Volatility Effect

QUANTITATIVE RESEARCH O'NEIL GLOBAL ADVISORS INC.

Volatility: Slow and Steady Wins the Race

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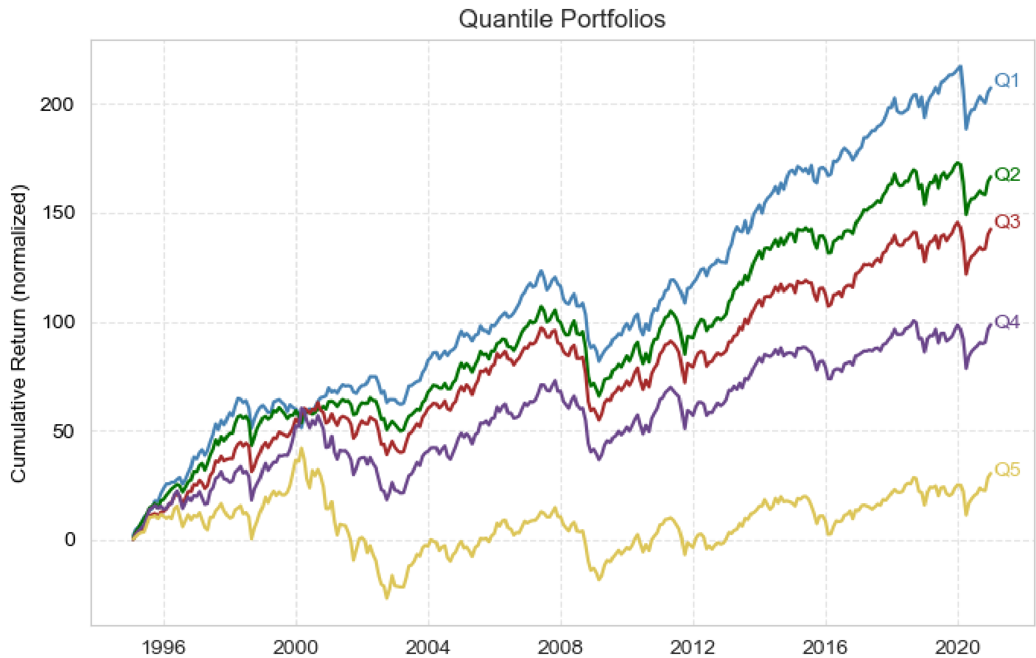

Figure 1: Cumulative monthly log returns for quantile portfolios constructed based on one-year trailing volatility across our U.S. equity market universe. Q1 stocks are the least volatile and Q5 are the most. Results are liquidity-weighted and normalized with respect to changes in market volatility over time.

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KEY FINDINGS:

- U.S. stocks in the top (highest) volatility quintile significantly underperform the bottom (lowest) volatility quantile.
- Long-short portfolios have solidly significant CAPM and Fama-French three-factor alphas.
- The resulting portfolios have positive exposure to size (SMB) and negative exposure to value (HML).
- However, these portfolios are prone to sharp short-term losses during bear markets.

EXECUTIVE SUMMARY

Previous studies have found evidence of persistent underperformance of high-volatility stocks compared with lower-volatility stocks on a risk-adjusted basis. Consistent with prior studies, our cross-sectional research found that U.S. stocks in the top (highest) volatility quintile significantly underperform those in the bottom (least volatile) quantile such that long-short portfolios constructed on the basis of volatility quintile rankings generate significantly negative returns while remaining market-neutral. These volatility Q5–Q1 portfolios have positive expo-

sure to size (SMB) and negative exposure to value (HML). However, these portfolios are prone to short-term losses during bear markets.

INTRODUCTION

Prior research by academics and industry practitioners has demonstrated a propensity for high-volatility stocks to underperform lower-volatility stocks on a risk-adjusted basis. In Andrew Ang's *Asset Management: A Systematic Approach to Factor Investing* (Columbia/Blackrock, 2014), he discusses the 'volatility anomaly,' stating that "returns of high-volatility stocks were abysmally low" and that "volatility is negatively related to future return." David Blitz and Pim van Vliet in *The Volatility Effect: Lower Risk without Lower Return* (Robeco, 2014) present empirical evidence that stocks with low volatility earn high risk-adjusted returns in stock markets in the U.S., Europe, and Japan.

