Value Investing Strategy

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1 VALUE INVESTING

1.1 Introduction to Value Investing

This strategy was popularised by the father of Value Investing, Benjamin Graham. The list of his ardent followers include the likes of Warren Buffet and Seth Klarman. The common intellectual theme of the investors from Graham-and-Doddsville is this: they search for discrepancies between the value of a business and the price of small pieces of that business in the market. Essentially, they exploit those discrepancies without the efficient market theorist's concern as to whether the stocks are bought on Monday or Thursday, or whether it is January or July, etc. Investors who use the value investing strategy hope the stock price will rise as more people come to appreciate the true intrinsic value of the company's fundamental business. Our Graham & Dodd investors, needless to say, do not discuss beta, the capital asset pricing model, or covariance in returns among securities. These are not subjects of any interest to them. The investors simply focus on two variables: **price and value**.

Value Investing can be characterised by three major principles:

- Margin of Safety: The greater the difference between the intrinsic value and the current stock price, the greater the **margin of safety** for value investors looking for investment opportunities. Graham writes in Chapter 20 of the Intelligent Investor: **"The function of the margin of safety is, in essence, that of rendering unnecessary an accurate estimate of the future."** According to Klarman: "A margin of safety is achieved when securities are purchased at prices sufficiently below underlying value to allow for human error, bad luck, or extreme volatility in a complex, unpredictable and rapidly changing world."
- Making Use of Volatility: Graham suggests two approaches to make use of this volatility:

  1. Dollar Cost Averaging: Buying equal dollar amounts of investments at regular intervals. This takes advantage of the dips in price so that a buyer doesn't have to buy at a premium when the market is overly optimistic.

  2. Diversifying your portfolio: Graham discusses buying both stocks and bonds so that the losses during market downturns can be offset by the income through bonds.
- Understanding Investor Mindset: Graham discusses two types of investors i.e., Active and Passive. An active investor combines intuition, market research and fundamental analysis of companies to arrive at a stock. The amount of commitment is generally equated to higher expected returns. For the passive investor it is suggested to invest in various market indices. That way they have a stake in the entire market and benefit on average as the market grows. It is paramount that an investor is clear about their skills, commitment and result they want to achieve.

1.2 Why Value Investing works?

The Efficient Market Hypothesis (EMH) states that shares prices reflect all information. Therefore, it should be impossible to for investors to purchase undervalued stocks or sell stocks for an inflated price. The supporters of this theory often throw out the idea that if you had 100 monkeys throwing darts at a list of stock tickers, you might observe that 9 or 10 of them beat the market but ascribing any skill to their efforts would not make a lot of sense. Although, a cornerstone of modern financial theory, EMH is highly controversial and disputed. The developer of the Efficient Markets Hypothesis, Eugene Fama, himself pointed out in a 1992 paper and several others that value stocks outperform growth stocks over time. This is because in reality all markets show some inefficiencies due to information asymmetries, low liquidity, transaction costs, and the human element. Since, humans are complicated and fallible, the human element is what makes a market the most inefficient. Since, people in general overestimate the impact of both positive and negative news and these ideas seem to linger for some time. This coupled with the fact that researchers have identified curious trends in markets, like the January effect, a seasonal increase in stock prices that takes place in January, implies inefficiencies. Therefore, the idea that all stock are exactly fairly priced with no speculation is too impractical for the current market.

2 QUANTILE ANALYSIS

2.1 Data Description:

We have a data set with monthly historical prices of several thousands of stocks starting from 1980 up to 2021. Similarly, we also have the monthly historical data for three value factors of the previously mentioned stocks, i.e., Quarterly Earnings per Share of stock (EPQ), Yearly Earning per Share of stock (EP12), and Book to Market ratio of stock (BTM). All the data sets have been normalised to a mean of 0 and a standard deviation of 1. These will be used to decide which value factor is strongest signal or alpha.

2.2 Preliminary Analysis:

2.2.1 Methodolgy:

To get an intuition of which factor is the strongest alpha, we created a function that groups the price data by date and returns a dataset with the average group returns as projected returns for that date. Following this we use another function to calculate various performance metrics of our portfolios. The grouped data for each date, contains the prices of all the stocks for that date and is divided into four quantiles depending on the strength of the signal provided. This way we can create a portfolio for each month and later rebalance our portfolio. We then use heatmaps and price graphs to evaluate the strength of each value factor. This preliminary analysis was enough to provide an objective view of each signal and their relative strength.

2.2.2 Results:

Evaluating performance metrics for the value factors we see:

Signal: EPQ

group	Mean Ret.	Std. Dev.	RR Ratio
1	-0.216346	0.291057	-8.919742
2	-0.028028	0.208456	-1.613470
3	0.075083	0.167613	5.375437
4	0.124912	0.187895	7.977583

Signal: EP12

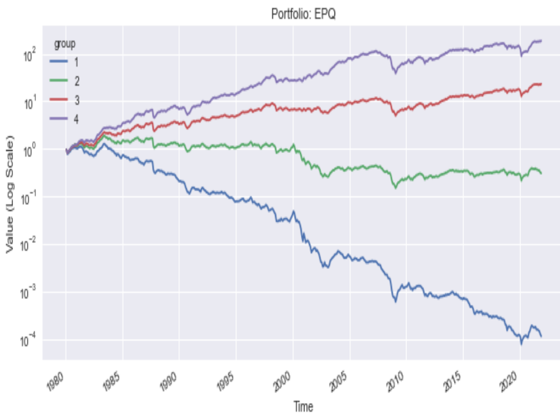
group	Mean Ret.	Std. Dev.	RR Ratio
1	-0.193946	0.298896	-7.786479
2	-0.016945	0.210603	-0.965537
3	0.064209	0.164762	4.676508
4	0.105968	0.184632	6.887306

