NEOMA BUSINESS SCHOOL

Financial Instruments and Portfolio Choice: Lottery demand (FMAX)

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Msc Finance & Big data

Summary

1 CRSP data cleaning

The first step of the project consisted in a large data cleaning step. In fact, the database provided by the CRSP is very voluminous. Once we had filtered out the prices more than $1, the trading in NYSE, AMEX, or NASDAQ and kept only the common shares, we had to merge the database with the database containing the factors and also the database containing the FMAX strategy that was allocated to our group. The database being excessively voluminous, we made the arbitrary choice to keep only the stocks for which we had values over the whole period of our observation. We thus go from 20k stocks to 141. Then, we obtain this final dataframe which will be used as a basis for our study :

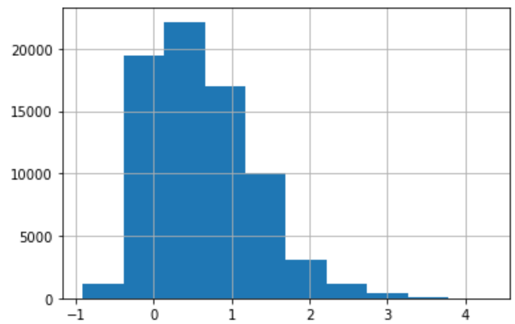
	PERMNO	SHRCD	EXCHCD	PRC	RET	SHROUT	FMAX	Mkt-RF	SMB	HML	RMW	CMA	RF	Excess_RET
date														
1973-01-01	10145	11.0	1.0	30.500	5.1724	27556.0	-7.377896	-3.29	-2.81	2.68	0.42	0.90	0.44	4.7324
1973-02-01	10145	11.0	1.0	32.250	6.7213	27556.0	-3.857187	-4.85	-3.91	1.60	-0.26	0.02	0.41	6.3113
1973-03-01	10145	11.0	1.0	34.500	6.9767	27556.0	-0.753801	-1.30	-2.33	2.62	-1.07	0.62	0.46	6.5167
1973-04-01	10145	11.0	1.0	33.500	-1.9420	27556.0	-6.988274	-5.68	-2.90	5.41	-1.58	2.60	0.52	-2.4620
1973-05-01	10145	11.0	1.0	33.125	-1.1194	27556.0	-2.591145	-2.94	-6.17	0.41	1.95	-1.57	0.51	-1.6294
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2021-08-01	56223	11.0	1.0	63.440	14.7547	95226.0	1.158663	2.91	-0.67	-0.16	-0.30	-1.76	0.00	14.7547
2021-09-01	56223	11.0	1.0	61.370	-3.2629	95226.0	0.154166	-4.37	1.14	5.08	-1.90	2.14	0.00	-3.2629
2021-10-01	56223	11.0	1.0	58.930	-3.9759	95226.0	-0.298968	6.65	-2.70	-0.48	1.68	-1.44	0.00	-3.9759
2021-11-01	56223	11.0	1.0	65.350	11.1997	87989.0	-2.750280	-1.55	-1.76	-0.44	7.22	1.74	0.00	11.1997
2021-12-01	56223	11.0	1.0	78.350	19.8929	87989.0	-9.242136	3.10	-0.77	3.28	4.92	4.43	0.01	19.8829

We have added an excess return column that we will use in the following analysis. Indeed, excess returns are the returns on investment which are in excess of a benchmark or risk-free rate. The benchmark or risk-free rate is used as a comparison to assess the performance of the investment : $E(t) = R(t) - I(t)$, where I(t) is the benchmark. Thus, we calculated for each stock the excess returns by substracting the rf at t time on the returns of the stock (RF from RT).

2 Lottery demand investment strategy

Lottery demande investment strategy differs from traditionals strategy based on beta. In fact, Turan G. Bali, Stephen J. Brown, Scott Murray, and Yi Tang suggest that the traditional interpretation of beta as a measure of risk may not be accurate. The study found that the beta anomaly, which is the tendency of high-beta stocks to deliver lower returns than predicted by the Capital Asset Pricing Model (CAPM), is driven by lottery demand from individual investors. This implies that a strategy that is long low-beta stocks and short high-beta stocks may outperform the market, even after controlling for the effect of lottery demand. This could be an attractive strategy for investors who are looking for a way to generate excess returns while reducing their exposure to market risk. Thus, we will try to apply this strategy in the rest of our study by buying low-beta stocks with high return month-to-month and shorting high-beta stocks with low-return month-to-month.

