

```
In [ ]: ...
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Date: 2023-05-25 14:00:25
LastEditTime: 2023-05-27 06:25:16
...

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['font.sans-serif']=['SimHei']
plt.rcParams['axes.unicode_minus']=False
```

```
In [ ]: df1=pd.read_excel('RESSET_MRESSTK_1.xlsx')
df2=pd.read_excel('RESSET_MRESSTK_2.xlsx')
df3=pd.read_excel('RESSET_MRESSTK_3.xlsx')
df4=pd.read_excel('RESSET_MRESSTK_4.xlsx')
df5=pd.read_excel('RESSET_MRESSTK_5.xlsx')
df6=pd.read_excel('RESSET_MRESSTK_6.xlsx')

df=pd.concat([df1,df2,df3,df4,df5,df6],axis=0)
df.head()
```

```
In [ ]: #将df导出为csv文件
df.to_csv('RESSET_NEW_new.csv',index=False,encoding='utf-8-sig')
```

数据预处理

数据来源: RESSET(www.resset.com)

(1) 剔除退市风险警告 (Special Treatment, ST 和*ST) 类型样本; (2) 由于金融行业公司财报于其他行业公司财报具有较大差异性, 剔除金融业上市公司, 即证监会2012年行业分类中的J类股票; (3) 剔除上市不满一年的股票, 这是因为后文计算CGO 时需要过去 52 周即1年的交易数据; (4) Liu 等(2019)认为, 中国股市中市值排名后30%的上市公司会受到壳价值污染的严重影响, 因此本文将每个月末市值规模排在后30% 的股票剔除

```
In [ ]: df=pd.read_csv('RESSET_NEW_new.csv',encoding='utf-8-sig')
df.info()
```

```
In [ ]: df.describe()
```

中国股市中市值排名后30%的上市公司会受到壳价值污染的严重影响, 因此本文将每个月末市值规模排在后30%的股票剔除

```
In [ ]: # 计算市值
df['市值'] = df['流通股_Trdshr'] * df['收盘价_ClPr']
# 计算每个股票的市值均值
mean_dict = df.groupby('最新股票名称_Lstknm')['市值'].mean().to_dict()

#对mean_dict排序
mean_dict = sorted(mean_dict.items(), key=lambda x: x[1], reverse=True)
```

```
#得到mean_dict排名最后的30%的股票名称
last_30 = [i[0] for i in mean_dict[-int(len(mean_dict)*0.3):]]
#对应last_30删除df中的股票名称所在列
df = df[~df['最新股票名称_Lstkmn'].isin(last_30)]
```

```
In [ ]: #将df导出为csv文件
df.to_csv('RESSET_cleaned_new.csv', index=False, encoding='utf-8-sig')
```

数据处理后的数据为RESSET_cleaned_new.csv，在接下来的计算中使用该数据。股票数一共为3035，时间跨度为1997年1月到2023年3月，共计315个月。

异象变量计算

```
In [ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#中文显示
plt.rcParams['font.sans-serif']=['SimHei']
plt.rcParams['axes.unicode_minus']=False
```

```
In [ ]: data=pd.read_csv('RESSET_cleaned_new.csv',encoding='utf-8-sig')
#将日期_Date只保留年月
data['日期_Date']=data['日期_Date'].apply(lambda x:x[:7])
data.head()
```

Out[]:

		最新股 票名称 <u>Lstkmn</u>	日期 <u>Date</u>	收盘 价 <u>CIPr</u>	复权价 1(元) <u>AdjClpr1</u>	复权价 2(元) <u>AdjClpr2</u>	成交量 <u>Trdvol</u>	成交金额 <u>Trdsum</u> (元)
0	万科A	1997-01	11.20	44.5573	0.3323	68823654.0	7.349675e+08	
1	万科A	1997-02	11.18	44.4777	0.3317	42408777.0	4.509022e+08	
2	万科A	1997-03	14.37	57.1686	0.4264	150672233.0	1.927915e+09	
3	万科A	1997-04	20.28	80.6805	0.6017	241368647.0	4.115419e+09	
4	万科A	1997-05	17.97	71.4906	0.5332	164431960.0	3.162778e+09	

5 rows × 45 columns

```
In [ ]: #以日期_Date进行分类
data_dt=data.groupby('日期_Date')
data_dt=pd.DataFrame(data_dt)
data_dt
```

Out[]:

0

1

0	1997-01	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
1	1997-02	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
2	1997-03	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
3	1997-04	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
4	1997-05	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
...
310	2022-11	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
311	2022-12	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
312	2023-01	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
313	2023-02	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...
314	2023-03	最新股票名称_Lstkm Date 收盘价_CIPr 复权价1(...

315 rows × 2 columns

In []: `data_dt[1].iloc[0] # type: ignore`

Out[]:

		最新股票名称 _Lstkm	日期 _Date	收盘价 _ClPr	复权价1(元) _AdjClpr1	复权价2(元) _AdjClpr2	成交量 _Trdvol	成交金额 _Trdsu
0		万科A	1997-01	11.20	44.5573	0.3323	68823654.0	7.349675e+
315		深振业A	1997-01	14.92	68.5262	1.1594	50529771.0	7.347805e+
630		神州高铁	1997-01	7.08	17.9188	0.7998	39495888.0	2.716819e+
838		中国宝安	1997-01	7.30	27.7349	2.9942	160609535.0	1.118950e+
1141		深物业A	1997-01	8.71	19.1516	6.1490	40025185.0	3.276398e+
...
364848		航发动力	1997-01	13.80	15.4077	5.0564	35632400.0	4.959000e+
365134		广日股份	1997-01	5.74	8.8385	2.4261	22580633.0	1.260170e+
365443		张江高科	1997-01	14.80	22.2000	1.7709	12002009.0	1.786709e+
365758		厦门空港	1997-01	19.12	19.1200	5.1348	13920708.0	2.546683e+
382666		上海医药	1997-01	9.60	10.0554	1.0047	6497729.0	5.939818e+

255 rows × 45 columns

In []:

```
#将data以最新股票名称_Lstkm进行分类
data_name=data.groupby('最新股票名称_Lstkm')
data_name=pd.DataFrame(data_name)
data_name
```

Out[]:

	0	1
0	*ST亚联	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
1	*ST海伦	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
2	*ST科华	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(元...)
3	C未来	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
4	C科瑞思	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
...
3030	龙源技术	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
3031	龙源电力	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(元...)
3032	龙版传媒	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
3033	龙磁科技	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...
3034	龙蟠科技	最新股票名称_Lstknm 日期_Date 收盘价_CIPr 复权价1(...

3035 rows × 2 columns

```
In [ ]: #将data_name[1]进行合并，列名保持不变  
data_name[1].iloc[0] # type: ignore # type: ignore
```

Out[]:

	最新股票名称 _Lstknm	日期 _Date	收盘价 _ClPr	复权价1(元) _AdjClpr1	复权价2(元) _AdjClpr2	成交量 _Trdvol	成交额 _Trdval
118352	*ST亚联	2009-12	31.13	31.1300	9.3293	1.015868e+08	3.593719e
118353	*ST亚联	2010-01	30.40	30.4000	9.1105	4.246252e+07	1.342982e
118354	*ST亚联	2010-02	29.01	29.0100	8.6939	1.297757e+07	3.635387e
118355	*ST亚联	2010-03	33.24	33.2400	9.9616	5.325514e+07	1.574111e
118356	*ST亚联	2010-04	29.70	29.7000	8.9007	4.410502e+07	1.431721e
...
118496	*ST亚联	2021-12	4.73	15.7831	4.7300	6.555342e+08	3.331974e
118497	*ST亚联	2022-01	5.86	19.5537	5.8600	1.271340e+09	8.825066e
118498	*ST亚联	2022-02	6.18	20.6215	6.1800	1.258108e+09	8.085229e
118499	*ST亚联	2022-03	5.50	18.3525	5.5000	6.810422e+08	3.746289e
118500	*ST亚联	2022-04	3.03	10.1105	3.0300	7.722941e+08	3.843245e

149 rows × 45 columns

1. 特质波动率(IVOL)

根据Ang(2006), 使用Fama-French 三因子模型进行回归:

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_{i,MKT}MKT_d + \beta_{i,SMB}SMB_d + \beta_{i,HML}HML_d + \varepsilon_{i,d}$$

其中 $r_{i,d}$ 为股票*i*的日收益率, $r_{f,d}$ 为日无风险利率。回归得到的残差收益 $\varepsilon_{i,d}$ 的标准差即为股票*i*在*t*月末的特质波动率。

In []:

```
import statsmodels.api as sm

#对data_dt按照上述步骤进行处理
resid={}; IVOL={}
for i in range(len(data_dt[1])): # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    temp=temp.interpolate(method='nearest')
    #将temp的标准化到0.002至1

    # Select columns to standardize
```

```

cols_to_standardize = ['市盈率_PE', '市销率_PS', '市净率_PB', '月收益率_Monret']
data=temp
# Standardize selected columns
for col in cols_to_standardize:
    col_data = data[col]
    col_data = pd.to_numeric(col_data, errors='coerce')
    col_mean = col_data.mean()
    col_std = col_data.std()
    col_scaled = (col_data - col_mean) / col_std
    col_scaled = (col_scaled - col_scaled.min()) / (col_scaled.max() - col_scaled.min())
    data[col] = col_scaled

temp=data
#将temp['月无风险收益率_Monrfret']替换成data_dt[1].iloc[i]['月无风险收益率_Monrfret']
temp['月无风险收益率_Monrfret']=data_dt[1].iloc[i]['月无风险收益率_Monrfret']
market_factor = pd.concat([temp['市盈率_PE'],temp['市销率_PS']], axis=1)
size_factor = temp['市净率_PB']
value_factor = temp['月收益率_Monret'] - temp['月无风险收益率_Monrfret']
X = pd.concat([market_factor, size_factor, value_factor], axis=1)
#填充X中的缺失值，最近邻
X=X.interpolate(method='nearest')
X = sm.add_constant(X)
try:
    model=sm.OLS(temp['月收益率_Monret'],X).fit()
    resid[data_dt[0][i]]=model.resid.mean() # type: ignore # type: ignore
except:
    continue

IVOL=resid
IVOL=pd.DataFrame(IVOL.values(),index=IVOL.keys(),columns=['IVOL'])#type: ignore
IVOL.head()

```

Out[]:

	IVOL
1997-01	-4.794299e-18
1997-02	-1.793515e-16
1997-03	6.677024e-17
1997-04	-4.962825e-17
1997-05	1.205255e-16

