Finance 485

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Idiosyncratic Momentum

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LAKE FOREST COLLEGE

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Executive Summary

This report provides an implementation of idiosyncratic momentum in the form documented by Chaves (2012). The model – an alternative definition of momentum – calculates the idiosyncratic returns from market regressions.

The implementation suggests momentum can be made less volatile by removing the return component due to market beta exposure. With regards to performance, the algorithm performs well when the market is volatile. However, when the market is relatively calm, the model fails to capture alpha and performs poorly. What we learn from this is that momentum as a strategy performs well when market fluctuations are at their highest.

Introduction

The momentum effect, discovered in 1993 by *Jegadeesh and Titman*, is a financial phenomenon which claims that past top market performers continue to outperform.[1] Specifically, assets that realized gains in the past 3 to 12 months will continue in their profitable performance. The typical implementation of a momentum-based strategy involves selecting a universe of assets within a class (equity, bonds, real estate, etc.), and tracking performance over a period, which is selected based on the investor's time horizon. At the end of the period, individual asset returns are calculated and ranked. Assets with top returns are bought, and conversely, the assets which performed subordinately are sold. The goal of momentum investing is to generate a long-only or long-short portfolio, which contains assets that generated positive returns in the previous period.

Given the momentum philosophy and implementation, a critical weakness subsists within the strategy: an inflection point exists, where momentum reverses. Consider the 2007 and 2009 financial crisis; markets reached an inflection point, where strong past performance winners began under-performing, and losers started to realize exceptional gains.[2] Thus, the momentum principle does not persist indefinitely. Rather, investors should implement risk management strategies, to prevent momentum crashes. This report realizes the existence of momentum inflection, and suggests idiosyncratic momentum, as the best risk mitigation technique.

Idiosyncratic momentum follows the investment philosophy of the momentum strategy, but focuses on an individual stock and its performance, rather than a comparison to a relative asset or sector performance. In other words, idiosyncratic momentum proposes that individual stock attributes drive momentum returns.

Literature Review

Related Financial literature delves into available momentum risk management strategies, including the idiosyncratic technique. Within literature, idiosyncratic momentum is established to be a distinct alpha factor, generating stable and robust long-term returns. The below literature critically focusses on equity, as the asset of choice, when considering momentum strategies.

***Three Methods to Fix Momentum Crashes*, QuantPedia**

A 2019 study by Matthias Hanauer and Steffan Windmueller analyzed three momentum risk mitigation techniques: idiosyncratic momentum, constant volatility-scaling, and dynamic scaling.[2] First, traders who risk manage using constant volatility scaling, seek to maintain a static level of risk exposure regardless of broader market trends and volatility. On the contrary, traders who implement the dynamic scaling technique actively adjust their investment position based on market conditions such as trends, company fundamentals, and technical analysis indicators.

The 2019 study considered the three momentum remedies and tested the strategies comparatively. The comparison involved using U.S. stock data, in addition to data from 48 international countries. The literature concluded that all strategies: idiosyncratic momentum, constant volatility-scaling, and dynamic scaling, significantly reduce momentum crashes. Reductions in crashes were measured by examining return distributions before and after strategy implementation. After the implementation of any of the three techniques, returns became more normally distributed, as noted by reductions in skewness and kurtosis. Further, all strategies resulted in higher Sharpe ratios reported. Finally, break-even transaction costs were raised, due to the higher frequency of trading, following the implementation of a risk management technique.

After a multi-model comparison was conducted between the strategies; idiosyncratic momentum emerged as the dominant risk mitigation technique. Idiosyncratic momentum outperformed constant volatility-scaling, and dynamic scaling strategies in both the U.S. and international sample. The strategy best reduced maximum drawdowns, resulted in a Sharpe ratio almost double that of the other techniques, and performed best during January, the month where standard momentum strategies fail.

***The Idiosyncratic Momentum Anomaly,* SSRN**

The Idiosyncratic Momentum Anomaly, by David Blitz, Matthias Hanauer, and Milan Vidojevic[3], explores the driving factors of the strategies atypical returns. In the study, researchers utilized a variety of data, both time-series and cross-sectional, to explore the anomaly. This literature review will outline the five key findings concluded by the study.

