Complicated Firms Made Easy

Using Industry Pure-Plays to Forecast Conglomerate Returns

Authors

Ryan Forsythe
Quantitative Analyst,
Quantamental Research
312-233-7153
rforsythe@spcapitaliq.com

Jim Osiol
Quantitative Analyst
Quantamental Research
312-233-7128
josiol@spcapitaliq.com

Regular readers of our research will know that one of our major areas of focus of late has been how investors can leverage industry-specific signals to enhance their portfolios' performance. Yet many of the most widely followed, largest companies span multiple industries and complex business lines.

Strong-form Efficient Market Hypothesis advocates would have us believe that prices for related stocks should react similarly as news becomes available, regardless of their complexity. Yet as our recent work on customer-supplier relationships suggests there are lead-lag relationships between firms which we believe are worth watching. Similarly, the research suggests that 'Complicated Firms' represent another possible source of inefficiency due to the market's difficulty in incorporating industry-level information into the stock price.

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. Our research shows…

- A long-short strategy using pseudo-conglomerates returns as a forecast of complicated firms returns yields a monthly return spread of 0.44%** and residual return spread of 0.34%** in the Russell 3000
- This is a tail strategy. The pseudo-conglomerate return strategy is most effective in a subset universe consisting of only the most complicated firms. This strategy generates a monthly return spread of 0.66%*** in the Russell 3000
- The magnitude of revisions to pseudo-conglomerate EPS estimates is a powerful signal for future revision magnitude in complicated firms with a revision magnitude spread significant at the 90% level
- Taking advantage of a valuation discount in earnings-to-price between complicated firms and their pseudo-conglomerates provides an excess one month raw return spread of 0.46%***[1]

[1] Significance levels of 1%, 5%, and 10% are denoted by ***, **, * respectively

Industry Information and Complicated Firms

Industry information is more easily digested for simple firms that operate primarily within one industry (>80% of total sales in one industry segment) compared to complicated firms that operate across multiple industries (maximum segment sales in any one industry <80% of total sales). Specifically, the same piece of industry news that would be quickly priced into a simple firm may take longer to be incorporated for a complicated firm. The market latency in incorporating this information will allow us to make more informed (and profitable) investment decisions with regards to complicated firms.

With this in mind, we classify simple firms in terms of their primary industry and complicated firms in terms of a representative pseudo-conglomerate. This pseudo-conglomerate is simply a combination of industries weighted proportionately to the complicated firm's reported sales in each industry. We can then calculate returns, analyst revisions, and industry valuation ratios for the pseudo-conglomerate that more comprehensively reflect the performance of the complicated firm's true industry exposures. For example, Company XYZ operates equally in two industries: 50% of sales in Industry A and 50% of sales in Industry B. Last month, Industry A had a return of 10%, and Industry B had a return of 5%. We say that Company XYZ's pseudo-conglomerate had a return of 7.5% (.5×5%+.5×10%) last month.

The operating segment sales are reported in a company's annual filing as required by FASB Statement 14 and are captured in Compustat Segment Data. We lag all segment sales data to June of the following year to be conservative given the data is not point-in-time. These weights are then static until June of the following year.

1. Pseudo-Conglomerate Momentum Strategy

We calculate SIC industry level returns as the average cap weighted, issue level returns of simple firms within each industry. These industry returns should be a pure representation of returns to that industry group as they are not muddied by firms that operate across multiple industries. We construct our pseudo-conglomerate return using these pure industry returns weighted by the complicated firm's industry segment sales as outlined above.

