Fundamental Factor Model Research for the Chinese Equity Market

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1. Abstract

China is for no doubt one of the major equity market of this world with Shanghai Stock Exchange and Shenzhen Stock Exchange ranking world no. 5 and 8 in terms of market capitalization. However, the academic study over Chinese stock market is very limited, for mostly two reasons: the limitation of availability of consistent, clean data; the language that some most useful data portal uses is Chinese. These issues placed a lot of hindrance for international researchers to get a deep insight into Chinese stock market.

One of the most desired information for both equity researchers and institutional investors is always the risk structure of assets. Yet because of the difficulty for obtaining good data resource for Chinese equity market, the risk structure of Chinese stock markets has been long wanted. The aim of this project is therefore to solve this problem by building a simple, convenient, and intuitive research tool on Chinese stock market. Based on fundamental factor model, the tool breaks down equity risks into multiple origins, thus providing a powerful and insightful picture into risk structure of Chinese equities.

2. Introduction

a. Background

Factor model as a pricing method on equity market is well-grounded in academic area. Since early 1960s with the introduction of capital asset pricing model (CAPM), arbitrage pricing theory (APT) in 1976, and Fama-French three factor model in 1992, 1993, factor model has been well developed and used by research and investment institutions. One of the major benefit of fundamental factor model, is that it intuitively shows the contribution of risk form different factors to the risk of a single stock or portfolio. Therefore factor model is an excellent tool for understanding the risk composition of equity market and other security markets.

b. Purpose

This project aims to provide insights on Chinese stock market based on the theory of fundamental multi-factor model and particularly the Fama-French three factor model. The purpose of the program is to offer a convenient, simple and informative tool for equity researchers to gain insight into the risk composition of stocks listed on two Chinese stock markets: Shanghai Stock Exchange and Shenzhen Stock Exchange. For inputs, the program requires ticker, start date, end date, and calculation unit. Then the program regress the returns of the designated stock over several factors: market excess return, industry excess return, concept excess return, SMB (big minus small), HML (high minus low), UMD (up minus down) using ordinary least square method. Shown in results are betas for different factors, statistical inference to each factor, and a graph presenting the risk composition of the investigated stock.

c. Scope

The time frame of data that can be investigated is 3 years, and the scope of data covers both Shenzhen Stock Exchange and Shanghai Stock Exchange.

3. Methodology

a. Programming language

This project is programmed in Python 3. Several most frequently used libraries are Pandas[1], Numpy[2], Statsmodel[3], Matplotlib[4], SciPy[5] and Sympy[6]. This project is compiled and visualized in jupyter notebook[7], which is a web application for creating, visualizing, and sharing coded programs.

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[1] http://pandas.pydata.org/

[2] http://www.numpy.org/

[3] http://statsmodels.sourceforge.net/

[4] http://matplotlib.org/

[5] https://www.scipy.org/

[6] http://www.sympy.org/en/index.html

[7] http://jupyter.org/

b. Data Source

Data used in the project are from tushare[8] and Datayes[9]. The former is an open source, free data portal based on Python 2 and 3. The drawback of this resource is its website is solely in Chinese. The latter is a paid data platform. The price used for calculation is daily closing price. The price has been adjusted for stock splits and dilutions.

c. Fundamental Factor Model

i. Fundamental Factor Model

A fundamental factor model of asset returns explains compositions of security returns using exogenously decided factors, such as market return, industry return and price-earning ratio. The factors are historical returns of portfolios that replicate the performance of desired explanatory variables. For example, we use historical return of CSI 300 index to resemble market return. After a robust linear regression of asset return over factor returns, the coefficient of each factor is called beta, representing the sensitivity of asset return in reaction to each unit change in factor return.

For this project, the factors are market excess return, industry excess return, concept excess return, SMB, HML and UMD. The choice of factors originates from Mark Cahart's four-factor model[10] with industry excess return and concept excess return added for a more comprehensive picture for Chinese stock market. The robust linear regression can be expressed in the following form:

$$r_a - r_f = \alpha_a + \beta_1 \times (r_m - r_f) + \beta_2 \times (r_i - r_f) + \beta_3 \times (r_c - r_f) + \beta_4 \times SMB + \beta_5 \times HML + \beta_6 \times UMD + \varepsilon_a$$

r_a : historical return of asset of investigation

$r_a - r_f$: asset excess return

r_f : risk free return, taken to be 0.035 according to J.P. Morgan practice

β : beta/sensitivity for 6 different factors, representing the level of change in investigated stock resulting from unit change in factors

$r_m - r_f$: market excess return

$r_i - r_f$: industry excess return

$r_c - r_f$: concept excess return

SMB, HML, UMD : the returns of portfolio of SMB, HML, UMD, representing the risk factor of size, value, and momentum

α_a : the intercept of the regression, representing excess return, which is the abnormal return usually generated by inefficiency of market

ε_a : error term, which is the vertical distance between data points and the regression line, representing the return not explained by existing factors

[8] http://tushare.org/index.html

[9] https://m.datayes.com/

[10] Mark Cahart (1997), 'On Persistence in Mutual Fund Performance'

d. Factors

i. Market Excess Return

The goal of this factor is to capture the overall market behavior as comprehensively as possible. Thus, the data used to calculate market return is CSI 300 index, a capitalization-weighted index reflecting the combined performance of Shenzhen and Shanghai stock exchange.

ii. Industry Excess Return

The industry return is obtained by summing up the capitalization-weighted return of every stock under the same industry category. The industry categorization is provided by Sina finance[11], an extensively used finance data website for both individual investors and investment institutions in China.

iii. Concept Excess Return

Besides overall market and industry, a single stock or portfolio's return can be also explained by significant macro event, such as government policy, regional economic shock, technology advancement. 'Concept' factor accounts for these effect by categorizing stocks according to the most prominent image people relate each stock to. It could be a recent government policy, a specific geographical area, or a new technology. For example, in early 2015 3D printing technology caught public's attention. For a period of time after that, 3D printing related stocks became 'trendy' to invest in. As a result, from March 2015 to August 2015, the concept of 3D printing, in average, increased by more than 50%, with several top runners reaching up to more than 100% increase. Isn't all companies in technology industry are related with 3D printing, thus, industry category does not apply in this case.

The categorization of concept is obtained from Sina finance.

iv. SMB & HML

In the 1992 paper Fama and French disclosed the finding that stock returns in the US market is positively related to book-to-market ratio (value effect) and inversely related to market capitalization of stocks (size effect)[12]. For value effect of book-to-market ratio, the logic behind is that stocks with higher book-to-market ratios are more likely to have been undervalued relative to the company's book size and its stock price has higher potential to rise in the future. To account for the size effect of market capitalization, usually companies with smaller size are more fragile against economical movements and shocks, and therefore have higher risks, which is interpreted as expected higher potential

[11] http://finance.sina.com.cn/stock/

[12] Eugene Fama & Kenneth French (1992), 'The Cross Section of Expected Stock Returns'

return in stock market. In the subsequent 1993 paper, Fama and French proved that the risk from capitalization can be concluded from returns of SMB portfolio, and book-to-market ratio from HML portfolio[13]. Thus, there is enough ground to use SMB and HML portfolio to replicate return effect from capitalization and book-to-market ratio.

