QF101 Quantitative Finance
Academic Year 2022/23 Term 2

Project - Section G1 Group 2

Trading Strategy using Fama-French 3 Factor Model

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Overview of Project

In our project, we aimed to design and implement a trading strategy using the Fama-French 3 Factor Model over the Russell 1000 Components. As an expansion on the Capital Asset Pricing Model (CAPM), we incorporated the size risk and value risk factors into the market risk factor and regressed each stock's excess returns against these factors. Thereafter, we constructed a dollar-neutral portfolio that maximises returns and compared its Profit and Loss (PnL) to that of a long position in the S&P500 Index. This report details our methodology and a discussion of our results along with the challenges that we met.

Brief Description of Fama-French 3 Factor Model (FF3)

$$\mathbf{R_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + e_{it}}$$

Figure 1: Fama-French 3 Factor Model Formula

- R(i) = Stock i's Risk Premium
- R(M) = Market Risk Premium
- SMB = Return on small stocks portfolio in excess of return on large stocks portfolio, taking Market Capitalisation as a proxy for the firm size
- HML = Return on high Book-to-Market ratio stocks portfolio in excess of the return on low Book-to-Market ratio stocks portfolio
- β(i, M), β(i, SMB), β i, HML) = Sensitivity of stock i to Risk Premium of each factor
- α(i) = Intercept of the equation, which is 0 if stock i's Risk Premium is fully explained by the 3 factors of Market Risk Premium, Small Minus Big, and High Minus Low

The first implication of this model is that firms with smaller Market Capitalisation experience higher returns than those with bigger Market Capitalisation, and this is because smaller firms have more opportunities to grow, and their potential is not yet saturated. Secondly, the model also implies that firms with high Book-to-Market ratios experience higher returns than those with low Book-to-Market ratios. This is because high Book-to-Market ratios suggest an undervaluation of the firm, and thus indicating more potential for price jumps and appreciation.

Motivating Factors for Project

The implementation of a trading strategy using the FF3 Model across the Russell 1000 components is interesting for various reasons. The first being that the FF3 Model is a widely used asset pricing model that provides accurate risk-adjusted returns as it considers not only the market risk factor, but also the size and risk factors. Secondly, such a trading strategy provides diversification benefits and reduces concentration risk. This is because the Russell 1000 index consists of the largest 1000 publicly traded U.S. companies (based on Market Capitalisation) that span a variety of industries and sectors. Thirdly, the FF3 Model has also been extensively researched and backtested, thus providing an abundance of information and historical data that can be employed to evaluate the performance of this trading strategy. Last but not least, implementing a trading strategy using the FF3 Model can provide practical insights into portfolio constructions and risk management techniques used in the industry as the model is used by many professional investors and asset managers in these two aspects.

Methodology

We first implemented our trading strategy using CAPM before incorporating the FF3 Model, using Book-to-Market values, Market Risk Premium and Size of firm. On top of these 3 factors, our group explored and implemented additional market and financial independent variables to the strategy, of which are backed by quantitative and qualitative reasonings. Apart from our methodologies, the following section will also detail the backtestings that we conducted on them.

<u>CAPM Methodology</u>

The first step in implementing CAPM over the Russell 1000 Components is to obtain historical data of the stocks, including data on stock prices, Market Capitalisation, Book-to-Market ratios, and Risk-Free rate.

	ticker	dimension	calendardate	datekey	reportperiod	lastupdated	accoci	assets	assetsavg	assetsc	...	sharesbas	shareswa	shareswadil	sps	tangibles	taxassets	taxexp	taxliabilities	tbvps	workingcapital
0	A	ARQ	2010-03-31	2010-06-07	2010-04-30	2020-09-01	-239000000.0	7.767000e+09	NaN	5.712000e+09	...	348062907.0	348000000.0	354000000.0	3.652	6.997000e+09	0.0	31000000.0	0.0	20.106	3.003000e+09
1	A	ARQ	2010-06-30	2010-09-07	2010-07-31	2020-09-01	-225000000.0	9.100000e+09	NaN	5.735000e+09	...	346370351.0	347000000.0	352000000.0	3.988	7.188000e+09	0.0	22000000.0	0.0	20.715	2.818000e+09
2	A	ARQ	2010-09-30	2010-12-20	2010-10-31	2020-09-01	-88000000.0	9.696000e+09	NaN	6.169000e+09	...	347604202.0	344000000.0	356000000.0	4.581	7.746000e+09	0.0	-49000000.0	0.0	22.517	3.086000e+09
3	A	ARQ	2010-12-31	2011-03-09	2011-01-31	2020-09-01	-63000000.0	8.044000e+09	NaN	4.598000e+09	...	345122160.0	347000000.0	355000000.0	4.378	6.129000e+09	0.0	5000000.0	0.0	17.663	3.192000e+09
4	A	ARQ	2011-03-31	2011-06-07	2011-04-30	2020-09-01	278000000.0	8.649000e+09	NaN	5.096000e+09	...	348045143.0	347000000.0	355000000.0	4.833	6.601000e+09	0.0	60000000.0	0.0	19.023	3.504000e+09
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
972144	SPRB	MRT	2018-12-31	2018-12-31	2018-12-31	2020-10-09	0.0	4.775000e+06	NaN	4.773000e+06	...	NaN	4912955.0	4912955.0	0.000	4.775000e+06	0.0	0.0	0.0	0.972	2.068000e+06
972145	SPRB	MRT	2019-12-31	2019-12-31	2019-12-31	2020-10-09	0.0	4.692000e+06	4733500.0	4.652000e+06	...	NaN	5000000.0	5000000.0	0.000	4.692000e+06	0.0	0.0	0.0	0.938	3.490000e+05
972146	SPRB	MRT	2020-06-30	2020-06-30	2020-06-30	2020-10-09	0.0	3.896800e+07	NaN	3.847800e+07	...	NaN	NaN	NaN	NaN	3.896800e+07	0.0	NaN	0.0	NaN	3.214300e+07
972147	SPRB	MRY	2018-12-31	2018-12-31	2018-12-31	2020-10-09	0.0	4.775000e+06	NaN	4.773000e+06	...	NaN	4912955.0	4912955.0	0.000	4.775000e+06	0.0	0.0	0.0	0.972	2.068000e+06
972148	SPRB	MRY	2019-12-31	2019-12-31	2019-12-31	2020-10-09	0.0	4.692000e+06	4733500.0	4.652000e+06	...	NaN	5000000.0	5000000.0	0.000	4.692000e+06	0.0	0.0	0.0	0.938	3.490000e+05