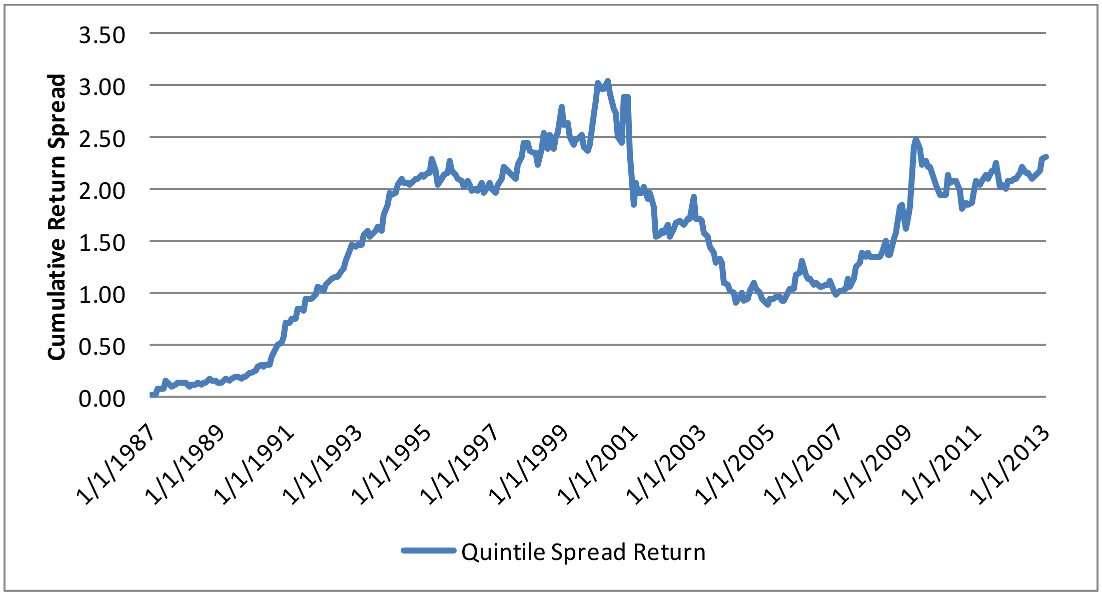
1.1 Backtest Results

We backtest[2] the complicated firm's pseudo-conglomerate return from the previous month as a stock selection signal within the Russell 3000 index (R3000). We go long firms whose pseudo-conglomerates had the highest returns (most good news/least bad news) and short those whose pseudo-conglomerates had the lowest returns (least good news/most bad news) in the prior

[2] Backtested performance is not actual performance but is hypothetical. Backtested hypothetical information is generally prepared with the benefit of hindsight and may not account for the impact of financial risk in actual trading. For example, there are numerous factors related to the equities markets in general which cannot be, and have not been accounted for in the preparation of the index information set forth, all of which can affect actual performance.

period. This strategy generates a monthly return spread of 0.44% (t-stat = 2.29) over the test period from 1987 – 2013.

Figure 1: Pseudo-Conglomerate Quintile Strategy Performance
Raw Complicated Firms Signal to Raw Forward Returns
Russell 3000 Index, 1987 – 2013



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

We check the robustness of our strategy by regressing out market (R3000), value (BP), size (LogMktCap), and momentum (12M1M) returns from our strategy's return spread stream (Table 1). After regressing out these common factors, significant alpha of 50 bps (t-stat=2.46) remains. The analysis shows a negative loading on the size factor. This makes intuitive sense when you consider that firms operating in multiple industries are predominantly large cap (see Appendix A).

Table 1: Fama French Return of Complicated Firms Spread
Russell 3000 Index, 1987 – 2013

	Coefficients	*Standard Error*	*t Stat*
Intercept	0.005	0.002	2.46
R3000	0.002	0.046	0.05
BP	-0.088	0.062	-1.42
LogMktCap	-0.131	0.053	-2.47
12M1M	-0.086	0.052	-1.63

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

1.2 Robustness Check - Residual Returns

We further test the robustness of our results by constructing a time series of issue level monthly residual returns. These residual returns remove the effect of common factors from the returns of both simple and complicated firms. Using these residual returns in place of raw returns, we construct a pseudo-conglomerate signal that is less influenced by industry returns explained by these factors. This new signal more explicitly focuses on industries with real information shocks (driven by something other than the factors). We extract our residuals each month from the following cross sectional regression within the Russell 3000:

$$RFR_i = \alpha + \beta_m Beta_i + \beta_v BtM_i + \beta_p PMOM_i + \beta_s LMcap_i + \epsilon$$

