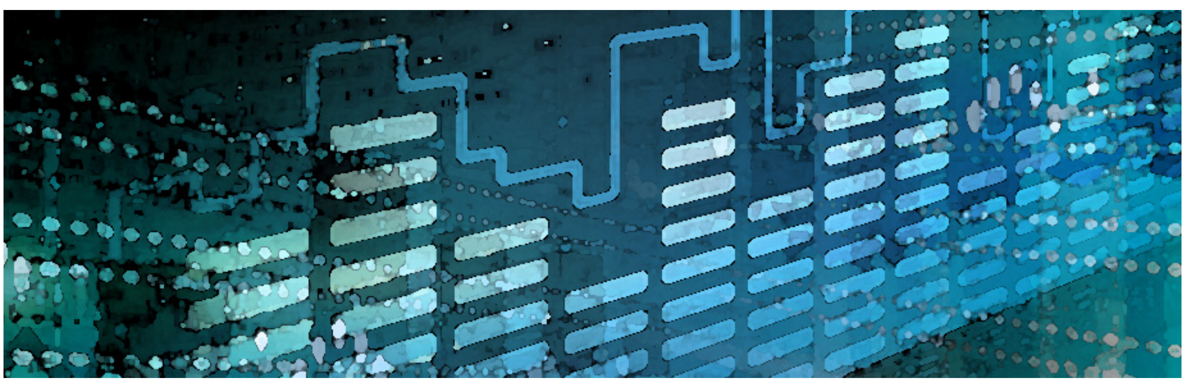
FIQ Managed Portfolios

FIQ Multi-Factor Equity Model



FRANKIE LIU, CFA, QUANTITATIVE ANALYST

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At the heart of our FIQ Managed Portfolios is a stock selection model that we call the FIQ Quantitative Equity Selection Model (FIQ QES).

FIQ QES is a largely quantitative, multi-factor model used to screen for stocks that we believe are likely to outperform the market. It allows us to pare down the universe of tradable securities to a shortlist of 170 securities, leaving us to focus our attention on the stocks that most deserve it.

What is a Multi-Factor Model?

As the name would imply, a multi-factor model is a method of ranking anything that is based on multiple factors. When ranking securities, the individual factors can be anything quantifiable and related to the specific asset. Models of this type have been used for decades in the world of institutional investing, and for good reason. They provide portfolio managers with a disciplined system to avoid common behavioral pitfalls, and help them hone in on the specific attributes of succesful companies.

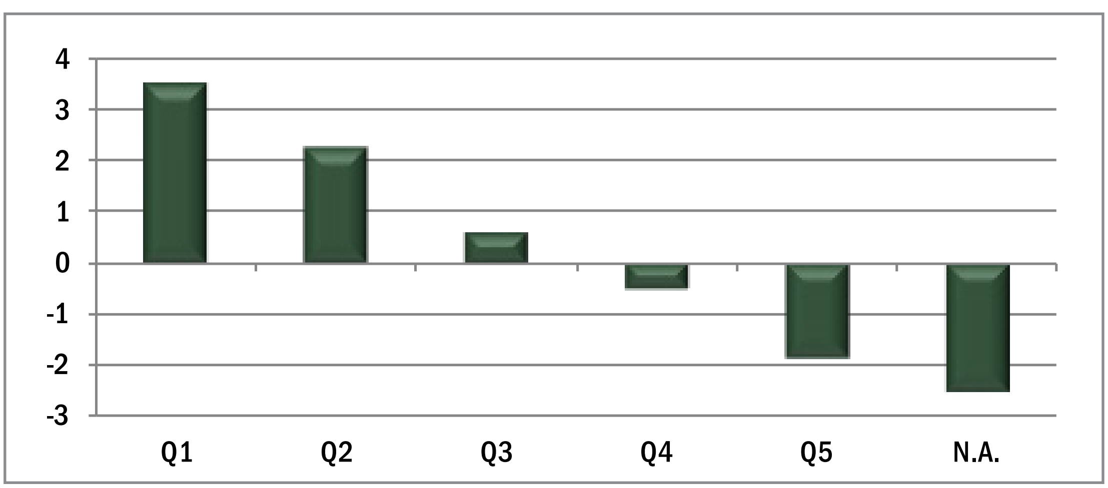
A good multi-factor model will consist of factors that demonstrate a strong statistical relationship with market outperformance (alpha), and the factors will also be 'rational', meaning that it's understandable how they relate to strong stock performance.