SMB represents 'small minus big', small stands for the returns of small-capitalized companies, and vice versa. To construct a SMB portfolio of time t, all stocks across the two stock exchanges are ranked by their market capitalization at time t. Simple averages of the return for top 30% and bottom 30% are calculated. The SMB factor is obtained by subtracting the simple average of bottom 30% from the top 30%.

HML stands for 'high minus low', and high means the return for high book-to-market ratio companies. To construct a HML portfolio of time t, all stocks are ranked by their P/B ratio (price-to-book ratio), which is the inverse of book-to-market ratio, of time t. The rank is split into top half and bottom half. The HML factor is obtained by simple average return of bottom half (that is, higher book-to-market ratio) minus the simple average return of the top half.

v. UMD

According to Mark Cahart's 1997 publishing on mutual fund return, abnormal return is found from buying last year's winner and selling last year's losers[14]. To account for this abnormal return, Cahart came up with the fourth factor UMD adding up to the existing three Fama-French factors. UMD stands for up minus down, in which up means returns of last period's best performing stocks while down means returns of last period's worst performing stocks. This factor explains the part of return of asset resulting from 'persistence' quality, and thus sometimes named as momentum factor.

To construct an UMD portfolio, last period's return of all stocks are ranked. Top 30% performing stock is taken and so are bottom 30% performing stocks. Capitalization-weighted returns are calculated for both top and bottom 30%, becoming the return for 'up' and 'down' portfolio. And then the factor is obtained by subtracting return of 'down' from 'up'.

e. Calculation for Risk Contribution

Risk contribution from a specific factor to stock return is calculated by taking partial derivative of the stock risk, and integrating it with respect to the weight of the factor from 0 to the designated factor weight:

[13] Eugene Fama & Kenneth French (1993), 'Common Risk Factors in the Returns on Stocks and Bonds'

[14] Mark Cahart (1997), 'On Persistence in Mutual Fund Performance'

$$\sigma_{stock} = \sqrt{(w_1\sigma_1)^2 + (w_2\sigma_2)^2 + ... + 2w_1w_2\sigma_{12} + ...}$$

contribution of risk from factor 1 $= \int_0^{w1} \frac{\partial \sigma_{stock}}{\partial w_1} dw_1 / \sigma_{stock}$

w_1 : weight of factor 1 asset, which is equal to factor return coefficient β

σ_1 : standard deviation, or risk of factor 1

4. Results and Interpretation

a. Result sample display

	Risk Free Rate	Market Return	Industry Return	Concept Return	SMB	HML	UMD
end date of week							
2016-07-29	0.035	-0.66	-0.014010	-0.028755	-0.037364	0.020066	-0.000080
2016-07-22	0.035	-1.56	-0.015982	-0.004466	0.010336	-0.007896	0.008120
2016-07-15	0.035	2.63	0.024653	0.020110	-0.020732	0.008714	0.008489
2016-07-08	0.035	1.21	0.016549	0.028480	0.008117	-0.010108	0.003014
2016-07-01	0.035	2.50	0.031132	0.034485	0.022671	-0.019018	-0.003076
2016-06-24	0.035	-1.07	0.002595	-0.007865	0.020978	-0.021483	-0.000770
2016-06-17	0.035	-1.70	-0.019611	-0.010581	0.010794	-0.011356	-0.001271
2016-06-08	0.035	-0.79	-0.005842	0.001193	0.016763	-0.013134	-0.009937
2016-06-03	0.035	4.14	0.056489	0.050286	0.035771	-0.030616	0.002277
2016-05-27	0.035	-0.51	-0.006429	0.001684	0.030567	-0.020015	-0.001558
2016-05-20	0.035	0.11	NaN	NaN	NaN	NaN	NaN
2016-05-13	0.035	-1.77	NaN	NaN	NaN	NaN	NaN

A. Calculated factor returns

Robust linear Model Regression Results

Dep. Variable:	y	No. Observations:	10
Model:	RLM	Df Residuals:	3
Method:	IRLS	Df Model:	6
Norm:	HuberT		
Scale Est.:	mad		
Cov Type:	H1		
Date:	Tue, 09 Aug 2016		
Time:	00:16:01		
No. Iterations:	2		

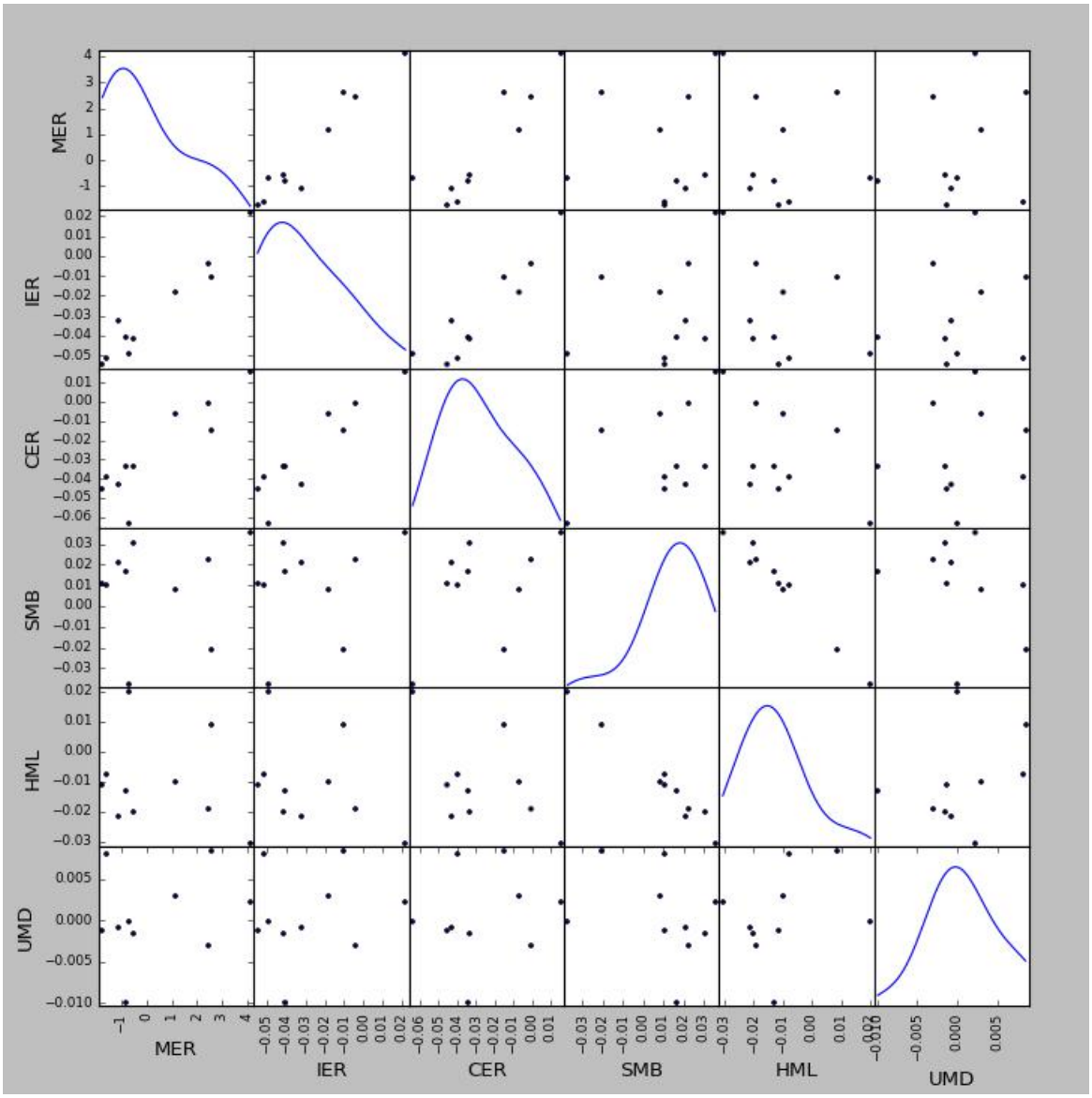
	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
const	-0.1081	0.017	-6.204	0.000	-0.142	-0.074
x1	0.0099	0.004	2.241	0.025	0.001	0.019
x2	0.2215	0.410	0.540	0.589	-0.582	1.025
x3	-0.6771	0.148	-4.586	0.000	-0.967	-0.388
x4	0.1036	0.487	0.213	0.832	-0.852	1.059
x5	0.4634	0.840	0.552	0.581	-1.182	2.109
x6	-0.1932	0.192	-1.007	0.314	-0.569	0.183