The first finding included a distinction of idiosyncratic momentum from the traditional momentum strategy. Researchers could not explain idiosyncratic momentum returns by standard asset pricing factors such as market size, value, and profitability. Further, researchers concluded that the idiosyncratic momentum effect is stronger for firms with high idiosyncratic risk and low levels of institutional ownership. Idiosyncratic risk pertains to firm specific shocks, rather than overall market fluctuations. Such risks result from factors such as management change, product development, legal compliance, and more. On the other hand, institutional ownership deals with the proportion of company shares owned by either mutual, pension, or hedge funds. A lower proportion of institutional investors can decrease market liquidity and reduce the influence of corporate governance in decision making.

The third conclusion examined the distinction between idiosyncratic momentum and standard risk factors. The researchers noted that the typical explanatory factors of portfolio success did not apply in the case of idiosyncratic momentum. For example, size, market, value, and momentum risk did not significantly influence the strategies returns. In lieu of traditional risk-factors, Blitz, Hanauer, and Vidojevic reasoned that idiosyncratic momentum was influenced by behavioral biases, such as the disposition effect and investor over-confidence. The former bias, the disposition effect, involves the tendency of investors to develop strong emotional attachments to their gains and losses. The latter, over-confidence, includes the individual tendency to take on too much risk, due to an overestimate of personal abilities. Finally, *The Idiosyncratic Momentum Anomaly* concluded that the strategy can be exploited for gains. The strategy produced significant excess risk-adjusted returns in both developing and emerging markets. Further, to best capitalize on gains, this strategy is recommended to be implemented with a long-short position, where assets with high idiosyncratic volatility are bought, and conversely, assets with low idiosyncratic volatility are sold.

Overall, *The Idiosyncratic Momentum Anomaly* suggests that the idiosyncratic momentum strategy is a distinct, yet robust, anomaly in financial markets. This anomaly cannot be explained by traditional risk factors such as market beta, size, or value. Lastly, investors may be able to generate excess risk-adjusted returns by implementing a long-short equity trading strategy.

Investment Philosophy

Investment philosophies define a set of principles by which a trader makes decisions. Regardless of the philosophy (growth, value, fundamental, technical, etc.), investors must establish personal beliefs regarding market efficiency, develop strategy goals, establish a time horizon, and outline their personal expectations.

The goal of the idiosyncratic momentum strategy is to select stocks based on asset specific momentum. Idiosyncratic momentum is the tendency of an asset to continue in its performance. A key assumption defining the success of the strategy is related to market efficiency. Strategy implementation involves an analysis of stock specific information; therefore, an assumption is made that an informational advantage exists.

For example, if the market was hypothesized to be fully efficient, all available information would already be integrated into an assets price, thus, no possibility of information arbitrage exists. However, the idiosyncratic momentum strategy relies on a data driven approach: specific stock data is analyzed and exploited. Thus, weak market efficiency must exist, especially considering the presumption that returns can be explained by factors outside of market returns.

Relevant literature further suggests that the market is weakly efficient: the consensus in academia is that the idiosyncratic momentum strategy is motivated by behavioral psychology. Literature sources thus claim that the market is explained by factors related to behavioral biases.

The next component of any investment philosophy distinguishes strategies which involve active versus passive trading. This strategy is actively traded, as individual stocks are continuously monitored and analyzed. This differs from passive strategies which focus on a performance comparison to a benchmark. In short, the idiosyncratic momentum strategy attempts to outperform the market (in this case, the Wilshire 5000) via the exploitation of market inefficiencies, mainly involving a focus on individual asset momentum.

Finally, an investor must consider their time horizon. The idiosyncratic momentum strategy is typically implemented over the shorter term, thus requiring the investor to make daily or weekly trades. This short-term horizon is driven by the strategies sensitivity to company specific news. Further, it is critical to note that strategies which are shorter-term imply more risk: the investor does not have time to ride out price fluctuations caused by short-term shocks.