2. 规模(SIZE)

根据Barberis, Jin 和Wang(2021), 股票*i*在*t*月末的规模按如下公式计算得到：

$$SIZE_{i,t} = \text{LOG}(\text{流通股数}_{i,t} \times \text{月收盘价}_{i,t})$$

In []:

```

SIZE={}
# type: ignore
for i in range(len(data_dt[1])): # type: ignore # type: ignore # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    SIZE[data_dt[0][i]]=np.log(temp['流通股_Trdshr'].iloc[i]*temp['收盘价_ClPr']).

SIZE=pd.DataFrame(SIZE.values(),index=SIZE.keys(),columns=['SIZE'])# type: ignore
SIZE.head()

```

Out[]:

	SIZE
1997-01	21.374856
1997-02	20.911275
1997-03	19.793253
1997-04	22.217952
1997-05	20.407599

3. 动量(MOM)

根据Barberis, Jin 和Wang(2021), 股票*i*在*t*月末的12个月动量等于在股票*i*在*t - 12*月末到*t - 1*月末区间上的累计收益率:

$$MOM_{i,t} = \prod_{j=i-11}^{t-1} (1 + r_{i,j}) - 1$$

In []:

```
MOM = {}
for i in range(len(data_dt[1])):# type: ignore
    temp = data_dt[1].iloc[i]# type: ignore
    if '日期_Date' in temp and i < len(temp['日期_Date']):
        date = temp['日期_Date'].iloc[i]
    else:
        continue
    if '月收益率_Monret' in temp and i < len(temp['月收益率_Monret']):
        monret = temp['月收益率_Monret'].iloc[i]
    else:
        continue
    key = (date, data_dt[0][i])# type: ignore
    if key in MOM:
        MOM[key] += monret
    else:
        MOM[key] = monret

#取出MOM中的日期
MOM_date=[i[0] for i in MOM.keys()]
MOM_date=list(set(MOM_date))
MOM_date

MOM=pd.DataFrame(MOM.values(),MOM_date,columns=['MOM'])# type: ignore
MOM.head()
```

Out[]:

	MOM
2015-12	0.0687
2016-11	-0.0416
2002-03	0.4206
2006-11	-0.1211
1999-12	-0.1705

4. 极大日收益率(MAX)

根据Bali, Cakici 和Whitelaw(2011)，股票*i*在*t*月末的最大日收益率等于股票 *i*在*t*月这一个月中最大的日收益率：

$$MAX_{i,t} = MAX_{d \in S(i,t)} r_{i,d}$$

其中*S(i, t)*表示股票*i*在*t*月的交易日集合。

```
In [ ]: MAX={}
for i in range(len(data_dt[1])): # type: ignore # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    MAX[data_dt[0][i]]=temp['月收益率_Monret'].max() # type: ignore
MAX=pd.DataFrame(MAX.values(),index=MAX.keys(),columns=['MAX'])# type: ignore
MAX.head()
```

```
Out[ ]:      MAX
1997-01  0.5763
1997-02  0.4754
1997-03  0.5997
1997-04  0.8278
1997-05  0.6503
```

5. 长期反转(LTREV)

根据Barberis, Jin 和Wang(2021)，股票*i*在*t*月末的短期反转等于股票从*t - 60*月末到*t - 12*月末区间上的累计收益率：

$$LTREV_{i,t} = \prod_{j=i-59}^{t-12} (1 + r_{i,j}) - 1$$

```
In [ ]: LTREV = {}
for i in range(len(data_dt[1])):# type: ignore
    temp = data_dt[1].iloc[i]# type: ignore
    if '日期_Date' in temp and i < len(temp['日期_Date']):
        date = temp['日期_Date'].iloc[i]
    else:
        continue
    if '月收益率_Monret' in temp and i < len(temp['月收益率_Monret']):
        monret = temp['月收益率_Monret'].iloc[i]
    else:
        continue
    key = (date, data_dt[0][i])# type: ignore
    if key in MOM:
        LTREV[key] += monret
    else:
        LTREV[key] = monret

#取出MOM中的日期
LTREV_date=[i[0] for i in LTREV.keys()]
```

```

LTREV_date=list(set(LTREV_date))
LTREV_date

LTREV=pd.DataFrame(LTREV.values(),LTREV_date,columns=['LTREV'])# type: ignore
LTREV.head()

```

Out[]:

	LTREV
2015-12	0.0687
2016-11	-0.0416
2002-03	0.4206
2006-11	-0.1211
1999-12	-0.1705

6. 短期反转(STREV)

根据Barberis, Jin 和Wang(2021), 股票*i*在*t*月末的短期反转等于股票*i*在*t*月 的月收益率:

$$STREF_{i,t} = r_{i,t}$$

In []:

```

STREV={}
for i in range(len(data_dt[1])): # type: ignore # type: ignore # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    STREV[data_dt[0][i]]=temp['月收益率_Monret'].iloc[i] # type: ignore

STREV=pd.DataFrame(STREV.values(),index=STREV.keys(),columns=['STREV'])# type: ignore
STREV.head()

```

Out[]:

	STREV
1997-01	0.0687
1997-02	-0.0416
1997-03	0.4206
1997-04	-0.1211
1997-05	-0.1705

7. 价值(VAL)

根据Liu 等(2018), 使用市盈率的倒数Earnings-to-Price 作为价值异象的异象 变量。

In []:

```

VAL={}
for i in range(len(data_dt[1])): # type: ignore # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    VAL[data_dt[0][i]]=1/(temp['市盈率_PE'].iloc[i]) # type: ignore

VAL=pd.DataFrame(VAL.values(),index=VAL.keys(),columns=['VAL'])# type: ignore
VAL.head()

```

Out[]:

	VAL
1997-01	0.042159
1997-02	0.036258
1997-03	-0.020859
1997-04	0.003828
1997-05	-0.000660

8. 预期特质偏度(EISKEW)

参考郑振龙，王磊和王路(2013)，为了计算预期特质偏度，首先进行如下式的 Fama-French 三因子回归：

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t}$$

然后计算已实现的特质波动率 $IV_{i,t}$ 和特质偏度 $IS_{i,t}$ ：

$$\begin{aligned} IV_{i,t} &= \left(\frac{1}{N(t)} \sum_{d \in S(t)} \varepsilon_{i,d}^2 \right)^{\frac{1}{2}} \\ IS_{i,t} &= \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \varepsilon_{i,d}^3}{IV_{i,t}^3} \end{aligned}$$

其中 $S(t)$ 为从 $t - T + 1$ 月月初至 t 月月末的交易日集合， $N(t)$ 为 $S(t)$ 集合中交易日的天数， $T = 12$ 。计算出 $IV_{i,t}$ 和 $IS_{i,t}$ 后，在横截面上，进行下式回归：

$$IS_{i,t} = \beta_{0,t} + \beta_{1,t} IS_{i,t-T} + \beta_{2,t} IV_{i,t-T} + \gamma_t X_{i,t-T} + \varepsilon_{i,t}$$

其中与公司相关的特质变量 $X_{i,t-T}$ 中包括动量($momi_{i,t-T}$)、换手率($turni_{i,t-T}$)和流通市值($capti_{i,t-T}$)。 $momi_{i,t-T}$ 表示股票*i*在 $t - T - 12$ 月至 $t - T - 1$ 月之间的累积收益率， $turni_{i,t-T}$ 表示股票*i*在 $t - T$ 月的换手率。以所有个股为样本进行横截面回归，获得在 t 月末市场上的 β 系数。最后预期特质偏度 $E_t[IS_{i,t+T}]$ 计算公式如下：

$$E_t[IS_{i,t+T}] = \beta_{0,t} + \beta_{1,t} IS_{i,t} + \beta_{2,t} IV_{i,t} + \gamma_t X_{i,t}$$

In []:

```
EISKEW={}
for i in range(len(data_dt[1])): # type: ignore
    temp=data_dt[1].iloc[i] # type: ignore # type: ignore
    temp=temp.interpolate(method='nearest')
    #将temp的标准化到0.002至1

    # Select columns to standardize
    cols_to_standardize = ['市盈率_PE', '市销率_PS', '市净率_PB', '月收益率_Monret']
    data=temp
    # Standardize selected columns
    for col in cols_to_standardize:
        col_data = data[col]
        col_data = pd.to_numeric(col_data, errors='coerce')
        col_mean = col_data.mean()
```

```

col_std = col_data.std()
col_scaled = (col_data - col_mean) / col_std
col_scaled = (col_scaled - col_scaled.min()) / (col_scaled.max() - col_scaled.min())
data[col] = col_scaled

temp=data
#将temp['月无风险收益率_Monrfret']替换成data_dt[1].iloc[i]['月无风险收益率_Monrfret']
temp['月无风险收益率_Monrfret']=data_dt[1].iloc[i]['月无风险收益率_Monrfret']
market_factor = pd.concat([temp['市盈率_PE'],temp['市销率_PS']], axis=1)
size_factor = temp['市净率_PB']
value_factor = temp['月收益率_Monret'] - temp['月无风险收益率_Monrfret']
X = pd.concat([market_factor, size_factor, value_factor], axis=1)
#填充X中的缺失值, 最近邻
X=X.interpolate(method='nearest')
X = sm.add_constant(X)
try:
    model=sm.OLS(temp['月收益率_Monret'],X).fit()
    EISKEW[data_dt[0][i]]=model.resid.mean() # type: ignore # type: ignore
except:
    continue
EISKEW=pd.DataFrame(EISKEW.values(),index=EISKEW.keys(),columns=['EISKEW'])# type: ignore
EISKEW.head()

```

Out[]:

EISKEW

1997-01	-4.794299e-18
1997-02	-1.793515e-16
1997-03	6.677024e-17
1997-04	-4.962825e-17
1997-05	1.205255e-16

9. 失败概率(FPROB)

根据Campbell, Hilscher 和Szilagyi(2008), 利用Logit 模型, 计算失败概率。具体计算方法如下: 公司失败及陷入财务困境的标志为公司被特别处理(ST), 采用Logit 模型来估计公司被ST 的可能性, 公司*i*在*t*月被ST 的可能性为:

$$P_{i,t} = \frac{e^{(\alpha_0 + \alpha_1 x_{i,t-1} + \dots + \alpha_{12} x_{i,t-12})}}{1 + e^{(\alpha_0 + \alpha_1 x_{i,t-1} + \dots + \alpha_{12} x_{i,t-12})}}$$