972149 rows × 111 columns

Figure 2: Dataset of 8754 unique stocks on 'corpfund.csv'

We received an initial data set, 'corpfund.csv', which had 8754 unique stocks with quarterly financial data over a period of 10 years. The data set had financial information ranging from working capital ratios, price-to-book ratios, and Market Capitalisation, from 31st March 2010 to 31st December 2019. For our trading universe, we narrowed down the number of stocks to 2000, and thereafter pulled data off Yahoo Finance (yfinance) API for daily trading numbers.

Using the yfinance API which includes each stock's daily price actions (i.e., open, close, trading volumes etc), we downloaded all relevant information of the 2000 stocks. Since some stocks were delisted over the period from 2010 to 2020, we initially arrived at 1294 unique tickers. Then, we cleaned the data and removed all stocks that had the following parameters:

a) Daily returns > 100%,
b) Trading volumes = 0, and
c) Trading dates <= 2768 (i.e., total possible trading dates in the 10 years)

This left us with 888 unique tickers in the data set, where we took the daily returns of each stock to be: $\frac{(Close_{ti} - Close_{ti-1})}{Close_{ti}}$.

As a proxy for expected market returns, we extracted the daily returns on the S&P 500 Index from 4th January 2010 to 30th December 2020, and combined them with the cleaned yfinance dataset. Lastly, we assumed a risk-free rate of 0.02 per annum.

Commented [CKT1]: Need to justify?

	Date	Ticker	Daily Returns	SP500 Returns
0	2010-01-04	AAPL	0.000000	0.000000
1	2010-01-04	MSFT	0.000000	0.000000
2	2010-01-04	GOOGL	0.000000	0.000000
3	2010-01-04	AMZN	0.000000	0.000000
4	2010-01-04	XOM	0.000000	0.000000
...	...	...	...	...
2457979	2020-12-30	PRAA	0.030580	0.001342
2457980	2020-12-30	IVR	0.000000	0.001342
2457981	2020-12-30	ABM	0.000530	0.001342
2457982	2020-12-30	BRC	0.015211	0.001342
2457983	2020-12-30	FDP	-0.008227	0.001342

2457984 rows × 4 columns

Figure 3: Daily Returns of S&P 500 and each ticker (4th January 2010 - 30th December 2020)

CAPM Portfolio Construction

For the portfolio construction using CAPM, we linearly regressed each of the 888 tickers to derive each stock's Beta corresponding to Market Risk Premium (MRP), Alpha (α), and P-value. The CAPM beta for each stock was calculated by regressing its excess returns on the MRP, where the regression was trained on 80% of the dataset (4th January 2010 to 9th October 2018) and tested on 20% of the same dataset (10th October 2018 to 30th December 2020). Then, we calculated the expected returns for each stock using the following CAPM formula:

$$\boxed{\text{Daily ER}_{\text{Stock}} = rf + \beta_{\text{Stock}} * \text{Market Risk Premium} + \alpha}$$

Where rf = risk free rate of 0.02 per annum
And α = Alpha; rate of return that exceeds or falls short of CAPM's prediction

Thereafter, we sorted the stocks into 2 different portfolios (i.e. Long portfolio and Short portfolio) by looking at their alphas. The Long portfolio consists of stocks with alphas above the risk-free rate, and the Short portfolio consists of stocks with alphas below the risk-free rate. Finally, we computed the expected return of the overall portfolio using the following formula:

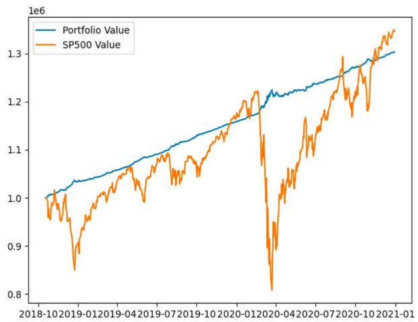
$$\boxed{\text{Daily ER}_{\text{Portfolio}} = \text{Average ER}_{\text{Portfolio (Long)}} - \text{Average ER}_{\text{Portfolio (Short)}}}$$

	Ticker	MRP Beta	Alpha	P Value	Position
0	AAPL	0.966667	0.000659	1.319716e-186	Buy
1	MSFT	1.025243	0.000293	1.343606e-287	Buy
2	GOOGL	1.017210	0.000312	2.688614e-237	Buy
3	AMZN	1.121278	0.000951	6.182274e-164	Buy
4	XOM	0.913782	-0.000200	0.000000e+00	Sell
...	...	...	...	...	...
883	PRAA	1.102409	0.000189	2.002599e-102	Buy
884	IVR	0.715207	-0.000361	1.350398e-123	Sell
885	ABM	1.049301	-0.000069	3.284780e-220	Sell
886	BRC	1.124212	-0.000135	2.679212e-208	Sell
887	FDP	0.825712	-0.000050	6.367634e-135	Sell

Figure 4: Evaluation and Classification of Stocks into Long and Short Portfolio

CAPM Backtesting

To evaluate the performance of the constructed portfolio, we conducted a backtest on the strategy by testing our CAPM model against the remaining 20% of the above-mentioned dataset. The figures below illustrate graphically, the performance of our strategy in comparison to the S&P 500 Index from 10th October 2018 to 30th December 2020.



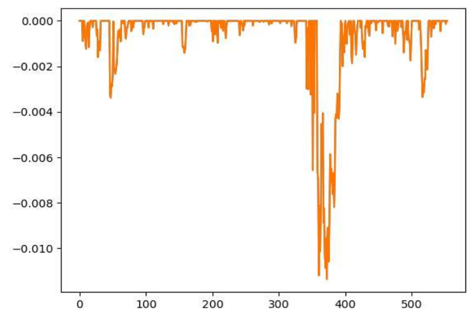


Figure 5: CAPM Backtesting Results

Correlation	-0.999
CAPM Annualised Sharpe Ratio	5.116
Calmar Ratio	10.625
Maximum Drawdown ($)	13923.0
Maximum Drawdown (%)	-0.011
Maximum Drawdown Duration	35.0

Table 1: Key CAPM Backtesting Results

Our CAPM Portfolio performed exceptionally well as compared to the S&P 500 Index, an industry benchmark for market returns. Our Sharpe Ratio of 5.116 further elaborates the excess returns from our portfolio. We can also observe that the portfolio performed relatively well during the Covid-19 black swan event (March 2020), where the maximum drawdown was significantly low.

FF3 Methodology

Instead of following the FF3 Model, we decided to perform the Fama-Macbeth regression using the same 3 factors of Market Risk Premium, Size Premium (i.e., Market Capitalisation), and Value Premium (i.e., Book-to-Market Ratios). In the figure below, the left half is the original data frame that we used for our CAPM methodology while the right half is the corresponding financial data of each ticker found in the 'corpfund.csv' file. The figure illustrates the merging of the CAPM data frame with relevant financial information from the 'corpfund.csv' file, such as each firm's Market Capitalisation, Price-to-Book ratio which is used to calculate the Book-to-Market ratio, and Market Risk Premium.

	Date	Ticker	Daily Returns	SP500 Returns	Market Cap	PB ratio	Market Risk Premium	BM ratio	Market Cap_Log	BM ratio_Log
53280	2010-03-31	A	-0.006644	-0.003273	1.047669e+10	3.993	-0.003352	0.250438	23.072419	-1.384543
54179	2010-04-01	A	0.004652	0.007414	1.047669e+10	3.993	0.007335	0.250438	23.072419	-1.384543
55067	2010-04-05	A	0.007815	0.007928	1.047669e+10	3.993	0.007849	0.250438	23.072419	-1.384543
55955	2010-04-06	A	-0.007467	0.001684	1.047669e+10	3.993	0.001605	0.250438	23.072419	-1.384543
56843	2010-04-07	A	-0.007812	-0.005877	1.047669e+10	3.993	-0.005956	0.250438	23.072419	-1.384543
...	...	...	...	...	...	...	...	...	...	...
2454762	2020-12-23	ZION	0.034967	0.000746	5.422842e+09	0.716	0.000666	1.396648	22.413886	0.334075
2455650	2020-12-24	ZION	-0.003907	0.003537	5.422842e+09	0.716	0.003457	1.396648	22.413886	0.334075
2456538	2020-12-28	ZION	0.000461	0.008723	5.422842e+09	0.716	0.008643	1.396648	22.413886	0.334075
2457426	2020-12-29	ZION	-0.013607	-0.002227	5.422842e+09	0.716	-0.002307	1.396648	22.413886	0.334075
2458314	2020-12-30	ZION	0.010521	0.001342	5.422842e+09	0.716	0.001262	1.396648	22.413886	0.334075

Figure 6: Fama-Macbeth Dataset

Since the 'corpfund.csv' file contains quarterly financial data of each stock, we did a forward fill by filling missing values with previous data. Additionally, since the file was also missing financial data from the first quarter of 2010, we removed all rows with trading dates in this period from the data frame. Lastly, we also decided to Log the columns of Market Capitalisation and Book-to-Market ratios to ensure that our methodology follows the assumption of Linear Regression that independent variables are linearly related to the dependent variable.

