Fama-French模型源代码学习笔记（Python）

- reference: https://github.com/nkuguanrui/FamaFrenchThreeFacorModel
- todo：多因子简化板复现，因子预处理、检验、分析、优化、风险预测等

In [133…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import copy
import seaborn
import statsmodels

# 使绘图在 Jupyter Notebook 中直接显示
%matplotlib inline

# 设置全局绘图尺寸（16x9 英寸）
plt.rcParams['figure.figsize'] = (16.0, 9.0)
```

数据

借用原项目收集好的数据集

- price.csv

> PERMNO: 股票唯一永久 ID 整数（CRSP 内部标识）
> date: 交易日期 YYYY-MM-DD
> PRCT收盘价美元，负值表示 Bid 价
> SHROUT流通股数千股（×1000 = 实际股数）
> EXCHCD:交易所代码 1=NYSE, 2=AMEX, 3=NASDAQ

- value.csv

> LPERMNO:Compustat 公司对应的 CRSP 股票 PERMNO, 连接财务数据与市场数据
> datadate: 财报截止日期, 时间对齐，避免未来函数
> bkvlps: 每股账面价值（美元), 计算 B/M，构建价值因子（HML）

- rf.csv

> date: 月份 rf： 每月无风险收益率（CRSP计算）

In [115…

```
price = pd.read_csv('price.csv',usecols=['PERMNO','date','PRC','SHROUT','EXCHC
value = pd.read_csv('book.csv',usecols=['LPERMNO','datadate','bkvlps'])
```

```python
rf = pd.read_csv('rf.csv',usecols=['qdate','ave_1'])
```

In [115…

```python
price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1660455 entries, 0 to 1660454
Data columns (total 5 columns):
 #   Column  Non-Null Count    Dtype  
---  ------  --------------    -----  
 0   PERMNO  1660455 non-null  int64  
 1   date    1660455 non-null  int64  
 2   EXCHCD  1646961 non-null  float64
 3   PRC     1593710 non-null  float64
 4   SHROUT  1645000 non-null  float64
dtypes: float64(3), int64(2)
memory usage: 63.3 MB
```

In [115…

```python
price.head()
```

Out[115…

	PERMNO	date	EXCHCD	PRC	SHROUT
0	10000	19851231	NaN	NaN	NaN
1	10000	19860131	3.0	-4.3750	3680.0
2	10000	19860228	3.0	-3.2500	3680.0
3	10000	19860331	3.0	-4.4375	3680.0
4	10000	19860430	3.0	-4.0000	3793.0

In [115…

```python
value.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116248 entries, 0 to 116247
Data columns (total 3 columns):
 #   Column    Non-Null Count   Dtype  
---  ------    --------------   -----  
 0   LPERMNO   116248 non-null  int64  
 1   datadate  116248 non-null  int64  
 2   bkvlps    108801 non-null  float64
dtypes: float64(1), int64(2)
memory usage: 2.7 MB
```

In [115…

```python
value.head()
```

Out[115…

	LPERMNO	datadate	bkvlps
0	25881	19701231	4.3107
1	25881	19711231	2.7987
2	25881	19721231	2.4194
3	25881	19731231	3.0165
4	25881	19741231	4.5781

In [115…

```
rf.info
```

Out[115…

```
<bound method DataFrame.info of          qdate  ave_1
0    19630131  2.929
1    19630228  2.843
2    19630329  2.853
3    19630430  2.858
4    19630531  2.960
..        ...    ...
343  19910830  5.306
344  19910930  4.989
345  19911031  4.786
346  19911129  4.063
347  19911231  3.717

[348 rows x 2 columns]>
```

In [116…

```
rf.head()
```

Out[116…

	qdate	ave_1
0	19630131	2.929
1	19630228	2.843
2	19630329	2.853
3	19630430	2.858
4	19630531	2.960

Data Wrangling

处理rf表格，形成月度数据

In [116…

```
rf.head()
```

Out[116…

	qdate	ave_1
0	19630131	2.929
1	19630228	2.843
2	19630329	2.853
3	19630430	2.858
4	19630531	2.960

In [116…
```
rf = rf.rename(columns={rf.columns[0]: 'date', rf.columns[1]: 'rf'}) # 重命名国
```

In [116…
```
rf.head()# 检查列名
```

Out[116…

	date	rf
0	19630131	2.929
1	19630228	2.843
2	19630329	2.853
3	19630430	2.858
4	19630531	2.960

In [116…
```
rf["date"].dtype # 检查日期列数据类型 'int64'
```

Out[116…
```
dtype('int64')
```

In [116…
```
rf['date'] = rf['date'].apply(str)
rf['date'] = pd.to_datetime(rf['date'])# int64 -> str -> 时间序列
```

In [116…
```
rf["date"].dtype # 检查日期列数据类型变为时间序列 '<M8[ns]'
```

Out[116…
```
dtype('<M8[ns]')
```

In [116…
```
rf['year_month'] = rf['date'].dt.to_period('M') # 日期数据按月进行归一化（取整）
```

In [116…
```
rf.head() # 增加“year_month”列
```

Out[116…

	date	rf	year_month
0	1963-01-31	2.929	1963-01
1	1963-02-28	2.843	1963-02
2	1963-03-29	2.853	1963-03
3	1963-04-30	2.858	1963-04
4	1963-05-31	2.960	1963-05

In [116…
```python
rf.drop(columns=['date'],inplace=True) #删除原date列，研究周期为月
```

In [117…
```python
rf.head()
```

Out[117…

	rf	year_month
0	2.929	1963-01
1	2.843	1963-02
2	2.853	1963-03
3	2.858	1963-04
4	2.960	1963-05

处理price数据

In [117…
```python
price = pd.read_csv('price.csv',usecols=['PERMNO','date','PRC','SHROUT','EXCHC
```

In [117…
```python
price.head()
```

Out[117…

	PERMNO	date	EXCHCD	PRC	SHROUT
0	10000	19851231	NaN	NaN	NaN
1	10000	19860131	3.0	-4.3750	3680.0
2	10000	19860228	3.0	-3.2500	3680.0
3	10000	19860331	3.0	-4.4375	3680.0
4	10000	19860430	3.0	-4.0000	3793.0

In [117…
```python
price = price.rename(columns={price.columns[0]: 'stock_code',
                              price.columns[1]: 'date',
                              price.columns[2]: 'exchange_code',
                              price.columns[3]: 'price',
                              price.columns[4]: 'shares'}) # 重命股价表
```

In [117…
```python
price.head()
```

Out[117…

	stock_code	date	exchange_code	price	shares
0	10000	19851231	NaN	NaN	NaN
1	10000	19860131	3.0	-4.3750	3680.0
2	10000	19860228	3.0	-3.2500	3680.0
3	10000	19860331	3.0	-4.4375	3680.0
4	10000	19860430	3.0	-4.0000	3793.0

In [117…
```
price['date'] = price['date'].apply(str)
price['date'] = pd.to_datetime(price['date'])
price['year'] = price['date'].dt.year
price['year_month'] = price['date'].dt.to_period('M')
price['price'] = abs(price['price'])
```

In [117…
```
price.head()
```

Out[117…

	stock_code	date	exchange_code	price	shares	year	year_month
0	10000	1985-12-31	NaN	NaN	NaN	1985	1985-12
1	10000	1986-01-31	3.0	4.3750	3680.0	1986	1986-01
2	10000	1986-02-28	3.0	3.2500	3680.0	1986	1986-02
3	10000	1986-03-31	3.0	4.4375	3680.0	1986	1986-03
4	10000	1986-04-30	3.0	4.0000	3793.0	1986	1986-04

处理value数据

In [117…
```
value = pd.read_csv('book.csv',usecols=['LPERMNO','datadate','bkvlps'])
```

In [117…
```
# value.columns = ['stock_code','date','bookvaluepershare']
value = value.rename(columns={value.columns[0]:"stock_code",
                              value.columns[1]:"date",
                              value.columns[2]:"bookvaluepershare"}) # 更换列名
```

In [117…
```
value.head()
```

Out[117…

	stock_code	date	bookvaluepershare
0	25881	19701231	4.3107
1	25881	19711231	2.7987
2	25881	19721231	2.4194
3	25881	19731231	3.0165
4	25881	19741231	4.5781

In [118…
```
value["date"].dtype# 检查date的数据类型
```

Out[118…
```
dtype('int64')
```

In [118…
```
value['date'] = value['date'].apply(str)
value['date'] = pd.to_datetime(value['date']) # int64->str-><M8[ns] #改为时间序
```

In [118…
```
value["date"].dtype
```

Out[118…
```
dtype('<M8[ns]')
```

In [118…
```
value['year'] = value['date'].dt.year #股票价值表增加year列
```

In [118…
```
value.head()
```

Out[118…

	stock_code	date	bookvaluepershare	year
0	25881	1970-12-31	4.3107	1970
1	25881	1971-12-31	2.7987	1971
2	25881	1972-12-31	2.4194	1972
3	25881	1973-12-31	3.0165	1973
4	25881	1974-12-31	4.5781	1974

清洗三张表NaN、不合理值

In [118…
```
#去掉空值（dropna）,na代表空值
value.dropna(inplace=True)
price.dropna(inplace=True)
rf.dropna(inplace=True)
```

In [118…
```
price['exchange_code'].unique()
```

Out[118…
```
array([ 3.,  1.,  2., 33., 32., 31.])
```

In [118…
```
price = price.loc[price['exchange_code'].isin([1,2,3]),:]#获取（保留）三大交易所的
price.head()
```

Out[118…

	stock_code	date	exchange_code	price	shares	year	year_month
1	10000	1986-01-31	3.0	4.37500	3680.0	1986	1986-01
2	10000	1986-02-28	3.0	3.25000	3680.0	1986	1986-02
3	10000	1986-03-31	3.0	4.43750	3680.0	1986	1986-03
4	10000	1986-04-30	3.0	4.00000	3793.0	1986	1986-04
5	10000	1986-05-30	3.0	3.10938	3793.0	1986	1986-05

In [118…
```
price['exchange_code'].unique()
```

Out[118…
```
array([3., 1., 2.])
```

In [118…
```
value.head()
```

Out[118…

	stock_code	date	bookvaluepershare	year
0	25881	1970-12-31	4.3107	1970
1	25881	1971-12-31	2.7987	1971
2	25881	1972-12-31	2.4194	1972
3	25881	1973-12-31	3.0165	1973
4	25881	1974-12-31	4.5781	1974

In [119…