WHY IT WORKS

This effect may best be explained by structural impediments to the use of leverage. Consider for example the choice faced by an investor with access to leverage. Such an investor would be expected to prefer the portfolio of securities that offered the best tradeoff in terms of expected return relative to risk, as such portfolio choices could be levered up or down to achieve parity of risk, and in which case the higher-returning portfolio would be preferred. However, in the case of an investor such as a pension fund that may be structurally impeded by its charter from employing leverage but nevertheless wishes to maximize the probability that returns exceed a given threshold, a preference could be reasoned for the higher-volatility portfolio whose higher standard deviation of return implies a higher probability of exceeding return targets, despite the matching of such return potential with losses that are commensurate in magnitude. If this results in a class of investors with a categorical preference for high-volatility stocks over low-volatility stocks, this axiomatically would result in the pushing up of prices for volatile stocks such that they have expected returns that are systematically lower than lower volatility stocks. This opens up the possibility for an investor with access to both leverage and short sales to systematically harvest such a return differential while limiting risk exposure to the movements of the broader equity market.

Consistent with the work of Ang and Blitz & van Vliet, we expect that if the 'volatility anomaly' exists, equity investors are effectively overpaying for risky, more volatile stocks. If this is true, we would expect such stocks to have lower average expected returns and, consequently, for low volatility stocks to outperform high volatility ones. We would further expect for portfolios constructed on the basis of volatility quantile rankings, those with higher average volatility rankings to underperform those with lower average volatility rankings on a risk-adjusted basis. Specifically, for such an anomaly to not exist, portfolios of securities constructed on the basis of differences in volatility should have differences in average risk-adjusted returns that are indistinguishable from zero.

METHODOLOGY

In general, when we speak of volatility, we mean the risk posed by the magnitude of standard deviation of returns over the given investment horizon. If we wish to objectively compare for quintile ranking purposes the volatility characteristics of one stock versus another, we require an objective definition and calculation methodology. For this study, we compute volatility as the standard deviation of logged returns over a trailing 252 days. The study period ranges from January 1995 to December 2020.

Each month, we sort all of the stocks in our U.S. equity universe[1] into one of five portfolios according to their quintile ranking with respect to trailing one-year volatility such that Q1 comprises the least volatile 20% of the universe and Q5 the most volatile 20%. Within each quintile, we weight each stock proportionately according to our model-based liquidity expectation. This has the effect of skewing the performance attribution within each quintile to the most liquid and recognizable names such that results can be expected to be both robust to transaction cost considerations as well as reflective of the issues in which a portfolio manager is most likely to trade. We then apply a normalizing adjustment in respect of point-in-time expectations of broader market volatility. This has the effect of down-weighting periods where high volatility is expected relative to periods when less volatility is expected, so that different time periods can be compared fairly and do not contribute to final results unduly. This also is tantamount and reflective of a portfolio manager that tactically reduces overall exposure when volatility is high and raises it when volatility is low, maintaining a target constant level of risk. Results are thus 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

1 Our universe construction methodology is free from 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 50% by liquidity are removed, with the remaining stocks weighted by liquidity.

periods of higher volatility contributing disproportionately to average returns and measures of risk.

With these weightings, we compute a monthly time series of returns for each portfolio. We then additionally compute the time series of returns of hypothetical long-short portfolios comprising long positions in Q5 portfolio stocks and short positions in Q1 stocks, with weights further scaled in consideration of systematic differences in volatility between the Q1 and Q5 portfolios such that each side has equal portfolio-level volatility, and then subtracting the Q1 return from the Q5 return.

From the resulting time series of Q1–Q5 long-only and Q5–Q1 long-short portfolios, we run ordinary least squares (OLS) regressions against the liquidity-weighted market portfolio (MKT) and portfolios that mimic the relative returns of small caps versus large caps (SMB) and the relative returns of value stocks versus growth stocks (HML).