Ideal Market Factors

The Price to Earnings (P/E) ratio is a good example of an ideal factor. There is little doubt that value investing is a viable investment strategy and P/E ratios are good indicators of how much a stock is over or undervalued. The lower the P/E ratio, the more undervalued the stock may be and thus the more attractive the stock could be as an investment. Additionally, the relationship between alpha and P/E ratio is statistically significant. Figure 1 depicts the annualized alpha gained from investing in stocks based on P/E ratios.

Figure 1: PE Ratio Annualized Alpha (%)

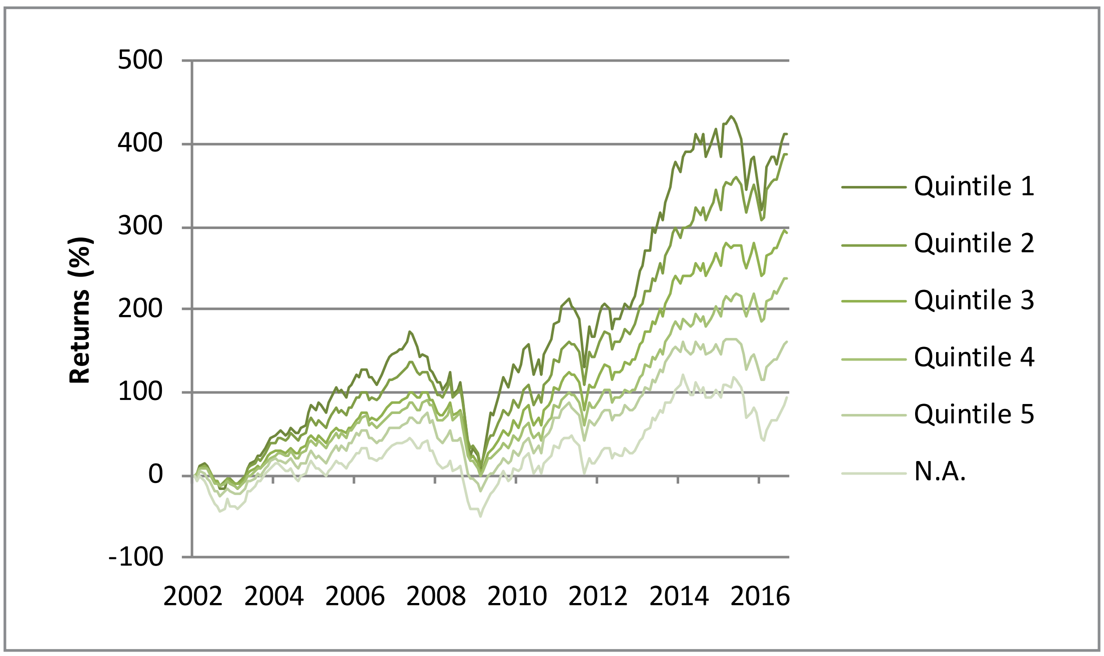
The universe of stocks included in all the tests mentioned in this document is the same as in Figure 1, namely US stocks with a market cap greater than $300 million.



Q1' refers to the first quintile group which consists of stocks with P/E ratios that rank in the lowest 20%, determined on a monthly basis. 'Q2' refers to the second quintile group which consists of stocks with P/E ratios that rank in the bottom 20-40%. 'Q3' through 'Q5' quintile groups consists of stocks with higher and higher P/E ratios, rising in much the same fashion as 'Q1' and 'Q2'. The N/A group consists of all stocks with negative earnings. The strong relationship between lower P/E ratios and higher alpha is quite apparent in this chart.

Like all quantitative investment strategies, factor models rely on the law of averages. Figure 2 (below), shows the back-tested performance history of investing in stocks based on P/E ratios on a month to month basis. The Q1-Q5 and 'N/A' groups are exactly the same as in Figure 1. From the graph, it is apparent that investing in stocks with the lowest P/E ratios (Q1) performs the best relative to the other groups. Even with an excellent multi-factor model, there may occasionally be times where a particular quintile group with worse P/E ratios will perform better than quintile groups with better P/E ratios, but over the long run the better quintile groups should outperform the worse quintile groups more often than not.

Figure 2: PE Ratio



A good multi-factor model will consist of factors that demonstrate a strong statistical relationship with market outperformance (alpha), and the factors will also be 'rational', meaning that it's understandable how they relate to strong stock performance.