If the model instance has been used for another fit with different fit parameters, then the fit options might not be the correct ones anymore .

B. Regression analysis

	Market Excess Return	Industry Excess Return	Concept Excess Return	SMB	HML	UMD
Market Excess Return	1.000000	0.967117	0.891409	0.138886	-0.209613	0.246429
Industry Excess Return	0.967117	1.000000	0.921257	0.313690	-0.400449	0.181979
Concept Excess Return	0.891409	0.921257	1.000000	0.485833	-0.531329	0.163691
SMB	0.138886	0.313690	0.485833	1.000000	-0.986599	-0.316509
HML	-0.209613	-0.400449	-0.531329	-0.986599	1.000000	0.294711
UMD	0.246429	0.181979	0.163691	-0.316509	0.294711	1.000000

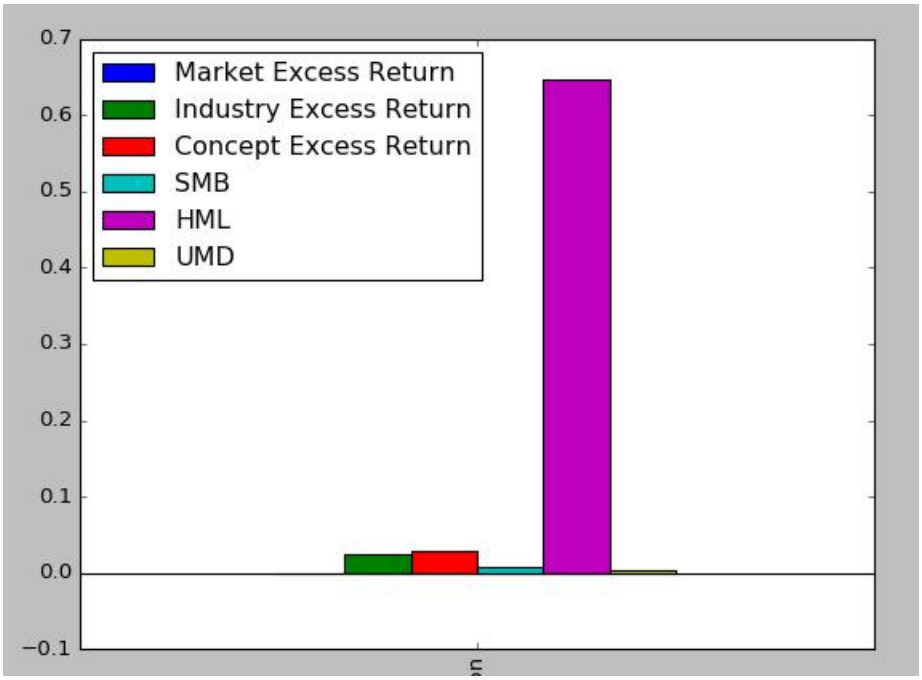
C. Factor correlation matrix



D. Covariance chart

*MER is short for Market Excess Return, IER for Industry Excess Return, CER for Concept Excess Return

	Market Excess Return	Industry Excess Return	Concept Excess Return	SMB	HML	UMD
risk contribution	-4.348519e-07	0.024082	0.029314	0.007396	0.646692	0.003979



D. Risk contribution charts

b. Interpretation of results

i. Regression analysis

1. Coefficients/Betas

Coefficient is the percentage of change in factor return that leads to the change in asset excess return. For example, coefficient of 1.2 represents for 10% increase in the according factor, there will be 12% increase in the asset excess return.

2. z (z-stats) and P (p-values)

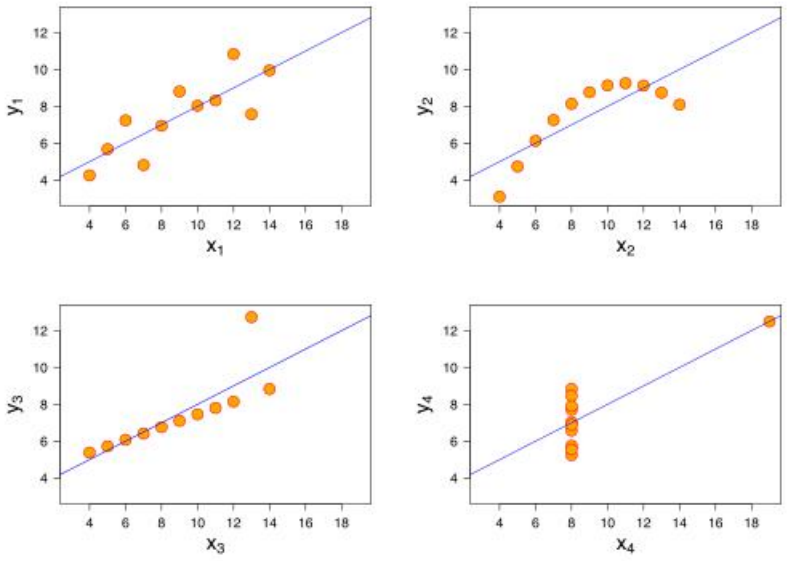
z-stats measures the deviation of the estimated coefficient from its hypothetical value, which is 0 in this case, in unit of standard error. In the graph, z-stats of market excess return is 1.97, meaning that the coefficient of market excess return is 1.97 standard error from 0. The more z-stats deviate from 0, the more significant the coefficient is.