```
rf.head()
```

Out[119…

	rf	year_month
0	2.929	1963-01
1	2.843	1963-02
2	2.853	1963-03
3	2.858	1963-04
4	2.960	1963-05

In [119…

```
for df_name, df in [('rf', rf), ('price', price), ('value', value)]: #检查是否还
    print(f"==== 检查 {df_name} 缺失值 ====")
    print(df.isna().sum())
    print("\n")
```

```
==== 检查 rf 缺失值 ====
rf            0
year_month    0
dtype: int64


==== 检查 price 缺失值 ====
stock_code       0
date             0
exchange_code    0
price            0
shares           0
year             0
year_month       0
dtype: int64


==== 检查 value 缺失值 ====
stock_code           0
date                 0
bookvaluepershare    0
year                 0
dtype: int64
```

数值计算

在分组前，计算所需数值。研究周期为年

BV(账面价值)=bookvaluepershare(每股账面价值)×shares(股本数量)

MktCap(市值)=price×shares

BM=BV/MktCap

shares(price)保留年度数据

In [119…
```
shares = copy.deepcopy(price.loc[:,['stock_code','exchange_code',
                                    'price','shares','year','year_month']])
```

In [119…
```
shares.head()
```

Out[119…

	stock_code	exchange_code	price	shares	year	year_month
1	10000	3.0	4.37500	3680.0	1986	1986-01
2	10000	3.0	3.25000	3680.0	1986	1986-02
3	10000	3.0	4.43750	3680.0	1986	1986-03
4	10000	3.0	4.00000	3793.0	1986	1986-04
5	10000	3.0	3.10938	3793.0	1986	1986-05

In [119…

```
shares = shares.sort_values(['stock_code','year_month'])
```

In [119…

```
shares.head(20)
```

Out[119…

	stock_code	exchange_code	price	shares	year	year_month
1	10000	3.0	4.37500	3680.0	1986	1986-01
2	10000	3.0	3.25000	3680.0	1986	1986-02
3	10000	3.0	4.43750	3680.0	1986	1986-03
4	10000	3.0	4.00000	3793.0	1986	1986-04
5	10000	3.0	3.10938	3793.0	1986	1986-05
6	10000	3.0	3.09375	3793.0	1986	1986-06
7	10000	3.0	2.84375	3793.0	1986	1986-07
8	10000	3.0	1.09375	3793.0	1986	1986-08
9	10000	3.0	1.03125	3793.0	1986	1986-09
10	10000	3.0	0.78125	3843.0	1986	1986-10
11	10000	3.0	0.82813	3843.0	1986	1986-11
12	10000	3.0	0.51563	3843.0	1986	1986-12
13	10000	3.0	0.40625	3893.0	1987	1987-01
14	10000	3.0	0.40625	3893.0	1987	1987-02
15	10000	3.0	0.25000	3893.0	1987	1987-03
16	10000	3.0	0.23438	3893.0	1987	1987-04
17	10000	3.0	0.21875	3893.0	1987	1987-05
20	10001	3.0	6.12500	985.0	1986	1986-01
21	10001	3.0	6.25000	985.0	1986	1986-02
22	10001	3.0	6.31250	985.0	1986	1986-03

In [119…

```
shares = shares.groupby(['stock_code','year']).last() # 只保留每年最后一天的股价,
```

```python
shares.head()
```

Out[119…

		exchange_code	price	shares	year_month
stock_code	**year**				
10000	**1986**	3.0	0.51563	3843.0	1986-12
	1987	3.0	0.21875	3893.0	1987-05
10001	**1986**	3.0	7.00000	991.0	1986-12
	1987	3.0	5.87500	992.0	1987-12
	1988	3.0	6.37500	998.0	1988-12

In [119…

```python
shares.reset_index(inplace=True)
shares
```

Out[119…

	stock_code	year	exchange_code	price	shares	year_month
0	10000	1986	3.0	0.51563	3843.0	1986-12
1	10000	1987	3.0	0.21875	3893.0	1987-05
2	10001	1986	3.0	7.00000	991.0	1986-12
3	10001	1987	3.0	5.87500	992.0	1987-12
4	10001	1988	3.0	6.37500	998.0	1988-12
...	...	...	...	...	...	...
145750	93316	1989	3.0	3.00000	2696.0	1989-12
145751	93316	1990	3.0	1.68750	2696.0	1990-12
145752	93316	1991	3.0	2.18750	2696.0	1991-12
145753	93324	1984	3.0	0.48438	14715.0	1984-12
145754	93324	1985	3.0	0.09375	14715.0	1985-11

145755 rows × 6 columns

In [119…

```python
shares.dropna(inplace=True)
shares.head()
```

Out[119…

	stock_code	year	exchange_code	price	shares	year_month
0	10000	1986	3.0	0.51563	3843.0	1986-12
1	10000	1987	3.0	0.21875	3893.0	1987-05
2	10001	1986	3.0	7.00000	991.0	1986-12
3	10001	1987	3.0	5.87500	992.0	1987-12
4	10001	1988	3.0	6.37500	998.0	1988-12

values保留年度数据

In [119…

```
value = value.sort_values(['stock_code','date'])
value = value.groupby(['stock_code','year']).last()
value.reset_index(inplace=True) # booktovaluepershare
# Book Value 的数据频率本身是年度
```

In [120…

```
value.head()
```

Out[120…

	stock_code	year	date	bookvaluepershare
0	10000	1986	1986-10-31	0.1088
1	10001	1986	1986-06-30	5.5147
2	10001	1987	1987-06-30	5.4178
3	10001	1988	1988-06-30	5.5565
4	10001	1989	1989-06-30	6.3147

In [120…

```
shares.drop(columns=['year_month'],inplace=True)
value.drop(columns=['date'],inplace=True)
```

合并股票股价和市值数据

In [120…

```
bm_df = pd.merge(shares,value,on=['stock_code','year'])
```

计算bm（年度）

In [120…

```
bm_df['bv'] = bm_df['bookvaluepershare']*bm_df['shares']*1000 #数据库中的股数除了
```

In [120…

```
bm_df['mktcap'] = bm_df['price']*bm_df['shares']*1000 # MktCap市值)=price×share
```

In [120…