Alpha Model

The most widely used statistical methodology in empirical asset pricing is portfolio sorting (e.g., Bali, Engle, and Murray 2016) . [4] This procedure is used extensively in identifying and exploring relationships between expected returns and asset class characteristics. That is, it is used to examine whether one or more variables can predict future excess returns. In general, the idea is to sort individual stocks into sub-portfolios, where the stocks within each sub-portfolio are similar with respect to a sorting variable, such as firm size.

The different portfolios then represent well-diversified investments that differ in the level of the sorting variable. You can then attribute the differences in the return distribution to the impact of the sorting variable. Often, a long-short zero-cost portfolio is constructed by initiating positions in the top and bottom sub-portfolios.

Alpha Generation

Our specific application used the univariate portfolio sort which considers only one sorting variable. In our case, this sorting variable was idiosyncratic momentum. The objective was to assess the cross-sectional relation between idiosyncratic momentum and excess return on stocks in the stock universe at a given time t.

To calculate idiosyncratic momentum, we started with the estimation of the Capital Asset Pricing Model, CAPM of Sharpe (1964) [5] and Lintner (1965) [6]. This model is expressed by Chaves (2012) [7] as

$$r_{i,t} - r_t^f = \alpha + \beta\left(r_t^m - r_t^f\right) + \varepsilon_{i,t}$$

With idiosyncratic momentum as the cumulative idiosyncratic return over days $\boldsymbol{t-252}$ and $\boldsymbol{t-21}$,

$$\boldsymbol{IMOM_{i,t} = \pi_{j=21}^{252}\left(1+\varepsilon_{t-j}\right) - 1}$$

This estimation follows Chaves (2012) who skips the most recent month in traditional momentum definitions to avoid reversals. In any case, intuition suggests that the main driver of performance in our portfolio, in this form, is the isolated exposure to idiosyncratic risk independent of market movements. Put another way, our approach indirectly seeks momentum returns via stock selection by hedging beta exposure.

The Algorithm

Method

The investment universe consists of all stocks in Nasdaq and NYSE. We use the Wilshire 5000 Total Market Index which covers all stocks actively traded in the United States. We set up an automatic ROC indicator and a 1-year rolling window to hold its daily return data for a year. We warm them up with historical data. We calculate idiosyncratic momentum using a CAPM like-equation of returns over a certain period. We choose a 1-year rolling window for the calculation. We create the SymbolData class to update the rolling window of return and the calculation of idiosyncratic momentum.

In the CoarseSelectionFunction, we filter the stocks which price is lower than $5 as they are not active in the market. We then try to avoid illiquid stocks by filtering out stocks with a Dollar Volume lower than $10 million. When the return rolling window is ready, stocks are then ranked in descending order on the basis of their estimated residuals. The algorithm goes long on the top 10 stocks in the list and short on the bottom 10 stocks in the list. In each portfolio, securities are weighted equally. The portfolios are rebalanced every calendar month.

Investment Universe

Our Universe is defined from the US Fundamental Data by Morningstar which tracks US Equity fundamentals. The data covers 5,000 US Equities, starts in January 1998, and is delivered on a daily frequency. According to the QuantConect documentation, the dataset depends on the US Equity Security Master dataset which contains information on splits, dividends, and symbol changes.

In any case, we further refine by excluding penny stocks using a given price threshold of $5. We do so for our strategy to essentially mimic the Wilshire 5000 Total Market Index. For reference, the Wilshire 5000 Total Market Index, or more simply the Wilshire 5000, is a market-capitalization index of the market value of all American-stocks actively traded in the United States.[8] The universe is further refined to avoid illiquid stocks by trading stocks with at least $10 million in daily dollar volume.

The primary data used for our algorithm, however, is price data – specifically, adjusted closing price.

