Relative Strength Rating

QUANTITATIVE RESEARCH O'NEIL GLOBAL ADVISORS INC.

RS Rating: It's All Relative

July 29, 2020

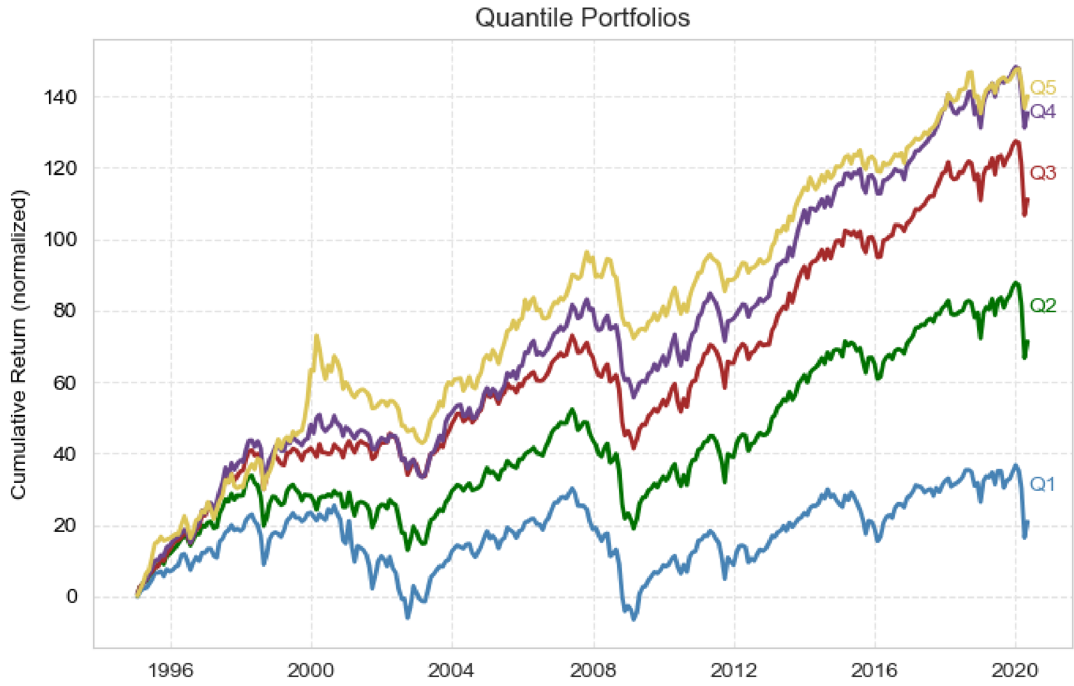

Figure 1: Cumulative monthly log returns for quantile portfolios constructed based on Relative Strength (RS) Rating across our U.S. equity market universe, with Q5 representing stocks with the highest RS Ratings. Results are liquidity-weighted and normalized with respect to intertemporal changes in market volatility.

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KEY FINDINGS:

- **Portfolios of stocks in the top RS Rating quintile have higher returns and lower volatility than those in the lowest quintile.**
- **Long/short portfolios built based on RS Ratings earned statistically significant positive returns.**
- **After adjusting for changes in market volatility over time, effects are consistently robust, though prone to shorter-term cycles.**

EXECUTIVE SUMMARY

In this paper, we demonstrate the effectiveness of William O'Neil + Co.'s Relative Strength (RS) Rating™ in picking stocks expected to outperform (or underperform) the market in the future such that they can be used to form market-neutral strategies that extract positive returns while hedged against broader market exposures. We perform cross-sectional studies using **quantile portfolios built based on RS Ratings, finding significant evidence of a momentum effect**. We show that quantile-based long/short portfolios built based on RS Rating earned statistically significant positive returns despite remaining ostensibly market neutral and demonstrate that, after properly adjusting for changes through time in broader market volatility, such effects are relatively robust over time.