```
bm_df.drop(columns=['bookvaluepershare','price'],inplace=True)
```

In [120…

```
bm_df.drop(columns=['shares'],inplace=True)
```

In [120…
```python
bm_df.head(20)
```

Out[120…

	stock_code	year	exchange_code	bv	mktcap
0	10000	1986	3.0	418118.4	1.981566e+06
1	10001	1986	3.0	5465067.7	6.937000e+06
2	10001	1987	3.0	5374457.6	5.828000e+06
3	10001	1988	3.0	5545387.0	6.362250e+06
4	10001	1989	3.0	6453623.4	1.034775e+07
5	10001	1990	3.0	7339107.4	1.001300e+07
6	10001	1991	3.0	7996925.0	1.558750e+07
7	10005	1986	3.0	1899898.2	4.336875e+05
8	10005	1987	3.0	2494372.8	1.177917e+06
9	10005	1988	3.0	1282365.6	7.852500e+05
10	10005	1989	3.0	1020196.8	5.235000e+05
11	10005	1990	3.0	714503.2	3.913074e+05
12	10006	1964	1.0	139425658.4	2.359560e+08
13	10006	1965	1.0	305563168.0	2.797200e+08
14	10006	1966	1.0	161297502.0	2.198610e+08
15	10006	1967	1.0	172465880.4	2.532296e+08
16	10006	1968	1.0	179917438.6	3.532676e+08
17	10006	1969	1.0	192780610.9	2.764090e+08
18	10006	1970	1.0	196616876.4	2.561388e+08
19	10006	1971	1.0	198588836.1	2.882455e+08

In [120…
```python
bm_df['bm'] = bm_df['bv']/bm_df['mktcap'] # BM=BV/MktCap
bm_df.drop(columns=['bv'],inplace=True)
```

In [120…
```python
bm_df.drop(columns=['mktcap'],inplace=True)
```

In [121…
```python
bm_df
```

Out[121…

	stock_code	year	exchange_code	bm
0	10000	1986	3.0	0.211004
1	10001	1986	3.0	0.787814
2	10001	1987	3.0	0.922179
3	10001	1988	3.0	0.871608
4	10001	1989	3.0	0.623674
...	...	...	...	...
106044	93316	1988	3.0	1.980296
106045	93316	1989	3.0	2.259033
106046	93316	1990	3.0	4.071644
106047	93316	1991	3.0	3.102994
106048	93324	1985	3.0	1.125333

106049 rows × 4 columns

计算市值

In [121…

```
mktcap_df = copy.deepcopy(price.loc[:,['stock_code','exchange_code',
                                         'price','shares','year_month']])
```

In [121…

```
mktcap_df.dropna(inplace=True)
mktcap_df['mktcap'] = mktcap_df['price']*mktcap_df['shares']*1000 # MktCap(市值
mktcap_df.drop(columns=['price','shares'],inplace=True)
```

In [121…

```
mktcap_df.head()
```

Out[121…

	stock_code	exchange_code	year_month	mktcap
1	10000	3.0	1986-01	16100000.00
2	10000	3.0	1986-02	11960000.00
3	10000	3.0	1986-03	16330000.00
4	10000	3.0	1986-04	15172000.00
5	10000	3.0	1986-05	11793878.34

计算股票收益率

In [121…

```
ret_df = copy.deepcopy(price.loc[:,['stock_code','price','year_month']])
```

In [121…

```
ret_df.dropna(inplace=True)
```

In [121…

```
ret_df.head()
```

Out[121…

	stock_code	price	year_month
1	10000	4.37500	1986-01
2	10000	3.25000	1986-02
3	10000	4.43750	1986-03
4	10000	4.00000	1986-04
5	10000	3.10938	1986-05

In [121…

```
ret_df['ret'] = ret_df.groupby(['stock_code'])['price'].pct_change() #月收益率
```

In [121…

```
ret_df.dropna(inplace=True)
ret_df.drop(columns=['price'],inplace=True)
ret_df.head()
```

Out[121…

	stock_code	year_month	ret
2	10000	1986-02	-0.257143
3	10000	1986-03	0.365385
4	10000	1986-04	-0.098592
5	10000	1986-05	-0.222655
6	10000	1986-06	-0.005027

转化国债收益率单位

In [121…

```
rf['rf'] = rf['rf']/12    # 合并月度表格
```

In [122…

```
rf['rf'] = rf['rf']/100
rf.head()
```

Out[122…

	rf	year_month
0	0.002441	1963-01
1	0.002369	1963-02
2	0.002378	1963-03
3	0.002382	1963-04
4	0.002467	1963-05

计算因变量超额收益率（因变量）

In [122…
```
exret_df = pd.merge(ret_df,rf,on=['year_month'])
```

In [122…
```
exret_df.sort_values(['stock_code','year_month'],inplace=True)
```

In [122…
```
exret_df.reset_index(drop=True,inplace=True)
exret_df['ex_ret'] = exret_df['ret'] - exret_df['rf']
exret_df.head()
```

Out[122…

	stock_code	year_month	ret	rf	ex_ret
0	10000	1986-02	-0.257143	0.005789	-0.262932
1	10000	1986-03	0.365385	0.005227	0.360158
2	10000	1986-04	-0.098592	0.004915	-0.103507
3	10000	1986-05	-0.222655	0.005127	-0.227782
4	10000	1986-06	-0.005027	0.004904	-0.009931

bm年份值向前shift一年合并超额收益表会计年度 t 的 BM → 标记为 t+1 才可用

In [122…
```
bm_df.head()
```

Out[122…

	stock_code	year	exchange_code	bm
0	10000	1986	3.0	0.211004
1	10001	1986	3.0	0.787814
2	10001	1987	3.0	0.922179
3	10001	1988	3.0	0.871608
4	10001	1989	3.0	0.623674

In [122…
```
exret_df['year'] = exret_df['year_month'].dt.year
exret_df['month'] = exret_df['year_month'].dt.month
```

In [122…
```
exret_df.head()
```

Out[122…

	stock_code	year_month	ret	rf	ex_ret	year	month
0	10000	1986-02	-0.257143	0.005789	-0.262932	1986	2
1	10000	1986-03	0.365385	0.005227	0.360158	1986	3
2	10000	1986-04	-0.098592	0.004915	-0.103507	1986	4
3	10000	1986-05	-0.222655	0.005127	-0.227782	1986	5
4	10000	1986-06	-0.005027	0.004904	-0.009931	1986	6

In [122…

```
exret_df['bm_date'] = exret_df['year'] - 1
```

In [122…

```
exret_df.head()
```

Out[122…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10000	1986-02	-0.257143	0.005789	-0.262932	1986	2	198
1	10000	1986-03	0.365385	0.005227	0.360158	1986	3	198
2	10000	1986-04	-0.098592	0.004915	-0.103507	1986	4	198
3	10000	1986-05	-0.222655	0.005127	-0.227782	1986	5	198
4	10000	1986-06	-0.005027	0.004904	-0.009931	1986	6	198

论文的 “July t – June t+1” 规则（BM Ratio）

In [122…

```
idx = exret_df['month'].isin([1,2,3,4,5,6])
exret_df.loc[idx,'bm_date'] = exret_df.loc[idx,'bm_date'] - 1
```

In [123…