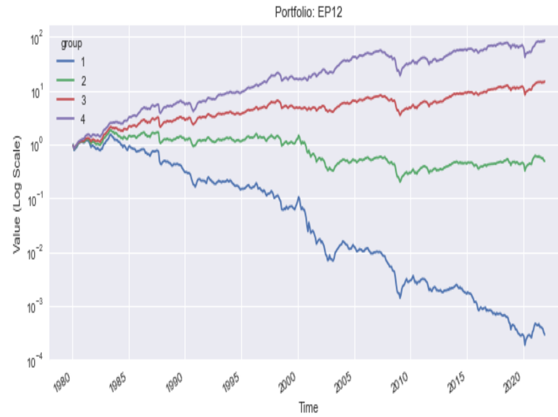
Signal: BTM

group	Mean Ret.	Std. Dev.	RR Ratio
1	-0.073424	0.232443	-3.790574
2	-0.010369	0.197822	-0.628991
3	0.031226	0.186549	2.008624
4	0.028269	0.222731	1.523061

For starters, one can easily notice that scrolling down the 'Mean Ret.' i.e., the mean returns column of the Signal: EPQ data frame shows an increase at every step. This pattern also emerges in the other two data frames, Signal: EP12 and Signal: BTM. Implying, that as the group number increases the mean returns also increase. Since, we grouped our data by signal strength i.e., Group 1 with the least signal strength and Group 4 with the highest. Notice that as these factor increase in strength so do, the projected returns. While the stocks with the weaker signals tend to eventually crash. Since, this is common among all three of the signals we can treat it as evidence of their predictive power. Therefore, it is safe to conclude that each of these value factors can be treated as an alpha because grouping stocks based on the strength of these signals outperform the weaker ones in each instance.

Of course, as is quite clear, even though each of these value factors are good alphas. One has certainly outperformed the rest in terms of mean returns. That is Signal: EPQ or the Quaterly Earnings per Share of Stock. This metric seems to be the strongest alpha. Since, the alpha produced by Signal: BTM is about one fifth the size of the lesser of the other two we can safely ignore it for now while comparing the other two. For better visualisation, we can take a look at the price graphs of the returns data for Signal: EPQ and Signal: EP12, which has been attached on the next page.





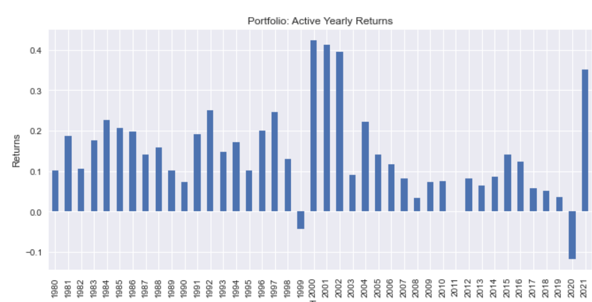
The above graphs clearly show the relationship between these factors and value. The graphs shadow each other which implies that they might have very similar stocks in each group. Since, these metrics are the same calculated at different times therefore, the portfolios created out of them shadow each other. However, as can be seen in the graph, the portfolio created with the Yearly Earnings per Share of stock lag behind the one created by the Quarterly Earnings per Share. Which indicates that EPQ might be a better signal. Furthermore, this makes sense in the real world since a Quarterly update is much better for revaluation and adjustments in real time than an yearly one. The more the data (without noise) the better! Another way to look at the returns is through a heatmap which has been attached in the Appendix (Ref. 2.2.1). It is now safe to conclude that EPQ is the strongest alpha a.k.a value factor out of the three. While EP12 is weaker but still potent factor that shadows EPQ and BTM is the least predictive signal.
We can further analyse the data by testing for Zero Investment Strategies, whereby, we can long on the best stocks and short on the worst or long on the best and short the market. The graph for this have been attached in the Appendix (Ref. 2.2.2).