P-values is another way of interpreting the significance of coefficient besides z-stats, measuring how extreme the coefficient is. According to common statistical practice, a p-value equal to or less than 0.05 means high significance while 0.01 means very high significance.

ii. Correlation Matrix

Linear correlation coefficient represents the extent to which two variables are linearly related. It ranges from -1 to 1. -1 indicates a perfect negative linear relationship, 1 indicates a perfect positive linear relation while 0 indicates no correlation between two variables.

However, correlation is not a robust measurement of linear relationship, and that makes visual inspection of the scatter plot crucial. Here is an example:



[15]

These are four sets of data with the same correlation 0.816, yet x2 does not show a linear relationship, while x3 and x4 have problem of extreme outlier.

Thus, a covariance chart is provided for visual inspection.

iii. Covariance Chart

Covariance chart presents scatter plots showing the relationship between factor returns. On the diagonal line are the density plots.

[15] Anscombe, Francis J. (1973) Graphs in statistical analysis. American Statistician, 27, 17–21

iv. Risk Contribution Charts

The risk contribution chart explains the composition of risk from each factor. Risk is defined as the standard deviation of historical return of assets. The horizontal scale presents different factors and the vertical scale represents the asset risk contributed by each factor out of the total risk of the investigated stock.

Note that the sum of all risk contributions is not necessarily 1. The discrepancy between the sum and 1 represents the risk not explained by existing factors.

5. Issues

One of the most outstanding issues of this program is the time required for fetching data. The total time spent on transporting data from the portal can be lengthy, since some factors require getting data for all stocks over the market of one day. Fetching 8 days of factor data can take up to 3 hrs to finish, which is not ideal. One way to solve this problem is by having a cache program. However, the current cache program in this system still needs the whole program to at least fetch the specific set of data once before storing those data. Thus, this is also a major potential for improvement.

6. Future Plans

Allowing for more customization will be the next step of this project. A list a factors will be provided for program users to choose from. A recommendation of factors will pop up when users have inputted their stock to research on.

The investigation subject will no longer be a single stock, but can be an industry or a portfolio. For the next step of the program, users can input their portfolio by indicating which stock and what percentage of the total capital they want to invest on the stock. The program will do a auto-rebalancing each time the capital distribution deviates from the desired distribution.

The model will be able to auto-test for the explanatory power of factors. Suggested by Connor and Korajczyk[16], if adding a factor doesn't not contribute to less variance in average asset specific variance, then the factor is redundant. Using this method, the program will be able to identify the set of factors with the most explanatory power.

7. Codes

[16] Connor, Gregory (1995), 'The Three Types of Factor Models: A Comparison of Their Explanatory Power'

In [1]:

```
import tushare as ts
import numpy as py
import pandas as pd
import math
import os
from datetime import datetime
from pandas.stats.api import ols
from pandas.tools.plotting import scatter_matrix
from __future__ import print_function
import statsmodels.api as sm
import matplotlib.pyplot as plt
import matplotlib
from statsmodels.sandbox.regression.predstd import wls_prediction_std
from scipy.integrate import quad
from sympy import *

ts.set_token('11ca1e622c4b228baa547fa4762dc8f28d97ef0decbc575c2f69aacf84baa7ad')
mkt=ts.Market()
```

In [2]:

```
#Cache downloaded data
CACHE_FOLDER = "./cache/"

def CacheConstructor(function):
    def CachedFunction(*args, **kargs):
        file_name = CACHE_FOLDER + function.__module__ + '.' + function.__name__ + '().hdf5'
        storage = pd.HDFStore(file_name, format='table')
        key = 'h'+ str(hash(str(args) + str(kargs))).replace('-','n')
        if key not in storage:
                storage.put(key, function(*args, **kargs))
        return storage.get(key)
    return CachedFunction

Cashed_get_h=CacheConstructor(ts.get_h_data)
Cashed_get_hist=CacheConstructor(ts.get_hist_data)
```

In [3]:

```
#Set basic variables

unit=''
ticker=''
start_date=''
end_date=''
#start
#end

market_excess=0
SMB=0
HML=0
UMD=0
REV=0
return_mom=0
industry_mom=0

data=pd.DataFrame()
```

In [4]:

```
# A program to receive input

def program():
    global unit, ticker, start_date, end_date
    print('Please fill in the question, input q for quitting')
    unit=input('Please indicate the time unit for calculating return, enter d for daily return, w for weekly
return, m for monthly return:')
    if unit != 'q':
        if unit == 'd' or unit == 'w' or unit =='m':
            start_date=input('Please indicate the start date (yyyy-mm-dd):')
            start=pd.to_datetime(start_date)
            if start_date != 'q':
                if start.isoweekday() == 6 or start.isoweekday()== 7:
                    print('The date you entered is not a business day.')
                    program()
                else:
                    end_date=input('Please indicate the end date (yyyy-mm-dd):')
                    end=pd.to_datetime(end_date)
                    if end_date!= 'q':
                            if end.isoweekday() == 6 or end.isoweekday()== 7:
                                print('The date you entered is not a business day.')
                                program()
                            else:
                                ticker=input('Please indicate the stock to investigate on, input ticker for
one stock, industry name, or market code:')
        else:
            print('There is an error in your input.')
            program()
```

In [6]:

```
program()
```

```
Please fill in the question, input q for quitting
Please indicate the time unit for calculating return, enter d for daily return, w for weekly return, m for m
onthly return:w
Please indicate the start date (yyyy-mm-dd):2016-05-15
The date you entered is not a business day.
Please fill in the question, input q for quitting
Please indicate the time unit for calculating return, enter d for daily return, w for weekly return, m for m
onthly return:w
Please indicate the start date (yyyy-mm-dd):2016-05-13
Please indicate the end date (yyyy-mm-dd):2016-08-02
Please indicate the stock to investigate on, input ticker for one stock, industry name, or market code:00000
1
```

In [7]:

```
# Calculate return for indicated stock
def cal_return(ticker, start_date, end_date, unit, date_index_string_hyphen):
    data=Cashed_get_h(ticker,start_date,end_date,autype='hfq')
    try:
        data=data.loc[data.index.isin(date_index_string_hyphen)]
        if unit == 'd':
            data_day=data
            data_day['daily_return']=data_day['close'].pct_change(-1)
            return data_day
        elif unit == 'w':
            data_week=data
            data_week['weekly_return']=data_week['close'].pct_change(-1)
            data_week['end date of week']=pd.to_datetime(data_week.index.to_series())
            data_week=data_week.set_index('end date of week')
            return data_week
        elif unit == 'm':
            data_month=data
            data_month['monthly_return']=data_month['close'].pct_change(-1)
            data_month['end date of month']=pd.to_datetime(data_month.index.to_series())
            data_month=data_month.set_index('end date of month')
            return data_month
    except:
        print('No data available for the indicated period.')

data_copy=ts.get_hist_data(ticker,start_date,end_date,ktype=unit)
data_copy['datetime']=pd.to_datetime(data_copy.index.to_series())
data_copy=data_copy.set_index('datetime')
date_index_string_hyphen=data_copy.index.to_series().apply(lambda x: x.strftime('%Y-%m-%d')).tolist()

return_dependent_variable=cal_return(ticker, start_date, end_date, unit,date_index_string_hyphen)
return_dependent_variable
```