R_i = Forward Return of Complicated Firm i

RF = Forward Risk Free Rate

$RFR_i = R_i - RF$

$Beta_i$ = Trailing 60 Month Beta Percentile

BtM_i = Trailing Book-to-Price Ratio Percentile

$PMOM_i$ = Trailing 12M - 1M Price Momentum Percentile

$LMcap_i$ = Trailing Log of Market Cap Percentile

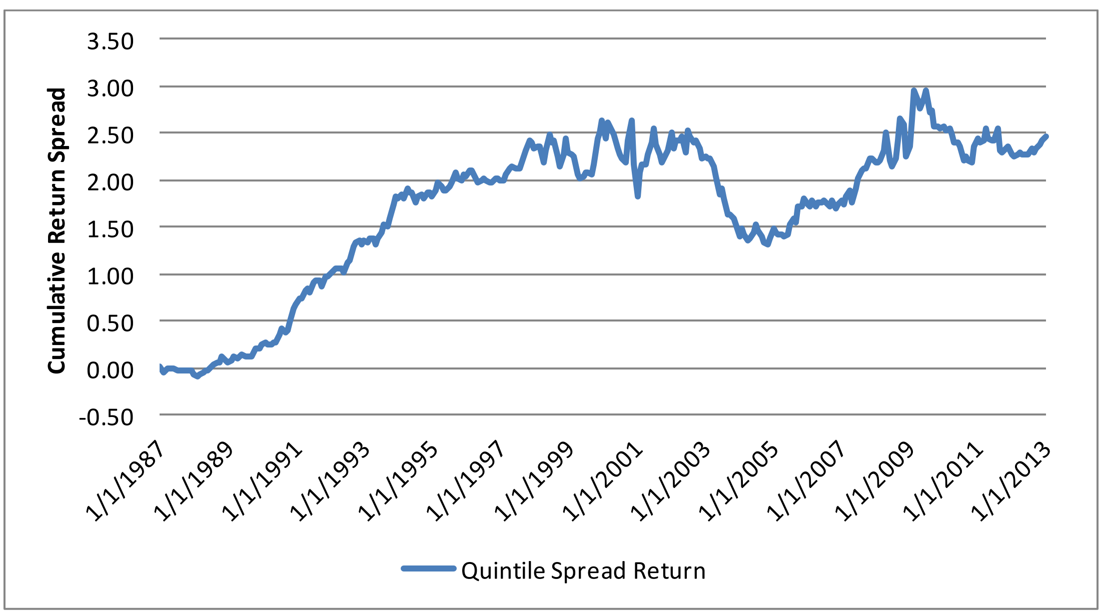
ϵ = Residual

Following the same conventions as above, we calculate SIC industry level residuals as the average equal weighted, issue level residuals of simple firms within each industry. We equal weight these residuals when rolling up because we have regressed out the impact of size. We construct our pseudo-conglomerate residual signal using these industry residual returns weighted by the complicated firm's industry segment sales. This new signal generates a slightly improved monthly quintile return spread of 0.45% (t-stat = 2.49) over our test period.

Figure 2: Pseudo-Conglomerate Quintile Strategy Performance

Residual Complicated Firms Signal to Raw Forward Returns

Russell 3000 Index, 1987 – 2013



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

Our return spread's final exposure to the factors decreases considerably using a residualized pseudo-conglomerate factor. We still observe a negative loading on the size factor, and we still have significant alpha.

Table 2: Fama French Return of Complicated Firms Spread
Russell 3000 Index, 1987 – 2013

	Coefficients	*Standard Error*	*t Stat*
Intercept	0.004	0.002	2.00
R3000	0.007	0.042	0.16
BP	-0.022	0.057	-0.38
LogMktCap	-0.087	0.049	-1.78
12M1M	0.033	0.048	0.68

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

When we examine our performance in terms of the average residual return from our monthly regression for both the long and short sides of our portfolio, we observe a similar Q1-Q5 residual return spread. This strategy also generates more alpha from the short side rather than the long side (Table 3).

Table 3: Residual Complicated Firms Signal to Forward Residuals
Russell 3000 Index, 1987 – 2013

	Quintile 1	Quintile 5	Residual Spread
Avg 1Mo Spread	0.10%	-0.24%	0.34%
T Stat	0.91	-2.15	2.17
Hit Rate	52%	45%	56%

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

1.3 Less Conservative Lags

Following the convention set forth by Cohen and Lou, we wait until June to incorporate the previous fiscal year's segment data into our strategy. Since this is a very conservative lag, we tested incorporating the segment sales in a timelier manner for our strategy. Instead of waiting until June of the following year, we incorporate the new segment sales weights 4 months after the period end date. However, this approach does not result in any noticeable gains above and beyond the initial strategy. As the relative segment sales are fairly stable and only estimate the importance of each individual operating segment to the firm, there is no considerable value derived from being more aggressive with our data. As such, we maintain the more conservative lags throughout the analysis.

