Can Fundamentals Give Insights into Future Sector Performance?

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Abstract

Fundamentals provides information to better value and judge the well-being of firms. In this paper we test to see what a systematic analysis of fundamentals can tell us about future performance. In particular, we will be using fundamentals to try and capture future trends for individual S&P 500 Sector ETF's. Our idea is that fundamental analysis across sectors of businesses will help us capture broader business trends.

1. Introduction

Fundamental data of a stock gives insight on its intrinsic value. While technical analysis extracts value largely from the price history of a company, fundamentals give an alternative look at its underlying value. Commonly, fundamental analysis is used for long-term investment decisions, being that the trend of a company's general business health is reflected over longer periods in the market. Technical analysis on the other hand is used in a variety of ways to profit off of a stock in a shorter time period. We aim to test if fundamental data can generate long-term alpha similar to how technical strategies aim to generate short-term predications. Our research focuses on the ten S&P 500 Sector ETF's to test the effectiveness of systematic fundamental analysis across different equity groups. We generated two strategies to test the following question: Can systematic fundamental analysis provide above-market performance over a long investment horizon?

2. Determining Fundamental Ability

2.1. Gathering Data

We acquired monthly fundamental data for the following S&P 500 sectors:

Sectors:

S5CONS	**S5TELS**	**S5ENRS**	**S5COND**	**S5FINL**
Consumer Staples	Telecommunications	Energy	Consumer Discretionary	Financials
S5INDU	**S5INFT**	**S5HLTH**	**S5MAT**	**S5UTIL**
Industrials	Information Technology	Health Care	Materials	Utilities

We gathered data from June 1990 to March 2018 from Bloomberg. We combined and analyzed each set to find any inconsistencies. Missing data was highlighted and avoided in our strategy. We then used Thomson Reuter's Datastream to generate the daily close price for each sector and the total S&P 500 Composite over the same 28 year period. While the actual trading instrument would be SPDR Sector ETFs, many of these ETFs started trading in the early 2000's. We examined the relationship between the S&P reported sectors and their ETFs to confirm they move in tandem. Thus, we used the S&P reported sector price data to allow us to analyze data since 1990.

Fundamentals:

Price/Earning, Positive	Price/Earnings before XO	Price/Book Value	EV/Sales
Dividend Yield	Gross Margin	Operating Margin	Profit Margin
Return on Assets	Return on Equity	Free Cash Flow Yield	EV/EBIT

2.2. Choosing Fundamentals

The next step was choosing which fundamentals we would use. We used three fundamentals for our first strategy: Price to Book Ratio, Price to Earnings, Positive, and Return on Equity. We chose these three because they not only provided us with the most consistent data, but they are also three of the most highly referenced and used fundamentals in the market. These would be implemented in a long-only monthly strategy.

The second strategy is a spread strategy that uses four fundamentals: Enterprise Value to EBIT, Return on Assets, Free Cash Flow Yield, and Gross Margin. We chose EV/EBIT multiple as a measure of how expensive a sector is trading. We felt this would be effective across sectors as it captures the multiple of firm's earnings without biases towards capital structure or tax rate. It is the most commonly used metric to assess purchases of private companies and value private equity transactions, which gave us confidence in its utility. Additionally, we chose ROA, FCF Yield and GM to create a "score" of the industry's current financial strength. We hypothesized that attributes like growing and positive ROA, FCF Yield, and GM would indicate a positive sector condition. We analyzed others but felt these metrics were best for testing due to the data available to us, and their common use across all sectors.

2.3. Creating the Strategies

Long-Only Threshold Strategy (P/B, P/E, ROE)

The long-only strategy generates signals from the P/B, P/E, and ROE metrics. The idea is if P/B or P/E are low, that means the sector is cheap in relation to underlying intrinsic value and earnings. If ROE is high, then it is generating strong returns for investors. Thus, if the sector is both cheap and profitable, it should be expected to outperform other sectors. Since each sector is unique, these ratios vary widely (P/B in industrials is expectedly lower than in information technology). To mitigate these variations we normalized the ratios. We started normalizing using two years of data for our initial point, including each additional month on a trailing basis. Using the normalized fundamentals we created thresholds and go long for the next month whenever all three of these conditions are met:

1) ROE goes above our threshold
2) P/E goes below our threshold
3) P/B goes below our threshold

This would result in a hit signal to go long. If no signal exists, take no position. In order to find which thresholds would be best for each sector, we created an optimizer to determine the best hit-values. This was only run on training data (1990 – 2012) to find the best thresholds to apply on our test data (2013-2018). This was to ensure avoid look-ahead bias during the testing period. The optimizer algorithm works as follows:

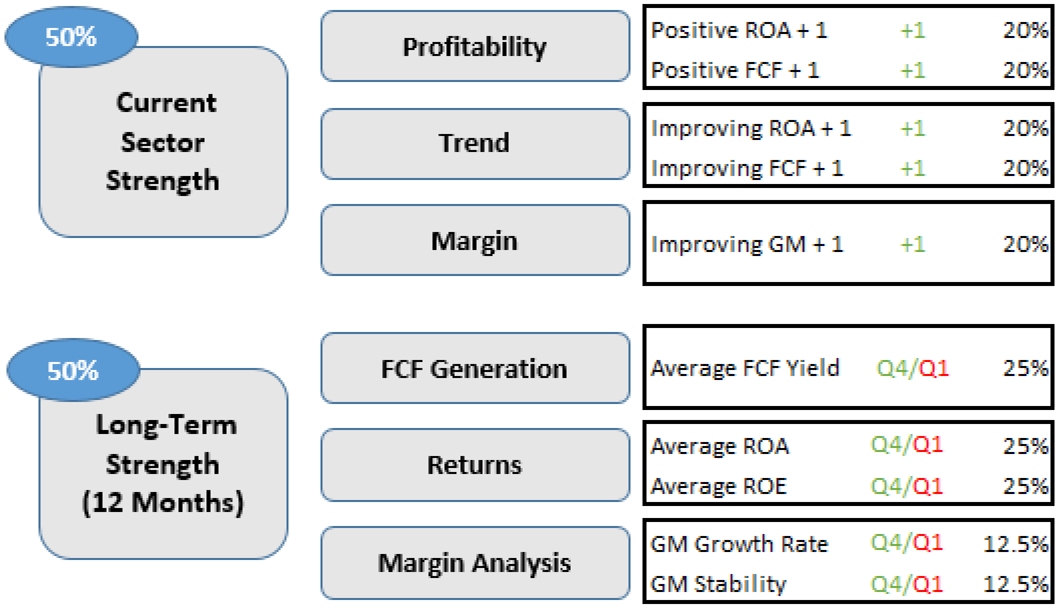
- Iterate through values from -3 to +3 sigma, moving up by .5 each time. We believe moving up by .5 will make the parameters more general and help us to avoid overfitting.
- For every combination of our 3 fundamental data fields, at each of these thresholds:
  - Find the amount of times we go long, and simulate going long using the monthly return for the next month
  - Calculate the Sharpe ratio of the strategy having done this
  - If the Sharpe exceeds our initial global Sharpe variable and we are in for at least 20% of the time, update our thresholds and continue.

  *****Full code included with our files

This algorithm is run for each sector and returns the thresholds that produce the best Sharpe ratio for the training period. Doing this leaves a five-year period free of overfitting and bias to test the strategy with the optimized thresholds.

Spread Fundamentals Strategy (EV/EBIT, ROA, FCF Yield, GM)

The second strategy generates long and short signals by placing sectors in two buckets. The rationale is to long cheap, well performing sectors and short expensive, underperforming sectors. There are two tests, value and quality. The first test ranks sectors into value buckets ranging from most expensive to cheapest. The range is based on the EV/EBIT multiple. The highest EV/EBIT sectors being expensive and lowest EV/EBIT being the cheapest. It’s important to note we normalized the EV/EBIT so these buckets are made by comparing how expensive sectors are relative to their normal levels. After creating these value buckets we built a second metric to screen for quality. The quality screen created a sector score using the follow tests:



[1] Alpha Architect

We created the quality metric based on this concept from Alpha Architect [1]. The score combines elements of a commonly used financial strength score, the F-Score, and long-term business strengths. A quality score is created by equally weighing each sector's current monthly strength and long term (one year) overall strength, calculated as follows:

Current Sector Strength: The current strength is awarded points if the current month has positive ROA and FCF, and improving ROA, FCF, and Gross Margins. These are all given a score of +1 (or 0 if the conditions are not met), and combined on an equal basis.

Long Term Strength: The long-term strength score is created by comparing sectors over the past twelve months. Step one is averaging each sector's FCF, ROA, and ROE over the past year. We then calculate the one-year growth rate of gross margin. Lastly, we create a test of margin stability by averaging the margin over the past twelve months and dividing it by the standard deviation of the margin over the same period. Each of these five metrics were then separately compared across sectors. Scores were divided into quartiles, with the top quartile receiving +1, middle two quartiles receiving 0, and the bottom quartile receiving -1. The scores from each metric were then combined at the weights shown above.