2.3 Period Analysis:

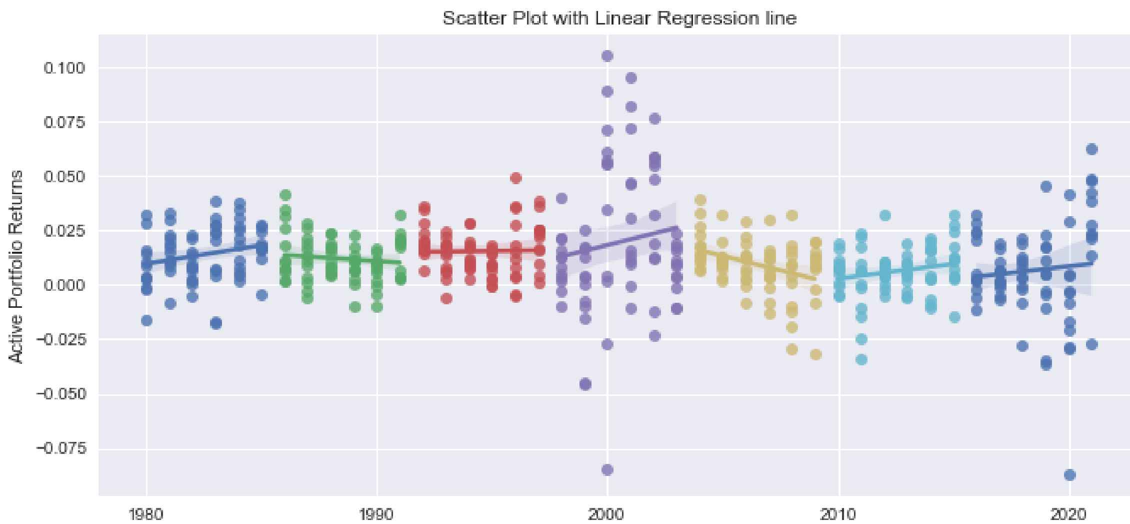
2.3.1 Methodology

We take the returns data we got from Quantile Analysis of the factor. We then divide the returns data into time chunks and compare these chunks.

2.3.2 Results:



Taking a look at the yearly returns data, we can see that our model failed during the dot-com bubble burst as well as during the COVID pandemic. The model seems to have been greatly successful for a few years succeeding the dot-com bubble burst. This can be accounted for by the market being hyper bullish and optimistic after a crash and the revival of tech based companies. However, one can notice that despite fluctuation the predictive power of the factor EPQ has been more or less constant across our sample. Another way to visualise this would be through a regression plot. What I have done is to divide the Active Portfolio returns data into seven chunks. Since, we have about 42 years of historical price data this is equivalent to dividing the already sorted data into 6 year chunks. We then fit a linear regression model into each chunk of the data. The slope and y-intercept of this fitted line will tell us about the changes in the predictive power of this factor. The figure is included in the next page.



The picture gets clearer when we look at this graph. We see that although there are minor fluctuation in both directions the regression line is more or less horizontal implying that EPQ is a consistent predictor of value stocks. Also, notice that the y-intercept of each line lies between 0 and 0.025, implying that the predictive power has also stayed more or less constant. Although, one might notice a drop in recent years especially after 2010, this drop is not significant for us to reverse our conclusion. Therefore, EPQ is a consistent value factor with almost constant predictive power.

3 BACKTESTING

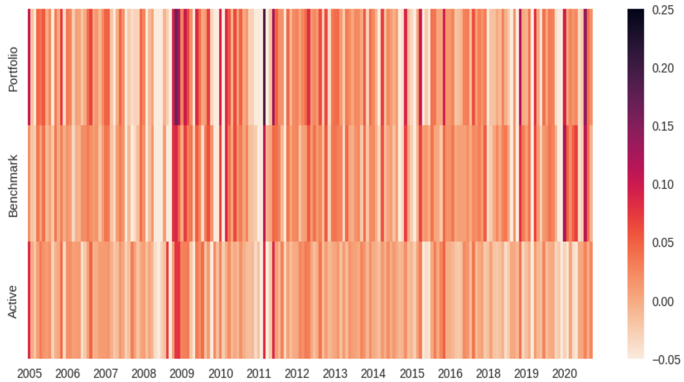
3.1 Methodology:

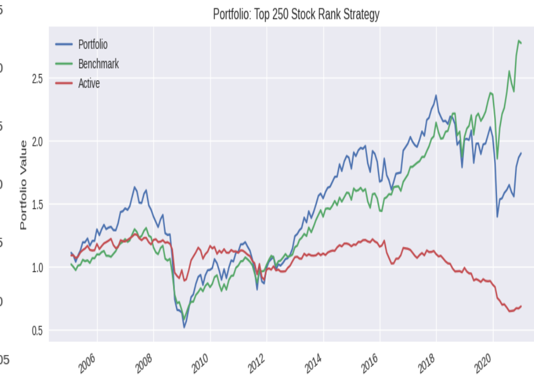
After we have ascertained that our information signal has some predictive power, now we can backtest it to assess whether this predicitive power can be translated into profits. We will be testing the performance of a **long-only strategy** that invests in the top 250 stocks ranked by our alpha i.e., EPQ. We test on data between 2005 and 2020, rebalance monthly while assuming a round trip transaction cost of 0.2%.

3.2 Portfolio Returns:

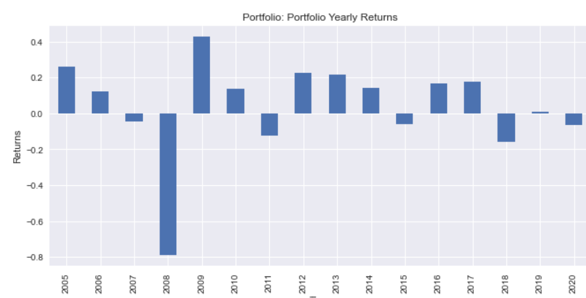
We see a mean return of 0.040 and an RR ratio of 0.174. Although, the picture will get clearer when we look at a price graph. We can see that the mean return for the Active Portfolio is negative implying that the Active Portfolio will underperform or fail. Also noticeable is that our portfolio has a heavy max drawdown of -1. However, looking at the graph (Ref. Appendix 3.2.1) this shortfall can be easily explained by the Global Financial crisis of 08-09. The Benchmark seems to outperform our long only portfolio and has a much higher RR Ratio. Also, noticeable is that our portfolio is more volatile than the Active or the Benchmark. Please look at the graphs included in the next page which has a heatmap and a price graph included. These will elucidate more upon the metrics contained in this data frame.

