U.S. Stock Selection Model Performance Review
2016 – The Year of "Risky" Value

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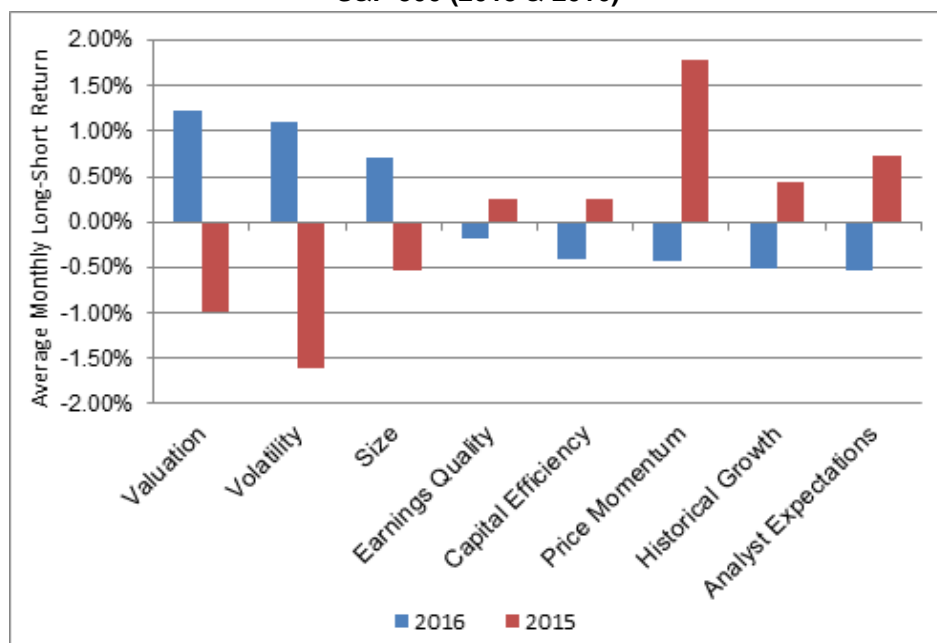Quantamental Research
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Last year was a difficult year for active managers with fewer than 1 in 5 large-cap active managers beating the S&P 500 index[1]. It was also a tough year for our U.S. stock selection models, with three of four models underperforming their benchmarks (Table 1), the first annual underperformance since the models' launch in January 2011. This report discusses the 2016 performance of all four models.

The year started with a sharp selloff in January as concerns about an economic slowdown in China and a continued fall in oil prices weighed on investors' minds. While markets subsequently rebounded strongly in March and closed the year in positive territory, equity markets were pressured in the days surrounding the vote on the departure of the United Kingdom from the European Union and the U.S elections.

Figure 1 shows the performance of eight strategy style composites[2] we track for both 2015 and 2016. After several years of lackluster performance, valuation was the dominant investing style in 2016, followed by volatility (high beta stocks outperformed low beta stocks) and size (small cap stocks outperformed large cap stocks).

Figure 1   Average Monthly Quintile Return Spreads For Popular Investment Styles S&P 500 (2015 & 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

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[1] http://www.cnbc.com/2017/01/06/2016-was-a-terrible-year-for-stock-picking-and-2017-may-not-get-much-better.html
[2] Quintile return spread is calculated as the equal-weighted return to the top 20% of stocks as ranked by a metric or style composite minus the equal-weighted return to the bottom 20% of stocks ranked by the same metric. See Appendix A for a definition of the strategy style composites.

An important aspect in 2016 was the correlation of returns between value and volatility strategies. Appendix B shows the 24-month rolling correlation between the two strategies ended 2016 at 0.55, well above its historical average of -0.03. The correlation between both strategies has climbed sharply since December 2014 and is approaching levels last seen in early 2011. This observation leads to the question: what type of "value" worked in 2016?

To answer this question, we selected the most attractive value stocks (top 20% of names by the Valuation Style Composite – see Appendix A for definition) and sorted these names into five buckets based on their 60-month Capital Asset Pricing Model (CAPM) beta. Results of the equal-weighted portfolios are shown in Figure 2. Even within the stocks that were most attractive on a valuation basis, "high-risk" value names outperformed "low-risk" value names by almost 1% monthly[3]. The valuation rally in 2016 could therefore be described as a "risky value" rally.

Figure 2   Average Monthly Quintile Return
Top Quintile Portfolio (Valuation Style Composite) Binned by Beta
S&P 500 (January 2016 – December 2016)
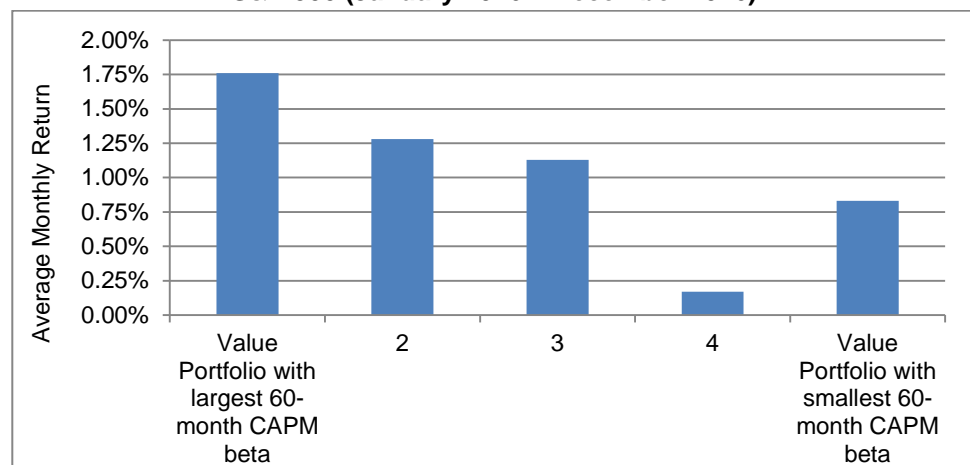
Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 01/05/2017.

Apart from valuation, volatility and size, the long-short returns to the other fundamental investment styles (the last five style composites in Figure 1) were all negative in 2016. This is an important observation as the Value, Growth and Quality Benchmark Models discussed in later sections were all constructed using a blend of fundamental style composites similar to those displayed in Figure 1. All four models discussed in this report had a challenging year, with three of the four posting flat or negative 1-month excess returns in 2016 (Table 1).

Another trend worth noting in 2016 was the strong performance of the Energy sector. Energy was the worst sector out of the 10 (now 11) GICS®[4] sectors in both 2014 and 2015, but the best in 2016 with a return of 24%. The Price Momentum Model benefited from underweighting the Energy sector in both 2014, 2015, and at the beginning of 2016 when oil prices were depressed. However, this under-weight was a drag on model performance in 2016 (see Table 1), as oil prices rallied and the Energy sector outperformed the broad market.

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[3] An analysis using size as a measure of risk yields similar conclusions
[4] GICS®: The Global Industry Classification Standard. Please see detailed information in Appendix C.

Table 1   2016 Model Summary Performance – January 2016 to December 2016
Russell 3000 Growth/Russell 3000 Value/Russell 3000

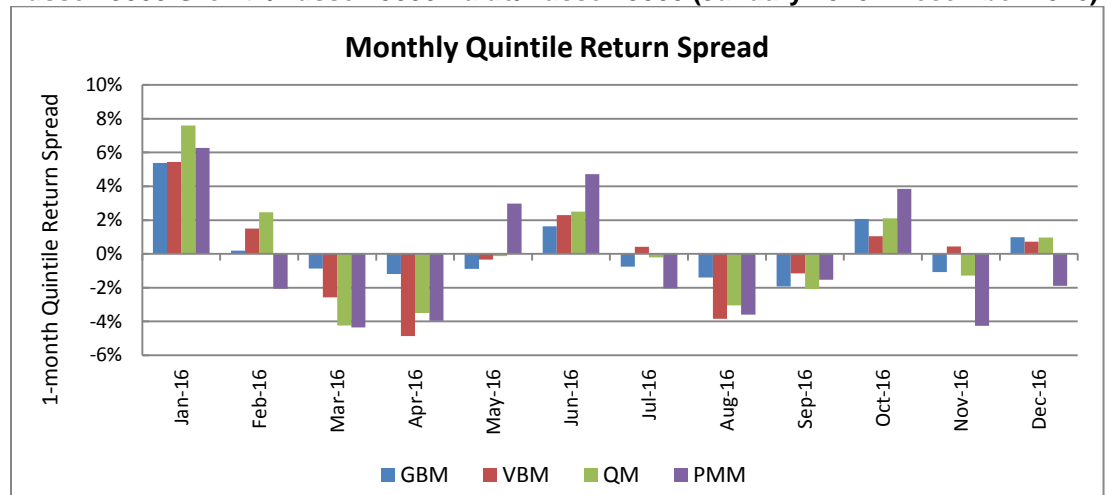| Model Name	Universe	Average 1-Month Quintile Spread	Average Q1 Monthly Excess Return	Average 1-Month IC
Growth Benchmark Model ("GBM")	Russell 3000 Growth	0.18%	0.14%	0.009
Value Benchmark ("VBM")	Russell 3000 Value	-0.08%	-0.28%	0.011
Quality ("QM")	Russell 3000	0.09%	-0.06%	0.005
Price Momentum ("PMM")	Russell 3000	-0.49%	-0.22%	-0.001

