Obtaining an Edge in Emerging Markets

S&P Capital IQ's Model Identifies Drivers of Return

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Following the introduction of our global stock selection models for developed markets (DM) in August 2013[1], we launch our stock selection model for emerging markets (EM) in this report. Leveraging S&P Capital IQ's Point-in-Time (PIT) data, our model offers a systematic and robust approach to stock picking in global emerging markets. We tested our model over the S&P BMI for emerging markets and report the following:

- **A systematic approach to stock-picking generates alpha in emerging markets.** From January 2002 – September 2013, our Emerging Market Model (EMM) generated an average 1-month top quintile excess return, monthly long-short spread and 1-month IC[2] of 0.90%, 1.76% and 0.065 respectively, all statistically significant at the 1% level.

- **The Model's performance is robust across regions and sectors.** EMM's 1-month top quintile excess return is positive and statistically significant at the 1% level in all the five regions and 10 GICS sectors we tested the model in, with the best performance recorded in Asia ex China & Taiwan (1.04%) and in the Healthcare sector (0.90%).

- **EMM's performance metrics are strong within the largest securities in emerging markets.** EMM generated an average 1-month excess return and IC of 0.97% and 0.056 respectively, both significant at the 1% level, when we restricted our universe to the largest 50% of names by market capitalization within the S&P BMI EM universe.

- **Model performance is identical in growth and value environments, and positive in periods of high volatility.** The model's 1-month average top quintile excess return is similar in both value (0.80%) and growth (0.79%) regimes. While the model posts its best performance in risk-averse periods, the results in risk-seeking periods are positive and statistically significant – the average 1-month top quintile excess return is 0.53% (significant at the 1% level) when volatility is elevated.

- **EMM outperforms the benchmark after accounting for transaction costs and applying several real world portfolio constraints.** A simulated portfolio generated an annualized excess return of 10.5% and information ratio of 1.8 between January 2002 and September 2013.

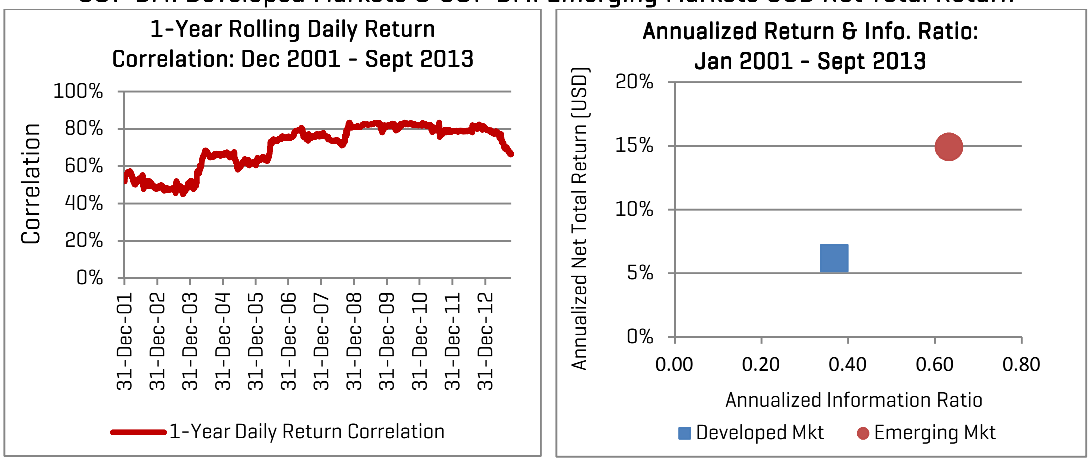
[1] Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets

[2] Excess return is the return of a quintile portfolio minus the benchmark; long-short return is the return of the top quintile portfolio minus the return of the bottom quintile portfolio; IC is the rank correlation of alpha forecasts to forward stock return

1 Introduction

Investing in emerging markets is desirable from two perspectives: First, from an asset allocation context, the moderate correlation of EM returns with DM returns illustrates that emerging markets can be treated as a distinct asset class from developed markets. Secondly, investing in the EM space provides a rich opportunity to capture alpha since emerging markets are considered to be less efficient than developed markets. The left chart of Figure 1 shows the 1-year daily rolling return correlation of the S&P BMI DM with the S&P BMI EM over the last 12 years. While correlation has risen over the years (it was especially elevated during the global financial crisis), it has recently fallen to 0.66, below the 12 year average of 0.70.

Figure 1: 1-Year Rolling Daily Correlation and Annualized Return/Information Ratio S&P BMI Developed Markets & S&P BMI Emerging Markets USD Net Total Return



Source: S&P Capital IQ Quantamental Research

Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

On a both a total return and risk-adjusted return basis, the performance of emerging markets has been superior to that of developed markets since the beginning of 2001 (the right chart of Figure 1). While the S&P BMI EM has returned 15% annualized since January 2001, the corresponding return of the S&P BMI DM has only been 6%. Over the same time interval, the information ratio of the S&P BMI EM has been 70% higher than that of the S&P BMI DM (0.63 vs 0.37).

However, there are challenges to investing in emerging markets, including data availability and reliability, liquidity constraints, and short-selling restrictions. S&P Capital IQ's PIT data provides a rich, look-ahead free and standardized history of financial information in emerging markets, and it serves as our primary source of financial data for our model. We will also focus mostly on long-only portfolio performance, thus side-stepping issues with varying short-selling restrictions across different markets.

2 Key Model Differentiators

100% Point-in-Time

We have highlighted the benefits of Point-in-Time data in our past research, but most of our previous work using PIT data was focused on the U.S and more recently, developed markets. This is the first time we are using S&P Capital IQ's PIT data extensively in the emerging market space for model construction, and we expect the benefit of using this form of data to be more pronounced within EM countries.

Point-in-Time data reflects the true state of information available to investors at any specific point in the past

Table 1: Company Filing Schedule for the U.S and China
S&P BMI January 2010 - December 2012

	U.S		China	
Filing Bin (Days)	*# of Filers*	*Cum %*	*# of Filers*	*Cum %*
<=60	5163	64.3%	40	2.4%
61-90	2819	99.4%	696	45.0%
91-120	25	99.8%	852	97.1%
121-150	4	99.8%	28	98.8%
>150	16	100.0%	19	100.0%

Source: S&P Capital IQ Quantamental Research

Table 1 shows the company filing schedule for the last three fiscal years for the U.S and China, the largest countries by market capitalization in the S&P BMI DM and S&P BMI EM respectively. The table shows the breakdown by number and cumulative percentage of filers within each filing bin (annual filings only). U.S and Chinese companies are required to file annual reports within 90 and 120 days respectively. Only 0.6% of U.S filers fail to file within the 90-day deadline; the proportion is 5 times as large for Chinese filers at 2.9%. Apart from the obvious look-ahead bias that PIT data eliminates, it also enables a user to take advantage of data published well before a filing deadline. For example, 64%and 45% of companies in the U.S and China respectively filed their annual report 30 days before the required filing deadline over the period 2010 - 2012.

Industry Specific Treatment for Banks

Identify industry drivers of performance

Regular readers of our research will be familiar with the work we have done using industry specific data, especially in the banking industry[3]. Since generic factors may not fully capture the operating dynamics of banks, we include industry specific information to derive a complete picture of a bank's funding mix, asset quality and capitalization level.

Distinct Regional and Country Models

Distinct models were built for China, Taiwan, Asia ex China & Taiwan, LATAM and Europe & Africa

Significant variation in factor performance has been documented within developed market nations[4], even though equity markets in these countries tend to be more integrated compared to emerging markets. Emerging market nations are often quite different in terms of political structure and capital market development; it is therefore likely that country effects are an important determinant of security returns in EM. Rather than use a "one-size" fits all approach, we built distinct regional models or country models for our emerging market universe.

[3] See The Banking Industry - New Bank Specific Data as an Alpha Source
[4] See Asness, Maskowitz and Pedersen, "Value and Momentum Everywhere" (2010)

3 Model Construction Methodology

The building block for our EM models are the 450+ global factors available in the Alpha Factor Library (AFL), S&P Capital IQ's web-based tool for factor analysis. We built country models for China and Taiwan, and regional models for Europe & Africa, Asia ex China & Taiwan (ASIA) and Latin America (LATAM) comprised of five different investment themes, rolled up into a final composite score. Incorporating a range of investment themes ensures that the model is robust and mitigates model underperformance when specific themes are performing poorly. The investment themes represented in each model are Valuation, Quality, Growth, Street Sentiment, and Price Momentum. We used a sector neutral formulation for factor ranking to avoid taking any implicit sector bet.

All the underlying factors in each investment theme or sub-component were chosen and weighted based on a factor's performance, turnover and covariance with other candidate factors within an in-sample period. We then applied a distinct weight to each sub-component to arrive at a final composite score. We also required that the sum of factor weights for each stock be at least 70% before we calculated a composite score. This ensures that a security's final ranking was a reflection of a broad range of information, and not just a few factors. For our in-sample period, we randomly selected half our data points between January 2002 and December 2012; the other half was used for out-of sample model validation.

The final emerging market model is a combination of the ranks of the underlying country/region models. All excess (active) returns, benchmark returns and long-short returns presented in this report are equal-weighted, winsorized to 3 standard deviations and denominated in USD, unless otherwise stated.

4 Model Testing & Results

The model's summary return and information coefficient statistics are displayed in Table 2[5]. Over the 11-year period we measured performance, the model's top quintile portfolio (Q1) generated an average monthly excess return of 0.90% and an annualized return of 11.29%, statistically significant at the 1% level. We observe a similar strong performance from the long-short portfolio, with a monthly and annualized spread of 1.76% and 23.25% respectively, also statistically significant at the 1% level. The top quintile generates consistent excess returns as indicated by the 1-month hit rate[6] of 86% and information ratio of 1.02.

We also report impressive summary statistics when we measure performance by information coefficient(IC): average 1-month IC of 0.065, with a 1-month hit rate of 90%, both significant at the 1% level.

[5] See Appendix A for country/regional model performance

[6] Hit Rate is the number of periods that the active return or IC is positive divided by total number of periods in the test window

Table 2: Summary Performance Statistics for Emerging Market Model S&P BMI Emerging Market Index (January 2002 – September 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	0.90%***	0.30%***	-0.04%	-0.22%***	-0.86%***	1.76%***
Annualized Excess Return	11.29%	3.63%	-0.44%	-2.55%	-9.87%	23.25%
Hit Rate	86%***	71%***	47%	36%***	19%***	87%***
Monthly Information Ratio	1.02	0.43	-0.06	-0.32	-0.76	1.00

Information Coefficient Summary	
Average 1-month IC	0.065***
1-month IC Informatio Ratio	1.23
1-month IC Hit Rate	90%***

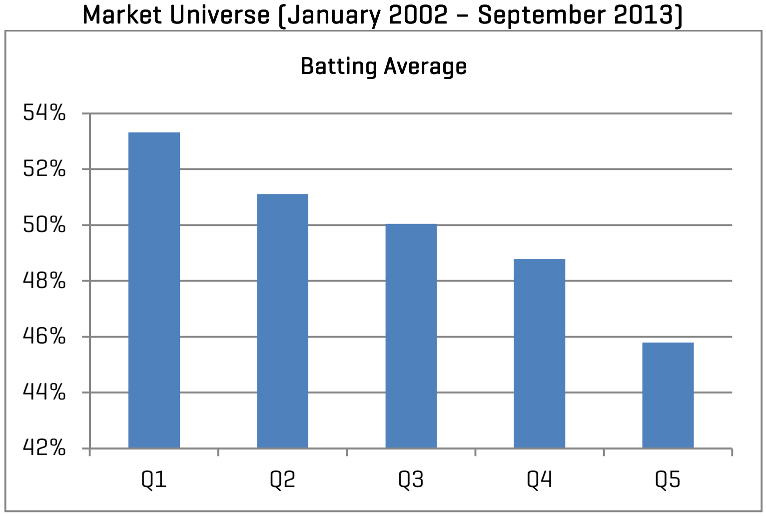
*** Significant at the 1% level

Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

The batting average[7] in Figure 2 also supports the superiority of the model's top quintile over other quintiles, particularly the bottom quintile (Q5). Quintile 1 has the highest batting average at 53%, while the batting average for quintile 5 is 46%. The difference in batting average between the top and bottom quintile is statistically significant at the 1% level.

Figure 2: Quintile Portfolio Batting Averages: Emerging Market Model – S&P BMI Emerging Market Universe (January 2002 – September 2013)



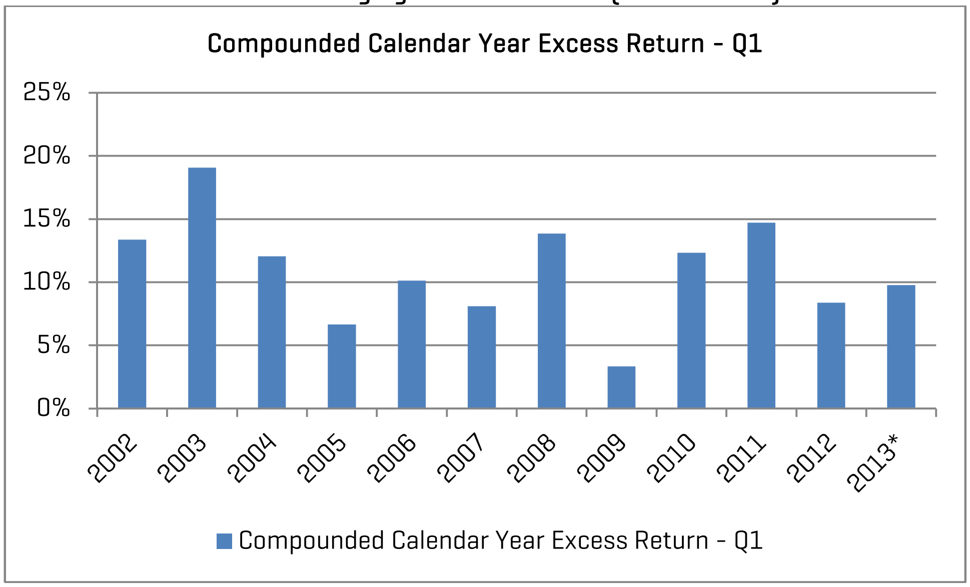
Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

The model's top quintile has delivered a positive excess return in every calendar year since 2002 (Figure 3), with the strongest and weakest excess returns of 19% and 3% recorded in 2003 and 2009 respectively. The model is on track for another positive year in 2013, with returns through September at 10%.

[7] The batting average for each quintile is the proportion of stocks in each quintile with returns above the median benchmark return for a given month, averaged over the entire test window

Figure 3: Quintile 1 Compounded Calendar Year Excess Return - Emerging Market Model: S&P BMI Emerging Market Universe (2002 – 2013)



*2013 data based on returns through end of September
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

4.1 The Five Sub-Components

The emerging market model is comprised of five complementary sub-components that each seek to exploit a documented market anomaly. The five sub-components include:

Value: Identifies companies that are attractive based on traditional valuation metrics such as earnings yield.

Quality. In addition to the well documented accruals anomaly[8], this sub-component includes several measures of balance sheet efficiency and capital utilization.

Street Sentiment: Our Street Sentiment theme rewards companies experiencing positive analyst upgrades.

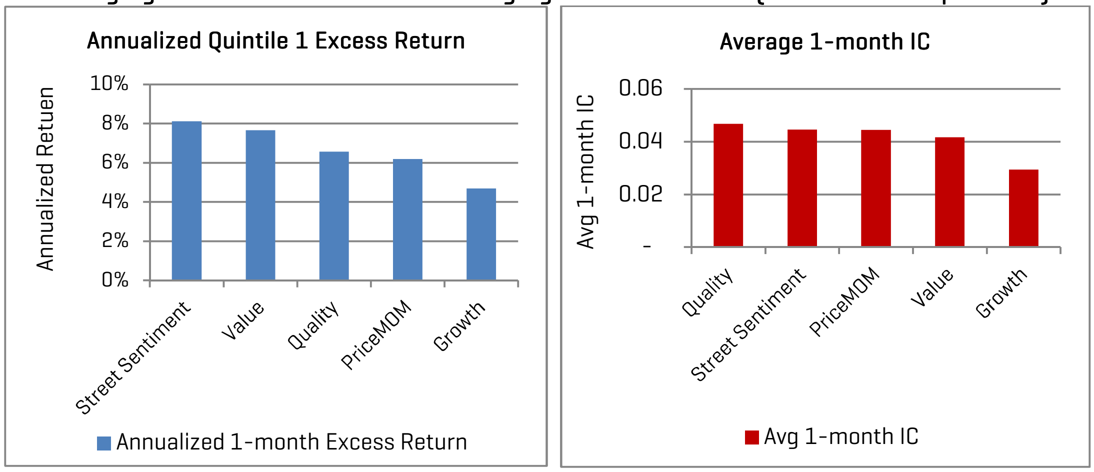
Growth: This sub-component rewards companies that have established a consistent track record of growing not only revenues and earnings, but also free cash flows.

Price Momentum: The Price Momentum Sub-Component includes both short-term signals (to capture reversal in stock returns) and trend following long-term signals.

Even though the efficacy of analyst revisions has declined in the U.S post regulation fair disclosure, it is still a powerful stock selection indicator in emerging markets. Our Street Sentiment sub-component is the best signal when performance is measured by annualized Q1 excess return (8.12%) and the second most effective signal when performance is judged on average 1-month IC (0.045). Value strategies also work quite well in the emerging market space with the Value sub-component generating an annualized Q1 excess return and monthly IC of 7.66% and 0.042 respectively. The Growth sub-component is the weakest of all the five themes represented in the model.

[8] See Sloan, R.G "Do Stock Prices Fully Reflect Information in Accruals and Cash flows About Future Earnings", 1996

Figure 4: Annualized Quintile 1 Excess Return and Average 1-month Information Coefficient: Emerging Market Model: S&P BMI Emerging Market Universe (Jan. 2002 – Sept. 2013)



Source: S&P Capital IQ Quantamental Research
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The annualized Q1 excess return (11.29%) and average 1-month IC (0.065) of the final model clearly dominate all the underlying sub-components used in its construction, suggesting that the sub-components are not highly correlated. Table 3 confirms that the sub-components have low to moderate correlation, with the highest correlation coefficient occurring between Price Momentum and Street Sentiment at 0.52.

Table 3: Sub-Components Monthly Quintile 1 Excess Return Correlation Matrix: S&P BMI Emerging Market Universe (January 2002 – September 2013)

	Value	PriceMOM	Quality	Street Sentiment	Growth
Value	1.00				
PriceMOM	-0.13	1.00			
Quality	0.31	0.36	1.00		
Street Sentiment	0.23	0.52	0.39	1.00	
Growth	0.26	0.05	0.22	0.13	1.00

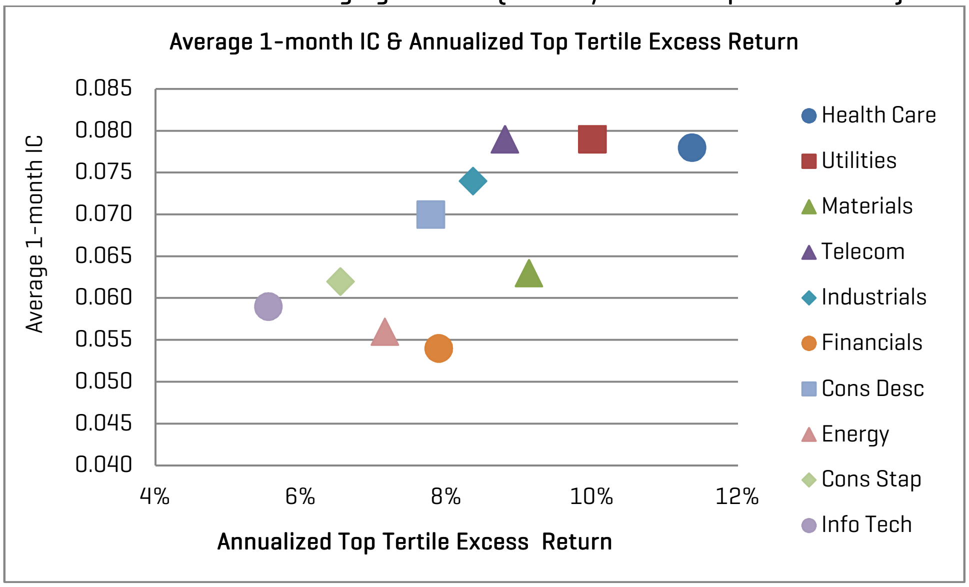
Source: S&P Capital IQ Quantamental Research

4.2 Sector Performance

Given the reduced security count when we divide our universe into the ten GICS sectors, we use tertiles instead of quintiles for our sector analysis. All sectors exhibit positive annualized top tertile excess return and average 1-month IC, statistically significant at the 1% level. Healthcare, Utilities and Materials delivered the highest annualized excess returns[9]. Model performance is also strong in the Financial sector with an annualized top tertile excess return of 7.89% and average 1-month IC of 0.054.

[9] Average security count in the top tertile was 18, 27 and 85 for the Healthcare, Utilities and Materials sectors respectively.

Figure 5: Sector Performance: Average 1-month IC and Annualized Top Tertile Excess Returns: S&P BMI Emerging Markets (January 2002 – September 2013)



Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future result

At the beginning of this report, we stated that one of the strengths of our model was our decision to model banks separately using S&P Capital IQ's industry specific data. Specifically, we used bank specific data for several of the signals in the Quality, Value and Growth sub-components. We show the correlation matrix for bank specific and generic signals used in the Quality sub-component in Figure 6[10]. As expected, bank specific factors represent differentiated ideas from generic signals with the largest correlation coefficient we observed standing at 0.31.

Figure 6: Top Tertile Excess Return Correlation Matrix
BMI Emerging Market Bank Universe (January 2004 – September 2013)

	Demand to Total Deposit	ChgOff-to-Sales	Loan Funding
Operating Earnings-to-Assets	0.31	0.23	0.30
Chg 1Y OPM	0.17	0.31	-0.04
ROE	0.22	0.19	0.22
Gross Profit Margin	0.17	0.18	0.26

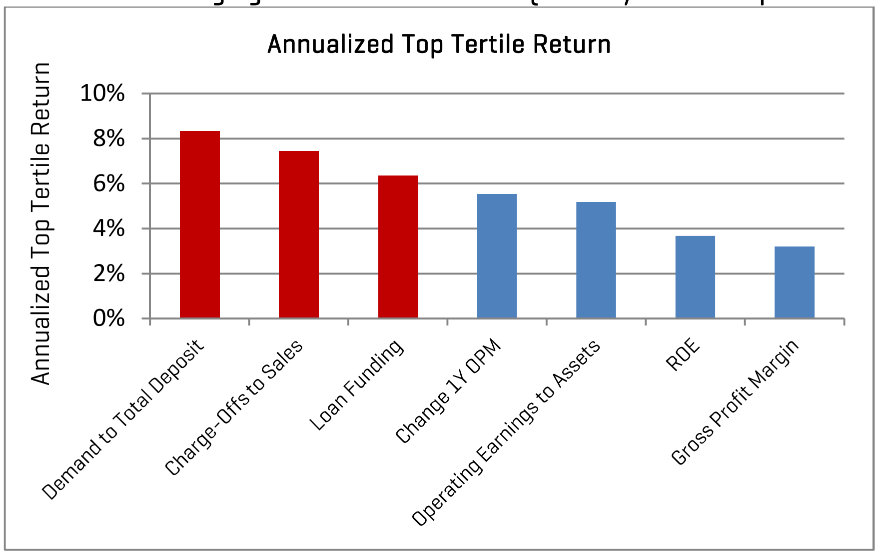
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future result

We report annualized top tertile excess returns for bank-specific and generic signals in Figure 7. Over all, industry specific signals (red bars) performed better than their generic counterparts (blue bars)[11] over the nine year period we measured performance. The best factor was Demand Deposit to Total Deposit, with an annualized top tertile excess return of 8.33%. This factor measures the proportion of cheap deposits to total deposits; banks with access to cheap and

[10] Bank specific factor coverage begins in January 2004.
[11] Coverage for banks specific factors is about 15% lower than coverage for generic signals.

stable deposits are preferred to those with expensive liabilities. The best generic signal was Change in 1Y OPM (examines the 1 year change in the operating profit margin of a bank).

Figure 7: Annualized Top Tertile Excess Return for Industry Bank Specific and Generic Factors: S&P BMI Emerging Market Bank Universe (January 2004 – September 2013)

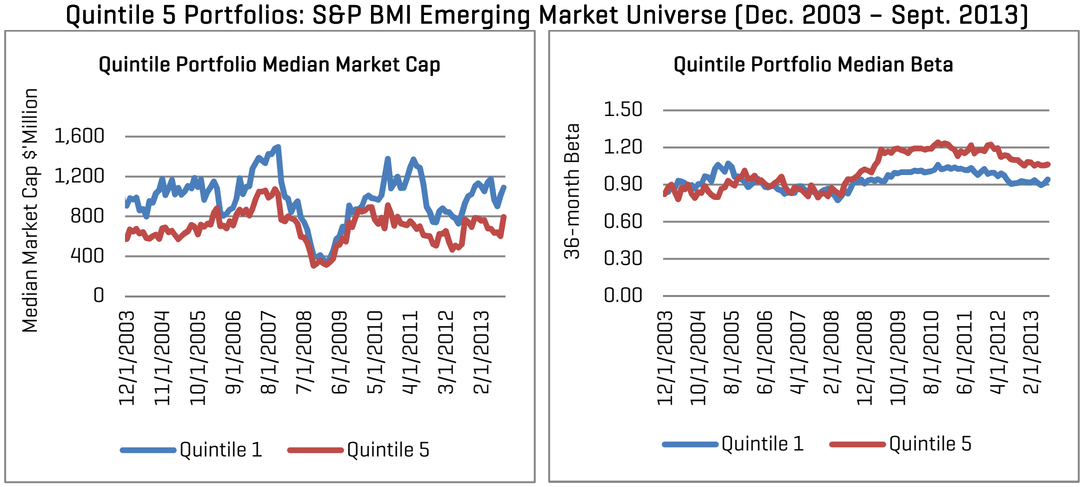


Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future result

5 Model Portfolio Characteristics & Neutralization

We show size and beta characteristics of the model's quintile 1 and 5 portfolios in Figure 8. The conclusion drawn from this chart is that the long portfolio is tilted towards large cap names and low beta stocks (compared to the short portfolio).

Figure 8: Time Series Median Market Cap and Median 36-month Beta for Quintile 1 and Quintile 5 Portfolios: S&P BMI Emerging Market Universe (Dec. 2003 – Sept. 2013)



Source: S&P Capital IQ Quantamental Research

We show the performance of the model after we eliminate both size and beta tilts together with our initial model in Table 4. We control for size and beta by taking the residuals from a monthly cross sectional regression of standardized ranks of market cap and beta. The results after the neutralization are similar to those of our initial model, with all metrics statistically significant at the 1% level.

Table 4: Original and Size/Beta Neutralized Performance: S&P BMI Emerging Market Universe (December 2003 – September 2013)

	Original Model	Size/Beta Neutral Model
Average 1-month Quintile 1 Excess Return	0.82%***	0.93%***
1-month Return Hit Rate	87%***	84%***
Average 1-month IC	0.064***	0.063***
1-month IC Hit Rate	90%***	91%***

*** Significant at the 1% level

Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

Up to this point, we have included all securities, irrespective of market capitalization, in our model results. We understand that even though we constructed our model using a universe that represents investible securities in emerging markets, large institutional investors may not be able to invest in some of the securities in the universe because of market cap or liquidity constraints. For example, the median dollar market cap and average dollar daily trading volume (ADTV) for the smallest 10% of securities (with model scores) by market cap in the universe over the last three years is $141 million and $0.56 million respectively. What if we only ran our model in a universe comprised of larger, more liquid names? What will our results look like?

Table 5: Model Performance based on Market-Cap Subsets: S&P BMI Emerging Market Universe (December 2002 – September 2013)

	ALL	Largest 90%	Largest 80%	Largest 70%	Largest 60%	Largest 50%
Average Monthly Q1 Excess Return	0.90%***	1.00%***	1.06%***	1.06%***	1.01%***	0.97%***
Average 1-month Long-Short Spread	1.76%***	1.76%***	1.74%***	1.67%***	1.53%***	1.44%***
Average 1-month IC	0.065***	0.067***	0.066***	0.063***	0.060***	0.056***
Median Market Cap ('Million)	$1,031	$1,270	$1,530	$1,870	$2,350	$3,007
Median $ ADTV (' Thousand)	$1,570	$1,900	$2,320	$2,800	$3,500	$4,815

*** Significant at the 1% level

Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

The performance of the model when we subset based on market capitalization is displayed in Table 5. The first column, "ALL", restates the performance of the model when we include all securities in the universe. The next five columns, subset the universe based on market capitalization – for instance, the column "Largest 90%" examines the performance of the model within the largest 90% of securities ranked by dollar market cap. The last two rows in the table display the dollar median market cap and average daily trading volume measured over the last three years within each market cap bucket.

The model's 1-month IC deteriorated by 16% when we compared "ALL" to "Largest 50%"; we also see a similar deterioration in average 1-month long-short spread. However, the model's average 1-month Q1 excess return improved slightly from 0.90% to 0.97%. We would point out that the performance of the model is statistically significant at the 1% level for all performance metrics and in all market cap buckets. Furthermore, liquidity improves dramatically as we subset the universe - the median market cap and average daily trading volume for securities in the "Largest 50%" bucket is about three times that of securities in the "ALL" universe.

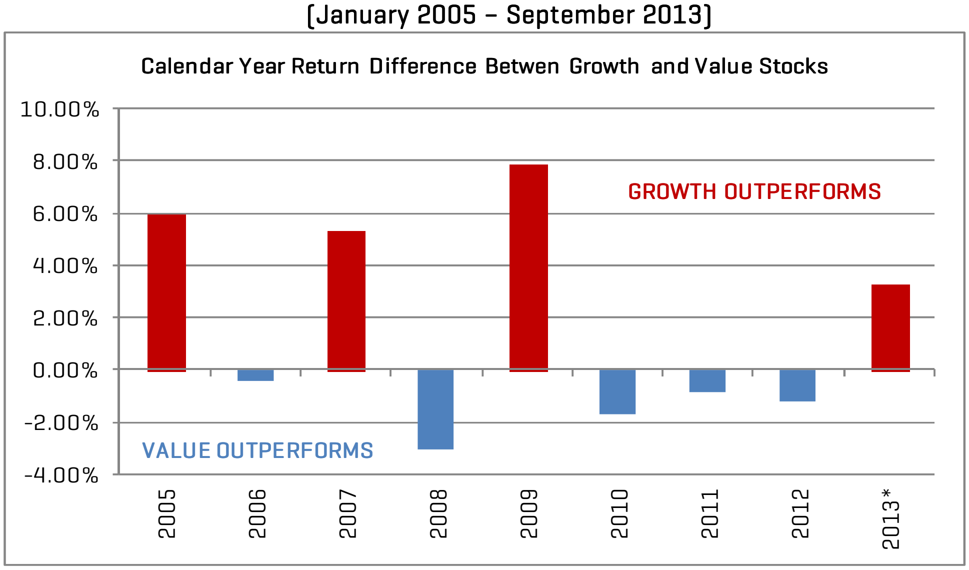
6 Regime Analysis

We assess the performance of the model in two enviroments - a style environment, where we compare the performance of the model in growth and value regimes, and a risk environment, where we look at model performance in risk-seeking and risk-averse periods.

6.1 Growth vs Value Environment

Returns between growth and value stocks can differ significantly. Figure 9 shows the return difference between the S&P BMI Emerging Market Growth Index and the S&P BMI Emerging Market Value Index in each calendar year (postive bars indicate that growth outperformed value in that year, while negative bars indicate the outperformance by value). The chart confirms that the difference in performance between growth and value stocks can indeed be large, with growth outperforming value by almost 8% in 2009. The calendar year outpeformance for value has been muted since 2005[12], with the largest difference in 2008 at 3%.

Figure 9: Calendar Year Return Difference between the S&P BMI Emerging Market Growth Index and the S&P BMI Emerging Market Value Index – USD Net Total Returns (January 2005 – September 2013)



*January – September 2013

Source: S&P Capital IQ Quantamental Research

12 Growth and Value Net Total Index Return series start in January 2005

We classified all months where the returns to the S&P BMI Emerging Market Growth Index were larger than those of the S&P BMI Emerging Market Value Index as "Growth"; all other months were classified as "Vaue". The performance of the model using this classification approach is displayed in Table 6. Performance is quite consistent in both value and growth regimes, although it is slightly better in value periods. All performance metrics are statistically significant at the 1% level in both growth and value regimes.

Table 6: Model Performance in Growth and Value Regime:
S&P BMI Emerging Market Universe (Jan. 2005 – Sept. 2013)

	1-month Q1 Excess Return	1-month IC	1-month Long-Short Return	Number of Months
All Months	0.79%***	0.063***	1.60%***	105
Growth	0.79%***	0.061***	1.55%***	55
Value	0.80%***	0.065***	1.66%***	50

*** Significant at the 1% level
Source: S&P Capital IQ Quantamental Research
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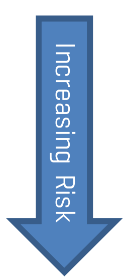
6.2 Model Performance in Different Risk Environments

In recent periods, global equity markets have oscillated between de-risking and re-risking episodes. Episodes of elevated re-risking, when high beta and/or low quality assets are in favor, can be challenging for model performance. We used the Alpha Factor Library's Volatility Style Composite (VSC)[13] to classify our entire history into three risk regimes – risk averse, risk neutral and risk seeking. We classify any month where VSC is the worst performing style (based on long-short return) out of the eight styles we track on AFL, in the S&P BMI Emerging Market Universe, as risk averse; months where VSC is the best style are categorized as "risk-seeking"; and all other months that do not fall into risk-averse or risk-seeking are classified as "risk-neutral". This approach enables us to separate the model's performance into periods when investors are extremely skeptical of risk taking (risk-averse), have high appetites for risk (risk-seeking) and have normal risk appetites (risk-neutral).

Table 7: Model Performance in Different Risk Environments:
S&P BMI Emerging Market Universe (Jan. 2005 – Sept. 2013)



	1-month Q1 Excess Return	1-month IC	1-month Long-Short Return	Number of Months
All Months	0.90%***	0.065***	1.76%***	140
Risk Averse	1.17%***	0.095***	2.68%***	45
Risk Neutral	0.93%***	0.065***	1.79%***	56
Risk Seeking	0.53%***	0.032***	0.64%*	39

*Significant at the 10% level; *** Significant at the 1% level
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

[13] See Appendix A for a list of factors in the VSC

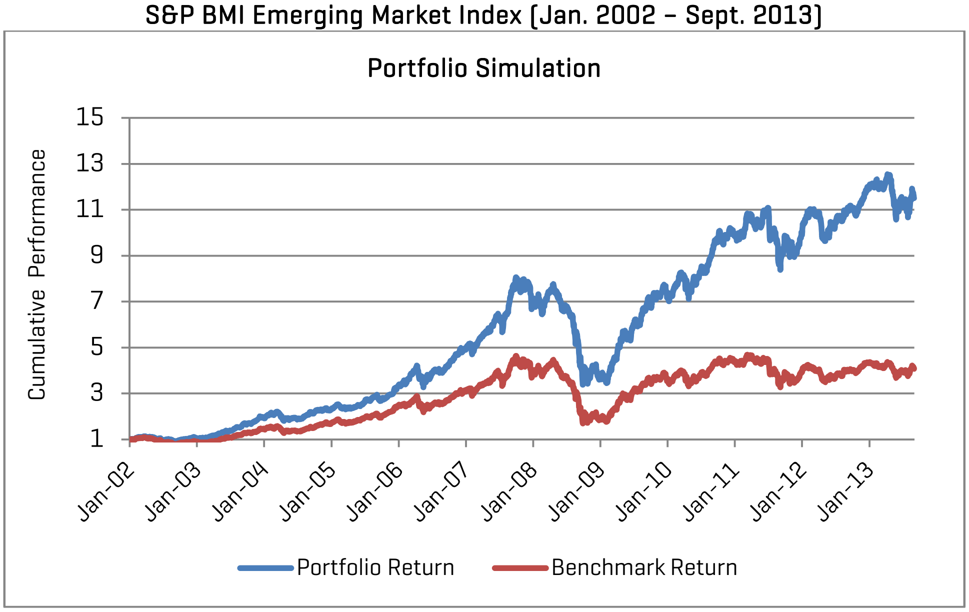
As we go up the risk spectrum, the performance of the model degrades; the model works best in risk-averse periods with an average 1-month Q1 excess return of 1.17% and 1-month IC of 0.095 (both significant at the 1% level). Even though model performance was weakest in the risk-seeking environment, the model still generated a 1-month excess return and IC of 0.53% and 0.032, both significant at the 1% level.

7 Portfolio Construction & Strategy Simulation

We now turn our attention to constructing an equity portfolio based on a given set of parameters that are of interest to portfolio managers. This strategy simulation was implemented using ClariFi's[14] Strategy Simulation workflow, which is based on a mean-variance optimization framework. Our strategy is long only with the following set of parameter constraints:

- Target annualized tracking error of 5%
- Maximum stock active weight of 2%
- Maximum sector active exposure of 3%
- Maximum country active exposure of 3%
- Beta neutral to the benchmark.
- Maximum annual turnover of 125% (one way)
- Transaction cost: 75bps per trade (one-way)

Figure 10: Cumulative Portfolio Return: Emerging Market Model Portfolio Simulation S&P BMI Emerging Market Index (Jan. 2002 – Sept. 2013)



Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

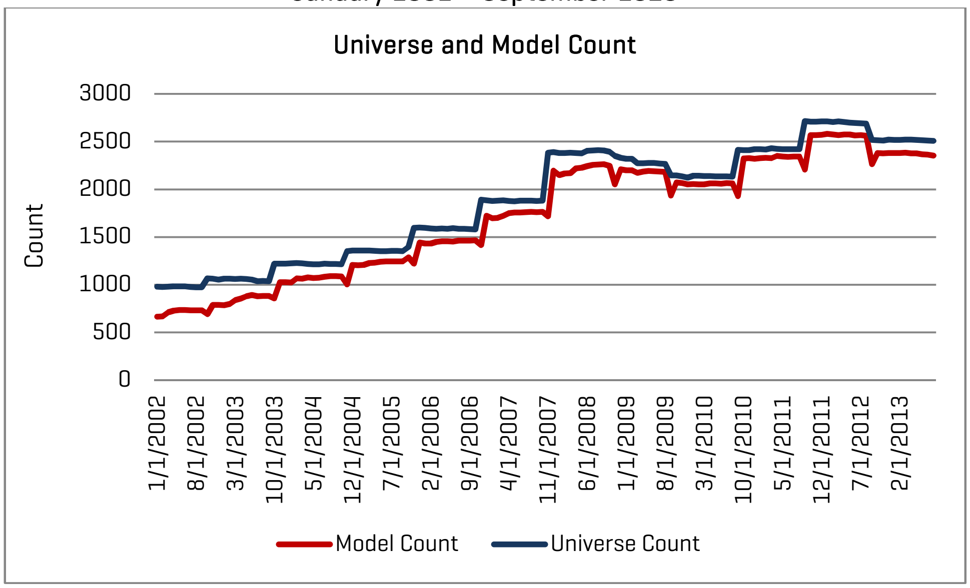
The cumulative portfolio performance is shown in Figure 10. The portfolio generated an annualized excess return of 10.48% over the entire test period with an information ratio of 1.79. Since bottoming out at the end of 2008, the model has done quite well compared to the benchmark; the portfolio is up by almost 200% since the end of 2008, twice the appreciation recorded for the benchmark.

[14] ClariFi is an advanced research and portfolio management platform built to provide asset managers with complete solutions for their research and production workflows.

8 Data and Universe Definition

We used S&P Capital IQ's Point-in-Time global database for this work. Our tests started in January 2002, when we have broad coverage for all the countries in our universe. For our universe, we used the S&P BMI for Emerging Markets. Model coverage was quite good (see Figure 11), even after we restricted model scores to only securities with broad factor coverage as described in section 3. Over the 11-year period, we have model scores for almost 90% of the securities in the universe on average.

Figure 11: Universe and Model Coverage: S&P BMI Emerging Market Universe January 2002 – September 2013



Source: S&P Capital IQ Quantamental Research

9 Conclusion

In this report, we outlined the methodology and process used to construct S&P Capital IQ's stock selection model for emerging markets. We document that the model has been successful in separating winners from losers in emerging markets, and performance is robust across sectors, countries/regions and size cohorts. We also document significant outperformance of a portfolio over a benchmark after accounting for transaction costs.

Appendix A: Summary Performance Statistics: Country/Regional Models

LATAM (Jan 2002 – Sept 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	0.92%***	0.10%	0.02%	-0.27%**	-0.72%***	1.64%***
Information Ratio	0.57	0.08	0.01	-0.20	-0.35	0.50

Information Coefficient Summary	
Average 1-month IC	0.067***
1-month IC Informatio Ratio	0.66

Europe & Africa (Jan 2002 – Sept 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	0.93%***	0.35%***	-0.04%	-0.27%**	-0.88%***	1.81%***
Information Ratio	0.64	0.27	-0.03	-0.21	-0.55	0.70

Information Coefficient Summary	
Average 1-month IC	0.067***
1-month IC Informatio Ratio	0.81

China (Jan 2002 – Sept 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	0.82%***	0.51%***	0.00%	0.00%	-0.79%***	1.62%***
Information Ratio	0.34	0.23	0.00	0.00	-0.36	0.39

Information Coefficient Summary	
Average 1-month IC	0.063***
1-month IC Informatio Ratio	0.45

Taiwan (Jan 2002 – Sept 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	0.67%***	0.18%	0.08%	-0.13%	-0.84%***	1.51%***
Information Ratio	0.41	0.12	0.07	-0.12	-0.43	0.48

Information Coefficient Summary	
Average 1-month IC	0.067***
1-month IC Informatio Ratio	0.63

*** Significant at the 1% level; ** Significant at the 5% level
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Appendix A: Summary Performance Statistics: Country/Regional Models

Asia ex China & Taiwan (Jan 2002 – Sept 2013)

	Return Summary					
	Q1	Q2	Q3	Q4	Q5	Long-Short Spread
Average Monthly Excess Return	1.04%***	0.51%***	-0.18%**	-0.23%**	-1.13%***	2.16%***
Information Ratio	0.63	0.40	-0.17	-0.18	-0.54	0.62

Information Coefficient Summary	
Average 1-month IC	0.086***
1-month IC Informatio Ratio	0.86

*** Significant at the 1% level; ** Significant at the 5% level
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Appendix B – Volatility Style Index Factors

Style	Factor	Definition
Volatility	12M Realized Volatility	This factor is computed as the annualized volatility of monthly stock returns over the prior 12 months.
	1M Vol	This factor is computed as the annualized volatility of daily stock returns over the prior month.
	60M CAPM Beta	This is the sensitivity of a stock's return to the return of the market.
	90DCV	This is calculated as the ratio of the standard deviation of daily closing prices over the prior 90 days to the average of daily closing prices over the past 90 days.

Source: S&P Capital IQ Quantamental Research

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Our Recent Research

February 2014: [U.S Stock Selection Model Performance Review]

The performance of S&P Capital IQ's four U.S. stock selection models since their launch in January 2011 has been strong, and 2013 was no exception. Key differentiators, such as distinct formulations for large and small cap stocks, bank-specific factors, sector-neutrality to target stock-specific alpha, and the combination of sub-components representing different investment themes have enabled the models to outperform across disparate market environment

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

We examine the returns surrounding buyback announcements to test whether, and when, buyback programs signal subsequent outperformance and shareholder value. We find:

- Buyback announcements precede excess returns in the US. Stocks on average outperformed the equally weighted Russell 3000 by 0.60% over one month, and by 1.38% over one year periods following buyback announcements.
- Outperformance is greatest among small caps or larger magnitude buybacks as a % of shares outstanding.
- Reported insider trading and buyback announcement signals are complementary.

In Europe, some post-buyback outperformance over 12 months, but no significant excess return after one month

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

In this report, we investigate the impact of the public disclosure of insider trading on equity prices, using both an event study framework and a portfolio formation approach. Leveraging S&P Capital IQ's Ownership database, we explore several practical methods of identifying "informative" insider trades, and how to construct a portfolio of stocks using recent "informed" insider transactions. We document the following results:

- Consistent with existing literature, insider trades are predictive of future stock returns.
- Outside investors can earn economically significant excess returns by trading on "informative" insider trading signals.
- Mimicking the net purchase actions of CEOs yielded an excess return of 1.27% over the next one week.
- A trading strategy based on the three characteristics: opportunistic, intensive and directional change, yielded 0.36% weekly excess returns after transaction costs.

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

Pension underfunding is a worldwide problem. There has been an unending wave of news stories about cities and states across the United States suffering from defined benefit pension funding shortfalls, but these issues extend far beyond the public sector and beyond the United States as well.

In this brief we leverage S&P Capital IQ datasets to examine:

- Companies with the strongest and weakest pension funding status globally.
- Companies with the most optimistic return and discount rate assumptions globally.
- The relationship between projected and realized pension portfolio returns.
- The historical global trends in funding status, portfolio returns, and discount rates.

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

In this report, we explore the efficacy of different stock selection strategies globally and use this information to develop a suite of robust global stock selection models targeting Canada and the developed markets of Europe and Asia Pacific. Our global models were developed using S&P Capital IQ's industry leading Global Point-in-Time data, as well as the Alpha Factor Library, our web-based global factor research platform. We find that each of our Global Stock Selection Models for Developed Markets yield significant long-short spread returns and information coefficients at the 1% level. This performance is also robust providing similar statistical significance after controlling for Market Cap and Beta exposures.

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

Inspiration drives innovation. The writings of Plutarch inspired Shakespeare, Galapagos finches inspired Darwin, and the German Autobahn inspired Eisenhower, but what inspires investment researchers to develop the next innovations for investors? When we get a new investment idea, we seek out literature on that topic to inspire us to bring the idea to fruition. This literature can help to further develop our own thoughts, polish up and expand on our priors, and avoid the pitfalls experienced by earlier researchers. Inspiration from academia enhances our ability to provide innovative solutions for our clients.

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

Leveraging Compustat customer segment data, we investigate the impact of news for customers and subsequent stock returns for their suppliers, over the time period May 2000 through April 2011 and find that:

- Shares of suppliers with major customer relationships reacted to positive and negative earnings surprise of their customers with a statistically significant 0.93% to 1.97% abnormal spread in the 5 to 60 trading days following the surprise.
- A monthly rebalanced backtest of long-short supplier portfolios based on customer momentum would have resulted in a statistically significant 0.81% average monthly return, or 0.70% after controlling for common risk factor exposures.
- The customer momentum signal historically performs best in cyclical sectors such as Materials and Consumer Discretionary.

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

In this paper, we revisit the asset growth anomaly. Our results indicate:

- Asset growth demonstrates return predictive power globally with and without controlling for size, value, 12-month price momentum, and 1-month price reversal factors.
- Information coefficient correlation analyses indicate that there are potential diversification benefits from adding asset growth to other alpha factors.
- The companies that demonstrated the highest asset growth show subsequent deterioration in their top-line and bottom-line growth rates while companies that had the lowest asset growth experience subsequent improvement in their top-line and bottom-line growth rates.

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

This month we build upon the work done by Cohen and Lou in their 2010 paper, "Complicated Firms", to determine if we can exploit industry level information from pure-play firms to predict the future performance of multi-industry, complicated firms. Leveraging Compustat segment data and Standard Industrial Classification (SIC) 2 digit codes, we exploit the lag in incorporating industry level information between simple and complicated firms to forecast the future performance of complicated firms. This is done by constructing pseudo-conglomerate returns, revisions, and valuation signals that combine the relevant information of all the industries in which a complicated firm operates. These pseudo-conglomerate signals simply weight industry level information (ex: industry return) proportionately to the complicated firm's reported sales in each industry.

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

Equity Risk models are subject to a common criticism. We examined three techniques to further enhance the S&P Capital IQ Fundamental Factor risk models: Utilized the cross sectional dispersion of stock and factor returns by adjusting model factors and stock specific volatilities, change the model production frequency from monthly to daily to capture recent data, and shorten data look back window (1 year as opposed to 2 years) resulting in a more reactive model. Dispersion based adjustments, and high frequency of model generation both improved model results, while a shortened calibration window showed no appreciable improvement.

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

Can profits be made by following the actions of activists? One month after the commencement of activism, the strategy yielded a market-adjusted excess return of 3.4%. After controlling for market, size, value, and industry, the excess return was 2.7. Twelve months after the disclosure of activist involvement, the strategy produced an average excess return of 14.1% after controlling for market, size, value, and momentum. We did not find evidence of return reversal up to two years after activism or of diminished excess returns in 2008 -- 2012 vis-à-vis those in 2003 -- 2007.

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

In this report, we review the performance of S&P Capital IQ's four U.S. stock selection models in 2012. These models were launched in January 2011, and this analysis will assess the underlying drivers of each model's performance over the 12 months ended December 31, 2012.

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

At the beginning of every year, one topic frequented by many institutional investors is the January Effect. Investors often point to January as the most pronounced example of seasonality, where longer term trend following strategies suddenly underperform and short-term reversal and mean-reversion dominate. But which strategies have performed well in January and is this performance sustainable? With several studies in the Literature documenting the January Effect on company capitalization, we decided to undertake our own review using our S&P Capital IQ Alpha Factor Library (AFL), to examine various strategies' effectiveness during the month.

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

In October of this year, the US equity market was caught off guard with the seemingly sudden departure of Citibank CEO Vikram Pandit. While CEO departures are almost always headline news, CFO departures are not often accompanied with such recognition. We explore the impact of CEO and CFO departures and find consistent results in the US and the Developed World. CEO and CFO departures often signify a turning point in both the company's stock performance and the company's operating metrics.

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

Investors routinely utilize industry intelligence in their investment process. But which information is relevant? Which is irrelevant? Our work yields some surprising results. This work complements our previous industry work on Retail [June 2011], Banking [Oct 2011], and Oil & Gas [May 2012]. Using S&P Capital IQ's Global Point-in-Time database and Compustat Industry-Specific data, we look at 70 factors in 11 industries: airlines, hospitals & facilities, managed healthcare, pharmaceuticals & biotechnology, homebuilding, insurance, telecommunications, utilities, gold miners, hotels & gaming, and restaurants

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

In July 2012 we released our regional risk models -- the Pan-Asia ex. Japan and the Pan-European Models, and updated versions of our US and Global Risk Models. Continuing in our efforts to provide a broad set of models to the asset management community, we are now releasing our second single country risk model -- Canada Fundamental Equity Risk Model.

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

May 2011: Topical Papers That Caught Our Interest

April 2011: Can Dividend Policy Changes Yield Alpha?

April 2011: CQA Spring 2011 Conference Notes

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