1.4 Levels of Complexity

The more complex a firm's operations become, the more difficult it should be to acquire and analyze all relevant industry level information. We use a Herfindahl Index to measure the complexity of our complicated firms. The index is the sum of squared segment percentages of total sales. Borrowing the example from before, Company XYZ operates equally in two industries: 50% of sales in Industry A and 50% of sales in Industry B. Squaring and then summing these values gives a Herfindahl Index score of 0.5 ($0.5^2+0.5^2$). So, firms with a high Herfindahl Index are relatively simple. This type of index is commonly used to measure industry concentrations, but it extends naturally to quantify the complexity of a complicated firm.

$$SegPctTotal_i = \frac{SegmentSales_i}{\sum_{i=1}^{I} SegmentSales_i}$$

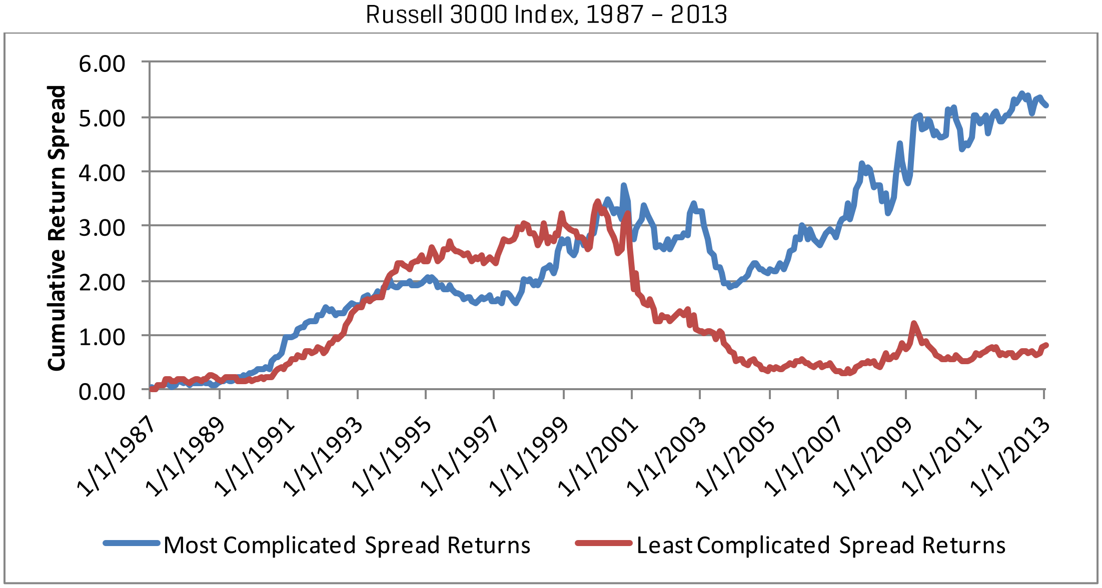
$$Herfindahl\ Index = \sum_{i=1}^{I} SegPctTotal_i^2$$

We test the importance of complexity by splitting our universe of complicated firms into two sub-universes based on their level of complexity. The sub-universes are the top and bottom halves of the complicated universe in a given month based on each company's Herfindahl Index. We then test the pseudo-conglomerate return signal in each sub-universe independently. We would anticipate the performance of our pseudo-conglomerate signal to generate stronger return spreads in the sub-universe of the most complicated firms. The long-short strategy generated a significant monthly return spread of 0.66% (t-stat=3.05) in the more complicated sub-universe compared to a monthly return spread of 0.25% (t-stat=1.26) in the less complicated universe.

Figure 3: Pseudo-Conglomerate Quintile Strategy Performance – Complicated Sub-Universes