FF3 Portfolio Construction

Employing a similar portfolio construction methodology as per CAPM, we will train our FF3 Model on 80% of the dataset and subsequently test our FF3 Model on the remaining 20%. We conducted a multi-variable linear regression for each stock using the factors of daily Market Risk Premium, (Log) daily Market Capitalisation, and (Log) daily Book-to-Market ratios. The outputs of the regression were therefore each stock's Alpha (α), Beta corresponding to Market Risk Premium, Beta corresponding to Market Capitalisation, and Beta corresponding to Book-to-Market ratios. Then, we calculated the expected returns for each stock using the following FF3 formula:

$$\begin{aligned} &\textbf{Daily ER}_{\text{Stock}} \\ &= rf + \alpha \\ &+ \beta_{\text{Stock, MRP}} * \textbf{Market Risk Premium} \\ &+ \beta_{\text{Stock, MC}} * \textbf{Market Capitalisation} \\ &+ \beta_{\text{Stock, BM}} * \textbf{Book-to-Market} \end{aligned}$$

Where rf = risk free rate of 0.02 per annum

And α = Alpha; rate of return that exceeds or falls short of FF3's prediction

Thereafter, we sorted the stocks into 2 different portfolios (i.e. Long portfolio and Short portfolio) by looking at their alphas. The Long portfolio consists of stocks with alphas above the risk-free rate, and the Short portfolio consists of stocks with alphas below the risk-free rate. Finally, we computed the expected return of the overall portfolio using the following formula:

$$\textbf{Daily ER}_{\textbf{Portfolio}} = \textbf{Average ER}_{\textbf{Portfolio (Long)}} - \textbf{Average ER}_{\textbf{Portfolio (Short)}}$$

	Ticker	MRP Beta	MRP P Value	Market Cap Beta	Market Cap P Value	BM ratio Beta	BM ratio P Value	Alpha	Position
0	A	1.439369	0.000000e+00	-0.000792	0.483251	-0.002217	0.458797	0.015906	Buy
1	AA	1.510871	5.912600e-46	0.014651	0.097707	0.015505	0.384399	-0.330009	Sell
2	AAL	1.405992	3.633415e-93	-0.005414	0.234940	-0.001022	0.514003	0.127628	Buy
3	AAP	0.779977	7.394663e-80	-0.000987	0.359015	0.000167	0.887628	0.023172	Buy
4	AAPL	0.959067	1.250261e-179	-0.000673	0.651466	-0.002490	0.535194	0.014777	Buy
...	...	...	...	...	...	...	...	...	...
883	XRX	1.278015	1.641202e-253	-0.000463	0.575039	0.000592	0.439744	0.010556	Buy
884	YUM	0.910057	1.578987e-197	-0.001866	0.242408	-0.000053	0.858502	0.045058	Buy
885	ZBH	0.917056	1.181511e-224	-0.000909	0.802278	-0.002513	0.557601	0.019488	Buy
886	ZBRA	1.173536	7.679668e-158	-0.001139	0.303212	-0.002714	0.236500	0.021923	Buy
887	ZION	1.469000	2.237748e-309	-0.000580	0.827027	-0.001174	0.765536	0.013371	Buy

Figure 7: Evaluation and Classification of Stocks into Long and Short Portfolio

FF3 Backtesting

To perform our backtest on the FF3 Model, we ran it through our test set to derive the daily portfolio returns and thereafter compare it with the daily returns of the S&P 500 Index from 2018 to 2020. This was done by allocating both portfolios an initial investment amount of $1,000,000 and calculating the portfolio's value and Profit and Loss (PnL) after each day.

	Date	Portfolio Returns	SP500 Returns	Portfolio Value	Portfolio PnL	SP500 Value	SP500 PnL
0	2018-11-05	0.000000	0.000000	1.000000e+06	0.000000	1.000000e+06	0.000000
1	2018-11-06	0.000208	0.006259	1.000208e+06	208.416736	1.006259e+06	6259.335137
2	2018-11-07	0.001109	0.021209	1.001318e+06	1109.309921	1.027601e+06	21341.630422
3	2018-11-08	-0.000320	-0.002509	1.000997e+06	-320.267784	1.025023e+06	-2578.232559
4	2018-11-09	-0.000723	-0.009199	1.000274e+06	-723.618902	1.015594e+06	-9429.173468
...	...	...	...	...	...	...	...
537	2020-12-23	-0.000401	0.000746	8.036829e+05	-322.304650	1.347550e+06	1004.269056
538	2020-12-24	-0.000232	0.003537	8.034965e+05	-186.403432	1.352316e+06	4765.713159
539	2020-12-28	0.000082	0.008723	8.035624e+05	65.879726	1.364111e+06	11795.596554
540	2020-12-29	-0.000581	-0.002227	8.030957e+05	-466.751738	1.361073e+06	-3038.370382
541	2020-12-30	-0.000365	0.001342	8.028027e+05	-292.978367	1.362899e+06	1825.943739