If there is no such volatility effect, we would expect no material risk-adjusted difference between the Q5 and Q1 portfolios, and two portfolios with comparable risk would on average produce comparable returns such that differences between the two would be statistically indistinguishable from zero. However, if the Q5–Q1 long-short portfolio produces a statistically significant positive (or negative) return, we may consider this evidence of the existence of a volatility anomaly. This would not necessarily prove by itself the existence of an inefficiency exploitable by arbitrage, however, and it could be true that while market-neutral long-short returns generate positive returns, such return could merely reflect compensation for carrying some other orthogonal but systematic risk exposure. For this reason, we will weigh careful resultant exposures to SMB and HML alongside any significant results.

RESULTS

Consistent with our general hypothesis, **we find significant evidence for the presence of a volatility anomaly**. Figure 2 shows the cumulative performance of each respective Q1 to Q5 volatility quintile portfolio. Through the study period, the Q1 (least volatile) portfolio is the top performer, while the Q5 (most volatile) portfolio is the lowest. Moreover, we can see a perfect inversely ordinal stacking of the line plots, reflective of relative performance increasing monotonically in accordance with the inverse of volatility ranking. This implies volatility-scaled Q5–Q1 long-short portfolios will have returns significantly different from zero, in line with our hypothesis.

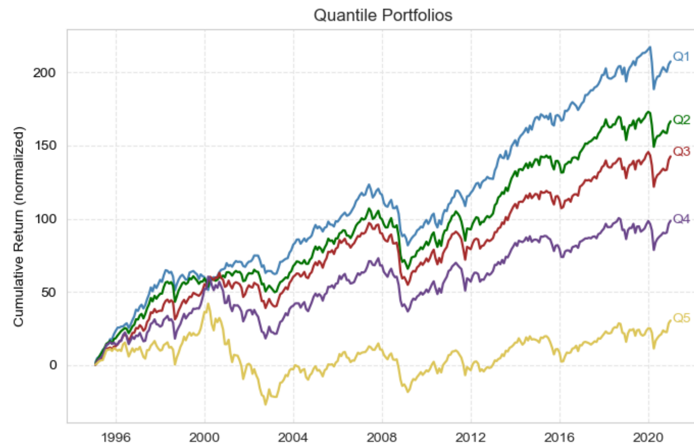

Figure 2: Cumulative monthly log returns for quantile portfolios constructed based on one-year trailing volatility across our U.S. equity market universe. Results are liquidity-weighted and normalized with respect to intertemporal changes in market volatility.

This is borne out by the summary statistics in Table 1. We find a significantly negative normalized monthly return to such portfolios with a t-statistic of 3.55. Such returns are largely reflective of CAPM alpha, whose intercept in an OLS regression against the market portfolio yields a similarly significant t-statistic of 3.61. Such returns, however, are not without attendant cost in terms of risk, market-neutral though they may be. The Fama-French factor loading for SMB is 1.79, indicating a significant size effect. Similarly, the Fama-French factor loading for HML is -1.73, reflecting a large loading on value.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Annualized Return*	9.12%	9.75%	9.92%	8.85%	3.58%	-18.45%
	(3.7903)	(3.0428)	(2.6059)	(1.8022)	(0.5575)	(-3.5479)
CAPM						
Annualized Alpha	3.18%	1.17%	-0.43%	-3.92%	-12.02%	-20.73%
	(2.7697)	(1.3145)	(-0.6016)	(-2.6187)	(-4.1023)	(-3.6054)
Fama-French 3-Factor						
Annualized Alpha	3.12%	1.27%	-0.11%	-3.83%	-11.54%	-20.11%
	(3.3660)	(1.5404)	(-0.1605)	(-3.3019)	(-4.6630)	(-4.3449)
Beta Market (MKT)	0.76	0.99	1.09	1.25	1.49	-0.58
Beta Size (SMB)	-0.34	-0.15	0.14	0.48	0.86	1.79
Beta Value (HML)	0.35	0.20	-0.04	-0.49	-0.77	-1.73
Annualized Volatility*	11.74%	15.59%	18.51%	23.99%	32.18%	29.32%
Sharpe*	0.74	0.60	0.51	0.35	0.11	-0.70

Table 1: Returns, alphas, and factor loadings for portfolios constructed based on one-year trailing volatility. Portfolios are liquidity-weighted and normalized with respect to intertemporal volatility shifts and rebalanced monthly. Q5–Q1 portfolios are scaled to have the same volatility.

