Designing Environment-Specific Equity Screens From Factors For Long RIA and Mutual Fund Portfolios

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There is extensive literature describing equity factor behavior as well as methodologies to capture returns based on cross sectional factor performance. Common examples include the exceptional work by the teams at AQR[1] and Research Affiliates[2]. Most of these implementations involve being long all securities in a top decile/quintile/group while being short all securities in the bottom grouping. "All" in this case certainly means hundreds of securities in each group with rebalancing as frequently as weekly or monthly.

While these may be ideal strategies for a hedge fund where transactions are invisible to investors and summarized in a single net asset value, it is far more difficult for a long portfolio manager at a Registered Investment Advisor ("RIA") or mutual fund to take advantage of this research and apply strategies in a manner more suited to portfolios that are limited in the number of holdings and turnover level. This paper will provide insight into how we do just that in the long portfolios of our RIA clients.[3]

We compare the performance of the 23 factors listed in Exhibit 14 against the broad market as well as to benchmarks that are sector-neutral to the resulting factor portfolios. We believe this comparison to sector-neutral indices is less well researched and documented. This paper provides evidence that factor performance is heavily influenced by the sector weights of factor groupings but that extreme factor quintiles have the ability to distinguish returns independent of those sector weights. We advocate a process whereby factor performance is first used to filter an equity universe for factors that underperform in multiple market environments. From there we develop a series of factor-driven screens using intuition over machine learning that identify companies that have historically generated attractive performance in specific market environments. Lastly, we rely on factor momentum and the performance of top and bottom factor quintile differentials themselves to direct us to which of those screens are most likely to outperform given the immediate market environment.

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[1] *Factor Momentum Everywhere – Tarun Gupta and Bryan Kelly, AQR Capital Management, LLC.*
[2] *Factor Momentum – Arnott, Clements, Kalesnil, and Linnainmaa, Research Affiliates, LLC.*
[3] *Autumn Wind Asset Management is a Registered Investment Advisor as well as the General Partner to a hedge fund. While the fund does employ traditional hedge fund strategies involving factors, this paper will focus on the application of factor research to the long portfolios of RIA clients.*

The Research Universe

We define our broad research universe as all US common stocks with market capitalizations greater than the 25th percentile of traded companies. We utilize the time period of January 1, 2000 – March, 15, 2019 to capture multiple bull, bear, flat, and early recovery market environments. To address the problem of survivorship bias we identify companies meeting the market cap criteria as of each quarter-end during this time period. Acquired or delisted securities remain in the research universe. In total, the research universe consists of 1,350 active companies today and 1,385 inactive companies for a total of 2,735 unique identifiers over the 20 year period. This highlights the tremendous challenge of survivorship bias in quantitative finance. For purposes of this research aimed at RIA and mutual fund long portfolios we have further filtered the universe with a cutoff at the median market capitalization. This results in a minimum market capitalization that fluctuates in a range of $4 – 8 billion over the 20 year time period. On average, there are between 500-600 companies in the research universe at all times when factor quintiles are calculated. All prices are adjusted for splits and dividends to create total return time series.

Building Quintiles and Measuring Performance

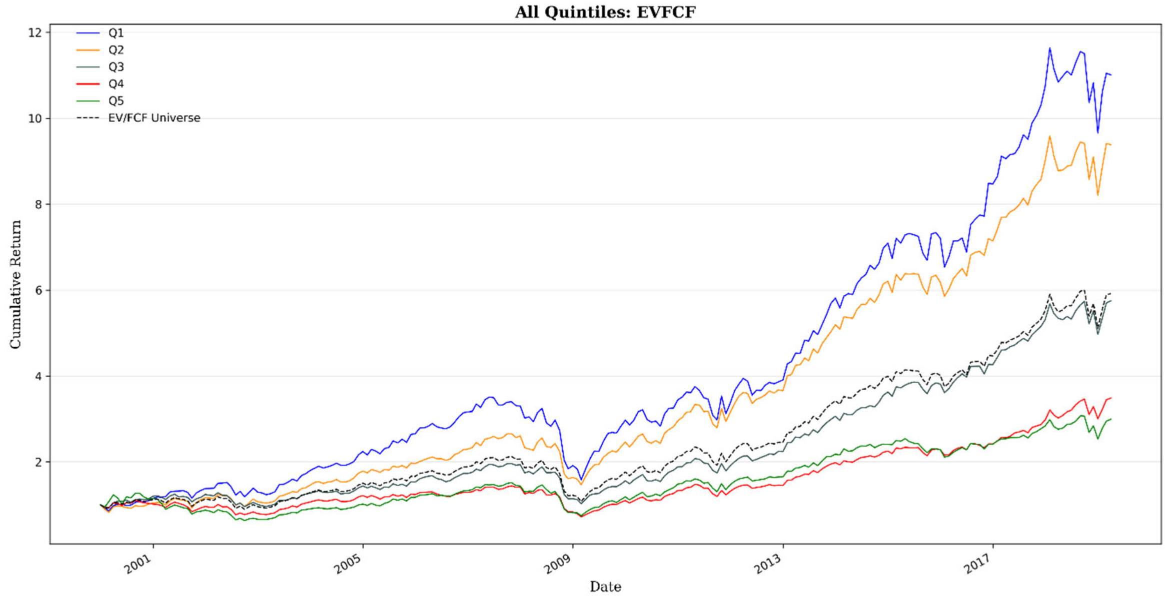
Each quarter we cross sectionally winsorize each of the 23 factors at the 1st and 99th percentile. We then create quintiles for each factor and join forward monthly total returns for the coming quarter for each stock in each quintile. We then build equally weighted portfolios for each factor quintile[4]. Since factor quintiles can have very large differences in sector weights, we build for each factor quintile a corresponding benchmark portfolio using sector returns weighted the same as the factor quintile portfolios. This ensures we have a sector-neutral benchmark against which to compare a factor quintile's performance. This methodology is particularly useful when comparing the performance of factors that are not available to all sectors and sub-industry groups. Valuation metrics based on Enterprise Value to EBIT, EBITDA, or Free Cash Flow, for example, are not calculated for most banks, REITS, and utilities. Comparing factor quintiles that exclude banks against a universe that includes banks would be misleading. The end result for each factor is a set of quintile total return time series, a universe return ("the market") consisting of securities for which a factor has values, and a set of corresponding sector-neutral benchmarks for each quintile. All are rebalanced quarterly. We utilize quarterly rebalancing not because it is optimal, but rather to reflect our objective of developing a factor-based methodology for a lower (not low, but lower) turnover, long portfolio.

As an example, one factor we consider is 'Enterprise Value / Free Cash Flow' ("EV/FCF"), a fundamental valuation metric used by many analysts and portfolio managers in hedge fund, RIA, private equity, and other institutional portfolios. The chart below shows the performance of its five quintiles for the periods January, 2000 – March, 2019 and January, 2007 – March, 2019.

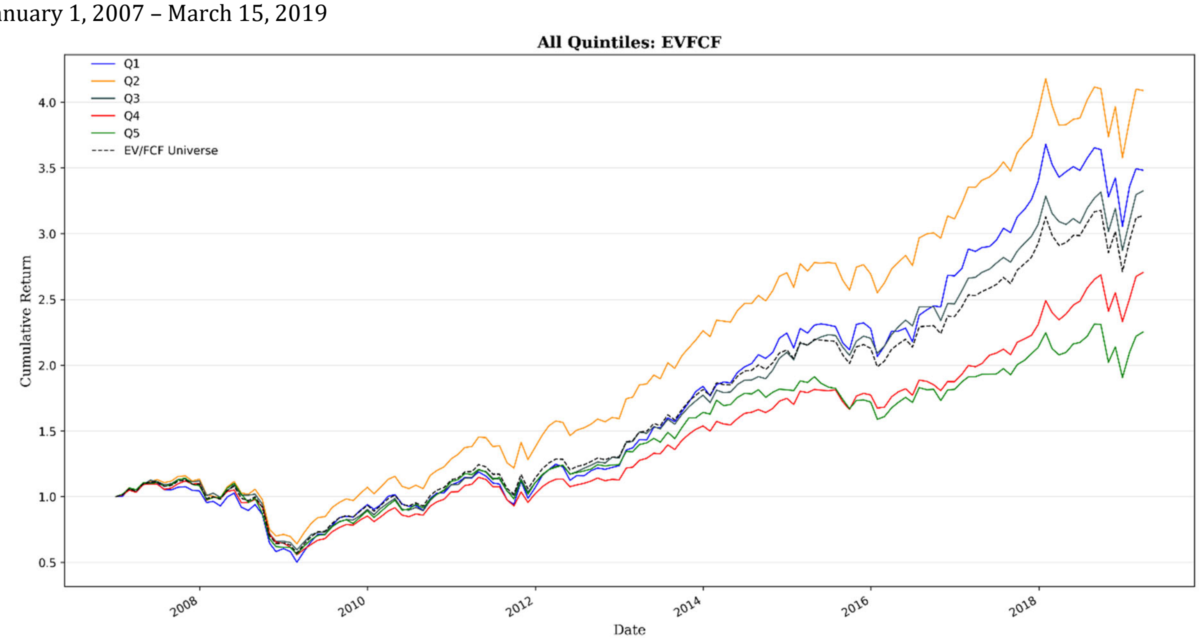
[4] *The definition of a 'factor quintile': "Free Cash Flow – 5th Quintile' is a time series of monthly forward returns for a portfolio of the top quintile companies for the factor Free Cash Flow Margin as rebalanced quarterly. It has a corresponding sector-neutral benchmark that is built using the identical methodology. This factor quintile is identified as FCF_Q5 and its sector-neutral benchmark as FCF_Q5_Idx.*

Exhibit 1: Representative Factor Quintiles - Enterprise Value / Free Cash Flow ("EV/FCF")

January 1, 2000 – March 15, 2019



January 1, 2007 – March 15, 2019



Companies with the lowest EV/FCF valuations outperform companies with the highest valuations. The quintiles line up sequentially over the past 20 years and near-sequentially since the Great Recession. Valuation matters. At this point, the standard implementation for a hedge fund would be to be long the top performing quintile (Q1) while short the bottom (Q5), i.e. "HML", or "LMH" to be specific as we do not invert valuation metrics (e.g. FCF/EV) so that "most favorable" is always Q5. Q1 is always the lowest numeric values of any factor and Q5 the highest.

Common Academic Terms Describing Hedge Fund Factor Strategies:

HML	High Minus Low	Most commonly used to describe being long high book value / market values while short low book value/market values.
UMD	Up Minus Down	Most commonly used to describe momentum strategies where one is long stocks with the highest trailing returns while short those with the lowest returns.
SMB	Small Minus Big	Most often used with market capitalization and describing being Long small cap while short large cap.