Another common factor used in the multi-factor models is Return on Equity (ROE), which is a measure of profitability (Net Income/Shareholders' Equity). The denominator, Shareholders' Equity, scales the ROE so that companies of differing sizes can be compared on their profitability. The higher the ROE, the more efficient the company is at making money, and therefore, the better the stock should be as an investment. The statistics support this conclusion, which can be seen in Figures 3 and 4 (below). Again Q1, the quintile group of stocks with the highest ROE, performs the best on average, whereas subsequent quintile groups with lower and lower ROE generally perform worse.

Figure 3: ROE Annualized Alpha (%)

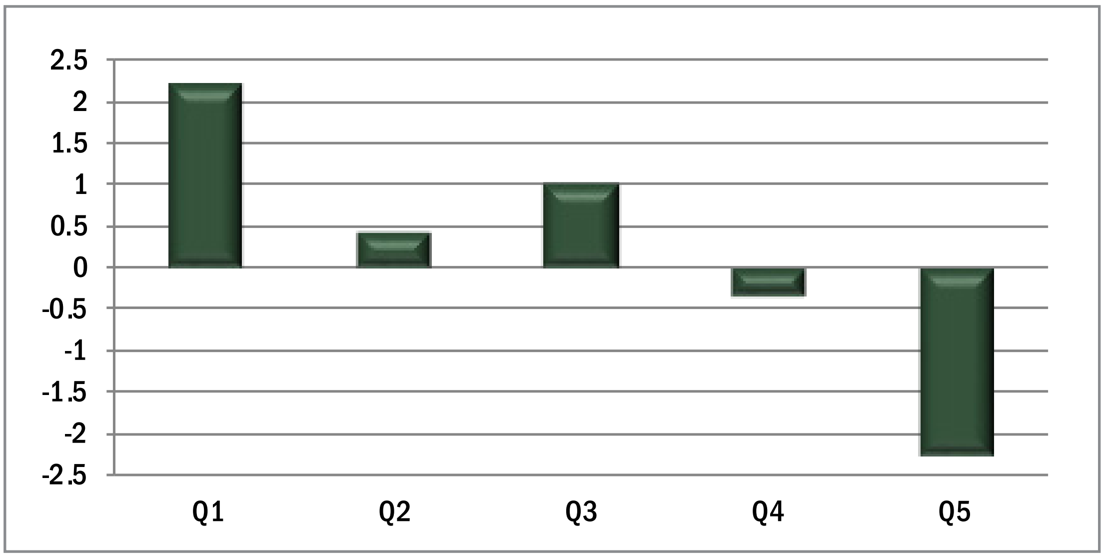
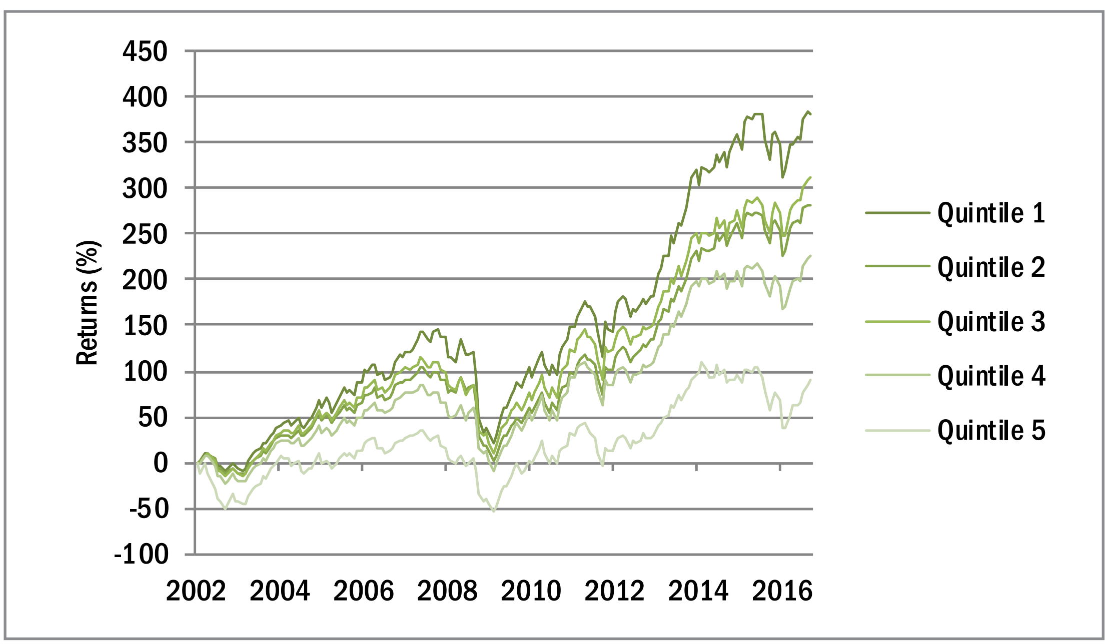