Back Test Methodology

Given Quant Connect's platform is event-driven, an event driven backtest was used to validate our strategy. In our case, our event-driven backtest derives from QCAlgorithm – the underlying class – and continually checks for new events before performing actions based on these events. In particular, it allows for the illusion of real-time response handling because events are continually checked for, which is precisely what we need to carry out our trading simulation.

Additionally, as Quantstart notes, 'an event-driven backtester, by design, can be used for both historical backtesting and live trading with minimal switch-out of components.' [9] Of course, this principle of code re-use in both trading and testing environments is highly desirable for our strategy.

Lastly, our event-driven backtester suits our trading simulation as it immunizes the portfolio against lookahead bias as market data receipt is treated as an "event" that must be acted upon. Put simply, it creates a realistic replication of how an order management and portfolio system would behave.

Portfolio Allocation

Within the idiosyncratic momentum strategy, portfolio allocation is equally weighted resulting in each stock within our portfolio being given the same weight regardless of its fundamental factors like size, trading activity, market capitalization, etc. The driving factor behind this use is that it limits the possibility of one stock dominating the entire portfolio. Given that the chosen strategy already carries higher levels of risk, equal weighting provides a simple form of risk management to be implemented within the strategy.

Intuitively, with more stocks contributing to the portfolio, the risk becomes spread across more stocks rather than it being over concentrated by one or a few of them. Position sizing in this manner is an important consideration for the strategy because it allows for a more diversified and risk-controlled portfolio. However, the desirability of this sizing method varies depending on the specific goals and risk tolerance pertaining to investors.

Code Implementation

<**Insert Code in Appendix Here* >

<u>Limitations</u>

A major limitation that is present within our implementation of the momentum strategy relates to the nature of the universe that data was derived from. We use a fixed universe for the algorithm which does not account for events like mergers after the data set had become available. An instance of a merger event that would be unaccounted for could be Amazon's acquisition of the retail store Whole Foods that took place in 2017. This event resulted in a major increase in Whole Foods' stock price.

The inclusion of stocks that may have been affected by a merging event similar to that of Amazon and Whole Foods within our universe allows for biases and skews to arise in relation to momentum signals. Ignoring this issue could cost investors money as the analysis of the strategy's historical market performance would be unrealistic and lead investors to the wrong conclusions (Amen 2020) .[10]

Another limitation that was noticed within our strategy was the lack of point-in-time data. This causes issues when analyzing backtesting results since there may be hindsight biases included within our dataset. This can lead to poor decision making and inaccurate analysis of strategy performance since we are attempting to use future data that is not available to us yet within our backtesting.

Algorithm Improvements

Given the limitations of the strategy, a possible solution to combat the issues presented would be to utilize a dynamic universe for data collection rather than a fixed universe. Dynamic universes combat several issues associated to fixed universes such as inaccurate reflection of market state, inaccuracy within data points, and hindsight bias. The characteristics of this kind of universe require the use of point-in-time data for backtesting ,allowing us to avoid hindsight bias that may present itself in our results. This is due to the nature of point-in-time data where it captures relevant stock data such as volume, price, market cap, etc. with a specific time stamp associated to it. [10]

Our analysis of the strategy's performance would become more accurate with the use of this kind of data since there would only be an inclusion of historical data within our back tests. By using a dynamic universe, which is updated in time, we also address earlier concerns about not accounting for merger events that occur after the collection of the dataset. This is because dynamic universes provide more up-to-date data that is being consistently updated.

Results

To conduct our backtest analysis, we performed four separate back tests that covered varying time periods. The primary backtest that was used for comparison purposes covered the years spanning

2016 to 2020. As part of our analysis, we examined several statistics that aided us in understanding the risk and return associated to the strategy during the period of interest. One of these statistics includes the Sharpe ratio which we found to be relatively low, standing at 0.443 (Appendix A). This means that the excess returns of the strategy over the span of years 2016-2020 are low compared to the risk the investor of the strategy would be taking. We also considered another risk-adjusted performance measure called the Treynor ratio that specifically measures reward to systematic risk (the risk that is attributable to market factors). Our measure of systematic risk is represented by beta which is 0.481 for this backtest. The Treynor ratio displayed similar findings to that of the Sharpe ratio as the excess return is relatively low compared to the systematic risk the strategy employs.

