Bridges for Sale: Finding Value in Sell-Side Estimates, Recommendations, and Target Prices

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In May 2002, in response to events leading up to the 2000 stock market crash, the SEC approved NYSE and NASD rule changes designed to mitigate research analyst conflicts of interest. Among other things, the rules prohibited analyst participation in investment banking (IB) sales activities and barred them from reporting to IB departments. While not eliminating conflicts, the rules (and accompanying enforcement actions) have clearly had a big effect on how research departments operate. In a 2008 study, Kadan, Madureira, Wang and Zach[1] found that the ratio of sell to buy ratings has improved, and the difference between ratings of IB affiliated and independent analysts has narrowed. This report looks at the informativeness of analyst recommendation revisions, target price revisions, and estimate dispersion, primarily within the post-2002 regulatory environment, and finds significant results in all three areas.

- **Investors should focus on shifts in consensus recommendations, as the recommendation level by itself often reflects pro-management and high-growth biases.** A strategy based on the three-month change in analyst buys vs. sells generates statistically significant results across all geographic regions, with particular strength in Europe (12.1% annualized long-short active return), developed Asia (11.1%), and emerging markets (15.1%). Recommendation changes foreshadow future fundamentals: top quintile companies have higher EPS growth, margins, and cash flow 1-year after portfolio formation, while bottom quintile companies see profitability and cash flow flag.

- **Target prices, labeled by some practitioners as "fiction[2]," likewise provide insight into changing analyst attitudes.** The six-month change in target price gap (the spread between target and market price) produces statistically significant results across market cap ranges in the U.S. (Russell 3000 annualized long-short returns of 9.4%), and for Europe (8.2%), Japan (5.0%), and emerging markets (6.2%). The efficacy of this strategy appears to be driven both by short-term price movement[3] and by fundamental strength or weakness, as signaled by target price level/direction. Strategy results are not subsumed by short-term price reversal itself.

- **Analyst estimate dispersion acts as an indicator of corporate quality – high quality companies have more stable revenue and income streams that are more amenable to forecasting.** One-month revenue estimate dispersion is effective as a small cap strategy in the U.S. (Russell 2000 annualized long-short return of 9.4%), as well as across the broad market indices for Europe (4.4%), and developed Asia (5.9%) including Japan (4.8%). Revenue estimate dispersion (ranked low to high) is positively correlated with fundamental quality and negatively correlated to price volatility. Lower dispersion companies also have more positive future earnings surprises. The strategy is surprisingly stable, with little active return decay over a 12-month horizon.

[1] Conflicts of Interest and Stock Recommendations: The Effects of the Global Settlement and Related Regulations. Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=568884
[2] McClellan, S.T. (2008), *Full of Bull: Do What Wall Street Does, Not What It Says, To Make Money In The Market,* FT Press, 2008, p. 26.
[3] I.e., short-term price dips for the long portfolio and short-term increases for the short portfolio.

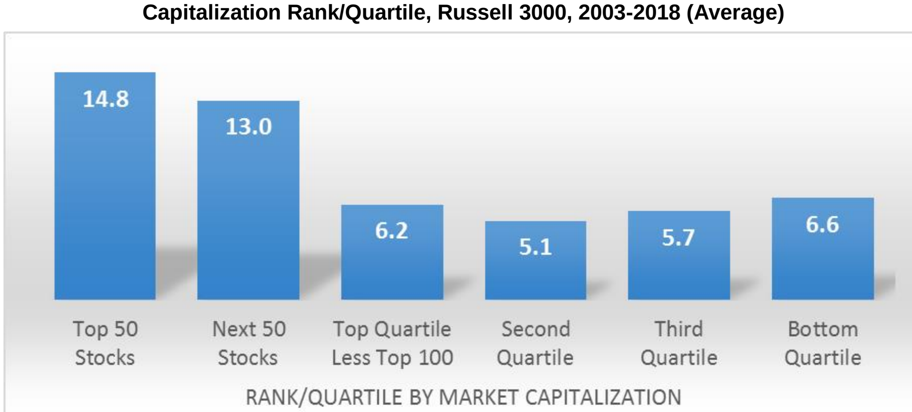
Introduction

Sell-side analysts, often maligned by the media and investors, nevertheless play an important role in the equities markets. Elgers, Lo and Pfeiffer (2001)[4] note that "low financial analyst coverage is associated with a variety of factors that impede the information efficiency of the security market." Despite potential bias associated with conflicts of interest, analysts provide some of the most in-depth company-level research available, disseminate that research widely, and often become industry experts.