```
exret_df.head(10)
```

Out[123…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10000	1986-02	-0.257143	0.005789	-0.262932	1986	2	198
1	10000	1986-03	0.365385	0.005227	0.360158	1986	3	198
2	10000	1986-04	-0.098592	0.004915	-0.103507	1986	4	198
3	10000	1986-05	-0.222655	0.005127	-0.227782	1986	5	198
4	10000	1986-06	-0.005027	0.004904	-0.009931	1986	6	198
5	10000	1986-07	-0.080808	0.004693	-0.085501	1986	7	198
6	10000	1986-08	-0.615385	0.004268	-0.619653	1986	8	198
7	10000	1986-09	-0.057143	0.004259	-0.061402	1986	9	198
8	10000	1986-10	-0.242424	0.004268	-0.246693	1986	10	198
9	10000	1986-11	0.060006	0.004133	0.055873	1986	11	198

In [123…
```
bm_df.rename(columns={'year':'bm_date'},inplace=True)
```

In [123…
```
bm_df.head()
```

Out[123…

	stock_code	bm_date	exchange_code	bm
0	10000	1986	3.0	0.211004
1	10001	1986	3.0	0.787814
2	10001	1987	3.0	0.922179
3	10001	1988	3.0	0.871608
4	10001	1989	3.0	0.623674

合并股票和BM表

In [123…
```
sort_df = pd.merge(exret_df,bm_df,on=['stock_code','bm_date'])
```

In [123…
```
sort_df.tail()
```

Out[123…

	stock_code	year_month	ret	rf	ex_ret	year	month
1093616	93316	1991-08	0.027778	0.004422	0.023356	1991	8
1093617	93316	1991-09	-0.081081	0.004157	-0.085239	1991	9
1093618	93316	1991-10	0.088235	0.003988	0.084247	1991	10
1093619	93316	1991-11	0.054054	0.003386	0.050668	1991	11
1093620	93316	1991-12	-0.102564	0.003098	-0.105662	1991	12

论文的 “July t – June t+1” 规则（BM Ratio）

In [123…
```
sort_df['mkt_date'] = sort_df['year']
idx = sort_df['month'].isin([1,2,3,4,5,6])
sort_df.loc[idx,'mkt_date'] = sort_df.loc[idx,'mkt_date'] - 1
```

In [123…
```
sort_df.head()
```

Out[123…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10001	1987-07	0.021277	0.004667	0.016609	1987	7	198
1	10001	1987-08	0.083333	0.004717	0.078616	1987	8	198
2	10001	1987-09	-0.038462	0.005417	-0.043878	1987	9	198
3	10001	1987-10	0.020000	0.003353	0.016648	1987	10	198
4	10001	1987-11	-0.029412	0.002927	-0.032339	1987	11	198

In [123…
```
sort_df.tail(12) # 检查mkt_date  # "July t – June t+1" 规则
```

Out[123…

	stock_code	year_month	ret	rf	ex_ret	year	month
1093609	93316	1991-01	0.222222	0.004897	0.217325	1991	1
1093610	93316	1991-02	-0.060606	0.004762	-0.065368	1991	2
1093611	93316	1991-03	0.161290	0.004906	0.156384	1991	3
1093612	93316	1991-04	0.000000	0.004513	-0.004513	1991	4
1093613	93316	1991-05	0.055556	0.004490	0.051066	1991	5
1093614	93316	1991-06	0.000000	0.004319	-0.004319	1991	6
1093615	93316	1991-07	-0.052632	0.004618	-0.057249	1991	7
1093616	93316	1991-08	0.027778	0.004422	0.023356	1991	8
1093617	93316	1991-09	-0.081081	0.004157	-0.085239	1991	9
1093618	93316	1991-10	0.088235	0.003988	0.084247	1991	10
1093619	93316	1991-11	0.054054	0.003386	0.050668	1991	11
1093620	93316	1991-12	-0.102564	0.003098	-0.105662	1991	12

FF模型 6月时间点规则 “年”不是时间点。

In [123…
```
sort_df['mkt_date'] = pd.to_datetime(sort_df['mkt_date'].astype('str')
                                     ,format='%Y') +pd.DateOffset(months=5)
```

In [123…
```
sort_df.head()
```

Out[123…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10001	1987-07	0.021277	0.004667	0.016609	1987	7	198
1	10001	1987-08	0.083333	0.004717	0.078616	1987	8	198
2	10001	1987-09	-0.038462	0.005417	-0.043878	1987	9	198
3	10001	1987-10	0.020000	0.003353	0.016648	1987	10	198
4	10001	1987-11	-0.029412	0.002927	-0.032339	1987	11	198

时间颗粒度变月

In [124…
```
sort_df['mkt_date'] = sort_df['mkt_date'].dt.to_period('M')
```

In [124…
```
mktcap_df.head()
```

Out[124…

	stock_code	exchange_code	year_month	mktcap
1	10000	3.0	1986-01	16100000.00
2	10000	3.0	1986-02	11960000.00
3	10000	3.0	1986-03	16330000.00
4	10000	3.0	1986-04	15172000.00
5	10000	3.0	1986-05	11793878.34

exchange_code_x / y

exchange_code 的作用不是“算因子”，而是“定义什么是‘正常市场结构’”

In [124…

```
mktcap_df.rename(columns={'year_month':'mkt_date'},inplace=True)
```

In [124…

```
sort_df = pd.merge(sort_df,mktcap_df,on=['stock_code','mkt_date'])
```

In [124…

```
sort_df.head()
```

Out[124…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10001	1987-07	0.021277	0.004667	0.016609	1987	7	198
1	10001	1987-08	0.083333	0.004717	0.078616	1987	8	198
2	10001	1987-09	-0.038462	0.005417	-0.043878	1987	9	198
3	10001	1987-10	0.020000	0.003353	0.016648	1987	10	198
4	10001	1987-11	-0.029412	0.002927	-0.032339	1987	11	198

因子计算

In [124…

```
sort_df_ = copy.deepcopy(sort_df)
```

In [124…

```
sort_df.drop(columns=['year','month','exchange_code_x'],inplace=True)
sort_df.rename(columns={'exchange_code_y':'exchange_code'},inplace=True)
```

In [124…

```
sort_df_.head()
```

Out[124…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10001	1987-07	0.021277	0.004667	0.016609	1987	7	198
1	10001	1987-08	0.083333	0.004717	0.078616	1987	8	198
2	10001	1987-09	-0.038462	0.005417	-0.043878	1987	9	198
3	10001	1987-10	0.020000	0.003353	0.016648	1987	10	198
4	10001	1987-11	-0.029412	0.002927	-0.032339	1987	11	198

分组

- New York Stock Exchange
- American Stock Exchange
- The Nasdaq Stock Market(SM)

In [124…

```
#对bm进行分组，准备HML分组
quantile_df = pd.DataFrame()
NYSE = copy.deepcopy(sort_df[sort_df['exchange_code'] == 1])
NYSE = copy.deepcopy(NYSE[NYSE['bm']>=0])
# We do not use negative-BE firms, when calculating the breakpoints for BM
#or when forming the size-BM portfolios.
```

In [124…

```
quantile_df['q1'] = NYSE.groupby(['year_month'])['bm'].quantile(0.3)
quantile_df['q2'] = NYSE.groupby(['year_month'])['bm'].quantile(0.7)
```

In [125…

```
sort_df = pd.merge(sort_df,quantile_df,on=['year_month']) # 把“BM 分组阈值（brea
```

In [125…

```
sort_df.head()
```

Out[125…

	stock_code	year_month	ret	rf	ex_ret	bm_date	bm	n
0	10001	1987-07	0.021277	0.004667	0.016609	1986	0.787814	
1	10001	1987-08	0.083333	0.004717	0.078616	1986	0.787814	
2	10001	1987-09	-0.038462	0.005417	-0.043878	1986	0.787814	
3	10001	1987-10	0.020000	0.003353	0.016648	1986	0.787814	
4	10001	1987-11	-0.029412	0.002927	-0.032339	1986	0.787814	

In [125…

```
quantile_size_df = pd.DataFrame()
quantile_size_df['Q'] = NYSE.groupby(['year_month'])['mktcap'].quantile(0.5)
```

In [125…

```
# NYSE[NYSE['year_month'].dt.year == 1963] ##？？？？？？？这步没理解
```

In [125…

```
sort_df = pd.merge(sort_df,quantile_size_df,on=['year_month'])
# 把 Size（市值）分组的断点（Small / Big）贴回到每一只股票上 每只股票对应Small/Big
```

In [125…

```
sort_df.head()
```

Out[125…

	stock_code	year_month	ret	rf	ex_ret	bm_date	bm	n
0	10001	1987-07	0.021277	0.004667	0.016609	1986	0.787814	
1	10001	1987-08	0.083333	0.004717	0.078616	1986	0.787814	
2	10001	1987-09	-0.038462	0.005417	-0.043878	1986	0.787814	
3	10001	1987-10	0.020000	0.003353	0.016648	1986	0.787814	
4	10001	1987-11	-0.029412	0.002927	-0.032339	1986	0.787814	

In [125…

```
sort_df.rename(columns={'Q_x':'Q'},inplace=True)
```

In [125…

```
sort_df.head()
```

Out[125…

	stock_code	year_month	ret	rf	ex_ret	bm_date	bm	n
0	10001	1987-07	0.021277	0.004667	0.016609	1986	0.787814	
1	10001	1987-08	0.083333	0.004717	0.078616	1986	0.787814	
2	10001	1987-09	-0.038462	0.005417	-0.043878	1986	0.787814	
3	10001	1987-10	0.020000	0.003353	0.016648	1986	0.787814	
4	10001	1987-11	-0.029412	0.002927	-0.032339	1986	0.787814	

In [125…