	Portfolio	Benchmark	Active
Mean Return	0.040140	0.063838	-0.023698
St. Dev.	0.230274	0.156919	0.111499
RR Ratio	0.174313	0.406818	-0.212539
% Positive	0.604167	0.651042	0.494792
Worst Month	-0.378713	-0.201336	-0.177377
Best Month	0.187581	0.123162	0.086454
Max DrawDown	-1.002301	-0.694557	-0.331825





The two graphs above complement each other spectacularly. Observing the heatmap we see that all three of the portfolios seems to mimic each other's returns or rather the market's. This is particularly true of the Benchmark and Portfolio we created. We see that the Portfolio while mimicking the Benchmark has stronger returns originally but the returns slowly seem to fade for Portfolio while growing stronger for the Benchmark by the time we get to 2020. So it's no surprise that the price graph of the two are almost tangled together with the Benchmark only overtaking the Portfolio after 2018.



Another way to visualise returns would be to look at the bar graph of the yearly returns of the Portfolio. We quickly notice that our model failed during the Global Financial Crisis and of course during the COVID Pandemic. That is more or less in tune with what was expected as the market crashes. The graph implies that our signal has not performed well in the recent years, however, that can easily be attributed to the pandemic and the restructuring of the world economy. There appears to be some form of periodic trend in the returns data with the pattern repeating every four years. But that would be out of scope of the current analysis we are undertaking so we will leave that for another day. I have also attached the returns for the Active Portfolio (Ref. Appendix 3.2.2) which has under performed severely especially in the recent years of 2015-2020. This could imply that a higher EPQ is an indicator of high value but the inverse may not be true. Therefore, shorting stocks rated low by EPQ may backfire. For a regression plot of the returns take a look at Appendix (Ref. 3.2.3).

3.3 Industry Composition:

3.3.1 Methodology:

We load a file that contains the name and industry affiliation of all the companies in our sample. We then join this file to our strategy data to estimate industry exposure by summing the weights of all the stocks in each industry for each month.