INTRODUCTION

RELATIVE STRENGTH RATING™ (RS)

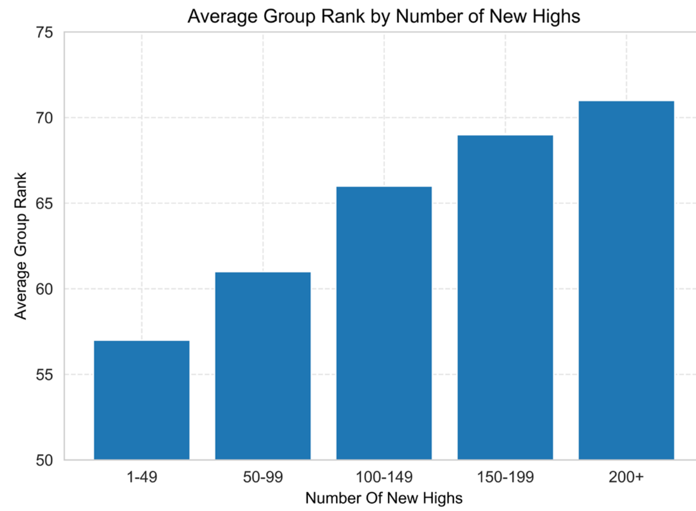
William O'Neil + Co.'s proprietary Relative Strength Rating measures a stock's relative price performance over the last 12 months against that of all stocks in our U.S. database, with extra weight assigned to the latest three-month period (with each remaining quarter receiving a lesser weighting). All stocks are ranked in order of greatest to least price percentage change and assigned a percentile rating from 1 (worst) to 99 (best). If a stock has been trading for less than one year, the earliest available price is used. If a stock has been trading less than five days, it does not receive a rating.

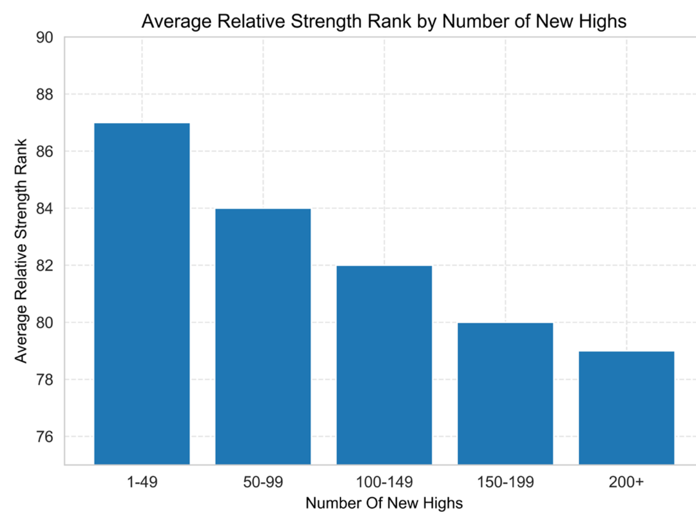
MOTIVATION

In our previous study of New Highs, we found that stocks making new five-year highs tended to outperform the market over the next year in general. In particular, stocks that made new highs when new highs were fewer in number tended to outperform the market by proportionately greater amounts; in other words, we found an inverse relationship between the number of new highs and the magnitude of the outperformance. We also found that stocks making new highs in times of new high scarcity differed in other ways from those in times of new high ubiquity; specifically, they tended to have higher RS Ratings and Group Rankings on average than those making new highs during times when new highs were plentiful.

Logically, we need to disentangle the effects of RS Rating and Group Rank on returns in the baseline absence of New High events in order to distill the potential predictive power of each component and its usefulness in forming portfolios of outperforming stocks, as well as identify strategies for extracting alpha while remaining effectively hedged against broader market risk. While we will reserve the study of Group Rank for a future paper, this paper will apply some quantitative finance best practices to cross-sectional studies involving hypothetical quantile-based long/short portfolios which, in a perfectly efficient market, would be expected to have expected returns indistinguishable from zero.

We hypothesize that the predictable outperformance we demonstrated in the case of rare new highs is driven in at least in part by primary and secondary momentum effects. In the same way that behavioral finance may explain momentum effects in price, it may also predict secondary momentum effects in relative performance. As with stocks showing proportionately higher positive outperformance following such new high events, we posit the presence of a momentum effect in relative performance that is influencing returns separate from the effects related to new highs in price. If such a momentum effect is present, and is captured effectively by the RS Rating, then we expect that portfolios with different average RS Ratings should diverge monotonically in average risk-adjusted returns.





Figures 2-3: Figure 2 shows the average Group Rank™ for stocks making five-year new highs for respective frequency count buckets. Figure 3 similarly shows the average Relative Strength Rating™ of such stocks.