Another risk indicator that investors may be interested in includes the drawdown of this strategy which sits at 25.100% (Appendix A). This means that there is a large range between the highest point of returns for the strategy and the lowest point which suggests that there may be more risk associated to this specific residual momentum strategy. This may not be a deterring factor to some investors with high-risk tolerance and acceptance of the higher risk for a higher return. In the case of residual momentum strategies, it is not uncommon to see larger drawdown percentages attached to their performance. This is due to the high likelihood of rapid price swings in held assets that were assumed to continue outperforming.

The strategy seems to perform well as 51% of the trades made during the four-year period were profitable trades. However, this is not an exceptional performance since there is still a loss rate of 49%. In multiple cases, the win and loss rates are very close in range with the win rate exceeding that of the loss rate. The momentum strategy produced a positive alpha of 0.012 meaning that the return of the investment strategy barely exceeded that of which it was expected to. Although the strategy seems to have high risk levels associated with its returns, it does prove to be profitable seeing as though there is a net profit of over $300,000 within this four-year period.

Comparison Between Back Tests

The first additional backtest that was conducted covered an expanded period that examined the strategies performance of the years 2014 to 2020. With an expanded time- period, it seems the strategy does not outperform the previous backtest where there was a shorter four-year period. This is reflected in the net profit becoming negative, and investors experiencing a loss of $40,000. The Sharpe ratio and Treynor ratio both decrease significantly, implying there is an extremely small return for the risk taken in this strategy. The beta slightly increases to 0.507 which can indicate there is a large factor of systematic risk related to this strategy even in longer periods. Considering that idiosyncratic momentum strategies are implemented for short term use to capture trends and fluctuations unique to specific stocks rather than broader markets, it is not surprising that the strategy did not perform well over this longer period. Due to the volatile nature of this specific strategy, more efforts would be needed to monitor and effectively manage the prevention of significant losses if it is going to be implemented for long term use.

To continue our analysis, we conducted a backtest with the period being shortened to two years ranging from 2018 to 2020. We found that the residual momentum strategy performs extremely worse relative to other time periods of interest. The investor loses a profit of over $90,000 implementing this strategy during these years. We also noticed that the Sharpe ratio and Treynor ratio both become negative meaning there is negative excess return associated to the expected risk of the investment strategy. The beta decreases to 0.182 meaning the strategy has become less correlated with the market. This may imply that the strategy is not being implemented well for these shorter time periods since the strategy does not seem to be fully capitalizing off market gains. However, we notice that the potential for high returns still exists since there is still a significant difference between the peak and trough of the strategy's performance, as evidenced by the drawdown percentage of over 24% (Appendix C). This reaffirms that the strategy is subject to significant volatility, which could result in large losses during periods of market turbulence or when momentum trends swiftly reverse. This seems to be the case for this two-year period since the beginning years of the COVID-19 pandemic is captured within this time frame. Within the strategy equity chart, there is a significant drop nearing the months where the pandemic begins (Appendix C). This may imply that the unexpected market turmoil caused by the pandemic caused significant losses for investors utilizing this strategy in those months.

To investigate the patterns of the strategy in relation to time length more thoroughly, we performed one last backtest running for a short time-period of three years. This time the strategy seemed to perform extremely well as it received a net profit of over $601,000 (Appendix D). Both the Sharpe ratio and Treynor ratio increased significantly from the previous period where they were negative, showing that excess returns are expected to be high in relation to the risk taken (Appendix D). The beta is still relatively low with a slight increase from the last period. This means that the strategies' performance may not be reliant on whether it is implemented over a shorter period or a longer period but rather the specific time frame itself. This greater performance during this time frame may be due to unique market conditions or data patterns that pertain to these years, which was an idea that was hinted at within the analysis of the previous back tests. Interestingly, the observed pattern of the residual momentum strategy' performance during the COVID-19 pandemic varies between the early stages of the pandemic and later ones that follow. The major losses that are related to the early stages of the pandemic could be attributed to investors' inability to counteract the losses that the unexpected swift and severe market conditions brought about. However, it seems that investors were able to profit from the use of this strategy as the pandemic progressed and market conditions restabilized to some extent (Appendix D, second chart).