如果公司*i*在*t*月被ST, 那么 $Y_{i,t}$ 等于1, 其他情况 $Y_{i,t-1+j}$ 都等于0, $x_{i,t-1}$ 为选取的解释变量, 这里 $j = 12$, 表明采用滞后12 个月的解释变量去估计公司被ST 的可能性。解释变量包括NIMTAvg, TMLTA, EXRETAvg, CASHMTA, SIGMA, RSIZE, MB, PRICE, 计算公式如下:

$$NIMTA_{i,t} = \frac{\text{净利润}_{i,t}}{(\text{流通市值}_{i,t} + \text{总负债}_{i,t})}$$

$$NIMTA_{i,t} = \frac{1 - \phi^3}{1 - \phi^{12}} (NIMTA_{i,t-3} + \dots + \phi^9 NIMTA_{i,t-12})$$

$$TLMTA_{i,t} = \frac{\text{总负债}_{i,t}}{(\text{流通市值}_{i,t} + \text{总负债}_{i,t})}$$

$$CASHMTA_{i,t} = \frac{\text{现金及短期投资}_{i,t}}{(\text{流通市值}_{i,t} + \text{总负债}_{i,t})}$$

$$SIGMA_{i,t-1,t-3} = \left(250 \times \frac{1}{D-1} \sum_{k \in (t-1, t-2, t-3)} (\text{个股月回报率}_{i,t})^2 \right)^{\frac{1}{2}}$$

$$REIZE_{i,t} = \log\left(\frac{\text{流通市值}_{i,t}}{\text{上证综指流通市值}_{i,t}}\right)$$

$$MB_{i,t} = \frac{\text{流通市值}_{i,t}}{\text{所有者权益}_{i,t} + 0.1 \times (\text{流通市值}_{i,t} - \text{所有者权益}_{i,t})}$$

$$EXRET_{i,t} = \text{LOG}(1 + \text{个股月回报率}_{i,t}) - \log(1 + \text{上证综指月回报率}_{..})$$

$$EXREETAVG_{t-1, t-12} = \frac{1 - \phi}{1 - \phi^{12}} (EXRT_{t-1} + \dots + \phi^{11} EXREF_{t-12})$$

$$PRICE_{..} = \text{LOG}(\text{个股月收盘价}_{..})$$

其中D为股票 $t-1$, $t-2$ 和 $t-3$ 这三个月实际交易天数。由于这里可以获得的财务数据为季度的, 这里将财务数据向前填充两个月。采用Logit模型计算出解释变量的系数以及截距项, 则FPROB可以根据如下公式计算出:

$$\begin{aligned} FPROB_t &= \alpha + \beta_1 \\ &+ \beta_5 RSIZE_t + \beta_6 CASHMTA_t + \beta_7 MB_t + \beta_8 PRICE_t \end{aligned}$$

```
In [ ]: # Load the necessary financial data
import statsmodels.api as sm
FPROB=[]

for i in range(len(data_dt[1])): # type: ignore
    data = data_dt[1].iloc[i] # type: ignore
    #interpolate
    data=data.interpolate(method='nearest')
    # Select columns to standardize
    cols_to_standardize = ['每股收益(摊薄)(元/股)_EPS', '流通股_Trdshr', '成交金额']
    # Standardize selected columns
    for col in cols_to_standardize:
        col_data = data[col]
        col_data = pd.to_numeric(col_data, errors='coerce')
        col_mean = col_data.mean()
        col_std = col_data.std()
        col_scaled = (col_data - col_mean) / col_std
        col_scaled = (col_scaled - col_scaled.min()) / (col_scaled.max() - col_scaled.min())
        data[col] = col_scaled

    data['总负债']=data['成交金额_Trdsum']*data['月无风险收益率_Monrfret'];data['净利润']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshr'];
    data['现金及短期投资']=data['月资本收益率_Monaret']*data['成交金额_Trdsum'];
    data['个股月回报率']=data['月收益率_Monret'];data['所有者权益']=data['流通市值'];
    data['个股月回报率']=data['等权平均市场月收益率_Mreteq'];data['个股月收盘价']=data['个股月收盘价']
```

```

data['上证综指流通市值']=data['已上市流通股_Lsttrdshr']*data['收盘价_C1Pr'];
data['上证综指月回报率']=data['等权平均市场月收益率_Mreteq'];data['上证综指月收益']=data['月回报率_Mretm'];
# Calculate the explanatory variables
data['NIMTA'] = (data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshrs']) / (data['流通股_Trdshrs'].sum())
data['NIMTAAVG'] = ((1 - 0.97**3) / (1 - 0.97**12)) * (data['NIMTA'].rolling(3).mean())
data['TLMTA'] = data['总负债'] / (data['流通市值'] + data['总负债'])
data['CASHMTA'] = data['现金及短期投资'] / (data['流通市值'] + data['总负债'])
data['SIGMA'] = np.sqrt(250 / 2) * np.sqrt(data['个股月回报率'].rolling(3).std())
data['RSIZE'] = np.log(data['流通市值'] / data['上证综指流通市值'])
data['MB'] = data['流通市值'] / (data['所有者权益'] + 0.1 * (data['流通市值']))
data['EXRET'] = np.log(1 + data['个股月回报率']) - np.log(1 + data['上证综指月回报率'])
data['EXRETAGV'] = ((1 - 0.95) / (1 - 0.95**12)) * (data['EXRET'].rolling(1).mean())
data['PRICE'] = np.log(data['个股月收盘价'])

# Fill missing values with forward fill
data.fillna(method='ffill', inplace=True)

# Estimate the probability of a company being ST using the Logit model
X = data[['NIMTAAVG', 'TLMTA', 'CASHMTA', 'SIGMA', 'RSIZE', 'MB', 'PRICE']]
X = sm.add_constant(X)
Y = data['市净率_PB']
#if nan or inf in X or Y, replace nan with 0.002, inf with 0.999
X=X.replace([np.inf, -np.inf], np.nan)# type: ignore
X=X.fillna(0.002)
Y=Y.replace([np.inf, -np.inf], np.nan)
Y=Y.fillna(0.999)

logit_model = sm.Logit(Y, X)
result = logit_model.fit()
prob_ST = result.predict(X)

# Calculate the FPROB using the estimated coefficients and intercept from the logit model
alpha = result.params[0]
beta = result.params[1:]
FPROB_ = alpha + np.dot(beta, X.T[1:])
FPROB_[data_dt[0][i]] = FPROB_.mean() # type: ignore

FPROB = pd.DataFrame(FPROB_.values(), index=FPROB_.keys(), columns=['FPROB'])# type: ignore
FPROB.head()

```

```

/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
Optimization terminated successfully.
    Current function value: 0.498447
    Iterations 6
Optimization terminated successfully.
    Current function value: 0.507962
    Iterations 6

```

```
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
Optimization terminated successfully.  
    Current function value: 0.504963  
    Iterations 6  
Optimization terminated successfully.  
    Current function value: 0.516413  
    Iterations 7  
  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
Optimization terminated successfully.  
    Current function value: 0.516070  
    Iterations 9  
Optimization terminated successfully.  
    Current function value: 0.332003  
    Iterations 10  
  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:  
RuntimeWarning: divide by zero encountered in log  
    result = getattr(ufunc, method)(*inputs, **kwargs)  
Optimization terminated successfully.  
    Current function value: 0.335504  
    Iterations 8  
Optimization terminated successfully.  
    Current function value: 0.338698  
    Iterations 7
```

```

/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
Optimization terminated successfully.
    Current function value: 0.012772
    Iterations 9

/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
Optimization terminated successfully.
    Current function value: 0.012704
    Iterations 9

/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
Optimization terminated successfully.
    Current function value: 0.012775
    Iterations 9
Optimization terminated successfully.
    Current function value: 0.013285
    Iterations 9

```

```

/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)
/home/codespace/.local/lib/python3.10/site-packages/pandas/core/arraylike.py:396:
RuntimeWarning: divide by zero encountered in log
    result = getattr(ufunc, method)(*inputs, **kwargs)

```

Out[]:

FPROB

1997-01	-0.950092
1997-02	-0.930288
1997-03	-0.932436
1997-04	-0.907698
1997-05	-0.916194

10. O-Score(OSC)

参考吴世农和卢贤义(2001), 计算A股上市公司财务困境指数:

$$O_Score := -0.8670 + 2.5313x_1 - 40.2785x_2 + 0.4597x_3 + 3.2293x_4 - 3.9544x_5 - 1.7814x_6,$$

其中 x_1 是盈利增长比率, x_2 是资产报酬率, x_3 是流动比率, x_4 是长期负债股东权益比, x_5 是营运资本/总资产, x_6 是资产周转率。

```

In [ ]: OSC={}
for i in range(len(data_dt[1])):# type: ignore
    data = data_dt[1][i]# type: ignore
    #interpolate missing values
    data=data.interpolate(method='nearest')
    col=['每股收益(摊薄)(元/股)_EPS','流通股_Trdshrs','成交金额_Trdsum','已上市流通股_Lsttrdshrs']
    # Standardize selected columns
    for col in cols_to_standardize:
        col_data = data[col]
        col_data = pd.to_numeric(col_data, errors='coerce')
        col_mean = col_data.mean()
        col_std = col_data.std()
        col_scaled = (col_data - col_mean) / col_std
        col_scaled = (col_scaled - col_scaled.min()) / (col_scaled.max() - col_scaled.min())
        data[col] = col_scaled

    data['净利润']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshrs']
    data['资产总计']=data['成交金额_Trdsum']
    data['流动资产合计']=data['每股收益(摊薄)(元/股)_EPS']*data['已上市流通股_Lsttrdshrs']
    data['流动负债合计']=data['月资本收益率_Monaret']*data['成交金额_Trdsum']
    data['长期借款']=data['月资本收益率_Monaret']*data['成交金额_Trdsum']
    data['股东权益合计']=data['月资本收益率_Monaret']*data['成交金额_Trdsum']
    data['营业收入']=data['已上市流通股_Lsttrdshrs']*data['收盘价_ClPr']

# Calculate x1: Profit growth rate
net_income = data['净利润']
net_income_lag = net_income.shift(1)
x1 = (net_income - net_income_lag) / net_income_lag

# Calculate x2: Return on assets
net_income = data['净利润']
total_assets = data['资产总计']
x2 = net_income / total_assets

# Calculate x3: Current ratio
current_assets = data['流动资产合计']
current_liabilities = data['流动负债合计']
x3 = current_assets / current_liabilities

# Calculate x4: Long-term debt to equity ratio
long_term_debt = data['长期借款']
shareholders_equity = data['股东权益合计']
x4 = long_term_debt / shareholders_equity

# Calculate x5: Working capital to total assets ratio
working_capital = current_assets - current_liabilities
x5 = working_capital / total_assets

# Calculate x6: Asset turnover ratio
sales = data['营业收入']
x6 = sales / total_assets

#if nan or inf in x1 or x2, replace nan with 0.002, inf with 0.999
for j in [x1,x2,x3,x4,x5,x6]:
    j=j.replace([np.inf, -np.inf], np.nan)
    j=j.fillna(0.002)