If markets are perfectly efficient, then we shouldn't be able to construct two portfolios with the same risk that have different average returns. When we identify a variable that carries information about future returns, relative or otherwise, we could potentially extract a superior risk/return tradeoff than that offered by the market portfolio. If, for example, stocks with higher RS Ratings can be expected to have predictably higher risk-adjusted returns, then a portfolio of such stocks with a high average RS Rating should outperform a portfolio with similar risk with a lower average RS Rating. This would mean that positive absolute return could be earned on average by going long the high RS portfolio and short the low RS portfolio while neutralizing risk associated with movements in the broader market. Conversely, the proof is in the pudding as to whether or not a variable such as RS Rating is predictive with regards to future returns, meaning the average returns from such portfolios are significantly different from zero from a statistical standpoint.

This type of portfolio is desirable because its returns are potentially from *alpha*, the portion of return left over after removing the influence of the overall market, and not beta, the portion which is attributable to the market, or other risk that can be reduced through diversification. An investor holding a portfolio of investment return streams driven by true alpha would expect to get the full benefit of diversification, seeing the return on their portfolio approach the average of the constituent return streams, while portfolio risk is minimized as the number of return streams increases as different uncorrelated investment returns offset one another. This is the basic distinction between *idiosyncratic* risks—those eliminated by diversification—and *systematic* risks such as those in the overall market, which is why, for example, long-only mutual funds still experience large swings as markets swoon despite large numbers of holdings. Being both long and short in ideal proportions would effectively cause these risks to offset one another, but there could be other systematic risks remaining, such as the relative returns of small stocks compared with large stocks or growth stocks compared with value stocks.

METHODOLOGY

We perform cross-sectional comparisons of the time series of the monthly returns of portfolios constructed using RS Rating in January 1995–April 2020. We form our investable U.S. equity universe[1] each period in a manner free from survivorship bias, ranked according to RS Rating, and sorted into quintile buckets on the basis of quantile rankings. We then form hypothetical portfolios according to two different weighting schemes: liquidity weighted and liquidity weighted-volatility corrected. Volatility corrected portfolios are effectively normalized for changes over time in broader market volatility expectations such that daily portfolio returns are determined as a function of constant risk levels to avoid periods of higher volatility contributing disproportionately to average returns and measures of risk.

This is accomplished by dividing portfolio returns by point-in-time market volatility estimates. From the resulting time series of Q5-Q1 portfolios we run Ordinary Least Squares (OLS) regressions against the liquidity-weighted market portfolio (MKT) and two Fama-French factor portfolios, which mimic the relative return of small caps versus large caps (SMB) and the relative returns of value stocks compared with growth stocks (HML). Additionally, we form a Q5-Q1 portfolio by running an OLS regression of Q5 returns against those of Q1 and using the resulting coefficient as a hedge ratio, and then subtracting the Q1 return under each weighting scheme from the Q5 return. In so doing, we additionally compute the average portfolio turnover required to replicate each respective portfolio, enabling comparisons of the tradeoff between performance and robustness with respect to transaction costs.

RESULTS

Plotting the time series of cumulative returns for each of our five RS Rating quantile portfolios reveals the clear presence of monotonically increasing average returns as average RS Ratings increase. Figure 4 shows the cumulative performance of quantile portfolios constructed based on RS Rating. Note that these plots have been scaled further such that each has the same volatility, or comparable level of risk. Contrary to expectations under conditions of market efficiency, **portfolios of stocks in the top RS Rating (labeled Q5) quintile have consistently higher returns than those in the bottom quintile (labeled Q1).**

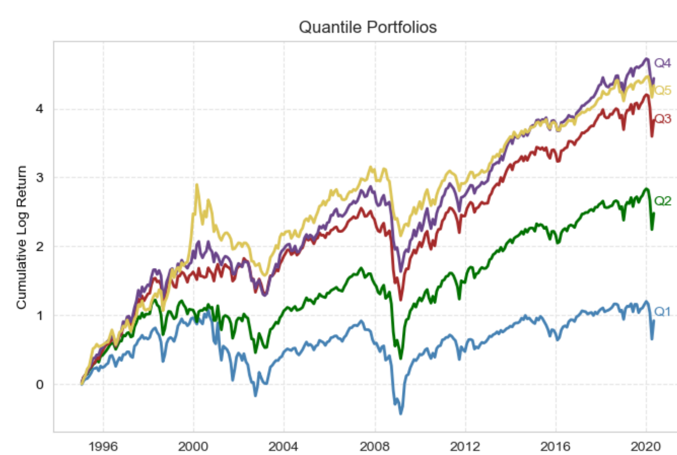


Figure 4: Cumulative monthly log returns for quantile portfolios constructed based on Relative Strength (RS) Rating across our U.S. equity market universe. Results are liquidity-weighted.