Raw Complicated Firms Signal to Raw Forward Returns

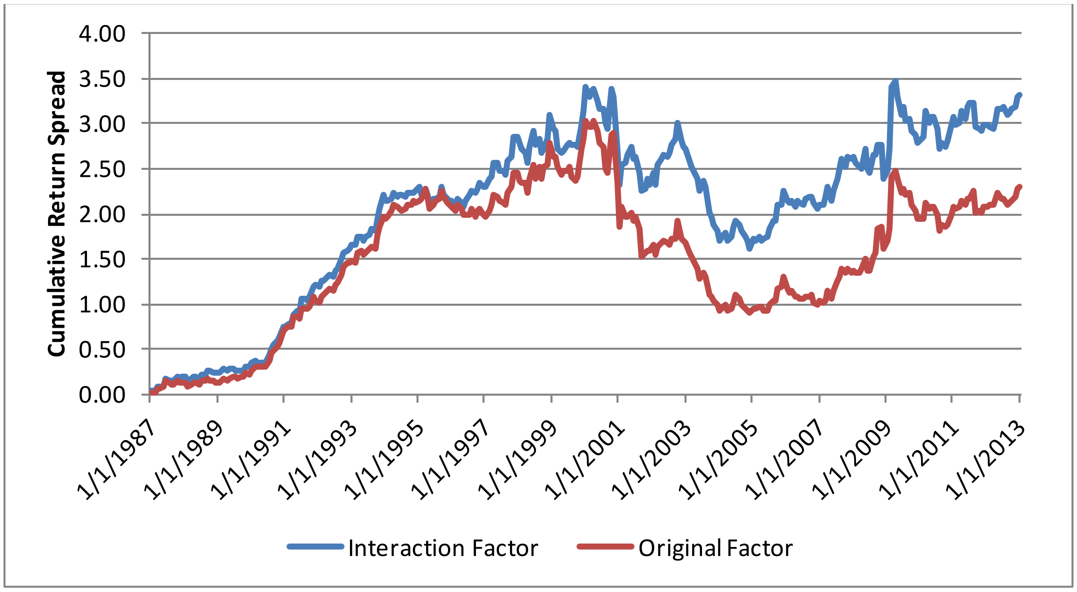
Russell 3000 Index, 1987 – 2013



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

We then incorporated the complexity index into the signal itself. We took the product of the pseudo-conglomerate return and (1 – Herfindahl Index) as our new signal. This interaction allows us to highlight companies that had strong pseudo-conglomerate returns with preference to more complex firms. When compared to the original signal, this interaction factor generates a slightly lower average monthly return spread, but it performs better in the long run due to lower volatility (0.42% & t-stat=2.88 vs. 0.44% & t-stat=2.29).

Figure 4: Pseudo-Conglomerate Quintile Strategy Performance – Original vs. Interaction
Raw Complicated Firms Signal to Raw Forward Returns
Russell 3000 Index, 1987 – 2013



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

2. Further Tests

2.1 Analyst EPS Estimates

If information lag from simple to complicated firms can have an impact on stock returns, then there may be other effects from this same story. Equity analysts may not incorporate all new information simultaneously into all firms when making their equity forecasts. As we have seen, some firms are more complicated and therefore potentially more difficult to analyze than other firms. We expand on our stock return approach by examining how analysts' EPS estimates differ between simple and complicated firms.

In order to compare the uncertainty of analyst estimates between simple and complicated firms, we use the metric Mean Absolute EPS Estimate Percent Difference (AbsEst%Diff). If it is more difficult to incorporate all information into analysts' forecasts for complicated firms, we would expect this metric to have higher values for complicated firms over simple firms.

Table 4: Simple & Complicated Analyst Factor Comparison
Russell 3000 Index, 2000 – 2013

	Complicated Firm Avg Value	Simple Firm Avg Value	Difference of Means t-stat
AbsEst%Diff	0.24	0.22	5.08

Source: S&P Capital IQ Quantamental Research.

Conforming to our priors, we see that since the start of the year 2000, Mean Absolute EPS Estimate Percent Difference for complicated firms is significantly higher on average than for simple firms (difference of means t-stat=5.08). Analysts have greater error and thus uncertainty in making their EPS forecasts for complicated firms compared to simple firms.

We took this analysis a step further by exploring whether pseudo-conglomerate EPS Revision Magnitude, which is the segment sales weighted Revision Magnitude (RevMagFY1) value for a complicated firm, leads the complicated firm's actual Revision Magnitude value. We constructed the RevMagFY1 pseudo-conglomerates the same way as previously but replacing the simple firm returns with simple firm RevMagFY1 values. A higher Revision Magnitude value means that analyst EPS estimates have been revised in a more positive direction over the last 3 months and could be a positive sign of a company's future earnings.