Figure 1 – Beta distribution



3 Stock's excess returns exposure

Once we had a base ready to go, we set about building our 60-month rollings windows. Thus, we constructed a loop that creates a rolling window of 60 months across all PERMNOS and estimates within each window a linear regression with excess return as the variable to be explained and FMAX (the factor allocated to our group) as the explanatory variable. We thus obtain values for the Beta coefficients resulting from each regression. The highest beta is 4.30 and the lowest is -0.90 but the majority of the distribution is between 0 and 1.

As we can see in the table below, the table is ordered chronologically.

	PERMNO	start_date	end_date	Price	RET	Beta	FMAX	Mkt-RF	SMB	HML	RMW	CMA	RF	Cat
59	10145	59	119	44.250	0.8547	1.276116	0.105970	0.27	1.59	-0.29	0.92	0.92	0.92	Q4
588	10516	59	119	18.000	-10.0000	1.306674	0.105970	0.27	1.59	-0.29	0.92	0.92	0.92	Q1
1117	10874	59	119	14.375	-4.1667	0.787994	0.105970	0.27	1.59	-0.29	0.92	0.92	0.92	Q1
1646	11308	59	119	37.250	-1.6502	0.301733	0.105970	0.27	1.59	-0.29	0.92	0.92	0.92	Q2
2175	11404	59	119	25.375	1.5000	-0.039756	0.105970	0.27	1.59	-0.29	0.92	0.92	0.92	Q4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
72470	51086	526	586	32.450	15.2212	1.273721	1.439624	4.86	7.04	8.19	-0.21	-0.21	-0.21	Q5
72999	52337	526	586	15.230	-22.7296	1.790118	1.439624	4.86	7.04	8.19	-0.21	-0.21	-0.21	Q1
73528	55001	526	586	27.790	30.1639	1.199615	1.439624	4.86	7.04	8.19	-0.21	-0.21	-0.21	Q5
74057	55511	526	586	31.600	-3.8052	-0.176561	1.439624	4.86	7.04	8.19	-0.21	-0.21	-0.21	Q1
74586	56223	526	586	19.340	5.3951	0.727075	1.439624	4.86	7.04	8.19	-0.21	-0.21	-0.21	Q3

The index model, can be used to relate the returns of an individual stock to the returns of the overall market. It works as a linear combination of the returns of the market to the individual stock, such as :

$$R_{Gt} = \alpha_G + \beta_G R_{Mt} + e_{Gt}$$

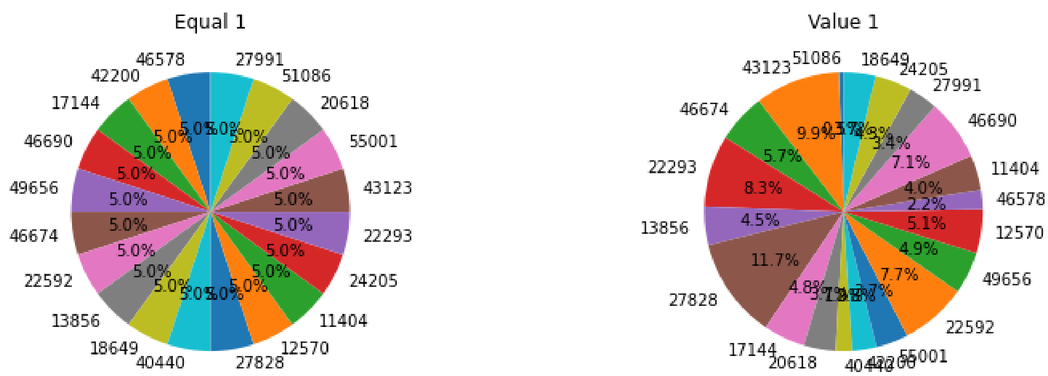
. Where β is an indicator of the relationship between the returns of the stock and the returns of the market. For each stock in our CRSP database we estimate a linear regression with market returns as the explanatory variable. We obtain for the first window from 1973 to december 1977.

4 Trading strategy

The first step of this part of the project was to create 10 portfolios as 5 equally-weighted and 5 values-weighted. These portfolios ares built at t0 (12/1977), the 59th window of our dataframe. We set a random budget of 100k for all portfolios. Each portfolios is composed of 20 stocks at the beggining. For equally-weighted portfolios, the code creates 5 portfolios with equal weights for each of the 20 selected stocks. The code assigns an equal weight of 1/20 for each stock and calculates the quantity and cost of each stock in each portfolio based on the total budget of 100,000. For value-weighted portfolios, the code also creates 5 portfolios, but this time with weights based on the market capitalization of each stock. The code calculates the weight of each stock by dividing the total value of the stock by the total price of all selected stocks (portfolio), and then calculates the quantity and cost of each stock in each portfolio based on the budget.