```
sort_df.dropna(inplace=True)
sort_df.head()
```

Out[125…

	stock_code	year_month	ret	rf	ex_ret	bm_date	bm	n
0	10001	1987-07	0.021277	0.004667	0.016609	1986	0.787814	
1	10001	1987-08	0.083333	0.004717	0.078616	1986	0.787814	
2	10001	1987-09	-0.038462	0.005417	-0.043878	1986	0.787814	
3	10001	1987-10	0.020000	0.003353	0.016648	1986	0.787814	
4	10001	1987-11	-0.029412	0.002927	-0.032339	1986	0.787814	

In [125…

```
sort_df.drop(columns=['bm_date','mkt_date'],inplace=True)
```

In [126…

```
sort_df.columns
```

Out[126…

```
Index(['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm',
       'exchange_code', 'mktcap', 'q1', 'q2', 'Q'],
      dtype='object')
```

BM 分组 (账面价值分三组)

p1: Low BM

p2: Medium BM

p3: High BM

In [126…
```
portfolios_by_bm = dict()
keep_cols= ['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm','mktcap']
idx = sort_df['bm']<=sort_df['q1']
portfolios_by_bm['p1'] = sort_df.loc[idx,keep_cols]
```

In [126…
```
idx = ((sort_df['bm']>=sort_df['q1']) & (sort_df['bm']<=sort_df['q2']))
portfolios_by_bm['p2'] = sort_df.loc[idx,keep_cols]
idx = sort_df['bm'] >= sort_df['q2']
portfolios_by_bm['p3'] = sort_df.loc[idx,keep_cols]
```

In [126…
```
for key in portfolios_by_bm.keys():
    portfolios_by_bm[key] = portfolios_by_bm[key][portfolios_by_bm[key]['bm']>
```

市值规模分2组

q1 : BM 30%

q2 : BM 70%

In [126…
```
portfolios_by_size = dict()
keep_cols= ['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm','mktcap']
idx = sort_df['mktcap']<=sort_df['Q']
portfolios_by_size['P1'] = sort_df.loc[idx,keep_cols]
idx = sort_df['mktcap']>=sort_df['Q']
portfolios_by_size['P2'] = sort_df.loc[idx,keep_cols]
```

In [126…
```
portfolios_by_size['P2'].head()
```

Out[126…

	stock_code	year_month	ret	rf	ex_ret	bm	mktc
102	10006	1965-07	0.009709	0.003140	0.006569	0.590897	22927800
103	10006	1965-08	0.048077	0.003152	0.044924	0.590897	22927800
104	10006	1965-09	-0.506116	0.003322	-0.509438	0.590897	22927800
105	10006	1965-10	0.108359	0.003208	0.105152	0.590897	22927800
106	10006	1965-11	-0.019553	0.003165	-0.022718	0.590897	22927800

交叉分组筛选股票池，把分组标签对应数据

In [126…
```
portfolios = dict()
for bm in portfolios_by_bm.keys():
```

```
    for mkt in portfolios_by_size.keys():
        portfolios[f'{bm}_{mkt}'] = pd.merge(portfolios_by_bm[bm][['stock_code
                                    portfolios_by_size[mkt],
                                     on=['stock_code','year_month'])
```

In [126…

```
portfolios.keys()
```

Out[126…

```
dict_keys(['p1_P1', 'p1_P2', 'p2_P1', 'p2_P2', 'p3_P1', 'p3_P2'])
```

组合的市值加权月收益（6个分组的每个周期加权收益，6*n）

In [126…

```
portfolios_vwret = dict()
for pf in portfolios.keys():
    temp = pd.DataFrame(portfolios[pf].groupby('year_month')['mktcap'].sum())#
    temp.columns = ['mktcap_sum']
    portfolios[pf] = pd.merge(portfolios[pf],temp,on=['year_month'])#将mktsum加
    portfolios[pf]['weight'] = portfolios[pf][
        'mktcap']/portfolios[pf]['mktcap_sum']#添加一列求市值权重
    portfolios[pf]['weighted_ret'] = portfolios[pf]['weight']*portfolios[pf]['
    portfolios_vwret[pf] = portfolios[pf].groupby(['year_month'])[
        ['weighted_ret']].sum()
```

In [126…

```
portfolios_vwret['p1_P1'].head()
```

Out[126…

	weighted_ret
year_month	
1964-07	0.047100
1964-08	-0.006055
1964-09	0.024405
1964-10	0.031740
1964-11	0.020627

In [127…

```
portfolios_vwret
```

```
Out[127… {'p1_P1':             weighted_ret
 year_month
 1964-07         0.047100
 1964-08        -0.006055
 1964-09         0.024405
 1964-10         0.031740
 1964-11         0.020627
 ...                  ...
 1991-08         0.027545
 1991-09         0.005383
 1991-10         0.015610
 1991-11        -0.030457
 1991-12         0.090287

 [330 rows x 1 columns],
 'p1_P2':             weighted_ret
 year_month
 1964-07         0.027194
 1964-08        -0.015123
 1964-09         0.026426
 1964-10         0.000392
 1964-11        -0.019613
 ...                  ...
 1991-08         0.024443
 1991-09        -0.024004
 1991-10         0.012668
 1991-11        -0.033387
 1991-12         0.115436

 [330 rows x 1 columns],
 'p2_P1':             weighted_ret
 year_month
 1964-07        -0.003801
 1964-08         0.000532
 1964-09         0.028011
 1964-10         0.014604
 1964-11         0.002863
 ...                  ...
 1991-08         0.033203
 1991-09         0.007286
 1991-10         0.015542
 1991-11        -0.041786
 1991-12         0.057175

 [330 rows x 1 columns],
 'p2_P2':             weighted_ret
 year_month
 1964-07         0.004489
 1964-08        -0.021728
 1964-09         0.014669
 1964-10         0.008365
 1964-11        -0.012537
 ...                  ...
 1991-08         0.017428
```

```
1991-09        -0.005245
1991-10         0.011284
1991-11        -0.050827
1991-12         0.071910

[330 rows x 1 columns],
'p3_P1':             weighted_ret
year_month
1964-07         0.016559
1964-08        -0.008961
1964-09         0.030932
1964-10         0.017790
1964-11        -0.021230
...                  ...
1991-08         0.032061
1991-09        -0.008837
1991-10         0.021268
1991-11        -0.052829
1991-12         0.055798

[330 rows x 1 columns],
'p3_P2':             weighted_ret
year_month
1964-07         0.011829
1964-08        -0.027789
1964-09         0.039027
1964-10         0.003543
1964-11        -0.034075
...                  ...
1991-08         0.014371
1991-09        -0.026078
1991-10         0.017241
1991-11        -0.071151
1991-12         0.086306

[330 rows x 1 columns]}
```

In [127…

```
### pivot table
```

In [127…

```
portfolios_vwret_df = pd.DataFrame(np.hstack([pf for pf in portfolios_vwret.va
portfolios_vwret_df.index = portfolios_vwret['p1_P1'].index
portfolios_vwret_df.columns = portfolios_vwret.keys()
```

In [127…

```
portfolios_vwret_df.head()
```

Out[127…

year_month	p1_P1	p1_P2	p2_P1	p2_P2	p3_P1	p3_P2
1964-07	0.047100	0.027194	-0.003801	0.004489	0.016559	0.011829
1964-08	-0.006055	-0.015123	0.000532	-0.021728	-0.008961	-0.027789
1964-09	0.024405	0.026426	0.028011	0.014669	0.030932	0.039027
1964-10	0.031740	0.000392	0.014604	0.008365	0.017790	0.003543
1964-11	0.020627	-0.019613	0.002863	-0.012537	-0.021230	-0.034075

根据论文重命名标签

In [127…

```
portfolios_vwret_df.rename(columns={"p1_P1": "SL",
                                    "p2_P1": "SM",
                                    "p3_P1": "SH",
                                    "p1_P2": "BL",
                                    "p2_P2": "BM",
                                    "p3_P2": "BH"},
                           inplace=True)
```

In [127…

```
portfolios_vwret_df.head()
```

Out[127…

year_month	SL	BL	SM	BM	SH	BH
1964-07	0.047100	0.027194	-0.003801	0.004489	0.016559	0.011829
1964-08	-0.006055	-0.015123	0.000532	-0.021728	-0.008961	-0.027789
1964-09	0.024405	0.026426	0.028011	0.014669	0.030932	0.039027
1964-10	0.031740	0.000392	0.014604	0.008365	0.017790	0.003543
1964-11	0.020627	-0.019613	0.002863	-0.012537	-0.021230	-0.034075

计算SMB因子*周期数个

In [127…

