Discussed with: Nanhao Wang

Q1.

- Shareholders' equity (SHE): variable reported in Compustat is "Stockholders' Equity Total" (SEQ). If not available, use "Common/Ordinary Equity Total" (CEQ) plus "Preferred/Preference Stock (Capital) Total" (PSTK). If not avail- able, use "Assets Total" (AT) minus "Liabilities Total" (LT) minus "Minority Interest (Balance Sheet)" (MIB). If not available, use AT minus LT.
- Deferred taxes and investment tax credit (DT): variable reported in Compustat is "Deferred Taxes and Investment Tax Credit" TXDITC. If not available, use "Investment Tax Credit (Balance Sheet)" (ITCB) plus "Deferred Taxes (Balance Sheet)" (TXDB). If not available, sum what is not missing.
- Book value of preferred stock (PS): Use redemption value, which is variable "Preferred Stock Redemption Value" (PSTKRV). If not available, use liquidation value, which is "Preferred Stock Liquidating Value" (PSTKL). If not available, use par value, which is "Preferred/Preference Stock (Capital) Total" (PSTK).
- Define book equity (BE) as: BE = SHE PS + DT PRBA (need value of SHE to compute BE, other variables included if not missing). The last variable is "Postretirement Benefit Asset" (PRBA), and you will have to get this variable from Compustat's Pension Annual data: merge to Compustat using Compustat's global variable key (GVKEY).
- (optional) For missing value of book equity, you can use historical book equity value available n French's website—Davis, Fama and French (2000)'s data.
- To calculate book-to-market, you will have to sum the market equity of subsidiaries.
 A company (permanent identifier variable: PERMCO) may have different securities
 (identified by PERMNO).

Reference: https://wrds-www.wharton.upenn.edu/pages/support/applications/risk-factors-and-industry-benchmarks/fama-french-factors-python/

Connect to WRDS using Python package wrds to download all the data sets: Compustat, CRSP, and linked table.

Create Shareholders' equity, deferred taxes and investment tax credit, preferred stock, and create book equity as the instructions above by using Compustat data set.

Create total market cap of all the firms by sum up all the me across different PERMNO according to the same PERMNO on a given date. And denote the market cap of each December as dec me.

Create a column called 'ffyear', which is the fiscal year corresponding to the period from July last year to this June.

Link link table with compustat by gvkey. And then link with CRSP by ffyear and PERMNO. Calculate book-to-market using be/dec me.

Extract July data as the benchmark to rebalance for the next fiscal year. And then extract NYSE data to create breakpoints for both size and book-to-market. And then create decile by using those breakpoints.

Merge back the deciles to get the final dataframe based on fiscal year, so that for each PERMNO, the decile does not change within the same fiscal year.

Calculate value-weighted return based on both size decile and book-to-market decile.

For SMB, it's similar to size decile except that the market cap is divided to 2 parts. And for HML, it's similar to book-to-market decile expect that the book-to-market is divided to 3 parts: the lower 30%, higher 30% and 40% in the middle. $SMB = \frac{1}{3}(Small\ value + Small\ neutral + Small\ growth) - \frac{1}{3}(Big\ value + Big\ neutral + Big\ growth)$ $HML = \frac{1}{2}(Small\ value + Big\ value) - \frac{1}{2}(Small\ growth + Big\ growth)$

Output of question 1

	Year	Month	port	Size_Ret	BtM_Ret	HML_Ret	SMB_Ret
0	1973	1	1.0	-0.036063	-0.010181	2.223979	-3.108647
1	1973	1	2.0	-0.041768	-0.049391	2.223979	-3.108647
2	1973	1	3.0	-0.050724	-0.050517	2.223979	-3.108647
3	1973	1	4.0	-0.066884	-0.047901	2.223979	-3.108647
4	1973	1	5.0	-0.054671	-0.018638	2.223979	-3.108647
5	1973	1	6.0	-0.046942	-0.004542	2.223979	-3.108647
6	1973	1	7.0	-0.057130	-0.017961	2.223979	-3.108647
7	1973	1	8.0	-0.047499	-0.011810	2.223979	-3.108647
8	1973	1	9.0	-0.066290	-0.029559	2.223979	-3.108647
9	1973	1	10.0	-0.005412	-0.048175	2.223979	-3.108647
10	1973	2	1.0	-0.077244	-0.024979	2.147442	-3.591549
11	1973	2	2.0	-0.086348	-0.046918	2.147442	-3.591549
12	1973	2	3.0	-0.076031	-0.049377	2.147442	-3.591549
13	1973	2	4.0	-0.064241	-0.042010	2.147442	-3.591549
14	1973	2	5.0	-0.075851	-0.053065	2.147442	-3.591549
15	1973	2	6.0	-0.065527	-0.050147	2.147442	-3.591549
16	1973	2	7.0	-0.064866	-0.046174	2.147442	-3.591549
17	1973	2	8.0	-0.049762	-0.057316	2.147442	-3.591549
18	1973	2	9.0	-0.036469	-0.025129	2.147442	-3.591549
19	1973	2	10.0	-0.032830	-0.039739	2.147442	-3.591549
20	1973	3	1.0	-0.025368	-0.015935	2.278014	-2.354737
21	1973	3	2.0	-0.029205	-0.008121	2.278014	-2.354737
22	1973	3	3.0	-0.017010	-0.021288	2.278014	-2.354737
23	1973	3	4.0	-0.027501	-0.014330	2.278014	-2.354737
24	1973	3	5.0	-0.021702	0.009721	2.278014	-2.354737
25	1973	3	6.0	-0.027830	0.007591	2.278014	-2.354737
26	1973	3	7.0	-0.015350	0.007414	2.278014	-2.354737
27	1973	3	8.0	-0.029137	0.004760	2.278014	-2.354737