The return differential between EV/FCF Q1 and Q5 from 2000-2019 is exploitable at 742 basis points per year and merits consideration under a traditional hedge fund approach. However, this strategy faces many real hurdles that render it impractical to a long portfolio manager seeking to exploit the expected performance between expensive and inexpensive groups of stocks:

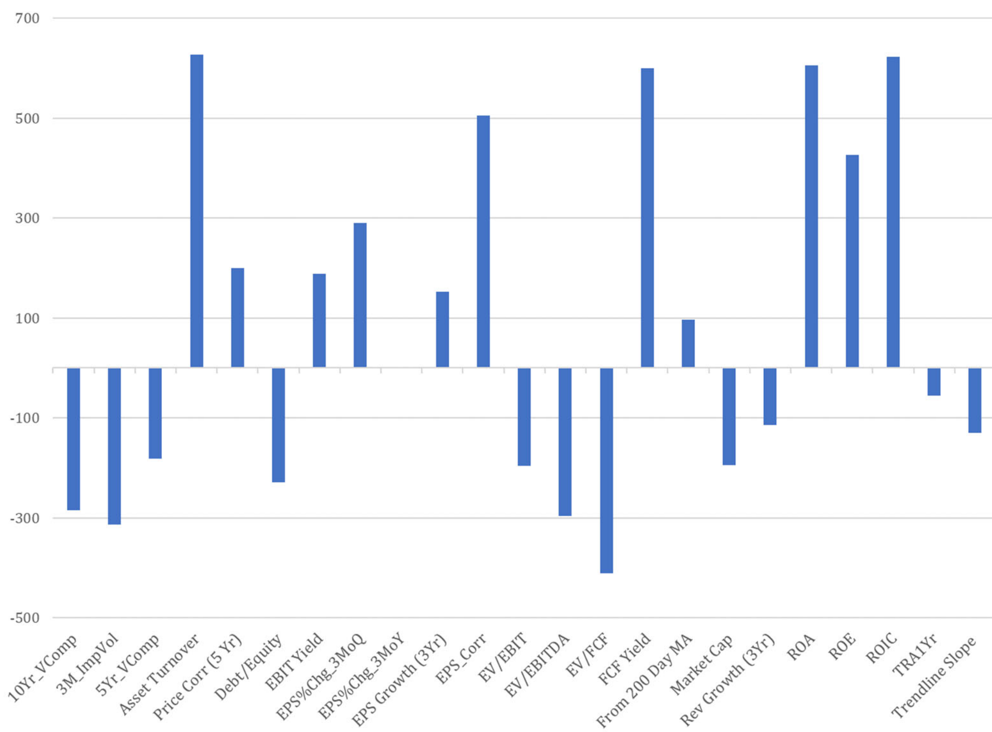
- It is impractical in long portfolios to be long and short hundreds of securities as is suggested by quintiles, particularly in managed accounts where every transaction results in a trade confirmation, i.e. "mailbox risk".
- HML implementations require frequent rebalancing that exacerbates the problem. Further, they are difficult to implement in a large number of individually managed RIA accounts versus a single fund account.
- RIA portfolios do not always benefit from the same economies of scale in regards to execution costs or abilities as does a single portfolio hedge fund making transaction costs impractical.
- Taxes. They simply matter more in a full disclosed RIA portfolio than a hedge fund's NAV. The tax implications of these higher turnover strategies is unrealistic to an RIA.

How can a long portfolio manager running a typical 30-50 stock portfolio take advantage of factor quintile performance differentials?

It is a problem worthy of research as the performance differentials between top and bottom quintiles suggests a real ability to separate winners from losers using factors from a wide range of investment disciplines. These include factors describing valuation, profitability, size, growth, and price behavior. The chart below shows the performance differential between the 1st and 5th quintiles (Q5-Q1) for the 23 factors used in this research for the period 2007-present[5].

[5] *For the duration of this paper we will use the time period January 1, 2007 – March 15, 2019 for simplicity, to avoid shifting time periods, and to focus on more recent data. There are no conclusions presented that are true for the 2007-2019 time period that are not also true for the full 2000-2019 time period.*

Exhibit 2: Annualized Return Differences in basis points - 5th minus 1st Quintile.
January 1, 2007 – March 15, 2019



Momentum, value, and price-based managers will all find factors with material differences in top and bottom quintile performance to assist in screening investment ideas. The difference in annualized returns between top and bottom quintiles across several disciplines is listed below. Negative values mean the 5th quintile underperformed the 1st and is common for valuation factors.

Profitability/Efficiency

FCF Yield	601 bp
ROIC	638 bp
ROE	427 bp

Valuation

EV/FCF	-387 bp
EV/EBITDA	-295 bp

Other

Asset Turnover	628 bp
EPS Growth (3 Yr)	153 bp
EPS Est Change Qtr	290 bp

Price

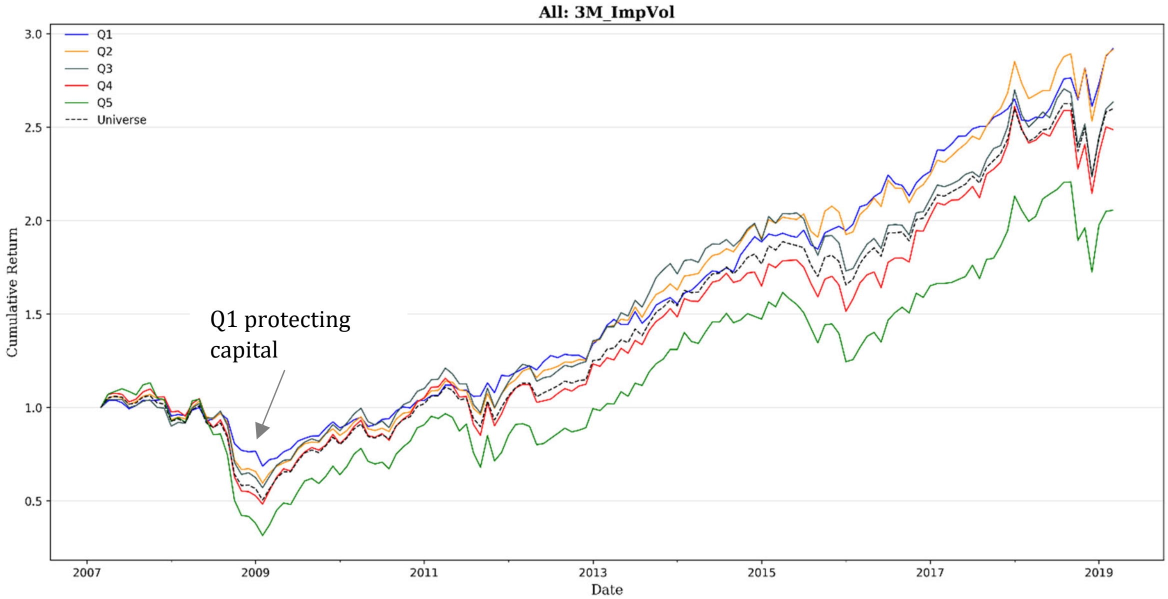
% From 200 Day	97 bp
Trailing 1 Yr Return	-32 bp
3 Mo. Implied Vol	-313 bp

This basic analysis of top and bottom quintile performance differentials is a sound starting point in understanding factor behavior. However, to understand how to proceed to combine factors into equity screens requires greater granularity of performance across different market environments.

Evaluating Factor Performance In Different Market Environments

Factor quintiles behave very differently across various market environments[6]. To illustrate Exhibit 3 plots the behavior of a less published factor, '3 Month At-The-Money Implied Volatility' ("IV"). From 2007 – 2019 this factor generated the following cumulative forward returns across quintiles.

Exhibit 3



The returns line up in descending order with the 1st quintile, low IV names, producing the highest return, the 2nd quintile the second highest return, and so forth through the 5th quintile which produces the smallest return. The spread between Q1 and Q5 is 313 basis points annually.

However, analyzing cross sectional performance across different market environments shows the real dynamics of this factor and why a simple HML strategy based on the full time period's performance is likely to disappoint.

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[6] *Refer to Appendix A for examples of time periods combined to form various market environments. .*

Exhibit 4: Bear Market Periods [7]

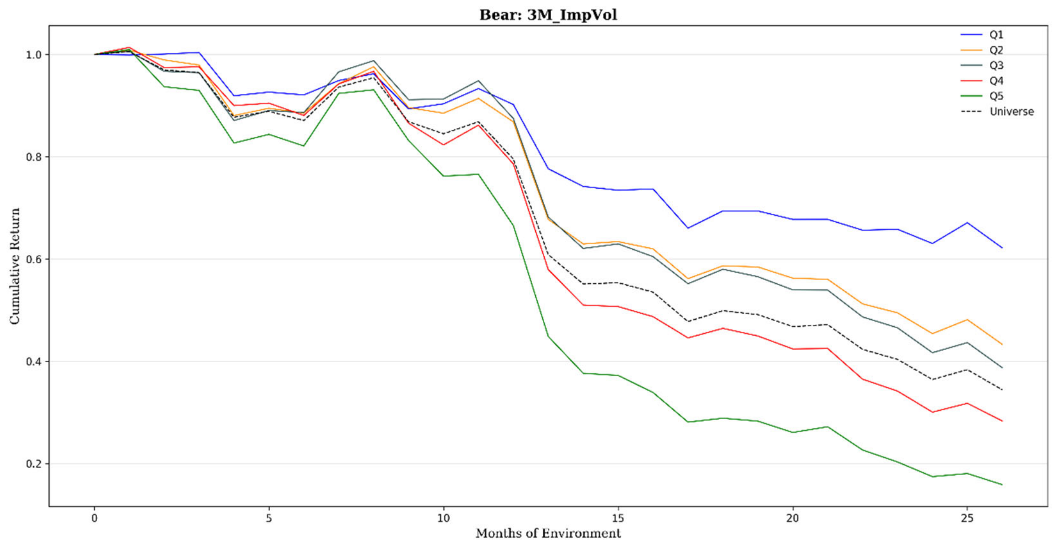
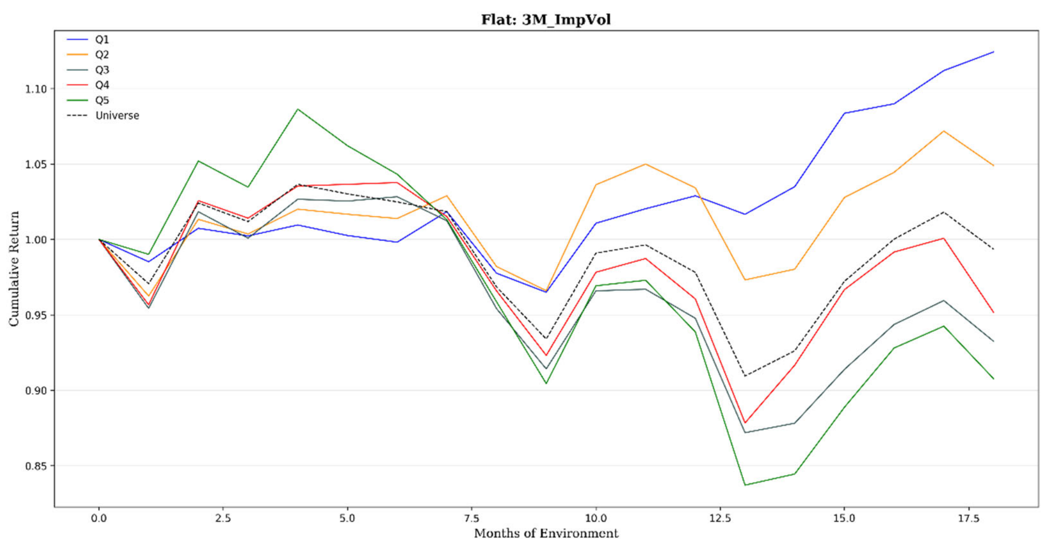


Exhibit 5: Flat Market Periods



Both environments confirm the findings of the full time period, that low IV (blue line) outperforms high IV (green line). Performance dramatically inverts, however, in a bull market and you would not see this if reviewing only the full time period.

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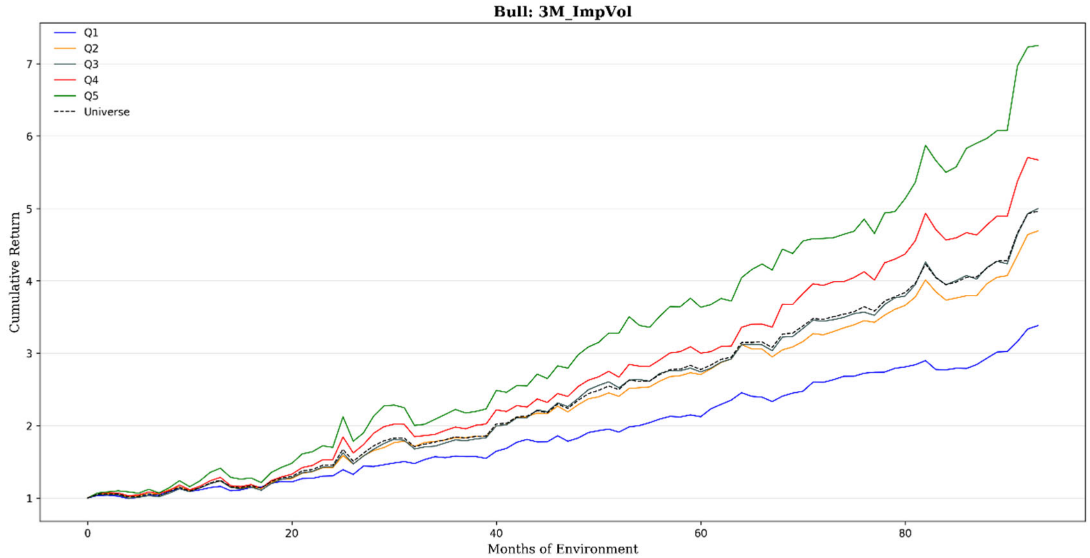
[7] *The x-axis switches from 'Date' to 'Months of Environment' when plotting common market environments separated in time. For example, the first chart in Exhibit 4 plots factor performance from the 2000-2002 and 2008-2009 bear market periods. The index of our Python dataframe is a datetime object with plots generated with Matplotlib. Matplotlib linearly interpolates the gap in time between the separate bear market periods and connects them with a straight line. This distorts the plot making it difficult to observe quintile behavior in the environments of interest. As such, we drop the datetime index in favor of an integer index which represents the total number of months in the environment.*

Exhibit 6: Bull Market Periods



Strong performance by high IV companies is logical in a bull market. The 1st and 5th quintiles of most factors result in portfolios with different types of companies and sector weights as you would expect. A low IV portfolio is overweight utilities, real estate, and financials. The high IV portfolio is overweight consumer discretionary, healthcare, and technology. You would expect a high IV portfolio to outperform in a bull market.

Exhibit 7: Average of quarterly sector weights for 2018 for Implied Volatility Quintiles:

	Quintiles				
Sector	**1**	**2**	**3**	**4**	**5**
Discretionary	3.8%	7.1%	11.8%	21.8%	25.4%
Energy	2.4%	5.7%	5.9%	7.9%	14.1%
Financials	19.2%	17.9%	22.3%	9.8%	2.7%
Healthcare	9.6%	13.3%	12.5%	14.1%	13.3%
Industrials	5.6%	19.4%	18.0%	15.2%	5.2%
Materials	2.0%	5.2%	5.9%	7.1%	4.1%
Real Estate	18.1%	7.3%	1.1%	0.5%	0.0%
Staples	9.5%	10.7%	4.6%	3.6%	2.2%
Technology	6.0%	11.4%	16.0%	17.7%	28.3%
Telecom	1.6%	0.7%	1.2%	1.9%	3.8%
Utilities	22.1%	1.4%	0.7%	0.4%	0.9%

Q5 outperforms Q1 by 1210 bp/year in an upmarket yet underperforms by 1400+ bp/year in a flat or down market. Averaging these to get a convenient full period number loses this dynamic behavior. The outperformance of the 1st quintile over the full period comes from the fact that it preserved capital in down markets by shifting capital to defensive sectors and began compounding from a higher level once the market rebounded. Q1 performance demonstrates the value of preserving capital in down markets. Yet, at some point a portfolio manager would need to invert his or her thinking to get aligned with an up market or risk significant underperformance if this factor is included as an equity screen criteria.

Simply owning Q1, or long Q1 while short Q5, is likely to significantly underperform unless a bear market is experienced in the period of use. You would not understand this dynamic if viewing only the full period**. As such, it is our belief that decisions based on factor performance must be contextual to the market environment. Do not judge a factor based solely on full period performance.** This view differs from most published research that focuses on a single period, particularly the June, 1963 – present time period covered by the dataset offered by the Center for Research in Security Prices ("CRSP").

Introducing the Sector-Neutral Benchmark

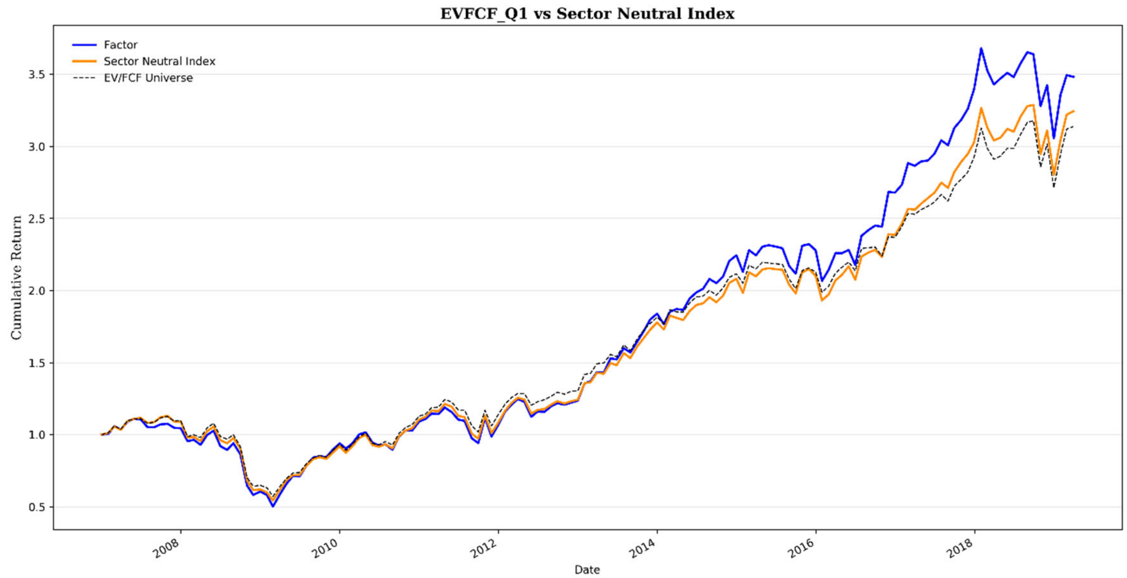
We noted above the significant sector weight differences between quintiles within a factor. There is nothing wrong with factor-driven investment performance being determined by sector bets. In fact, in our view, that is one of the primary benefits of a factor-driven investment approach. Another benefit is that a factor-driven process effectively navigates between (a) the market's need for a margin of safety as measured by factors describing a company's ability to generate cash and survive difficult times and (b) a time to think about the future through companies unprofitable today but with large prospects for future growth. This vacillation takes places within the context of the certainty of economic growth.

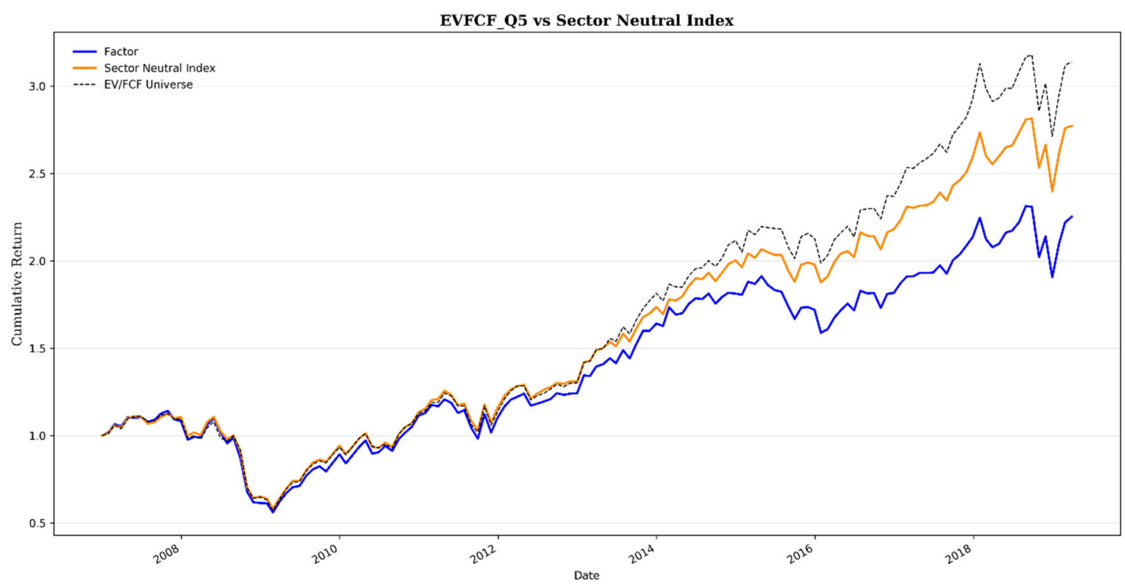
It is useful to dig deeper into a factor quintile's performance to understand to what degree it is a function of sector weights or the factor itself. To accomplish this we build benchmarks from sector returns that are sector-neutral to the factor quintile being reviewed. Refer to Appendix B for additional details. Specifically, each quarter as we create factor quintiles we also calculate sector weights for every factor quintile using the full universe of securities that have a value for that factor. We then utilize sector returns to build a custom index with the same sector weightings. We rebalance the custom index at the same time we recalculate factor quintiles each quarter. In the same way we have a time series for every quintile of the factor '3 Year Revenue Growth' we have a corresponding time series that is sector neutral to each of those quintiles at every point in time.

Is It Sector or Factor Driving Returns?

The chart in Exhibit 1 plotted the quintile performance for EV/FCF and showed the inexpensive 1st quintile outperformed the market while the overvalued 5th quintile significantly underperformed. The charts below compare the performance of these two quintiles to their respective sector-neutral benchmark and highlights how effective EV/FCF is as a differentiating factor.

Exhibit 8: Q1 and Q5 of EV/FCF versus Sector-Neutral Benchmarks





Note the performance of the respective sector neutral benchmarks (orange lines). Q1's neutral benchmark outperforms the universe by 30 bp annually while Q5's benchmark lags the universe return by -111 bp annually. The factor is driving the selection of better sector weights, and perhaps more importantly, avoiding strong underperforming sectors.

This is a good starting point but can the factor itself add additional return? In the case of Q1 the factor (blue line) adds an additional 64 bp annually of return over its neutral benchmark while Q5 underperforms its underperforming sector neutral benchmark by -183 bp annually. Low valuation, as measured by low EV/FCF, is important even after adjusting for sector weights. 5th quintile EV/FCF companies are weak relative performers because the quintile contains sector weights that cannot keep up with market returns and the group of overvalued companies in the quintile cannot keep up with its underperforming sector neutral benchmark. Bad news on both counts. We generalize the attribution of factor quintile alpha (a factor quintile's return – its universe return) as:

Factor Alpha = Return Due to Sector (Sector Neutral Benchmark Return – Universe Return) – Return Due to Factor (Factor Return – Sector Neutral Benchmark Return)

- EVFCF_Q1 beats the universe return by +94 bp annually. +30 bp of that comes from sector and +64 from factor.

- EVFCF_Q5 underperforms the universe return by -293 bp annually. -111 bp of that comes from sector and -183 from factor.

Exhibit 9 repeats this exercise for two additional factors, the valuation factor, Return on Invested Capital ("ROIC"), and a price momentum factor, Trailing 1 Year Total Return.

EXHIBIT 9: Performance Attribution the Factors EV/FCF, ROIC, and 1 Year Total Return

Factor	Q	Factor Return	Sector Neutral Return	Universe Return	**Due To Sector +** Sector - Universe	**Due To Factor =** Factor - Sector	**Total Factor Alpha** Factor - Universe
EV/FCF	1	10.72	10.08	9.78	30	64	94
EV/FCF	2	12.18	10.62	9.78	84	156	240
EV/FCF	3	10.30	10.19	9.78	40	12	52
EV/FCF	4	8.46	9.75	9.78	-3	-129	-132
EV/FCF	5	6.85	8.68	9.78	-111	-183	-293
ROIC	1	4.40	6.71	8.61	-190	-231	-421
ROIC	2	8.46	7.80	8.61	-81	67	-14
ROIC	3	8.85	8.81	8.61	20	4	24
ROIC	4	10.19	9.96	8.61	136	23	159
ROIC	5	10.78	9.60	8.61	99	118	218
TRA_1Yr	1	5.83	7.76	8.35	-60	-193	-252
TRA_1Yr	2	9.88	8.75	8.35	39	113	153
TRA_1Yr	3	9.94	9.06	8.35	71	88	159
TRA_1Yr	4	9.95	8.89	8.35	54	106	160
TRA_1Yr	5	5.51	7.21	8.35	-115	-169	-284

Return on Invested Capital ("ROIC") is a core factor in many investment processes. It is one of the few factors that offers alpha from both sector and factor. Quintiles 3, 4, and 5's sector neutral benchmark outperforms the market. Likewise, the factor outperforms the outperforming benchmark. The higher the quintile the greater the degree of outperformance. Q5 is a terrific factor quintile from which to select outperforming companies in outperforming sectors. It is also a well-diversified factor quintile as will be shown in Exhibit 13.

Conversely, most of the results observed for price-based factors (Percent from 200 Day Moving Average, Slope of Trendline, Trailing Returns) show little value in an UMD application from 2007-2019[8]. The factor, Trailing One Year Return ("TR_1Yr"), shows negative returns in an UMB application (5.51% - 5.83% = -32 bp annually). Nether Q1 nor Q5 adds value from sector weights or factor performance. Q5 shows poor absolute performance as a long momentum strategy as well (5.51% - universe return of 8.35% = -284 bp annually). Results improve in the middle quintiles. Quintiles 2-4 show above market returns with alpha coming from both sector and the factor. These results suggest to us that a better price momentum strategy than Long Q5 / Short Q1 would be long Q 2, 3, and 4 while short liquid sector ETFs neutral to the portfolio.

While results differ across factors, the portion of return that is attributable to sector is similar in magnitude as the portion attributable to factor. A disciplined factor-driven investment approach that emphasizes attractive quintiles in profitability, valuation, or momentum factors will be driven to better company attributes (factors) that have the additional benefit of being in better performing sectors. **For purposes of this paper, the importance of this finding to a long portfolio manager is that he or she must be willing to accept sector weights that may differ from index levels in order to fully realize the return potential of any factor. Sector weights must be accepted semi-passively.**

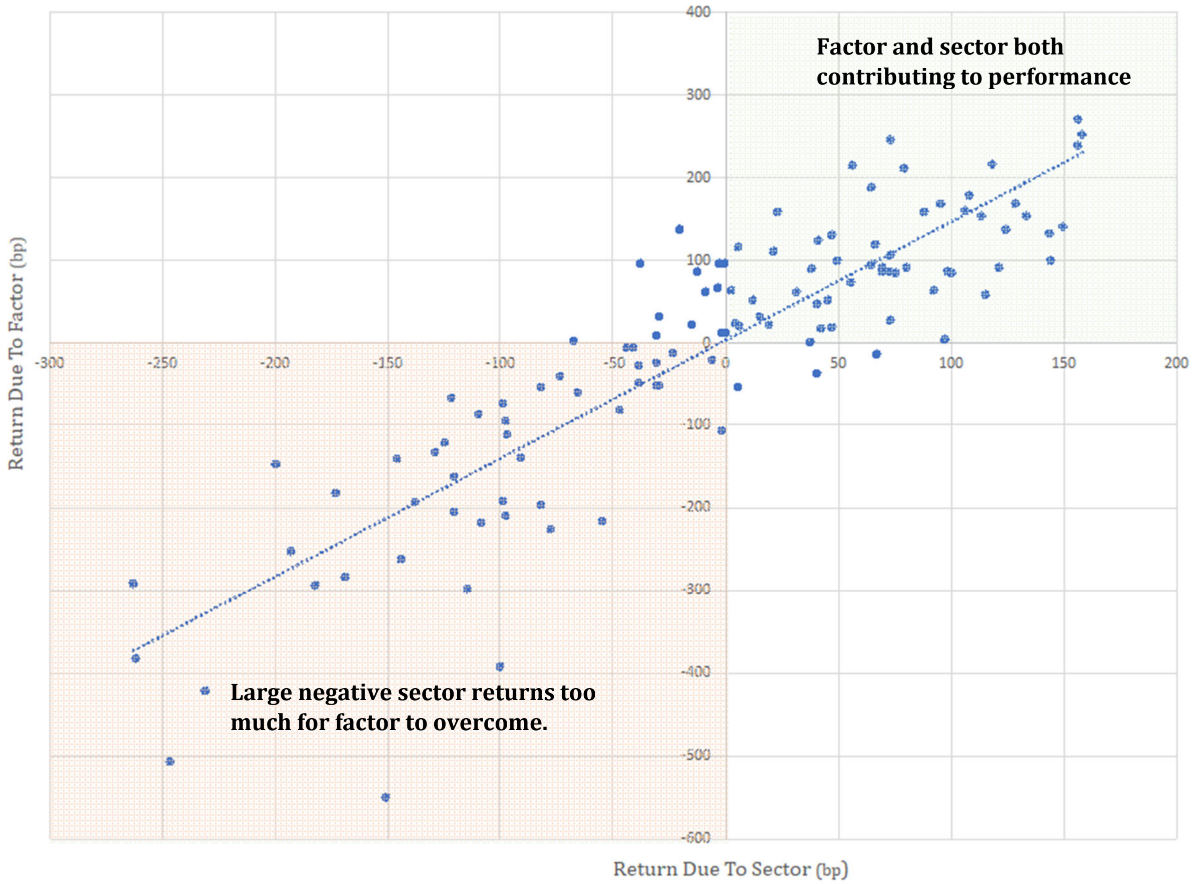
In total there are 115 unique Factor quintiles across our universe of 23 factors. 74 of the 115, or 64%, have sector neutral benchmarks that outperform the market. In general, factor investing is driving you to sectors that work for you on average. 44 of those 74 factor quintiles also outperform their sector neutral benchmarks. Together, 58 of the 74 (78%) outperform the market. Conversely, only 29% of factor quintiles whose sector-neutral benchmark underperforms the market are able to overcome this sector handicap and go on to outperform the market. There is synergy at work but it begins with sector performance.

A factor quintile that realizes value through sector is also more likely to realize additional value thru the performance of the factor itself. When one works the other works. The opposite is also true. Exhibit 10 illustrates this for all 115 factor quintiles.

[8] *We acknowledge strong price momentum from 2000-2007 and large periods of time in 1980's and 1990's as shown in the original Fama French Three Factor Model. However, a factor being out of favor for twelve years presents a large challenge to us in its core adaptation.*

EXHIBIT: 10: Performance Attribution For All 115 Factor Quintiles

Return Due to Factor = 3.55 + 1.429 Return Due to Sector
R Squared: 76.6%. T Stat: 19.2



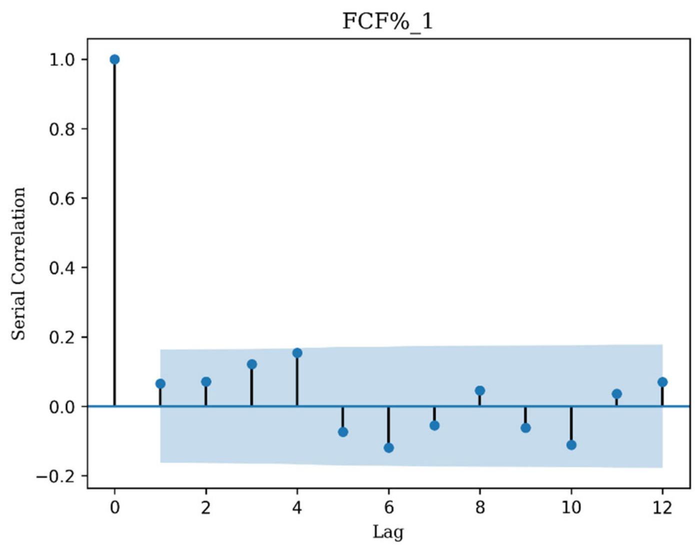
One More Concept and Then to The Point: Serial Correlation

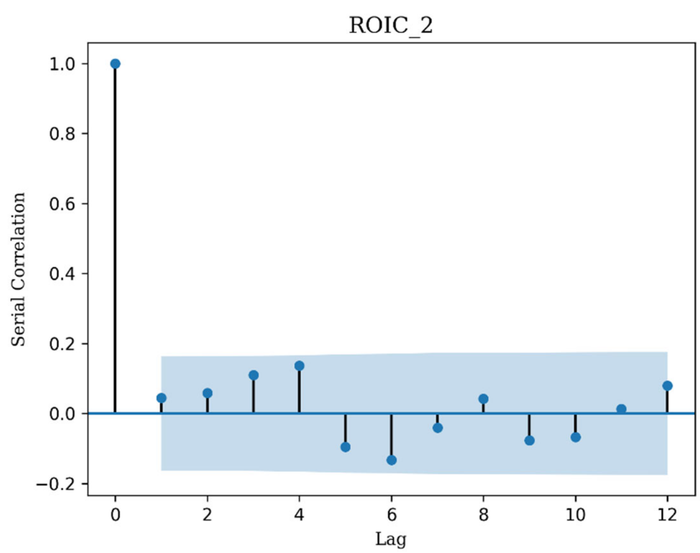
Fortunately, factor quintiles, at large, demonstrate strong serial correlation. *Factor Momentum Everywhere*[9] argued this point well. The factor quintiles that have been working of late have a tendency to continue working. Likewise, what has not been working is not likely to help you much in the coming months. The plots in Exhibit 11 show the typical serial correlation pattern for factors with lags of 1-12 months. These are representative of factor serial correlations at large. The 3rd and 4th month serial correlations of 0.20 are high. It then abruptly drops. This suggests the mean holding period for stocks entering a portfolio solely on the basis of this factor would be less than 5 months.

[9] *Factor Momentum Everywhere – Tarun Gupta and Bryan Kelly, AQR Capital Management, LLC.*

Is 4-5 months an acceptable long portfolio holding period? That has to be determined by each manager. However, it is not one month as is the case with most UMD applications by hedge funds. This brings us to the point of this exercise. How is a long portfolio manager to take advantage of this research?

Exhibit 11: Typical serial correlation pattern for a factor quintiles.





Designing Environment-Specific Equity Screens From Factors

As stated, we believe factors, and screens built from factors, must be designed for specific market environments as illustrated in the Implied Volatility example. We do not believe in "all weather" equity screens. Neither do we believe in making a top down prediction about the direction of the equity market. So, how do we proceed?

"This is not a problem for machine learning. Leave TensorFlow and Keras behind for once."

We build factor-based screens that are designed ex-ante with an intuitive basis for their expected performance in a given market environment. While we regularly employ machine learning algorithms in a wide variety of trading and investment applications, this is not one of them. At best there is 40-50 years of data on factors and more likely, 20-25 for non-Fama/French factors. 25 years of monthly factor data is a mere 300 data points, far too few to turn a neural network or classifier algorithm loose using k-fold cross validation and hyperparameter tunings. Stick with intuition here. The risk of overfitting the data is too high given the practical intuition around company attributes that should perform well under certain market conditions. How often can this be written about a problem in quantitative finance?

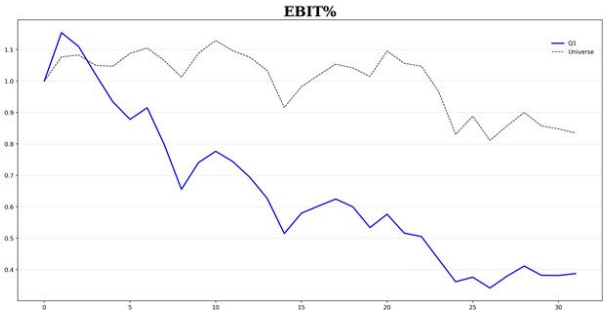
While we urge caution on the use of machine learning algorithms for this problem the risk of overfitting nevertheless remains. We strongly advocate in favor of sound research processes to limit this risk. These include the use of multiple test and validate periods, being aware that there is no such thing as truly out of sample under an iterative research process, and the challenge of dimensionality. In the charts that follow we present two distinct time periods, 2000-2007 and 2007-present. Within each we utilize test and training periods for confirmation of factor and screen performance.

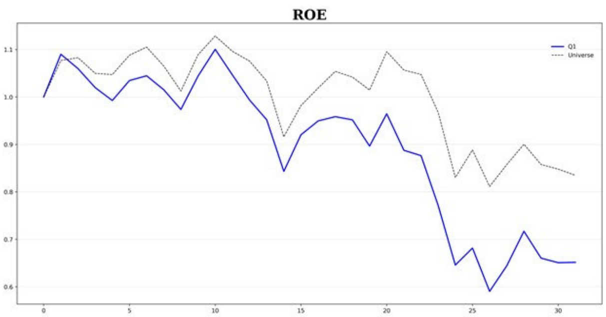
We develop screens that are tailored to different market environments and allow factor momentum, and the similar momentum property that exists in screens built from factors, to drive the selection of securities from different screens. We are less interested in a market call than investing in factors that are currently being rewarded by the market. While we refer to collections of factor criteria as bull or bear screens they would more accurately be described as screens that reward factors in unique market environments and that demonstrate high serial correlation. We buy names from bear screens in bull markets if the bear screens have momentum. The reverse is also true. We invest in factor momentum and note that certain factors tend to behave in ways that lead to the common labels of bull or bear market.

Examples
In a bear market the intuitive factors and quintiles are those that describe the ability to weather the storm of a recession and protect capital. Why own the lowest quintile of profitability factors EBIT Margin or ROE in a non-bull market environments?

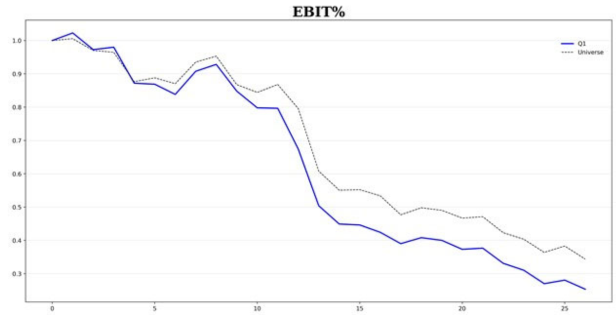
Exhibit 12: 1st Quintile Performance (blue) for EBIT Margin and ROE in Bear Market Environments

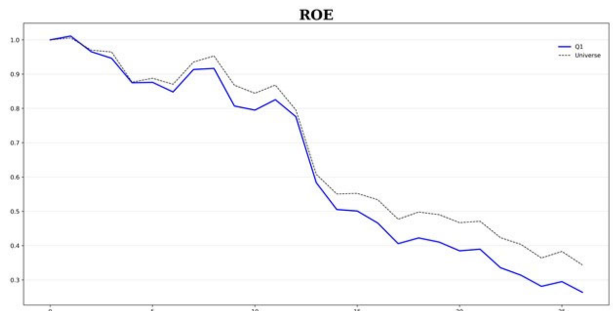
Bear Market Periods 2000-2007





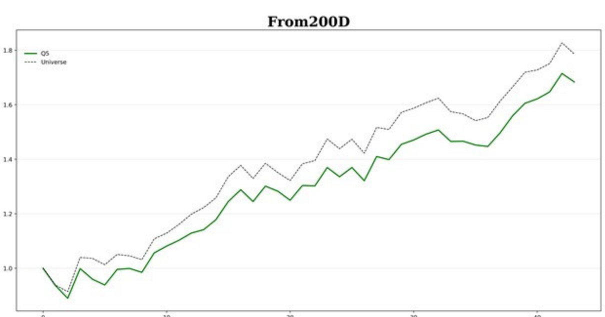
Bear Market Periods 2007-2019



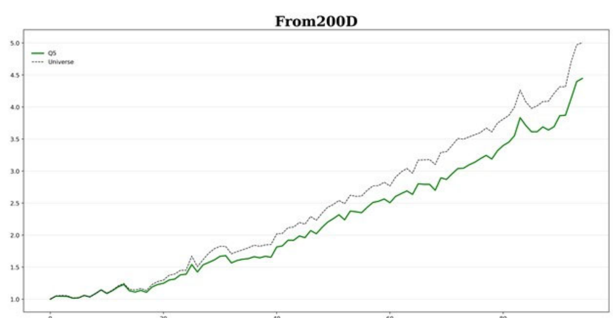


Likewise, in a strong market why own the highest quintile (green) of '5 Year EPS Correlation' or "Percent From 200 Day Moving Avg' in a long portfolio benchmarked to the market?

Bear Market Periods 2000-2007



Bear Market Periods 2007-2019

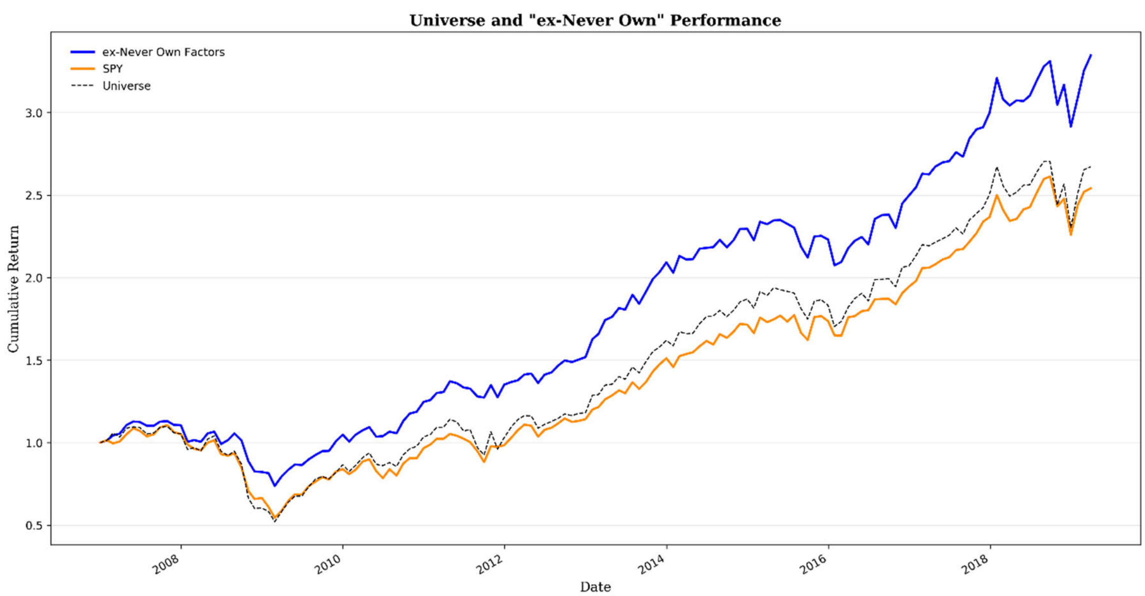


Step 1: Addition by Subtraction. Remove "Never Own" Factor Quintiles.

The first step we advocate in building equity screens is to remove these intuitive factor quintiles that are negative to the environment for which we are developing a screen. Internally, we call these 'Never Own' factor quintiles, appropriately abbreviated 'NO'. **With each decision to remove Never Own factor quintiles, we are biasing our research universe by the return differential of a series of UMD hedge fund strategies as we retain the better performing quintile while removing the bottom performing from our universe.** Clearly, the universe remains long market risk and is not market neutral as any of the UMD portfolios we have referenced but we do not have that option under a long portfolio. Our goal is to utilize the same research that drives large scale, high turnover factor portfolios to bias and narrow the long portfolio universe.

Excluding the weak quintile from the factors plotted above plus two additional factors, one related to earning revisions and another to profitability, results in improvement in the performance of the universe by 186 bp annually from 2007-2019.

Exhibit 12: Universe and 'Never Own' Performance



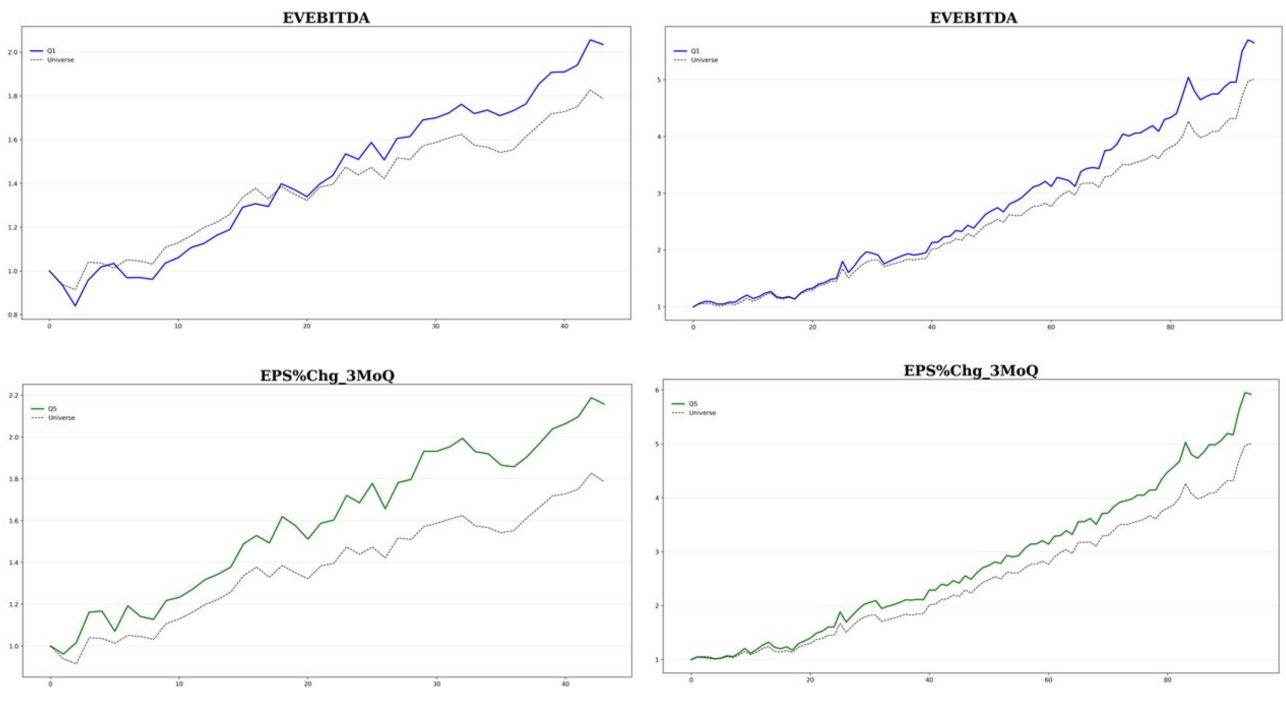
A long manager seeking to outperform the market may strongly consider starting with this idea prior to assembling additional "positive" factor attributes into an equity screen. We feel the majority of smart beta products on the market today suffer from a failure to do just this. Products are launched in isolation based on a single factor quintile(s) with no regard to the values those stocks have with a few basic additional factors. We suggest a low volatility product, for example, could be improved if it also removed the bottom quintile of ROA, ROIC, and EBIT Margin.

The number of companies after applying this criteria is remarkably stable over time and is far more manageable for the long portfolio manager in the move towards 30-50 names. On average, the number of companies remaining after applying this criteria is 250 with a minimum of 146 and a maximum of 315 over the past 10 years.

Step 2: Add factors that perform well in specific market environments.

High free cash flow, high profitability, low debt/equity, and the sector weights resulting from low implied volatility quintiles are the optimal equity qualities in a weak market. In a bull market these factors flip and the market rewards low valuation, momentum, and upward earnings revisions while caring less about profitability. This is the time when low EBIT margin or ROA companies, those that have low or negative earnings but are building products and platforms for future growth dominate. Low valuation as measured by EV/EBITDA (blue) and high 'EPS Revisions to Current Quarter' quintiles (green) do well in all bull market periods.

Bull Market Periods 2000-2007 | Bull Market Periods 2007-2019

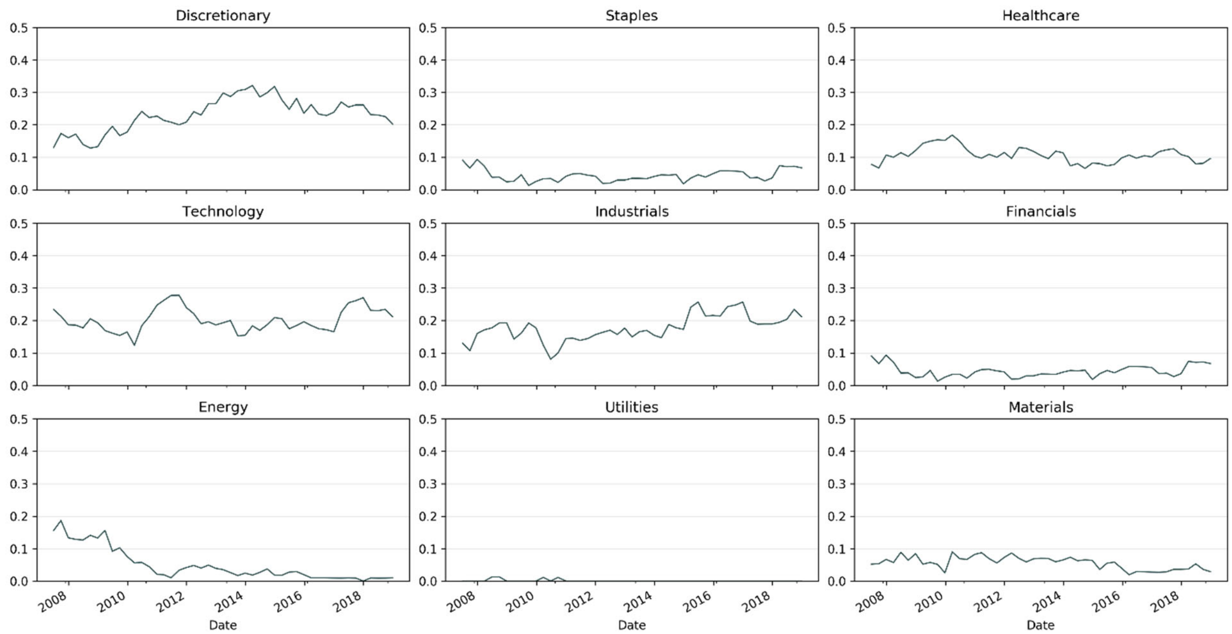


Applying this intuition we continue to add pro-Environment factors to create baseline Bull, Bear, and Flat market screens. The objective is to enhance performance over the 'Never Own' universe and to further filter the number of companies remaining for research.

We maintain several variations of pro-Bull, pro-Flat, and pro-Bear screens. Each excludes Never Own criteria then keys on either Profitability, Valuation, Earning Behavior, or Implied Volatility. We monitor the performance of these screens in real time and select stocks for long portfolios from these screens based on screen performance and their tendency to demonstrate high serial correlation. As such, we let factor performance suggest the appropriate screens to us. We are able to do this because we understand the mapping of top or bottom quintile performance in difference environments combined with the high serial correlation of factor returns that offers a chance to make intermediate term market direction calls in a frequency that works in an RIA or mutual fund portfolio.

Why the Extensive Focus On Sector Neutral Performance?
Factor-driven investing will create portfolios that are not too concentrated for active managers but will make closet indexers uncomfortable. The chart below plots sector exposure at each quarter end from 2007-2019 for the factor quintile ROIC_Q5. The quintile is well diversified by sector yet decoupled from S&P500 levels.

Exhibit 13: Sector Weights 01/01/2007 – 03/15/2019



We suggest a factor-driven process requires a manager to be semi-passive to sector weights. A portfolio may have loose constraints on the maximum a sector can represent as we rarely see any sector exceeding 40% for any factor quintile. However, we routinely see sectors with no exposure for nearly all factor quintiles. We do not believe a no minimum weight policy requirement could be enforced under a factor-driven approach. In short, a factor-based manager must pay little regard to sector weights versus the S&P500 and yet, that requirement is not a large request given the naturally high degree of sector diversification across factor quintiles.

This is a critical issue as most managers or investment policy committees will hesitate at this final step fearing short term performance that deviates too far from the benchmark. If that is a concern then we caution against the use of a factor-driven screening process. The table in Exhibit 9 and chart in Exhibit 10 show that sector is as significant as factor in accounting for performance. A decision to overlay sector constraints cuts in half a manger's potential alpha and limits it to the column labelled 'Return Due To Factor'. Further, factor momentum will conflict with a constrained sector policy eventually. In a bear market the factors describing low implied volatility, low debt/equity, high free cash flow will drive a portfolio to be concentrated in consumer staples, utilities, and REITS. To the extent those sectors have been capped by policy constraints or manager fear where is the excess capital above the caps to go?

We recommend a manager seek higher performing factor quintiles that add value both from sector as well as the factor itself. That requires a more passive acceptance of sector weights. A manager who is held to weights closer to the market but is still inclined to make factor-based decisions should seek lower, but still attractive, returning factor quintiles where alpha is derived from factor alone. ROIC, for example, is an ideal factor candidate for this type of manager.

Closing

Lastly, in our view all long portfolio managers are factor investors. Warren Buffett is a factor investor. The analyst on CNBC encouraging investment in stocks with strong EPS growth, upward EPS revisions, and attractive valuations is a factor investor, although more likely than not has never tested the ideas quantitatively. While Mr. Buffett may not have ever tested factor performance in different environments he has learned through experience what the rest of us seek to learn through data science. Listen to the market's message provided through environment-specific factor performance and through the performance of Q5-Q1. Build portfolios of companies with factors consistent with that message from a research universe than now numbers less than 50 names versus 500+.

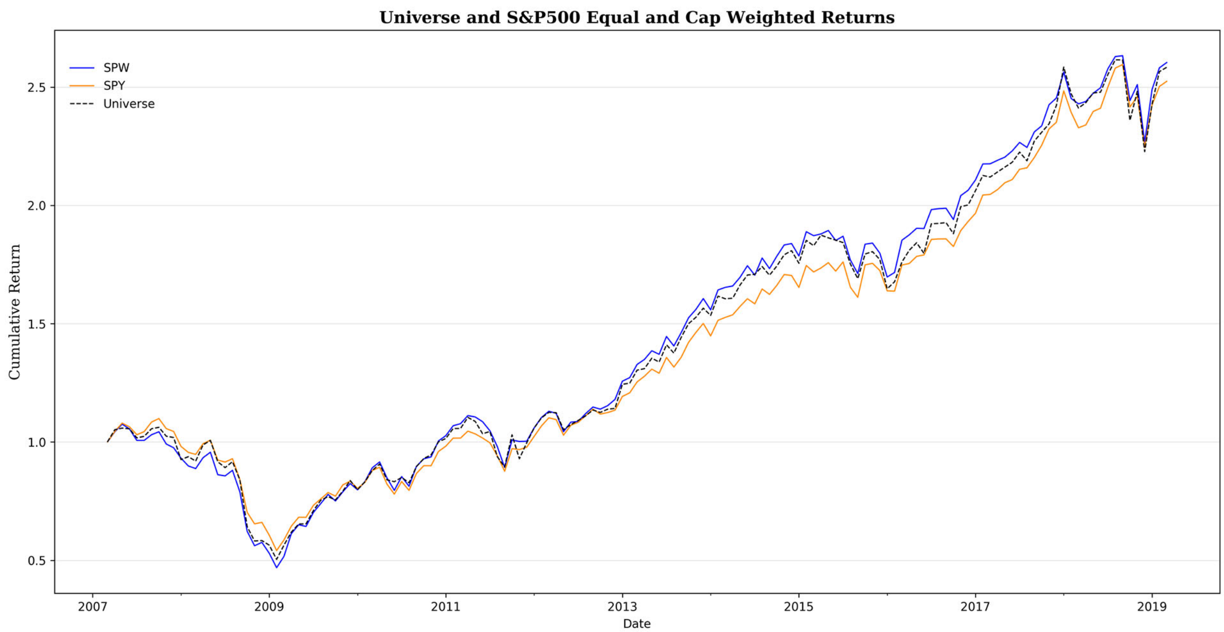
Can a portfolio capture a factor or set of factors in a 30-50 stock long-biased RIA portfolio rather than being long and short two quintiles and several hundred of names? Not perfectly as idiosyncratic risks remain but our experience suggests you can significantly improve your performance by first improving the quality of your research universe by removing factors than do not perform well in any environment then developing screens that are intuitive to specific market environments. Lastly, we suggest it is more advantageous to understand a few factors across valuation, profitability, growth and momentum disciplines and their behavior in different market cycles than to try to make sense of 25+ factors.

Exhibit 14: List of Factors

Factor	Description
10Yr_VComp	Valuation Composite - 10 Year Z score of weighted P/E, P/CF, P/BV.
5Yr_VComp	Valuation Composite - 5 Year Z score of weighted P/E, P/CF, P/BV.
Asset Turnover	Trailing 12M Net Sales / ((Total Assets – Current Period + Total Assets – Prior Year Period) /2)
Debt/Equity	Total Debt/ Shareholder's Equity.
EBIT Yield	Trailing 12M Operating Income / Stock Price
EPS 3 Mo % Change - Current Qtr	Change in consensus EPS estimates over the past 3 months for the current quarter.
EPS 3 Mo % Change - Current Year	Change in consensus EPS estimates over the past 3 months for the current full year.
EPS Correlation - 5 Year	Correlation coefficient of quarterly EPS against a series of consecutive integers.
EPS Growth - 3 Year	Compound annual growth rate in diluted earnings per share over the trailing 3 years.
EV/EBIT	Enterprise Value / Trailing 12M EBIT.
EV/EBITDA	Enterprise Value / Trailing 12M EBITDA.
EV/FCF	Enterprise Value / Trailing 12M FCF.
FCF Margin	Trailing 12M Free Cash Flow per Share / Stock Price.
From 200 Day	The percent difference in the closing price of a stock and its 200 day moving average.
3 Mo Implied Volatility	3 month implied volatility at 100% moneyness (at the money).
Market Cap	Standard market cap measure.
Price Correlation - 5 Year	Correlation coefficient of price against a series of consecutive integers.
Revenue Growth - 3 Year	Compound annual growth rate in revenue over the trailing 3 years.
ROA	Trailing 12M Net Income / Average Total Assets.
ROE	Trailing 12M Net Income Available to Common Shareholders / Average Total Common Equity.
ROIC	Trailing 12M Net Operating Profit After Tax / Average Invested Capital.
TRA_1Yr	Classic momentum factor based on trailing 1 year total return.
TL_Slope	The slope of a regression line connecting pivot lows in weekly prices.

Exhibit 15: Research universe versus equal and cap weighted S&P500 Index. 2007-2019.

We use the performance of "the universe" interchangeably with "the market" as the two are nearly identical. The chart below shows the universe return constructed from factors that always have raw factors values. These include market cap and price-based factors. This universe is equal-weighted and is highly correlated with the equal-weighted S&P500 Index ("SPW").

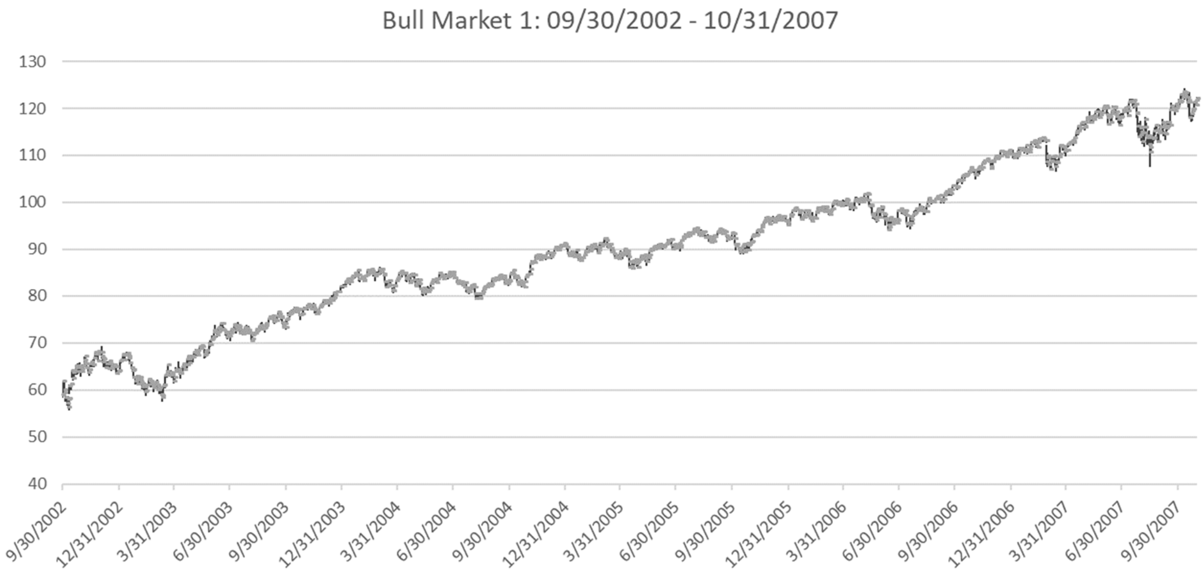


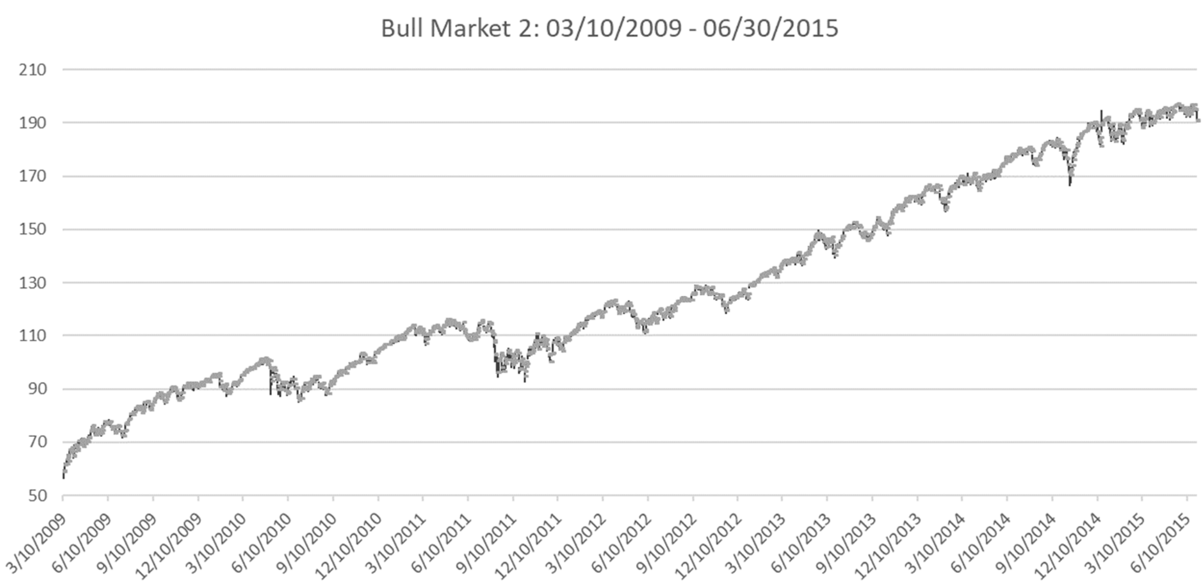
When a factor such as EV/EBITDA or EV/FCF produces a universe of securities that id materially different we have built an equal-weighted universe return consisting of just those securities with values for the factor. In this case, if we state a "quintile outperforms the market" we mean it outperforms its factor-specific universe which is still similar, but may differ slightly from SPW.

Appendix A:
Time Periods Combined To Form Various Market Environment Classifications

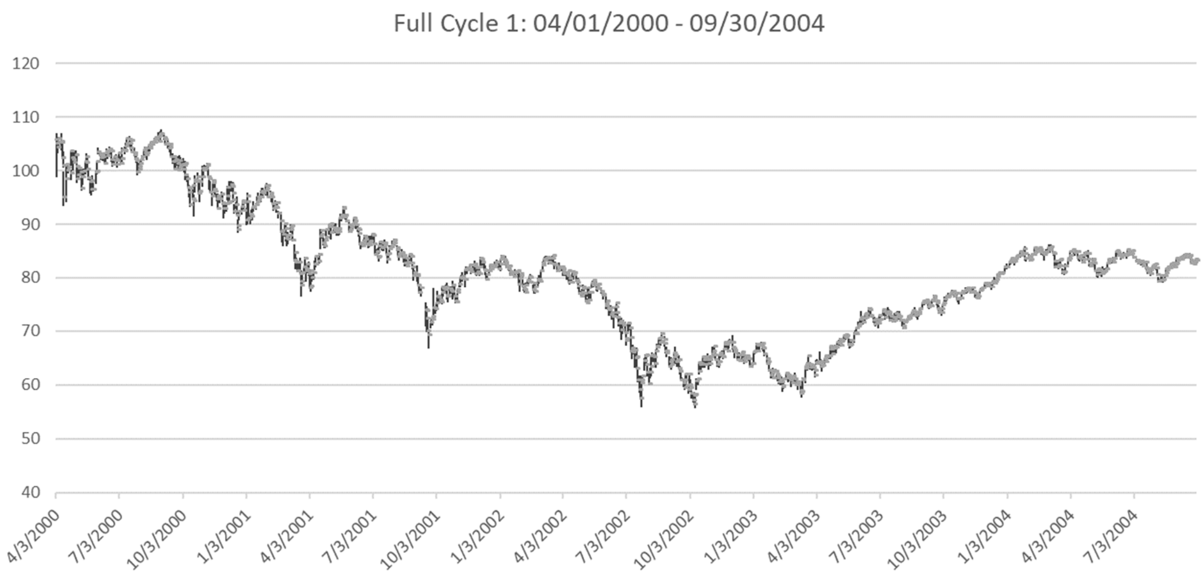
Bear Market Periods

Bull Market Periods





Flat Market Periods

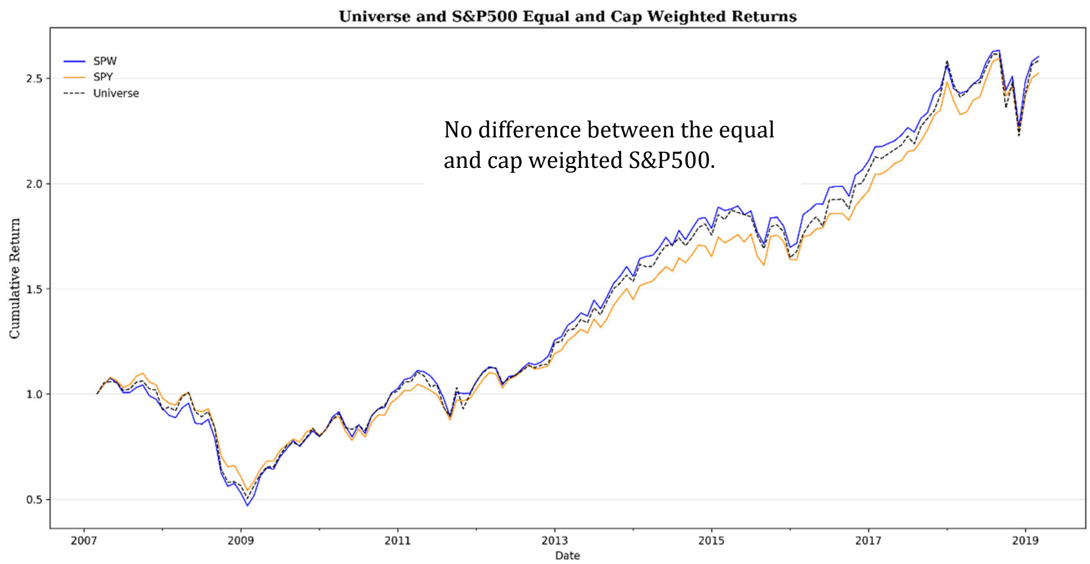


Appendix B:
The Construction of Universe and Sector Neutral Benchmark Returns

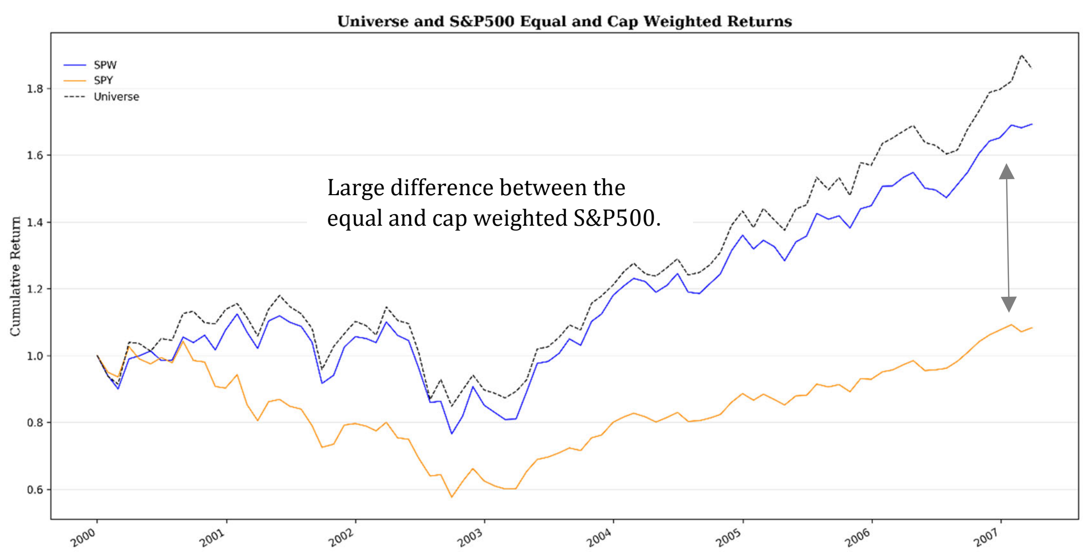
The task of comparing factor and screen performance against an appropriate benchmark is surprising complex. A few of the challenges are described below.

Challenge 1: Cap Weighted versus Equal Weighted Sector Data

The difference in performance between cap weighted and equal weighted indices has not been significant since 2007-2008 so many have forgotten the issue but it presents a real problem when evaluating equal weighted portfolios over longer periods of time.



Between 2000-2007 the performance difference was significant.



In both cases the research universe used in this paper produces the highest return of either S&P500 index and sets a higher standard. The universe closely follows the SP500 equal weighted index as expected.

We evaluated several data sources when attempting to build sector neutral benchmarks. The obvious solution was to use the liquid SPDR sector ETFs. However, these ETFs are cap weighted and fail to serve as fair sectors against which to compare an equal weighted portfolio prior to 2007. They produce returns that are far too easy to beat in the 2000-2007 time period where SPW outperformed SPX by 600+ bp annually. As such, we rejected the use of SPDRs.

Next we tried the equal weighted sector indices produced by the CME (S15 <Index> and S25 <Index>, for example). These indices solve the cap weighted challenge but the data does not begin until 2007, too late for this research where we require multiple market environments and require the 2000-2002 bear market specifically. In addition, these indices have market capitalizations that differ from this research universe's cutoff at the 50th percentile of US company market cap. We rejected their use as well.

Challenge 2: Not all factors have the same number of securities and hence, universe.

This is a particularly significant issue for valuation factors that utilize Enterprise Value relative to EBIT, EBITDA, or Free Cash Flow. These metrics are not available for all industries, particularly financials. Comparing EV/FVF quintiles created from a universe without financials to a universe return that includes financials is an unfair comparison, one that works in both directions. EV/FCF quintile performance would exclude financials in the financial crisis of 2008-2009 and returns would be overstated against a universe that included financials. Alternatively, the spectacular rally financials had from 2013-2015 would be included in the universe return but have no factor representation and hence, understate factor performance.

Solution: Build Your Own

We adopted a policy of comparing any factor to the universe of securities for which the factor has values. The universe to compare EV/EBITDA quintile performance includes all securities that have EV/EBITDA values. As a result, there are 23 universes paired with the 23 factors. The universes of "common" factors like market capitalization and price-based measures are identical as all securities have values for these factors. The EV-based factors show the largest differences. A middle group exists for 3 and 5 year growth rates where it takes time for newer companies to reach this quantity of history. Every chart in this paper plots a factor and its quintiles against the factor-specific universe from which quintiles were constructed.

Similarly, when performing performance attribution a factor is compared against a sector neutral benchmark where the sector returns are also constructed from the set of securities that have values for the particular factor. In summary, for each factor drop all null records. Of the remaining securities build an equal weighted universe return as well as equal weighted sector returns. For each factor there will be a corresponding universe return and a set of sector returns. Use those exclusively for benchmarking the factor's performance.

Abstract

Designing Environment-Specific Equity Screens From Factors For Long RIA and Mutual Fund Portfolios

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Chief Investment Officer
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Date Written: March 29, 2019

Abstract
This paper describes the application of research into the behavior of a wide range of valuation, growth, profitability, and momentum factors to the development of equity screening systems designed for the construction of long RIA, mutual fund, and institutional portfolios. The research describes the construction of cross-sectional factor quintiles and the attribution of factor quintile performance between sector-neutral benchmarks and the factors themselves. The paper suggests the literature comparing factors to benchmarks that are sector-neutral is less well researched and provides insight into how factor research can transition from traditional hedge fund long top quintile – short bottom quintile methods to one designed for lower turnover, long equity selection systems.

The paper suggests that at least half of the performance of factors can be explained by the sector returns that emerge from quintile construction. A factor-driven investment process benefits from a disciplined sector rotation process in addition to emphasizing attractive company qualities (factors) that are rewarded by the market.

While the author is a large user and proponent of machine learning in quantitative finance, the paper against its use in this particular application due to the limited availability of factor data and the risk of overfitting versus an intuitive ex-ante economic approach to the problem.

Suggested Citation:
Falkenberry, Neal. Designing Environment-Specific Equity Screens From Factors For Long RIA and Mutual Fund Portfolios (March 29, 2019). Autumn Wind Asset Management Internal Research Paper 9f14.