[Getting data:]#

Out[7]:

	open	high	close	low	volume	amount	weekly_return
end date of week							
2016-07-29	1035.68	1053.93	1049.37	1029.98	67142534	614972669	0.029077
2016-07-22	1025.42	1025.42	1019.72	1017.43	29554964	264379250	-0.005559
2016-07-15	1020.86	1026.56	1025.42	1016.29	35203395	315555254	0.028609
2016-07-08	1002.61	1002.61	996.90	995.76	26134229	228778674	0.003442
2016-07-01	991.20	995.76	993.48	990.06	34893019	303652375	0.016337
2016-06-24	985.50	992.34	977.51	971.81	42766409	367771054	-0.001175
2016-06-17	977.51	982.08	978.66	974.09	31517300	270236698	-0.004830
2016-06-08	987.16	987.16	983.41	979.67	26818824	281651741	-0.000010
2016-06-03	980.61	985.29	983.42	974.99	42338929	443039581	0.022404
2016-05-27	957.19	963.75	961.87	954.38	22281892	228377555	-0.002913
2016-05-20	959.06	967.49	964.68	954.38	20670377	212277642	-0.004838
2016-05-13	969.37	974.05	969.37	967.49	18426611	191007256	NaN

In [8]:

```
#Set factor variables
date_index=return_dependent_variable.index
date_index_string=return_dependent_variable.index.to_series().apply(lambda x: x.strftime('%Y%m%d')).tolist()

Factor_Data=pd.DataFrame(index=date_index)
Factor_Data['Risk Free Rate']=py.nan
Factor_Data['Market Return']=py.nan
Factor_Data['Industry Return']=py.nan
Factor_Data['Concept Return']=py.nan
Factor_Data['SMB']=py.nan
Factor_Data['HML']=py.nan
Factor_Data['UMD']=py.nan
```

In [9]:

```
#Calcuate factor returns

######################  Market Return & Risk Free Rate ##########################
market_return=ts.get_hist_data('hs300',start_date,end_date,ktype=unit)
market_return['date']=pd.to_datetime(market_return.index)
market_return=market_return.set_index('date')

for mr in range(len(date_index)):
    Factor_Data['Market Return'][date_index[mr]]=market_return['p_change'][date_index[mr]]

rf=0.035 #the number used by Morgan Stanley
Factor_Data['Risk Free Rate']=[rf]*len(date_index)
```

In [10]:

```
Factor_Data
```

Out[10]:

	Risk Free Rate	Market Return	Industry Return	Concept Return	SMB	HML	UMD
end date of week							
2016-07-29	0.035	-0.66	NaN	NaN	NaN	NaN	NaN
2016-07-22	0.035	-1.56	NaN	NaN	NaN	NaN	NaN
2016-07-15	0.035	2.63	NaN	NaN	NaN	NaN	NaN
2016-07-08	0.035	1.21	NaN	NaN	NaN	NaN	NaN
2016-07-01	0.035	2.50	NaN	NaN	NaN	NaN	NaN
2016-06-24	0.035	-1.07	NaN	NaN	NaN	NaN	NaN
2016-06-17	0.035	-1.70	NaN	NaN	NaN	NaN	NaN
2016-06-08	0.035	-0.79	NaN	NaN	NaN	NaN	NaN
2016-06-03	0.035	4.14	NaN	NaN	NaN	NaN	NaN
2016-05-27	0.035	-0.51	NaN	NaN	NaN	NaN	NaN
2016-05-20	0.035	0.11	NaN	NaN	NaN	NaN	NaN
2016-05-13	0.035	-1.77	NaN	NaN	NaN	NaN	NaN

In [11]:

```
###################  Industry  ######################
def add_zeros(tickers):
    for k in range(len(tickers)):
        tickers[k]=str(tickers[k])
        if len(tickers[k])!=6:
            tickers[k]='0'*(6-len(tickers[k]))+tickers[k]
    return tickers

#Getting industry information
industry_classification=ts.get_industry_classified()
industry_name=industry_classification.loc[industry_classification['code']==ticker]['c_name'].to_string()[-4:
]
all_companies_same_industry=industry_classification.loc[industry_classification['c_name']==industry_name]

####Industry return
for each_date in range(len(date_index_string)-2):
    all_companies_same_industry['return '+ date_index_string[each_date]]=py.nan
    all_companies_same_industry['market cap '+ date_index_string[each_date]]=py.nan
    all_companies_same_industry['percentage '+ date_index_string[each_date]]=py.nan
    all_companies_same_industry['weighted return '+ date_index_string[each_date]]=py.nan

number_industry=all_companies_same_industry.count()['code']
all_companies_same_industry=all_companies_same_industry.set_index(pd.Series(list(range(number_industry))))
list_of_company=all_companies_same_industry['code'].tolist()

#Getting returns, market cap
for each_company in range(number_industry):
    try:
        company_return=cal_return(all_companies_same_industry['code'][each_company],start_date,end_date,unit
,date_index_string_hyphen)
    except TypeError:
        continue
    for each_date in range(len(date_index_string)-2):
        try:
            all_companies_same_industry['return '+ date_index_string[each_date]][each_company]=company_retur
n.loc[date_index[each_date]][-1]
        except KeyError:
            continue

for each_date in range(len(date_index)-2):
    try:
        industry_stock_cap_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[each_date],field='ASS
I,ticker')
    except :
        industry_stock_cap_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[each_date],field='ASS
I,ticker')
    industry_stock_cap_one_day['ticker']=pd.Series(add_zeros(industry_stock_cap_one_day['ticker'].tolist()))
    for each_company in range(number_industry):
        try:
            market_cap_one_company=industry_stock_cap_one_day.loc[industry_stock_cap_one_day['ticker']==list
_of_company[each_company]]['ASSI'].__float__()
            all_companies_same_industry['market cap '+ date_index_string[each_date]][each_company]=market_ca
p_one_company
        except (ValueError,TypeError):
            continue

#calculating weighted return
for each_date in range(len(date_index)-2):
    all_companies_same_industry['percentage '+ date_index_string[each_date]]=all_companies_same_industry['ma
rket cap '+ date_index_string[each_date]]/all_companies_same_industry['market cap '+ date_index_string[each_
date]].sum()
    all_companies_same_industry['weighted return '+ date_index_string[each_date]]=all_companies_same_industr
y['percentage '+ date_index_string[each_date]]*all_companies_same_industry['return '+ date_index_string[eac
h_date]]

#Industry Return
for each_date in range(len(date_index)-2):
    Industry_Return=all_companies_same_industry['weighted return '+ date_index_string[each_date]].sum()
    Factor_Data['Industry Return'][each_date]=Industry_Return
```