Finally, we combine the current and long-term score and use this number to screen for financial quality in each sector. We believed that combining both the value screen (the EV/EBIT screen explained earlier) and this quality screen could be a strong basis for a spread trade in which we go long cheap, high quality sectors and short expensive, low quality sectors.

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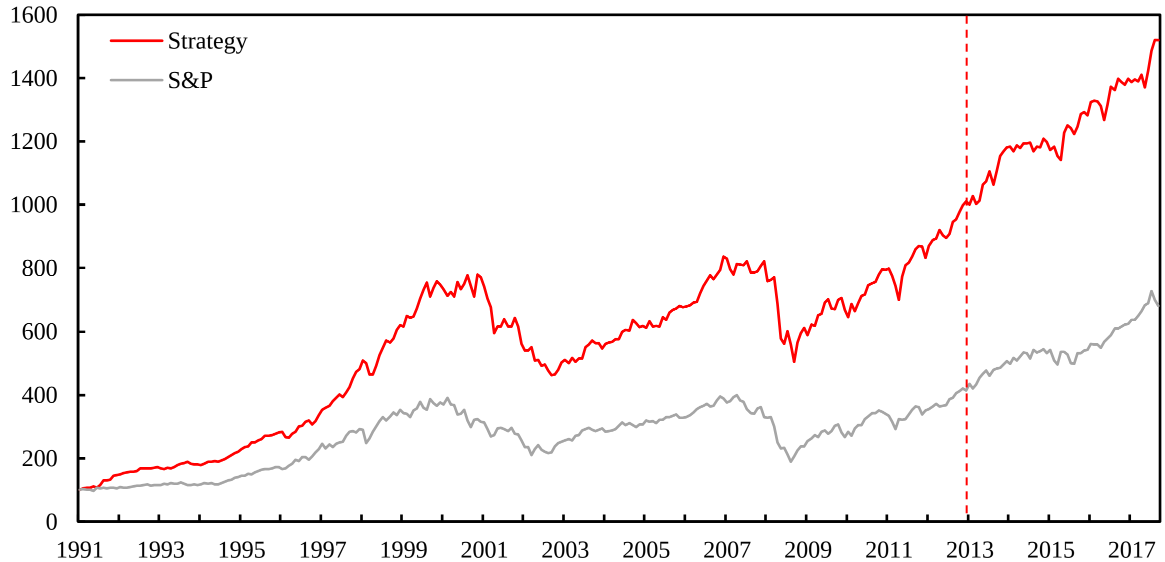
[1] Gray, Wes, and Jack Vogel. "The Quantitative Value Investing Philosophy."*Alpha Architect*, 7 Oct. 2014, alphaarchitect.com/2014/10/07/the-quantitative-value-investing-philosophy/.

2.4. Back testing the Fundamentals Strategies

2.4.1 Long Only Threshold Strategy

We applied the threshold optimizer discussed above to the out-of-sample data. We then equally weighted each long sector's return for that month and compared this to the S&P 500's monthly performance. The equity graph and results are as follows:



	Training Sample 1990-2012			Test Sample 2013-2018			Total Sample 1990-2018		
	Sharpe	Return	Sortino	Sharpe	Return	Sortino	Sharpe	Return	Sortino
Long Only Fundamentals	0.86	807%	1.46	1.34	67%	3.30	0.91	1420%	1.57
S&P Composite	0.50	286%	0.82	1.25	76%	2.57	0.58	581%	0.97

The results showed an increase in performance when applying fundamental analysis on P/E, P/B, and ROE. There is strong performance in the out-of-sample test set. Given the positive S&P 500 performance of low volatility and strong returns during our test set, the ability for our strategy to outperform both Sharpe and Sortino further supports the notion that fundamentals are able to predict future sector performance. While the strategy shows lower overall returns for our test sample, it had significantly lower volatility. It also saw smaller drawdowns, with the largest drawdown over the 5 year test period being 5.5%, compared to an 8.9% drawdown in the S&P. Given the strategies results we move forward with the notion that fundamentals can capture information about future performance.