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

Table 2   Model Historical Summary Performance – Live Performance
(January 2011 to December 2016)
Russell 3000 Growth/Russell 3000 Value/Russell 3000

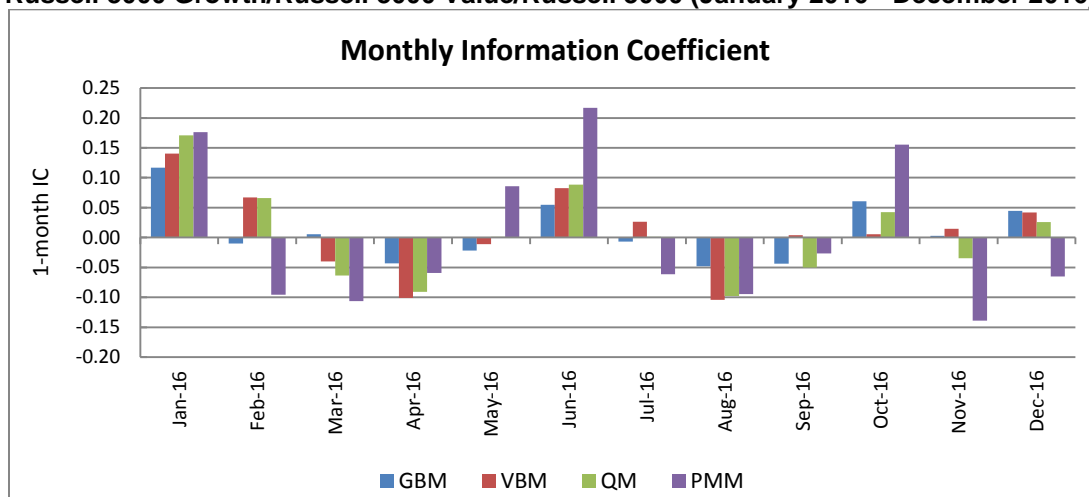| Model Name	Universe	Average 1-Month Quintile Spread	Average Q1 Monthly Excess Return	Average 1-Month IC
Growth Benchmark Model ("GBM")	Russell 3000 Growth	1.13%	0.32%	0.041
Value Benchmark Model ("VBM")	Russell 3000 Value	0.99%	0.24%	0.042
Quality Model ("QM")	Russell 3000	0.80%	0.30%	0.040
Price Momentum Model ("PMM")	Russell 3000	0.85%	0.30%	0.049

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

Figure 3   Monthly Historical Equal-Weighted Quintile Return Spread
Russell 3000 Growth/Russell 3000 Value/Russell 3000 (January 2016 - December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

Figure 4   Monthly Information Coefficient
Russell 3000 Growth/Russell 3000 Value/Russell 3000 (January 2016 - December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

Explanation of Returns Presented in this Paper

This paper presents the returns of portfolios formed based on the model scores. All returns are calculated based on actual historical returns of the underlying stocks, but do not represent actual trading results and do not include payments of any sales charges, fees, or trading costs. Such costs would have lowered performance. It is not possible to invest directly in an index or the model portfolios on which the results presented here are based. Past performance is not a guarantee of future results.

"Spread" returns, also referred to as return spreads or long-short return spreads, are the returns of a screened portfolio of the top 20% of ranked stocks (quintile 1) minus the returns of the bottom 20% screened portfolio (quintile 5). Stock returns within each portfolio are equally-weighted. The model portfolios are rebalanced at calendar month end.

"Q1 Excess" returns are returns of model portfolios formed from the top 20% of ranked stocks (referred to as "quintile 1" or "Q1") minus the return of the equally-weighted universe. Where noted in tables, Q2, Q3, Q4, and Q5 present the returns of hypothetical portfolios of the lower-ranked quintiles, each containing a distinct 20% portion of the universe.

"Absolute" returns are the model return of the equally-weighted portfolio without subtracting benchmark returns.

"Information Coefficient", or "IC" is the rank correlation of the model monthly scores with the forward 1-month returns of the underlying stocks. An IC score measures how closely related the model rankings (scores) are to the returns that follow. The closer the score/return relationship, the higher the IC.

"Information Ratio" or "IR", of a result is the average of monthly values over the period divided by the standard deviation of these values.

The return of the equally-weighted universe is the return of a portfolio containing the constituents of the reference index (such as the Russell 3000), with equal weighting and a monthly rebalance.

The models were released in January 2011 and were constructed with benefit of hindsight for returns prior to 2011. We refer to the historical period before 2011 as "back-test". We refer to the performance of the model from 2011 and beyond as the "live" performance.

1   Growth Benchmark Model

The Growth Benchmark Model ("GBM") was created to outperform a growth benchmark, defined as the Russell 3000 Growth Index. The model identifies companies with a consistent track record of earnings growth, as well as emerging growth candidates. The model scores are based on seven subcomponents: Earnings Momentum, Historical Growth, Liquidity & Leverage, Price Momentum, Value, Quality, and Capital Efficiency. Table 3 shows the summary performance of the model from January 1987 to December 2016.

Table 3   Summary Historical Performance Statistics for Growth Benchmark Model Russell 3000 Growth Universe (January 1987 – December 2016)

	Q1	Q2	Q3	Q4	Q5	Long-Short Quintile Return Spread
Average Monthly Absolute Return[5]	1.61%***	1.18%***	0.93%***	0.63%*	0.00%	1.61%***
Annualized Absolute Return	21.09%	15.12%	11.75%	7.88%	0.0%	21.10%
Annualized Information Ratio[6]	1.05	0.75	0.56	0.35	0.00	1.79

Information Coefficient Summary	
Average 1-Month IC	0.055***
1-Month IC Information Ratio	0.89
1-Month IC Hit Rate[7]	83%***

*** 1% level of significance; * 10% level of significance

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

1.1   Model Performance in 2016

Figure 5 displays the 1-month average quintile return spreads and 1 month ICs for the model in 2016. The GBM generated positive average return spread of 0.18% and IC of 0.009 in 2016. The model's best months were in January and October when investors were concerned about the slowdown of the Chinese economy and the outcome of the U.S presidential elections respectively. These concerns led to a flight to quality in both months which benefited the GBM as it was constructed to select high quality names with historical and forecasted growth characteristics.
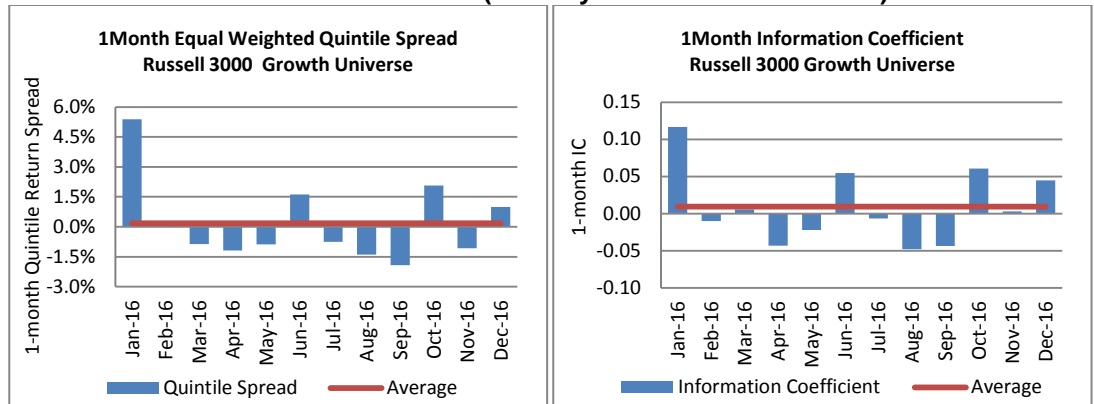
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[5] Average Monthly Returns are absolute returns based on a monthly rebalanced portfolio.

[6] Information Ratio calculated on monthly excess returns relative to the equal-weighted benchmark.

[7] IC Hit Rate is defined as the percentage of months where the IC is positive.