Figure 8: FF3 Backtesting Results

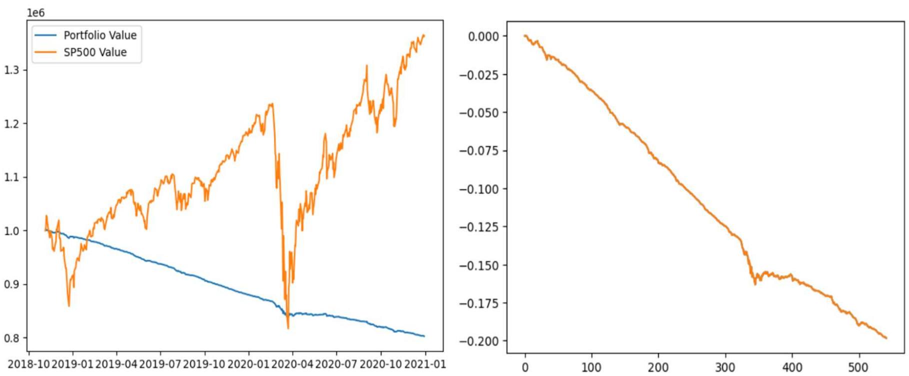


Figure 9: FF3 Backtesting Results

Correlation	0.993
CAPM Annualised Sharpe Ratio	-7.798
Calmar Ratio	-0.514
Maximum Drawdown ($)	198515.0
Maximum Drawdown (%)	-0.198
Maximum Drawdown Duration	539.0

Table 2: Key FF3 Backtesting Results

Our FF3 Portfolio observed a steady decline in PnL, with the drawdown duration stretching throughout the backtest duration. We can also observe that the FF3 Portfolio was heavily impacted during the two large drawdowns in S&P 500, as compared to our CAPM Portfolio. As a result of this overall loss, our Sharpe Ratio and Calmar Ratio for the FF3 Portfolio are negative.

Exploratory and Discussion

Apart from the two portfolios constructed using the CAPM and FF3 Model, we explored constructing portfolios based on parameters other than Market Capitalisation (i.e., size Risk Premium) and Book-to-Market ratios (i.e., value Risk Premium). This section will detail the motivation behind each of the four portfolios constructed, as well as an analysis of its performance using similar back test methods.

We first extracted all relevant financial information that we would be using for the portfolio construction subsequently. These include: PE ratio, PS ratio, Revenue (USD), EBIT, EBITDA, Interest Expense, EBITDA Margin, Net Income (USD), RND, Equity, and DE Ratio. We subsequently did two sanity checks on our data points.

To address potential multicollinearity issues, we ran a correlation test on these variables. It was intuitive for us to not run a correlation of income line items as these would likely exhibit high correlation values. Consequently, we would refrain from running regression on such variables to avoid the issue. From the figure below, we observed only RND and Equity have a higher positive correlation. We would therefore avoid running a regression on these two variables together.

	PE Ratio	PS Ratio	Net Income	RND	Equity	DE Ratio
PE Ratio	1.000000	0.000164	-0.001484	-0.000788	-0.001058	0.000071
PS Ratio	0.000164	1.000000	-0.005851	-0.008790	-0.011384	-0.002365
Net Income	-0.001484	-0.005851	1.000000	0.061431	0.199037	0.002934
RND	-0.000788	-0.008790	0.061431	1.000000	0.398061	-0.000257
Equity	-0.001058	-0.011384	0.199037	0.398061	1.000000	-0.000092
DE Ratio	0.000071	-0.002365	0.002934	-0.000257	-0.000092	1.000000

Figure 10: Correlation of Variables to Identify Potential Multicollinearity Issues

Next, we did a skew test on these variables. We are only using one firm's data points to determine skewness and assume it to be relatively representative of other firms' values. We would natural log all variables that exhibit an absolute skew value of greater than 0.75. As evident in the figure below, we would natural log the variables that satisfied the condition mentioned before.

```
PE Ratio            2.134575
PS Ratio            0.463745
Revenue             0.123217
EBIT               -0.535375
EBITDA             -0.488248
Interest Expense    0.595008
EBITDA Margin      -0.760165
Net Income         -1.146969
RND                 0.148146
Equity             -0.888249
DE Ratio            2.607805
dtype: float64
```

Figure 11: Results of Skew Test on Variables

<u>Portfolio 1: Behavioural</u>

For Portfolio 1, we constructed it based on the belief that market sentiments and investor behavioural biases can influence investment decisions and thus stock prices. One of such behavioural biases is that individual investors trade more significantly with respect to what they see or read about on the news.