```
SMB = (portfolios_vwret_df['SL'] + portfolios_vwret_df['SM'] + portfolios_vwre
      (portfolios_vwret_df['BL'] + portfolios_vwret_df['BM'] + portfolios_vwre
```

In [127…

```
SMB.head()
```

Out[127…

```
year_month
1964-07    0.005448
1964-08    0.016718
1964-09    0.001075
1964-10    0.017278
1964-11    0.022828
Freq: M, dtype: float64
```

计算HML因子*周期数个

In [127…

```
HML = (portfolios_vwret_df['SH'] + portfolios_vwret_df['BH']) / 2 - \
      (portfolios_vwret_df['SL'] + portfolios_vwret_df['BL']) / 2
```

In [127…

```
HML.head()
```

Out[127…

```
year_month
1964-07   -0.022953
1964-08   -0.007786
1964-09    0.009564
1964-10   -0.005399
1964-11   -0.028159
Freq: M, dtype: float64
```

In [128…

```
sort_df_.head()
```

Out[128…

	stock_code	year_month	ret	rf	ex_ret	year	month	bm_dat
0	10001	1987-07	0.021277	0.004667	0.016609	1987	7	198
1	10001	1987-08	0.083333	0.004717	0.078616	1987	8	198
2	10001	1987-09	-0.038462	0.005417	-0.043878	1987	9	198
3	10001	1987-10	0.020000	0.003353	0.016648	1987	10	198
4	10001	1987-11	-0.029412	0.002927	-0.032339	1987	11	198

In [128…

```
keep_cols = ['stock_code', 'year_month', 'ret', 'rf', 'mktcap']
_sort_df_ = sort_df_[keep_cols]
```

In [128…

```
_sort_df_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1090910 entries, 0 to 1090909
Data columns (total 5 columns):
 #   Column      Non-Null Count    Dtype
---  ------      --------------    -----
 0   stock_code  1090910 non-null  int64
 1   year_month  1090910 non-null  period[M]
 2   ret         1090910 non-null  float64
 3   rf          1090910 non-null  float64
 4   mktcap      1090910 non-null  float64
dtypes: float64(3), int64(1), period[M](1)
memory usage: 41.6 MB
```

In [128…

```
temp = pd.DataFrame(_sort_df_.groupby(['year_month'])['mktcap'].sum())
```

把一堆股票，变成“一只可投资的组合”，并算出它每个月的收益率

In [128…

```
temp.columns = ['mktcap_sum']
_sort_df_ = pd.merge(_sort_df_,temp,on=['year_month']) # 把“当月组合总市值”贴回到
_sort_df_['weight'] = _sort_df_['mktcap']/_sort_df_['mktcap_sum'] # 计算 市值权
_sort_df_['weighted_ret'] = _sort_df_['weight']*_sort_df_['ret'] # 每只股票对组
vwret_df = _sort_df_.groupby(['year_month'])[['weighted_ret']].sum() # 按月加总
```

In [128…

```
vwret_df.columns = ['vwret']
```

In [128…

```
vwret_df.head()
```

Out[128…

	vwret
year_month	
1964-07	0.016481
1964-08	-0.017993
1964-09	0.022616
1964-10	0.004800
1964-11	-0.016783

In [128…

```
vwret_df = pd.merge(vwret_df,rf,on=['year_month'])
vwret_df['RM-RF'] = vwret_df['vwret'] - vwret_df['rf']
vwret_df.set_index(['year_month'],inplace=True)
```

计算RM_RF

In [128…

```
RM_RF = vwret_df['RM-RF']
```

In [128…

```
RM_RF.head()
```

Out[128…

```
year_month
1964-07    0.013765
1964-08   -0.020713
1964-09    0.019680
1964-10    0.001944
1964-11   -0.019761
Freq: M, Name: RM-RF, dtype: float64
```

整合SMB,HML,RM_RF三个因子的收益率值

In [129…

```
factors_df = pd.DataFrame(np.vstack([SMB,HML,RM_RF])).T
```

In [129…

```
factors_df.columns = ['SMB','HML','RM-RF']
factors_df.index = SMB.index
```

In [129…

```
factors_df.head()
```

Out[129…

	SMB	HML	RM-RF
year_month			
1964-07	0.005448	-0.022953	0.013765
1964-08	0.016718	-0.007786	-0.020713
1964-09	0.001075	0.009564	0.019680
1964-10	0.017278	-0.005399	0.001944
1964-11	0.022828	-0.028159	-0.019761

Plot并分析这三个“风险因子本身”的历史行为与经济含义。

a. CAPM 只刻画了市场整体风险（RM—RF）

b. 但实证发现，与企业规模（SMB）和账面—市值特征（HML）相关的系统性风险，也会被市场定价

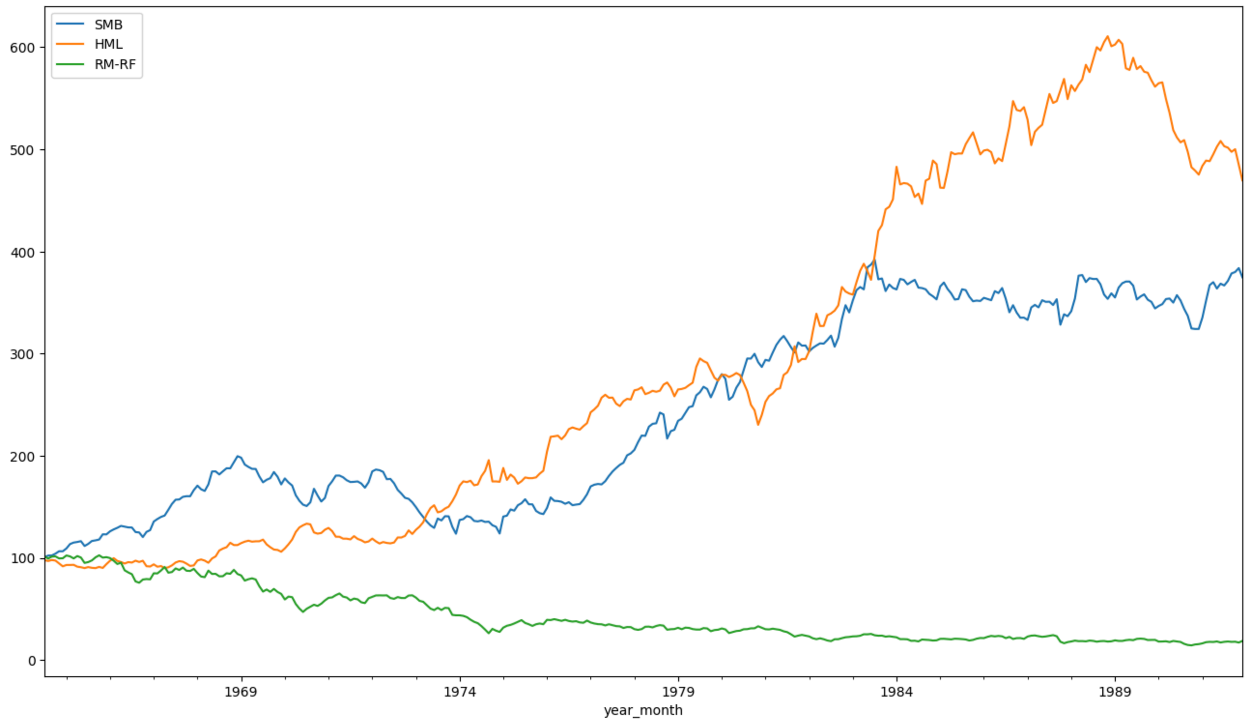
c. 这些风险在长期中表现为小盘股和高 BM 股票的超额收益。

In [129…