2.4.2 Spread Fundamentals Strategy

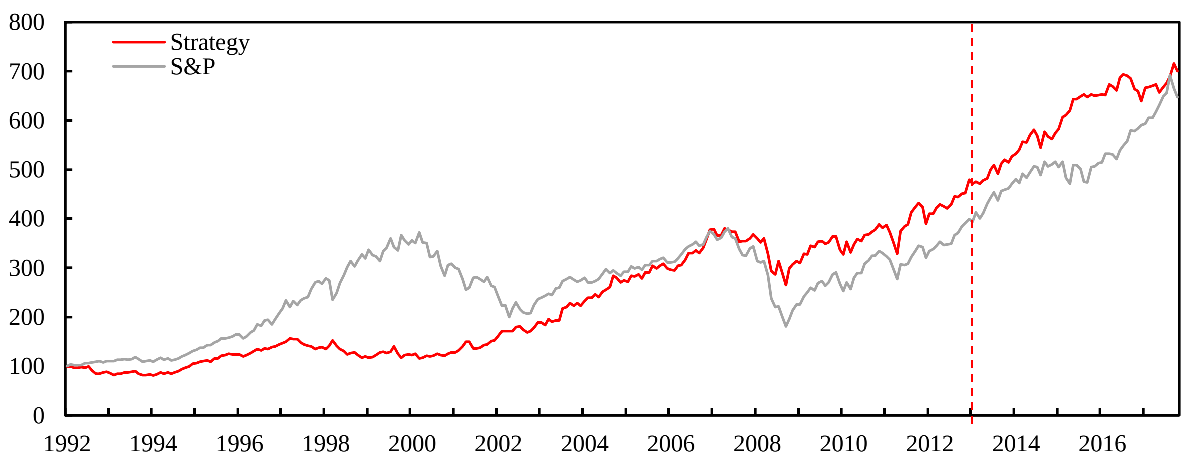
Value Screen

As mentioned earlier, the spread strategy holds two parts, the value and quality screen. To best understand the full strategy, we examined each separately before attempting to combine them. First, we looked to determine if EV/EBIT could effectively identify underpriced and overpriced sectors. The rule is if EV/EBIT is below our low threshold, go long, if is above our high threshold, go short. We took two approaches to this rule. The first was to create uniform long and short rules across all sectors. We quickly identified the wide variation of EV/EBIT averages across sectors and time periods. To be able to compare across all sectors we needed to normalize our EV/EBIT.

We conducted a few experiments on our training data from 1992-2012 (first two years used for normalizing – 1990 and 1991). Our final test used the following guidelines to generate signals for the next month:

1) Go long if normalized EV/EBIT is greater than +2σ
2) Go short if normalized EV/EBIT is less than -0.5σ

The results are long biased (as is the market), with 3.2 times more longs triggered than shorts. We also noted a significant variation of performance between sectors. Financials, Healthcare, Information Technology widely outperformed their peers. We noted these three sectors went short the least, indicating a correlation between our short threshold and negative effectiveness. We also noted that due to normalizing of EV/EBIT the signals were often unaligned with traditional market logic. Seeing a long signal with an EV/EBIT multiple over 30 made us consider if this was the right approach. While the strategy showed some promise, we were underwhelmed by the profitability of short positions and significant underperformance in the first 15 years. The back test data is show below:

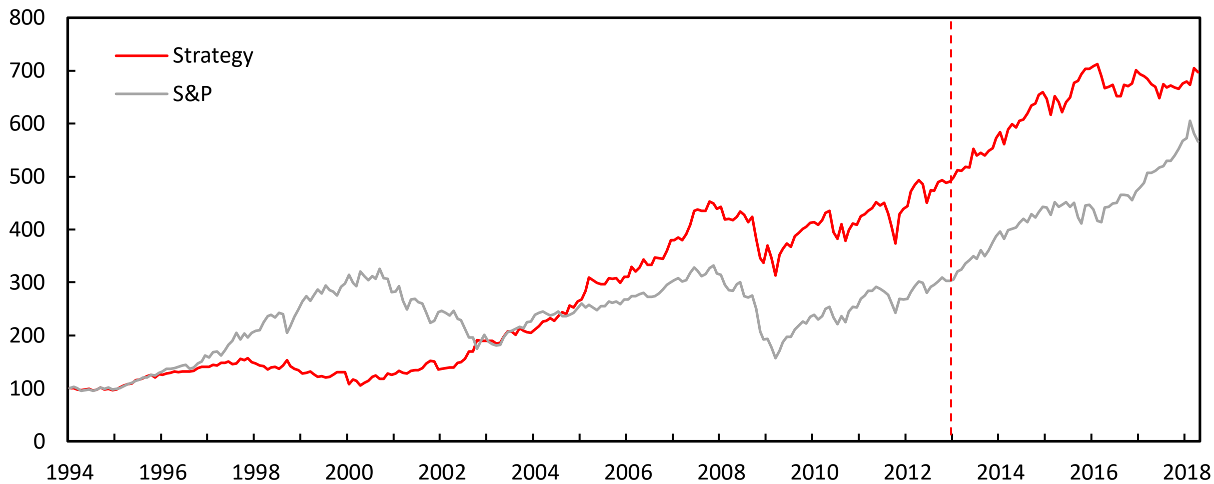


	Training Sample 1992-2012			Test Sample 2013-2018			Total Sample 1992-2018		
	Sharpe	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**
Group Value (Spread Strategy pt. 1)	0.60	330%	1.07	1.07	57%	2.81	0.68	600%	1.20
S&P Composite	0.49	249%	0.80	1.25	76%	2.57	0.59	547%	0.96