1 Our universe construction methodology is free of survivorship bias and considers each stock each day for inclusion on the basis of investability while excluding potential confounders such as penny stocks, ADRs, ETFs, and corporate events. The bottom 20% of stocks by price and the bottom 40% by liquidity are removed, with the remaining stocks weighted by liquidity.

Table 1 shows the returns of each of the five quintile portfolios as well as that of the properly sized Q5-Q1 long/short portfolio. The Q5 portfolio has both a higher annualized return (12.06% versus 3.61%) and lower annualized volatility (20.92% versus 29.72%) than the Q1 portfolio. As we can leverage up and down the returns to either portfolio to achieve a desired return, the relevant question is what we would have to pay in terms of risk to achieve such a return. In this respect, the superior risk/return tradeoff offered by the higher RS portfolio costs significantly less, or rather provides more return per unit of risk, a tradeoff summed up succinctly in the Sharpe ratio, the ratio of expected return to expected volatility or risk, annualized. This metric is 0.57 for the Q5 portfolio and only 0.12 for the Q1 portfolio.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Annualized Return	3.61%	6.26%	7.83%	8.79%	12.06%	9.52%
	(0.62)	(1.66)	(2.56)	(2.96)	(2.89)	(2.54)
CAPM						
Alpha	-0.78%	-0.19%	0.07%	0.16%	0.31%	0.86%
	(0.62)	(1.66)	(2.56)	(2.96)	(2.89)	(2.54)
Fama-French 3-Factor						
Alpha	-0.62%	-0.11%	0.10%	0.13%	0.18%	0.62%
	(-3.28)	(-1.18)	(1.57)	(1.70)	(1.30)	(2.48)
Beta Market (MKT)	1.52	1.08	0.91	0.84	0.88	-0.19
Beta Size (SMB)	0.4	0	-0.1	-0.1	0.18	-0.1
Beta Value (HML)	0.43	0.49	0.33	-0.07	-0.96	-1.26
Annualized Volatility	29.72%	19.02%	15.35%	14.83%	20.92%	18.71%
Sharpe	0.12	0.33	0.51	0.59	0.57	0.51
Annualized Turnover	5.05%	6.33%	6.65%	5.90%	3.96%	4.50%

Table 1: Returns, alphas, and factor loadings for portfolios constructed based on RS Rating. Portfolios are liquidity-weighted and rebalanced monthly. Q5-Q1 reflects the scaling of Q1 portfolio exposure according to a simple hedge ratio derived from the coefficient to an OLS regression of Q5 returns against Q1. CAPM and Fama-French three-factor alphas are the intercepts to one- and three-factor regressions of portfolio returns against the market replicating portfolio as well as small minus big (SMB) and high minus low book/market cap (HML) factors.

An additional implication of this divergence in Sharpe ratio is that it is possible to combine these two portfolios into a long/short portfolio whose broader market exposures offset one another, effectively neutralizing market risk while maintaining a positive expected return irrespective of the overall market direction. The results of such a long-short portfolio, having correctly scaled up or down the Q5 portfolio exposure in accordance with a properly reckoned hedge ratio, are shown in the furthest right column. Such a portfolio yields a statistically significant non-zero average annualized return of 9.52%, reflective of and comprised of substantially significant non-zero monthly CAPM and Fama-French three-factor alphas of 0.86% and 0.62%, respectively. This suggests that a substantial portion of this return stream is a *diversifiable* risk, meaning it could be combined with other like return streams to comprise a portfolio whose average return approaches the average of each return stream but whose risk is minimized as the number of such return streams grows.