The implementation of the idiosyncratic momentum strategy over varying time periods revealed several key findings. It appears the performance of the strategy is optimized within shorter time frames where stabilized market conditions exist. Profitability of the strategy is not exclusive to the short-term implementation but if long term implementation is being considered, then higher levels of management are required to sufficiently monitor and adjust the strategy as market conditions change through time. Therefore, it is important for investors to consider their personal preferences in relation to risk tolerance and strategy involvement before deciding which time horizon they would like to execute the idiosyncratic momentum strategy on. The high level of risk associated with the strategy became apparent during the period covering the COVID-19 pandemic as the destabilized market conditions significantly impacted the strategy's performance. Due to the nature of the idiosyncratic momentum strategy, the observed high-risk levels highlight the importance of proper risk management and monitoring by investors if they choose to use this strategy. Overall, the strategy proves itself to be profitable given proper implementation efforts and market luck.

Conclusion

Numerous studies have demonstrated the existence of momentum effect in different asset classes. Among stocks, these studies confirm momentum investing typically is a market-beating strategy — but also that it isn't foolproof. It doesn't work in every market environment and its reversal can leave trend-followers badly bloodied.

However, as Chaves (2012) shows, the risk of momentum is highly predictable with it being mainly related to market exposures. Thus, managing this momentum's risk via idiosyncratic momentum has the potential to eliminate exposure to crashes and increase the Sharpe ratio of the strategy substantially. Our results confirm this appears to be the case with evidence contained in the low betas recorded across multiple backtests. If anything, idiosyncratic appears to be robust.

However, the implemented strategy did prove to hold its own faults - specifically varying with market volatility. This led us to conclude that a more thorough of investment management process would be required to offset unexpected losses. Our results show idiosyncratic momentum has the possibility to earn significant returns during times of high economic and market volatility. Overall, the momentum strategy can be an effective and profitable trading strategy for the right investors.

Appendix A (2016 to 2020)

Overview Report Orders Insights Logs Code Share

Download Results

PSR	8.573%	Sharpe Ratio	0.443
Total Trades	817	Average Win	0.87%
Average Loss	-0.73%	Compounding Annual Return	7.528%
Drawdown	25.100%	Expectancy	0.113
Net Profit	33.715%	Loss Rate	49%
Win Rate	51%	Profit-Loss Ratio	1.19
Alpha	0.012	Beta	0.481
Annual Standard Deviation	0.139	Annual Variance	0.019
Information Ratio	-0.293	Tracking Error	0.141
Treynor Ratio	0.128	Total Fees	$17289.20
Estimated Strategy Capac…	$2000000.00	Lowest Capacity Asset	WD USGI91RMTXET
Portfolio Turnover	4.84%		

Appendix B (2014 to 2020)

Download Results

PSR	0.300%	Sharpe Ratio	0.069
Total Trades	1326	Average Win	0.80%
Average Loss	-0.76%	Compounding Annual Return	-0.403%
Drawdown	44.300%	Expectancy	0.003
Net Profit	-2.396%	Loss Rate	51%
Win Rate	49%	Profit-Loss Ratio	1.06
Alpha	-0.033	Beta	0.507
Annual Standard Deviation	0.169	Annual Variance	0.029
Information Ratio	-0.447	Tracking Error	0.169
Treynor Ratio	0.023	Total Fees	$24225.93
Estimated Strategy Capac…	$1800000.00	Lowest Capacity Asset	WRLD R735QTJ8XC9X
Portfolio Turnover	5.14%		

Rolling Statistics

Sharpe Ratio

Appendix C (2018 to 2020)