$$RevMagFY1_{i,t} = \frac{EPSEstFY1Median_{i,t} - EPSEstFY1Median_{i,t-3}}{EPSEstFY1_{i,t}}$$

$$EPSEstFY1Median_{i,t} = \text{Median EPS FY1 Estimate of firm i in time t}$$

$$EPSEstFY1_{i,t} = \text{Mean EPS FY1 Estimate of firm i in time t}$$

The trailing one month pseudo-conglomerate Revision Magnitude values were grouped into quintiles each month, where high revision values are in Q1 and low values in Q5. We then compare the quintile scores to the forward complicated firm raw Revision Magnitude values each month. This results in a statistically significant Revision Magnitude Q1 – Q5 spread of 0.025 (t-stat = 1.93). Complicated firms whose pseudo-conglomerates have the highest Revision Magnitude values generally have higher Revision Magnitude values themselves compared to firms with the lowest pseudo-conglomerate Revision Magnitudes. Those pseudo-conglomerates with the lowest Revision Magnitude scores are particularly powerful in predicting negative revisions for their related complicated firms (t-stat = -3.30).

Table 5: RevMagFY1 Quintile Signal to Complicated RevMagFY1
Russell 3000 Index, 2004 – 2013

	Quintile 1	Quintile 5	Q1-Q5 Spread
Avg RevMag Score	-0.007	-0.032	0.025
T Stat	-0.56	-3.30	1.93

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

The information lag story holds up not just on returns, but among analyst revisions as well. Analysts process information more quickly for simple firms and revise their estimates accordingly. The new information is only later factored into analyst estimates for complicated firms. Pseudo-conglomerate revisions are a good predictor of issue revisions, especially when they are the most negative. Major negative revisions among simple firms may be a sign of industry wide problems. These problems would ultimately have a significant effect on complicated firms with operations in that industry, leading to downward EPS revisions for those firms as well.

2.2 Valuation Metrics – BP & EP

Are complicated firms cheap relative to simple firms? We explore this prospect by examining two common valuation metrics: Book-to-Price (BP) and Earnings-to-Price (EP). First, we run a simple comparison of BP & EP values in each of the simple and complicated firm universes from 01/31/1987 – 03/31/2013. We find that complicated firms on average have higher BP ratios (t-stat = 2.53) and EP ratios (t-stat = 7.24).

Table 6: Simple & Complicated Value Factor Comparison

Russell 3000 Index, 1986 – 2013

	Complicated Firm Avg Value	Simple Firm Avg Value	Difference of Means t-stat
Book-to-Price (BP)	0.58	0.60	-2.53
Earnings-to-Price (EP)	0.04	0.06	-7.24

Source: S&P Capital IQ Quantamental Research.

To test whether the pseudo-conglomerate valuation discount exists, we follow the same methodology to construct pseudo-conglomerate BP & EP ratios using simple firms' BP & EP values averaged by industry and weighted using complicated firms' segment sales. We then create a metric called BPPercDiff (EPPercDiff), which is defined below.

$$BPPercDiff_{i,t} = \frac{BP_{i,t} - BPPC_{i,t}}{BPPC_{i,t}}$$

$$BP_{i,t} = \text{BP of complicated firm i}$$

$$BPPC_{i,t} = \text{BP of the psuedo-conglomerate of firm i}$$

We theorize that the BP of a complicated firm and its pseudo-conglomerate should converge in time and, due to the comparative stability of a firm's book value relative to its price, that the convergence should be due to price movement. Therefore, firms with a high BPPercDiff score are expected to outperform those firms with a low score. We quintile the BPPercDiff scores and backtest this signal on one month forward returns and one month residuals (following the same methodology described in section 1.2). The same process is applied to EP as well.

Table 7: BPPercDiff & EPPercDiff Quntile Backtest Results
Russell 3000 Index, 1987 – 2013

	Forward Raw Returns		Forward Residuals	
	BPPercDiff	EPPercDiff	BPPercDiff	EPPercDiff
Avg 1Mo Spread	0.13%	0.46%	-0.14%	0.40%
T Stat	0.72	2.74	-0.94	2.85
Hit Rate	50%	58%	50%	56%

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

The Q1-Q5 monthly spread for BPPercDiff is not significant in either raw returns or residual returns. However, the situation for EPPercDiff is quite different with a spread significant at the 99% level and a hit rate of at least 56% for both raw returns and residual returns. There does appear to be a valuation discount when we measure by EP. Complicated firms whose EP ratio is especially high compared to their pseudo-conglomerate are undervalued and can expect to outperform in the coming month. The outperformance of the EPPercDiff signal relative to the BPPercDiff signal may in large part be due to the higher predictive power of EP relative to BP. BP measures the total of past share issues and past retained earnings relative to price whereas EP represents the most recent earnings reported by the company relative to its share price and generally proves to be a more powerful signal.