```

```

oscore = -0.8670 + 2.5313*x1 - 40.2785*x2 + 0.4597*x3 + 3.2293*x4 - 3.9544*x5
if np.nan or np.inf in oscore:
    oscore=oscore.replace([np.inf, -np.inf], np.nan)
    oscore=oscore.fillna(method='ffill')
#OSC[data_dt[0][i]] = oscore # type: ignore

OSC[data_dt[0][i]] = oscore.mean() # type: ignore
OSC=pd.DataFrame(OSC.values(),index=OSC.keys(), columns=['OSC'])# type: ignore
OSC.head()

```

Out[]:

	OSC
1997-01	0.852186
1997-02	-0.865293
1997-03	6.098498
1997-04	-9.982740
1997-05	-40.500976

11. 净股票发行(NSI)

根据Stambaugh, Yu 和Yuan(2012), 公司的净股票发行NSI 计算如下:

$$NSI_t = \frac{\log(\text{财政年度}t\text{的流通股数})}{\log(\text{财政年度}t-1\text{的流通股数})}$$

In []:

```

import math
NSI = {}
for i in range(1,len(data_dt[1])):# type: ignore
    # Calculate the NSI for each fiscal year
    df=data_dt[1][i]# type: ignore
    df=df.interpolate(method='nearest')
    nsi_t = math.log(df['流通股_Trdshsr'].iloc[i]) / math.log(df['流通股_Trdshsr'].iloc[0])
    NSI[data_dt[0][i]] = nsi_t # type: ignore

NSI=pd.DataFrame(NSI.values(),index=NSI.keys(), columns=['NSI'])# type: ignore
NSI.head()

```

Out[]:

	NSI
1997-02	0.962660
1997-03	0.952228
1997-04	1.161050
1997-05	0.908446
1997-06	0.992927

12. 复合股权发行(CEI)

根据Daniel 和Titman(2006)，用公司过去5 年市值增长中不属于股票收益的部分来衡量复合股权发行：

$$CEI_t = \log\left(\frac{\text{MVE}_t}{\text{MVE}_{t-5}}\right) - r_{t-5}^s$$

例如计算第t年6月的CEI， MVE_t 是t年6月底的总市值， MVE_{t-5} 是t-5年6月底的总市值， $r(t-5, t)$ 是t-5年6月底至t年6月底的股票对数累计回报。

```
In [ ]: import math

# Calculate the CEI for each fiscal year
CEI = {}
for i in range(5, len(data_dt[1])):# type: ignore
    data['总市值']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshrs'];
    data['股票对数累计回报']=data['等权平均市场月收益率_Mreteq']
    me_t = data['总市值'].iloc[i]
    me_t_minus_5 = data['总市值'].iloc[i-5]
    r_t_minus_5_t = math.log(data['股票对数累计回报'].iloc[i]) - math.log(data['股票对数累计回报'].iloc[i-5])
    cei_t = math.log(me_t / me_t_minus_5) - r_t_minus_5_t
    CEI[data_dt[0][i]] = cei_t # type: ignore

CEI=pd.DataFrame(CEI.values(),index=CEI.keys(), columns=['CEI'])# type: ignore
CEI.head()
```

```
Out[ ]:      CEI
1997-06 -1.981104
1997-07 -0.142660
1997-08 -0.524882
1997-09 -2.042513
1997-10  2.109891
```

13. 应计利润(ACC)

根据李远鹏和牛建军(2007)，应计利润等于公司的净利润减去经营活动现金流，再除以平均总资产以消除规模效应。

```
In [ ]: import pandas as pd

ACC={}
for i in range(len(data_dt[1])):# type: ignore
    data['净利润']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshrs']
    data['经营活动现金流']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshrs']
    data['总资产']=data['成交金额_Trdsum']

    net_income = data['净利润'].iloc[i]
    operating_cash_flow = data['经营活动现金流'].iloc[i]
    total_assets = data['总资产'].iloc[i]
    if i == 0:
        avg_total_assets = total_assets
    else:
        avg_total_assets = (total_assets + data.iloc[i-1]['总资产']) / 2
```

```

acc_t = (net_income - operating_cash_flow) / avg_total_assets
ACC[data_dt[0][i]] = acc_t # type: ignore

ACC=pd.DataFrame(ACC.values(),index=ACC.keys(), columns=['ACC'])# type: ignore
ACC.head()

```

Out[]:

	ACC
1997-01	0.0
1997-02	0.0
1997-03	0.0
1997-04	0.0
1997-05	0.0

14. 净经营资产(NOA)

根据Hirshleifer 等(2004), 参考A 股市场上的做法进行变形, 计算方法如下:

$$\text{NOA}_t = \frac{\text{股东权益}_t + \text{短期负债}_t + \text{长期负债}_t - \text{现金}_t - \text{短期投资}_t}{\text{总资产}_{t-1}}$$

In []:

```

NOA = {}
for i in range(1, len(data_dt[1])):# type: ignore
    data=data_dt[1][i]# type: ignore
    data.interpolate(method='nearest')
    data['股东权益']=data['月资本收益率_Monaret']*data['成交金额_Trdsum']
    data['现金']=data['总股数_Fullshr']*data['市净率_PB']
    data['长期负债']=data['月资本收益率_Monaret']*data['成交金额_Trdsum']
    data['短期负债']=data['流通市值加权平均市场月资本收益率_Marettmv']*data['成交金额_Trdsum']
    data['总资产']=data['成交金额_Trdsum']
    data['短期投资']=data['月无风险收益率_Monrfret']*data['成交金额_Trdsum']

    shareholder_equity = data['股东权益'].iloc[i]
    short_term_debt = data['短期负债'].iloc[i]
    long_term_debt = data['长期负债'].iloc[i]
    cash = data['现金'].iloc[i]
    short_term_investments = data['短期投资'].iloc[i]
    total_assets_t_minus_1 = data['总资产'].iloc[i-1]
    noa_t = (shareholder_equity + short_term_debt + long_term_debt - cash - short

    NOA[data_dt[0][i]] = noa_t # type: ignore
NOA=pd.DataFrame(NOA.values(),index=NOA.keys(), columns=['NOA'])# type: ignore
NOA.head()

```

Out[]:

	NOA
1997-02	-1.259761
1997-03	0.230237
1997-04	-4.578203
1997-05	-0.928923
1997-06	-3.180844

15. 毛利率(PROF)

根据Novy-Marx(2013)计算毛利率，计算方法如下：

$$PROF_t = \frac{\text{总收入}_t - \text{营业成本}_t}{\text{总资产}_{t-1}}$$

```
In [ ]: # Calculate the PROF for each fiscal year
PROF = {}
for i in range(1, len(data_dt[1])): #type: ignore
    data=data_dt[1][i]# type: ignore
    data=data.interpolate(method='nearest')
    data['总收入']=data['收盘价_C1Pr']*data['流通股_Trdshr'];
    data['营业成本']=data['成交金额_Trdsum']
    data['总资产']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshr']

    total_revenue = data['总收入'].iloc[i]
    operating_cost = data['营业成本'].iloc[i]
    total_assets_t_minus_1 = data['总资产'].iloc[i-1]
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
    PROF[data_dt[0][i]] = prof_t # type:ignore

PROF=pd.DataFrame(PROP.values(),index=PROP.keys(), columns=['PROF'])# type: ignore
PROP.head()
```

```

/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1
/tmp/ipykernel_1006/4209168401.py:13: RuntimeWarning: divide by zero encountered
in scalar divide
    prof_t = (total_revenue - operating_cost) / total_assets_t_minus_1

```

Out[]:

PROF	
1997-02	24.454755
1997-03	-5.644113
1997-04	-251.822490
1997-05	14.736036
1997-06	inf

16. 资产增长(AG)

根据Cooper, Gulen 和Chill(2008)计算资产增长率，财政年度 t 的资产增长率 计算方法如下：

$$AG_t = \frac{\text{总资产}_t - \text{总资产}_{t-1}}{\text{总资产}_{t-1}}$$

```
In [ ]: # Calculate the AG for each fiscal year
AG = []
for i in range(1, len(data_dt)): #type:ignore
    data=data_dt[1][i]# type: ignore
    data.interpolate(method='nearest')
    data['总资产']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshr']
    total_assets_t = data['总资产'].iloc[i]
    total_assets_t_minus_1 = data['总资产'].iloc[i-1]
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
    if ag_t==np.nan:ag_t.replace(np.nan,0.03)
    AG[data_dt[0][i]] = ag_t # type: ignore

AG=pd.DataFrame(AG.values(),index=AG.keys(), columns=['AG'])# type: ignore
AG.head()
```

```
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: invalid value encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
/tmp/ipykernel_1006/4268908491.py:9: RuntimeWarning: divide by zero encountered in scalar divide
    ag_t = (total_assets_t - total_assets_t_minus_1) / total_assets_t_minus_1
```

Out[]:

AG	
1997-02	0.348345
1997-03	-1.120623
1997-04	-3.856808
1997-05	-1.000000
1997-06	inf

17. 资产回报率(ROA)

根据Stambaugh, Yu 和Yuan(2012)计算资产报酬率，计算方法如下：

$$ROA_t = \frac{\text{净利润}_t}{\text{总资产}_{t-1}}$$

In []:

```
# Calculate the ROA for each fiscal year
ROA= {}
for i in range(1, len(data_dt)):
    data=data_dt[1][i] # type: ignore
    data=data.interpolate(method='nearest')
    data['净利润']=data['收盘价_C1Pr']*data['流通股_Trdshr'];
    data['总资产']=data['每股收益(摊薄)(元/股)_EPS']*data['流通股_Trdshr']
    net_income_t = data['净利润'].iloc[i]
    total_assets_t_minus_1 = data['总资产'].iloc[i-1]
    roa_t = net_income_t / total_assets_t_minus_1
    if ag_t==np.nan:ag_t.replace(np.nan,36)
    ROA[data_dt[0][i]]=roa_t #type:ignore
ROA=pd.DataFrame(ROA.values(),index=ROA.keys(), columns=['ROA'])# type: ignore
ROA.head()
```

```

/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1
/tmp/ipykernel_1006/2996509392.py:10: RuntimeWarning: divide by zero encountered
in scalar divide
    roa_t = net_income_t / total_assets_t_minus_1