Figure 4: ROE



As a whole, the statistical relationship is good but not as strong as that of the P/E ratio, possibly because the market has priced in the ROE information to some extent while the P/E ratio inherently accounts for the market valuation.

Next up is a more unconventional, in-house-developed factor, which we have coined Modified Altman, where the underlying principle of the statistical relationship is less straightforward. The Modified Altman factor evaluates the capital efficiency of a company. It employs a well established method, the Altman Z-score formula, normally used to evaluate bankruptcy risk However, instead of taking the Z-score at face value, the Modified Altman instead looks at how different companies' bankruptcy risk is compared to its peers.
Understandably, companies with a higher relative bankruptcy risk are less attractive investments. Surprisingly perhaps, companies with a very low relative bankruptcy risk are also likely to underperform the market. Why? Very low bankruptcy risk could mean that a company is using earnings to pad the balance sheet instead of prudently investing the earnings, paying dividends or buying back shares. Among other things, this can be indicative of poor management or a real lack of growth opportunities for the company's business.

Regardless, the statistical relationship is apparent in both Figures 5 and 6 (below and next page), which show the back-tested alpha and performance history respectively. Q5 represents the quintile group with the most extreme relative bankruptcy readings, whether to the high or low side, and Q1 represents the quintile group with the most "normal" relative bankruptcy readings.

Figure 5: Modified Altman Annualized Alpha (%)