D

PSR	2.203%	Sharpe Ratio	-0.188
Total Trades	242	Average Win	1.41%
Average Loss	-0.85%	Compounding Annual Return	-4.474%
Drawdown	24.400%	Expectancy	-0.073
Net Profit	-8.748%	Loss Rate	65%
Win Rate	35%	Profit-Loss Ratio	1.65
Alpha	-0.04	Beta	0.182
Annual Standard Deviation	0.125	Annual Variance	0.016
Information Ratio	-0.706	Tracking Error	0.16
Treynor Ratio	-0.129	Total Fees	$4431.11
Estimated Strategy Capacity	$2900000.00	Lowest Capacity Asset	BMA TH817L14OZ8L
Portfolio Turnover	3.11%		

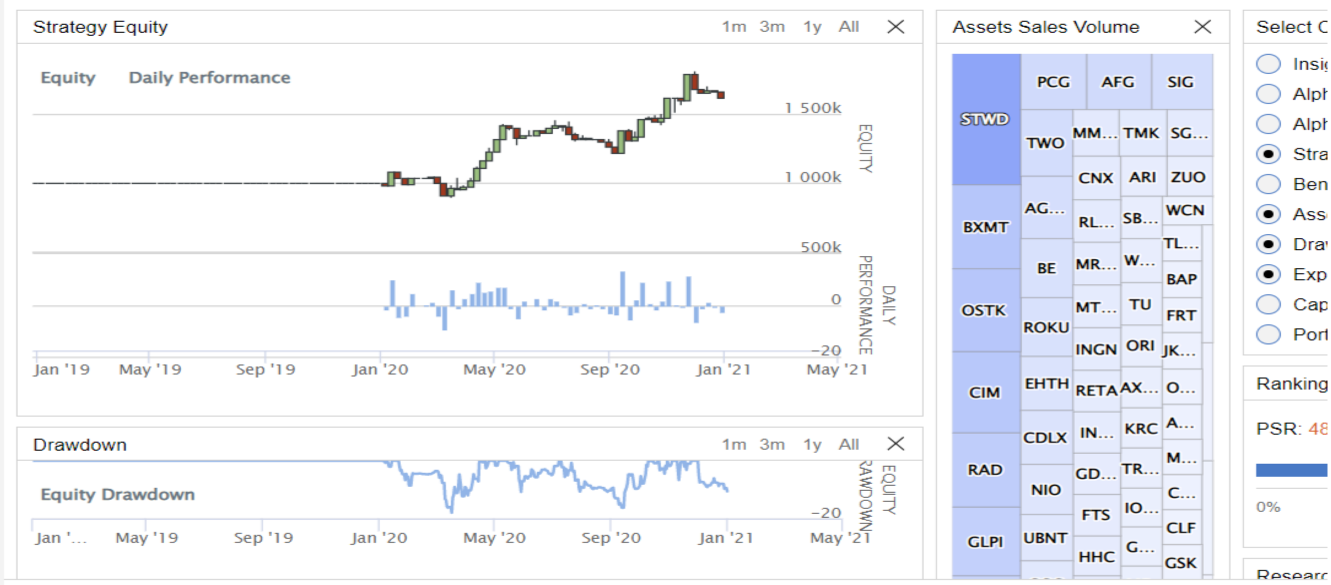
Rolling Statistics Sharpe Rati

Appendix D (2019 to 2020)

Overview Report Orders Insights Logs Code Share

PSR	48.216%	Sharpe Ratio	1.069
Total Trades	293	Average Win	2.22%
Average Loss	-1.24%	Compounding Annual Return	27.041%
Drawdown	18.000%	Expectancy	0.289
Net Profit	61.499%	Loss Rate	54%
Win Rate	46%	Profit-Loss Ratio	1.79
Alpha	0.152	Beta	0.254
Annual Standard Deviation	0.188	Annual Variance	0.035
Information Ratio	0.044	Tracking Error	0.239
Treynor Ratio	0.791	Total Fees	$7491.92
Estimated Strategy Capacity	$2600000.00	Lowest Capacity Asset	UBNT V0QUPDLS0J1H
Portfolio Turnover	3.62%		