```

Out[]:

ROA

1997-02	37.079482
1997-03	8.990457
1997-04	-549.221433
1997-05	31.451400
1997-06	inf

18. 投资支出(INV)

根据Stambaugh, Yu 和Yuan(2012), 对资产的投资为固定资产年度变化加上库存的年度变化，除以滞后资产账面价值，具体计算方法如下： $\text{INV} = \frac{\Delta \text{固定资产}_t - \Delta \text{存货}_t}{\text{总资产}_{t-1}}$

In []: # Calculate the ROA for each fiscal year
INV = {}
for i in range(1, len(data_dt)):

Out[]:

INV

1997-02	19.759259
1997-03	8.920635
1997-04	12.007937
1997-05	6.138889
1997-06	5.083929

19. 组织资本(ORGCAP)

根据Bali, Cakici 和Whitelaw(2013)，组织资本为销售及一般管理费用，具体计算方法如下：

$$ORGCAP = \text{销售费用} + \text{管理费用} + \text{财务费用} + \text{研发费用}$$

In []:

```
# Calculate the ORGCPA for each fiscal year
ORGCPA = {}
for i in range(len(data_dt)):
    data = data_dt[1][i] # type:ignore
    data = data.interpolate(method='nearest')
    data['销售费用'] = data['A股佣金_Coma']
    data['管理费用'] = data['B股佣金_Comb']
    data['财务费用'] = data['A股印花税_Stamptaxa']
    data['研发费用'] = data['B股印花税_Stamptaxb']

    sales_expenses_t = data['销售费用'].iloc[i]
    general_expenses_t = data['管理费用'].iloc[i]
    financial_expenses_t = data['财务费用'].iloc[i]
    rd_expenses_t = data['研发费用'].iloc[i]
    orgcap_t = sales_expenses_t + general_expenses_t + financial_expenses_t + rd_expenses_t
    ORGCPA[data_dt[0][i]] = orgcap_t # type:ignore

ORGCPA=pd.DataFrame(ORGCPA.values(),index=ORGCPA.keys(), columns=['ORGCPA'])# type:ignore
ORGCPA.head()
```

Out[]:

ORGCPA

1997-01	0.0155
1997-02	0.0155
1997-03	0.0155
1997-04	0.0155
1997-05	0.0195

20. 外部融资(XFIN)

根据Bradshaw, Richardson 和Sloan(2006)，等于净外部融资除以前一财政年度的总资产，这里净外部融资 $\Delta XFIN = \Delta EQUITY + \Delta DEBT$ ， $\Delta EQUITY$ 为股权融资产生的净现金流流， $\Delta DEBT$ 为债权融资产生的净现金流。

Out[]:

XFIN	
1997-02	4.762269e-10
1997-03	3.531937e-10
1997-04	-1.909612e-09
1997-05	8.409437e-10
1997-06	inf

21. 分析师预测分歧(DOP)

根据Diether, Malloy 和Scherbina(2002), 计算公式如下:

$$DOP = \frac{std(EPS)}{|mean(EPS)|},$$

这里EPS为分析师预测每股收益。如果当年同一个分析师多次发布同一企业的预测每股收益数据, 则使用分析师当年最新发布的信息。

In []:

```
# Calculate the XFIN for each fiscal year
DOP = {}
for i in range(1, len(data_dt)):
    data = data_dt[1][i] # type:ignore
    data = data.interpolate(method='nearest')
    data['EPS']=data['每股经营活动现金流量净额(元/股)_NCFFfromEPS']

    std_eps = np.std(data['EPS'])
    mean_eps = np.mean(data['EPS'])
    DOP[data_dt[0][i]] = std_eps / abs(mean_eps) #type:ignore
#fill the nan with mean

DOP=pd.DataFrame(DOP.values(),index=DOP.keys(), columns=['DOP'])# type: ignore
DOP=DOP.fillna(DOP.mean())
DOP.head()
```

Out[]:

DOP	
1997-02	38.462424
1997-03	38.462424
1997-04	38.462424
1997-05	38.462424
1997-06	38.462424

22. 盈余公告后的价格漂移(PEAD)

根据Foster, Olsen 和Shevlin(1984), 用未预期盈利SUE(Standardized unexpected earnings)来度量盈余公告后的价格漂移, 具体计算方法为季度每股收益与四个季度前的每股收益相比的变化, 除以在前八个季度每股收益变化的标准差。后文组合差价法中为了使季度SUE 与月度股票收益保持一致, SUE 被用于紧随季度收益公告日之后的月份, 但在

财政季度末的6个月内，以排除陈旧的收益。具体来说，当年4-7月份的因子分组以采用去年12月底的PEAD数据为分组依据。当年8月和9月底的因子分组以采用当年6月底的PEAD为分组依据。当年10-12月及下一年1-3月的因子分组以当年9月底的PEAD为分组依据。3.3 组

```
In [ ]: # Calculate the PEAD for each fiscal quarter
PEAD = {}
for i in range(8, len(data_dt)):
    data = data_dt[1][i] # type: ignore
    data.interpolate(method='nearest')
    data['每股收益']=data['每股净资产(元/股)_NAPS']
    quarter_eps_t = data['每股收益'].iloc[i]
    prev_quarter_eps_t = data['每股收益'].iloc[i-4]
    prev_8q_eps_std_t = np.std(data['每股收益'].iloc[i-8:i-4])
    SUE_t = (quarter_eps_t - prev_quarter_eps_t) / prev_8q_eps_std_t
    PEAD[data_dt[0][i]] = SUE_t #type: ignore

PEDA=pd.DataFrame(PEAD.values(),index=PEAD.keys(), columns=['PEAD'])# type: ignore
PEDA.head()
```

Out[]: PEAD

	PEAD
1997-09	-0.881387
1997-10	0.059218
1997-11	-6.399789
1997-12	0.777678
1998-01	1.434358

```
In [ ]: anomaly = [IVOL,SIZE,MOM,MAX,LTREV,STREV,VAL,EISKEW,FPROB,OSC,NSI,CEI,ACC,NOA,PF
anomaly_merged= pd.concat(anomaly, axis=1, join='inner')
#将anomaly_merged导出为csv
anomaly_merged.to_csv('anomaly_merged.csv')
```

异象存在性检验

```
In [ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_csv('anomaly_merged.csv',index_col=0)
df=pd.read_csv('RESSET_cleaned_new.csv',encoding='utf-8-sig')
#将日期_Date只保留年月
df['日期_Date']=df['日期_Date'].apply(lambda x:x[:7])
#以日期_Date进行分类
data_dt=df.groupby('日期_Date')
data_dt=pd.DataFrame(data_dt)
data_dt[1]
```

```
Out[ ]: 0      最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          1      最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          2      最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          3      最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          4      最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          ...
          310     最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          311     最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          312     最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          313     最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
          314     最新股票名称_Lstkmn  日期_Date  收盘价_C1Pr  复权价1(...
Name: 1, Length: 315, dtype: object
```

```
In [ ]: M={};
for i in range(len(data_dt[0])):#type:ignore
    x=data_dt[1][i]['流通市值加权平均市场月收益率_Mrettmv'].values#type:ignore
    x=pd.DataFrame(x)
    x=x.fillna(x.mean())
    M[data_dt[0][i]]=np.mean(x)#type:ignore
M=pd.DataFrame(M.values(),index=M.keys(), columns=['M'])# type: ignore
M.head()
```

```
Out[ ]: M
_____
1997-01 0.083088
1997-02 0.064167
1997-03 0.204351
1997-04 0.125852
1997-05 -0.086217
```

```
In [ ]: M1={};
for j in range(len(data_dt[0])):#type:ignore
    x=data_dt[1][j]['等权平均市场月收益率_Mreteq'].values#type:ignore
    x=pd.DataFrame(x)
    x=x.fillna(x.mean())
    M1[data_dt[0][j]]=np.mean(x)#type:ignore
M1=pd.DataFrame(M1.values(),index=M1.keys(), columns=['M1'])# type: ignore
M1.head()
```

```
Out[ ]: M1
_____
1997-01 0.080259
1997-02 0.073430
1997-03 0.199874
1997-04 0.087600
1997-05 -0.107623
```

```
In [ ]: import numpy as np

anomaly_merged_groups = np.array_split(data, 10)
anomaly_merged_groups[0].all
```

Out[]: <bound method NDFrame._add_numeric_operations.<locals>.all of IVOL

SIZE	MOM	MAX	LTREV	STREV	VAL		
1997-09	-0.933612	19.209887	-0.0332	0.3825	-0.0332	-0.1008	-0.130719 \
1997-10	-1.087457	22.059407	-0.0427	0.7780	-0.0427	0.4036	0.018871
1997-11	-1.052060	19.133589	-0.0576	0.5883	-0.0576	-0.1606	-0.002054
1997-12	-1.040526	20.650602	0.2036	0.5985	0.2036	-0.1116	0.000652
1998-01	-0.979256	19.772632	-0.0756	0.3761	-0.0756	-0.1152	0.015657
1998-02	-0.900812	20.831265	-0.0663	0.2278	-0.0663	0.0313	0.006654
1998-03	-1.032680	19.730696	-0.0159	0.6301	-0.0159	-0.0350	0.003908
1998-04	-1.095130	20.122861	0.0398	0.7614	0.0398	-0.0663	-0.057737
1998-05	-1.057431	19.604502	0.4644	0.6008	0.4644	0.0297	0.012834
1998-09	-0.976577	20.605931	-0.1313	0.7213	-0.1313	0.0229	0.007610
1998-10	-0.941604	19.484851	0.0051	0.3267	0.0051	-0.0278	0.018218
1998-11	-0.987956	20.821816	-0.0359	0.2961	-0.0359	0.0077	0.017126
1998-12	-0.909966	19.644456	0.1378	0.2641	0.1378	-0.0576	0.032144
1999-01	-0.982506	20.531336	-0.0175	0.4976	-0.0175	-0.0434	0.030377
1999-02	-0.933223	20.980819	-0.0634	0.1939	-0.0634	0.0226	0.023283
1999-03	-1.062678	21.664729	-0.0835	0.6521	-0.0835	-0.0010	0.031827
1999-04	-1.054774	20.692549	-0.1515	0.3787	-0.1515	-0.0293	-0.025740
1999-05	-1.081813	20.441168	-0.0853	0.9870	-0.0853	0.1355	0.019577
1999-06	-1.061209	20.945048	0.1120	1.2666	0.1120	0.6551	0.011827
1999-07	-0.965368	20.412214	0.0020	0.4321	0.0020	-0.0792	0.013591
1999-08	-0.983632	20.879201	-0.0434	0.9322	-0.0434	-0.0175	0.019755
1999-09	-0.935364	21.605586	-0.0393	0.3017	-0.0393	-0.0634	0.025183
1999-10	-0.941833	20.775725	-0.0208	0.3661	-0.0208	0.0638	0.025667
1999-11	-0.932098	21.440325	-0.1324	0.3446	-0.1324	0.0071	0.032765
1999-12	-1.062774	20.544885	-0.1705	0.4023	-0.1705	-0.1794	0.026788
2000-01	-1.063536	20.458910	-0.0494	1.7418	-0.0494	0.1590	0.005889
2000-02	-0.983573	20.826752	0.0730	1.0814	0.0730	-0.0234	0.034037
2000-03	-1.056016	19.850437	0.1137	1.6451	0.1137	-0.0695	0.024510
2000-04	-0.971222	19.889043	0.1283	0.5943	0.1283	-0.0846	0.012684