28 29	1973 1973	3	9.0 10.0	-0.010600 0.002189	-0.008195 0.019358		-2.354737 -2.354737	
 5490	2018	10		-0.106321			-4.552330	
5491	2018	10	2.0	-0.112489	-0.066827	3.490169	-4.552330	
5492	2018	10		-0.117944		3.490169	-4.552330	
5493	2018	10	4.0	-0.114711	-0.066817	3.490169	-4.552330	
5494	2018	10	5.0	-0.112032	-0.091214	3.490169	-4.552330	
5495	2018	10	6.0	-0.095991	-0.049168	3.490169	-4.552330	
5496	2018	10	7.0	-0.104168	-0.044148	3.490169	-4.552330	
5497	2018	10	8.0	-0.088892	-0.059503	3.490169	-4.552330	
5498	2018	10	9.0	-0.078257	-0.060141	3.490169	-4.552330	
5499	2018	10	10.0	-0.066754	-0.083860	3.490169	-4.552330	
5500	2018	11	1.0	-0.020913	0.035290	0.375407	-0.890703	
5501	2018	11	2.0	-0.006387	-0.024576	0.375407	-0.890703	
5502	2018	11	3.0	0.012520	0.024782	0.375407	-0.890703	
5503	2018	11	4.0	0.031010	0.040562	0.375407	-0.890703	
5504	2018	11	5.0	0.015718	0.016926	0.375407	-0.890703	
5505	2018	11	6.0	0.015628	0.025952	0.375407	-0.890703	
5506	2018	11	7.0	0.039732	0.018410	0.375407	-0.890703	
5507	2018	11	8.0	0.020782	0.020342	0.375407	-0.890703	
5508	2018	11	9.0	0.017583	0.028547	0.375407	-0.890703	
5509	2018	11	10.0	0.017759	-0.001027	0.375407	-0.890703	
5510	2018	12	1.0	-0.125755	-0.081975	-1.121218	-2.589685	
5511	2018	12	2.0	-0.122696	-0.095641	-1.121218	-2.589685	
5512	2018	12	3.0	-0.116662	-0.080497	-1.121218	-2.589685	
5513	2018	12	4.0	-0.124721	-0.083660	-1.121218	-2.589685	
5514	2018	12	5.0	-0.121940	-0.109434	-1.121218	-2.589685	
5515	2018	12	6.0	-0.116842	-0.108027	-1.121218	-2.589685	
5516	2018	12	7.0	-0.112798	-0.113162	-1.121218	-2.589685	
5517	2018	12	8.0	-0.105454	-0.110789	-1.121218	-2.589685	
5518	2018	12	9.0	-0.093070	-0.099780	-1.121218	-2.589685	
5519	2018	12	10.0	-0.087640	-0.121404	-1.121218	-2.589685	

Q2.

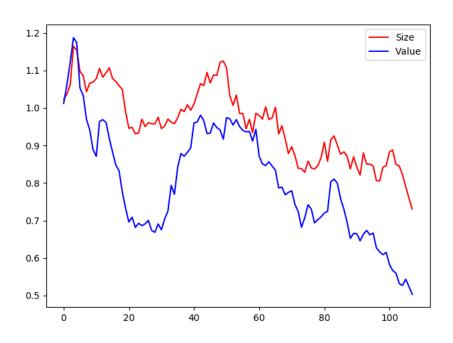
	1	2	3	4	5	6
Annualized Mean	4.956	6.166	7.519	7.755	7.186	7.552
Annualized Volatility	18.290	16.487	16.095	16.462	15.850	15.625
Sharpe Ratio	0.271	0.374	0.467	0.471	0.453	0.483
Skewness	-0.236	-0.443	-0.547	-0.491	-0.472	-0.367
correlation	0.991	0.980	0.971	0.970	0.964	0.968
	6	7	8	9	10	Long-Short
Annualized Mean	7.552	7.571	7.987	8.289	9.297	4.341
Annualized Volatility	15.625	15.442	15.895	15.847	19.332	15.390
Sharpe Ratio	0.483	0.490	0.502	0.523	0.481	0.282

Skewness	-0.367	-0.273	-0.520	-0.284	-0.162	0.354
correlation	0.968	0.952	0.952	0.943	0.951	0.906

Q3.

	1	2	3	4	5	6
Annualized Mean	4.956	6.166	7.519	7.755	7.186	7.552
Annualized Volatility	18.290	16.487	16.095	16.462	15.850	15.625
Sharpe Ratio	0.271	0.374	0.467	0.471	0.453	0.483
Skewness	-0.236	-0.443	-0.547	-0.491	-0.472	-0.367
correlation	0.991	0.980	0.971	0.970	0.964	0.968
	6	7	8	9	10	Long-Short
Annualized Mean	7.551558	7.570848	7.987096	8.289102	9.296549	4.340931
Annualized Volatility	15.625131	15.442419	15.895425	15.847016	19.331899	15.389518
Sharpe Ratio	0.483296	0.490263	0.502478	0.52307	0.480892	0.282071
Skewness	-0.367341	-0.273134	-0.520222	-0.284202	-0.161642	0.353955
correlation	0.968325	0.952223	0.951935	0.943369	0.951071	0.905526

Q4.



According to the graph above, the value and size anomaly worked in the past few years.

Q5.

decile	SMB	HML
Annualized Mean	2.305072	3.844527
Annualized Volatility	10.661128	10.415698
Sharpe Ratio	0.216213	0.369109
Skewness	0.540577	0.036251
correlation	0.992527	0.971065

Q6.