There are, however, no variable with a direct tie to investors' behaviour. Potential proxy data points could be Relative Strength Index or Daily Trading Volume. For the project, we decided to use Log Daily Trading Volumes as a measure of the investors' behaviour and sentiment for a stock. Since majority of individual investors trade on 'buy' signals, we assume high trading volume would usually entail an increase in stock prices.

$$\boxed{ER_{Stock} = \alpha + \beta_{Stock,MRP} MRP + \beta_{Stock,Trading\ Volume} Log\ Volume}$$

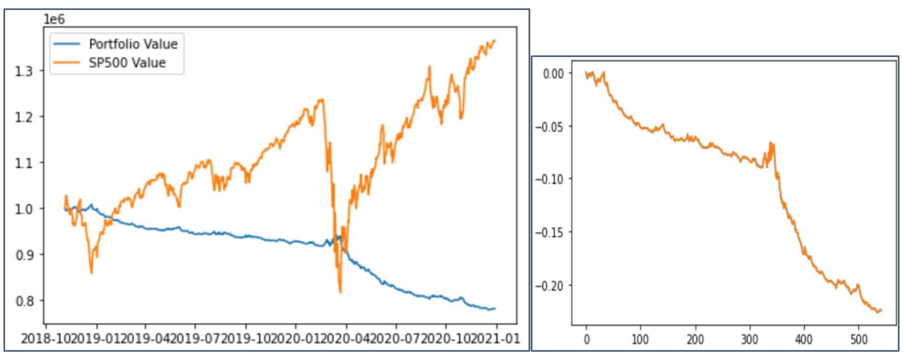


Figure 12: Portfolio 1 Backtesting Results

Correlation	-0.974
CAPM Annualised Sharpe Ratio	-3.21
Calmar Ratio	-0.5
Maximum Drawdown ($)	228474.0
Maximum Drawdown (%)	-0.226
Maximum Drawdown Duration	508.0

Table 3: Key Portfolio 1 Backtesting Results

Through our backtest, we observed a steady decline in PnL. It is, however, worth noting that whilst the SP500 experienced its two largest drawdowns during the test split, the portfolio experienced gains. Since we experienced an overall loss, our sharpe and calmar ratios are naturally negative.

Portfolio 2: Value Ratios

For Portfolio 2, we constructed it based on intrinsic valuation ratios. We were curious to find out how the key ratios that investors look at when valuing a company would perform. Therefore, we regressed against the stock's return with industry-wide used ratios such as the Price-to-Earnings (PE) and Price-to-Sales (PS).

$$\boxed{ER_{Stock} = \alpha + \beta_{Stock,MRP}MRP + \beta_{Stock,PE}Log\ PE + \beta_{Stock,PS}PS}$$

Where PE ratio = Market Capitalisation/ Net Income
And PS ratio = Market Capitalisation/ Total Sales

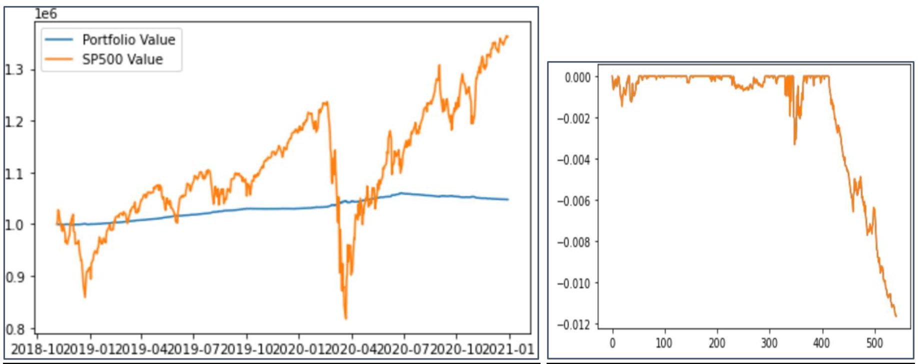


Figure 13: Portfolio 2 Backtesting Results

Correlation	-0.942
CAPM Annualised Sharpe Ratio	0.276
Calmar Ratio	1.863
Maximum Drawdown ($)	12349.0
Maximum Drawdown (%)	-0.012
Maximum Drawdown Duration	129.0

Table 4: Key Portfolio 2 Backtesting Results

This portfolio performed relatively better than the portfolio constructed based on trading behaviours. We can observe a relatively low yet steady gain for most of the test period. As the decline towards the end was gradual, our drawdown was significantly low. This allowed our Calmar ratio to be relatively high.