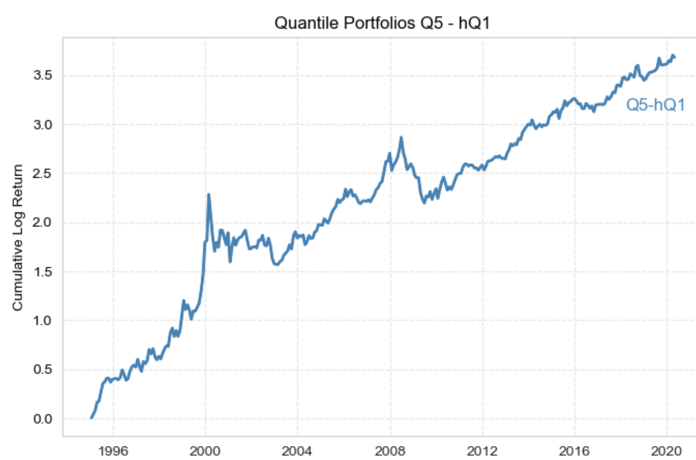


Figure 5: Cumulative return of Q5-Q1 long/short portfolios constructed based on RS Rating. Returns are liquidity-weighted.

Unfortunately, on its own as currently configured and significant though the returns and alphas may be, the Q5-Q1 portfolio doesn't really give us a better deal than being outright long the top RS Rating quantile (Q5) portfolio. The Sharpe ratio of the Q5-Q1 portfolio is 0.51, compared with 0.57 for the Q5 portfolio, likely explained at least partially by the noise associated with the change in overall volatility over time. Figure 5 shows the cumulative returns to the Q5-Q1 long/short portfolio over time. We see a big spike in 1995–2000 and less steady performance for the ensuing 10 or so years, followed by a more recent uptrend resumption. Investors caught in the intervening years of choppiness might have reasonably grown impatient or otherwise suffered from unmet expectations. We can address this partially by considering that in 1995–2000 there might have been more volatility overall such that positive returns would have been greater in magnitude as well. We can therefore remove some of this noise by normalizing over time using point-in-time estimates of broader market volatility.

Once we remove the noise associated with changes in volatility over time, **despite short-term cycles, the effect has been consistent and robust over time**. We can achieve this by dividing each day's portfolio returns by model-based point-in-time estimates of market volatility. This results in performance figures expressed in constant volatility units, rather than actual percent returns, but can be converted for practical estimation purposes into percentages by multiplying by the portfolio manager's target volatility. In our database, the market volatility estimate has averaged approximately 3% over time, so a reasonable back-of-envelope estimate can be created by multiplying by 0.03. In reality, the true estimate on any given day is generated by multiplying the *current day's* estimated volatility by these figures, which are prone to change, as has happened, for example, in the course of the COVID-19 pandemic selloff. The figures are tantamount to a more realistic and proactive risk-control strategy that categorically reduces exposure during times of turmoil and increases it when markets are calm.

Figure 6 shows the cumulative performance of volatility-scaled quantile portfolios constructed based on RS Rating. Visually we see shallow peaks and troughs for each of the five portfolio's return lines, the slopes of which appear more constant and distinctly different through time. The lines appear to diverge in a somewhat consistent pattern through time, largely maintaining a vertical ordering consistent with their quantile ranking. For the purposes of visualization, plots have been scaled so that each is reflective of comparable time-series volatility, so that differences in slope are reflective primarily of their long-term average changes.

Such patterns would exist in charts if the RS Rating carried information about future performance that could be used to construct portfolios with the same levels of risk but significantly different returns such that they could be combined profitably into long/short portfolios.

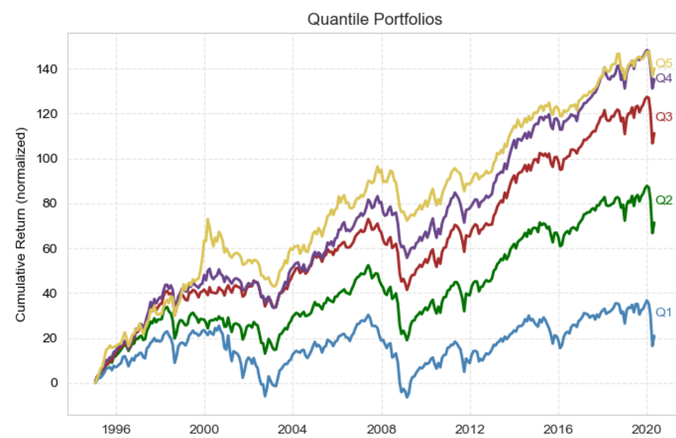


Figure 6: Cumulative monthly log returns for quantile portfolios constructed based on RS Rating across our U.S. equity market universe. Results are liquidity-weighted and normalized with respect to intertemporal changes in market volatility.