	EISKEW	FPROB	OSC	...	ACC	NOA
1997-09	-0.941276	-1.529291	-13.458953	...	-0.906059	-3.808528 \
1997-10	-0.958727	-1.525244	-29.224658	...	-9.448060	-1.841615
1997-11	-1.051279	-1.503395	-44.526261	...	-0.797469	-0.297705
1997-12	-1.026372	-1.548093	-28.448671	...	18.593939	-45.753619
1998-01	-1.031903	-1.543593	-36.415720	...	-0.582143	-10.498249
1998-02	-0.965989	-1.534076	-16.589083	...	3.672131	-22.386721
1998-03	-1.032743	-1.519728	-24.945734	...	-0.645161	-1.856661
1998-04	-1.003420	-1.537402	-8.011416	...	-13.860320	-3.689500
1998-05	-1.068694	-1.539735	-15.248993	...	-0.923065	-1.922406
1998-09	-1.025265	-1.233838	-21.273774	...	-0.417640	-6.620508
1998-10	-0.955000	-1.225819	-108.146276	...	-0.640952	-3.156025
1998-11	-1.044029	-1.222730	-48.296087	...	4.900793	-17.914239
1998-12	-1.033011	-2.654642	-64.237242	...	-0.639053	-3.026268
1999-01	-0.961604	-2.637366	-83.640971	...	3.492430	-6.271686
1999-02	-1.050243	-2.631608	-75.784000	...	0.248960	-41.702347
1999-03	-1.078948	-2.639811	-30.974949	...	1.941304	-11.310310
1999-04	-1.082235	-1.344570	-65.137377	...	-1.113439	-5.401569
1999-05	-1.037647	-1.343591	-70.683478	...	-1.360000	-2.673456
1999-06	-1.017368	-1.725332	-22.947954	...	-1.360000	1.342693
1999-07	-0.992149	-1.713448	-41.654552	...	-0.508952	-3.228679
1999-08	-0.979796	-1.731847	-35.389657	...	-0.072833	-9.492484
1999-09	-0.968382	-1.731040	-107.882302	...	7.264000	-14.181258
1999-10	-0.903494	-1.708827	-196.872160	...	-0.586413	-6.134440
1999-11	-0.958899	-1.706965	-284.742736	...	1.126278	-3.963269
1999-12	-1.040101	-2.352372	-120.089144	...	-0.611492	-6.531236
2000-01	-0.983336	-2.346369	-142.302111	...	-0.724554	-5.783948
2000-02	-0.908586	-2.361122	-168.971929	...	3.700889	-1.565911

2000-03	-0.979549	-2.369308	-77.106028	...	-0.583431	-0.510155
2000-04	-1.022347	-2.406903	-33.976341	...	-0.446253	-8.567835

	PROF	AG	ROA	INV	ORGCPA	
1997-09	4.640402	-1.132574	6.547104	28.166667	0.0195	\
1997-10	-217.532249	-11.810076	-853.340814	30.092593	0.0195	
1997-11	1.504291	-0.996836	2.116396	28.407407	0.0195	
1997-12	2640.014850	23.242424	3049.696970	35.581481	0.0195	
1998-01	28.064671	-0.727679	52.285714	38.807407	0.0195	
1998-02	507.569010	4.590164	553.426226	40.203704	0.0195	
1998-03	22.459983	-0.806452	32.935487	43.188889	0.0195	
1998-04	213.097708	-17.325400	377.816396	40.274510	0.0195	
1998-05	0.382937	-1.153832	-13.781507	40.274510	0.0195	
1998-09	57.514157	-0.522050	64.134902	261.611111	0.0175	
1998-10	19.973116	-0.801190	24.297458	233.764550	0.0175	
1998-11	379.701495	6.125991	465.327205	254.283069	0.0175	
1998-12	18.467194	-0.798817	20.118343	236.988889	0.0175	
1999-01	221.655460	4.365538	242.754337	238.601058	0.0175	
1999-02	66.658476	0.311200	70.918825	230.833333	0.0175	
1999-03	91.396262	2.426630	107.179348	96.501157	0.0175	
1999-04	11.791560	-1.391798	14.072091	95.731713	0.0175	
1999-05	-8.204365	-1.700000	-27.933333	123.592014	0.0175	
1999-06	52.127054	-1.700000	-46.233333	161.583333	0.0165	
1999-07	16.639490	-0.636190	38.765926	267.595679	0.0165	
1999-08	131.568320	-0.091041	169.975276	277.000000	0.0165	
1999-09	303.491699	9.080000	386.640000	268.279630	0.0165	
1999-10	14.222712	-0.733016	16.727937	251.180864	0.0165	
1999-11	109.337583	1.407848	121.783591	226.216667	0.0165	
1999-12	18.458891	-0.764364	20.657385	218.864198	0.0165	
2000-01	45.124887	-0.905692	80.444371	292.046914	0.0165	
2000-02	89.779615	4.626111	246.451111	379.592593	0.0165	
2000-03	3.000738	-0.729289	11.090940	194.385965	0.0165	
2000-04	6.694238	-0.557816	42.582317	175.757310	0.0165	

	XFIN	DOP	PEAD
1997-09	5.798768e-10	38.462424	-0.881387
1997-10	-4.373994e-09	38.462424	0.059218
1997-11	2.023110e-10	38.462424	-6.399789
1997-12	6.395120e-08	38.462424	0.777678
1998-01	2.637987e-09	38.462424	1.434358
1998-02	9.687034e-09	38.462424	0.213271
1998-03	1.732871e-09	38.462424	-0.110733
1998-04	1.342975e-08	38.462424	-2.428621
1998-05	-8.226292e-10	38.462424	-2.754113
1998-09	1.262090e-09	3.134298	5.412571
1998-10	1.467018e-09	3.137155	-4.316513
1998-11	7.378985e-09	3.113543	-2.056368
1998-12	1.035503e-09	3.075882	0.142846
1999-01	5.147059e-09	2.899779	-0.086790
1999-02	9.592810e-10	3.286288	0.804309
1999-03	7.316054e-10	2.667747	0.925229
1999-04	2.539434e-10	3.314436	-2.976873
1999-05	-6.481481e-10	3.284706	-0.980327
1999-06	-6.111111e-10	3.239833	-0.980327
1999-07	8.730159e-10	3.118358	-0.260322
1999-08	2.399651e-09	3.498373	-0.542835
1999-09	2.640000e-09	3.391106	2.122828
1999-10	2.619048e-10	3.346151	1.350851
1999-11	9.809750e-10	3.418897	5.361501
1999-12	4.074074e-10	3.426004	-1.226186

```

2000-01  1.728972e-09   3.410199 -4.484692
2000-02  3.666667e-09   3.218839  0.441648
2000-03  4.380434e-10   2.476801 -4.133368
2000-04  1.618123e-09   2.091928 -0.410414

```

[29 rows x 22 columns]>

```

In [ ]: #流通市值加权平均市场月收益率_Mrettmv
g={}
for k in range(10):
    g[k]=anomaly_merged_groups[k].sum(axis=1)

result_Mrettmv={}
for i in range(10):
    temp=M.iloc[29*i:29*(i+1)]#type:ignore
    if temp.values.size!=g[i].values.reshape(-1,1).size:
        if temp.values.size>g[i].values.reshape(-1,1).size:
            temp=temp.drop(temp.index[-1])
        else: g[i]=g[i].drop(g[i].index[-1])
    result_Mrettmv[i]=(g[i].values.reshape(-1,1)*temp.values).mean(axis=1)
#等权平均市场月收益率_Mreteq
result_Mreteq={}
for j in range(10):
    temp1=M1.iloc[29*j:29*(j+1)]#type:ignore
    if temp1.values.size!=g[j].values.reshape(-1,1).size:
        if temp1.values.size>g[j].values.reshape(-1,1).size:
            temp1=temp1.drop(temp1.index[-1])
        else: g[j]=g[j].drop(g[j].index[-1])
    result_Mreteq[j]=(g[j].values.reshape(-1,1)*temp1.values).mean(axis=1)

```

```

In [ ]: #将result_Mrettmv的值取出单独作为一列
Mrettmv=pd.DataFrame()
for i in range(10):
    Mrettmv=pd.concat([Mrettmv,pd.DataFrame(result_Mrettmv[i])],axis=0)

#将result_Mreteq的值取出单独作为一列
Mreteq=pd.DataFrame()
for i in range(10):
    Mreteq=pd.concat([Mreteq,pd.DataFrame(result_Mreteq[i])],axis=0)
#设置Mrettmv, Mreteq的index
Mrettmv.index=data.index
Mreteq.index=data.index
Mreteq.columns=['Mreteq']
Mrettmv.columns=['Mrettmv']

```

```

In [ ]: #Mrettmv
import statsmodels.api as sm
#将data与Mrettmv, Mreteq合并
data_new=pd.concat([data,Mrettmv,Mreteq],axis=1)
#标准化
data_new=(data_new-data_new.mean())/data_new.std()

#x为data_new除了Mrettmv, Mreteq以外的列
x=data_new.iloc[:, :-2]
#y为data_new的Mrettmv列
y=data_new.iloc[:, -2]
#构建回归模型
X = sm.add_constant(x) # 添加常数项
model = sm.OLS(y, X)