[Getting data:]##

In [13]:

```
##################  Concept  ###################

#Getting concept information
concept_classification=ts.get_concept_classified()
concept_name=concept_classification.loc[concept_classification['code']==ticker]['c_name'].to_string()[-4:]
all_companies_same_concept=concept_classification.loc[concept_classification['c_name']==concept_name]

####Concept return
for each_date in range(len(date_index_string)-2):
    all_companies_same_concept['return '+ date_index_string[each_date]]=py.nan
    all_companies_same_concept['market cap '+ date_index_string[each_date]]=py.nan
    all_companies_same_concept['percentage '+ date_index_string[each_date]]=py.nan
    all_companies_same_concept['weighted return '+ date_index_string[each_date]]=py.nan

number_concept=all_companies_same_concept.count()['code']
all_companies_same_concept=all_companies_same_concept.set_index(pd.Series(list(range(number_concept))))
list_of_company_concept=all_companies_same_concept['code'].tolist()

#Getting returns, market cap
for each_company in range(number_concept):
    try:
        company_return=cal_return(all_companies_same_concept['code'][each_company],start_date,end_date,unit,
date_index_string_hyphen)
    except TypeError:
        continue
    for each_date in range(len(date_index_string)-2):
        try:
            all_companies_same_concept['return '+ date_index_string[each_date]][each_company]=company_return
.loc[date_index[each_date]][-1]
        except KeyError:
            continue

for each_date in range(len(date_index)-2):
    try:
        concept_stock_cap_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[each_date],field='ASSI
,ticker')
    except :
        concept_stock_cap_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[each_date],field='ASSI
,ticker')
    concept_stock_cap_one_day['ticker']=pd.Series(add_zeros(concept_stock_cap_one_day['ticker'].tolist()))
    for each_company in range(number_concept):
        try:
            market_cap_one_company=concept_stock_cap_one_day.loc[concept_stock_cap_one_day['ticker']==list_o
f_company_concept[each_company]]['ASSI'].__float__()
            all_companies_same_concept['market cap '+ date_index_string[each_date]][each_company]=market_cap
_one_company
        except (ValueError,TypeError):
            continue

#calculating weighted return
for each_date in range(len(date_index)-2):
    all_companies_same_concept['percentage '+ date_index_string[each_date]]=all_companies_same_concept['mark
et cap '+ date_index_string[each_date]]/all_companies_same_concept['market cap '+ date_index_string[each_dat
e]].sum()
    all_companies_same_concept['weighted return '+ date_index_string[each_date]]=all_companies_same_concept[
'percentage '+ date_index_string[each_date]]*all_companies_same_concept['return '+ date_index_string[each_d
ate]]

#Concept Return
for each_date in range(len(date_index)-2):
    Concept_Return=all_companies_same_concept['weighted return '+ date_index_string[each_date]].sum()
    Factor_Data['Concept Return'][each_date]=Concept_Return
```

```
[Getting data:]##########################################################################################
############################################################
```

In [14]:

```
#################  SMB & HML  ###################
x=0.3
for k in range(len(date_index_string)-2):
    try:
        all_stock_cap_PB_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[k],field='ASSI,PB,ticke
r')
    except:
        all_stock_cap_PB_one_day=mkt.StockFactorsOneDay(tradeDate=date_index_string[k],field='ASSI,PB,ticke
r')


    all_stock_cap_PB_one_day=all_stock_cap_PB_one_day[all_stock_cap_PB_one_day['PB'].notnull()]
    all_stock_cap_PB_one_day=all_stock_cap_PB_one_day[all_stock_cap_PB_one_day['ASSI'].notnull()]

    number=all_stock_cap_PB_one_day.index.__len__()
    number_x=int(number*x)
    ###############  SMB  ###############
    sorted_stock_cap=all_stock_cap_PB_one_day.sort_values(by='ASSI',ascending=True).set_index(pd.Series(list
(range(number))))

    #Creating Sorting index and Sum
    sorted_stock_cap['sorting index']=number_x*['A']+(number-2*number_x)*[' ']+number_x*['B']

    #Getting tickers
    small_tickers_cap=sorted_stock_cap.loc[list(range(number_x))]['ticker'].tolist()
    big_tickers_cap=sorted_stock_cap.loc[list(range(number-number_x,number))]['ticker'].tolist()

    small_tickers_cap=add_zeros(small_tickers_cap)
    big_tickers_cap=add_zeros(big_tickers_cap)

    #Getting Returns
    sorted_stock_cap['return']=py.nan

    for y in range(0,number_x):
        try:
            sorted_stock_cap['return'][y]=cal_return(small_tickers_cap[y], start_date, end_date, unit,date_i
ndex_string_hyphen).loc[date_index[k]][-1]
        except:
            sorted_stock_cap['return'][y]=py.nan

    for z in range(number-number_x,number):
        try:
            sorted_stock_cap['return'][z]=cal_return(big_tickers_cap[z-(number-number_x)],start_date,end_dat
e,unit,date_index_string_hyphen).loc[date_index[k]][-1]
        except:
            sorted_stock_cap['return'][z]=py.nan

    #Weighted Return
    grouped_cap=sorted_stock_cap.groupby("sorting index")

    Small_Index=grouped_cap.get_group('A')['return'].mean()
    Big_Index=grouped_cap.get_group('B')['return'].mean()

    SMB=Small_Index-Big_Index

    Factor_Data['SMB'][date_index[k]]=SMB


    ############  HML  ############

    #Creating Sorting index and Sum
    sorted_stock_PB=sorted_stock_cap.sort_values(by='PB',ascending=True).set_index(pd.Series(list(range(numb
er))))
    sorted_stock_PB['sorting index']=int(number*0.5)*['A']+(number-2*int(number*0.5))*[' ']+int(number*0.5)
*['B']

    #Getting tickers
    small_tickers_PB=sorted_stock_PB.loc[list(range(int(number*0.5)))]['ticker'].tolist()
    big_tickers_PB=sorted_stock_PB.loc[list(range(number-int(number*0.5),number))]['ticker'].tolist()

    small_tickers_PB=add_zeros(small_tickers_PB)
    big_tickers_PB=add_zeros(big_tickers_PB)

    #Getting Returns
    for y in range(0,int(number*0.5)):
        if math.isnan(sorted_stock_PB['return'][y]):
```

```
            try:
                sorted_stock_PB['return'][y]=cal_return(small_tickers_PB[y],start_date,end_date,unit,date_in
dex_string_hyphen).loc[date_index[k]][-1]
            except:
                sorted_stock_PB['return'][y]=py.nan

    for z in range(number-int(number*0.5),number):
        if math.isnan(sorted_stock_PB['return'][y]):
            try:
                sorted_stock_PB['return'][z]=cal_return(big_tickers_PB[z-(number-number_x)],start_date,end_d
ate,unit,date_index_string_hyphen).loc[date_index[k]][-1]
            except:
                sorted_stock_PB['return'][z]=py.nan

    #Calculating weighted return
    grouped_PB=sorted_stock_PB.groupby("sorting index")

    High_Index=grouped_PB.get_group('A')['return'].mean()
    Low_Index=grouped_PB.get_group('B')['return'].mean()

    HML=High_Index-Low_Index

    Factor_Data['HML'][date_index[k]]=HML
```