As we can leverage up and down the returns to either portfolio to achieve a desired risk target, the relevant question is what we receive in return for taking such a risk. In this respect, the relatively superior risk/return tradeoff offered by the higher RS portfolio costs significantly less, or rather provides more return per unit of risk. Table 2 shows the volatility-normalized returns of each of the five quintile portfolios as well of that of the properly hedged Q5-Q1 long/short portfolio. (Note that such returns are expressed in constantly volatility units, which can roughly be translated into percentage returns by multiplying by 0.03). The Q5 portfolio has both a higher annualized return, 5.15 versus 0.85 (equating to 15.5% and 2.55%, respectively), and lower annualized volatility, 6.45 versus 8.33 (19.4% versus 25.0%), than the Q1 portfolio. The risk-return tradeoff is summed up succinctly by the Sharpe ratio of 0.66 for the Q5 portfolio versus 0.1 for the Q1 portfolio. The effect of noise removal is now evident in the superior Sharpe ratio of 0.66 for the volatility-adjusted Q5-Q1 portfolio compared with 0.51 for the raw return Q5-Q1 portfolio in Table 1.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Annualized Return (normalized)	0.85	2.2	2.95	3.58	5.15	4.26
	(0.50)	(1.70)	(2.65)	(3.23)	(3.34)	(3.32)
CAPM						
Alpha	-0.25	-0.07	0.02	0.06	0.13	0.32
	(0.50)	(1.70)	(2.65)	(3.23)	(3.34)	(3.32)
Fama-French 3-Factor						
Alpha	-0.17	-0.03	0.03	0.05	0.06	0.2
	(-3.36)	(-1.08)	(1.61)	(2.06)	(1.64)	(2.82)
Beta Market (MKT)	1.34	1.08	0.94	0.89	0.9	-0.13
Beta Size (SMB)	0.38	0.0	-0.09	-0.1	0.16	-0.13
Beta Value (HML)	0.5	0.49	0.28	-0.1	-0.94	-1.33
Annualized Volatility	8.33	5.96	5	4.89	6.45	5.52
Sharpe	0.1	0.34	0.53	0.64	0.66	0.66
Annualized Turnover	5.05	6.33	6.65	5.9	3.96	4.5

Table 2: Normalized returns, alphas, and factor loadings for portfolios constructed based on RS Rating. Portfolios are liquidity-weighted and normalized with respect to intertemporal volatility shifts and rebalanced monthly. Q5-Q1 reflect the scaling of Q1 portfolio exposure according to a simple hedge ratio derived from the coefficient to an OLS regression of Q5 returns against Q1. Monthly returns are expressed in standardized volatility units. CAPM and Fama-French three-factor alphas are the intercepts to one- and three-factor regressions of portfolio returns against the market replicating portfolio as well as small minus big (SMB) and high minus low book/market cap (HML) factors.

As we have suggested, divergent Sharpe ratios imply the ability to combine these two portfolios into a long/short portfolio that can be expected to have broader market exposures that offset one another, effectively neutralizing market risk while maintaining a positive expected return irrespective of the overall market direction. Visual confirmation of this is provided in Figure 7, which reflects the cumulative returns to the properly hedged Q5-Q1 portfolio inclusive of market-volatility adjustments. Again we see much shallower spikes and troughs around both the 2000 Internet bubble/burst and the 2008–2009 financial crisis, with a relatively consistent general slope over time. As the trends are not perfectly smooth but retain some clear short-term cycles after volatility adjustments, we can infer that investing by RS Rating is not a risk-free enterprise but rather represents an orthogonal risk to that of broader market movements, and returns experienced may reflect compensation for that risk.