You can see below the composition of one equal-weighted and one values-weighted portfolio :

Figure 2 – Portfolios compositions

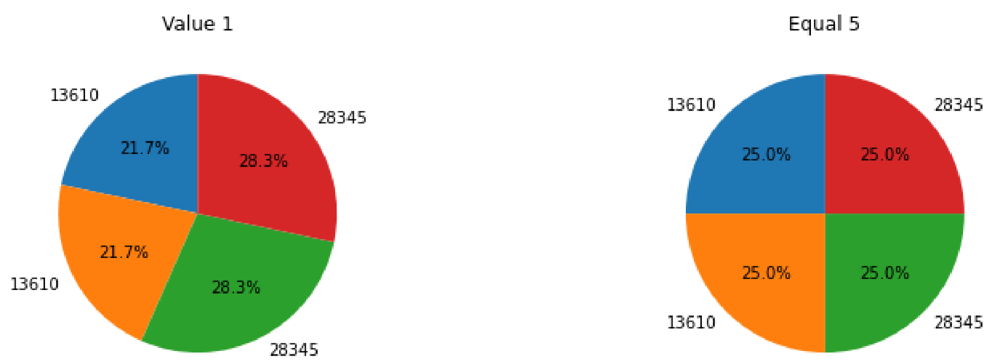


	PERMNO	start_date	Price	RET	Beta	Cat	weights	quantity	cost	portfolio
0	22509	59	27.000	-4.8458	0.471135	Q1	0.050000	18.518519	500.000000	Equal 1
1	24985	59	15.000	-3.3701	0.137482	Q2	0.050000	33.333333	500.000000	Equal 1
2	49015	59	34.750	0.7246	0.628781	Q4	0.050000	14.388489	500.000000	Equal 1
3	23229	59	24.125	1.0471	0.090397	Q4	0.050000	20.725389	500.000000	Equal 1
4	47896	59	42.500	-3.0812	0.217744	Q2	0.050000	11.764706	500.000000	Equal 1
...	...	...	...	...	...	...	...	...	...	...
195	39642	59	31.500	2.1935	0.918251	Q4	0.035498	11.269193	354.979575	Value 5
196	28345	59	38.625	19.7674	1.635850	Q5	0.043527	11.269193	435.272574	Value 5
197	17144	59	30.375	-0.8163	-0.101283	Q3	0.034230	11.269193	342.301733	Value 5
198	14795	59	51.000	0.0000	0.675832	Q3	0.057473	11.269193	574.728835	Value 5
199	56223	59	13.000	-7.1429	1.231389	Q1	0.014650	11.269193	146.499507	Value 5

The quantity of a given stock in the portfolio is calculated by multiplying the weight of that stock by the budget allocated to the portfolio, then dividing by the price of the stock. In this trading strategy we assume no transactionnal cost as the aim is not to study a cost-minimization problem, rather, the consequence of the selection of a given stock over another in the produced returns. Hence transactionnal costs are irrelevant. As defined above, we will systematically buy low-beta stock and short high-beta stocks, we will do so by each rolling window as we get new prices, beta... By the end of the trading perdiod, if the strategy was significant we should be able to observe systematic gains among our portfolio.

As we can see, a 'Category' column has been added. It designates the quantiles to which each return value in the window belongs. This column is important because we have based our trading strategy on it. The objective is to see if the strategy has a significant influence on the returns that can be earned. Indeed, we randomly selected 20 permnos multiplied by 10 portfolios. The idea of our strategy is to resell at t+1, all the stocks held and to buy back accordingly, only the stocks with the highest returns (belonging to the last quantile). By following this strategy we obtain the following portfolios on 11/2021:

Figure 3 – Portfolios compositions at the end date



	PERMNO	start_date	Price	RET	Beta	Cat	Mkt-RF	SMB	HML	RMW	CMA	RF	weights	quantity	cost	portfolio
0	13610	526	26.0	19.4710	0.553213	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	78.628753	2044.347570	Equal 4
1	13610	526	26.0	19.4710	0.553213	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.019119	38.875714	1010.768573	Value 2
2	13610	526	26.0	19.4710	0.553213	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	38.875714	1010.768573	Equal 5
3	13610	526	26.0	19.4710	0.553213	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.019119	38.875714	1010.768573	Value 3
4	13610	526	26.0	19.4710	0.553213	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.019119	38.875714	1010.768573	Value 4
115	49015	526	64.1	30.5765	0.673573	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.047136	30.066145	1927.239919	Value 1
116	49015	526	64.1	30.5765	0.673573	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	38.875714	2491.933289	Equal 3
...	...	...	...	...	...	...	...	...	...	v	...	...	...	...	...	...
117	49015	526	64.1	30.5765	0.673573	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	31.893098	2044.347570	Equal 4
118	49015	526	64.1	30.5765	0.673573	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	38.875714	2491.933289	Equal 5
119	49015	526	64.1	30.5765	0.673573	Q5	4.86	7.04	8.19	-0.21	-0.21	-0.21	0.050000	31.893098	2044.347570	Equal 3

As we can see, our strategy being very restrictive, the stocks that make up the equally weighted and value weighted portfolios are the same. Moreover, all our portfolios in both categories contain exactly the same stocks and proportions. We thus observe a convergence effect. Our strategy is therefore flawed and the sample we have adopted is supposedly too small.

5 Strategy feedback and metrics calculation

5.1 Results for the 10 portfolios

Since we have the same stocks for all our portfolios and very similar proportions, we cannot be surprised to have equal results for all the portfolios. To overcome this issue one might judge relevant to include stocks from others exchanges, like Euronext. However, even though we cannot compare our portfolios, we can still try to interpret our coefficients:

— **CAPM alpha** : The α coefficient from CAPM model is positive, we can conclude that these portfolios outperformed its expected returns given its level of risk (RF).

— **The Fama-French 3 factor alpha** : Fama-French 3-factor alpha is a measure of a portfolio's performance relative to its expected return as predicted by the Fama-French three-factor model, which takes into account not only market risk (as in the CAPM), but also the size and value factors. All the alpha coefficients are positive which means that the portfolios is outperforming its expected returns given its level of risk as predicted by the Fama-French three-factor model.

— **The Fama-French 5 factor alpha** : Fama-French 5-factor alpha is similar to the Fama-French 3-factor alpha, but takes into account two additional factors: profitability and investment. The conclusion is the same way the portfolios is outperforming its expected returns given its level of risk.

	Raw Return	CAPM Alpha	FF3 Alpha	FF5 Alpha
Equal 1	25.7579	5.290102	0.892246	0.891686
Equal 2	25.7579	5.290102	0.892246	0.891686
Equal 3	25.7579	5.290102	0.892246	0.891686
Equal 4	25.7579	5.290102	0.892246	0.891686
Equal 5	25.7579	5.290102	0.892246	0.891686
Value 1	25.7579	5.290102	0.892246	0.891686
Value 2	**27.853533**	5.290102	0.892246	0.891686
Value 3	25.7579	5.290102	0.892246	0.891686
Value 4	25.7579	5.290102	0.892246	0.891686
Value 5	**23.662267**	5.290102	0.892246	0.891686

5.2 Long-short arbitrage portfolio

We also constructed a long-short arbitrage portfolio by taking a long position in the stocks that belong to the 10th portfolio and a short position in the stocks that belong to the 1st portfolio. This arbitrage can be usefull to capture the spread between these two portfolios which are supposed to have different expected returns. The idea is to create a market-neutral position, where the long and short positions offset each other in terms of risk exposure to the overall market, and the profit or loss comes from the difference in the returns of the two portfolios.

In our case, all the portfolios have the same expected returns and we cannot expect earn the difference in returns. However, we can anyway calculate the returns from the Value-weighted 1 portfolio and the 5th one as long as there is a little difference between these two. Substracting Value 1 from Value 5, we get a negative return of **-2.0956**.

6 Conclusion

The big data dimension of the project was the first difficulty we had to face. Perhaps we fell into the trap of wanting to reduce the sample too much to be able to focus on the financial aspect of the strategy, which led us to have a sample that was too small to have a broad view of what the trading strategy that we opted for could allow. Indeed, we focused on 200 randomly selected stocks which showed us that the strategy adopted led to a convergence of the portfolios towards the same stocks at similar proportions regardless of whether they were value-weighted or equally-weighted. Secondly, creating the portfolios was difficult too, especialy when trying to advocate for the best random process to obtain value-weighted protfolios. Lastly, being able to actually code the trading process was such a challenge. How to pick stocks and buy the relevant ones and sell the other ? We try to simplify this by selling all and buying from scratch the portoflio each time. Which acted as a kind of "reset", being in a no-transactionnal costs scenario made this possible, otherwise it would have implied a maximisation of costs, killing our returns.

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