While we mainly care about the performance of a strategy, it is useful to know in which type of stocks we are actually investing to keep an eye on our exposure to different risk factors. At the start our portfolio seems to have a heavy bias for Business Equipment and Finance. Let's plot an area graph of the same dataset so that we have a clearer picture of what's going on.

```
date        industry
2005-01-31  Business Equipment         0.044655
            Chemicals                  0.008139
            Consumer Durables          0.008863
            Consumer non Durables      0.020332
            Finance                    0.173620
Name: Portfolio, dtype: float64
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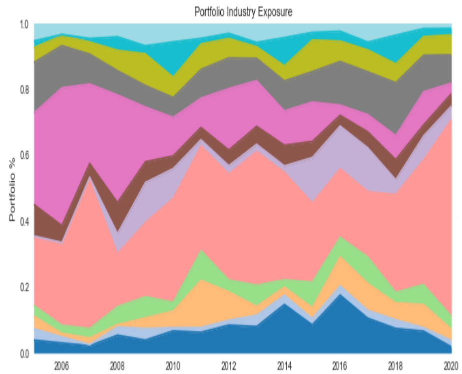
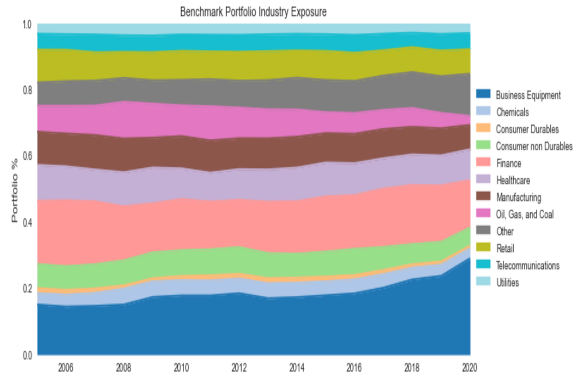




We can still see the strong bias towards Business Equipment, although our exposure has reduced in the recent years especially after 2016. Similar pattern is followed by our exposure to Oil, Gas, and Coal, Utilities, Chemicals and Consumer Durables and non Durables. The most noticeable aspect is the increase in our exposure to Finance. This has gone through various fluctuations throughout the years with our exposure skyrocketing after 2016. Comparing to the benchmark we seems to have an implied long bet on Business Equipment and implied short bet on Finance.

4 LOW VOLATILITY BETA COMBINATION STRATEGY

4.1 Data Description:

We have a data set TVOL which contains the volatility factor for all the stocks in the Price data from the month of July 1996 to the end of 2020. This data has been normalised and therefore contains negative numbers even though volatility is always positive. The data has also been inverted i.e., the lower values represent higher volatility and higher values represent lower volatility.

4.2 Methodolgy:

We have used several algebraic functions to combine the alpha i.e., EPQ and beta i.e., TVOL into a single series that we can then pass on to the functions created for quantile analysis and backtesting. Ideally we want a function that would combine both, a strong EPQ signal and a strong TVOL signal. For Quantile Analysis, we divide the data into five chunks approximating five years of data in each chunk. Results from the quantile analysis will determine which model are chosen for backtesting. After which the results of the backtesting, i.e., the mean returns and the information ratio of the portfolio are used to select the best performing model. For **a, x** be Signal EPQ and Signal TVOL respectively,

4.3 Linear Models:

1.

$$\mathbf{f(a,x) = a - x}$$

This function would favour the negative values of TVOL which are greater in magnitude. This however, ignores the signal EPQ if TVOL is negative and large in magnitude it would overshadow EPQ.

Mean Return
Signal Group 5: -0.005737, Benchmark: 0.046671, Active: -0.052409
RR Ratio
Signal Group 5: -0.023752, Benchmark: 0.257902, Active: -0.554294

2.

$$\mathbf{f(a,x) = a + x}$$

This function favours positive values of TVOL which are large in magnitude. Since it is additive, stronger EPQ will produce a stronger signal but negative values get ignored.

Mean Return
Signal Group 5: 0.118118, Benchmark: 0.046671, Active: 0.071447
RR Ratio
Signal group 5: 0.931185, Benchmark: 0.257902, Active: 0.763986

3.

$$\mathbf{f(a,x)} = \sum^{n} (x_i + |a_i|)$$

This function will take into account both the positive and negative values of TVOL which are large in magnitude. Since, it's additive to EPQ, a stronger EPQ will produce a stronger signal.
