least Squares	F-statistic:		2119.		
Date:	Tue, 20 Aug 2019	Prob (F-statistic):		4.44e-154		
Time:	18:44:07	Log-Likelihood:		1123.3		
No. Observations:	245	AIC:		-2241.		
Df Residuals:	242	BIC:		-2230.		
Df Model:	2					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
Intercept	-0.0002	0.000	-0.992	0.322	-0.000	0.000
Rm_Rf	1.0740	0.019	58.009	0.000	1.038	1.110
Weight	-0.0563	0.026	-2.127	0.034	-0.109	-0.004
=====						
Omnibus:	0.606	Durbin-Watson:		1.994		
Prob(Omnibus):	0.739	Jarque-Bera (JB):		0.348		
Skew:	0.040	Prob(JB):		0.840		
Kurtosis:	3.166	Cond. No.		180.		
=====						

- Secondly, we consider both  $R_m - R_f$  and  $R_B - R_S$
- $R_S - R_B$  has a negative parameter, which means larger company usually brings lower return
- $R^2$  only increased by 0.001



# Part 3 - Regression and Result

## OLS Regression Results

```
=====
Dep. Variable:          Ri_Rf      R-squared:          0.948
Model:                  OLS        Adj. R-squared:       0.947
Method:                 Least Squares    F-statistic:       1451.
Date:                  Tue, 20 Aug 2019    Prob (F-statistic): 6.49e-154
Time:                  18:44:09          Log-Likelihood:     1127.0
No. Observations:      245             AIC:               -2246.
Df Residuals:          241             BIC:               -2232.
Df Model:               3
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.0001	0.000	-0.911	0.363	-0.000	0.000
Rm_Rf	1.0770	0.018	58.808	0.000	1.041	1.113
Weight	-0.0732	0.027	-2.722	0.007	-0.126	-0.020
Volume	0.0934	0.035	2.693	0.008	0.025	0.162

```
=====
Omnibus:                0.668      Durbin-Watson:       2.014
Prob(Omnibus):          0.716      Jarque-Bera (JB):     0.393
Skew:                   0.013      Prob(JB):             0.821
Kurtosis:               3.195      Cond. No.             230.
=====
```

- Finally, we consider  $R_m - R_f$ ,  $R_S - R_B$  and  $R_H - R_L$
- $R_H - R_L$  has a positive parameter, so security with higher liquidity has higher return
- $R^2$  increased by 0.002
- It seems that  $R_{mkt} - R_f$  can explain  $R_i - R_f$  pretty well, adding new factors doesn't influence the result much





# Thank you