Our second approach was to create specific EV/EBIT thresholds for each sector, rather than a global threshold for all sectors. We expected that this approach would be more successful in capturing each sector's relative value. For this strategy we did not normalize EV/EBIT, as we see this as more in line with the traditional value screening process and makes the signal levels more explicable. To create thresholds we took top and bottom percentiles of EV/EBIT for each sector from the beginning of our sample to the month prior. We started our test in 1994, utilizing a four year period to gather sector averages. With these numbers we create the following simple entry rules:

1) Go long if EV/EBIT is below 25% of previous values
2) Go short if EV/EBIT is above 95% of previous values

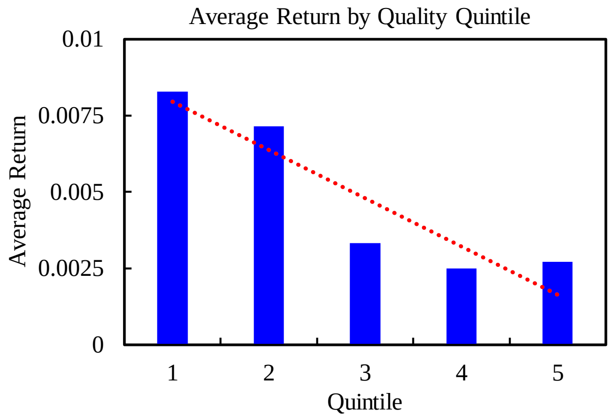
Since equity markets are long biased and valuation multiples have steadily climbed since the 1990's we hypothesized that our short threshold would have to be very stringent. In a similar logic our long cut off would be equally generous. With these percentiles our long/short ratio is 2.0. This method generated more short signals than our first test, which was preferential given that we are aiming to build a spread based strategy. This test performed slightly worst out-of-sample. Below you can see the strategies performance:

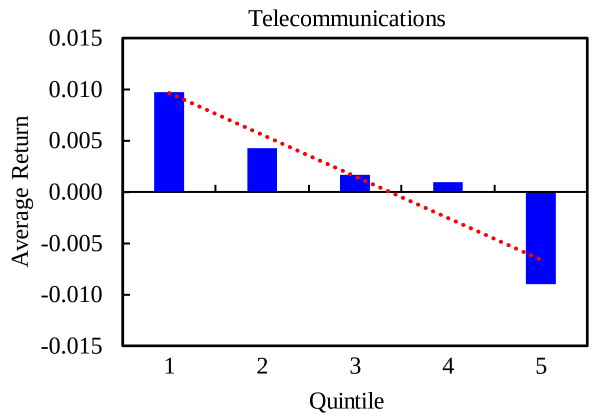


	Training Sample 1994-2012			Test Sample 2013-2018			Total Sample 1994-2018		
	Sharpe	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**
Individual Value (Spread Strategy pt. 1)	0.68	412%	1.17	0.82	36%	1.70	0.67	597%	1.16
S&P Composite	0.46	221%	0.78	1.25	76%	2.57	0.58	466%	0.94