[Getting data:]#[Getting data:]#[Getting data:]#[Getting data:]#[Getting data:]#[Getting data:]#[Getting dat
a:]#[Getting data:]#[Getting data:]#

In [15]:

```
############## UMD ################
#Getting a chart of all stocks and their return for all dates
all_stock_basics=ts.get_stock_basics()
all_tickers=all_stock_basics.index.tolist()
Momentum_Data=pd.DataFrame(index=all_stock_basics.index)
Momentum_Data['market cap']=py.nan

for each_date in date_index_string[:-1]:
    Momentum_Data[each_date]=py.nan

for each in all_tickers:
    try:
        each_stock_record=cal_return(each,start_date,end_date,unit,date_index_string_hyphen)
    except:
        continue
    for a_number in range(len(date_index)-1):
        try:
            Momentum_Data.loc[each][date_index_string[a_number]]=each_stock_record.loc[date_index[a_number]]
[-1].__float__()
        except:
            continue

Momentum_Data_clean=Momentum_Data
for each_date in range(len(date_index_string)-1):
    Momentum_Data_clean=Momentum_Data_clean[Momentum_Data_clean[date_index_string[each_date]].notnull()]


def cal_UMD_one_period(k, Momentum_Data_clean, date_index, date_index_string):
    Momentum_Data_clean.sort_values(by=date_index_string[k],ascending=False)

    all_tickers_new=Momentum_Data_clean.index.tolist()

    try:
        all_stock_cap_one_day_momentum=mkt.StockFactorsOneDay(tradeDate=date_index_string[k],field='ASSI,ti
cker')
    except:
        all_stock_cap_one_day_momentum=mkt.StockFactorsOneDay(tradeDate=date_index_string[k],field='ASSI,ti
cker')

    for each in all_tickers_new:
        Momentum_Data_clean['market cap'][each]=all_stock_cap_one_day_momentum.loc[all_stock_cap_one_day_mom
entum['ticker']==int(each)]['ASSI'].__float__()

    Momentum_Data_clean=Momentum_Data_clean[Momentum_Data_clean['market cap'].notnull()]

    number_momentum=Momentum_Data_clean.count()[date_index_string[k]]
    number_momentum_x=int(0.3*number_momentum)

    #adding sorting index
    Momentum_Data_clean['sorting index']=number_momentum_x*['A']+(number_momentum-2*number_momentum_x)*[' '
]+number_momentum_x*['B']
    grouped_momentum=Momentum_Data_clean.groupby('sorting index')
    big_cap=grouped_momentum.get_group('A').sum()['market cap']
    small_cap=grouped_momentum.get_group('B').sum()['market cap']
    Momentum_Data_clean['sum']=[big_cap]*number_momentum_x+(number_momentum-2*number_momentum_x)*[py.nan]+[
small_cap]*number_momentum_x
    Momentum_Data_clean['percentage']=Momentum_Data_clean['market cap']/Momentum_Data_clean['sum']

    #Getting weighted return
    Momentum_Data_clean['weighted return']=Momentum_Data_clean[date_index_string[k]]*Momentum_Data_clean['p
ercentage']

    #Getting Final Result
    grouped_momentum_again=Momentum_Data_clean.groupby('sorting index')
    top_30=grouped_momentum_again.get_group('A').sum()['weighted return']
    bottom_30=grouped_momentum_again.get_group('B').sum()['weighted return']
    Momentum_one_period=top_30-bottom_30

    return Momentum_one_period


for k in range(1,len(date_index)-1):

    Factor_Data['UMD'][date_index[k-1]]=cal_UMD_one_period(k, Momentum_Data_clean, date_index, date_index_st
ring)
```

Out[153]:

	Risk Free Rate	Market Return	Industry Return	Concept Return	SMB	HML	UMD
end date of week							
2016-07-29	0.035	-0.66	-0.014010	-0.028755	-0.037364	0.020066	-0.000080
2016-07-22	0.035	-1.56	-0.015982	-0.004466	0.010336	-0.007896	0.008120
2016-07-15	0.035	2.63	0.024653	0.020110	-0.020732	0.008714	0.008489
2016-07-08	0.035	1.21	0.016549	0.028480	0.008117	-0.010108	0.003014
2016-07-01	0.035	2.50	0.031132	0.034485	0.022671	-0.019018	-0.003076
2016-06-24	0.035	-1.07	0.002595	-0.007865	0.020978	-0.021483	-0.000770
2016-06-17	0.035	-1.70	-0.019611	-0.010581	0.010794	-0.011356	-0.001271
2016-06-08	0.035	-0.79	-0.005842	0.001193	0.016763	-0.013134	-0.009937
2016-06-03	0.035	4.14	0.056489	0.050286	0.035771	-0.030616	0.002277
2016-05-27	0.035	-0.51	-0.006429	0.001684	0.030567	-0.020015	-0.001558
2016-05-20	0.035	0.11	NaN	NaN	NaN	NaN	NaN
2016-05-13	0.035	-1.77	NaN	NaN	NaN	NaN	NaN

In [57]:

```
#####################  Linear Regression  #####################
'''
Method 1, Not Robust!!!
'''
#Combining data
Factor_Data['Market Excess Return']=Factor_Data['Market Return']-Factor_Data['Risk Free Rate']
Factor_Data['Industry Excess Return']=Factor_Data['Industry Return']-Factor_Data['Risk Free Rate']
Factor_Data['Concept Excess Return']=Factor_Data['Concept Return']-Factor_Data['Risk Free Rate']
Complete_Data=Factor_Data.copy()[0:-2]
Complete_Data['stock return']=return_dependent_variable.iloc[:,-1]
Complete_Data['dependent variable']=Complete_Data['stock return']-Complete_Data['Risk Free Rate']
#regression=sm.ols('stock return~ Market Return + SMB', data=Complete_Data)
regression=ols(y=Complete_Data['stock return']-Complete_Data['Risk Free Rate'],x=Complete_Data[['Market Excess Return','Industry Excess Return','Concept Excess Return','SMB','HML','UMD']])
regression
```