To understand sell-side analysts it is important to understand who their customers are: institutional investors, investment banking clients, and their own firms' trading desks. None of these groups value recommendations, as published in research reports. Based on the results of an analyst survey, Brown, Call, Clement and Sharp (2014)[5] reported that 44% of respondents said underwriting business or trading commissions were "very important" to their compensation and 83% reported that buy-side "broker votes" were very important to career advancement. Brown et al. also noted that "*Institutional Investor* surveys regularly find that sell-side analysts' industry knowledge is extremely valuable to their buy-side clients."

Because of their institutional client base, and industry pressure for stock calls to prove out quickly, analysts favor high-momentum, high-growth, large cap names, and tend to avoid value stocks. Jegadeesh, Krische and Lee (2004)[6] characterize analysts as "trend chasers" rather than "news watchers" with regard to recommendations. Due to investment banking ties and the need for information access, analysts are also often wary of offending management. However, analysts do have an important voice in the marketplace, and analyst sentiment, if examined correctly, can serve as an aid to the investment process.

Figure 1 – Wall Street's Obsession with Mega-Caps: Aggregate BUY TO SELL RATIO by Market Capitalization Rank/Quartile, Russell 3000, 2003-2018 (Average)



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

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[4] Delayed Security Price Adjustments to Financial Analysts' Forecasts of Annual Earnings. *The Accounting Review*, 76(4), 613-632.

[5] Inside the "Black Box" of Sell-Side Financial Analysts. Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2228373

[6] Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance*, 59, 1083-1124.

1. Analyst Recommendation Revisions

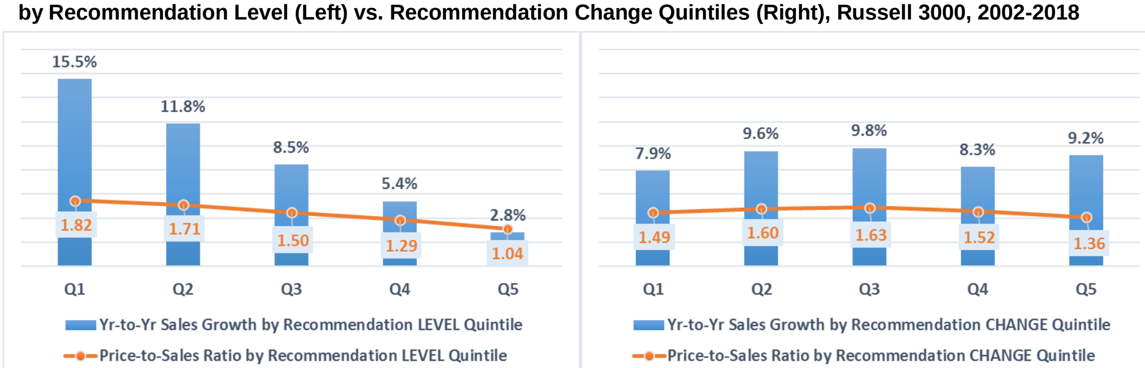
> *"A large part of Wall Street's business is selling new and used stocks and bonds, which strangely they do make recommendations about." – attributed to Cliff Asness*[7]

Although analysts are, by and large, experts on the companies and industries they cover, their stock recommendations often fail to deliver. As previously mentioned, institutional investors do not stress this function and it is generally not tied to analyst compensation. Jegadeesh, Kim, Krische, and Lee (2004) found that while recommendation level is not predictive alone, the quarterly change in consensus recommendation is "a robust return predictor," orthogonal to other indicators. Our research bears out these results, and proposes a more effective way to capture recommendation change.

1.1 Why Doesn't Recommendation Level Work?

Analysts may issue biased recommendations to market a stock, appease management or avoid frustrating clients who hold shares, or they may simply lack skill. Analysts tend to chase so-called *glamour* stocks. Figure 2, below, shows that bins sorted by recommendation *level* (left graph) favor high sales-growth, high-valuation stocks in the best recommendation bin (Q1) and low sales-growth, low-valuation stocks in the worst recommendation bin (Q5). Recommend change (right graph), on the other hand, does not exhibit this same bias. In fact, the most favorable recommendation change bin (Q1) has the *lowest* sales growth and the next to lowest price-to-sales ratio. These results support the idea that analysts' recommendations favor high-growth, high-valuation (and high-momentum) stories that are often susceptible to minor disappointments in growth rates.