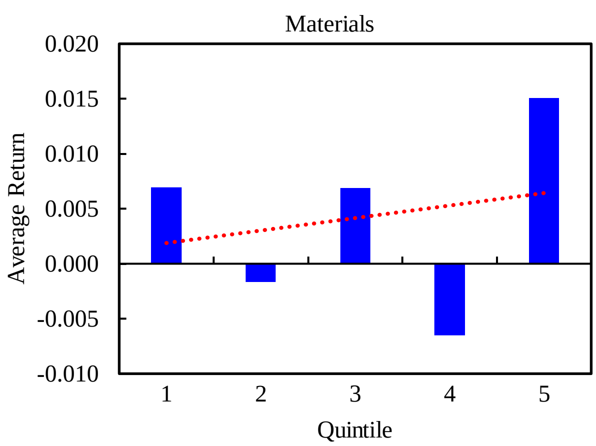
Quality Screen

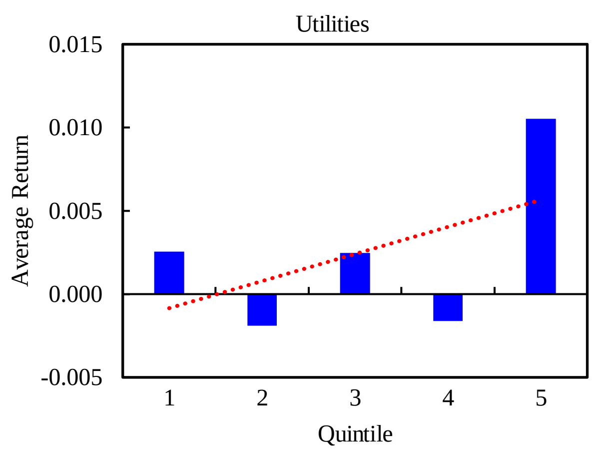
Next we looked at the second part of the spread strategy which is based on the quality scoring. First we generated monthly scores for each sector. Before we attempted to create trading signals with these scores, we tested if the quality hypothesis was true. The hypothesis was that the highest quintile scores would yield the highest average return in the next month. Conversely the lowest quintile scores would yield the lowest average return. We tested this for each sector by creating quintiles by quality scores and then took average return for each quintile (see data files for individual sector results). The following represents an average of all sectors and Telecommunications:



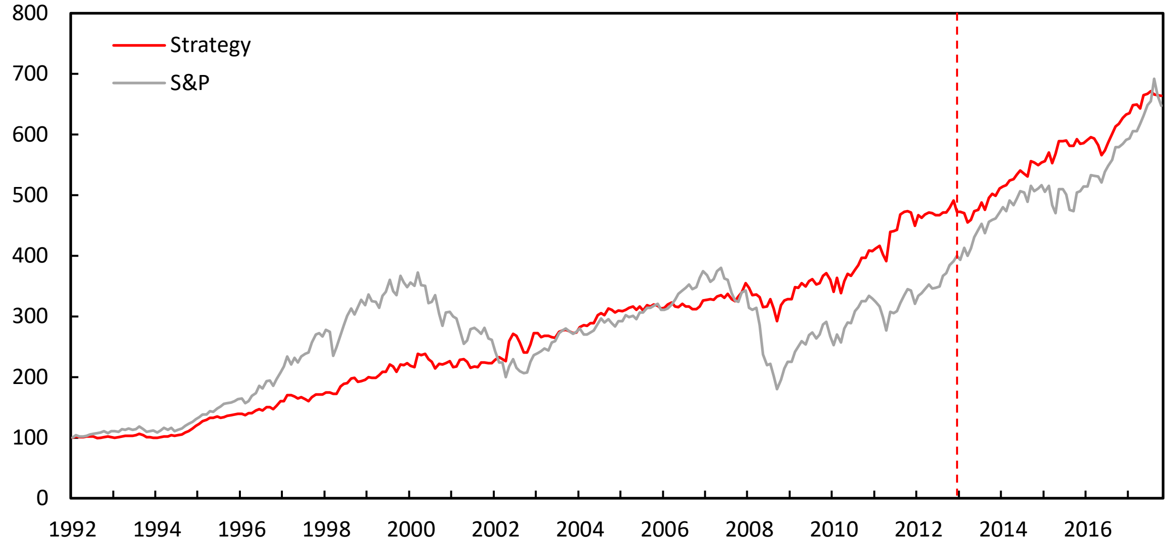


The results showed a strong correlation between returns and quality score. Telecommunications represents expected results from the quality scoring. Interestingly two sectors, Materials and Utilities, were oppositely correlated to the average:





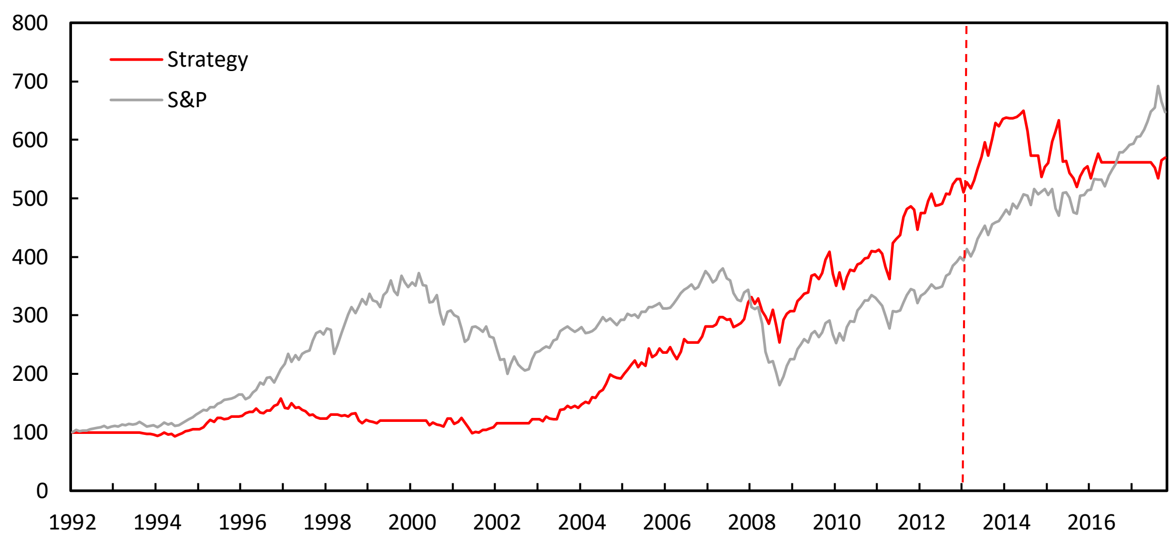
The trading rule is simple: long the top two quintiles, and short the bottom quintile for the next month. We reversed this rule for Materials and Utilities, due to their unique nature shown above. The strategy outperformed both of our EV/EBIT-based value strategies, yet still did not outperform the market in the test period:



	Training Sample 1992-2012			Test Sample 2013-2018			Total Sample 1992-2018		
	Sharpe	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**
Quality Strategy (Spread Strategy pt. 2)	0.82	367%	1.78	1.15	41%	2.27	0.86	564%	1.83
S&P Composite	0.49	249%	0.80	1.25	76%	2.57	0.59	547%	0.96

Combining the Value and Quality Metrics

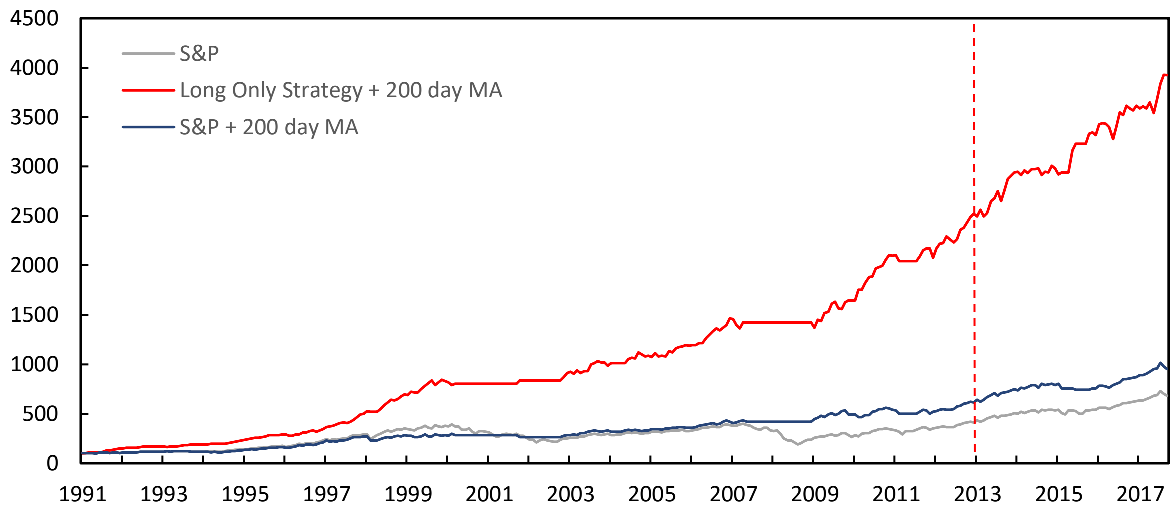
Finally, we tested our initial two-part spread based strategy, both ranking sectors into value buckets and screening based on their quality scored. The strategy works by taking a position only if both the quality score strategy above, and the individual sector-based EV/EBIT strategy indicated to take the same position, i.e. go long if both signals indicate long (and short if both signals indicate short), and take no position if the signals differ. Our performance fell below both of these strategies' individual performance, recording a total sample Sharpe of .67. A main driver of this was the lack in overlap between the value and quality signals. Often when one indicated entry, the other would not.