*Returns are expressed in linear returns, while volatility and Sharpe are computed with logged returns.

From the returns to the Q5–Q1 portfolio, we see that, over the long run, the volatility anomaly has been robust with little indication of a decay in inefficacy. However, there is evidence that associated returns are not necessarily reflective of a perfectly exploitable inefficiency but may rather partially reflect compensation for exposure to an orthogonal risk factor. In Figure 3, the consistent downward trend of the cumulative returns to the Q5–Q1 portfolio is of keen interest since, in practice, we could harvest the anomaly by merely inverting our process and shorting the Q5 portfolio and going long the Q1 portfolio. However, note the sharp downturns in performance that such an investor would have experienced during the bear market periods of 2000–2001, 2008–2009, and, more recently, in 2020 during the COVID-19 pandemic. In each case, such painful losses would have been many times larger than expected, which would have been based on the time series of returns over the prior several years. This chart behavior combined with significant factor loadings on SMB and HML are consistent with that of an orthogonal risk factor whose risk-return profile might be superior to that of other risk factors such as that of the broader market but whose risk is nonzero nonetheless.

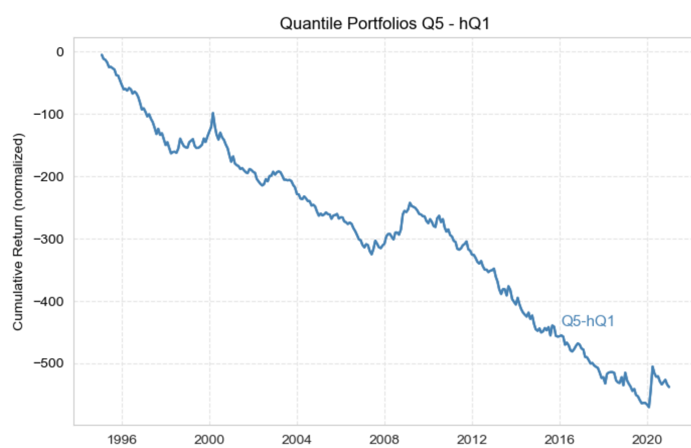

Figure 3: Cumulative returns of the Q5–Q1 portfolio. We construct Q5–Q1 portfolios by scaling the returns of the Q1 portfolio up or down by such scaling factor that results in the two time series having equal volatility, and then subtracting the Q1 return from the Q5 return.

CONCLUSION

We have demonstrated through our cross-sectional studies and significant returns to Q5–Q1 long-short portfolios constructed based on volatility quintile rankings that trailing volatility does in fact carry information about future returns, such that significantly nonzero returns can be earned from market-neutral portfolios that are tactically engineered to exploit and extract the associated alpha. We theorize that such returns reflect not arbitrage but compensation for exposure to potentially orthogonal risk factors. One interesting implication of the results in the prior section is that, while such long-short portfolios carried sharp exposure to SMB and HML of 1.79 and -1.73 (or inversely -1.79 and 1.73), respectively, the associated Fama-French three-factor alpha remains significantly positive with a t-score of -4.34, more significant yet than that of the -3.61 associated with CAPM alpha. This implies that, despite the strong loadings on SMB and HML, significant returns would remain in the presence of neutralizing through holding instruments or portfolios with offsetting exposures. This suggests that such risks could potentially be offset by such a factor investing program with complementary risk exposures, resulting in superior risk-return tradeoffs at the portfolio level than we have shown here.

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