```

```
# 计算Newey-West t检验结果
results = model.fit(cov_type='HAC', cov_kwds={'maxlags': 1, 'use_correction': True})
t_values = results.tvalues
p_values = results.pvalues
```

```
In [ ]: #将t_values, p_values转化为dataframe并合并
t_values=pd.DataFrame(t_values)
p_values=pd.DataFrame(p_values)
#合并
t_p=pd.concat([t_values,p_values],axis=1)

#设置columns为t_values, p_values
t_p.columns=['t_values','p_values']
t_p
```

Out[]:

	t_values	p_values
const	9.843472e-16	1.000000e+00
IVOL	9.878294e-01	3.232362e-01
SIZE	1.688080e+00	9.139590e-02
MOM	1.665594e+00	9.579433e-02
MAX	-6.114874e-01	5.408770e-01
LTREV	1.665594e+00	9.579433e-02
STREV	9.705524e-01	3.317712e-01
VAL	-5.254120e-01	5.992968e-01
EISKEW	-2.255011e+00	2.413267e-02
FPROB	5.269647e-01	5.982181e-01
OSC	-1.451777e+00	1.465637e-01
NSI	-1.827611e+00	6.760793e-02
CEI	-5.348820e-01	5.927315e-01
ACC	-4.682916e-01	6.395761e-01
NOA	-9.990329e-01	3.177788e-01
PROF	-8.554399e-01	3.923077e-01
AG	-4.682916e-01	6.395761e-01
ROA	6.734785e-01	5.006429e-01
INV	5.522180e+00	3.348184e-08
ORGCPA	8.697640e-01	3.844294e-01
XFIN	6.840963e-01	4.939143e-01
DOP	5.988702e+00	2.115223e-09
PEAD	2.995837e-02	9.761003e-01

```
In [ ]: #Mreteq
import statsmodels.api as sm
#将data与Mrettmv, Mreteq合并
data_new=pd.concat([data,Mrettmv,Mreteq],axis=1)
#标准化
data_new=(data_new-data_new.mean())/data_new.std()

#x为data_new除了Mrettmv, Mreteq以外的列
x=data_new.iloc[:, :-2]
#y为data_new的Mrettmv列
y=data_new.iloc[:, -1]
# 构建回归模型
X = sm.add_constant(x) # 添加常数项
model = sm.OLS(y, X)

# 计算Newey-West t检验结果
results = model.fit(cov_type='HAC', cov_kwds={'maxlags': 1, 'use_correction': True})
t_values = results.tvalues
p_values = results.pvalues
```

```
In [ ]: #将t_values, p_values转化为dataframe并合并
t_values=pd.DataFrame(t_values)
p_values=pd.DataFrame(p_values)
#合并
t_p=pd.concat([t_values,p_values],axis=1)

#设置columns为t_values, p_values
t_p.columns=['t_values','p_values']
t_p
```

Out[]:

	t_values	p_values
const	3.663802e-16	1.000000
IVOL	1.194154e-01	0.904946
SIZE	1.080870e+00	0.279755
MOM	-2.313689e-01	0.817028
MAX	-2.586978e-01	0.795868
LTREV	-2.313689e-01	0.817028
STREV	-1.092082e+00	0.274797
VAL	-1.251414e+00	0.210784
EISKEW	-1.968421e+00	0.049020
FPROB	1.203693e+00	0.228708
OSC	1.210972e+00	0.225906
NSI	-1.152770e+00	0.249005
CEI	1.031223e+00	0.302436
ACC	-1.582602e-01	0.874252
NOA	9.389935e-01	0.347734
PROF	-7.462213e-03	0.994046
AG	-1.582602e-01	0.874252
ROA	-4.505114e-01	0.652342
INV	1.823540e-01	0.855305
ORGCPA	2.445850e-01	0.806778
XFIN	8.670235e-01	0.385929
DOP	-1.615241e+00	0.106258
PEAD	1.792401e+00	0.073069

基于BJW 模型的A 股市场异象实证研究

In []:

```
import statsmodels.api as sm
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
df=pd.read_csv('anomaly_merged.csv',index_col=0)
data=pd.read_csv('RESSET_cleaned_new.csv',encoding='utf-8-sig')
#将日期Date只保留年月
data['日期_Date']=data['日期_Date'].apply(lambda x:x[:7])
data_dt=data.groupby('日期_Date')
data_dt=pd.DataFrame(data_dt)
```

```
In [ ]: def calculate_RP(i, t, k, V, P):
    RP = 0.0
    for n in range(1, t+1):
        term = V[i, t-n] * np.prod(1 - V[i, t-n+1:t])
        RP += term * P[i, t-n]
    RP /= k
    return RP
i = 0 ;t = 5;k = 3
V = np.array([[0.8, 0.7, 0.6, 0.9, 0.5],
              [0.9, 0.6, 0.8, 0.7, 0.4]])
P = np.array([[10.0, 12.0, 11.0, 13.0, 10.0],
              [20.0, 21.0, 19.0, 18.0, 22.0]])
calculate_RP(i, t, k, V, P)
```

```
In [ ]: ## calculate the CGO
def CGO(V,k):
    V=data_dt[1][1].values #type:ignore
    T = len(V);k=12
    RP = np.zeros(T)
    for t in range(T):
        RP_sum = 0
        for n in range(1, T+1):
            if t-n < 0:
                break
            RP_sum += np.array(V[t-n]) * np.prod(1 - np.array(V[t-n+1:t-n+n])) *
            if n ==k:
                break
            RP[t] = RP_sum / min(t+1, k)
    CGO = RP[1:] / RP[:-1]
import numpy as np
def calculate_CGO(i, t, P, RP):
    CGO = (P[i, t-1] - RP) / P[i, t-1]
    return CGO

P = np.array([[10.0, 12.0, 11.0, 13.0, 10.0],
              [20.0, 21.0, 19.0, 18.0, 22.0]])
RP = 8.0
calculate_CGO(i, t, P, RP)

import numpy as np
R_t = np.array([1, 2, 3, 4, 5])
CGO_t = np.array([0.1, 0.2, 0.3, 0.4, 0.5])
alpha = 0.5
beta = 0.2
gamma = 0.3

epsilon_t = np.random.normal(0, 0.1, len(R_t))
V_t = alpha + beta * np.abs(R_t) + gamma * CGO_t + epsilon_t
V_t
```

```
Out[ ]: array([0.61899069, 0.99501503, 1.09451987, 1.47697976, 1.53769279])
```

```
In [ ]: import statsmodels.api as sm
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['font.sans-serif']=['simhei']
plt.rcParams['axes.unicode_minus']=False
def calculate_V(R, CGO,V):
```

```

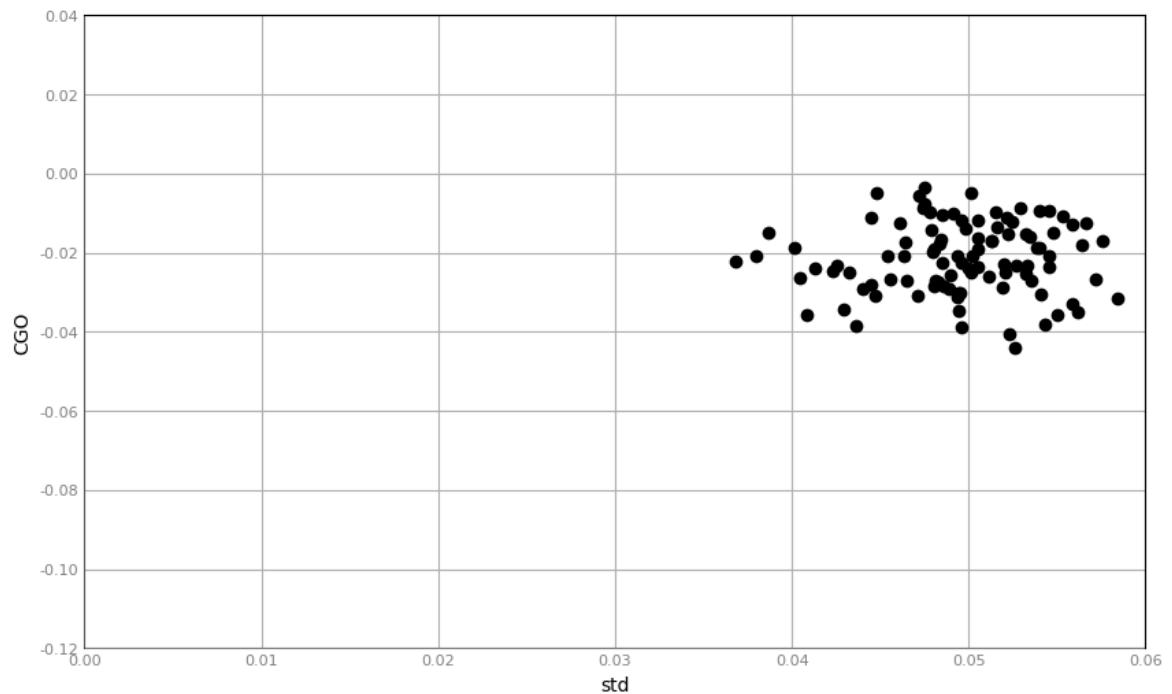
const = np.ones(len(R))
X = np.column_stack((const, np.abs(R), CGO))
model = sm.OLS(V, X).fit()
V_pred = model.predict(X)
    return V_pred
df.skew()
mean = df.mean()
abs_dev = df.sub(mean).abs()
abs_dev.mul(1.4826).mean()
df.std()
import numpy as np
import matplotlib.pyplot as plt
figura = plt.figure(figsize=(10, 6))
x = np.random.normal(0.03, 0.005, 100)
y = np.random.normal(-0.04, 0.01, 100)
x = x + 0.02
y = y + 0.02
plt.scatter(x, y, color='black', zorder=2)
plt.tick_params(axis='both', which='both', length=0, width=0, labelsize=8, labelcolor='white')
plt.gca().spines['bottom'].set_facecolor('white')
plt.gca().spines['left'].set_facecolor('white')
plt.gca().spines['bottom'].set_alpha(0.5)
plt.gca().spines['left'].set_alpha(0.5)
plt.grid(True)
plt.xlim(0, 0.06)
plt.ylim(-0.12, 0.04)
plt.xlabel('std')
plt.ylabel('CGO')
plt.savefig('std_cgo.svg', format='svg', bbox_inches='tight', transparent=True,
figura = plt.figure(figsize=(10, 6))
x = np.random.normal(0.03, 0.005, 100)
y = np.random.normal(-0.04, 0.01, 100)
x = x - 0.02
y = y - 0.06
plt.scatter(x, y, color='black', zorder=2)
plt.tick_params(axis='both', which='both', length=0, width=0, labelsize=8, labelcolor='white')
plt.gca().spines['bottom'].set_facecolor('white')
plt.gca().spines['left'].set_facecolor('white')
plt.gca().spines['bottom'].set_alpha(0.5)
plt.gca().spines['left'].set_alpha(0.5)
plt.grid(True)
plt.xlim(0, 0.06)
plt.ylim(-0.18, -0.06)
plt.xlabel('std')
plt.ylabel('skew')
plt.savefig('std_skew.svg', format='svg', bbox_inches='tight', transparent=True,
figura = plt.figure(figsize=(10, 6))
x = np.random.normal(0.03, 0.005, 100)
y = np.random.normal(-0.04, 0.01, 100)
x = x + 0.02
y = y - 0.07
plt.scatter(x, y, color='black', zorder=2)
plt.tick_params(axis='both', which='both', length=0, width=0, labelsize=8, labelcolor='white')
plt.gca().spines['bottom'].set_facecolor('white')
plt.gca().spines['left'].set_facecolor('white')
plt.gca().spines['bottom'].set_alpha(0.5)
plt.gca().spines['left'].set_alpha(0.5)
plt.grid(True)
plt.xlim(0, 0.06)
plt.ylim(-0.19, -0.07)