The model struggled in two periods during the year - March through May and July through September. Both periods were generally risk-seeking as investors' risk appetite increased in the light of better than expected economic data, a commodity rally and the Federal Reserve's decision to limit its expected number of rate hikes to two from four. High beta and low quality stocks outperformed low beta and high quality stocks in both periods.
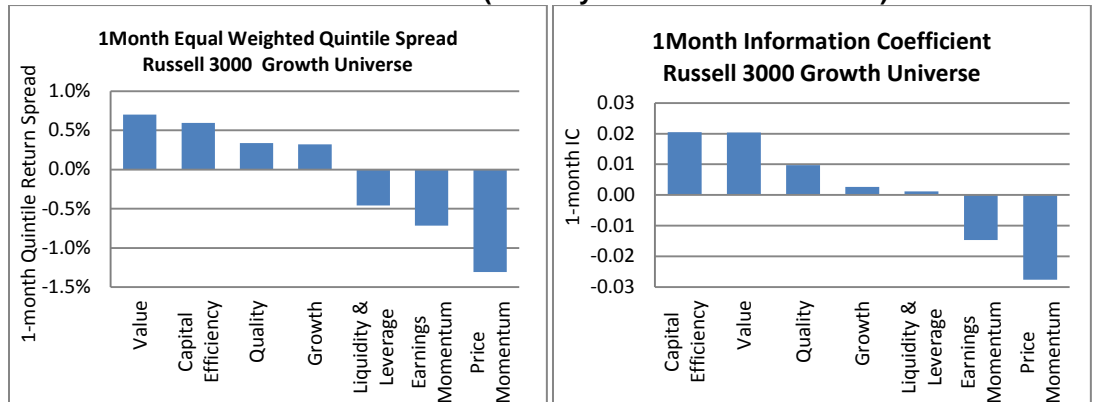
Figure 5   Growth Benchmark Model: Historical 1Month Equal Weighted Quintile Return Spread and Information Coefficient Russell 3000 Growth (January 2016 - December 2016)
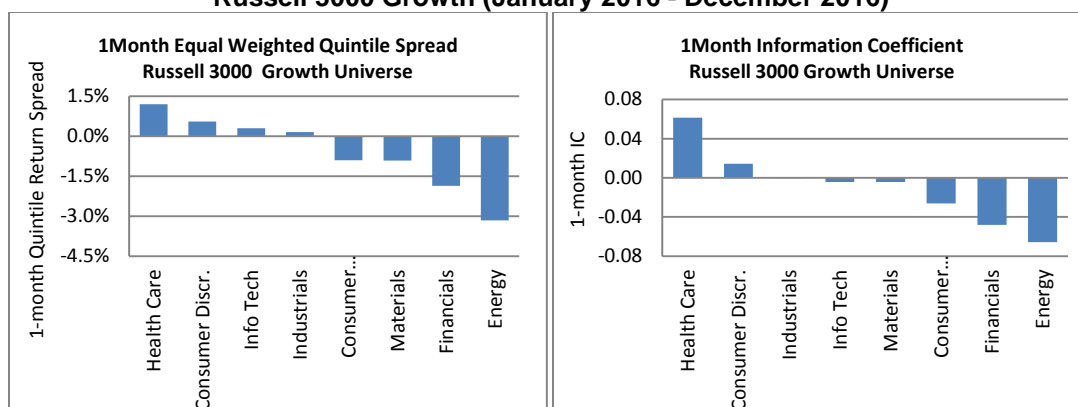

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 01/05/2017.

Figure 6 shows the average 1-month quintile return spread and IC for each subcomponent of the Growth Benchmark Model for 2016. Four of the seven subcomponents – Value, Capital Efficiency, Quality and Growth posted positive return spreads and ICs during the year. The Price Momentum subcomponent was the worst and this is attributable to the short position in Energy names which rallied in 2016.

Figure 6   Growth Benchmark Model Subcomponents:
Historical 1Month Equal Weighted Quintile Return Spread and Information Coefficient Russell 3000 Growth (January 2016 - December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017

1.2   Sector Performance in 2016

Figure 7 breaks out the 2016 quintile return spread and information coefficient of the model for eight of the 11 GICS sectors. Telecommunications and Utilities are excluded because of limited coverage in the benchmark, while Real Estate was left out since it was only carved out into a separate sector in September 2016.

Figure 7   Growth Benchmark Model Sector: 1Month Equal Weighted Historical Quintile Return Spread and IC Russell 3000 Growth (January 2016 - December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The GBM showed positive 1-month average quintile spreads (ICs) in four (three) of eight sectors. The model performed poorly in the Energy sector where it was down by 3% monthly on a long-short return basis.

1.3   Quintile Portfolio Characteristics and Portfolio Tilt Neutralization

Table 4 reports the median market capitalization and 60-month Capital Asset Pricing Model (CAPM) beta of the top and bottom quintile portfolios. The median market cap of the long portfolio (quintile 1) was $1,736 million compared with $1,402 million for the short portfolio, indicating that the model is slightly tilted toward large cap names. The median betas of the long and short portfolios are similar (1.19 vs. 1.17), indicating that the performance of the model was not influenced by the performance of high vs. low beta stocks in 2016.

Table 4   Growth Benchmark Model: Median Market Cap and 60-Month CAPM Beta Quintile 1 and Quintile 5 - Russell 3000 Growth Universe (January 2016 - December 2016)

Median Measure	Quintile 1	Quintile 5
Market Cap ($ Million)	1,736	1,402
60M CAPM Beta	1.19	1.17

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The Russell 2000 Growth Index (a proxy for small cap growth stocks) outperformed the Russell 1000 Growth Index (a proxy for large cap growth stocks) by 4.1% in 2016. Therefore, it is possible that a portion of the underperformance of the GBM could be attributed to a large cap tilt. We show model results after adjusting for size and beta

exposures in Table 5. After neutralizing for size and beta, the performance of the GBM was mostly unchanged.

Table 5   Growth Benchmark Model:
Original and Beta/Size Neutralized Historical Performance
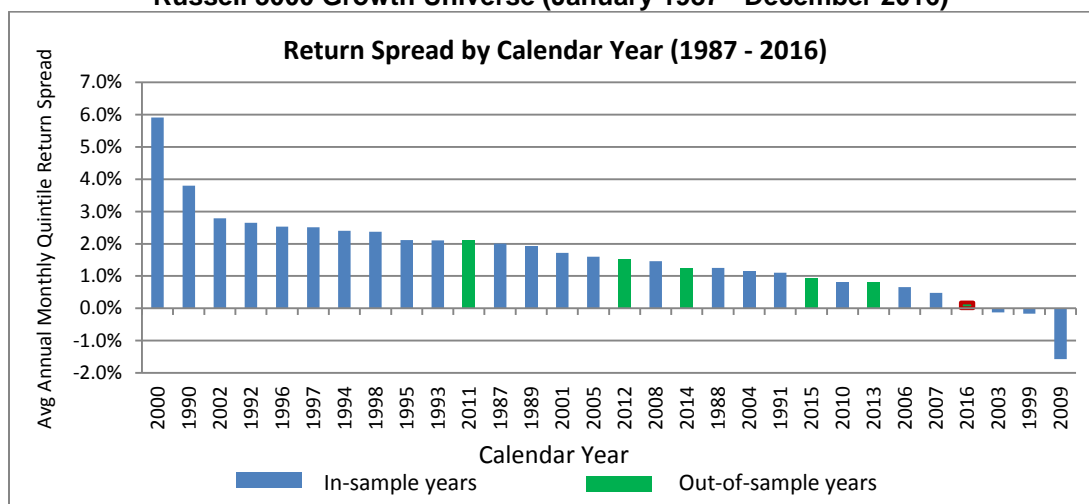**Russell 3000 Growth Universe (January 2016 - December 2016)**

Model	Average 1-Month Quintile Return Spread	Average 1-Month IC
Original GBM	0.18%	0.009
Size/Beta Neutral GBM	0.16%	0.007

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

1.4   Historical Comparison

Figure 8 shows the calendar-year performance of the GBM since 1987. The average monthly quintile spread for 2016 (green bar with red border) was in the 10th percentile of all 30 calendar years. The return spread for the model in the 'live' period (green bars 2011-2016) is 1.13%, compared to 1.73% for the 'back-test' period (blue bars 1987-2010). The worst performing year was 2009 (low price, high beta rally) at -1.57% average monthly spread. Other calendar years with a negative spread were 1999 ("tech bubble") and 2003 ("junk rally").

Figure 8   Growth Benchmark Model: Historical Year Average Monthly
Quintile Return Spread
Russell 3000 Growth Universe (January 1987 - December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. . Data as of 01/05/2017.

2   Value Benchmark Model

The Value Benchmark Model ("VBM") identifies underpriced stocks with strong underlying fundamentals, using intrinsic and relative valuation measures. The model selects companies with low valuations, high earnings quality, stable growth rates, and increasing street sentiment. The Value Benchmark Model has six subcomponents: Valuation, Earnings Quality, Financial Health, Growth Stability, Street Sentiment, and Price Momentum.

Summary performance results from January 1987 to December 2016 are presented in Table 6.

Table 6   Summary Historical Performance Statistics for Value Benchmark Model Russell 3000 Value Universe (January 1987 – December 2016)

	Q1	Q2	Q3	Q4	Q5	Long-Short Quintile Return Spread
Average Monthly Absolute Return	1.41%***	1.07%***	0.83%***	0.50%*	-0.28%	1.70%***
Annualized Absolute Return	18.35%	13.65%	10.44%	6.17%	-3.35%	22.39%
Annualized Information Ratio	1.05	0.79	0.60	0.33	-0.16	2.72

Information Coefficient Summary	
Average 1-month IC	0.056***
1-month IC Information Ratio	0.97
1-month IC Hit Rate	84%***

*** 1% level of significance; * 10% level of significance

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

2.1   Model Performance in 2016

Figure 9 shows the monthly quintile return spreads and ICs for the VBM in the Russell 3000 Value Index for 2016. The average monthly return spread and IC were -0.08% and 0.011, respectively. Similar to the Growth Benchmark Model, the Value Benchmark Model had two stretches of underperformance (March – May and August – September) in 2016. The model posted positive quintile spreads and ICs in the last three months of the year.
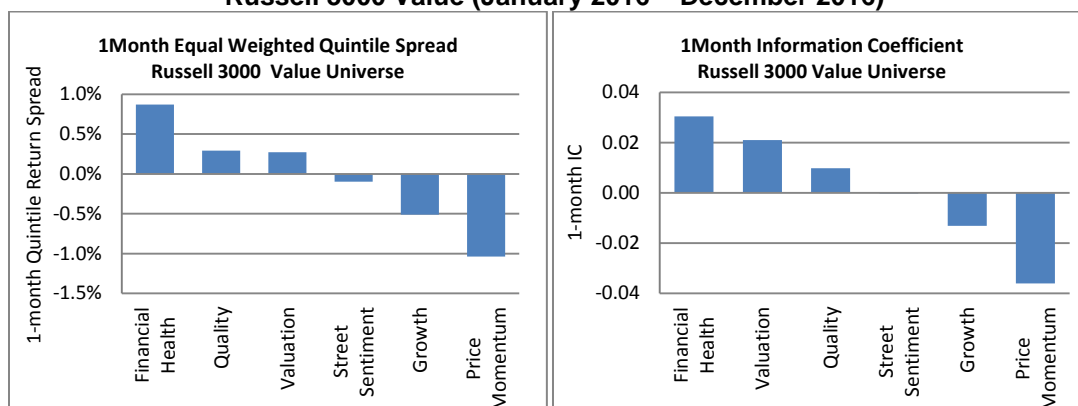
Figure 9   Value Benchmark Model: Historical 1Month Equal Weighted Quintile Spread and IC
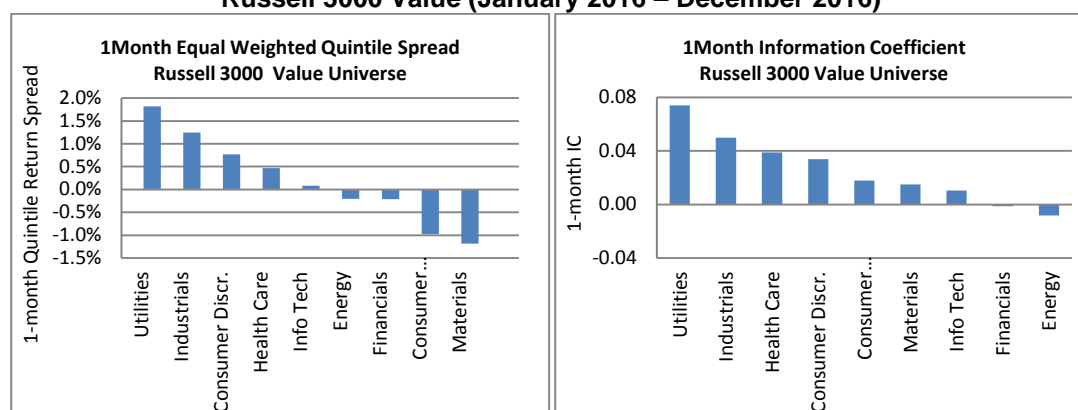**Russell 3000 Value (January 2016 – December 2016)**

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

Figure 10 shows the average 1-month quintile spread and average 1-month IC of each sub-component of the Value Benchmark Model over the Russell 3000 Value universe for 2016. Three of the six subcomponents posted positive ICs and 1-month return spreads during the year. Financial Health, which prefers companies with a strong ability to cover interest payments and short-term obligations, was the best performing component in terms of average 1-month return spread and IC. Similar to the GBM, the Price Momentum subcomponent was the worst component in 2016.

Figure 10   Value Benchmark Model Subcomponents:
Historical 1Month Equal Weighted Quintile Spread and IC
Russell 3000 Value (January 2016 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

2.2   Sector Performance in 2016

The 1-month average quintile return spreads and ICs of the model within nine of the ten GICS sectors are shown in Figure 11. Telecom and Real Estate are excluded because of limited coverage and data history, respectively.

Figure 11   Value Benchmark Model Sector: 1Month Equal Weighted
Historical Quintile Spread and IC
Russell 3000 Value (January 2016 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The Value Benchmark Model produced positive 1-month average return spreads in five out of nine sectors and positive 1-month ICs in 7 out of the 9 sectors. The worst performance

was in the Materials sector with an average 1-month quintile spread of -1.19%. This large monthly negative spread returns was driven by negative returns in three months (February, April and July) that were all greater than -10%. An analysis of VBM's subcomponents in the Materials sector for these three months showed that two subcomponents - Street Sentiment and Growth, had large drawdowns (each down by at least 29% cumulatively) during this period.

2.3   Quintile Portfolio Characteristics and Portfolio Tilt Neutralization

Table 7 details the median market capitalization and median 60-month CAPM beta of quintile 1 (long) and quintile 5 (short) portfolios.

Table 7   Value Benchmark Model: Median Market Cap and 60-Month CAPM Beta
Quintile 1 and Quintile 5: Russell 3000 Value Universe
(January 2016 – December 2016)

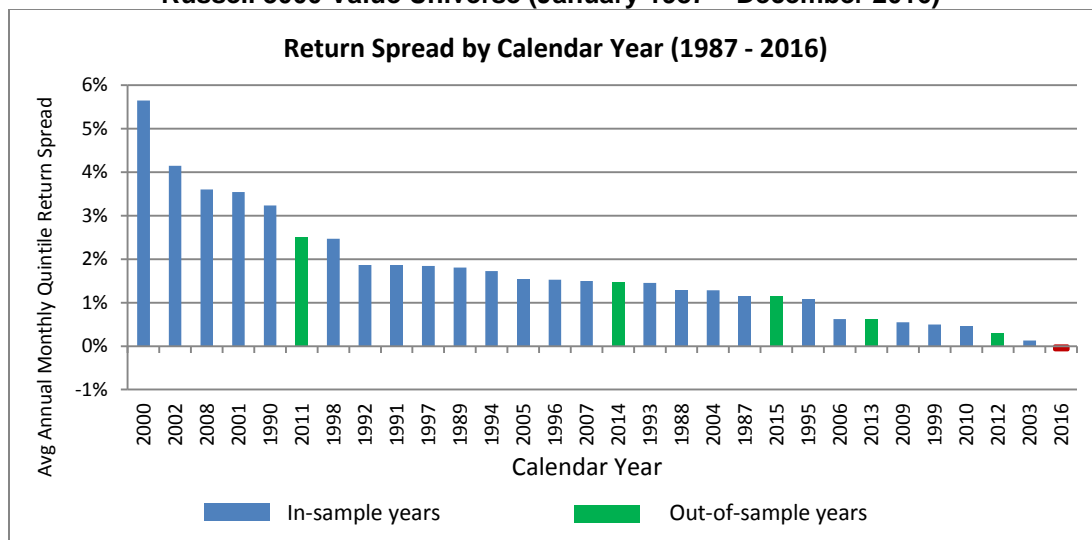| Median Measure	Quintile 1	Quintile 5
Market Cap ($ Million)	1,715	845
60M CAPM Beta	1.10	1.24

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The median market cap of the long portfolio (Q1) was $1.7 billion compared to $0.9 billion for the short portfolio (Q5), indicating a large cap tilt for the VBM's long portfolio. In addition, Q1 had a slightly lower 60-month CAPM beta (1.16) compared to Q5 (1.26). In 2016 the Russell 1000 Value Index (a proxy for large cap value stocks) trailed the Russell 2000 Value Index (a proxy for small cap values stocks) by 14%. Therefore, the performance of VBM was likely impacted negatively by this large cap exposure. To account for this impact, we show the performance of the VBM after we eliminate both beta and market biases in Table 8.

Table 8   Value Benchmark Model:
Original and Beta/Size Neutralized Historical Performance
Russell 3000 Value Universe (January 2016 – December 2016)

Model	Average 1-Month Quintile Return Spread	Average 1-month IC
Original VBM	-0.08%	0.011
Size/Beta Neutral VBM	0.54%	0.019

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The Value Benchmark Model delivered an average monthly quintile return spread of 0.54% after applying beta and size neutralizations, an improvement of 62 basis points over the -0.08% return prior to beta and size neutralizations. We also observe an improvement in IC from 0.011 to 0.019.

2.4   Historical Comparison

The VBM's 'back-test' (1987-2010: shown in blue bars) and 'live' (2011-2016: shown in green bars) quintile return spreads are displayed in Figure 12. Last year was the first time the model's long-short returns was negative either in back-test or live period.
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Figure 12   Value Benchmark Model: Historical Year Average Monthly Quintile Return Spread
Russell 3000 Value Universe (January 1987 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

3   Quality Model

The Quality Model ("QM") seeks to extend the analysis of earnings quality beyond accruals and includes several measures of balance sheet efficiency/strength that have been shown to be good indicators of medium and long-term earnings quality. The Quality Model is comprised of five subcomponents: Growth Stability, Operating Efficiency, Valuation, Financial Health and Earnings Quality. We detail the summary performance statistics for the model from January 1987 to December 2016 in Table 9.

Table 9   Summary Historical Performance Statistics for Quality Model
Russell 3000 (January 1987 – December 2016)

	Q1	Q2	Q3	Q4	Q5	Long-Short Quintile Return Spread
Average Monthly Absolute Return	1.33%***	1.08%***	0.78%***	0.43%	-0.23%	1.56%***
Annualized Absolute Return	17.23%	13.80%	9.74%	5.28%	-2.68%	20.40%
Annualized Information Ratio	0.99	0.45	-0.84	-2.32	-2.24	2.15

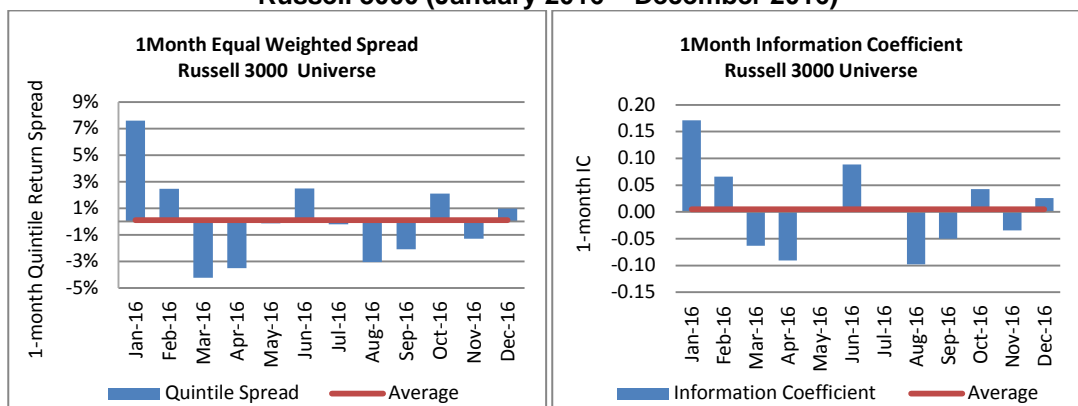| Information Coefficient Summary	
Average 1-month IC	0.054***
1-month IC information Ratio	0.85
1-month IC Hit Rate	81%***

*** 1% level of significance

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

3.1   Model Performance in 2016

The QM yielded an average 1-month equal-weighted quintile return spread and 1-month IC of 0.09% and 0.005, respectively in 2016 (Figure 13). The model posted negative return spreads (ICs) in seven (five) out of 12 months. January was the best performing month with a return spread and IC of 7.59% and 0.17, respectively, during the flight to high quality names as concerns of a slowing Chinese economy mounted. The model posted positive spreads and ICs across all five subcomponents during this month.

Figure 13   Quality Model: Historical 1Month Equal Weighted Quintile Return Spread and IC Russell 3000 (January 2016 – December 2016)
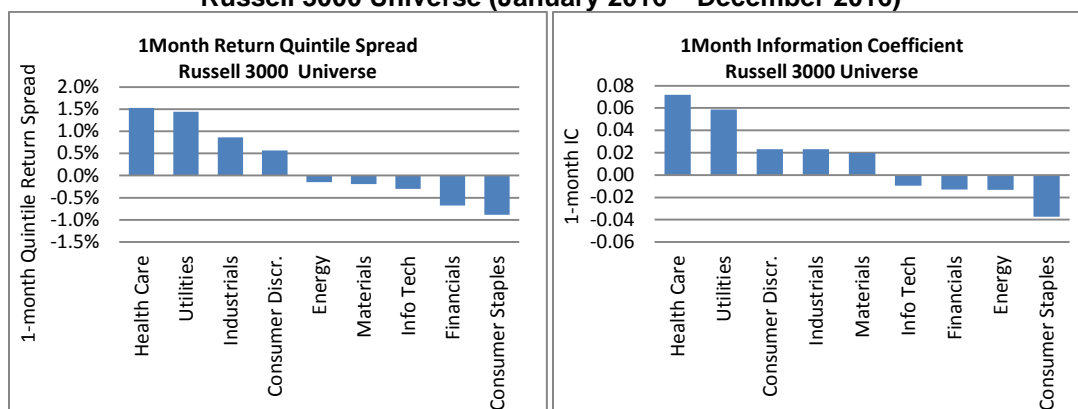

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 01/05/2017.

Figure 14 shows the average 1-month quintile return spread and average IC for each subcomponent of the Quality Model over the Russell 3000 universe for 2016.   Growth Stability was the main reason for the tepid performance of the QM – the subcomponent generated a negative monthly return spread and IC of -0.49% and -0.009, respectively.

Figure 14   Quality Model Subcomponents: Historical 1Month Equal Weighted Quintile Return Spread and IC Russell 3000 (January 2016 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

3.2   Sector Performance in 2016

The average historical 1-month quintile return spread and IC of the QM for nine GICS sectors are detailed in Figure 15. Telecom and Real Estate are excluded because of limited coverage and data history, respectively. Four of the nine sectors posted positive 1-month average return spreads and ICs. Health Care and Utilities were the top two performing sectors, while Consumer Staples was the weakest on both return spread and IC.

**Figure 15   Quality Model Sector: 1Month Equal Weighted
Historical Quintile Spread and IC
Russell 3000 Universe (January 2016 – December 2016)**

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

3.3   Quintile Portfolio Characteristics and Portfolio Tilt Neutralization

The QM's median market capitalization and median 60-month CAPM beta of the top (Quintile 1) and bottom (Quintile 5) portfolios are shown in Table 10. As expected, the long portfolio (Quintile 1) was tilted towards large cap names, as these names tend to provide more stable earnings and dividend streams compared to small cap stocks. We also observe that the Q1 portfolio had a smaller beta compared to Q5.

**Table 10   Quality Model: Median Market Cap and 60-Month CAPM Beta
Quintile 1 and Quintile 5 – Russell 3000 Universe (January 2016 – December 2016)**

Median Measure	Quintile 1	Quintile 5
Market Cap ($Million)	2,072	886
60M CAPM Beta	1.06	1.26

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The Russell 2000 Index (a proxy for small cap stocks) outperformed the Russell 1000 Index (a proxy for large cap stocks) by 9.3% in 2016. Therefore, it is possible that a portion of the weak performance of the QM could be attributed to its large cap tilt. To adjust for this impact, we back-test the model after adjusting for size and beta exposures and show the performance in Table 11. The Quality Model delivered an average monthly quintile spread of 0.32% in 2016, after applying the beta and size neutralization. This is slightly higher than that of the original model (0.09%). The average 1-month IC also improved marginally from 0.005 to 0.008.
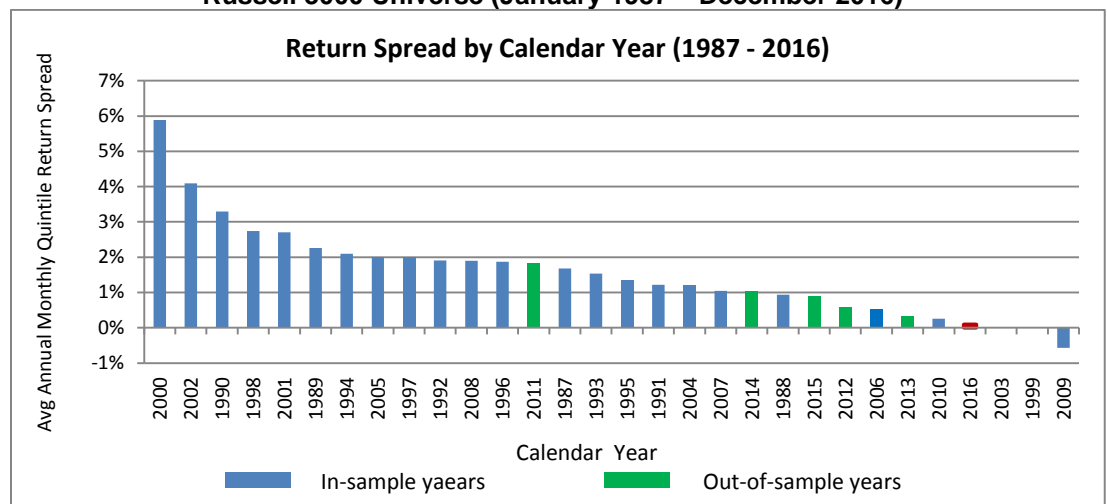
Table 11   Quality Model: Original and Beta/Size Neutralized Historical Performance Russell 3000 Universe (January 2016 – December 2016)

Model	Average 1-Month Quintile Return Spread	Average 1-Month IC
Original QM	0.09%	0.005
Size/Beta Neutral QM	0.32%	0.008

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

3.4   Historical Comparison

We display the model's average 1-month quintile return spread by calendar year in Figure 16. 2016's long-short return spread ranks in the 10th percentile of calendar year since 1987. The best average long-short return spread was in 2000 (5.89%) when value and high quality stocks rallied after the collapse of the tech bubble. The worst return for the QM was in 2009 (-0.57%) when high beta and low price stocks outperformed the broader market.

Figure 16   Quality Model: Historical Year Average Monthly Quintile Return Spread Russell 3000 Universe (January 1987 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

4   Price Momentum Model

The Price Momentum Model ("PMM") was constructed to capture relative strength in stocks based on trailing price momentum and trading volume data. The model is made up of Short-Term and Long-Term components: the short term component uses a look-back window of 1 to 3 months, while the longer term component is based on a window of 3 to 12 months. We detail the summary performance statistics for the PMM in Table 12.

Table 12   Summary Historical Performance Statistics for Price Momentum Model
Russell 3000 (January 1987 – December 2016)

	Q1	Q2	Q3	Q4	Q5	Long-Short Quintile Return Spread
Average Absolute Monthly Return	1.48%***	1.12%***	0.76%**	0.26%	-0.46%	1.94%***
Annualized Absolute Return	19.28%	14.31%	9.45%	3.14%	-5.38%	25.93%
Annualized Information Ratio	1.01	0.56	-1.00	-2.48	-2.49	2.15

Information Coefficient Summary	
Average 1-Month IC	0.068***
1-month IC information Ratio	0.75
1-month IC Hit Rate	81.3%***

*** 1% level of significance; ** 5% level of significance

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

4.1   Model Performance in 2016

Figure 17 shows the 1-month equal-weighted quintile return spread and IC for the PMM over the Russell 3000 universe in 2016. The average monthly spread (IC) was -0.49% (-0.001) for the year. The model posted negative return spread in eight out of 12 months, hurt by an under-weight in the Energy sector, which rallied in 2016.

Figure 17   Price Momentum Model: Historical 1Month Equal Weighted
Quintile Return Spread and IC
Russell 3000 (January 2016 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.
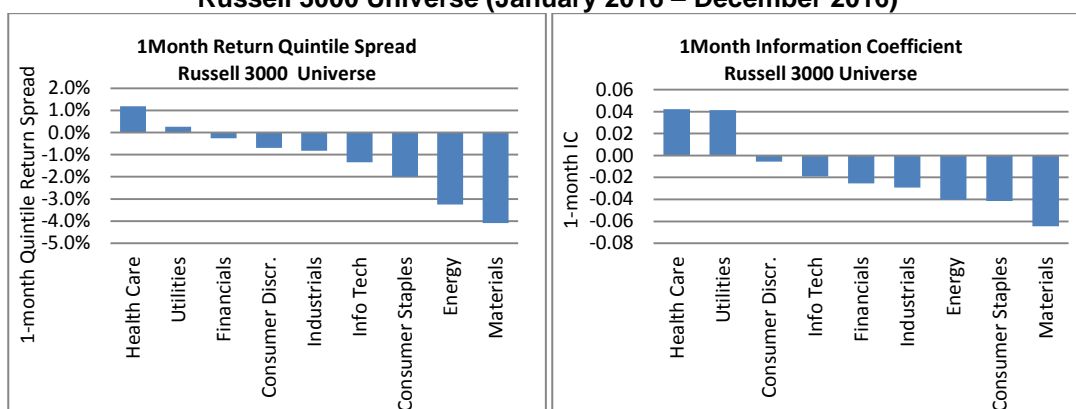
Table 13 and Figure 18 show the average 1-month quintile spread and IC for both the Short- and Long-Term components of the Price Momentum Model. The performance of the Long-Term component was particularly weak, with negative return spreads (ICs) of -1.08% (-0.022) for the year. In March and November, drawdowns for the Long-Term component exceeded 5% as high beta stocks outperformed low beta stocks.

**Table 13   Summary Historical Performance Statistics for
Price Momentum Model Subcomponents
Russell 3000 (January 2016 – December 2016)**

Component	Average 1-Month Quintile Return Spread	Average 1-Month IC
Short-Term Component	0.38%	0.019
Long-Term Component	-1.08%	-0.022

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

**Figure 18   Price Momentum Model Subcomponents:
Historical 1Month Equal Weighted Quintile Return Spread
Russell 3000 (January 2016 – December 2016)**
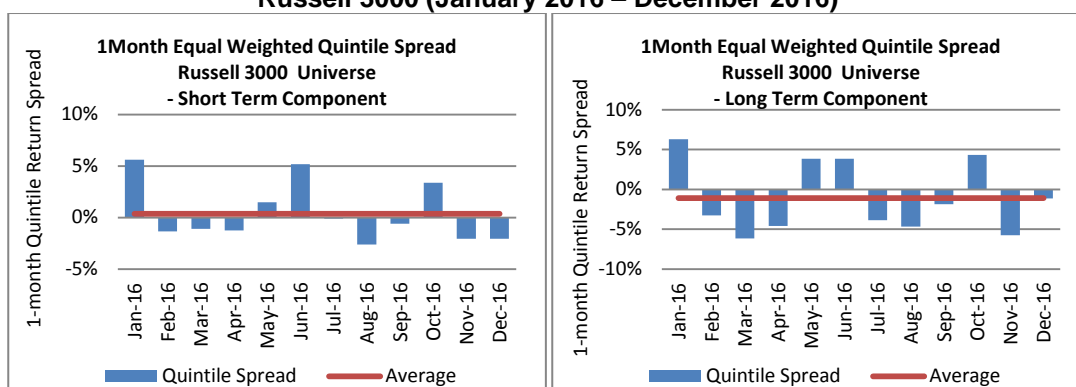
Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 01/05/2017.

4.2   Sector Performance in 2016

Figure 19 breaks out the average monthly quintile return spread and information coefficient of the model for the nine GICS sectors. Telecom and Real Estate are excluded because of limited coverage and data history, respectively. The Price Momentum Model showed positive 1-month average spreads and IC in only two sectors: Health Care and Utilities.

**Figure 19   Price Momentum Model Sector: 1Month Equal Weighted
Historical Quintile Spread and IC
Russell 3000 Universe (January 2016 – December 2016)**

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

4.3   Quintile Portfolio Characteristics and Portfolio Tilt Neutralization

Table 14 shows the median market capitalization and 60-month CAPM beta of the top and bottom quintile portfolios. Similar to the other models, the Price Momentum Model had a large cap bias. The median market cap of the long portfolio (quintile 1) was $2,493 million compared with $966 million for the short portfolio. The PMM also tilted toward low beta stocks. The median beta of the long portfolio was 0.90 while that of the short portfolios was 1.39.

Table 14   Price Momentum Model: Median Market Cap and 60-Month CAPM Beta
Quintile 1 and Quintile 5 – Russell 3000 Universe (January 2016 – December 2016)

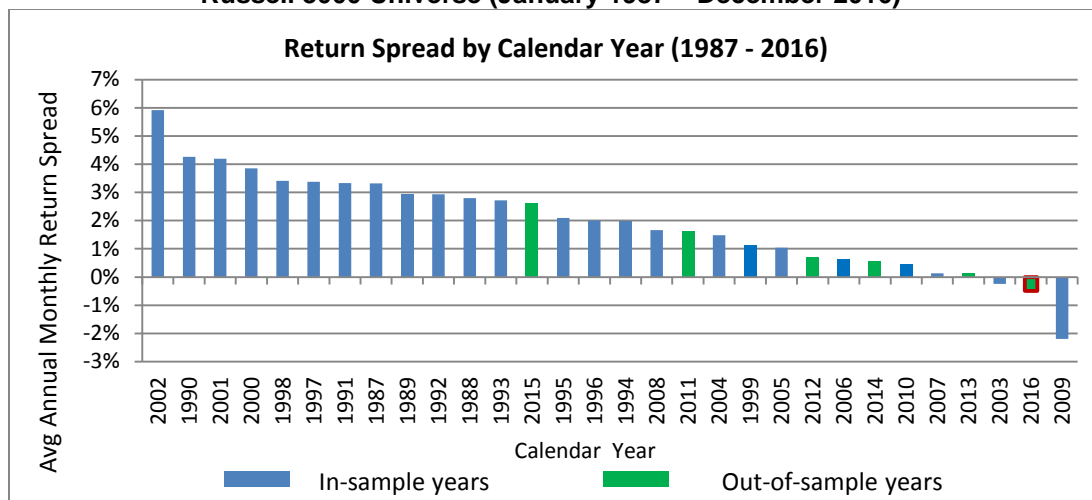| Median Measure	Quintile 1	Quintile 5
Market Cap ($ Million)	2,493	966
60M CAPM Beta	0.90	1.39

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

The Russell 2000 Index (a proxy for small cap stocks) outperformed the Russell 1000 Index (a proxy for large cap stocks) by 9.3% in 2016. Also, high beta stocks (the 20% stocks with the highest beta in the Russell 3000 Index) outperformed low beta stocks (the 20% stocks with the lowest beta in the same index) by an annualized 4.2%[8] for the year. The large cap and low beta biases of the model could have a negative impact on performance. To adjust for this impact, we back-test the model after adjusting for size and beta exposures. Table 15 demonstrates that the neutralization had marginal effect on the model performance.

Table 15   Price Momentum Model:
Original and Beta/Size Neutralized Historical Performance
Russell 3000 Universe (January 2016 – December 2016)

Model	Average 1-Month Quintile Return Spread	Average 1-Month IC
Original PMM	-0.49%	-0.001
Size/Beta Neutral PMM	-0.48%	-0.003

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

4.4   Historical Comparison

The model's 2016 monthly quintile return spread of -0.49% (green bar with red border) was the second lowest among all calendar years (Figure 20). The worst performing year historically was 2009 when momentum as a theme failed dramatically.

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[8] The return difference is calculated as the difference between the equal-weighted monthly return of the 20% stocks with the highest and lowest beta in the Russell 3000 Index, multiplied by 12.

Figure 20   Price Momentum Model:
Historical Year Average Monthly Quintile Return Spread
Russell 3000 Universe (January 1987 – December 2016)

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

5   Model Stability

We measure model stability in 2016 using the autocorrelation of monthly ranks, shown in Table 16. The correlation numbers are in line with what were observed during model back-tests. The relatively high autocorrelation observed for GBM, VBM and QM suggests that there is limited turnover in the quintile portfolios formed based on these models. High autocorrelation is a favorable characteristic for the reduction of portfolio turnover and trading costs.

Table 16   Model 1-Month Rank Autocorrelation
Russell 3000 Growth/Russell 3000 Value/Russell 3000
(January 2016 – December 2016)

Model	1-month Rank Autocorrelation
Growth Benchmark Model	0.92
Value Benchmark Model	0.92
Quality Model	0.90
Price Momentum Model	0.62

Source: S&P Global Market Intelligence Quantamental Research. All returns and 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. Data as of 01/05/2017.

6   Conclusions

2016 proved to be a challenging year for active investing. Against a backdrop of a sharp selloff in equities at the beginning of the year and political uncertainty over the course of the year, a majority of popular investment strategies posted lackluster performance, with value being the only fundamental investing style that delivered positive return spreads. The underperformance of the other fundamental investing styles took a toll on the GBM, VBM and QM, which all generated weak returns for the year. The rally in oil also hurt PMM's performance as the model carried over its underweight of the Energy sector from 2015 into 2016.

Appendix A

Definitions of Strategy Style Composites

Style Composites	Description
Analyst Expectations	A combination of analyst forecast based factors that reflect the sentiment among the analysts.
Capital Efficiency	A combination of factors that measure a firm's ability to deliver excess returns over its cost of capital.
Earnings Quality	A combination of factors that measure the persistence and stability of a firm's earnings.
Historical Growth	A combination of growth in a firm's earnings, cash flows and turnover.
Price Momentum	A combination of short- and long-term stock price movements.
Size	A combination of market capitalization and sales of a firm.
Valuation	A combination of six valuation metrics to assess the relative attractiveness of a firm based on its fundamentals.
Volatility	A combination of stock return dispersions and beta.

Appendix B

24-Month Rolling Correlation between Long-Short Monthly Returns of the Value Style Composite and Volatility Style Composite
(S&P 500 Index: January 1989 – December 2016)
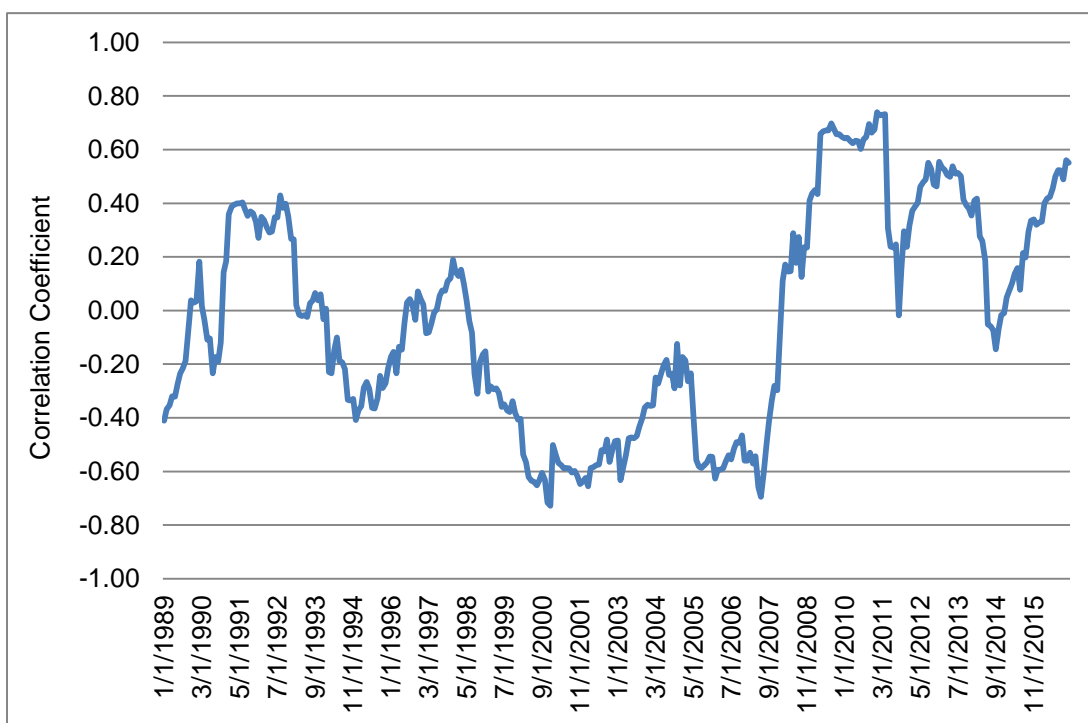
Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 01/05/2017.

Appendix C

The Global Industry Classification Standard (GICS®) was jointly developed by Standard & Poor's and MSCI Barra to meet the global financial community's need for one complete, consistent set of global sector and industry definitions. The GICS methodology has helped pave the way for sector-based investing by providing transparency and efficiency to the investment process. With GICS, sell-side research and reporting can be organized around industry data without geographic limitations.

The GICS methodology has been commonly accepted as an industry analysis framework for investment research, portfolio management and asset allocation. The GICS classification system currently consists of 11 sectors, 24 industry groups, 68 industries and 157 sub-industries. The GICS sectors are:

- Consumer Discretionary
- Consumer Staples
- Energy
- Financials
- Health Care
- Industrials
- Information Technology
- Materials
- Telecommunication Services
- Utilities
- Real Estate

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Vivian Ning and Li Ma, February 2016, "U.S. Stock Selection Model Performance Review, The most effective investment strategies in 2015", S&P Global Market Intelligence Quantamental Research

Our Recent Research

November 2016: Electrify Stock Returns in U.S. Utilities
The U.S. utilities sector has performed especially well in the past several years as the Federal Reserve and central banks around the world enacted accommodative monetary policies to spur growth. As global active investors flock to the U.S. utilities sector in search of yields and high risk-adjusted returns, we explore a number of utility-specific metrics from a unique database that is dedicated to the utilities sector – S&P Global Market Intelligence's Energy (Source: SNL Energy) – to ascertain whether investors could have historically made stock selection decisions within the sector to achieve excess returns.

October 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 2
SNL Financial's ("SNL") 1 global real estate database contains property level and geographical market-based demographic information that can be difficult for investors to obtain. These unique data points are valuable to investors seeking an understanding of the relationship between property level information and future stock price movement. In this report, we demonstrate how investors can use these data points as alpha strategies. Our back-tests suggest that metrics constructed from property level information may provide insights about future price direction not captured by fundamental or estimates data. Investors may want to consider incorporating information on a REIT's property portfolio when building a robust REIT strategy

September 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 1
This month REITs (Real Estate Investment Trusts) have been separated from the GICS (Global Industry Classification Standard) Financial sector into a sector of their own. Even prior to the sector reclassification, investors have been attracted to REITs' strong performance and attractive yield. REITs differ from traditional companies in several important ways. Metrics that investors typically use to value or evaluate the attractiveness of stocks such as earnings yield or book-to-price are less meaningful for REITs. For active investors interested in understanding their REITs portfolio, an understanding of the relationship between REIT financial ratios and price appreciation is instructive. Is dividend yield relevant? What about funds from operations ("FFO"), one of the most widely used metrics?

August 2016: Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)
In this study we show that, among Russell 3000 firms with acquisitions greater than 5% of acquirer enterprise value, post-M&A acquirer returns have underperformed peers in general. Specifically, we find that:
- Acquirers lag industry peers on a variety of fundamental metrics for an extended period following an acquisition.
- Stock deals significantly underperform cash deals. Acquirers using the highest percentage of stock underperform industry peers by 3.3% one year post-close and by 8.1% after three years.
- Acquirers that grow quickly pre-acquisition often underperform post-acquisition.
- Excess cash on the balance sheet is detrimental for M&A, possibly due to a lack of discipline in deploying that cash.

July 2016: Preparing for a Slide in Oil Prices -- History May Be Your Guide
With the price of West Texas Intermediate (WTI) in the mid-forties, oversupply concerns and the continued threat of a global slowdown have led many to fear a resumed oil price decline. The year-to-date performance of Oil & Gas (O&G) companies, particularly Integrated O&G entities has been strong, further contributing to concerns that oil may be poised to retrench.

June 2016: Social Media and Stock Returns: Is There Value in Cyberspace?
This review of social media literature represents a selection of articles we found particularly pragmatic and/or interesting. Although we have not done research in the area of social media, we are always on the hunt for interesting insights, and offer these papers for your thoughtful consideration.

April 2016: An IQ Test for the "Smart Money" – Is the Reputation of Institutional Investors Warranted?
This report explores four classes of stock selection signals associated with institutional ownership ('IO'): Ownership Level, Ownership Breadth, Change in Ownership Level and Ownership Dynamics. It then segments these signals by classes of institutions: Hedge Funds, Mutual Funds, Pension Funds, Banks and Insurance Companies. The study confirms many of the findings from earlier work – not only in the U.S., but also in a much broader geographic scope – that Institutional Ownership may have an impact on stock prices. The analysis then builds upon existing literature by further exploring the benefit of blending 'IO' signals with traditional fundamental based stock selection signals.

March 2016: Stock-Level Liquidity – Alpha or Risk? - Stocks with Rising Liquidity Outperform Globally
Most investors do not associate stock-level liquidity as a stock selection signal, but as a measure of how easily a trade can be executed without incurring a large transaction cost or adverse price impact. Inspired by recent literature, such as Bali, Peng, Shen and Tang (2012), we show globally that a strategy of buying stocks with the highest one-year change in stock-level turnover has historically outperformed the market and has outperformed strategies of buying stocks with strong price momentum, attractive valuation, or high quality. One-year change in stock-level turnover has a low correlation (i.e., <0.15) with commonly used stock selection signals. When it is combined with these signals, the composites have yielded higher excess returns and information ratios (IR) than the standalone raw signals.

February 2016: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2015
Since the launch of the four S&P Capital IQ® U.S. stock selection models in January 2011, **the performance of all four models (Growth Benchmark Model, Value Benchmark Model, Quality Model, and Price Momentum Model) has been positive each year**. The models' key differentiators – a distinct formulation for large cap versus small cap stocks, incorporation of industry specific information for the financial sector, sector neutrality to target stock specific alpha, and factor diversity – enabled the models to outperform across disparate market environments. In this report, we assess the underlying drivers of each model's performance in 2015 and since inception (2011), and provide full model performance history from January 1987.

January 2016: What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News
This study examines stock price movements surrounding earnings per share (EPS) guidance announcements for U.S. companies between January 2003 and February 2015 using S&P Capital IQ's Estimates database. Companies that experienced positive guidance

news, i.e. those that announced optimistic guidance (guidance that is higher than consensus estimates) or revised their guidance upward, yielded positive excess returns. We focus on guidance that is not issued concurrent with earnings releases in order to have a clear understanding of the market impact of guidance disclosures. We also explore practical ways in which investors may benefit from annual and quarterly guidance information.

December 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 6

November 2015: Late to File - The Costs of Delayed 10-Q and 10-K Company Filings

October 2015: Global Country Allocation Strategies

September 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 5

September 2015: Research Brief: Building Smart Beta Portfolios

September 2015: Research Brief – Airline Industry Factors

August 2015: Point-In-Time vs. Lagged Fundamentals – This time i(t')s different?

August 2015: Introducing S&P Capital IQ Stock Selection Model for the Japanese Market

July 2015: Research Brief – Liquidity Fragility

June 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 4

May 2015: Investing in a World with Increasing Investor Activism

April 2015: Drilling for Alpha in the Oil and Gas Industry – Insights from Industry Specific Data & Company Financials

March 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 3

February 2015: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2014

January 2015: Research Brief: Global Pension Plans - Are Fully Funded Plans a Relic of the Past?

January 2015: Profitability: Growth-Like Strategy, Value-Like Returns Profiting from Companies with Large Economic Moats

November 2014: Equity Market Pulse – Quarterly Equity Market Insights Issue 2

October 2014: Lenders Lead, Owners Follow - The Relationship between Credit Indicators and Equity Returns

August 2014: Equity Market Pulse – Quarterly Equity Market Insights Issue 1

July 2014: Factor Insight: Reducing the Downside of a Trend Following Strategy

May 2014: Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model

April 2014: Riding the Coattails of Activist Investors Yields Short and Long Term Outperformance

March 2014: Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources

February 2014: Obtaining an Edge in Emerging Markets

February 2014: U.S Stock Selection Model Performance Review

January 2014: Buying Outperformance: Do share repurchase announcements lead to higher returns?

October 2013: Informative Insider Trading - The Hidden Profits in Corporate Insider Filings

September 2013: Beggar Thy Neighbor – Research Brief: Exploring Pension Plans

August 2013: Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets: The Foundations of Outperformance

July 2013: Inspirational Papers on Innovative Topics: Asset Allocation, Insider Trading & Event Studies

June 2013: Supply Chain Interactions Part 2: Companies – Connected Company Returns Examined as Event Signals

June 2013: Behind the Asset Growth Anomaly – Over-promising but Under-delivering

April 2013: Complicated Firms Made Easy - Using Industry Pure-Plays to Forecast Conglomerate Returns.

March 2013: Risk Models That Work When You Need Them - Short Term Risk Model Enhancements

March 2013: Follow the Smart Money - Riding the Coattails of Activist Investors

February 2013: Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012

January 2013: Research Brief: Exploiting the January Effect Examining Variations in Trend Following Strategies

December 2012: Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover

November 2012: 11 Industries, 70 Alpha Signals -The Value of Industry-Specific Metrics

October 2012: Introducing S&P Capital IQ's Fundamental Canada Equity Risk Models

September 2012: Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?

August 2012: Supply Chain Interactions Part 1: Industries Profiting from Lead-Lag Industry Relationships

July 2012: Releasing S&P Capital IQ's Regional and Updated Global & US Equity Risk Models

June 2012: Riding Industry Momentum – Enhancing the Residual Reversal Factor

May 2012: The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions

March 2012: Exploring Alpha from the Securities Lending Market – New Alpha Stemming from Improved Data

January 2012: S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011

January 2012: Intelligent Estimates – A Superior Model of Earnings Surprise

December 2011: Factor Insight – Residual Reversal

November 2011: Research Brief: Return Correlation and Dispersion – All or Nothing
October 2011: The Banking Industry

September 2011: Methods in Dynamic Weighting

September 2011: Research Brief: Return Correlation and Dispersion

July 2011: Research Brief - A Topical Digest of Investment Strategy Insights
June 2011: A Retail Industry Strategy: Does Industry Specific Data tell a different story?

May 2011: Introducing S&P Capital IQ's Global Fundamental Equity Risk Models

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April 2011: Can Dividend Policy Changes Yield Alpha?

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March 2011: How Much Alpha is in Preliminary Data?

February 2011: Industry Insights – Biotechnology: FDA Approval Catalyst Strategy

January 2011: US Stock Selection Models Introduction

January 2011: Variations on Minimum Variance

January 2011: Interesting and Influential Papers We Read in 2010

November 2010: Is your Bank Under Stress? Introducing our Dynamic Bank Model

October 2010: Getting the Most from Point-in-Time Data

October 2010: Another Brick in the Wall: The Historic Failure of Price Momentum

July 2010: Introducing S&P Capital IQ's Fundamental US Equity Risk Model