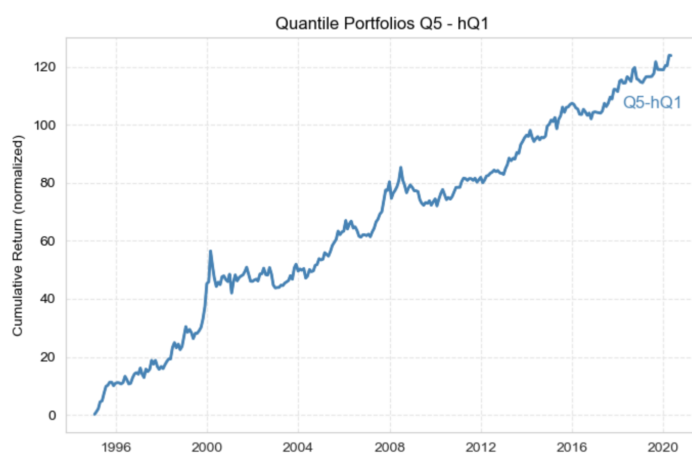


Figure 7: Cumulative return of Q5-Q1 long/short portfolios constructed based on RS Rating. Returns are liquidity-weighted. Q5-Q1 portfolio returns reflect the scaling of Q1 portfolio exposure according to a simple hedge ratio derived from the coefficient to an OLS regression of Q5 returns against Q1. The returns are further normalized by changing market volatility expectations over time to reflect downweighting during volatile market periods and upweighting of returns during calmer periods.

CONCLUSION

As theorized, the presence of secondary momentum effects in relative, in addition to outright performance between stocks, could explain some of the conditional behavior we saw in stocks making new highs. If this is the case, a relative performance measure such as RS Rating could be used to identify stocks most likely to outperform or underperform in the future. This is precisely what we have found. In our cross-sectional studies we show that quantile-based long/short portfolios constructed based on RS Rating earned statistically significant positive returns despite remaining ostensibly market neutral and demonstrate that, after properly adjusting for changes in broader market volatility over time, such effects are relatively robust over time. Consistent with this proposition, our results provide clear evidence of the efficacy of using the RS Rating to identify future outperformers and underperformers, such that market-neutral portfolios of stocks can be formed that earn alpha while remaining hedged against broader market movements.

About the O'Neil Capital Management Quantitative Services Group
Over the years we have described the investment process used by William J. O'Neil as 'Qualitative Quant.' This type of investor looks at quantitative measures to accurately evaluate and efficiently compare companies but ultimately invests based on their own qualitative analysis of the data.

The O'Neil Capital Management Quantitative Services Group grew out of a desire to create quantitative research based on the work pioneered by Mr. O'Neil. The Quant Group develops quantitative research and systematic investment strategies for the O'Neil family of companies. The program comprises a global team of data scientists, software engineers, and investment professionals. Our research is composed primarily of factor studies for discretionary and quantitative portfolio managers, and our current interests include factor investing, time series analysis, and machine learning techniques.

The Quant Group provides quantitative research and data science expertise for O'Neil Global Advisors. The two benefit from a common heritage and passion for finding what leads to outperformance in global equity markets.

GLOSSARY OF TERMS

Return

The percentage change in price of a stock or index from one period to the next, expressed in decimal format. For example, if a stock price moves from 20 to 25, its return is:

$$25/20 - 1.0 = 0.25$$

$$= 25\%$$

Log Return

The natural logarithm of simple (percentage) returns. Converting from percent to logs has the effect of making positive returns less extreme and negative returns more so, which makes them more symmetrical and allows you to aggregate them mathematically over time. For example, if a stock price falls from 20 to 10 (a drop of 50%) and then rises back to 20 (a 100% gain), it will have a return of 0% over that time period. However, if we take the average of simple returns, we get (-50% + 100%) / 2 = 25%. However, if instead:

$$\mathrm{LN}(10/20) = -.693$$

$$\mathrm{LN}(20/10) = .693$$

$$(-.693 + .693)/2 = 0.0.$$

MKT

The Market Portfolio. The time series of returns (typically log returns) to the broader market-replicating portfolio, such as the S&P 500. In our case, we are using the returns to our daily survivorship-bias-free U.S. equity universe, which will closely track the index.

SMB

Small Minus Big. The time series of returns to a hypothetical portfolio that is long small-cap stocks and short large-cap stocks.