```
((1 + factors_df).cumprod()*100).plot()
```

Out[129…

```
<Axes: xlabel='year_month'>
```

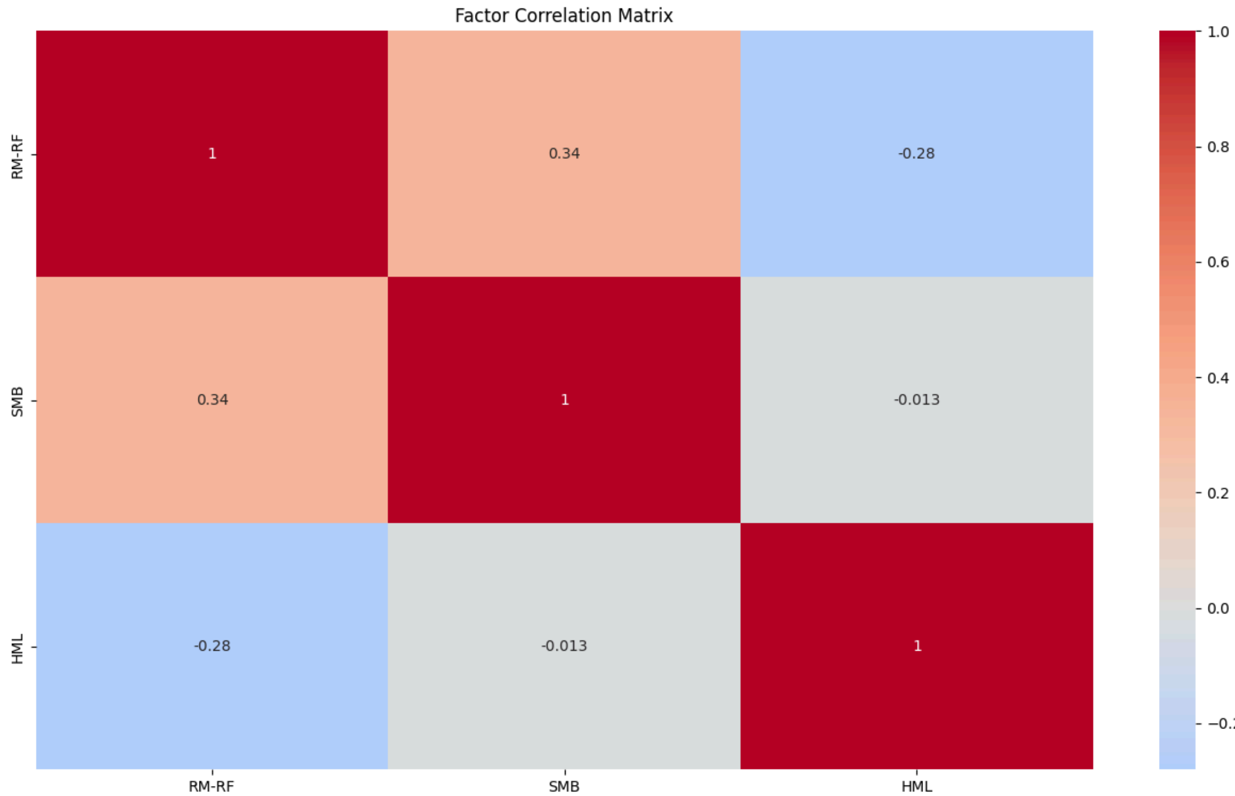


In [129…
```
sort_df_.drop(columns=['year','month','exchange_code_x'],inplace=True)
sort_df_.rename(columns={'exchange_code_y':'exchange_code'},inplace=True)
```

3个因子的相关性分析

In [129…
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.heatmap(
    factors_df[['RM-RF','SMB','HML']].corr(),
    annot=True,
    cmap='coolwarm',
    center=0
)
plt.title('Factor Correlation Matrix')
plt.show()
```



1. 因子独立性 SMB 和 HML 几乎不相关（-0.013）→ 说明它们代表不同风险维度，可同时使用。
2. 市场因子主导性 RM-RF 与 SMB 正相关（0.34）、与 HML 负相关（-0.28） 市场涨跌会带动规模/价值风格切换。
   牛市时，投资者风险偏好上升 → 更愿意买波动大、弹性高的小盘股 & 成长股 → 导致 SMB 正收益、HML 负收益；熊市则相反。
3. 没有多重共线性风险 所有因子间相关系数绝对值 < 0.4
4. 符合经典理论 结果与 Fama-French 1993 美股结论一致

因变量（公式左侧预期超额回报）计算

构造25个投资组合，构造方法和因子构建中的方法一致，唯一的差别是做5x5独立双重排序。
计算25个组合的月度加权收益率，计算超额收益
以25个组合的超额收益为因变量，以三因子为自变量，进行时间序列回归，股票定价误差和β
对定价误差进行α检验，如果定价误差不显著不等于0，则多因子模型有效
对β进行检验，发现β显著不等于0，说明因子对25个投资组合的超额收益率有显著的解释能力。

todo: 理解因变量的计算过程

todo: 理解因变量的计算过程

In [129…
```
sort_df_.columns
```

Out[129…
```
Index(['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm_date', 'bm',
       'mkt_date', 'exchange_code', 'mktcap'],
      dtype='object')
```

In [129…
```
q = dict()
keys = ['q'+str(i) for i in range(1, 5)]
values = [0.2,0.4,0.6,0.8]
q.update(zip(keys,values))
```

In [129…
```
list(zip(keys,values))[3]
```

Out[129…
```
('q4', 0.8)
```

In [129…
```
q.items()
```

Out[129…
```
dict_items([('q1', 0.2), ('q2', 0.4), ('q3', 0.6), ('q4', 0.8)])
```

In [130…
```
quantile_df = pd.DataFrame()
for key, value in q.items():
    quantile_df[key] = sort_df_.groupby(['bm_date'])['bm'].quantile(value)
```

In [130…
```
sort_df_ = pd.merge(sort_df_, quantile_df, on='bm_date')
```

In [130…
```
sort_df_.columns
```

Out[130…
```
Index(['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm_date', 'bm',
       'mkt_date', 'exchange_code', 'mktcap', 'q1', 'q2', 'q3', 'q4'],
      dtype='object')
```

In [130…
```
q = dict()
keys = ['Q'+str(i) for i in range(1, 5)]
values = [0.2,0.4,0.6,0.8]
q.update(zip(keys,values))
quantile_df = pd.DataFrame()
for key, value in q.items():
    quantile_df[key] = sort_df_.groupby(['mkt_date'])['mktcap'].quantile(value
sort_df_ = pd.merge(sort_df_, quantile_df, on='mkt_date')
```

In [130…
```
sort_df_.head()
```

Out[130…

	stock_code	year_month	ret	rf	ex_ret	bm_date	bm	n
0	10001	1987-07	0.021277	0.004667	0.016609	1986	0.787814	
1	10001	1987-08	0.083333	0.004717	0.078616	1986	0.787814	
2	10001	1987-09	-0.038462	0.005417	-0.043878	1986	0.787814	
3	10001	1987-10	0.020000	0.003353	0.016648	1986	0.787814	
4	10001	1987-11	-0.029412	0.002927	-0.032339	1986	0.787814	

In [130…

```
portfolios_bm = dict()
keep_cols = ['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm_date', 'bm
       'mkt_date', 'exchange_code', 'mktcap' ]

portfolios_bm['bm1'] = sort_df_.loc[sort_df_['bm'] <= sort_df_['q1'],keep_cols
for i in range(2,5):
    idx = (sort_df_[f'q{i-1}'] <= sort_df_['bm']) & (sort_df_['bm'] <= sort_df
    portfolios_bm[f'bm{i}'] = sort_df_.loc[idx,keep_cols].copy()
portfolios_bm['bm5'] = sort_df_.loc[sort_df_['bm'] >= sort_df_['q4'],keep_cols
```

In [130…

```
portfolios_mkt = dict()
keep_cols = ['stock_code', 'year_month', 'ret', 'rf', 'ex_ret', 'bm_date', 'bm
       'mkt_date', 'exchange_code', 'mktcap' ]

portfolios_mkt['mkt1'] = sort_df_.loc[sort_df_['mktcap'] <= sort_df_['Q1'],kee
for i in range(2,5):
    idx = (sort_df_[f'Q{i-1}'] <= sort_df_['mktcap']) & (sort_df_['mktcap'] <=
    portfolios_mkt[f'mkt{i}'] = sort_df_.loc[idx,keep_cols].copy()
portfolios_mkt['mkt5'] = sort_df_.loc[sort_df_['mktcap'] >= sort_df_['Q4'],kee
```

In [130…

```
portfolios_bm.keys()
```

Out[130…

```
dict_keys(['bm1', 'bm2', 'bm3', 'bm4', 'bm5'])
```

In [130…

```
portfolios_dpt = dict()
for bm in portfolios_bm.keys():
    for mkt in portfolios_mkt.keys():
        portfolios_dpt[f'{bm}_{mkt}'] = pd.merge(portfolios_bm[bm][['stock_coc
                                                   portfolios_mkt[mkt],
                                                    on=['stock_code','year_month'])
```