$2.6M	$1,614,990.65	-$7,491.92	$276,267.06	$601,697.49	48.216%	61.50 %	$13,273
Capacity	Equity	Fees	Holdings	Net Profit	PSR	Return	Unrealized



Code Implementation

```
#region imports
from AlgorithmImports import *
#endregion
from QuantConnect.Data.UniverseSelection import *
from QuantConnect.Python import PythonData
from collections import deque
from datetime import datetime
import math
import numpy as np
import pandas as pd
import scipy as sp
from decimal import Decimal


class ResidualMomemtumInStocks(QCAlgorithm):

    def Initialize(self):
        self.SetStartDate(2016, 1, 1)
        self.SetEndDate(2020, 1, 1)
        self.SetCash(1000000)

        self.UniverseSettings.Resolution = Resolution.Daily
        self.AddUniverse(self.CoarseSelectionFunction)
        self.AddEquity("SPY", Resolution.Daily)
```

```
        # Add Wilshire 5000 Total Market Index data from Dropbox
        self.price5000 = self.AddData(Fred, Fred.Wilshire.Price5000, Resolution.Daily).Symbol
        # Setup a RollingWindow to hold market return
        self.market_return = RollingWindow[float](252)
        # Use a ROC indicator to convert market price index into return, and save it to the RollingWindow
        self.roc = self.ROC(self.price5000, 1)
        self.roc.Updated += lambda sender, updated: self.market_return.Add(updated.Value)
        # Warm up
        hist = self.History(self.price5000, 253, Resolution.Daily)
        for point in hist.itertuples():
            self.roc.Update(point.Index[1], point.value)

        self.data = {}
        self.monthly_rebalance = False
        self.long = None
        self.short = None

        self.Schedule.On(self.DateRules.MonthStart("SPY"), self.TimeRules.AfterMarketOpen("SPY"), self.rebalance)

    def CoarseSelectionFunction(self, coarse):
        CoarseWithFundamental = [x for x in coarse if x.HasFundamentalData and x.DollarVolume>10000000]
        for c in CoarseWithFundamental:
            if c.Symbol not in self.data:
                self.data[c.Symbol] = SymbolData(c.Symbol)
            self.data[c.Symbol].Update(c.EndTime, c.AdjustedPrice)
```

```
        if self.monthly_rebalance:
            filtered_data = {symbol: data for symbol, data in self.data.items()
                             if data.last_price > 5 and data.IsReady()}
            if len(filtered_data) > 100:
                # sort the dictionary and select top and bottom 10 stocks
                sorted_beta = sorted(filtered_data,
                                     key = lambda x: filtered_data[x].beta(self.market_return),
                                     reverse=True)
                self.short = sorted_beta[-10:]
                self.long = sorted_beta[:10]
                return self.long + self.short

            else:
                self.monthly_rebalance = False
                return []

        else:
            return []

    def rebalance(self):
        self.monthly_rebalance = True

    def OnData(self, data):
        if not self.monthly_rebalance: return

        # Liquidate symbols not in the universe anymore
        for symbol in self.Portfolio.Keys:
            if self.Portfolio[symbol].Invested and symbol not in self.long + self.short:
                self.Liquidate(symbol)


        if self.long is None or self.short is None: return
```

```python
        for symbol in self.long:
            self.SetHoldings(symbol, 1/len(self.long))

        for symbol in self.short:
            self.SetHoldings(symbol, -1/len(self.short))

        self.monthly_rebalance = False
        self.long = None
        self.short = None


class SymbolData:
    def __init__(self, symbol):
        self.Symbol = symbol
        self.last_price = 0
        self.returns = RollingWindow[float](252)
        self.roc = RateOfChange(1)
        self.roc.Updated += lambda sender, updated: self.returns.Add(updated.Value)

    def Update(self, time, price):
        if price != 0:
            self.last_price = price
            self.roc.Update(time, price)

    def IsReady(self):
        return self.roc.IsReady and self.returns.IsReady
```

Works Cited

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