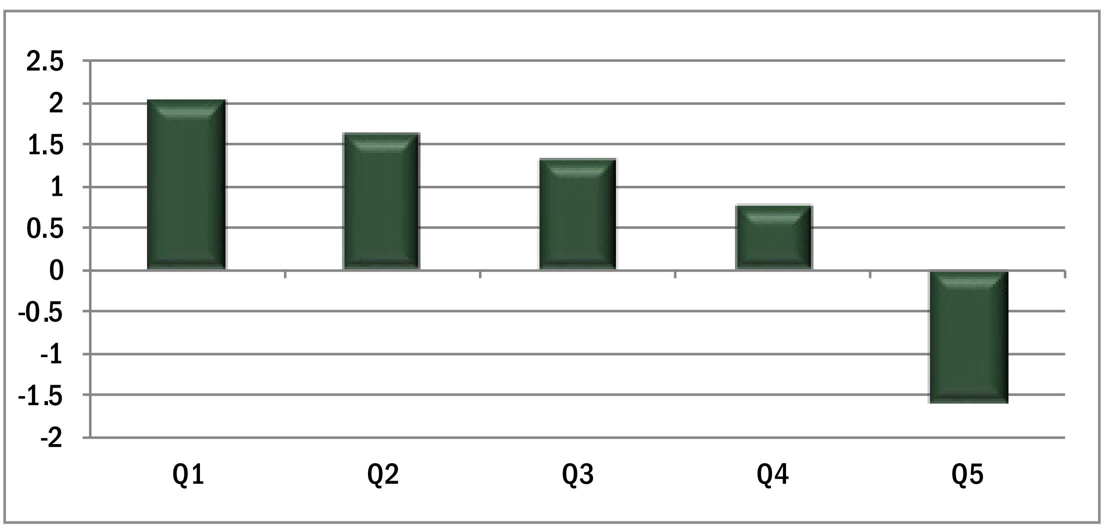


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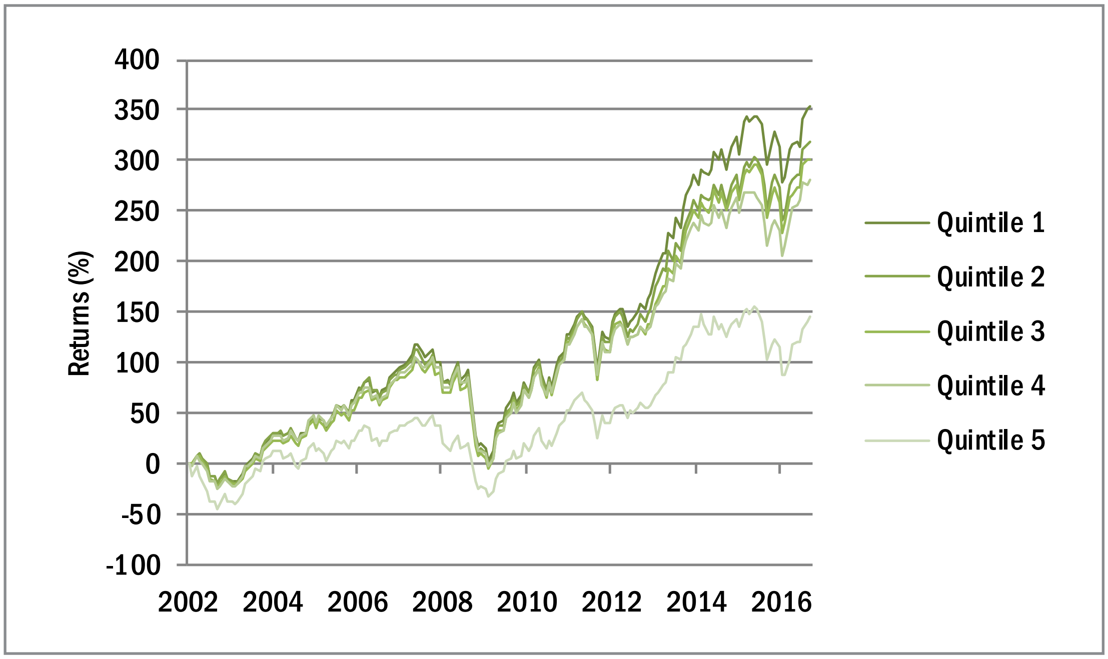
Figure 6: Modified Altman



Building a Better Multi-Factor Model

The key to building a good multi-factor model is how all the individual factors, like the ones mentioned above, are tuned to mesh together. The types of tuning required depends on what factors are in the model.

First, the factors all need to undergo mathematical translation to better compare them against other factors in the model. Such translations may include outlier management, peer comparisons, probability distribution transformations, etc.

Second, the weightings for each factor may also need to be adjusted depending on the similarity between factors and/or the alpha associated with those factors. For example, factors with higher alphas should have bigger weightings while factors that are similar to other factors in the model should have smaller weightings. Ultimately, all these factors come together to form an aggregate score that ranks individual stocks.

To illustrate the potential of multi-factor models, we've constructed a relatively straightforward example called the Composite Value Factor Model. This model consists of the following four equally weighted factors, all of which are related to value investing principles:

1. Price to Earnings (P/E) ratio (price divided by reported earnings.
2. Forward Price to Earnings (Forward P/E) ratio (price divided by forecast earnings).
3. Price to Sales (P/S) ratio (price divided by reported sales).
4. Price to Cash Flow (P/CF) ratio (price divided by reported cash flows).

As well, the raw factors have undergone the following mathematical translations:

1. Outlier Management (prevents very large ratios from overtly affecting a stock's score singlehandedly).
2. Peer comparison (compares the raw ratios against those of the firm's industry peers to get a relative ratio).

3. Distribution transformation (each factor is log transformed and rescaled to zero mean and one standard deviation).

Both the outlier management and distribution transformation facilitate inter-factor comparisons so P/E ratios can be compared to P/S or P/CF ratios. The peer comparison facilitates intra-factor comparisons so the P/E ratios of technology stocks can be compared to the P/E ratios of bank stocks.

Comparing the back-tested alpha of the Composite Value factor (Figures 7 and 8) to the alpha of the P/E ratio factor (Figures 1 and 2), it is easy to see that the Composite Value factor outperforms the singular P/E ratio factor in the top quintile groups, which represent the set of companies that are most “undervalued”.