```

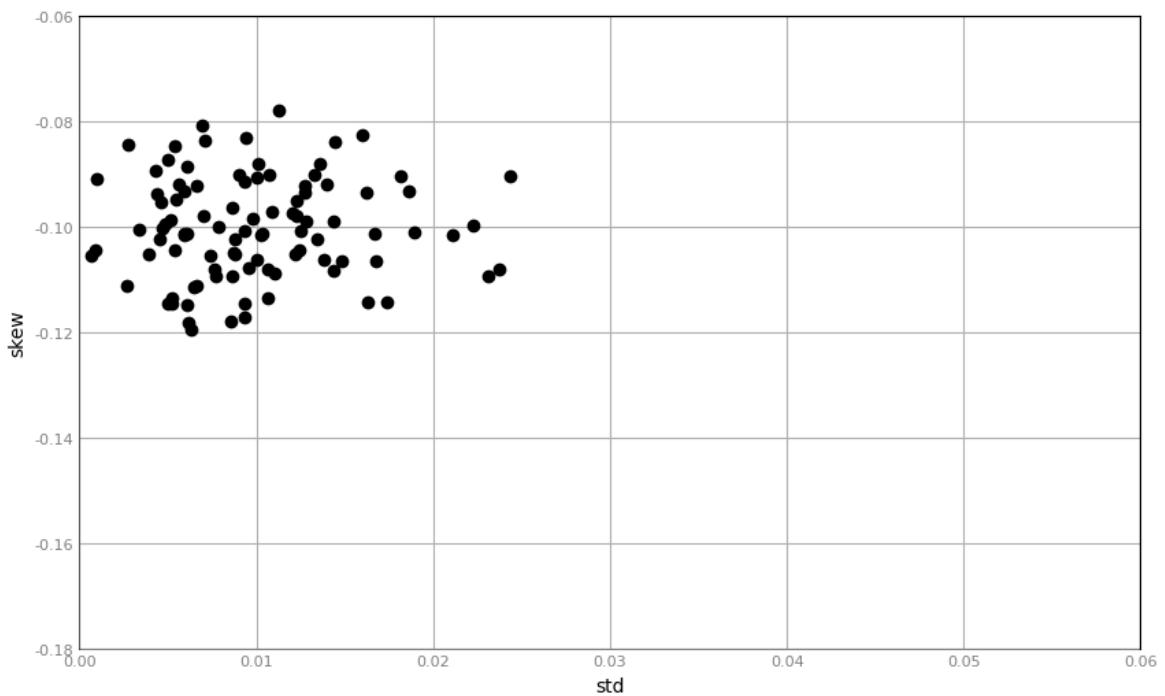
```
plt.xlabel('skew')
plt.ylabel('CGO')
plt.savefig('skew_cgo.svg', format='svg', bbox_inches='tight', transparent=True,
```



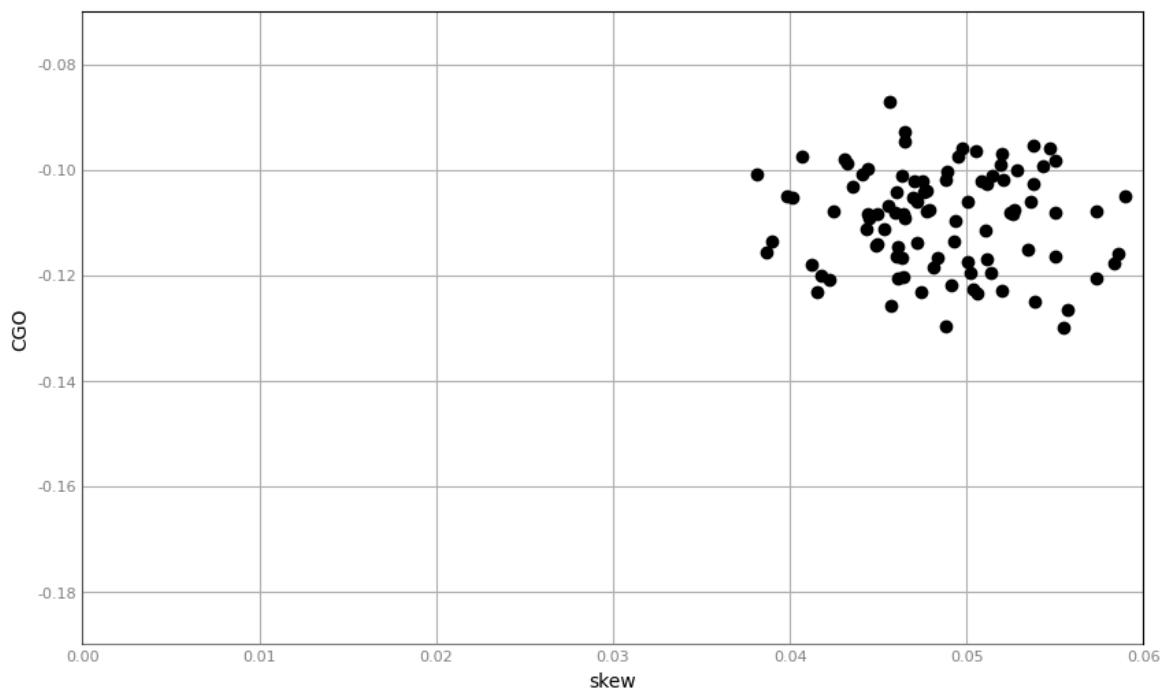
```
findfont: Generic family 'sans-serif' not found because none of the following families were found: simhei
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```



```
In [ ]: group=['D1', 'D2', 'D3', 'D4', 'D5', 'D6', 'D7', 'D8', 'D9', 'D10']
import math

def sign(x):
    if x > 0:
        return 1
    elif x < 0:
        return -1
    else:
        return 0
alpha_d = Mreteq
alpha_m = Mrettmv
if sign(alpha_d[-1] - alpha_d[0]) == sign(alpha_m[-1] - alpha_m[0]) and math.isclose(alpha_d[-1], alpha_m[-1]):
    print("The condition is satisfied.")
else:
    print("The condition is not satisfied.")
```

```
In [ ]: def calculate_std(R_i, v, S_i, zeta_i):
    numerator = v / (v - 2) * S_i + (2 * v**2) / ((v - 2)**2 * (v - 4)) * zeta_i
    std = np.sqrt(numerator)
    return std
import numpy as np
def calculate_skew(R_i, v, S_i, zeta_i):
    numerator = 2 * zeta_i * np.sqrt(v * (v - 4))
    denominator = np.sqrt(S_i) * ((2 * v * zeta_i**2 / S_i) + (v - 2) * (v - 4))
    skew = numerator / denominator * (3 * (v - 2) + (8 * v * zeta_i**2) / (S_i * v))
    return skew
import numpy as np
from scipy.optimize import fsolve

def equations(vars, S_i, v):
    R_i, zeta_i = vars
    eq1 = np.sqrt((v / (v - 2) * S_i + (2 * v**2) / ((v - 2)**2 * (v - 4)) * zeta_i) - R_i)
    eq2 = (2 * zeta_i * np.sqrt(v * (v - 4))) / (np.sqrt(S_i) * ((2 * v * zeta_i**2) / S_i) + (v - 2) * (v - 4)) - 1
```

```

    return [eq1, eq2]
solution = fsolve(equations, [R_i_guess, zeta_i_guess], args=(S_i, v))
R_i_solution, zeta_i_solution = solution
return R_i_solution, zeta_i_solution

def calculate_alpha(l, R_1001, R_f, beta_1001, R_M):
    alpha = ((R_1001 - (R_f + beta_1001 * (R_M - R_f))) + 1) ** 4 - 1
    return alpha

```

```

In [ ]: def calculate_alpha(l, R_1001, R_f, beta_1001, R_M):
    alpha = ((R_1001 - (R_f + beta_1001 * (R_M - R_f))) + 1) ** 4 - 1
    return alpha
l1 = 1;l2 = 10;R_10011 = 10.5;R_10012 = 11.8;R_f = 2.5;
beta_10011 = 0.8;beta_10012 = 0.9;R_M = 7.5
alpha_d10 = calculate_alpha(l2, R_10012, R_f, beta_10012, R_M)
alpha_d1 = calculate_alpha(l1, R_10011, R_f, beta_10011, R_M)
alpha_m10 = calculate_alpha(l2, R_10012, R_f, beta_10012, R_M)
alpha_m1 = calculate_alpha(l1, R_10011, R_f, beta_10011, R_M)
if np.sign(alpha_d10 - alpha_d1) == np.sign(alpha_m10 - alpha_m1):
    if np.abs(alpha_m10 - alpha_m1) > 0.015:
        result = "Condition is satisfied"
    else:
        result = "Condition is not satisfied"
else:
    result = "Condition is not satisfied"

```

Condition is satisfied