Portfolio 3: Profitability Indicators

For Portfolio 3, we valued each stock based on the corresponding firm's ability to pay off its debt and interest obligations, and thus constructed the portfolio based on profitability indicators. These profitability indicators tend to analyse the firm's financial health. Interest coverage ratio signals the firm's ability to pay interest due on its outstanding debt. A higher ratio entails a better capital management to meet its interest obligations. Higher EBITDA Margin indicates the firm's better management of cash flow and operating expenses. Higher ROE Ratio indicates the ability of a firm to better convert its equity financing into profits.

$$\boxed{\begin{aligned} ER_{Stock} = \alpha + \beta_{Stock,MRP} MRP + \beta_{Stock,EBITDA\ Margin} Log\ EBITDA\ Margin \\ + \beta_{Stock,ICR} ICR + \beta_{Stock,ROE} ROE \end{aligned}}$$

Where EBITDA Margin = EBITDA/ Total Sales
And ICR = EBIT/ Equity
And ROE = Net Income/ Equity

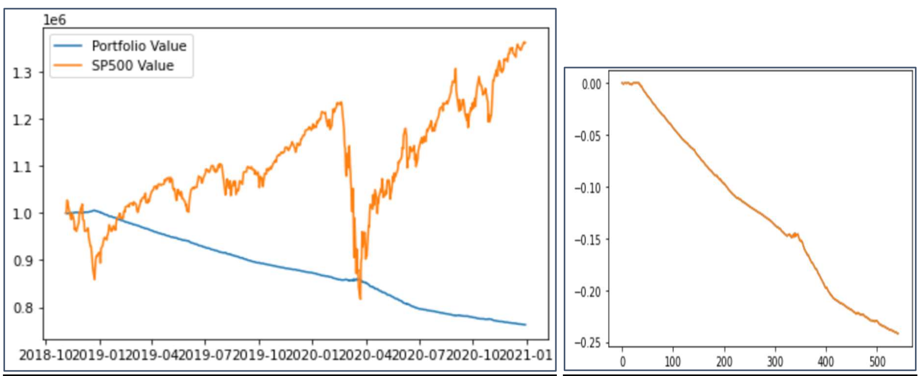


Figure 14: Portfolio 3 Backtesting Results

Correlation	-0.914
CAPM Annualised Sharpe Ratio	-15.053
Calmar Ratio	-0.52
Maximum Drawdown ($)	243317.0
Maximum Drawdown (%)	-0.242
Maximum Drawdown Duration	508.0

Table 5: Key Portfolio 3 Backtesting Results

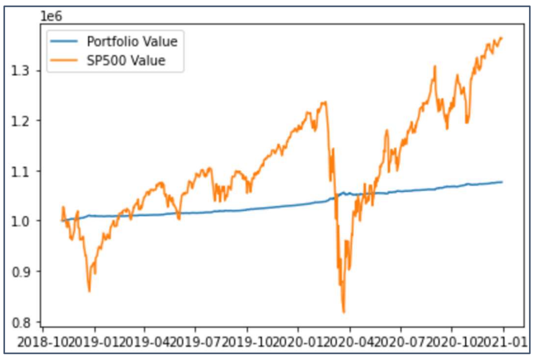
Similar to our Portfolio 1 result, the profitability factors are not very good indicators of stock performance. We obverse a gradual decrease in portfolio value since inception and as such our key performance ratios returned a negative result.

Portfolio 4: Growth Factors

For Portfolio 4, we valued each stock based on the corresponding proxy variables that determine the firm's expected revenue growth, and thus constructed the portfolio based on growth factors. Therefore, we used each firm's Research & Development (RND), Revenue Growth (Q-on-Q), and Debt-to-Equity Ratio (D/E) as proxy variables for growth factors.

$$\boldsymbol{ER_{Stock} = \alpha + \beta_{Stock,MRP}MRP + \beta_{Stock,RND}RND(MM) + \beta_{Stock,DE}LogD/E + \beta_{Stock,Rev\ Growth}Revenue\ Growth}$$

Where D/E = Debt/ Equity



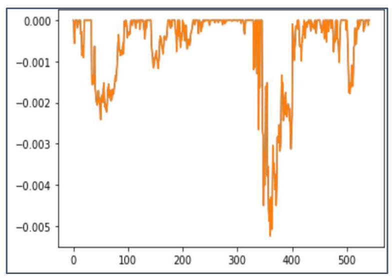


Figure 15: Portfolio 4 Backtesting Results

Correlation	-0.993
CAPM Annualised Sharpe Ratio	1.75
Calmar Ratio	7.038
Maximum Drawdown ($)	5148.0
Maximum Drawdown (%)	-0.005
Maximum Drawdown Duration	59.0

Table 6: Key Portfolio 4 Backtesting Results

Overall Portfolio 4 performed the best amongst the other exploratory portfolios. Albeit the gradual increase in portfolio value, it is for noting that the maximum drawdown for this portfolio was less than 1%. Due to the low drawdown, our Calmar ratio was exemplified. It is also interesting to see the portfolio performed against market downturn as represented by the two major dips in SP500.

Summary of Findings

All in all, none of the portfolios created fared well against the market. Although the returns are not comparable, we were surprised by the overall performance of the portfolios when they were measured with the max drawdown. All the portfolios outperformed the market's max drawdown and some even outperformed in terms of Sharpe and Calmar ratio. This can be seen in the figure and table below.