HML

High Minus Low. In the traditional Fama-French framework, after sorting stocks on the basis of the ratio of book value to market cap (book-to-market), the time series of returns to a portfolio which is long high book-to-market (BM) stocks and short low BM stocks. In other words, a proxy for the relative performance of value stocks compared with growth stocks. In our framework, we use our own hopefully more thoughtful definitions of growth and value to define segments and form portfolios.

CAPM Alpha

From the **C**apital **A**sset **P**ricing **M**odel, the resulting intercept from a regression of log returns against the return of the market portfolio. The average monthly alpha of the CAPM is the proportion of return that remains after removing the effects of the broader market. In the naïve formulation, this would represent an entirely diversifiable risk such that in a diversified portfolio, the expected portfolio return would approach the average of the constituent return streams.

Fama-French Three-Factor Alpha

The resulting intercept in a three-factor regression of the portfolio's returns against the market (MKT) and two others formed using size (SMB) and style (HML). This is the proportion of return that remains after removing that which is attributable to systematic risk factors, specifically those represented by MKT, SMB, and HML. If these were the only such non-diversifiable risks, then the resulting alpha should represent diversifiable risk. This means as the number of such alphas increases, the average return approaches the averages of each return stream but stays the same as the risk starts to recede.

Beta Market (MKT)

The coefficient in a linear regression of log returns against the returns of the market portfolio. A coefficient of 1, for example, implies that a 1% move up (down) in the market will result in a 1% up (down) move in the stock.

Beta Size (SMB)

The coefficient in a three-factor regression to SMB (small minus big). Effectively, portfolio risk associated with changes in the market's relative preference for small-cap stocks compared with large-cap stocks. When small caps outperform large caps, SMB goes up, when they underperform, SMB goes down. If the SMB beta is positive, then the portfolio has a positive correlation with small caps performing better than large caps. If SMB is positive, and small caps outperform large caps, then our portfolio goes up, and if small caps underperform large caps, then the portfolio goes down. If beta is negative, then we have a portfolio that has a negative correlation with the SMB, so the results are the opposite of the above.

Beta Value (HML)

The coefficient in a three-factor regression to HML (high minus low). The portfolios risk associated with changes in the market's relative preference for growth stocks over value stocks. If we have a positive HML beta, the portfolio will have positive returns when value outperforms growth and negative returns when growth outperforms value.

Volatility

The standard deviation of period-wise log returns scaled according to the square root of time. Volatility-adjusted portfolios reflect normalizing portfolio returns according to broader market volatility expectations, which average approximately 3% over the long term. These portfolios reflect a strategy of reducing or increasing overall exposure in proportion to the ratio of expected market volatility to its long-term average. This has the effect of removing some noise and allows for fairer comparison of returns over time. In these portfolios, the values are expressed in volatility-standardized units and can be converted to rough return estimates by, for example, multiplying by 0.03.

Sharpe (Annualized)

The ratio of average annualized returns to annualized volatility. This, rather than simply annualized returns, is a superior measure of the performance and merits of a returns stream, as in a world where leverage is allowed, any return can be increased or decreased by leveraging up or down with margin usage, but constraints remain for an investor with respect to the maximum level or risk (volatility) they can tolerate. We can think of this as their 'risk budget.'

REFERENCES

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BACKTESTED PERFORMANCE

Backtested performance and past live trading performance are NOT indicators of future actual results. The results reflect performance of a strategy not historically offered to investors and do NOT represent returns that any investor actually attained. Backtested results are calculated by the retroactive application of a model constructed on the basis of historical data and based on assumptions integral to the model which may or may not be testable and are subject to losses.

The backtesting process assumes that the strategy would have been able to purchase the securities recommended by the model and the markets were sufficiently liquid to permit all trading. Changes in these assumptions may have a material impact on the backtested returns presented. Certain assumptions have been made for modeling purposes and are unlikely to be realized. No representations and warranties are made as to the reasonableness of the assumptions. This information is provided for illustrative purposes only.

Backtested performance is developed with the benefit of hindsight and has inherent limitations. Specifically, backtested results do not reflect actual trading or the effect of material economic and market factors on the decision-making process. Since trades have not actually been executed, results may have under- or over-compensated for the impact, if any, of certain market factors, such as lack of liquidity, and may not reflect the impact that certain economic or market factors may have had on the decision-making process. Further, backtesting allows the security selection methodology to be adjusted until past returns are maximized. Actual performance may differ significantly from backtested performance.