Value and Momentum: *Everywhere, But Not All the Time*

Author
Daniel J. Sandberg, PhD, CFA
Quantamental Research
212.438.1407
Daniel.Sandberg@spglobal.com

"Momentum" and "Value" strategies[1] have had well-documented return premia in multiple geographies and asset classes (Asness, Moskowitz, & Pedersen 2013). Average monthly returns to momentum are larger than average returns to value, caveated by large pullbacks ("crashes") in the momentum portfolio. Practitioners often include both approaches in their investment strategy. **We present a dynamic risk-weighting scheme (Orange Line, Fig. 1), which historically outperforms both value and momentum strategies as well as a naïve equal-weighting of the two, by capturing the upside of momentum while avoiding large drawdowns.**

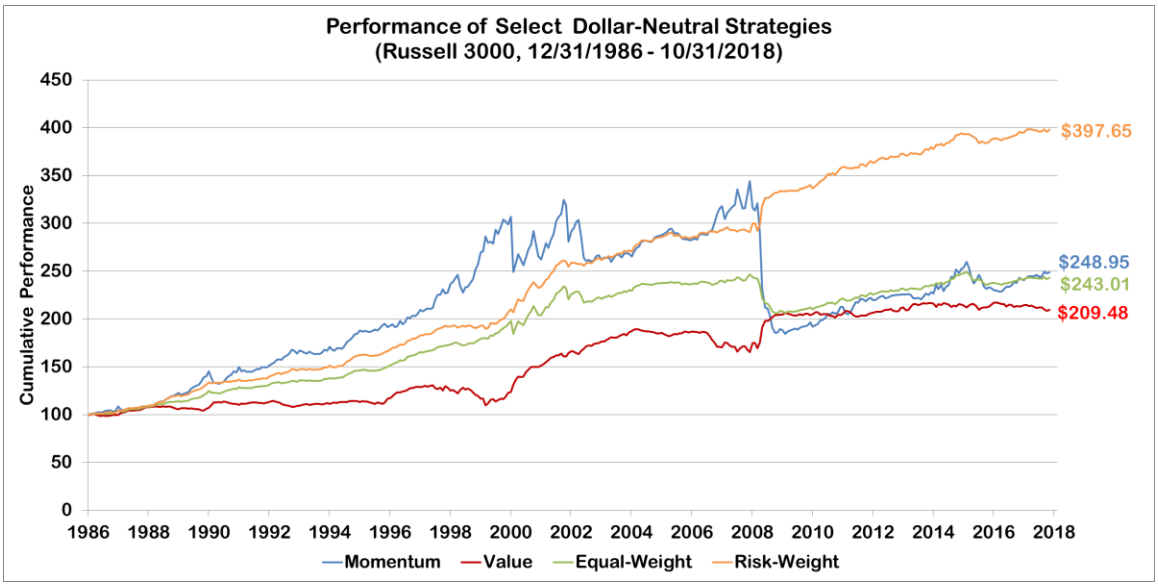

Figure 1. Performance of Select Strategies. The performance of momentum (blue) and value (red) strategies (as defined in section 1) is shown alongside the performance of an equally-weighted (green) and risk-weighted (orange) blend of the factor mimicking strategies (as defined in section 2).
Source: S&P Global Market Intelligence Quantamental Research. Data as of October 31, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

- Dynamically weighting value and momentum strategies by a function of the trailing volatility in the momentum portfolio produces a superior information ratio (IR), total return, and lower maximum drawdown compared to a naïve equal weighting.
- Results are consistent in six regions (U.S., Europe, Asia Ex-Japan, Japan, Latin America, and Emerging Markets) and in multiple robustness checks. We maintain dollar neutrality[2] and persistent leverage[3] of 1.0 in all specifications.
- Monte Carlo simulation supports the conclusion that the shift of tail density from left- to right-tail drives the performance improvements. That is, large drawdowns are avoided.

[1] Strategies are explicitly defined in section 1. "Momentum" describes intermediate term price momentum.
[2] Dollar neutrality is a strategy that invests the same total amount in long positions as the total amount in short positions.
[3] Leverage is defined as the sum of the dollar value of long and short positions divided by the net worth of the portfolio. For long-only portfolios, a leverage of 1.0 indicates that the entire net worth of the portfolio is invested in long positions. For a long-short portfolio, a leverage of 1.0 indicates that half the net worth of the portfolio is invested in long positions and half the net worth of the portfolio collateralizes short positions.

1. Background

The novel approach proposed in this paper involves placing unequal and dynamically weighted bets in two factor-mimicking portfolios: one which relies on exposure to the "momentum factor" and the other which relies on exposure to the "value factor". The former is a strategy which exploits the tendency of stocks that have performed well in a prior period to continue performing well in the forward period. For our treatment, momentum stocks are scored by equation 1,

$$MomScore_t^k = \frac{Price_{t-21}^k - Price_{t-252}^k}{Price_{t-252}^k} \quad \text{Eq.1}$$

where $Price_t^k$ is the closing price of security k at time t, where t indexes over a series of daily returns. (Jegadeesh & Titman 1993) The value strategy purports to identify stocks that are cheap or expensive relative to an intrinsic value, justified by the company's fundamentals. One representation of this strategy utilizes a ranking by earnings yield, shown in equation 2,

$$ValScore_t^k = \frac{TTM\ Earnings_t^k}{Price_t^k} \quad \text{Eq. 2}$$

where $TTM\ Earnings_t^k$ is the total earnings over the trailing twelve months. (Basu 1977)

The manifestation of each factor-mimicking strategy comes from taking equally-weighted long positions in the top quantile stocks and equally-weighted short positions in the bottom quantile stocks, ranked and rebalanced monthly[4]. Long and short sides of each strategy's portfolio were combined to form dollar-neutral, leverage[5] 1.0 portfolios.

Significant return premia to these value and momentum long-short portfolios have been well documented in the literature (Asness, Moskowitz, & Pedersen 2013). Also well documented is the crash risk of the momentum strategy (Daniel and Moskowitz 2014). The tendency of the momentum strategy to descend in a free fall is evident in the distribution of monthly returns in the form of a fat left tail (negative skew and leptokurtosis). These free fall periods tend to follow a structural break in the equity markets, such as the Great Financial Crisis (2007-2009) which preceded a 48% decline in the momentum portfolio in 2009.

Momentum becomes more palatable to the risk-averse investor when blended with the value strategy. Value returns are not only negatively correlated to momentum, but the characteristics of the distribution of returns are a stark contrast. Value returns tend to be

[4] For both momentum and value strategies, scores were turned into quantile assignments by ranking stocks within the same GICS level 1 (sector) category and then combining scores to form a sector-neutral portfolio. For the value strategy, only the securities with positive earnings were included in the ranking. An alternative value approach, using sales/price and including the full investible universe, produced similar results. No securities were filtered from the investible universe when forming the momentum portfolio. Equally-weighted and risk-weighted portfolios were formed by portfolio blending and not signal blending. That is, allocations to the individual factor-mimicking portfolios produced the blended portfolios.

[5] Leverage is defined as the total absolute market value of long and short positions divided by the portfolio equity. That is, a $100 portfolio has a leverage of 1.0 if $50 of long equity is collateralized with $50 of short equity and the $100 is held in cash (position size = portfolio equity).

smaller and more consistent (left-shifted mode and lower volatility) and the strategy occasionally yields large positive returns (positive skew and lower kurtosis).

2. Risk-Weight Approach

While equally-weighting the value and momentum strategies produces an attractive blend of characteristics, an alternative weighting scheme, which we term "risk-weighted", produces a larger information ratio, a lower drawdown, and a positive shift in skew. Dynamically weighting momentum portfolios by risk is an extension of the work of Barroso and Santa-Clara (2015, hereafter BSC). In their seminal contribution to the examination of momentum crash risk, BSC propose a strategy in which the dollar-neutral momentum portfolio adopts unconstrained leverage based on the following expression,

$$MomWeight_t^{BSC} = \frac{\sigma_{target}}{\sigma_{Mom}^{obs}} \quad \text{Eq. 3}$$

where $MomWeight_t^{BSC}$ is the leverage on the momentum portfolio, σ_{target} is a specified constant representing the target risk (standard deviation) attributable to the momentum portfolio, and σ_{Mom}^{obs} is the 6-month trailing standard deviation of daily returns to the momentum long-short portfolio[6]. In BSC, the use of volatility to dynamically scale the leverage of the momentum portfolio is shown to control momentum's left tail risk, at the expense of leverage between 0.13 and 2.0 in their backtest from 1927 to 2011.

In this work, a leverage of 1.0 is maintained by 1) capping the momentum weight at a ceiling of 1.0 (that is, 100% momentum) and 2) monetizing any available cash created from deleveraging momentum, by investing that cash in the value portfolio. Specifically,

$$MomWeight_t^{Risk-Weight} = min\left(\frac{\sigma_{target}}{\sigma_{Mom}^{obs}}, 1.0\right) \quad \text{Eq. 4a}$$

$$ValueWeight_t^{Risk-Weight} = 1.0 - MomWeight_t^{Risk-Weight} \quad \text{Eq. 4b}$$

where $MomWeight_t^{Risk-Weight}$ is the risk-weight momentum exposure and $ValueWeight_t^{Risk-Weight}$ is the risk-weight value exposure. (See example in appendix II)

3. Performance Results

In all specifications, the risk-weighted (RW) protocol reduced the likelihood of left-tail events and right-shifts the mode of returns, compared to a naïve equal-weighting (EW). This means the most probable return for the RW strategy was larger, and the probability of an extremely large negative return was smaller. Generally, avoiding a left-tail event will result in a higher mean, lower standard deviation, more positive skew, and lower kurtosis in the distribution of returns; as well as larger cumulative return, lower max drawdown, and higher information ratio (IR) in the backtest period. Again, this was achieved without introducing additional leverage. Full results are tabulated in the appendix for backtest statistics (table A1), distribution statistics (table A2), comparative distribution statistics (table A3), and Monte-Carlo results (table A4).

[6] In all sections, σ_{target}= 2%, except where noted.

3.1. U.S. Performance

The RW strategy outperformed both pure strategies and the EW blend in the Russell 3000 universe. Compared to EW, RW generated double the cumulative return (297.89% RW vs. 143.15% EW) and half the maximum drawdown (7.06% RW vs. 17.57% EW) over the backtest period. Returns to the RW strategy were statistically larger than EW at the 99% level in a paired T-test and volatility was statistically lower for RW than all other strategies in an F-test. We believe the most important improvement is the shift in skewness from -1.80 for EW to +1.53 for RW, both significant at the 95% level. These improvements in the distribution of returns led to a larger IR (1.8 RW vs. 1.1 EW, 0.7 value and 0.5 momentum).

Figure 2. Global Performance of Select Strategies (Top) and U.S. Monte Carlo (Bottom). (Top) The average return (solid bars) and the maximum drawdown (line pattern bars) for the momentum, value, equal-weight (EW), and risk-weight (RW) strategies shown for the 6 backtested regions. **(Bottom)** Moment matching Pearson distributions were sampled via Monte-Carlo to generate a return series with characteristics similar to each of the observed strategy distributions. The four strategies were ranked by cumulative return and the relative frequency of rank is plotted.
Source: S&P Global Market Intelligence Quantamental Research. Data as of October 31, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

The implications of modifying the higher moments of a return distribution are not obvious. Rather than a detailed discussion of this topic, we offer the results of a Monte-Carlo simulation as support that the characteristics of the RW return distribution are more desirable than EW. Specifically, the four moments (mean, variance, skewness, and kurtosis) of the monthly return distributions to each of the four strategies (momentum, value, EW, RW) were separately fit to a Pearson distribution[7]. A Monte-Carlo (MC) process was then used to sample each distribution to generate 4 series of 360-monthly returns. The simulation was repeated 10,000 times and, for each, the 4 strategies were ranked on cumulative total return. In the Monte-Carlo framework, the RW strategy dominates first place (76.47%) and rarely places last (0.08%). Momentum's nearly equal probability of placing in any position is an implication of the high standard deviation and kurtosis. Momentum on its own is luck of the Monte Carlo draw.

3.2. Return Distribution and Volatility

An examination of the long and short portfolios, separately, for each pure strategy provided additional detail on the source of skewness and kurtosis, as well as the connection to the volatility of the momentum long-short portfolio. First, each date cross section was assigned to a 'low', 'medium', or 'high' volatility regime. The regimes were obtained by using Eq. 4 and separating the range of possible values (0 to 1) into three equal subspaces (thirds). Specifically, a high (low) volatility regime was any cross section in which the RW strategy allocated more than two-thirds or 66.7% to the value (momentum) portfolio and one-third to momentum (value). Date cross sections in between low and high were labeled 'medium'.[8]

The momentum strategy strongly favors the low volatility environment. Both long and short sides of momentum contribute significantly to the average long-short monthly return of 69 bps. As the volatility increases, the economic and statistical significance of momentum returns decreases. Figure 3 and Table 1 show that the return distribution of the long-short momentum portfolio skews negative and becomes leptokurtic when trailing volatility increases. In other words, the momentum strategy becomes unpredictable and likely to crash following periods of volatility.

In contrast, the value strategy thrives on volatility. In the low volatility environment, value returns are normally distributed, but center around 0. As volatility increases, the value strategy becomes more leptokurtic and skewed, similar to momentum, but the long and short sides of the strategy skew in the correct direction. In other words, stock prices more closely resemble intrinsic value following periods of volatility.

[7] The savvy reader may ask, "why not randomly sample the observed returns, rather than fit to a distribution?". Indeed, this would be a valid approach and, in calculations not reported, this approach yielded very similar results. However, the conclusions would be limited to exactly the set of returns over the backtest period, which could have any shape (e.g. bimodal). The aim of this simulation is to show that sampling from a bell curve (Pearson distribution) with identical moments to the observed distribution will produce similar results. That is, the bell curve remains an appropriate assumption, but normality does not.

[8] An important note is that volatility regimes are assigned by using trailing returns. This approach does not introduce any lookahead bias when classifying date cross-sections, as was done in BSC.

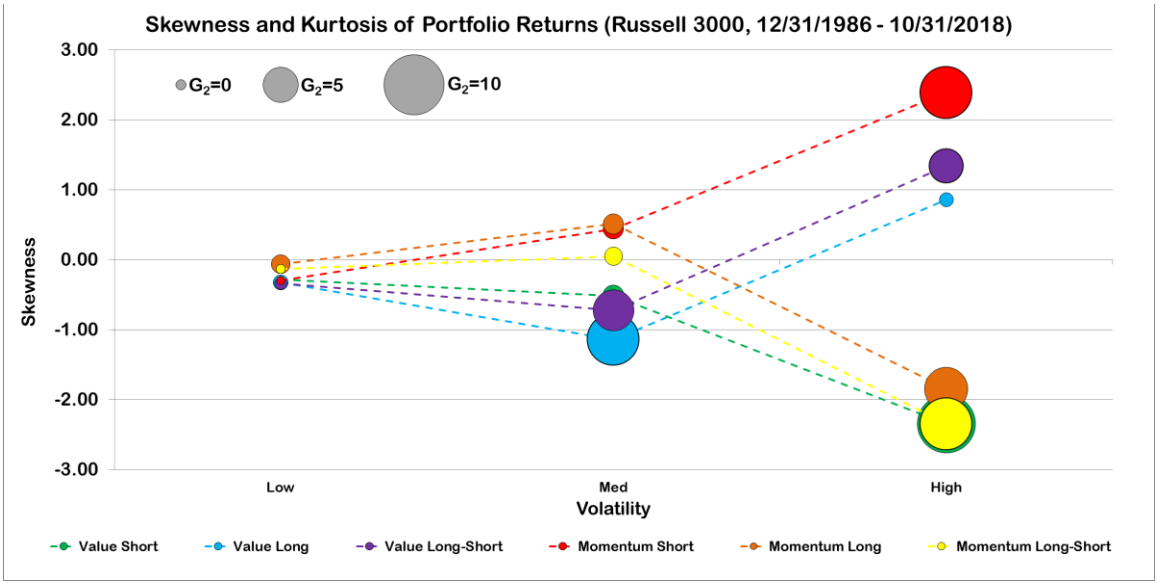

Figure 3. Depiction of the higher moments of the return distribution to select strategies in different volatility regimes. The skewness of returns for long, short, and long-short value and momentum strategies is plotted (left axis) in low, medium, and high volatility. The size of the data points is proportional to the excess kurtosis.

Source: S&P Global Market Intelligence Quantamental Research. Data as of October 31, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

Table 1: Moments of the Distribution of Returns to Long, Short, and Long-Short portfolios of Momentum and Value Strategies (Russell 3000, 12/31/1986 – 10/31/2018)[9]

Momentum Volatility			Low	Med	High	Momentum Volatility			Low	Med	High
Count			79	207	96						
Avg. Return	Momentum	Short	-0.82%***	-0.55%***	0.55%	Skewness	Momentum	Short	-0.29	0.44	2.39***
		Long	0.56%***	0.40%***	-0.32%			Long	-0.06	0.51**	-1.84**
		Long-Short	0.69%***	0.48%***	-0.43%			Long-Short	-0.13	0.05	-2.35**
	Value	Short	0.15%	-0.02%	-0.32%*		Value	Short	-0.28	-0.51**	-2.35***
		Long	0.04%	0.20%**	0.87%***			Long	-0.32	-1.14	0.86***
		Long-Short	-0.05%	0.11%*	0.59%***			Long-Short	-0.34	-0.72	1.34***
Std. Dev.	Momentum	Short	1.11%	1.90%	5.55%	Kurtosis	Momentum	Short	-0.31	2.02***	8.34***
		Long	1.09%	1.59%	3.36%			Long	1.71***	1.93**	6.56***
		Long-Short	0.97%	1.57%	4.36%			Long-Short	-0.17	1.69***	8.38***
	Value	Short	0.69%	1.06%	2.27%		Value	Short	-0.43	2.15**	9.58***
		Long	0.85%	1.34%	2.52%			Long	1.02*	8.38**	0.89
		Long-Short	0.67%	1.01%	1.81%			Long-Short	0.30	6.13**	4.87*

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

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[9] Long and short returns represent the return premium over a benchmark formed by equally-weighting all securities in the investible universe.

Much of the discussion, thus far, has been around the downside protection afforded the RW strategy. However, the data above show that the RW strategy outperforms in both high and low volatility environments, by overweighting the more attractive strategy in either case. Indeed, the RW strategy outperforms the EW strategy by an average of 4.55% and 2.24% per year, in the low and high volatility periods, respectively (sig. at the 95% level in paired T-test). Note that in the medium volatility regime, the RW and EW portfolios are nearly identical in construction and performance.

3.3. International Performance

A total of 5 regions were evaluated (Fig. 2), in addition to the U.S. Russell 3000: the S&P Developed Europe BMI; the S&P Developed Asia Ex-Japan BMI; the S&P Japan BMI; the S&P Latin America BMI; and the S&P Emerging Markets BMI. All results reported in USD. Each ex-U.S. region was backtested from 12/31/2004–10/31/2018. A summary of results specific to each region follows, with the detail-interested reader referred to appendix I.

3.3.1. Developed Europe & Developed Asia Ex-Japan

At first glance, developed Europe and developed Asia Ex-Japan stand out from the other regions, because the highest cumulative return over the backtest period was realized in the momentum strategy (129% in Europe and 121% in Asia) and not RW (113% in Europe and 109% in Asia). However, consistent with the other regions, RW offers a much larger information ratio (2.7 RW vs 1.2 Mom in Europe and 2.2 RW vs 1.0 Mom in Asia), a much lower drawdown (3.64% RW vs 32.32% Mom in Europe and 3.75% RW vs 35.23% Mom in Asia), and a non-skewed (RW) vs negative skewed (Mom) distribution. The 14-year backtest in these two regions was similar to the first 14 years of the U.S. backtest, where momentum did outperform RW based solely by cumulative returns. However, in the U.S., the momentum strategy eventually gave back excess returns and converged onto the RW performance. The difference in average monthly returns between momentum and RW strategies was statistically no different than 0 in paired T-tests.

Further, if one strategy dominates others in a particular region, investors have the option to pursue the dominant strategy, undiversified. If seeking to blend momentum and value, does a RW approach offer a benefit over an EW approach? Over our backtest period, the answer is a resounding yes. RW outperforms EW along every metric we considered including cumulative return, drawdown, IR, volatility, and skew.

3.3.2. Japan

The RW results were surprisingly favorable in Japan, where the momentum strategy has notoriously struggled. Consistent with the U.S. results, the RW strategy IR is double that of EW with half the drawdown. The skewness and kurtosis of the RW strategy was statistically no different than normal whereas, EW and momentum skew negative. In paired statistical tests, the monthly return distribution of the RW strategy had larger mean, more positive

skew, lower kurtosis, and larger hit rate compared to the EW strategy. MC simulation showed the RW strategy outperforming the other 3 strategies in 70% of simulations.

3.3.3. Latin America

Similar to other regions, the RW approach yielded the highest IR and cumulative returns over the backtest period in Latin America. The backtest in Latin America was unique in that the maximum drawdown of the EW (11.25%) and the RW (10.97%) strategies were comparable. However, the EW strategy had drawdowns in excess of a 5% threshold on 4 occasions over the backtest period, whereas RW only had 1. Further, the kurtosis of the RW strategy was lower than that of EW at the 99% level of significance and MC simulation showed the RW strategy yielded the largest cumulative returns in 67% of simulations.

3.3.4. Emerging Markets

In the Emerging Markets (EM) space, the RW strategy outperformed both pure strategies and the EW blend over the backtest period. The IR of RW (1.9) bested that of EW (1.5), Value (1.1) and Momentum (0.5). The maximum drawdown for the RW strategy (8.55%) was the lowest of the 4 and volatility was significantly lower in an F-test at the 95% level. The distribution of monthly returns to the RW strategy was positively skewed, similar to the value strategy in the region and in contrast to both momentum and the EW blend. MC simulation showed the RW strategy outperformed the other 3 strategies in 67% of simulations.

4. Robustness Checks

In the remainder of the paper, the results of robustness checks are discussed. Specifically, the RW performance improvements are robust 1) to the choice of lookback window and target volatility used in eq. 4; 2) inside of a market beta neutral framework; 3) in sub-periods; 4) in a long-only strategy; and 5) in a small and large market capitalization universe.

4.1. Sensitivity to the choice of discretionary parameters

The RW strategy relies entirely on eq. 4, which requires a discretionary choice for the value of the σ_{target} parameter (set to 2.0%) and the lookback window over which the standard deviation is calculated (set to 6-months).

The σ_{target} parameter represents half the level of volatility above which the value strategy is preferred and below which the momentum strategy is preferred. For example, when σ_{target}=2.0%, the RW strategy is identical to the EW strategy when trailing volatility is exactly 4.0% (because $\frac{\sigma_{target}}{\sigma_{Mom}^{obs}} = \frac{2.0\%}{4.0\%} = 50\%$ by equation 4a, see Appendix II for more examples). The 4.0% value ($2 * \sigma_{target}$) becomes the tipping point for trailing volatility, where RW will hold more (less) of the value portfolio when volatility is above (below) that tipping point.

For extreme values of σ_{target}, the RW approach will permanently bias one strategy versus the other. If the RW approach is benefiting from dynamic weighting and not from a bias towards one strategy, then σ_{target} should be robust to a wide range of values. We find that RW outperforms EW for σ_{target} in the broad range of 0.5% - 7.0%.

To put this range in perspective, over the backtest period, when σ_{target} =0.5%, the strategy never exceeds a 25% allocation to the momentum factor portfolio (permanent value bias); when σ_{target} =7.0% the RW strategy is 100% allocated to the momentum factor portfolio in 80% of cross sections (permanent momentum bias). Absent a permanent bias, i.e. any σ_{target} value inside these extremes, the RW strategy outperforms the EW strategy.

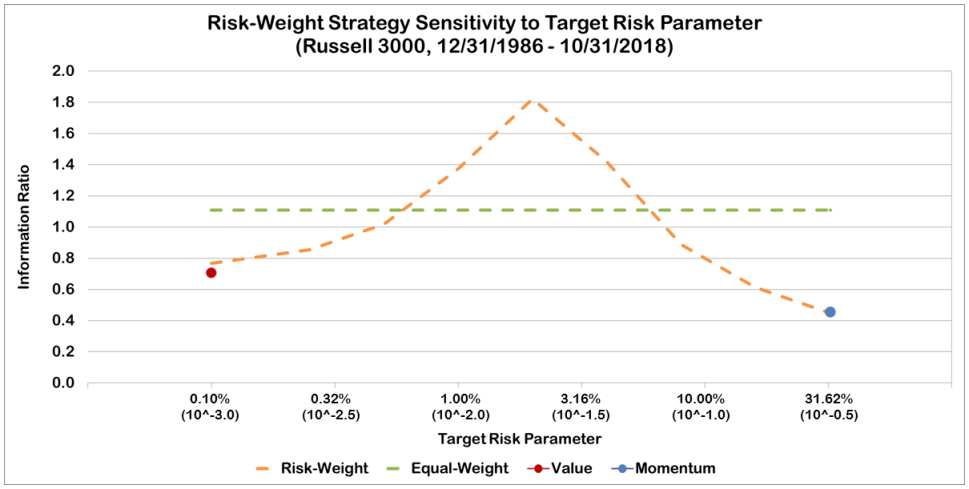

Figure 4. Information Ratio (IR) of Select Strategies, with different values for σ_{target}. The risk-weight (RW) strategy (orange) is sensitive to the choice of σ_{target}. The IR of the RW strategy is plotted as a function of σ_{target}. At large values of σ_{target}, RW is identical to momentum (blue dot) and at small values RW is close to value (red dot). The equal-weight strategy is represented by the green dashed line.
Source: S&P Global Market Intelligence Quantamental Research. Data as of October 31, 2018. Indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results.

The speed of the momentum/value signal (eq. 4) can be increased (decreased) by shortening (lengthening) the lookback window, over which the standard deviation of returns is calculated. Throughout the paper, a 6-mo lookback was used, similar to the approach in BSC. Analyses were also performed with 1-mo, 3-mo, 6-mo, 9-mo and 12-mo lookback windows. Although some small differences in IR (range 1.74-1.84) and max drawdown (range 6.6%-8.07%) were observed, the relation between these metrics and the window size was non-monotonic. We conclude that the strategy is robust to the choice of window size.

4.2. Market Beta Neutrality

The momentum strategy, in particular, is known to take large and varying market CAPM beta exposures (Grundy & Martin 2001). When the market is on a rising trend, “winners” tend to be the high beta stocks and “losers” tend to be low or negative beta stocks. In a market

decline, the opposite is true. Consequently, the momentum strategy will go long high beta and short low beta stocks following a rising market, and vice versa. Daniel and Moskowitz (2012) and BSC both show that hedging momentum with ex-ante betas does not avoid momentum crashes. However, to disentangle varying market beta exposures from the RW approach, the four strategies were evaluated in a beta neutral framework[10].

In the beta neutral framework, the same performance enhancements were observed between the different strategies. Comparing EW and RW, the RW approach yielded superior cumulative returns (200% vs 120%), IR (1.7 vs. 1.3), and maximum drawdown (3.64% vs. 9.66%) over the backtest period. Both momentum and EW strategies had significantly negative skew, whereas value and RW had positive skew. In MC simulation, the beta neutral RW approach outperformed the other 3 beta neutral strategies in 82% of simulations.

4.3. Sub-period Analysis

To confirm that the advantage of a RW strategy over an EW strategy was robust to different market environments, all analyses were separately calculated within six distinct sub periods: Black Monday and the early 90s recession (12/31/1986 – 04/30/1991); the 90s irrational exuberance (04/30/1991 – 06/30/1997); the tech wreck (06/30/1997 – 12/31/2002); the 2000s recovery (12/31/2002 – 12/31/2007); the Great Financial Crisis or GFC (12/31/2007-12/31/2009); and the post-crisis period (12/31/2009 – 10/31/2018).

In all periods, except the 90s irrational exuberance (IE period), results were consistent with the full period analysis. The RW strategy yielded a higher IR, larger cumulative returns, substantially lower drawdown, and a favorable distribution of returns relative to EW. In the IE period, RW still outperformed EW by a small margin (30.76% for RW vs 28.51% for EW) and performed slightly better in MC simulation. However, the drawdown (1.88% for RW and 1.49% for EW) and IR (2.6 for RW and 2.9 for EW) over the period slightly favored EW. One interpretation of the sub-period results is that the RW strategy adds more value during a period that includes a change in market behavior, versus within a single market regime. That is, RW added little to the EW approach in the IE period because the returns to momentum were consistent over the period.

4.4. Long-Only Robustness

Long-only momentum active returns exhibited negative skew and leptokurtosis. Permutation testing indicates that the distribution of RW monthly active returns is positively skewed with lower kurtosis, relative to both momentum (change of +4.73 skew, -25.56 kurtosis) and equal-weight (change of +3.68 skew, -16.94 kurtosis), significant at the 99% level. The change in the distribution of active returns translated to about 1.5x cumulative returns over the backtest period compared to EW. MC simulation showed the RW strategy placed first or second in 62% of simulations.

[10] Details on the beta neutral approach are summarized in appendix I.

4.5. Size Robustness Checks

All reported benefits of the RW strategy are robust in the Russell 1000 and Russell 2000. Total returns were substantially larger and maximum drawdowns substantially lower in the backtest period, for RW compared to all other strategies. Statistics comparing the moments of the distributions indicate that RW returns have a higher mean, lower standard deviation, and more positive skew compared to EW at or above the 95% level of significance.

5. Data

All research presented in this paper was performed with S&P Global data via Xpressfeed™. U.S. data was obtained from the Compustat® point-in-time database and international data was obtained from the S&P Capital IQ Premium Financials database.

6. Conclusions

Value and Momentum strategies have separately rewarded investors with statistically-significant and positive returns over several decades. These strategies each offer the investor a different, attractive return profile. The differences in the profile of returns, and the negative correlation between the two strategies, incentivize investors to combine the strategies in an attempt to improve performance. This research shows that combining these strategies with a dynamic weighting that favors momentum following periods of low volatility and value following periods of high volatility outperforms a naïve equal-weighting. The performance improvement is owed to superior control over the higher moments of the distribution, particularly the skewness of returns.

7. References

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Appendix I. Tabulated Full Results

This appendix contains 4 tables, each split over two pages. For each table, 16 separate universe / date range specifications were considered:

- **U.S. (1x):** Russell 3000, 12/31/1986 – 10/31/2018
- **International (5x):** international regions (**section 3.3**), 12/31/2004 – 10/31/2018
- **Size (2x):** Russell 1000 and Russell 2000, 12/31/1986 – 10/31/2018
- **Long-Only (1x)**: Russell 3000, 12/31/1986 – 10/31/2018
- **Beta Neutral (1x)**: Russell 3000, 12/31/1986 – 10/31/2018
- **Sub-period Robustness (6x)**: Russell 3000, sub-periods (**section 4.3**)

Each of the four strategies was backtested and analyzed separately within each specification. For the international and size specifications, the only adjustments were to the securities included in the investible universe and the date range of the backtest (to reflect the time period over which the investible universe was available within the database).

For the long-only approach, the entire net worth of the portfolio was allocated to the long side of each strategy. Results are presented in both absolute and active return space, where active returns are relative to an equally-weighted benchmark of the Russell 3000 securities.

For the beta neutral approach, the portfolios were constrained to be dollar neutral, beta neutral and have leverage 1.0. To implement these constraints, first a dollar neutral “hedge portfolio” was constructed by sorting securities by 60-month CAPM beta and taking equally-weighted long positions in the top decile and equally-weighted short positions in the bottom decile. Each strategy portfolio was then hedged with the hedge portfolio by allocating net worth to the strategy portfolio (momentum, value, EW, or RW) and (long or short) the hedge portfolio inversely proportional to the calculated betas.

Table A1 summarizes the results of backtests such as cumulative returns, max drawdown, and information ratio. Statistical significance testing does not apply to these metrics.

Table A2 summarizes the distribution statistics for each strategy, compared to a normal distribution of mean 0. Statistical significance testing on the mean was performed via the student’s T-test. Statistical significance testing was performed on the skewness and kurtosis metrics by permutation testing. (See Hesterberg et al. 2005)

Table A3 summarizes comparative statistics against the strategy distributions. Returns were compared by paired T-test, standard deviation by F-test, skewness and kurtosis by permutation testing, and hit rates by binomial probability expansion.

Table A4 summarizes Monte-Carlo simulation results. A series of 360 monthly returns were propagated by geometric mean, to generate annualized returns, standard deviation, and max drawdown, as well as cumulative return used for ranking.

Table A1: Portfolio Backtest Statistics for Select Strategies
(Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
	Russell 3000	12/31/1986 - 10/31/2018	Cumulative Return	149.17%	109.72%	143.15%	297.89%
			Max Drawdown	48.19%	17.56%	17.57%	7.06%
			Num. Drawdowns > 5%	8	3	5	1
			Information Ratio	0.453	0.703	1.108	1.821
			Avg. Constituents	1013	788	1475	1475
			Turnover	175%	123%	133%	143%
International	S&P Developed Europe BMI	12/31/2004 - 10/31/2018	Cumulative Return	129.01%	35.82%	80.16%	113.05%
			Max Drawdown	32.32%	11.57%	8.35%	3.64%
			Num. Drawdowns > 5%	7	1	1	0
			Information Ratio	1.174	0.786	2.23	2.714
			Avg. Constituents	739	623	1104	1095
			Turnover	165%	107%	121%	132%
	S&P Developed Asia Ex-Japan BMI	12/31/2004 - 10/31/2018	Cumulative Return	120.59%	54.30%	88.60%	109.18%
			Max Drawdown	35.23%	11.53%	8.67%	3.75%
			Num. Drawdowns > 5%	4	3	1	0
			Information Ratio	1.049	0.888	1.826	2.199
			Avg. Constituents	512	409	754	754
			Turnover	175%	116%	129%	130%
	S&P Japan BMI	12/31/2004 - 10/31/2018	Cumulative Return	10.13%	31.72%	22.40%	44.27%
			Max Drawdown	33.30%	15.54%	13.08%	6.93%
			Num. Drawdowns > 5%	2	3	1	1
			Information Ratio	0.124	0.574	0.615	1.13
			Avg. Constituents	599	525	900	888
			Turnover	169%	107%	123%	132%
	S&P Latin America BMI	12/31/2004 - 10/31/2018	Cumulative Return	65.97%	104.01%	95.65%	139.51%
			Max Drawdown	35.39%	21.23%	11.25%	10.97%
			Num. Drawdowns > 5%	7	4	4	1
			Information Ratio	0.484	0.934	1.209	1.563
			Avg. Constituents	119	108	177	176
			Turnover	176%	118%	134%	130%
	S&P Emerging Markets BMI	12/31/2004 - 10/31/2018	Cumulative Return	46.17%	79.22%	65.92%	100.91%
			Max Drawdown	44.15%	11.58%	11.46%	8.55%
			Num. Drawdowns > 5%	2	3	1	1
			Information Ratio	0.507	1.051	1.531	1.896
			Avg. Constituents	992	882	1490	1490
			Turnover	169%	108%	121%	127%
Size Robustness	Russell 2000	12/31/1986 - 10/31/2018	Cumulative Return	218.82%	123.12%	185.85%	317.29%
			Max Drawdown	48.55%	18.25%	16.24%	6.78%
			Num. Drawdowns > 5%	9	5	5	3
			Information Ratio	0.552	0.664	1.14	1.646
			Avg. Constituents	662	479	949	949
			Turnover	182.60%	136.30%	143.61%	145.82%
	Russell 1000	12/31/1986 - 10/31/2018	Cumulative Return	58.12%	86.67%	82.23%	161.04%
			Max Drawdown	46.40%	18.83%	17.07%	7.89%
			Num. Drawdowns > 5%	10	6	5	3
			Information Ratio	0.22	0.521	0.737	1.21
			Avg. Constituents	356	311	529	529
			Turnover	174.21%	115.24%	127.16%	135.51%

Table A1 (Cont.): Portfolio Backtest Statistics for Select Strategies (Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
Long-Only	Russell 3000 (Abs. Returns)	12/31/1986 - 10/31/2018	Cumulative Return	5102.87%	6710.57%	6140.74%	8967.77%
			Max Drawdown	59.08%	68.11%	63.11%	64.67%
			Num. Drawdowns > 15%	13	8	10	11
			Information Ratio	0.643	0.728	0.709	0.751
			Avg. Constituents	511	398	858	858
			Turnover	170%	123%	143%	151%
Beta Neutral	Russell 3000 Beta-Hedged	12/31/1986 - 10/31/2018	Cumulative Return	102.18%	52.77%	120.23%	199.82%
			Max Drawdown	25.42%	16.72%	9.66%	3.64%
			Num. Drawdowns > 5%	7	4	2	0
			Information Ratio	0.52	0.481	1.268	1.732
			Avg. Constituents	1322	1175	1690	1690
			Turnover	152.10%	107.54%	109.61%	118.13%
Subperiod Robustness	Russell 3000	12/31/1986 - 04/30/1991	Cumulative Return	32.14%	12.97%	22.44%	33.21%
			Max Drawdown	11.02%	4.45%	4.64%	3.52%
			Num. Drawdowns > 5%	1	0	0	0
			Information Ratio	1.566	0.901	1.741	2.197
			Turnover	179%	129%	137%	162%
	Russell 3000	04/30/1991 - 06/30/1997	Cumulative Return	48.86%	10.30%	28.51%	30.76%
			Max Drawdown	4.34%	6.32%	1.49%	1.88%
			Num. Drawdowns > 5%	0	1	0	0
			Information Ratio	1.886	0.636	2.94	2.639
			Turnover	178%	134%	139%	152%
	Russell 3000	06/30/1997 - 12/31/2002	Cumulative Return	48.36%	33.46%	43.58%	48.62%
			Max Drawdown	20.49%	17.56%	7.24%	3.07%
			Num. Drawdowns > 5%	5	1	3	0
			Information Ratio	1.028	1.275	2.229	2.982
			Turnover	189%	147%	147%	149%
	Russell 3000	12/31/2002 - 12/31/2007	Cumulative Return	8.99%	2.55%	6.18%	13.20%
			Max Drawdown	15.46%	10.77%	6.02%	2.91%
			Num. Drawdowns > 5%	1	1	1	0
			Information Ratio	0.432	0.225	0.597	1.133
			Turnover	176%	116%	131%	148%
	Russell 3000	12/31/2007 - 12/31/2009	Cumulative Return	-40.71%	19.99%	-13.36%	13.92%
			Max Drawdown	48.19%	9.79%	17.54%	7.06%
			Num. Drawdowns > 5%	3	2	1	1
			Information Ratio	-1.389	1.345	-1.362	1.476
			Turnover	208%	82%	154%	152%
	Russell 3000	12/31/2009 - 10/31/2018	Cumulative Return	32.14%	2.48%	16.92%	19.24%
			Max Drawdown	13.45%	4.36%	5.95%	3.41%
			Num. Drawdowns > 5%	2	0	1	0
			Information Ratio	0.619	0.117	0.858	1.133
			Turnover	170%	109%	127%	131%

Table A2: Monthly Return Distribution Statistics for Select Strategies (Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
	Russell 3000	12/31/1986 - 10/31/2018	Avg Return (T-Stat)	3.28%* (1.39)	2.42%** (2.07)	2.85%*** (3.14)	4.38%*** (5.66)
			Std. Dev	8.76%	4.33%	3.37%	2.87%
			Skew	-3.30***	1.34**	-1.80**	1.53***
			Kurtosis	21.84***	10.13***	12.44***	9.54***
			Hit Rate	65.45%***	55.24%**	67.02%***	68.59%***
International	S&P Developed Europe BMI	12/31/2004 - 10/31/2018	Avg Return (T-Stat)	6.30%*** (3.09)	2.29%** (2.19)	4.29%*** (6.48)	5.51%*** (8.92)
			Std. Dev	7.57%	3.88%	2.47%	2.29%
			Skew	-3.01***	2.52*	-1.57***	1.09
			Kurtosis	19.29***	19.66***	6.35***	7.60**
			Hit Rate	71.08%***	62.05%***	75.9%***	80.72%***
	S&P Developed Asia Ex-Japan BMI	12/31/2004 - 10/31/2018	Avg Return (T-Stat)	6.15%*** (2.97)	3.15%** (2.19)	4.65%*** (4.83)	5.39%*** (5.68)
			Std. Dev	7.69%	5.35%	3.58%	3.53%
			Skew	-1.00**	0.77**	-0.77*	-0.19
			Kurtosis	3.54***	3.17***	2.9***	3.11***
			Hit Rate	66.27%***	56.63%**	68.67%***	72.29%***
	S&P Japan BMI	12/31/2004 - 10/31/2018	Avg Return (T-Stat)	0.87% (0.47)	2.05%** (1.94)	1.46%** (1.83)	2.65%*** (3.69)
			Std. Dev	6.83%	3.91%	2.96%	2.67%
			Skew	-1.44***	-0.54	-1.06**	-0.14
			Kurtosis	6.49**	2.07**	4.07**	1.00
			Hit Rate	54.55%	65.45%***	59.39%***	65.45%***
	S&P Latin America BMI	12/31/2004 - 10/31/2018	Avg Return (T-Stat)	4.22%* (1.52)	5.37%*** (3.08)	4.97%*** (3.95)	6.42%*** (5.66)
			Std. Dev	10.34%	6.50%	4.68%	4.22%
			Skew	-1.52***	0.16	-0.61**	-0.22
			Kurtosis	5.24***	0.58	2.39**	0.87
			Hit Rate	65.06%***	60.24%***	66.87%***	68.07%***
	S&P Emerging Markets BMI	12/31/2004 - 10/31/2018	Avg Return (T-Stat)	3.14%* (1.35)	4.40%*** (2.75)	3.71%*** (4.79)	5.11%*** (5.59)
			Std. Dev	8.63%	5.94%	2.88%	3.40%
			Skew	-2.34***	2.56***	-0.56***	1.56**
			Kurtosis	9.58***	11.57***	1.16*	8.42***
			Hit Rate	66.27%***	56.02%*	71.08%***	69.88%***
Size Robustness	Russell 2000	12/31/1986 - 10/31/2018	Avg Return (T-Stat)	4.09%** (1.66)	2.63%** (2.13)	3.37%*** (3.46)	4.54%*** (5.54)
			Std. Dev	9.16%	4.57%	3.61%	3.04%
			Skew	-3.24***	1.28	-1.83***	1.60**
			Kurtosis	20.82***	10.38***	12.34***	12.15***
			Hit Rate	64.66%***	56.28%***	66.49%***	70.16%***
	Russell 1000	12/31/1986 - 10/31/2018	Avg Return (T-Stat)	1.79% (0.81)	2.06%** (1.68)	1.94%** (2.28)	3.06%*** (4.00)
			Std. Dev	8.17%	4.55%	3.15%	2.84%
			Skew	-3.18***	0.66*	-1.77*	0.92**
			Kurtosis	26.14***	5.26***	16.88***	5.02***
			Hit Rate	58.38%***	55.76%**	62.3%***	64.66%***

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Table A2 (Cont.): Monthly Return Distribution Statistics for Select Strategies (Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
Long-Only	Russell 3000 (Active Returns)	12/31/1986 - 10/31/2018	Avg Return (T-Stat)	2.21% (1.12)	3.12%** (1.90)	2.67%*** (2.58)	4.03%*** (3.40)
			Std. Dev	7.31%	6.09%	3.84%	4.40%
			Skew	-2.35***	0.44	-1.15	0.44
			Kurtosis	15.91***	7.28***	11.06***	8.51***
			Hit Rate	60.47%***	56.54%***	64.14%***	65.45%***
Beta Neutral	Russell 3000 Beta-Hedged	12/31/1986 - 10/31/2018	Avg Return (T-Stat)	2.40%* (1.47)	1.39%* (1.46)	2.51%*** (3.96)	3.48%*** (5.69)
			Std. Dev	6.08%	3.56%	2.36%	2.27%
			Skew	-1.68***	0.18	-0.90*	0.64
			Kurtosis	9.03***	2.89***	6.48***	1.86***
			Hit Rate	60.99%***	54.97%*	64.66%***	65.18%***
Subperiod Robustness	Russell 3000	12/31/1986 - 04/30/1991	Avg Return (T-Stat)	6.59%*** (2.57)	2.86%** (2.13)	4.70%*** (4.41)	6.67%*** (5.63)
			Std. Dev	5.34%	2.79%	2.22%	2.46%
			Skew	-0.80	0.88***	0.63	0.34
			Kurtosis	2.78***	1.03	1.35*	1.04*
			Hit Rate	82.69%***	59.62%*	78.85%***	88.46%***
	Russell 3000	04/30/1991 - 06/30/1997	Avg Return (T-Stat)	6.56%*** (3.66)	1.63%* (1.40)	4.1%*** (5.94)	4.38%*** (4.94)
			Std. Dev	4.46%	2.90%	1.72%	2.20%
			Skew	-0.15	0.97**	0.05	0.1
			Kurtosis	-0.03	2.13	-0.57	-0.48
			Hit Rate	63.51%***	52.70%	74.32%***	70.27%***
	Russell 3000	06/30/1997 - 12/31/2002	Avg Return (T-Stat)	8.12%* (1.44)	5.47%** (1.97)	6.77%*** (2.80)	7.3%*** (4.39)
			Std. Dev	13.24%	6.49%	5.68%	3.90%
			Skew	-2.63**	-0.20	-1.74***	0.17
			Kurtosis	10.87***	1.54*	6.36**	0.31
			Hit Rate	68.18%***	65.15%***	72.73%***	72.73%***
	Russell 3000	12/31/2002 - 12/31/2007	Avg Return (T-Stat)	1.90% (0.72)	0.55% (0.41)	1.22% (1.13)	2.5%*** (2.84)
			Std. Dev	5.88%	2.95%	2.41%	1.97%
			Skew	-2.43**	-0.5	-2.14**	0.2
			Kurtosis	10.1***	0.96**	8.88**	0.27
			Hit Rate	63.33%**	46.67%	63.33%**	61.67%**
	Russell 3000	12/31/2007 - 12/31/2009	Avg Return (T-Stat)	-23.89% (-1.74)	9.56%* (1.44)	-7.03% (-1.83)	**6.70%* (1.59)**
			Std. Dev	19.45%	9.42%	5.42%	5.97%
			Skew	-1.65*	1.43*	-1.52***	2.00*
			Kurtosis	3.97*	3.17*	3.46**	6.43
			Hit Rate	45.83%	54.17%	37.50%	58.33%
	Russell 3000	12/31/2009 - 10/31/2018	Avg Return (T-Stat)	3.27%** (1.99)	0.29% (0.35)	1.78%*** (2.65)	2.00%*** (3.55)
			Std. Dev	4.87%	2.46%	2.00%	1.68%
			Skew	-0.28	0.03	-0.36**	-0.04
			Kurtosis	0.71*	0.20	0.36	0.00
			Hit Rate	62.26%***	53.77%	61.32%***	61.32%***

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Table A3: Monthly Return Distribution Statistics for Select Strategies (Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Equal-Weight		Risk-Weight		
				- Momentum	- Value	- Momentum	- Value	- Equal-Weight
	Russell 3000	12/31/1986 - 10/31/2018	Return Prem (T-Stat)	-0.43% (-0.40)	+0.43% (0.40)	+1.11% (0.70)	+1.97%*** (2.79)	+1.54%*** (2.60)
			Volatility Prem (F-Stat)	-5.39%*** (6.76)	-0.96%*** (1.65)	-5.89%*** (9.31)	-1.46%*** (2.28)	-0.50%*** (1.38)
			Skewness Prem	+1.50*	-3.15***	+4.83***	+0.19	+3.34***
			Kurtosis Prem	-9.41***	+2.30	-12.30***	-0.59	-2.89
			Hit Rate Prem	+1.57%	+11.78%***	+3.14%*	+13.35%***	+1.57%
International	S&P Developed Europe BMI	12/31/2004 - 10/31/2018	Return Prem (T-Stat)	-2.01%* (-1.36)	+2.00%* (1.36)	-0.80% (-0.37)	+3.22%*** (3.44)	+1.21%* (1.58)
			Volatility Prem (F-Stat)	-5.11%*** (9.43)	-1.41%*** (2.48)	-5.28%*** (10.89)	-1.59%*** (2.86)	-0.17% (1.16)
			Skewness Prem	+1.43**	-4.09***	+4.10***	-1.42*	+2.67***
			Kurtosis Prem	-12.94***	-13.31***	-11.69***	-12.06***	+1.25
			Hit Rate Prem	+4.82%*	+13.86%***	+9.64%***	+18.67%***	+4.82%*
	S&P Developed Asia Ex-Japan BMI	12/31/2004 - 10/31/2018	Return Prem (T-Stat)	-1.49% (-0.99)	+1.50% (1.01)	-0.76% (-0.37)	+2.24%** (2.17)	+0.74% (1.16)
			Volatility Prem (F-Stat)	-4.11%*** (4.62)	-1.77%*** (2.24)	-4.16%*** (4.75)	-1.82%*** (2.30)	-0.05% (1.03)
			Skewness Prem	+0.23	-1.53***	+0.81*	-0.96**	+0.57
			Kurtosis Prem	-0.64	-0.26	-0.43	-0.05	+0.21
			Hit Rate Prem	+2.41%	+12.05%***	+6.02%**	+15.66%***	+3.61%
	S&P Japan BMI	12/31/2004 - 10/31/2018	Return Prem (T-Stat)	+0.59% (0.46)	-0.58% (-0.46)	+1.77% (1.01)	+0.60% (0.68)	+1.18%** (2.04)
			Volatility Prem (F-Stat)	-3.87%*** (5.32)	-0.95%*** (1.75)	-4.17%*** (6.56)	-1.25%*** (2.15)	-0.30% (1.23)
			Skewness Prem	+0.38	-0.52	+1.30***	+0.40	+0.92***
			Kurtosis Prem	-2.42	+2.00	-5.48***	-1.06	-3.07***
			Hit Rate Prem	+4.85%*	-6.06%*	+10.91%***	+0.00%	+6.06%**
	S&P Latin America BMI	12/31/2004 - 10/31/2018	Return Prem (T-Stat)	+0.75% (0.40)	-0.40% (-0.20)	+2.20% (0.77)	+1.04% (0.90)	+1.45%* (1.42)
			Volatility Prem (F-Stat)	-5.66%*** (4.89)	-1.82%*** (1.93)	-6.12%*** (6.00)	-2.28%*** (2.37)	-0.46% (1.23)
			Skewness Prem	+0.91**	-0.77**	+1.30***	-0.39	+0.38
			Kurtosis Prem	-2.84**	+1.82**	-4.36***	+0.30	-1.52***
			Hit Rate Prem	+1.81%	+6.63%**	+3.01%	+7.83%**	+1.2%
	S&P Emerging Markets BMI	12/31/2004 - 10/31/2018	Return Prem (T-Stat)	+0.57% (0.32)	-0.69% (-0.37)	+1.98% (0.76)	+0.72% (0.60)	+1.40%* (1.53)
			Volatility Prem (F-Stat)	-5.75%*** (8.98)	-3.06%*** (4.26)	-5.23%*** (6.43)	-2.54%*** (3.05)	+0.52%** (1.40)
			Skewness Prem	+1.78***	-3.12***	+3.90***	-1.00	+2.12***
			Kurtosis Prem	-8.42***	-10.41***	-1.17	-3.15	+7.26***
			Hit Rate Prem	+4.82%*	+15.06%***	+3.61%	+13.86%***	-1.20%
Size Robustness	Russell 2000	12/31/1986 - 10/31/2018	Return Prem (T-Stat)	-0.72% (-0.65)	+0.74% (0.67)	+0.45% (0.27)	+1.91%*** (2.85)	+1.17%** (1.92)
			Volatility Prem (F-Stat)	-5.55%*** (6.44)	-0.97%*** (1.61)	-6.12%*** (9.09)	-1.53%*** (2.26)	-0.57%*** (1.41)
			Skewness Prem	+1.41*	-3.11***	+4.83***	+0.32	+3.43***
			Kurtosis Prem	-8.49**	+1.96	-8.67	+1.77	-0.19
			Hit Rate Prem	+1.83%	+10.21%***	+5.50%***	+13.87%***	+3.66%*
	Russell 1000	12/31/1986 - 10/31/2018	Return Prem (T-Stat)	+0.14% (0.14)	-0.13% (-0.12)	+1.27% (0.82)	+0.99%* (1.53)	+1.12%** (1.91)
			Volatility Prem (F-Stat)	-5.02%*** (6.73)	-1.40%*** (2.09)	-5.33%*** (8.28)	-1.71%*** (2.57)	-0.31%** (1.23)
			Skewness Prem	+1.41	-2.43***	+4.10***	+0.26	+2.69***
			Kurtosis Prem	-9.26	+11.62	-21.13***	-0.24	-11.86***
			Hit Rate Prem	+3.93%*	+6.54%***	+6.28%***	+8.90%***	+2.36%

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Table A3 (Cont.): Monthly Return Distribution Statistics for Select Strategies (Assorted Universes and Date Ranges, Labeled per Row)

	Universe	Date Range	Metric	Equal-Weight		Risk-Weight		
				- Momentum	- Value	- Momentum	- Value	- Equal-Weight
Long-Only	Russell 3000 (Active Return)	12/31/1986 - 10/31/2018	Return Prem (T-Stat)	+0.46% (0.47)	-0.45% (-0.46)	+1.83%* (1.33)	+0.91% (1.26)	+1.36%*** (2.75)
			Volatility Prem (F-Stat)	-3.47%*** (3.62)	-2.25%*** (2.51)	-2.91%*** (2.76)	-1.69%*** (1.92)	+0.56%*** (1.31)
			Skew ness Prem	+1.20	-1.58**	+2.79***	+0.01	+1.59***
			Kurtosis Prem	-4.85	+'3.78	-7.4***	+1.23	-2.55
			Hit Rate Prem	+3.66%*	+7.59%***	+4.97%**	+8.90%***	+1.31%
Beta Neutral	Russell 3000 Beta-Hedged	12/31/1986 - 10/31/2018	Return Prem (T-Stat)	+0.11% (0.13)	+1.12%* (1.44)	+1.08% (1.02)	+2.08%*** (3.37)	+0.97%*** (2.85)
			Volatility Prem (F-Stat)	-3.72%*** (6.65)	-1.20%*** (2.28)	-3.81%*** (7.15)	-1.29%*** (2.45)	-0.08% (1.07)
			Skew ness Prem	0.78	-1.08**	2.32***	0.46**	1.54***
			Kurtosis Prem	-2.55	3.59	-7.16***	-1.03*	-4.61***
			Hit Rate Prem	3.66%	9.69%	4.19%	10.21%	0.52%
Subperiod Robustness	Russell 3000	12/31/1986 - 04/30/1991	Return Prem (T-Stat)	-1.88% (-1.08)	+1.85% (1.06)	+0.08% (0.04)	+3.81%** (2.02)	+1.96%*** (3.22)
			Volatility Prem (F-Stat)	-3.11%*** (5.77)	-0.57% (1.58)	-2.87%*** (4.69)	-0.32% (1.28)	+0.24% (1.23)
			Skew ness Prem	+1.43***	-0.25	+1.13***	-0.54	-0.30
			Kurtosis Prem	-1.42*	+0.33	-1.74***	+0.01	-0.32
			Hit Rate Prem	-3.85%	+19.23%***	+5.77%*	+28.85%***	+9.62%**
	Russell 3000	04/30/1991 - 06/30/1997	Return Prem (T-Stat)	-2.46% (-1.83)	+2.47%** (1.83)	-2.19% (-1.79)	+2.74%** (1.73)	+0.28% (0.64)
			Volatility Prem (F-Stat)	-2.74%*** (6.76)	-1.18%*** (2.86)	-2.26%*** (4.10)	-0.70%** (1.73)	+0.49%** (1.65)
			Skew ness Prem	+0.20	-0.92***	+0.25	-0.87***	+0.05
			Kurtosis Prem	-0.54	-2.70	-0.45	-2.61***	+0.09
			Hit Rate Prem	+10.81%**	+21.62%***	+6.76%*	+17.57%***	-4.05%
	Russell 3000	06/30/1997 - 12/31/2002	Return Prem (T-Stat)	-1.35% (-0.36)	+1.30% (0.35)	-0.82% (-0.16)	+1.83% (0.74)	+0.52% (0.36)
			Volatility Prem (F-Stat)	-7.56%*** (5.44)	-0.82% (1.31)	-9.34%*** (11.55)	-2.6%*** (2.78)	-1.78%*** 2.12
			Skew ness Prem	+0.90	-1.54	+2.80	+0.37	+1.91
			Kurtosis Prem	-4.51	+4.82	-10.56	-1.23	-6.05
			Hit Rate Prem	+4.55%	+7.58%*	+4.55%	+7.58%*	+0.00%
	Russell 3000	12/31/2002 - 12/31/2007	Return Prem (T-Stat)	-0.67% (-0.38)	+0.68% (0.38)	+0.60% (0.26)	+1.95% (1.28)	+1.28%* (1.56)
			Volatility Prem (F-Stat)	-3.47%*** (5.96)	-0.54% (1.50)	-3.91%*** (8.93)	-0.98%*** (2.25)	-0.44% (1.50)
			Skew ness Prem	+0.28	-1.64	+2.62***	+0.70*	+2.34***
			Kurtosis Prem	-1.22	+7.92**	-9.83***	-0.70	-8.61***
			Hit Rate Prem	+0.00%	+16.67%***	-1.67%	+15.00%***	-1.67%
	Russell 3000	12/31/2007 - 12/31/2009	Return Prem (T-Stat)	+16.86%* (1.67)	-16.59% (-1.65)	+30.59%* (1.73)	-2.86% (-0.99)	+13.73%* (1.80)
			Volatility Prem (F-Stat)	-14.03%*** (12.86)	-3.99%** (3.01)	-13.48%*** (10.62)	-3.45%** (2.49)	+0.55% (1.21)
			Skew ness Prem	+0.13	-2.95***	+3.65***	+0.57	+3.52***
			Kurtosis Prem	-0.51	+0.29	+2.46	+3.26	+2.97
			Hit Rate Prem	-8.33%	-16.67%	+12.50%*	+4.17%	+20.83%**
	Russell 3000	12/31/2009 - 10/31/2018	Return Prem (T-Stat)	-1.49% (-1.34)	+1.49% (1.34)	-1.27% (-0.91)	+1.71%** (1.89)	+0.22% (0.58)
			Volatility Prem (F-Stat)	-2.87%*** (5.93)	-0.46%** (1.51)	-3.19%*** (8.42)	-0.78%*** (2.15)	-0.32%* (1.42)
			Skew ness Prem	-0.07	-0.39	+0.24	-0.07	+0.32
			Kurtosis Prem	-0.35	+0.15	-0.71	-0.2	-0.35
			Hit Rate Prem	-0.94%	+7.55%**	-0.94%	+7.55%**	+0.00%

*** = Significant at the 1% level; ** = Significant at the 5% level; * = Significant at the 10% Level

Table A4: Monte-Carlo Simulation Results
(Assorted Universes and Date Ranges, Labeled per Row)

	Univ.	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
	Russell 3000	12/31/1986 - 10/31/2018	Annual Return	3.35%	2.46%	2.89%	4.47%
			Annual Std. Dev.	7.57%	4.10%	3.37%	2.56%
			Max DD	-31.52%	-10.87%	-8.90%	-3.21%
			Fourth Place	32.64%	47.33%	19.95%	0.08%
			Third Place	18.65%	35.60%	44.31%	1.44%
			Second Place	28.31%	15.80%	33.88%	22.01%
			First Place	20.40%	1.27%	1.86%	76.47%
International	S&P Developed Europe BMI	12/31/2004 - 10/31/2018	Annual Return	6.48%	2.32%	4.38%	5.66%
			Annual Std. Dev.	7.84%	3.79%	2.73%	1.95%
			Max DD	-21.32%	-8.47%	-4.69%	-2.02%
			Fourth Place	1.22%	98.11%	0.67%	0.00%
			Third Place	10.68%	1.85%	85.78%	1.69%
			Second Place	23.40%	0.04%	12.89%	63.67%
			First Place	64.70%	0.00%	0.66%	34.64%
	S&P Developed Asia Ex-Japan BMI	12/31/2004 - 10/31/2018	Annual Return	6.30%	3.21%	4.75%	5.53%
			Annual Std. Dev.	8.63%	5.79%	3.58%	3.71%
			Max DD	-18.94%	-13.38%	-6.87%	-5.69%
			Fourth Place	4.48%	87.05%	7.45%	1.02%
			Third Place	14.98%	9.88%	58.83%	16.31%
			Second Place	20.19%	2.60%	26.57%	50.64%
			First Place	60.35%	0.47%	7.15%	32.03%
	S&P Japan BMI	12/31/2004 - 10/31/2018	Annual Return	0.91%	2.07%	1.48%	2.69%
			Annual Std. Dev.	6.41%	3.93%	3.16%	2.60%
			Max DD	-30.64%	-11.74%	-9.47%	-5.46%
			Fourth Place	67.11%	8.69%	23.71%	0.49%
			Third Place	17.06%	25.67%	52.76%	4.51%
			Second Place	10.15%	44.95%	20.58%	24.32%
			First Place	5.68%	20.69%	2.95%	70.68%
	S&P Latin America BMI	12/31/2004 - 10/31/2018	Annual Return	4.32%	5.52%	5.08%	6.59%
			Annual Std. Dev.	10.30%	6.21%	4.42%	4.25%
			Max DD	-33.35%	-13.85%	-9.72%	-6.57%
			Fourth Place	62.64%	16.27%	20.04%	1.05%
			Third Place	17.29%	31.62%	44.43%	6.66%
			Second Place	11.82%	34.32%	28.74%	25.12%
			First Place	8.25%	17.79%	6.79%	67.17%
	S&P Emerging Markets BMI	12/31/2004 - 10/31/2018	Annual Return	3.19%	4.49%	3.79%	5.24%
			Annual Std. Dev.	8.18%	7.06%	2.77%	3.01%
			Max DD	-30.47%	-9.94%	-5.32%	-3.71%
			Fourth Place	64.90%	13.02%	21.59%	0.49%
			Third Place	16.13%	27.13%	52.05%	4.69%
			Second Place	12.04%	36.75%	24.07%	27.14%
			First Place	6.93%	23.10%	2.29%	67.68%
Size Robustness	Russell 2000	12/31/1986 - 10/31/2018	Annual Return	4.19%	2.67%	3.42%	4.63%
			Annual Std. Dev.	10.06%	4.20%	3.86%	2.89%
			Max DD	-31.02%	-11.40%	-9.13%	-3.50%
			Fourth Place	25.06%	58.46%	16.21%	0.27%
			Third Place	19.02%	30.21%	46.48%	4.29%
			Second Place	23.78%	9.89%	32.58%	33.75%
			First Place	32.14%	1.44%	4.73%	61.69%
	Russell 1000	12/31/1986 - 10/31/2018	Annual Return	1.80%	2.07%	1.96%	3.10%
			Annual Std. Dev.	7.58%	4.85%	3.33%	2.68%
			Max DD	-33.43%	-13.56%	-9.46%	-4.77%
			Fourth Place	50.71%	24.67%	23.85%	0.77%
			Third Place	17.86%	34.86%	42.11%	5.17%
			Second Place	16.40%	29.44%	29.27%	24.89%
			First Place	15.03%	11.03%	4.77%	69.17%

Table A4 (Cont.): Monte-Carlo Simulation Results (Assorted Universes and Date Ranges, Labeled per Row)

	Univ.	Date Range	Metric	Momentum	Value	Equal-Weight	Risk-Weight
Long-Only	Russell 3000 (Abs. Returns)	12/31/1986 - 10/31/2018	Annual Return	15.24%	16.40%	15.89%	17.46%
			Annual Std. Dev.	18.86%	21.88%	18.64%	16.40%
			Max DD	-43.92%	-41.72%	-41.59%	-41.65%
			Fourth Place	33.12%	24.45%	25.53%	16.90%
			Third Place	26.98%	25.06%	26.83%	21.13%
			Second Place	22.53%	25.44%	25.80%	26.23%
			First Place	17.37%	25.05%	21.84%	35.74%
Beta Neutral	Russell 3000 Beta-Hedged	12/31/1986 - 10/31/2018	Annual Return	2.38%	1.42%	2.53%	3.52%
			Annual Std. Dev.	5.34%	3.63%	2.43%	2.42%
			Max DD	-21.16%	-11.67%	-5.19%	-2.93%
			Fourth Place	25.27%	70.41%	4.31%	0.01%
			Third Place	34.41%	25.63%	38.49%	1.47%
			Second Place	25.99%	3.76%	53.29%	16.96%
			First Place	14.33%	0.20%	3.91%	81.56%
Subperiod Robustness	Russell 3000	12/31/1986 - 04/30/1991	Annual Return	6.78%	2.89%	4.80%	6.87%
			Annual Std. Dev.	5.81%	2.83%	2.16%	2.46%
			Max DD	-10.38%	-4.62%	-2.02%	-2.05%
			Fourth Place	0.06%	99.72%	0.22%	0.00%
			Third Place	4.39%	0.28%	95.26%	0.07%
			Second Place	52.66%	0.00%	4.51%	42.83%
			First Place	42.89%	0.00%	0.01%	**57.10%**
	Russell 3000	04/30/1991 - 06/30/1997	Annual Return	6.78%	1.64%	4.18%	4.46%
			Annual Std. Dev.	4.45%	2.94%	1.62%	2.26%
			Max DD	-6.75%	-7.43%	-1.55%	-2.39%
			Fourth Place	0.00%	99.99%	0.01%	0.00%
			Third Place	0.20%	0.01%	69.89%	29.90%
			Second Place	0.79%	0.00%	30.00%	69.21%
			First Place	99.01%	0.00%	0.10%	0.89%
	Russell 3000	06/30/1997 - 12/31/2002	Annual Return	8.47%	5.61%	6.98%	7.54%
			Annual Std. Dev.	13.76%	5.78%	5.52%	3.83%
			Max DD	-37.90%	-14.32%	-12.61%	-4.55%
			Fourth Place	21.19%	62.22%	13.89%	2.70%
			Third Place	16.88%	26.77%	37.17%	19.18%
			Second Place	14.57%	8.53%	32.45%	44.45%
			First Place	47.36%	2.48%	16.49%	33.67%
	Russell 3000	12/31/2002 - 12/31/2007	Annual Return	1.92%	0.56%	1.23%	2.53%
			Annual Std. Dev.	5.31%	3.10%	2.31%	1.89%
			Max DD	-22.34%	-13.08%	-8.10%	-3.15%
			Fourth Place	14.01%	72.33%	13.66%	0.00%
			Third Place	19.29%	22.94%	57.30%	0.47%
			Second Place	40.89%	4.71%	28.48%	25.92%
			First Place	25.81%	0.02%	0.56%	73.61%
	Russell 3000	12/31/2007 - 12/31/2009	Annual Return	-21.44%	10.00%	-6.81%	6.91%
			Annual Std. Dev.	20.49%	8.44%	5.26%	5.43%
			Max DD	-99.93%	-13.18%	-88.09%	-6.70%
			Fourth Place	100.00%	0.00%	0.00%	0.00%
			Third Place	0.00%	0.00%	100.00%	0.00%
			Second Place	0.00%	9.16%	0.00%	90.84%
			First Place	0.00%	90.84%	0.00%	9.16%
	Russell 3000	12/31/2009 - 10/31/2018	Annual Return	3.31%	0.28%	1.80%	2.02%
			Annual Std. Dev.	4.58%	2.50%	1.99%	1.64%
			Max DD	-12.46%	-12.23%	-4.51%	-2.97%
			Fourth Place	0.20%	99.34%	0.43%	0.03%
			Third Place	5.57%	0.63%	64.15%	29.65%
			Second Place	6.86%	0.03%	31.43%	61.68%
			First Place	87.37%	0.00%	3.99%	8.64%

Appendix II. Risk-Weighting Approach Example

The risk-weighted approach to blend momentum and value is achieved by allocating to the two factor portfolios as prescribed by the following equations.

$$MomWeight_t^{Risk-Weight} = min\left(\frac{\sigma_{target}}{\sigma_{Mom}^{obs}}, 1.0\right) \quad \text{Eq. 4a}$$

$$ValueWeight_t^{Risk-Weight} = 1.0 - MomWeight_t^{Risk-Weight} \quad \text{Eq. 4b}$$

$MomWeight_t^{Risk-Weight}$ is the decimal formatted percentage of capital allocated to the momentum factor portfolio and $ValueWeight_t^{Risk-Weight}$ is the decimal formatted percentage of capital allocated to the value factor portfolio; the σ_{target} value represents a target for the annualized standard deviation of daily returns (a constant) and σ_{Mom}^{obs} represents the observed trailing annualized standard deviation of daily returns. Both σ_{target} and σ_{Mom}^{obs} values are strictly positive, by construction. In this work σ_{target} is chosen to be 2% (see section 4.1 for discussion).

As an example, in November of 1988, the 6-month trailing standard deviation of the momentum factor portfolio was $\sigma_{Mom}^{obs} = 2.089\%$. The resulting allocation to the momentum portfolio was therefore, $MomWeight_t^{Risk-Weight} = \frac{\sigma_{target}}{\sigma_{Mom}^{obs}} = \frac{2.0\%}{2.089\%} = 95.7\%$, which dictates a 95.7% allocation to the momentum factor portfolio and a, $ValueWeight_t^{Risk-Weight} = 1.0 - 0.957 = 4.3\%$ allocation to the value factor portfolio.

In the next month, the σ_{Mom}^{obs} drops below 2.0% to 1.99% and the ratio alone, $\frac{\sigma_{target}}{\sigma_{Mom}^{obs}} = \frac{2.0\%}{1.99\%} = 100.5\%$, suggests that more than 100% of the portfolio should be allocated to the momentum factor portfolio. However, the expression we use caps the allocation to the momentum factor portfolio at strictly 100%, and consequently the allocation to the value factor portfolio at 0%. That is, $MomWeight_t^{Risk-Weight} = min(1.005, 1.0) = 1.0$ and $ValueWeight_t^{Risk-Weight} = 1.0 - MomWeight_t^{Risk-Weight} = 1.0 - 1.0 = 0.0$.

Comparatively, when the observed volatility in the momentum factor portfolio increased to $\sigma_{Mom}^{obs} = 28.9\%$ in 5/31/2009, the momentum portfolio only received an allocation of $MomWeight_t^{Risk-Weight} = \frac{\sigma_{target}}{\sigma_{Mom}^{obs}} = \frac{2.0\%}{28.9\%} = 6.9\%$ and the value factor portfolio received an allocation of 93.1%.

Our Recent Research

November 2018: Forging Stronger Links: Using Supply Chain Data in the Investing Process

- Lower latency, higher frequency and finer granularity vs. financial data: Insights into corporate activity can be enhanced with Panjiva's Supply chain data which can be updated as often as on a daily basis - well ahead of, and at a higher frequency than - financial reports at a high level of product granularity. Examples include the underperformance vs. consensus earnings by UPS and LG Electronics in Q3 2018 as well as the near-term impact of solar panel duties.
- Detection of anomalous activity: Spikes in imports can indicate inventory build, new products introductions, attempts to boost market share or even capital markets events. Honda's accelerated imports ahead of new tariffs, Sony's launch of the "PlayStation Classic", Target's aim to replace Toys'R'Us and PepsiCo's bid for Sodastream are all examples of this use case.
- Risk event impact assessment: Panjiva's supply chain graph includes geographical references for corporate entities, allowing the rapid assessment of the impact of natural disasters and geopolitical actions such as border closures.

September 2018: Their Sentiments Exactly: Sentiment Signal Diversity Creates Alpha Opportunity

- Companies where management is both positive/optimistic and fact-focused outperform historically.
- Hedge fund sentiment confirms and complements management sentiment.
- Market sentiment surrounding earnings calls amplifies the effectiveness of earnings transcript-based signals.

Analyst sentiment, as reflected in target price/recommendation changes, adds an important voice to ownership-based signals.

September 2018: Natural Language Processing – Part II: Stock Selection: Alpha Unscripted: The Message within the Message in Earnings Calls

Highlights include:

- Sentiment-based signals: Firms whose executives and analysts exhibited the highest positivity in sentiment during earnings calls outperformed their counterparts. Firms with the largest year-over-year positive sentiment change and firms with the strongest positive sentiment trend outperformed their respective counterparts.
- Behavioral-based signals: Firms whose executives provided the most transparency by using the simplest language and by presenting results with numbers outperformed their respective counterparts.
- Sentiment- and behavioral-based signals are not subsumed by commonly used alpha and risk signals.

- Positive language from the unscripted responses by the executives during the Q&A drove the overall predictability of the positive sentiment signal.
- The sentiment of CEOs has historically been more important than the sentiment of other executives.
- The aggregate sentiment of analysts historically enhanced the predictability of the 3-month FY1 EPS analyst revision signal.

July 2018: A Case of 'Wag the Dog'? - ETFs and Stock-Level Liquidity

Highlights include:

- We present an ETF price impact model, which posits single-day impact of up to 370 bps / day on an individual security and up to 250 bps / day on the index itself. Analyses indicate the effect is transitory and reverses over a period of 3-5 trading days.
- The Feb 2018 market correction was accompanied by a $25B outflow of assets from ticker SPY, the SSGA S&P 500 Trust ETF. Modeling suggests that as much as one-third of the pullback was due to price pressure from ETF trading and that securities more sensitive to ETF flow underperformed.
- Sensitivity to ETF flow is used to build a risk model, which generates improved performance in a historical optimization. We offer a method for estimating ETF sensitivity for funds, using the S&P Global Ownership dataset.

June 2018: The (Gross Profitability) Trend is Your Friend

Trend strategies based on changes in stock price or earnings are widely used by investors. In this report, we examine the performance of a trend strategy derived from gross profitability ("GP"). Gross profitability trend ("GPtrend"), was proposed by Akbas et al. who argued that the trajectory of a firm's profitability is just as important as the level (GP). We define GPtrend as the year-on-year difference in either quarterly or trailing twelve month GP, where GP is calculated as revenue minus cost of goods sold, divided by total assets. Our back-tests confirm that GPtrend has historically been an effective stock selection signal globally, with the added benefit of low to moderate correlation with commonly used investment strategies.

May 2018: Buying the Dip: Did Your Portfolio Holding Go on Sale?

'Buy the Dip' ("BTD"), the concept of buying shares after a steep decline in stock price or market index, is both a Wall Street maxim, and a widely used investment strategy. Investors pursuing a BTD strategy are essentially buying shares at a "discounted" price, with the opportunity to reap a large pay-off if the price drop is temporary and the stock subsequently rebounds. BTD strategies are especially popular during bull markets, when a market rally can be punctuated by multiple pullbacks in equity prices as stock prices march upwards.

March 2018: In The Money: What Really Motivates Executive Performance?

CEO compensation has soared over the past four decades, aided by consultants, compensation committees, the CEOs themselves, and an extended bull market (1982-1999). "Pay for performance" has become dogma and large equity grants de rigueur. But

there is a cost to such largesse. Figure 1 shows that realized pay1 for a company's top five executives can approach 6%-11% of earnings before interest and taxes (EBIT), on the index level, for small and mid-cap firms. What types of compensation motivate top executives to boost shareholder returns? And what are the fundamental characteristics of companies in which executives are motivated to boost stock performance?

February 2018: The Art of (no) Deal: Identifying the Drivers of Cancelled M&A Deals
Terminated deals impact capital market participants in various ways. Predicting deals that are likely to be canceled is of interest to both M&A advisers and equity investors. This report identifies several drivers of cancelled deals, including size, deal proportionality, perceived price discount, CEO age, and regulatory risk, and concludes with a model built from four of these drivers.

January 2018: U.S Stock Selection Model Performance Review

September 2017: Natural Language Processing - Part I: Primer

July 2017: Natural Language Processing Literature Survey

June 2017: Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment

April 2017: Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data

March 2017: Capital Market Implications of Spinoffs

January 2017: U.S. Stock Selection Model Performance Review 2016

November 2016: Electrify Stock Returns in U.S. Utilities
October 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 2**

September 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 1**

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