3. Additional Findings

3.1. Bull Market

Our first strategy showed the best performance on our test data. However, one problem was its high volatility in bear markets. It had success in picking which sectors will have highest returns in bull markets, but did poorly when deciding when to exit out of those positions. To combat, we added a 200 day moving average filter. If previous month close price fell below the 200 day moving average of the months before that, then we would take no positions for the following month. We implemented this for the S&P as well to better compare results. As mentioned when discussing our first strategy, the optimizer ran from 1990-2012, thus the key part of this graph is the test sample using the thresholds generated by the algorithm from the time period prior. The following shows our strategy with this implementation as well as the S&P with and without the 200 day moving average filter:



	Training Sample 1992-2012			Test Sample 2013-2018			Total Sample 1992-2018		
	Sharpe	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**	**Sharpe**	**Return**	**Sortino**
Long Only with 200MA	1.74	2164%	4.62	1.47	73%	3.65	1.69	3825%	4.43
S&P Composite	0.50	286%	0.82	1.25	76%	2.57	0.58	581%	0.97
S&P Composite 200MA	0.83	472%	1.51	1.30	66%	2.59	0.89	849%	1.64

3.2. Trading Costs

Examining trading costs is important to better estimate the strategies live performance. The costs for trading stocks on Interactive Brokers is $0.005 per share [2]. All of our strategies are monthly, with only 1-2 new trades per month, as we often retain positions across multiple months. Due to the monthly nature of our strategy, trading commissions are minimal. More significant are shorting costs and the management fee of holding ETF's. The gross annual expense ratio for our SPDR sector ETF's is 0.13% [3]. The short cost of borrowing on Interactive Brokers is 2.7%. We applied this management cost to our monthly values by splitting the cost by 12 for each month, and applied this 2.7% borrowing fee to each short for our second, strategy. With fees, our first long-only strategy recorded an out-of-sample Sharpe ratio of 1.318, and our 200 day moving average implementation yielded a Sharpe ratio of 1.467. The costs show minimal effects of on performance, only decreasing the Sharpe ratio by about .02 for both strategies. This is logical for a strategy that rebalances on a monthly basis and incurs minor ETF management fees.

4. Conclusion

The tests showed mixed yet promising results for fundamentals to predict future sector performance. The first strategy proved to be the best, perhaps indicating a stronger sector predictability from ROE, P/B, and P/E. However, this may also be the result of the long-only strategy itself. We may have produced similar results using other fundamentals to indicate a sector was cheap or profitable. The positive effect of the 200 day moving average, which better signaled our exits, also reveals a possible problem with fundamentals in predicting when sectors will underperform.

This may have been a similar reason why our quality and value long-short strategy showed underwhelming results. While it may be a result of the chosen fundamental, its might actually allude to an overall struggle of fundamentals to time underperformance. In addition to this, our quality scores did not prove the hypothesis behind them to be entirely correct, as the Materials and Utilities sectors gave us the opposite result of what the scores should have indicated. However, while it did not outperform the market, it still showed an ability to generate some returns, and perhaps would be better suited for a strategy utilizing a large amount of individual stocks.

Going off this, our strategies may have performed much better if we were looking at a larger basket of individual equities and not limiting ourselves to 10 sector ETF's. Doing so would allow greater diversification, as there were months where the strategies were in only one or two sectors. This lack of diversification may have exposed the strategy to risk that could be avoided with a wider array of stocks. In traditional portfolio selection, it is common practice to limit sector or industry concentration at a certain threshold.

The monthly nature of the strategies could also be tested. Fundamental analysis is traditionally associated with long-term holding periods. Perhaps longer holding periods in our strategy would allow signals to unlock additional value. We are interested in pursuing a quarterly strategy in the future. Problems associated with the long and often painful holding periods related to fundamental-based strategies lead us to further realize why technical analysis is used so often. Strategies of varying time length can be easily explored due to the frequency of signal generation possible with technical indicators. What we may look at next is the ability for a fundamentals based strategy to improve a technical strategy, utilizing some of the value predicting abilities of fundamentals combined with the faster indication of price movement that technical indicators provide. We were already somewhat exposed to this ability when our 200 day moving average signal improved our first fundamental strategy's performance.

In the end, we saw an ability to predict future performance and capitalize on it to outperform the market, especially shown in our first strategy. Many parts of this project gave us more questions about what can be done with fundamentals, serving as potential future projects. For now, we are satisfied with our positive and negative results and learned from each of them.

References

[1] Gray, Wes, and Jack Vogel. “The Quantitative Value Investing Philosophy.”*Alpha Architect*, 7 Oct. 2014, alphaarchitect.com/2014/10/07/the-quantitative-value-investing-philosophy/.

[2] Reinkensmeyer, Blain. “Interactive Brokers Review.” *StockBrokers.com*, 27 Apr. 2018, www.stockbrokers.com/review/interactivebrokers.

[3] “Sector & Industry ETFs.” *State Street Global Advisers - SPDR*, State Street Corporation, 2018, us.spdrs.com/en/strategies/sector-industry-etf