Mean Return
Signal Group 5: 0.032302, Benchmark: 0.046671, Active: -0.014369
RR Ratio
Signal Group 5: 0.168656, Benchmark: 0.257902, Active: -0.238236

4. Combination Strategy

$$P = P_1 + P_2$$

We use both the signal to select stocks and then combine the portfolios by taking the average of the returns. We could backtest this strategy by backtesting with each signal for half the stocks and then adding the returns.
Mean Return
Signal Group 5: 0.023161, Benchmark: 0.014784, Active: 0.008377
RR Ratio
Signal Group 5: 0.106837, Benchmark: 0.077330, Active: 0.197877

Since, we want a long only strategy, therefore, judging by the mean returns and information ratio of the strongest signal group to sieve through the models will suffice. The picture can be made clearer by backtesting of the best models out of these. We notice that the second model has performed the best out of these but before we proceed I'd like to test out a few non linear models.

4.4 Non Linear Models:

1.

$$\mathbf{f(a,x)} = \sum^{n} a_i \cdot |x_i|$$

This function preserves the sign and magnitude of the Signal EPQ while scaling it up by the absolute value of the Signal TVOL. This was only the magnitude of TVOL matters, not the sign.
Mean Return
Signal group 5: 0.020679, Benchmark: 0.046671, Active: -0.025992
RR Ratio
Signal Group 5: 0.112378, Benchmark: 0.257902 Active: -0.582427

2.

$$\mathbf{f(a,x)} = \sum^{n} \frac{a_i}{|x_i|}$$

Even though I was informed that the TVOL data is normalised and then inverted so that higher values correspond to lower volatility. I have an inkling that I should try an inverse model and see how it performs. This function will preserve the sign and magnitude of the Signal EPS while being scaled by the inverse of the absolute value of the Signal TVOL. This would bias the function towards smaller values of TVOL while ignoring the sign.

Mean Return
Signal Group 5: 0.107195, Benchmark: 0.046671, Active: 0.060523
RR Ratio
Signal Group 5: 0.570858, Benchmark: 0.257902, Active: 1.814785

It seems like my guess was right and although, I am currently unable to explain this, perhaps because the data was only normalised and not inverted, the inverse model performs very well. Out of the above two groups of models we see that the linear additive and inverse scaled model performed the best. I'd like to combine properties from both of these models to create a few other test functions. Particularly, the properties I'm interested in are:
1. Linear Additive model favouring the positive.
2. Inverse model biased towards smaller values while ignoring sign.

Let's combine these properties into the below listed functions:

1. Positive Bias:

$$\mathbf{f(a,x)} = \sum^{n} a_i \cdot \left| 1 + \frac{1}{x_i} \right|$$

This function would preserve the sign and magnitude of Signal EPQ, while having a slight bias towards small positive values of Signal TVOL.

Mean Return

Signal Group 5: 0.113969, Benchmark: 0.046671, Active: 0.067298

RR Ratio

Signal Group 5: 0.624616, Benchmark: 0.257902, Active: 1.851270

2. Negative Bias:

$$\mathbf{f(a,x)} = \sum^{n} a_i \cdot \left| -1 + \frac{1}{x_i} \right|$$

This function would preserve the sign and magnitude of Signal EPQ, while having a slight bias towards small negative values of Signal TVOL.

Mean Return

Signal Group 5: 0.105692, Benchmark: 0.046671, Active: 0.059021

RR Ratio

Signal Group 5: 0.545668, Benchmark: 0.257902, Active: 1.782532