3. Data

In this study Compustat segment data is used to define our industries. We exclusively used two digit SIC codes for our industry classifications. Compustat collects SIC operating segment data back to 1976 and provides company financial data for each segment in which a company operates. For this paper, we use the segment sales data from the Compustat segment dataset.

When calculating valuation ratios we use S&P Capital IQ Point-In-Time (PIT) Financials data. Estimates data comes from Capital IQ's analyst estimate data set. The market, value, size, and momentum factor values used in the regressions are from S&P Capital IQ's Alpha Factor Library (AFL), which contains 450+ quantitative factors with associated metrics such as information coefficients and factor spreads viewable and downloadable by time period, regime, country, and sector dimensions.

Because Compustat segment data is available for U.S. companies only, our universes consisted only of U.S. firms. We constructed the simple and complicated firm universes within the Russell 300 index comprising entirely of simple or complicated firms respectively.

4. Conclusion

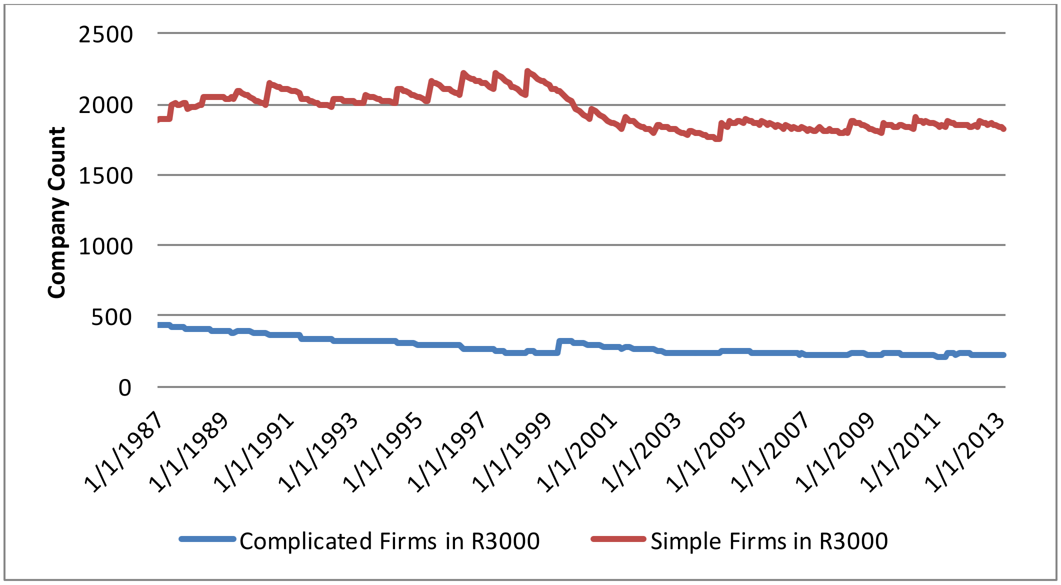
We have demonstrated several ways to exploit the delay in information processing from simple to more complicated firms. Using only simple firms to calculate pure industry returns, a strategy that systematically combines these industry returns into a pseudo-conglomerate signal, generates excess returns for complicated firms in our test period. Based on our review, this signal also appears to become more effective when firms are more complicated. Beyond simply looking at returns, we also find that this phenomenon is apparent in analyst revisions. Analyst EPS revision magnitude of simple firms, particularly downward revisions, can be considered a leading indicator of the magnitude of future EPS revisions of complicated firms. We found similar results in looking at valuation metrics. Complicated firms that trade at a high EP relative to their pseudo-conglomerate portfolio generate a statistically significant positive one month return spread of 0.46% in the following month in our test period. Understanding how information delay affects the equity market can give investors valuable insight into asset pricing and open the door for various trading strategies based on this anomaly.

Appendix A

From our universe constructions we can make several useful observations about the firms that make up the simple and complicated universe.