Figure 7: Composite Value Annualized Alpha (%)

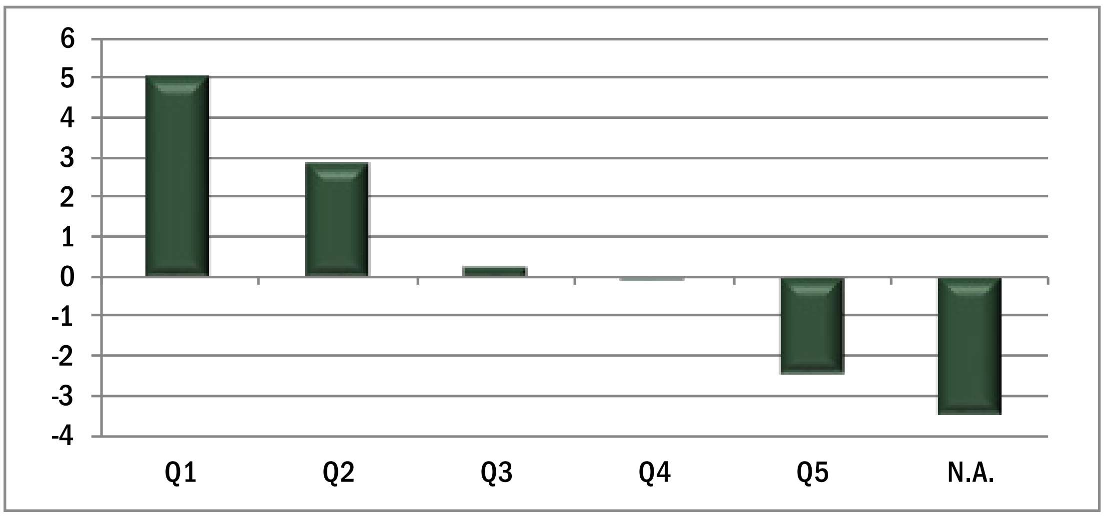
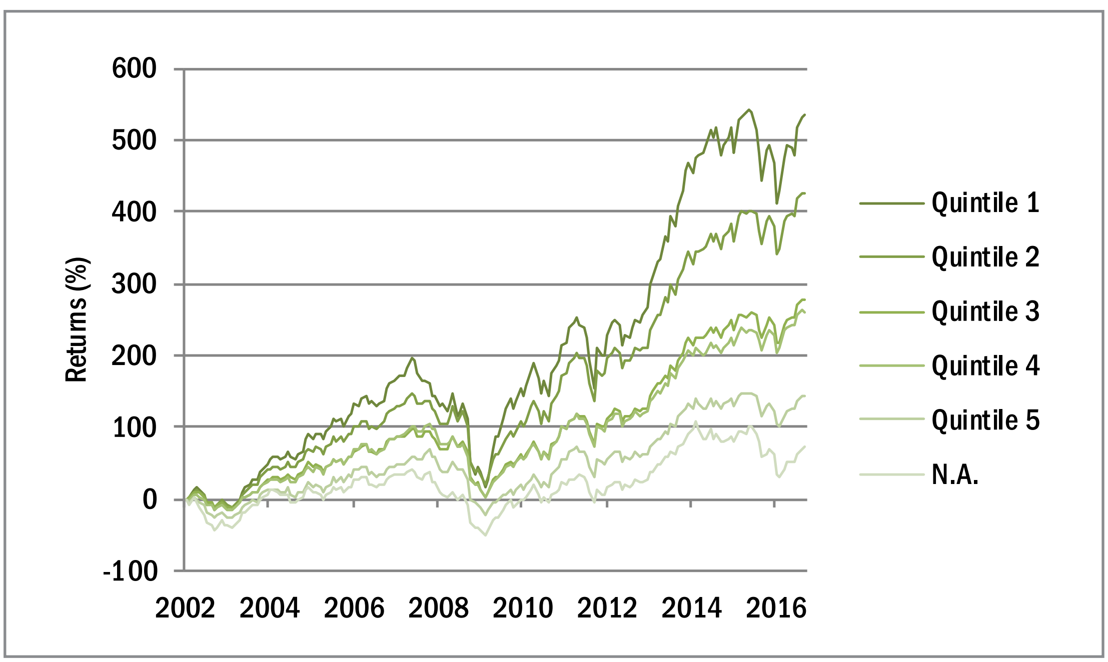


Figure 8: Composite Value



FIQ Quantitative Equity Selection Model

The FIQ QES model is even more powerful than the simple Composite Value Factor Model. Rather than just four factors, the FIQ QES model employs approximately 15 different factors, with specific weightings customized to the particularities of both the Canadian and US markets.

These factors all fall under one the following broad categories:

- **Value:** Includes the P/E ratio and various other price ratios as factors;
- **Growth:** Includes both ROE and Modified Altman as factors, among others;
- **Safety:** Includes factors that are indicative of how risky or safe a particular stock is;
- **Technical:** Factors look at the momentum and mean reversion of stock prices;
- **Sentiment:** Factors measure how analysts rate the stock.

As a whole, these factors have been chosen to not only improve overall returns but also decrease downside risk during periods of crisis such as late 2008. To further mitigate risk, the final stocks that make it into the portfolio are filtered to maximize diversification among the various market sectors (ie. Energy, Technology, Financial, etc).

The Plausibility Quotient

Developing a robust model is more than just data mining. We believe that in order for a multi-factor model to work, the developer must have the requisite market experience to justify the rationale behind the statistical relationships being considered. In fact, this may be just as important as the statistical significance of the relationships themselves.

The FIQ QES model only accepts factors that are ‘reasonable and plausible’ sources of market outperformance. Factors with implausibly outstanding alpha are either quickly arbitraged away or not viable in the actual market due to practical limitations. Suffice it to say, it was our intention in building the FIQ QES model to stay well clear of factors such as these. In the end, determining whether a factor has reasonable and plausible alpha can truly be the most taxing part of such a model, in that the decision draws from the market experience of the developer and requires seasoned judgement.

While a well-tuned model will give the portfolio manager conviction in times of crisis, blind adherence to any model will likely produce poor results. It is our hope that the breadth of market experience contained within the FIQ portfolio management team provides a sufficiently deep understanding of the markets that will allow us to strike the

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right balance between allowing the model to adapt to structural changes in market dynamics as they happen over time, while not tinkering with the model at the first sign of trouble. Tinkering too much can lead to an endless cycle of changing the model to chase after the latest statistical aberration, which we believe will result in uninspiring returns.

Figures Lie, and Liars Figure

There is an additional "red flag" overlay in the model whereby portfolio managers screen the FIQ QES stock picks in areas that cannot be easily analyzed through quantitative means. For example, sometimes a stock may make its way into our top scoring group after a significant decline related to accounting regularities, lawsuits, or aggressive regulatory action. In situations like these where the market is attempting to price in a binary outcome, we disqualify the security from our universe of tradable securities. A non-exhaustive list of other red flags would include heavy short interest, frothy media coverage, wildly disparate analyst opinion, and disreputable management reputation.

A Balanced Portfolio Approach

We are confident that the depth of our market experience and addition of multiple overlays on top of the FIQ QES model will help our quantitative model sustain long term outperformance. However, the FIQ QES model produces a long-only equity portfolio, and despite our best efforts in stock diversification, the portfolio will be highly correlated to the equity markets during periods of crisis as with all other kinds of portfolios with long-only equity exposure. Beating our benchmark by a few percentage points during those times will offer little comfort. Therefore, it would not be prudent to construct a portfolio consisting only of stocks. Ideally, a balanced portfolio would include other asset classes that offer better diversification during equity market panics.

At FIQ Managed Portfolios, our FIQ QES equity portfolio is part of a bigger, more balanced portfolio with exposures to fixed income, cash, and alternative investments, with specific exposures to these asset classes determined, of course, by the personal circumstances and risk tolerance of the particular client.

While a reasonable and plausible model will give the portfolio manager conviction in times of crisis, blind adherence to any model will likely produce poor results. The breadth of market experience contained within the FIQ Managed Portfolios team provides a sufficiently deep understanding of the markets that will allow us to strike a balance.

Frankie Liu, CFA®, Quantitative Analyst

Frankie is the Quantitative Analyst responsible for the ongoing research and development of the FIQ security selection model.

A graduate of the University of Chicago in Mathematics and Economics, Frankie received his CFA charter in 2013.

In addition to his work at Foster, Frankie is Head of Research at alternative investing firm Blackheath Fund Management Inc, where he also developed and trades his own trend-following futures strategy.

FOSTER & ASSOCIATES FINANCIAL SERVICES INC.

372 BAY STREET
SUITE 1100
TORONTO ON M5H 2W9
416.369.980
800.559.8853
WWW.FOSTERGROUP.CA

FIQ MANAGED PORTFOLIOS

INFO@FOSTERIQ.CA
WWW.FOSTERIQ.CA

Raw data for this research was sourced from Bloomberg, LP on Oct 3, 2016 and analyzed in-house by the FIQ Quant Team.