It seems like both of these performed well enough to be considered for backtesting. However, I would not like to be too arrogant and since I was told that the TVOL values have already been inverted I'd like to test out two more functions of a similar kind which should perform similar or rather better to the above if the TVOL values have already been inverted.

3. Positive Bias:

$$\mathbf{f(a,x)} = \sum^{n} a_i \cdot |1 + x_i|$$

Mean Return

Signal Group 5: 0.130542, Benchmark: 0.046671, Active: 0.083871

RR Ratio

Signal Group 5: 0.918713, Benchmark: 0.257902, Active: 1.175588

4. Negative Bias:

$$\mathbf{f(a,x)} = \sum^{n} a_i \cdot |-1 + x_i|$$

Mean Return

Signal Group 5: 0.092486, Benchmark: 0.046671, Active: 0.045814

RR Ratio

Signal Group 5: 0.430896, Benchmark: 0.257902, Active: 0.834782

We see that the third model has the best mean returns yet, and also the most spectacular information ratio. For backtesting, I have decided to choose the top four models categorised by mean returns. These are the linear additive model, the first, the second, and the third model in this group. Let's start backtesting to get a better feel for the performance of each model.

4.5 Backtesting:

1. Linear Additive Model: $\mathbf{f(a,x)} = \mathbf{a+x}$

	Portfolio	Benchmark	Active
Mean Return	0.068328	0.063560	0.004768
St. Dev.	0.115091	0.156942	0.078049
RR Ratio	0.593682	0.404989	0.061087

2. Inverse Positive Bias: $\mathbf{f(a,x)} = \sum^n a_i \cdot \left|1 + \frac{1}{x_i}\right|$

	Portfolio	Benchmark	Active
Mean Return	0.079590	0.063560	0.016031
St. Dev.	0.207615	0.156942	0.085274
RR Ratio	0.383357	0.404989	0.187989

3. Inverse Negative Bias: $\mathbf{f(a,x)} = \sum^n a_i \cdot \left|-1 + \frac{1}{x_i}\right|$

	Portfolio	Benchmark	Active
Mean Return	0.085648	0.063560	0.022088
St. Dev.	0.206287	0.156942	0.087096
RR Ratio	0.415187	0.404989	0.253603

4. Scaled Positive Bias: $\mathbf{f(a,x)} = \sum^n a_i \cdot |1 + x_i|$

	Portfolio	Benchmark	Active
Mean Return	0.069768	0.063560	0.006208
St. Dev.	0.129957	0.156942	0.070615
RR Ratio	0.536850	0.404989	0.087910

We see that both the linear and the scaled model has similar mean returns with high Information Ratio and low volatility compared to the inverse models. However, the inverse models produce better mean returns which implies that they will likely outperform the other two portfolios. The first and the fourth model can be grouped together and the fourth can be selected as the better of the two since it has higher returns and similar Information Ratio as the linear model. Although, the linear model cannot be brushed off easily as despite being such a simplistic model, it does perform spectacularly well. Either of these can be picked. I have decide to go for the fourth one. Similarly, the second and the third model can be grouped together out of which the third one is a pretty obvious choice since it has higher returns and a higher Information Ratio combined with a lower volatility.

Now, we must decide between model 3 and model 4. Model 3 has higher returns but model 4 is safer and less volatile. Although, neither of these portfolios are too volatile. It is really a question of whether or not one is willing to accept a 29% increase in risk for a 22% increase in mean monthly returns. I, for one, am willing to accept that! The higher the risk, the higher the reward is one of the basic foundation stones of beating the market. Therefore, I have decided to go for the third model as my strategy of choice. For better visualisation, I have plotted the price graph of my strategy along with the EPQ only strategy, and the Benchmark. It seems that our portfolio shadows the Value Only portfolio for more than a decade. After 2018, however, the two diverge with the graph for the value signal slumping while the combined signal performs well. Please have a look at the graph below:

5 STRATEGY OPTIMISATION

5.1 Methodology:

We will use our newly created signal and the backtesting function to run and test several parameters on how they affect the performance of our portfolio. In particular, we will be interested in maximising the Information Ratio and maximising the mean returns. Ideally, one single combination would fulfill both of those requirements. To do so we will vary the parameters namely, the number of stocks and the rebalancing frequency. Here we will be using 9 iterations to test for the performance of each of the combinations of a 100, 250, and a 1000 stocks being rebalanced every 1, 3, or 12 months. After which the Information Ratio and Mean Returns will determine the most optimal parameters for our portfolio.

5.2 Results:

Information Ratio

	100 shares	250 shares	1000 shares
1 month(s)	0.416939	0.253603	0.120261
3 month(s)	0.363386	0.332831	0.096838
12 month(s)	0.578968	0.265022	0.136943

Mean Return

	100 shares	250 shares	1000 shares
1 month(s)	0.101448	0.085648	0.069967
3 month(s)	0.097454	0.091517	0.068701
12 month(s)	0.123511	0.087676	0.070262

Going down each column of the Information Ratio data frame one can see that the Information Ratio increases as the number of months increases. Similar pattern can be seen for the Mean Return data frame. Of course, it is easily noticeable that this relationship is certainly not linear. For example, for a 100 shares the Information Ratio dips as we go from rebalancing every month to every three months. Then it picks up again at 12 months, being the highest. While the Information Ratio for 250 shares first rises when changing from rebalancing every month to every three months and then dips when rebalancing every 12 months. Therefore, I must conclude that the increase in number of months till rebalance does not always correspond to the increase in the Information Ratio. The relationship is not linear or always in the same direction. Hence, it would be hard to predict the most optimal number of months to rebalance without trying out dozens of combinations. On the contrary, travelling sideways on each row would tell us that both the Information Ratio and the Mean Returns always seem to decrease as we move rightwards. Although, this relationship is not linear either, it is safe to say that an increase in the number of shares generally corresponds to a decrease in both the Information Ratio and the Mean Return. However, as is easily noticeable the 100 shares portfolio, rebalanced every 12 months maximises both the Information Ratio and the Mean Return, which is the most ideal!

Optimal Portfolio: 100 shares rebalanced every 12 months.

References

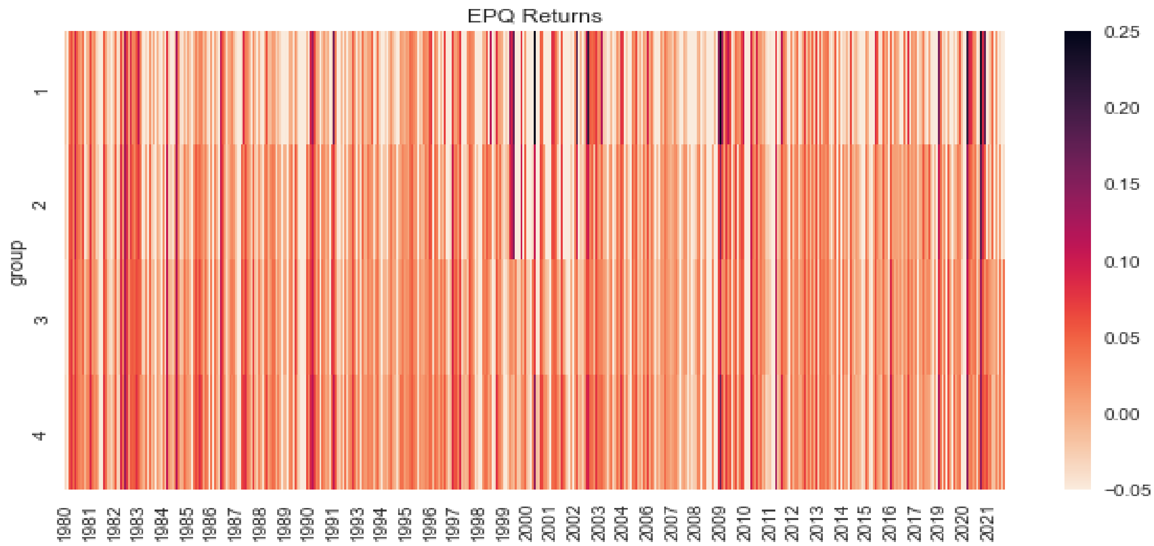
[1] Benjamin Graham and David Dodd (1934) *Security Analysis*, McGraw-Hill Book Co.

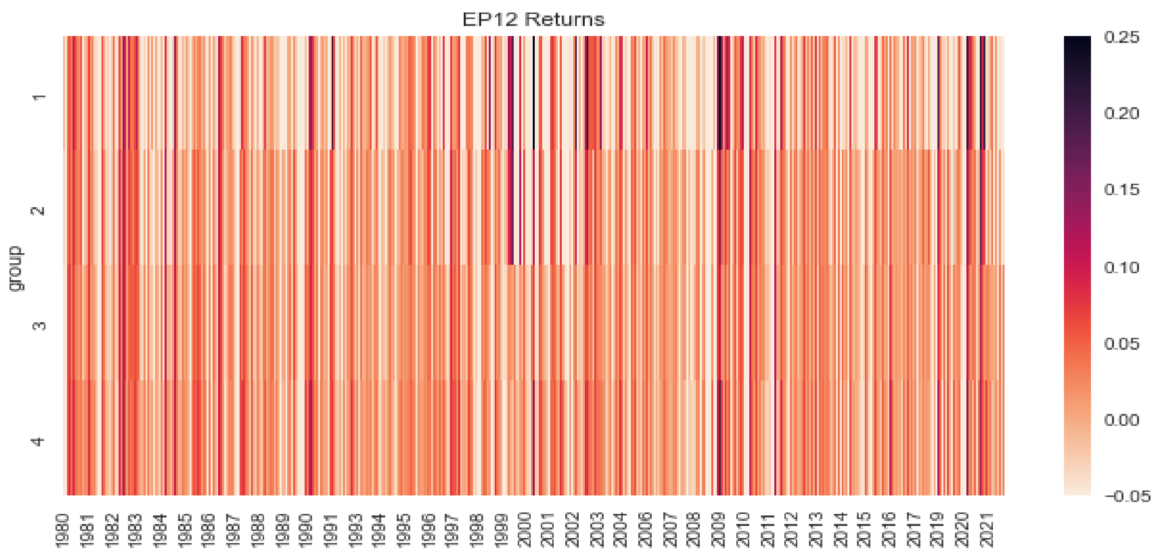
[2] Benjamin Graham and David Dodd (1949) *The Intelligent Investor*, Harper and Brothers.

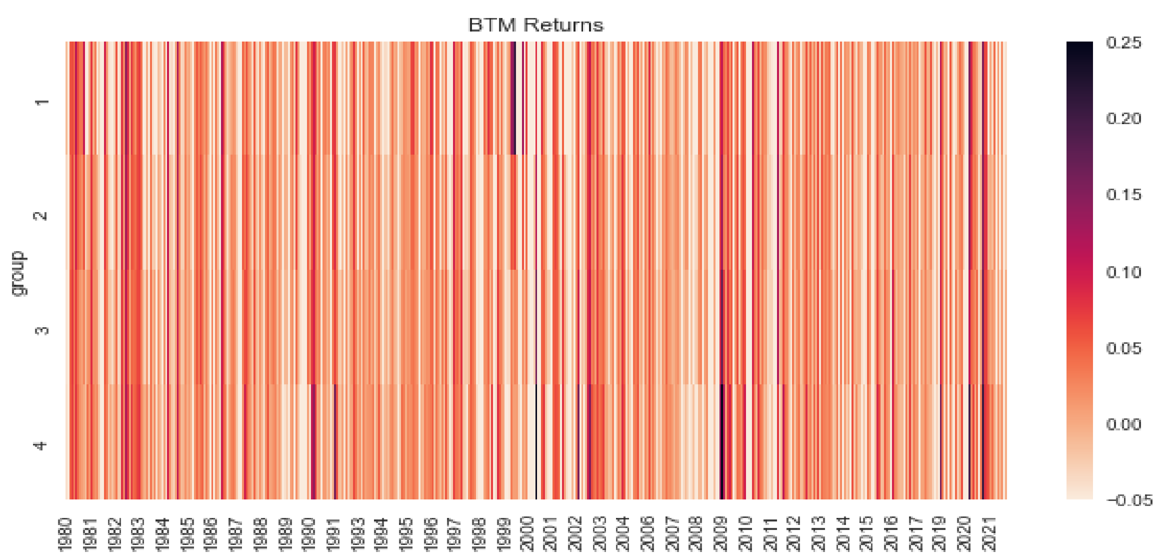
[3] Eugene F. Fama and Kenneth R. French (1998) *Value versus Growth: The International Evidence* The Journal of Finance, VOL. LIII, NO. 6.

Appendix

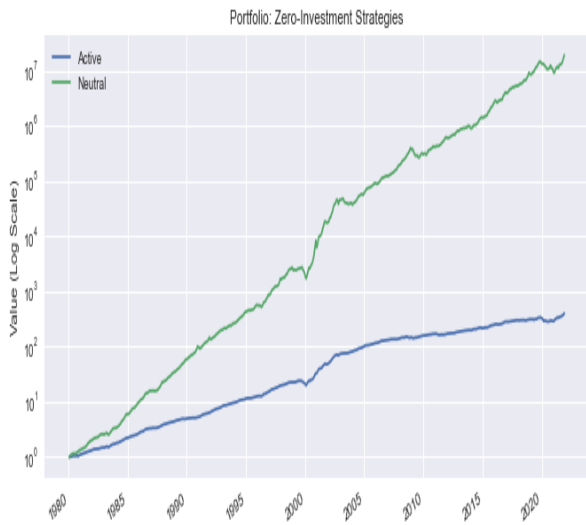
2.2.1 Heatmaps:





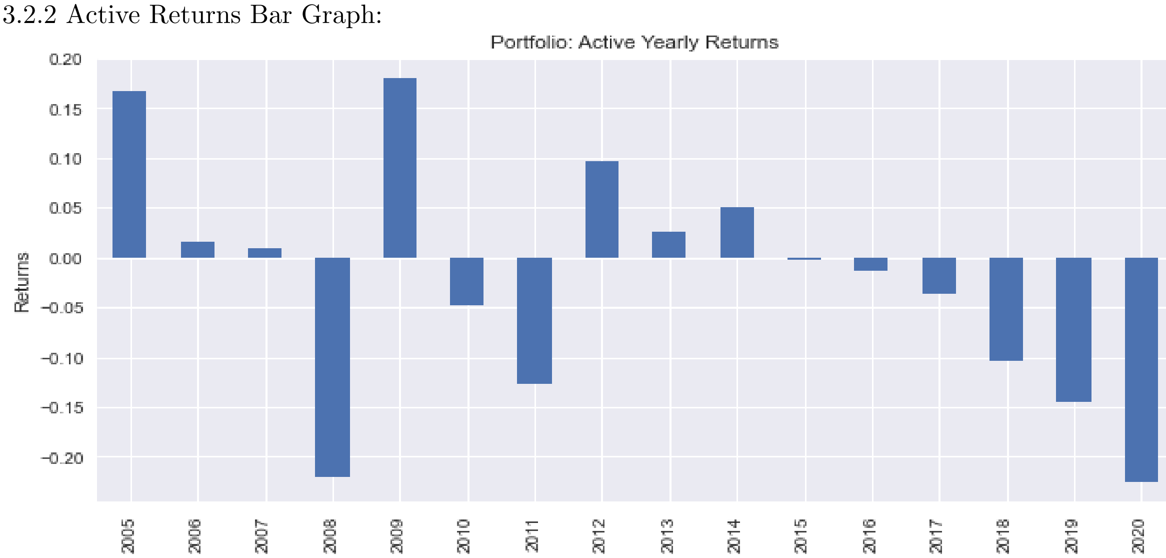


2.2.2 Zero Investment Portfolio Graph:



3.2.1 Drawdown Graph:

3.2.2 Active Returns Bar Graph:



3.2.3 Regression Plot: