Behind the Asset Growth Anomaly

Over-promising but Under-delivering

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Best Buy, the consumer electronics retailer, ramped up its expansion efforts by opening 285 new stores in 2008, a year-over-year increase of 21.7%.[1] Correspondingly, its total assets grew by 24.0% in that fiscal year and another 15.6% in the next. Top- and bottom-line growth, however, did not follow suit. In fact, for the next four fiscal years[2], its annual same-store sales growth averaged -1.5%, and its annual earnings growth averaged -7.4%. Its stock price returned -24.1% while the S&P 500 returned 106.5% in the same period.[3]

There is a growing body of papers that examine the asset growth anomaly, in which high asset growth stocks consistently underperform low asset growth stocks.[4] The anomaly prompts us to ask: why do investors seem to persistently misprice the growth rates of total assets, one of the most readily available pieces of financial information?

Using S&P Capital IQ's Global Point-In-Time data, we contribute to the existing body of studies on the asset growth anomaly by extending global results to the end of December 2012 and providing behavior-based arguments why the anomaly exists.

Our results from the sample period January 1993 to December 2012 indicate that:

- Asset growth demonstrates return predictive power globally with and without controlling for size, book-to-market equity, 12-month price momentum, and 1-month price reversal factors.

- The annualized return spreads between lowest and highest asset growing firms controlled for size and book-to-market equity in the U.S., Europe, and Asia Pacific regions are 17.4%, 8.5%, and 8.0%, respectively.

- 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- and bottom-line growth rates while companies that had the lowest asset growth experience subsequent improvement in their top- and bottom-line growth rates.

- The return to asset growth is stronger in risk-off periods and weaker or no longer predictive of returns in risk-on periods.

[1] See Form 10-K for the fiscal year 2008 that ended on February 28, 2009
[2] Fiscal years 2009 – 2012
[3] Dates used in the returns calculation are 5/4/2009 and 5/21/13
[4] The anomaly was first documented by Cooper, Gulen, and Schill in 2007

1. Cross-Sectional Regressions

Utilizing the Fama-MacBeth (1973) framework[5], we examine the return predictive power of asset growth with and without controls for size, book-to-market equity, and price momentum factors in the U.S., Europe, and Asia Pacific regions from January 1993 to December 2012. In this paper, we define asset growth as the one-year percentage change in total assets. Since the meaning of total assets is different for financial companies, all financials with GICS code of 40 are excluded from the following results.

1.1 Standalone Return Predictive Power

We start by examining the standalone return predictive power of the asset growth factor without controlling for other variables. Exhibit 1 reports the results from the monthly cross-sectional regressions where the reported average monthly estimated coefficient is the time-series average of the estimated coefficients from the cross-sectional regressions of subsequent monthly stock returns on the asset growth factor. The t-statistics are based on the distribution of the monthly estimated coefficients. The results indicate that the asset growth factor has predictive power of future returns in the cross-section in all the regions. Specifically, the average monthly estimated coefficients for all the regions are negative and significant at the 5% level. The negative sign on the average monthly estimated coefficients indicates that stocks with lowest asset growth outperform those with highest asset growth. The strategy indicates that an investor would go long the lowest asset growth stocks and short the highest asset growth stocks in order to capture the returns from the asset growth effect.

$$R_{i,t} = a_{0,t-1} + a_{1,t-1} * \text{asset growth}_{i,t-1} + e_t$$

where (i) $R_{i,t}$ denotes the return of the i^{th} stock at month t above the 1-month US Treasury-Bill

(ii) asset growth $_{i,t-1}$ denotes the asset growth variable for the i^{th} stock at month t-1

Exhibit 1: Average Monthly Estimated Coefficient to the Asset Growth Factor

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2012

Index	Average Monthly Intercept	Average Monthly Estimated Coefficient
Russell 3000	0.81% **	-0.31% ***
S&P BMI Dev Mkts Europe	0.53% *	-0.27% **
S&P BMI Dev Mkts Asia Pacific	0.23%	-0.17% **

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

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5 Fama, Eugene F., and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 81, 607–636.

To ensure the results are not overly influenced by small-cap stocks, we perform a robustness check by examining the factor's performance separately in the Russell 1000 and the Russell 2000 indices. The results indicate that the factor demonstrates return predictive power in both indices confirming that the exhibited return predictive power in the Russell 3000 is not solely driven by small- or micro-cap stocks. Unsurprisingly though, this factor, like most other factors, does perform somewhat better within smaller market capitalization stocks. See Exhibit 2.

Exhibit 2: Average Monthly Estimated Coefficient to the Asset Growth Factor

Russell 1000 and Russell 2000

1/1993 – 12/2012

Index	Average Monthly Intercept	Average Monthly Estimated Coefficient
Russell 1000	0.81% **	-0.20% **
Russell 2000	0.82% *	-0.36% ***

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively
Source S&P Capital IQ Quantamental Research
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1.2 Return Predictive Power in the Presence of Other Predictive Variables

From the section above, the results show that the asset growth factor does have standalone return predictive power globally. The next logical question that we ask is whether it still has predictive power in the presence of other factors.

Specifically, the variables that we explore in conjunction with the asset growth factor are:

- market capitalization: Ln(MktCap)
- book-to-market equity ratio: BE/ME
- intermediate price momentum from past 12 month through past 1 month: MOM12
- 1-month price reversal: MOM1

$$R_{i,t} = a_{0,t} + a_{1,t-1} * \text{asset growth}_{i,t-1} + a_{2,t-1} * \ln(\text{mktCap})_{i,t-1} + a_{3,t-1} * BE/ME_{i,t-1} + a_{4,t-1} * MOM12_{i,t-1} + a_{5,t-1} * MOM1_{i,t-1} + e_{t+1}$$

where (i) $R_{i,t}$ denotes the return of the i^{th} stock at month t above the 1-month US Treasury-Bill

The results in Exhibit 3 indicate that the asset growth factor exhibits return predictive power even after we control for the above four factors. The results are consistent globally with significance at the 5% level. In fact, our results show that the asset growth factor, along with the 1-month price reversal and the 12-month price momentum factors, has the strongest predictive power of subsequent returns as indicated by its t-statistics during our sample period. The three- and the four-factor Fama-French models also call for estimates of market betas. According to Fama and French (2008), individual stock estimated betas in the three- and the four-factor models are less disperse (close to 1) than those of the CAPM and there is little reason to expect individual firm betas are correlated with the anomaly variables. Therefore, the estimated coefficients in Exhibit 3 are not affected from their omission.

Exhibit 3: Average Monthly Estimated Coefficient to the Asset Growth Factor

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2012

Index	Avg Mthly Intercept	Avg Mthly Asset Growth Estimated Coefficient	Avg Mthly ln(mktCap) Estimated Coefficient	Avg Mthly BE/ME Estimated Coefficient	Avg Mthly MOM12 Estimated Coefficient	Avg Mthly MOM1 Estimated Coefficient
Russell 3000	0.81% **	-0.34% ***	-0.06%	0.13%	0.20%	-0.28% ***
S&P BMI Dev Mkts Europe	0.55% *	-0.24% **	0.07%	-0.10%	0.47% ***	-0.15% *
S&P BMI Dev Mkts Asia Pacific	0.24%	-0.17% ***	0.00%	0.37% ***	0.20% *	-0.20% **

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively
Source S&P Capital IQ Quantamental Research
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1.3 Sub-periods

As an additional robustness check, we split our sample period into two sub-periods: 1/1993 – 12/2002 and 1/2003 – 12/2012 and ran the same analysis as in Section 1.1. Our results indicate that asset growth exhibits return predictive power in both sub-periods and the differences between the two sub-periods are not statistically significant. See Exhibit 4.

Exhibit 4: Sub-periods Average Monthly Estimated Coefficient to the Asset Growth Factor

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2002; 1/2003 – 12/2012

	1993 - 2002	2003 - 2012	Difference between Two Sub-periods
Index	Avg Mthly Estimated Coefficient	Avg Mthly Estimated Coefficient	Avg Mthly Estimated Coefficient
Russell 3000	-0.38% **	-0.24%***	-0.14%
S&P BMI Developed Markets Europe	-0.39% *	-0.14% **	-0.25%
S&P BMI Developed Markets Asia	-0.11%	-0.21% **	0.10%

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively
Source S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

1.4 Summary

Our results indicate that the asset growth factor demonstrates predictive power of future returns globally with and without controls for size, book-to-market equity, and price momentum factors.

2. Risk-Adjusted Sorts

We complement our cross-sectional regressions analysis from Section 1 with a quintile return spread analysis where we control for size and book-to-market equity risk dimensions. Following the Fama and French (1993) framework[6], we create 25 portfolios from a two-way 5x5 independent sort where the returns of the portfolios are value-weighted to mitigate the influence of small- and micro-caps. Each stock's raw return is subsequently adjusted for the return of one of the 25 portfolios in which the stock belongs to arrive at the stock's abnormal return. Next, the stocks are grouped into five portfolios based on the asset growth factor at the beginning of each month. The five portfolios created in this fashion are held for one month before rebalancing. In each of the charts in this section, the returns are the average monthly abnormal returns from the process outlined above. The leftmost bar shows the average monthly abnormal return of the portfolio containing stocks with the lowest asset growth and the second bar (left of the dotted line) from the right shows the average monthly abnormal return of the portfolio containing stocks with the highest asset growth. The rightmost bar (right of the dotted line) is the average monthly quintile return spread, which is the average monthly abnormal return of the lowest asset growth portfolio less the average monthly abnormal return of the highest asset growth portfolio. Since the meaning of total assets is different between industrial and financial companies, all financials with GICS code of 40 are excluded from the results.

2.1 U.S. Results

After controlling for size and book-to-market, the average monthly abnormal returns to the five portfolios sorted on the asset growth characteristic exhibit a monotonic return pattern with the top quintile portfolio and the bottom quintile portfolio contributing about equally to the average monthly quintile return spread of 1.45%, with significance at the 1% level. The results indicate that an investor could earn abnormal returns from both the long and the short sides. Furthermore, the asset growth factor doesn't just work in the extreme portfolios. For instance, the average monthly quintile return spread by buying stocks in Bin2 and selling stocks in Bin4 yields 0.64% with significance at the 1% level. See Exhibit 5.

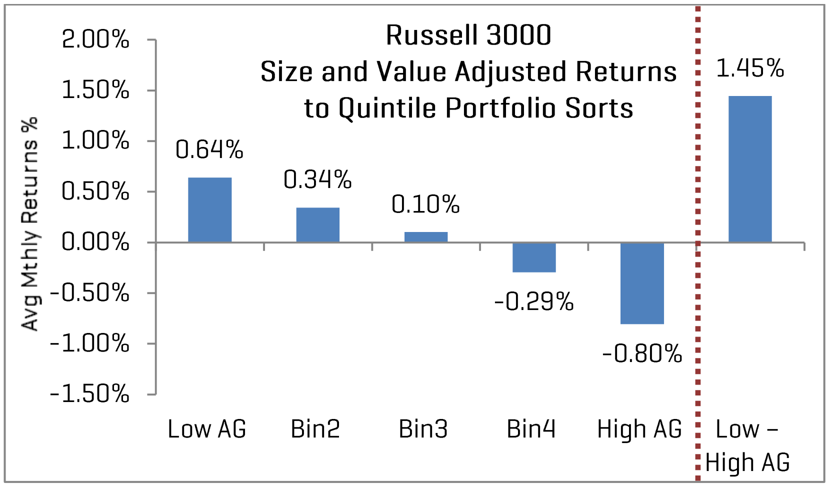
Similar to the cross-sectional regressions analysis, we examine the impact of small-cap stocks on the performance of the asset growth factor by looking at the results of the quintile return spreads in the Russell 1000 and the Russell 2000 indices separately. The results in Exhibit 6a and 6b indicate that the asset growth factor also exhibits return predictive power in each index and confirm that the results from the Russell 3000 are not overly influenced by small- or micro-caps. The average monthly quintile return spread is 0.89% for the Russell 1000 and 1.65% for the Russell 2000 with significance at the 1% level. The results here also indicate that the long and short sides both make approximately equal contribution to the overall long-short strategy in both indices. We do see, however, the asset growth factor does appear to predict returns better in a universe of smaller stocks with the difference in the average monthly quintile return spreads between the Russell 1000 and the Russell 2000 amounting to 0.76%.

[6] Fama, E.F., and K.R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56

Exhibit 5: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

Russell 3000

1/1993 – 12/2012



Source S&P Capital IQ Quantamental Research

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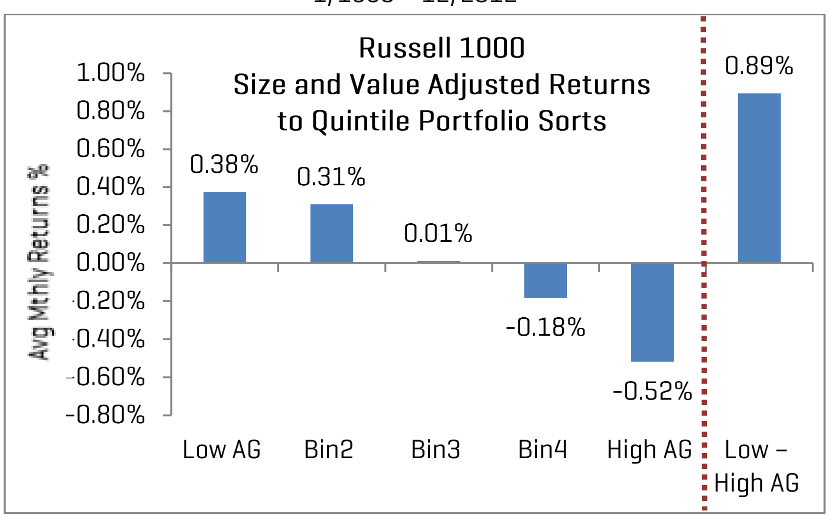
Exhibit 6a: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

Russell 1000

1/1993 – 12/2012



Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

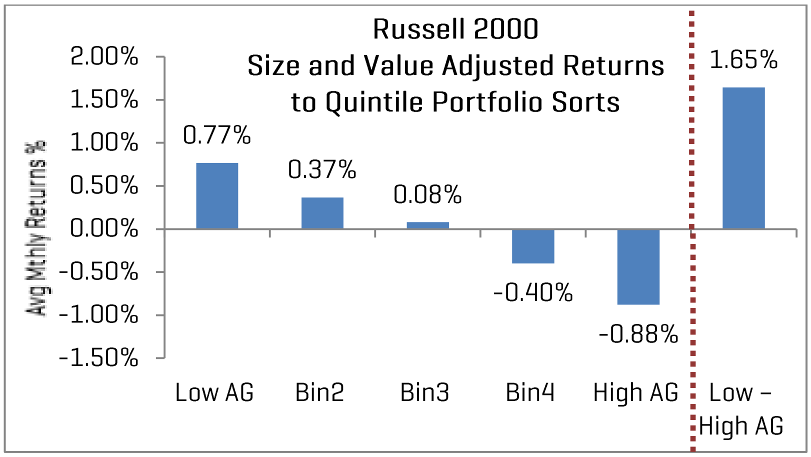
2.2 International Results

Internationally, the results are consistent with those in the U.S. Within the S&P BMI Developed Markets Europe (Asia Pacific), the average monthly quintile return spread after controlling for size and book-to-market equity is 0.73% (0.64%) with significance at the 1% level. As in the U.S. results, both the long and short sides contribute to the overall quintile return spread strategy. The international results reinforce what we see in the U.S. results that the asset growth anomaly isn't solely from the extreme portfolios. For example, the average monthly quintile return spread, which buys the stocks in Bin2 and sells the stocks in Bin4, yields 0.35% (0.22%) for the S&P BMI Developed Markets Europe (Asia Pacific) with significance at the 1% level. See Exhibit 7a and 7b.

Exhibit 6b: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

Russell 2000

1/1993 – 12/2012

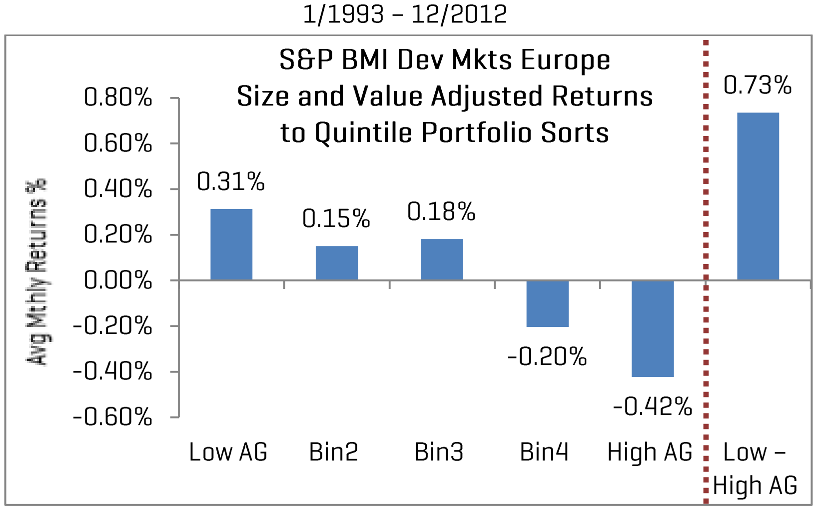


Source S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Exhibit 7a: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

S&P BMI Developed Markets Europe

1/1993 – 12/2012

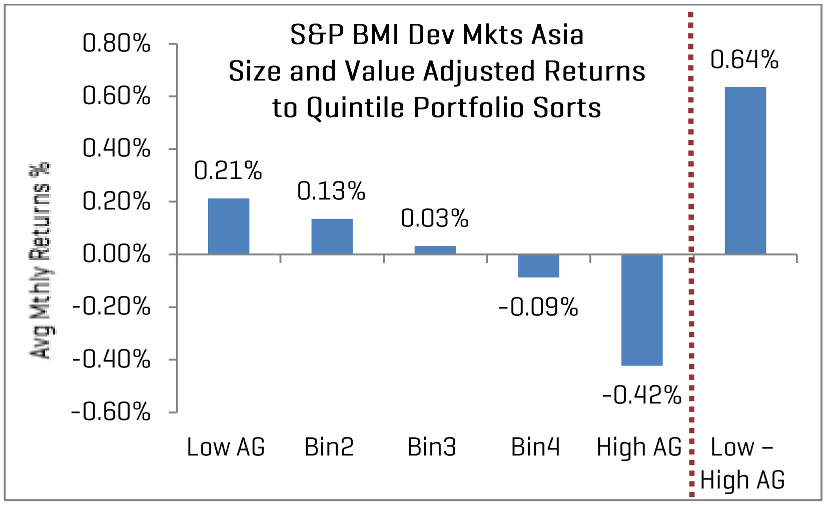


Source S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Exhibit 7b: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2012



Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

Exhibit 8 has the consolidated results in tabular form for the U.S., Europe, and Asia Pacific regions.

Exhibit 8: Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

Russell 3000, S&P BMI Developed Markets Europe. and S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2012

index	Low AG	Bin2	Bin3	Bin4	High AG	Low – High AG
Russell 3000	0.64% ***	0.34% ***	0.10%	-0.29% ***	-0.80% ***	1.45% ***
S&P BMI Developed Markets Europe	0.31% ***	0.15% **	0.18% ***	-0.20% ***	-0.42% ***	0.73% ***
S&P BMI Developed Markets Asia Pacific	0.21% **	0.13% **	0.03%	-0.09% *	-0.42% ***	0.64% ***

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

2.3 Sub-periods

As an additional robustness check, we split our sample period into two sub-periods: 1/1993 – 12/2002 and 1/2003 – 12/2012 and ran the same analysis as in Section 2.1 and 2.2. Our results indicate that asset growth exhibits return predictive power in both sub-periods and the differences between the two sub-periods are not statistically significant. See Exhibit 9.

Exhibit 9: Sub-periods Size and Value Adjusted Equal-Weighted Returns of Portfolios Sorted on Asset Growth Factor

Russell 3000, S&P BMI Developed Markets Europe. and S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2002; 1/2003 – 12/2012

	1993 - 2002	2003 - 2012	Difference between Two Sub-periods
Index	Avg Mthly Quintile Return Spread	Avg Mthly Quintile Return Spread	Avg Mthly Quintile Return Spread
Russell 3000	1.71% ***	1.18% ***	0.53%
S&P BMI Developed Markets Europe	0.82% ***	0.65% ***	0.17%
S&P BMI Developed Markets Asia	0.43% ***	0.84% ***	-0.41%

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

2.4 Summary

After controlling for size and book-to-market equity risk dimensions, the average monthly quintile return spreads in all the regions exhibit both economic and statistical significance. Our results also indicate that both the long and the short sides contribute to the quintile return spreads and the asset growth anomaly does not solely work in the extreme portfolios.

3. What Explains the Asset Growth Effect?

In Sections 1 and 2, the global results from two different methods with various robustness checks show that the asset growth factor demonstrates return predictive power with and without controls for other variables. The results prompt us to ask: why does the asset growth anomaly exist? In this section, we present both qualitative and quantitative arguments demonstrating that behavior-based explanations, rather than risk-based explanations, are more likely to explain the asset growth effect.

3.1 Fama-French Three-Factor Model Can't Explain Asset Growth Effect

In Section 2, we examine the quintile abnormal return spreads using asset growth as the sorting variable. In effect, these abnormal return spreads are returns that can't be explained by the Fama-French three-factor model according to Fama and French papers (2003 and 2008).[7] Yet after controlling for the factors in the Fama-French three-factor model, the asset growth effect is still pronounced, which is evident by the largely positive and statistically significant quintile return spreads in Section 2.

3.2 Mean Reversion in the Top- and Bottom-Line Growths

With traditional risk factors unable to explain the asset growth anomaly, we hypothesize that the existence of the anomaly is due to the fact that investors (linearly) extrapolate stocks' past growth

[7] Fama, Eugene F., and Kenneth R. French, 1993, "Common Risk Factors in the Returns on Bonds and Stocks", *Journal of Financial Economics* 33, 3-56; Fama, Eugene F., and Kenneth R. French, 2008, "Dissecting Anomalies", *Journal of Finance* 63, 1653-1678

rates and margins into the future. Specifically, our hypothesis is that high asset growth stocks, which previously enjoyed strong growth rates, couldn't maintain those same growth rates into the future even after aggressively expanding their asset base to meet the expectations of the investors, whereas low asset growth companies, which previously suffered low or declining growth rates, are able to exceed their conservatively projected growth rates after prudently investing in high-performing assets or selectively pruning the non-performing assets as a part of their restructuring efforts.

Some underlying laws of economics that lend support to our hypothesis are:

- The law of large numbers in the context of this section says that companies experience high revenue and earnings growth will indubitably slow as they grow bigger.
- The law of diminishing returns in the context of this section says that companies will receive lower per-unit of return at some point as they add one additional input while holding other inputs constant.

To test the validity of our hypothesis, we examine the industry-relative (GICS Level 2) 3-year percentage change in the growth of revenues, EPS, gross margins, and operating margins of stocks in the highest and the lowest asset growth portfolio bins. Our results indicate that the highest asset growth stocks experience strong industry-relative top- and bottom-line growth rates (3-year percentage change in revenue and EPS) and margins (gross and operating margins) prior to entering the highest asset growth quintile. However, these same stocks experience declining industry-relative top- and bottom-line growth rates (3-year percentage change in revenue and EPS) and margins (gross and operating margins) in the subsequent three years after entering the highest asset growth quintile. The reverse also appears to be true for those companies that enter the lowest asset growth quintile (Exhibit 10). These results are supportive of our hypothesis that highest asset growth companies couldn't maintain their past torrid growth rates and high margins even after aggressively expanding their asset base, while lowest asset growth companies are able to improve their growth rates and margins. In Europe and Asia Pacific, we find similar results. See Exhibits 11 and 12.

Exhibit 10: Industry Relative 3-Year Percentage Change in the Top- and Bottom-Line Growths and Margins for the Highest and the Lowest Asset Growth Stocks

Russell 3000

1/1993 – 12/2012

Highest Asset Growth Bin	Before	After	Lowest Asset Growth Bin	Before	After
Revenue 3Y Change	56.75%	26.35%	Revenue 3Y Change	-20.04%	-11.63%
EPS 3Y Change	38.05%	-8.76%	EPS 3Y Change	-52.62%	17.68%
Gross Margin 3Y Change	2.47%	-1.00%	Gross Margin 3Y Change	-2.43%	1.79%
Operating Margin 3Y Change	19.86%	-7.94%	Operating Margin 3Y Change	-16.00%	13.56%

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

Exhibit 11: Industry Relative 3-Year Percentage Change in the Top- and Bottom-Line Growths and Margins for the Highest and the Lowest Asset Growth Stocks

S&P BMI Developed Markets Europe

1/1993 – 12/2012

Highest Asset Growth Bin	Before	After	Lowest Asset Growth Bin	Before	After
Revenue 3Y Change	32.48%	17.32%	Revenue 3Y Change	-17.76%	-11.67%
EPS 3Y Change	25.80%	-6.68%	EPS 3Y Change	-42.28%	20.57%
Gross Margin 3Y Change	1.44%	-0.08%	Gross Margin 3Y Change	-1.04%	0.47%
Operating Margin 3Y Change	5.77%	-4.85%	Operating Margin 3Y Change	-11.54%	11.44%

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

Exhibit 12: Industry Relative 3-Year Percentage Change in the Top- and Bottom-Line Growths and Margins for the Highest and the Lowest Asset Growth Stocks

S&P BMI Developed Markets Asia Pacific

1/1993 – 12/2012

Highest Asset Growth Bin	Before	After	Lowest Asset Growth Bin	Before	After
Revenue 3Y Change	34.02%	15.14%	Revenue 3Y Change	-9.36%	-5.94%
EPS 3Y Change	32.54%	-11.40%	EPS 3Y Change	-33.32%	22.12%
Gross Margin 3Y Change	1.45%	-1.97%	Gross Margin 3Y Change	-1.46%	2.29%
Operating Margin 3Y Change	10.63%	-9.11%	Operating Margin 3Y Change	-13.80%	16.78%

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

3.3 Return Predictive Power in Risk-On and Risk-Off States

Lastly, we analyze the return predictive power of the asset growth factor in high and low volatility states, which we use as proxy for risk-on and risk-off environments, respectively. We hypothesize if the asset growth anomaly is a compensation for some type of systematic risk, then we would expect its performance in risk-on periods to be better than those in risk-off periods much in the same way that factors such as CAPM beta perform better in risk-on periods than in risk-off periods.

We use high (low) volatility periods as proxy for risk-on (risk-off) periods. Specifically, we use the 12-month realized price volatility from S&P Capital IQ's Alpha Factor Library (AFL) [8] to demarcate high and low volatility periods. The 12-month realized price volatility factor is sorted in a

[8] S&P Capital IQ's Alpha Factor Library consists of 450+ stock selection signals with associated metrics such as information coefficients and factor spreads. All factor performance is downloadable by time period, regime, country, and sector dimensions

descending fashion where stocks near the top (bottom) of the sort have exhibited the most (least) price volatility in the past 12 months. Next, we use the sign of the monthly quintile return spread, which is the average return from the top quintile portfolio with the highest price volatility stocks less the average return from the bottom quintile portfolio with the lowest price volatility stocks, to determine whether a month is in a high or a low volatility state. When the sign is positive (negative), we mark that month as high (low) volatility. To ensure that the 12-month realized price volatility is a good metric to bifurcate high and low volatility periods, we look at the performance of the monthly quintile return spreads of the 60-month CAPM beta factor from the AFL in high volatility and low volatility states as determined by the 12-month realized price volatility factor. We expect the 60-month CAPM beta factor to do well in high volatility periods and do poorly in low volatility periods. The empirical results do show the 60-month CAPM beta factor works in high volatility periods and doesn't work in low volatility periods. This confirms the 12-month realized volatility is a good metric to classify high and low volatility periods.

Our results indicate that although the asset growth variable demonstrates its return predictive power in our entire sample period, its predictive power behaves very differently in high and low volatility periods. In low volatility periods, its predictive power is especially strong. In fact, most of its power comes from this state. Conversely, in high volatility periods, its predictive power weakens or even becomes a contrarian indicator. See Exhibits 13a and 14a. Our results also show that the differences in the two volatility regimes are statistically different. In other words, return predictive power of asset growth does behavior differently in different volatility regimes. See Exhibits 13b and 14b. This is observed in all the regions. If the asset growth anomaly exists as a compensation for some type of systematic risk, then it could be expected that the asset growth factor would do better in risk-on environments using high volatility states as proxy than in risk-off environments using low volatility states as proxy. However, our results indicate just the opposite.

Exhibit 13a: Size and Book-to-Market Adjusted Returns to Quintile Portfolios in High and Low Volatility Periods

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

U.S. 1/1993 – 12/2012; International 1/1995-12/2012[9]

	Russell 3000			S&P BMI Dev Mkts Europe			S&P BMI Dev Mkts Asia Pacific		
	1/1993 – 12/2012			1/1995 – 12/2012			1/1995 – 12/2012		
	All Periods	Low Volatility Regime	High Volatility regime	All Periods	Low Volatility Regime	High Volatility regime	All Periods	Low Volatility Regime	High Volatility regime
Monthly Average	1.45%***	2.25%***	0.46%	0.71%***	0.93%***	0.45%**	0.64%***	0.74%***	0.51%**
Number of Months	240	132	108	216	114	102	216	120	96

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

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9 For the S&P BMI Developed Markets Europe (Asia), 114 (120) out of 216 months are marked as risk-off. The difference in total number of months between the U.S. and international regions is due to the fact that the 12-month price volatility factor starts in January 1995, as opposed to in January 1993, for the international regions.

Exhibit 13b: Difference in Average Monthly Quintile Spread Returns Between High and Low Volatility Periods (Low Volatility Less High Volatility)

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

U.S. 1/1993 – 12/2012; International 1/1995-12/2012[10]

	Russell 3000	S&P BMI Dev Mkts Europe	S&P BMI Dev Mkts Asia Pacific
	1/1993 – 12/2012	1/1995 – 12/2012	1/1995 – 12/2012
Difference in Average Returns	1.79% ***	0.48% *	0.23%

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

Exhibit 14a: Average Monthly Estimated Coefficient to the Asset Growth Factor in High and Low Volatility Periods

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

U.S. 1/1993 – 12/2012; International 1/1995-12/2012

	Russell 3000			S&P BMI Dev Mkts Europe			S&P BMI Dev Mkts Asia Pacific		
	1/1993 – 12/2012			1/1995 – 12/2012			1/1995 – 12/2012		
	All Periods	Low Volatility Regime	High Volatility regime	All Periods	Low Volatility Regime	High Volatility regime	All Periods	Low Volatility Regime	High Volatility regime
Monthly Average	-0.31%***	-0.78%***	0.27%**	-0.26%*	-0.66%***	0.19%	-0.16%**	-0.39%***	0.12%
Number of Months	240	132	108	216	114	102	216	120	96

Exhibit 14b: Difference in Average Monthly Estimated Coefficients Between High and Low Volatility Periods (Low Volatility Less High Volatility)

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

U.S. 1/1993 – 12/2012; International 1/1995-12/2012[11]

	Russell 3000	S&P BMI Dev Mkts Europe	S&P BMI Dev Mkts Asia Pacific
	1/1993 – 12/2012	1/1995 – 12/2012	1/1995 – 12/2012
Difference in Average Returns	-1.05% ***	-0.85% ***	-0.51% ***

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

[10] For the S&P BMI Developed Markets Europe (Asia), 114 (120) out of 216 months are marked as risk-off. The difference in total number of months between the U.S. and international regions is due to the fact that the 12-month price volatility factor starts in January 1995, as opposed to in January 1993, for the international regions.

[11] For the S&P BMI Developed Markets Europe (Asia), 114 (120) out of 216 months are marked as risk-off. The difference in total number of months between the U.S. and international regions is due to the fact that the 12-month price volatility factor starts in January 1995, as opposed to in January 1993, for the international regions.

3.4 Summary

To summarize, our view is that the asset growth anomaly is more likely to be explained by behavioral-based explanations than by risk-based explanations. Firstly, the anomaly can't be explained by standard risk-based models such as the Fama-French three-factor model. Secondly, we find the high asset growth companies couldn't maintain their high growth rates and margins whereas low asset growth companies are able to improve upon their low growth rates and margins. Lastly, the anomaly is predictive of future returns in our sample period but its predictive power is especially pronounced in risk-off periods and weakens or even becomes a contrarian indicator in risk-on periods.

4. Correlations

In this section, we explore monthly information coefficient (IC) correlations between asset growth and each of the eight quantitative equity factor styles from S&P Capital IQ's Alpha Factor Library to ascertain potential diversification benefits of adding asset growth to other alpha factors. Each of the factor styles is comprised of two or more factors representative of the factor style in equal-weights. See definitions of factor styles below and additional details in Section 5. In order to make the interpretation of IC correlation results more intuitive, monthly ICs of asset growth are multiplied by -1.

The factor styles are:

- Analyst Expectation: a composite of factors measuring sell-side analysts' forecasts on companies
- Capital Efficiency: a composite of factors measuring how well companies are doing in relation to their cost of capital
- Earnings Quality: a composite of factors measuring the persistence of companies' earnings
- Historical Growth: a composite of factors measuring the historical growth of companies' top- and bottom-line growth and cash flow growth
- Price Momentum: a composite of factors measuring the short- and intermediate- price performance
- Size: a composite of factors measuring the market capitalization and sales of companies
- Valuation: a composite of factors measuring the relative attractiveness of companies
- Volatility: a composite of factors measuring the dispersion in prices and uncertainties in the market place

Our results in Exhibit 15 indicate that there are potential diversification benefits from adding asset growth factor to other alpha factors. Results from our sample period indicate that asset growth has positive correlations with both valuation and earnings quality factor styles, but they're not sizeable to a point where no diversification benefits could be derived from the addition of asset growth to each. We attribute the positive correlation between asset growth and valuation factor style to the same underlying behavioral cause[12] – investors (linearly) extrapolate top- and bottom-line growth rates from the past into the future and are, therefore, willing to pay higher valuations for that potential future growth. However, when high asset growth companies don't live up to investors' expectations, they underperform their low asset growth counterparts, hence the positive correlation. We see this relationship in both the U.S. and Europe, but surprisingly not in Asia. As for the positive correlation between asset growth and earnings quality factor style, our view is that the quality of earnings for high asset growth companies deteriorates as they try to sustain their past torrid growth and meet investors' high growth expectations by aggressively expanding their asset base, whereas the quality of earnings for low asset growth companies improves through conservative growth of their asset base or through selectively pruning of their non-performing assets. We see this relationship in all the regions, especially so in Asia. In our view, the positive correlations among asset growth factor, valuation factor composite, and earnings quality factor composite suggest that companies that are deemed attractive (unattractive) by all three of them do share some similar financial characteristics.

Exhibit 15: Monthly IC Correlations of Asset Growth and Quantitative Equity Factor Styles

Russell 3000, S&P BMI Developed Markets Europe, and S&P BMI Developed Markets Asia Pacific

U.S. 1/1993 – 12/2012; International 1/1995-12/2012

	Analyst Expectations	Capital Efficiency	Earnings Quality	Historical Growth	Price Momentum	Size	Valuation	Volatility
Russell 3000	-0.46 ***	0.14 **	0.39 ***	-0.03	-0.12 *	-0.18 ***	0.48 ***	-0.28 ***
S&P BMI Dev Mkts Europe	-0.28 ***	-0.21 ***	0.14 **	-0.26 ***	-0.09	0.02	0.43 ***	-0.01
S&P BMI Dev Mkts Asia Pacific	-0.14 **	-0.21 ***	0.61 ***	-0.44 ***	-0.10	0.07	-0.14 **	0.00

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

Source S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

Our results also indicate that asset growth has negative correlation with analyst expectation factor composite. Our view is that high asset growth companies have higher growth expectations vis-à-vis low asset growth companies. The higher growth expectations of high asset growth companies could come from sell-side analysts, who may project future growth rates based on past growth rates, or could come from company management, who may provide an overly optimistic guidance. In fact, according to Cotter et al. (2006) and Yu (2008), sell-side analysts' estimates and company managements' guidance exert influence on each other. Moreover, Chan et al. (2002) find estimated long-term earnings growth rates from the sell-side consistently exceed realized growth rates. Consequently, when high asset growth companies fail to meet their expected growth, they

[12] Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, Journal of Finance 49, 1541 - 1578

underperform vis-à-vis their low asset growth counterparts, hence the negative relationship. We see this negative relationship in all the regions.

5. Data

The study covers both the U.S. and the international markets. The Russell 3000 index is used as a representative of the U.S. market. The Russell 1000 is used as a proxy for larger market capitalization companies in the U.S. while the Russell 2000 serves the same purpose for smaller market capitalization companies in the U.S. S&P BMI Developed Markets Europe, which contains developed European countries, is used as a proxy for the European market. As of March 29, 2013, the countries in this index include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom. S&P BMI Developed Markets Asia Pacific, which contains developed Asian countries, represents the Asian market. As of March 29, 2013, the countries in this index include Australia, Hong Kong, Japan, New Zealand, Singapore, and South Korea. The sample data time period goes from January 1993 to December 2012. The financial data are from S&P Capital IQ's Point-In-Time global data. The total returns data are from S&P Capital IQ's market data package. The eight quant equity factor styles are from S&P Capital IQ's Alpha Factor Library (AFL). Subscribers of AFL will be able to drill down into the factor styles and see the individual factors that comprise each of the factor styles as well as have access to the formulation of each of the underlying factors.

6. Conclusion

Our results indicate that the asset growth factor demonstrates return predictive power globally with or without controls for size, value, and price momentum factors during January 1993 – December 2012. The results are both economically and statistically significant. Our results also suggest that behavioral-based explanations are more likely to explain the asset growth effect than risk-based explanations. We attribute the existence of the asset growth anomaly mainly to the fact that the high asset growth companies, which previously enjoyed high growth rates and margins, couldn't maintain those same growth rates and margins even after aggressively expanding their asset base whereas the low asset growth companies, which previously suffered from low or declining growth rates and margins, were able to improve their growth rates and margins without aggressively expanding their asset base. Lastly, our IC correlation analyses indicate that potential diversification benefits could be had by using asset growth in conjunction with other predictive factors.

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Our Recent Research

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?

In this report, we compare the performance of SUE to one based on returns around a firm's earnings announcement date (EAR), proposed by Brandt et al (2008). We test both factors globally and find EAR dominates SUE in the U.S in the post Reg FD era on both a long-short return and top quintile excess return basis.

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

Supply chain relationships are among the most visible and measurable, as revenues and costs shape the realized economic and financial performance of connected companies. Studies have shown that events within a supply chain do introduce these ripple effects, and theories incorporating this information into an investment process have garnered attention in recent years. We construct a map quantifying industry level connections along the supply chain. Using this map, and trailing industry returns as a proxy for industry level information shocks, we construct inter-industry momentum signals. These signals exhibit lead-lag relationships over short horizons, as the information shocks diffuse through the market and manifest themselves in the performance of related industries.

July 2012: Releasing S&P Capital IQ's Regional and Updated Global & US Equity Risk Models
Over the course of the last two years we released our Global and US Fundamental Equity Risk Models. As a natural progression we are releasing the first set of Regional Models – the Pan-Asia ex. Japan and the Pan-Europe Fundamental Equity Risk Models. This document will explain some of the salient aspects of the process adopted for constructing the Regional Models. We have also made additional improvements to our US & Global Equity Risk Models, and we shall explain these changes.

June 2012: Riding Industry Momentum – Enhancing the Residual Reversal Factor
Unlike individual stocks whose short-term returns tend to revert from one month to the next, industry portfolios exhibit return momentum even at a one-month horizon. We examine a strategy that takes advantage of both industry level momentum and stock level reversal. We combine our residual reversal factor with an industry momentum score, and find that the factor performance is greatly enhanced in the Russell 3000 universe between January 1987 and February 2012. The decile return spread is increased by 42 bps per month on average.

May 2012: The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data
In the oil & gas industry, a key determinant of value and future cash flow streams is the level of oil & gas reserves a firm holds. While most fundamental analysts/investors take into consideration a company's reserves in arriving at price targets, a majority of systematic driven processes do not. Using S&P Capital IQ's Global Point-in-Time database, we investigate the importance of reserve and production information provided by oil & gas companies.

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions
Ten years ago, AAPL traded just below $12 and closed at $583.98 on April 30, 2012. That is an average annual return of 48.1% over the period. During this same time the S&P 500 grew at an annual rate of only 2.65%. On April 2nd, Topeka Capital Markets initiated coverage of AAPL with a price target of $1001. If achieved, this would make AAPL the first company to ever reach a $1 trillion market cap. In this case study, we highlight some key S&P Capital IQ functionality in analyzing AAPL hypothetically reaching $1000:

March 2012: Exploring Alpha from the Securities Lending Market – New Alpha Stemming from Improved Data
Numerous studies have examined the information content of short interest and found that heavily shorted stocks tend to underperform and liquid stocks with low levels of short interest subsequently outperform. Most studies relied on short interest data obtained directly from the exchanges available with a significant delay.

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

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

January 2012: Intelligent Estimates – A Superior Model of Earnings Surprise
As residual stakeholders, equity investors place enormous importance on a company's earnings. Analysts regularly forecast companies' future earnings. The prospects for a company's future earnings then become the basis for the price an investor will pay for a company's shares. Market participants follow sell side analysts' forecasts closely, identifying those analysts that demonstrate predictive prowess and track those analysts' forecasts going forward.

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 - Tough Times for Active Managers

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