1. There are roughly seven simple firms for every one complicated firm in the Russell 3000 index.

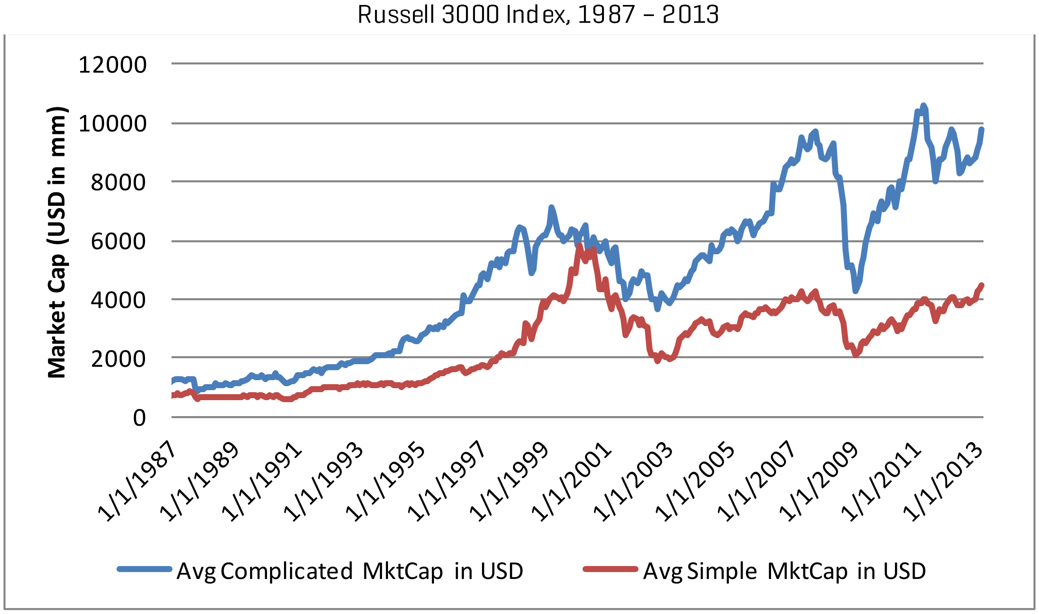
Figure 5: Count of Simple & Complicated Firms
Russell 3000 Index, 1986 – 2013



Source: S&P Capital IQ Quantamental Research.

2. Complicated firms are generally larger than simple firms. This is intuitive given the nature of complicated firms operating across multiple industries.

Figure 6: Market Cap Comparison
Russell 3000 Index, 1987 – 2013

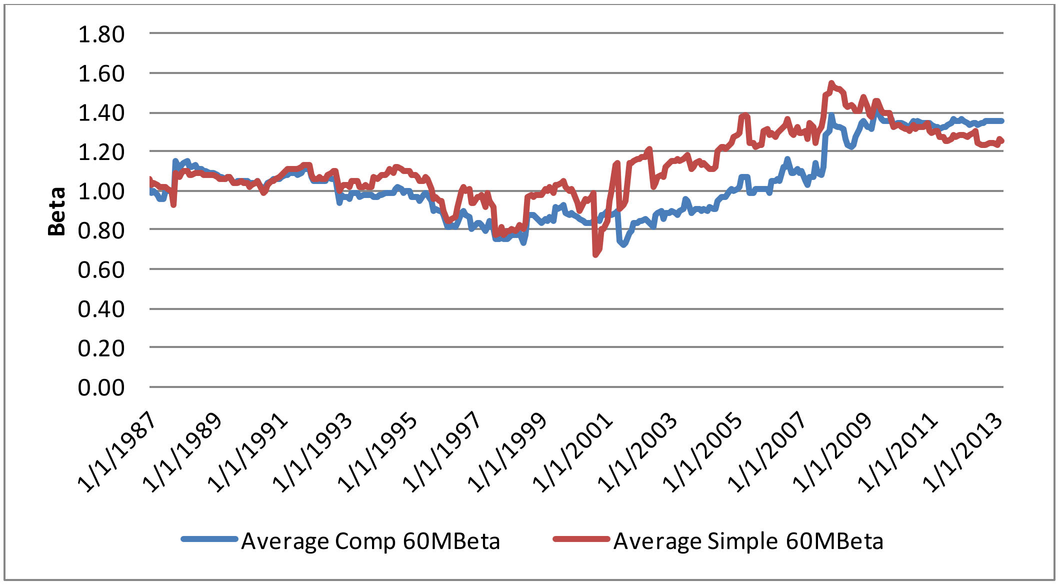


Source: S&P Capital IQ Quantamental Research.

3. Complicated firms tend to have lower betas compared to simple firms.

Figure 7: Beta Comparison

Russell 3000 Index, 1987 – 2013



Source: S&P Capital IQ Quantamental Research.

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Our Recent Research

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

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 - 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