In [130…

```
portfolios_dpt.keys()
```

Out[130…

```
dict_keys(['bm1_mkt1', 'bm1_mkt2', 'bm1_mkt3', 'bm1_mkt4', 'bm1_mkt5', 'bm2_m
kt1', 'bm2_mkt2', 'bm2_mkt3', 'bm2_mkt4', 'bm2_mkt5', 'bm3_mkt1', 'bm3_mkt2',
'bm3_mkt3', 'bm3_mkt4', 'bm3_mkt5', 'bm4_mkt1', 'bm4_mkt2', 'bm4_mkt3', 'bm
4_mkt4', 'bm4_mkt5', 'bm5_mkt1', 'bm5_mkt2', 'bm5_mkt3', 'bm5_mkt4', 'bm5_mkt
5'])
```

In [131…

```
portfolios_ret_mean = dict()
for k in portfolios_dpt.keys():
```

```
    portfolios_dpt[k]['weight'] = portfolios_dpt[k].groupby('year_month')['mkt
    portfolios_dpt[k]['vw_ret'] = portfolios_dpt[k]['ret'] * portfolios_dpt[k]
    portfolios_ret_mean[k] = portfolios_dpt[k].groupby(['year_month'])['vw_ret
```

In [131…

```
for k in portfolios_ret_mean.keys():
    portfolios_ret_mean[k] = pd.DataFrame(portfolios_ret_mean[k])
    portfolios_ret_mean[k].columns = ['vw_ret']
    portfolios_ret_mean[k] = pd.merge(portfolios_ret_mean[k],rf,on=['year_mont
    portfolios_ret_mean[k]['vw_ex_ret'] = portfolios_ret_mean[k][
        'vw_ret'] - portfolios_ret_mean[k]['rf']
```

In [131…

```
portfolios_ret_mean.keys()
```

Out[131…

```
dict_keys(['bm1_mkt1', 'bm1_mkt2', 'bm1_mkt3', 'bm1_mkt4', 'bm1_mkt5', 'bm2_m
kt1', 'bm2_mkt2', 'bm2_mkt3', 'bm2_mkt4', 'bm2_mkt5', 'bm3_mkt1', 'bm3_mkt2',
'bm3_mkt3', 'bm3_mkt4', 'bm3_mkt5', 'bm4_mkt1', 'bm4_mkt2', 'bm4_mkt3', 'bm
4_mkt4', 'bm4_mkt5', 'bm5_mkt1', 'bm5_mkt2', 'bm5_mkt3', 'bm5_mkt4', 'bm5_mkt
5'])
```

In [131…

```
portfolios_ret_mean['bm1_mkt1'].head()
```

Out[131…

	year_month	vw_ret	rf	vw_ex_ret
0	1964-07	8.332754e+06	0.002716	8.332754e+06
1	1964-08	4.521976e+07	0.002720	4.521976e+07
2	1964-09	6.209684e+07	0.002936	6.209684e+07
3	1964-10	7.755734e+07	0.002856	7.755734e+07
4	1964-11	-1.127932e+07	0.002978	-1.127932e+07

In [131…

```
for key in portfolios_ret_mean.keys():
    portfolios_ret_mean[key].set_index(['year_month'],inplace=True)
```

In [131…

```
portfolios_ret_mean['bm1_mkt1'].head()
```

Out[131…

	vw_ret	rf	vw_ex_ret
year_month			
1964-07	8.332754e+06	0.002716	8.332754e+06
1964-08	4.521976e+07	0.002720	4.521976e+07
1964-09	6.209684e+07	0.002936	6.209684e+07
1964-10	7.755734e+07	0.002856	7.755734e+07
1964-11	-1.127932e+07	0.002978	-1.127932e+07

In [131…

```
dependance = pd.DataFrame(np.hstack([pf[['vw_ex_ret']] for pf in portfolios_re
```

```python
dependance.index = portfolios_ret_mean['bm1_mkt1'].index
dependance.columns = portfolios_ret_mean.keys()
```

In [131…
```python
dependance.to_csv('dependance.csv')
```

In [132…
```python
pd.merge(dependance, factors_df, on=['year_month']).to_csv('data.csv', index=F
```

In [132…
```python
for k in portfolios_ret_mean.keys():
    portfolios_ret_mean[k].drop(columns =['vw_ret','rf'],inplace=True)
```

In [132…
```python
factors_df.head()
```

Out[132…

	SMB	HML	RM-RF
year_month			
1964-07	0.005448	-0.022953	0.013765
1964-08	0.016718	-0.007786	-0.020713
1964-09	0.001075	0.009564	0.019680
1964-10	0.017278	-0.005399	0.001944
1964-11	0.022828	-0.028159	-0.019761

模型回归

In [133…
```python
import statsmodels.api as sm

# 假设 df 已经是你的合并数据
# 因变量
y = df['vw_ex_ret']

# 自变量
X = df[['RM_RF','SMB','HML']]

# 加上截距项
X = sm.add_constant(X)

# OLS 回归
model = sm.OLS(y, X).fit()

# 查看结果
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:             vw_ex_ret   R-squared:                       0.565
Model:                           OLS   Adj. R-squared:                  0.561
Method:                Least Squares   F-statistic:                     141.3
Date:               Sat, 03 Jan 2026   Prob (F-statistic):           1.20e-58
Time:                       17:04:44   Log-Likelihood:                -8189.5
No. Observations:                330   AIC:                         1.639e+04
Df Residuals:                    326   BIC:                         1.640e+04
Df Model:                          3                                         
Covariance Type:           nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       4.524e+09   8.32e+08      5.437      0.000    2.89e+09    6.16e+09
RM_RF       2.436e+11   1.93e+10     12.616      0.000    2.06e+11    2.82e+11
SMB          3.32e+11   3.12e+10     10.627      0.000    2.71e+11    3.93e+11
HML         1.803e+11   3.22e+10      5.591      0.000    1.17e+11    2.44e+11
==============================================================================
Omnibus:                      49.425   Durbin-Watson:                   1.628
Prob(Omnibus):                 0.000   Jarque-Bera (JB):              286.646
Skew:                          0.409   Prob(JB):                     5.70e-63
Kurtosis:                      7.492   Cond. No.                         43.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
```

回归分析

1. 模型概览

本次分析使用 Fama-French 三因子模型回归组合市值加权超额收益（`vw_ex_ret`）：

- 因变量：`vw_ex_ret`（组合超额收益）
- 自变量：市场超额收益 `RM_RF`、规模因子 `SMB`、价值因子 `HML`
- 样本期：330 个观测值

模型拟合情况：

指标	数值
R-squared	0.565
Adjusted R-squared	0.561
F-statistic	141.3 (p ≈ 0)
Durbin-Watson	1.628

> 说明：模型解释了约 56% 的组合收益波动，整体显著，但残差存在轻微自相关。

---

2. 回归系数及组合风格

因子	系数 (coef)	标准误 (std err)	t 值	P-value	95% 置信区间	风格解读
const	4.524e+09	8.32e+08	5.437	0.000	[2.89e+09, 6.16e+09]	基础超额收益，当因子为零时仍有正收益
RM_RF	2.436e+11	1.93e+10	12.616	0.000	[2.06e+11, 2.82e+11]	市场敏感度高，组合随市场波动明显
SMB	3.320e+11	3.12e+10	10.627	0.000	[2.71e+11, 3.93e+11]	正且显著 → 投资组合偏向小盘股风格
HML	1.803e+11	3.22e+10	5.591	0.000	[1.17e+11, 2.44e+11]	正且显著 → 投资组合偏向价值股风格

> 说明：所有系数显著且为正，组合为“小盘价值股”风格，同时高度暴露于市场因子。

---

3. 市值/小盘股特性分析

- **小盘股特性**：
    - 市值小，波动大，流动性相对低。
    - 长期超额收益倾向高于大盘股。
- **SMB 系数解读**：
    - 系数 = 3.32e+11，显著为正 → 小盘股对组合收益贡献明显。
    - 说明组合持仓中小盘股票比例高，风险溢价来源主要之一为小盘股效应。
- **HML 系数解读**：
    - 系数 = 1.803e+11，显著为正 → 高账面价值比股票贡献正收益。
    - 说明组合偏向价值股，存在价值溢价。

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4. 综合结论

- 投资组合属于 **小盘价值股风格**，对市场波动敏感。
- 市值因子（SMB）贡献大，说明组合超额收益部分来源于小盘股溢价。
- 价值因子（HML）贡献次之，说明组合同时受价值股溢价驱动。
- 残差偏态略高、峰度大 → 极端收益存在，需要关注尾部风险。
- 建议可通过图示展示因子贡献，或扩展到四因子模型加入动量因子，进一步分析组

合收益来源。

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