Out[57]:

```
-------------------------Summary of Regression Analysis-------------------------

Formula: Y ~ <Market Excess Return> + <Industry Excess Return>
             + <Concept Excess Return> + <SMB> + <HML> + <UMD> + <intercept>

Number of Observations:         10
Number of Degrees of Freedom:   7

R-squared:         0.9882
Adj R-squared:     0.9645

Rmse:              0.0026

F-stat (6, 3):    41.8014, p-value:     0.0055

Degrees of Freedom: model 6, resid 3

-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
Market Excess Return     0.0099     0.0044       2.24     0.1109     0.0012     0.0186
Industry Excess Return     0.2215     0.4100       0.54     0.6265    -0.5820     1.0250
Concept Excess Return    -0.6771     0.1477      -4.59     0.0195    -0.9665    -0.3877
           SMB     0.1036     0.4873       0.21     0.8453    -0.8516     1.0588
           HML     0.4634     0.8398       0.55     0.6195    -1.1825     2.1094
--------------------------------------------------------------------------------
           UMD    -0.1932     0.1919      -1.01     0.3881    -0.5693     0.1828
     intercept    -0.0731     0.0174      -4.19     0.0247    -0.1072    -0.0389
---------------------------------End of Summary---------------------------------
```

In [86]:

```
'''
Method 2, Robust analysis
'''
Complete_Data=Complete_Data[['Market Excess Return','Industry Excess Return','Concept Excess Return','SMB','
HML','UMD']]

Complete_Data_array=Complete_Data.as_matrix()
Complete_Data_array=sm.add_constant(Complete_Data_array)
Complete_Data_array

return_dependent_variable.iloc[:,-1]=return_dependent_variable.iloc[:,-1]-rf
Dependent_Variable_array=return_dependent_variable.iloc[:-2,-1].as_matrix()
Dependent_Variable_array

regression_model = sm.RLM(Dependent_Variable_array, Complete_Data_array, M=sm.robust.norms.HuberT())

regression_result=regression_model.fit()
print(regression_result.summary())
```

```
                    Robust linear Model Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   10
Model:                            RLM   Df Residuals:                        3
Method:                          IRLS   Df Model:                            6
Norm:                         HuberT
Scale Est.:                      mad
Cov Type:                         H1
Date:                Tue, 09 Aug 2016
Time:                        00:16:01
No. Iterations:                    2
==============================================================================
                 coef    std err          z      P>|z|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const         -0.1081      0.017     -6.204      0.000        -0.142    -0.074
x1             0.0099      0.004      2.241      0.025         0.001     0.019
x2             0.2215      0.410      0.540      0.589        -0.582     1.025
x3            -0.6771      0.148     -4.586      0.000        -0.967    -0.388
x4             0.1036      0.487      0.213      0.832        -0.852     1.059
x5             0.4634      0.840      0.552      0.581        -1.182     2.109
x6            -0.1932      0.192     -1.007      0.314        -0.569     0.183
==============================================================================

If the model instance has been used for another fit with different fit
parameters, then the fit options might not be the correct ones anymore .
```

In [37]:

```
#####################   Correlation Matrix  ######################
Correlation_Matrix=Complete_Data[['Market Excess Return','Industry Excess Return','Concept Excess Return','S
MB','HML','UMD']]
Correlation_Matrix=Correlation_Matrix.corr()
Correlation_Matrix
```

Out[37]:

	Market Excess Return	Industry Excess Return	Concept Excess Return	SMB	HML	UMD
Market Excess Return	1.000000	0.967117	0.891409	0.138886	-0.209613	0.246429
Industry Excess Return	0.967117	1.000000	0.921257	0.313690	-0.400449	0.181979
Concept Excess Return	0.891409	0.921257	1.000000	0.485833	-0.531329	0.163691
SMB	0.138886	0.313690	0.485833	1.000000	-0.986599	-0.316509
HML	-0.209613	-0.400449	-0.531329	-0.986599	1.000000	0.294711
UMD	0.246429	0.181979	0.163691	-0.316509	0.294711	1.000000

In [154]:

```
##################  Covariance Scatter Plot  ######################
Complete_Data_Plot=Complete_Data.copy()
Complete_Data_Plot.columns=['MER', 'IER','CER', 'SMB', 'HML', 'UMD']

Covariance_Plot=scatter_matrix(Complete_Data_Plot, alpha=1, figsize=(10, 10), diagonal='kde')

matplotlib.pyplot.show()
```

In [132]:

```
################ Risk Contribution Chart  ########################
Covariance_Matrix=Complete_Data[['Market Excess Return','Industry Excess Return','Concept Excess Return','SM
B','HML','UMD']]
Covariance_Matrix=Covariance_Matrix.cov()
se=regression_result.bse
coef=regression_result.params

#Calculate porfolio risk
portfolio_risk=0
for item in range(1,len(se)):
    each=(se[item]*coef[item])**2
    portfolio_risk=portfolio_risk+each


for row in range(len(Covariance_Matrix.columns)):
    for column in range(row+1,len(Covariance_Matrix.iloc[row])):
        each=2*Covariance_Matrix.iloc[row,column]*coef[row+1]*coef[column+1]
        portfolio_risk=portfolio_risk+each
portfolio_risk=portfolio_risk**0.5
portfolio_risk


# Calculate individual risk contribution
def cal_risk_contribution(k,se,coef,Covariance_Matrix,portfolio_risk):
    def integrand(x,k,se,coef,Covariance_Matrix,portfolio_risk):
        risk_x=0
        li=list(range(1,len(se)))
        li.remove(k+1)

        for item in li:
            each=(se[item]*coef[item])**2
            risk_x=risk_x+each

        li2=list(range(len(Covariance_Matrix.columns)))
        li2.remove(k)

        for row in li2:
            for column in range(row+1,len(Covariance_Matrix.iloc[row])):
                each=2*Covariance_Matrix.iloc[row,column]*coef[row+1]*coef[column+1]
                risk_x=risk_x+each
        risk_x

        y=Symbol('y')

        summation=0
        for column in range(k+1,len(Covariance_Matrix.iloc[row])):
            each=2*Covariance_Matrix.iloc[row,column]*y*coef[column+1]
            summation=summation+each

        risk=(y**2*se[k+1]**2+summation+risk_x)**0.5
        return risk.diff(y).replace(y,x)
    I = quad(integrand, 0, coef[k+1], args=(k,se,coef,Covariance_Matrix,portfolio_risk))
    contribution=I[0]/portfolio_risk
    return contribution

##Risk Contribution Chart in number
risk_contribution_chart=pd.DataFrame(py.nan,index=['risk contribution'],columns=Covariance_Matrix.columns)
for k in range(len(Covariance_Matrix.columns)):
    risk_contribution_chart.iloc[0,k]=cal_risk_contribution(k,se,coef,Covariance_Matrix,portfolio_risk)
risk_contribution_chart
```

In [230]:

```
##Risk Contribution Chart in graphics
risk_contribution_chart.plot.bar(); plt.axhline(0, color='k')
matplotlib.pyplot.show()
```