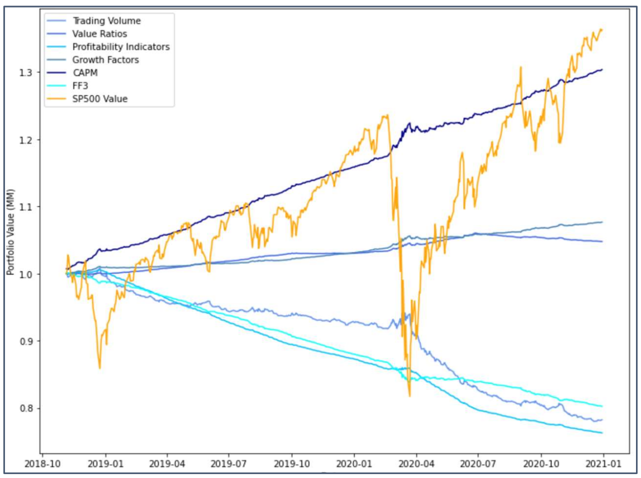


Figure 16: Comparison of Performances of all Portfolios Constructed

	Returns (%)	Sharpe Ratio	Calmar Ratio	Max Drawdown (%)
SP500 (Benchmark)	34.79	0.61	0.52	-33.9
CAPM	30.36	5.12	10.63	-1.14
FF3	-19.78	-7.84	-0.52	-19.88
Behavioural PF	-21.77	-3.21	-0.5	-22.66
Value PF	4.77%	0.28	1.86	-1.16
Profitability PF	-23.73	-15.05	-0.52	-24.19
Growth PF	7.65%	1.75	7.04	-0.49

Table 7: Comparison of Performances of all Portfolios Constructed

Limitations and Improvements

During our data processing and back test stages, we made several assumptions before constructing the models, of which would usually fail to hold true in practice. In this section we aim to discuss the limitations, possible effects, and steps to be taken in the future.

Firstly, during our extraction of stock prices using the yfinance API, we ignored tickers that could not pull any values from Yahoo Finance despite them having higher Market Capitalisation values. In this case, some firms with relatively large cap were excluded from our data frame due to possible name changes or mergers and acquisitions. Furthermore, we removed all stocks that had less than a required number of trading days for simpler calculations in the later stages. Therefore, we could have done a more in-depth data processing to achieve a better trading universe at the start.

Next, we assumed betas to be constant throughout the test period. This is unlikely to hold true for firms in the long run. In the future, we should be running a regression based on monthly or quarterly data points to allow the beta to be adjusted overtime. This is likely to result in a more representative Risk Premium on the different variables.

We also assumed a simple average when we adopted Jensen's alpha as our trading strategy. This is with the assumption that with a fixed capital, we would divide the capital with the number of long and short positions. This may however be impractical as we are unlikely to own fractions of the stocks to the exact decimal point that our portfolio was created on. Furthermore, the portfolio should have been rebalanced regularly to better optimise the positions.

Lastly, we could have potentially normalised our data points to remove anomalies that could have been caused by unprecedented events. This could potentially improve the accuracy of our historical dataset.

Presentation Feedback

There were several concerns that were raised during the presentation. We seek to address these concerns and turn them into discussion points that could be beneficial to the project in the future.

Firstly, a student raised a potential issue that our group might have faced when constructing the portfolios and running the back test. He was worried that we might have run into forward bias, that is the use of future known values to run the back test. We addressed his concern by demonstrating that our regressions were only run with the train dataset. This comprised of 80% of the trading dates. With the alphas and betas obtained from the regression result, we constructed our portfolio and simulated the PnL by using the test dataset.

Secondly, there was another concern regarding our oddly high negative correlation between the constructed portfolios and the SP500. While we are unsure of the exact reasons, one possibility is collinearity issues when we run regression on log variables and non-log variables concurrently. We should have checked for such issues prior to running the regression with a correlation table first. We should also have checked for skewness after performing natural log on the variables to ascertain that the variables were indeed loglinear initially.

Lastly, as a key learning point from Professor Ee, a gradual decline in the PnL does not necessarily imply that the variables were not good. In fact, Jensen's Alpha trades on the methodology that a positive alpha indicates an outperformance against the method, vice versa. This is motivated by the idea that if a given security is fairly priced, the expected returns should be the same as the one given by the regression result. And, if the security were to earn more than the risk-adjusted returns, the alpha will be positive.

However, a negative performance by a portfolio constructed following this methodology could in fact indicate that the variables chosen were able to explain the performance. As such, if we constructed our portfolio using the beta values instead of the alpha, our portfolio would likely have performed better, and this can be verified in the future. Therefore, our overall takeaway was that the negative performance of a portfolio may not necessarily indicate an error or a mistake in the trading strategy employed. Instead, analysing it from a different perspective may help us derive new and valuable insights.

Conclusion

Albeit the many challenges the group faced during this project; we had a taste of data processing when dealing with real-world data. It gave us the opportunity to experience with problematic datasets and the chance to manoeuvre around it. Despite the initial intention to simulate the performance between Fama-French 3 Factor model against the SP500, we have learnt the difference between the FF3 Model and the Fama-Macbeth model, on top of the methods itself and its limitations. The exploratory part was insightful and fun as we managed to test out some of these indicators that we learnt in our finance modules. We would definitely explore other factors in the future, potentially less common ones, to generate more significant alphas or even discover new variables that could better explain a security's return.