Figure 2 – Why Doesn't Recommendation Level Work? Year to Year Sales Growth and Price to Sales Ratio by Recommendation Level (Left) vs. Recommendation Change Quintiles (Right), Russell 3000, 2002-2018



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

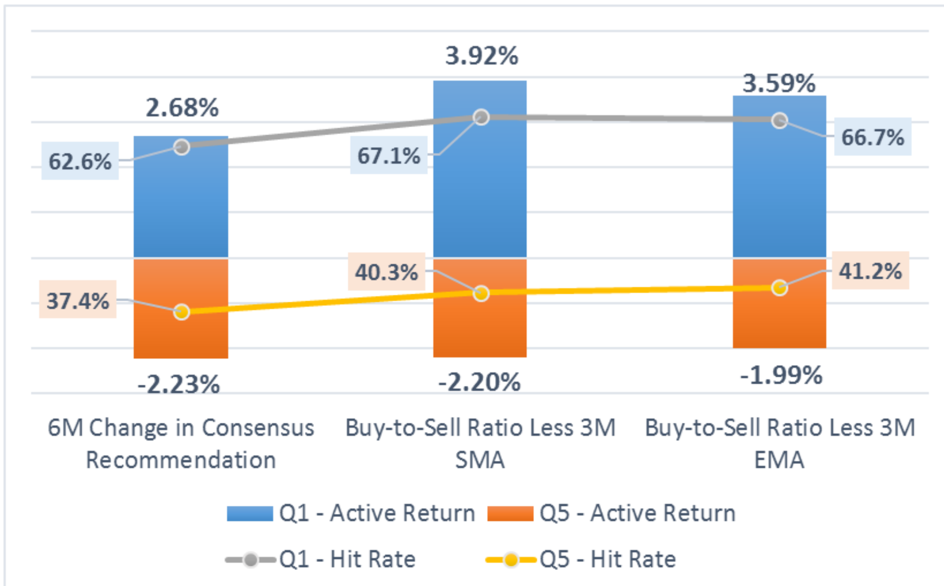
1.2 Formulating a Robust Recommendation Change Indicator

Recommendation change is robust to different formulations. Figure 3 shows that a simple six-month change in consensus recommendation (left column) produces significant excess

[7] McClellan, S. T. (2008). *Full of Bull: Do What Wall Street Does, Not What It Says, To Make Money in The Market.* Upper Saddle River: FT Press, p. 21.

returns (all results shown are statistically significant at the 1% level). However, recommendations change slowly and thus a simple-six month change contains a large number of stocks, binned in the middle, for which consensus recommendation has changed little. To ameliorate this, we use a formula that calculates the change in buys versus sells by subtracting a moving average. The two right-hand columns in Figure 3 show the results of counting each 'bullish' vs. 'bearish' analyst and subtracting from this ratio a simple (middle) or exponential (right) moving average of buys to sells.

Figure 3 – Three Methods of Calculating Recommendation Change, Q1 and Q5 Active Returns and Hit Rates, Russell 3000, January 1999 - March 2019, Carhart Four-Factor Adjusted Returns



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

The recommendation change formula used in this paper is:

$$RecChg_{t0} = \left(\frac{Buys_{t0} - Sells_{t0}}{Total_{t0}}\right) - 3M\ EMA\left(\frac{Buys_{t-1} - Sells_{t-1}}{Total_{t-1}}\right)$$

Where *Buys* equals all stocks ranked *buy* or *outperform*, under S&P Global Market Intelligence's standardized ranking system, and *Sells* equals all stocks ranked *sell* or *underperform*. S&P Global converts a variety of three- and five-scale broker recommendations to its five-scale system (e.g., *accumulate, outperform, trading buy,* and *add* all become "outperform," and *lighten, reduce, underperform,* and *under*weight all become "underperform"). The formula shown above captures subtle changes in analyst sentiment, for example a decrease in sells (positive sentiment change) and or decrease in buys (negative).

1.3 U.S. Results

Table 1 shows results for the recommendation change strategy, as defined above, for the Russell indices. All results for the Russell 3000 and 2000 indices are significant at the 1% level. Results for the Russell 1000 Index are weaker but are all significant at the 5% level. Large-cap stocks tend to be widely covered, and thus analyst information may be efficiently priced-in. Table 1 also shows strong information ratios for the Russell 2000, indicating that the strategy has produced very stable returns over the past 20 years.

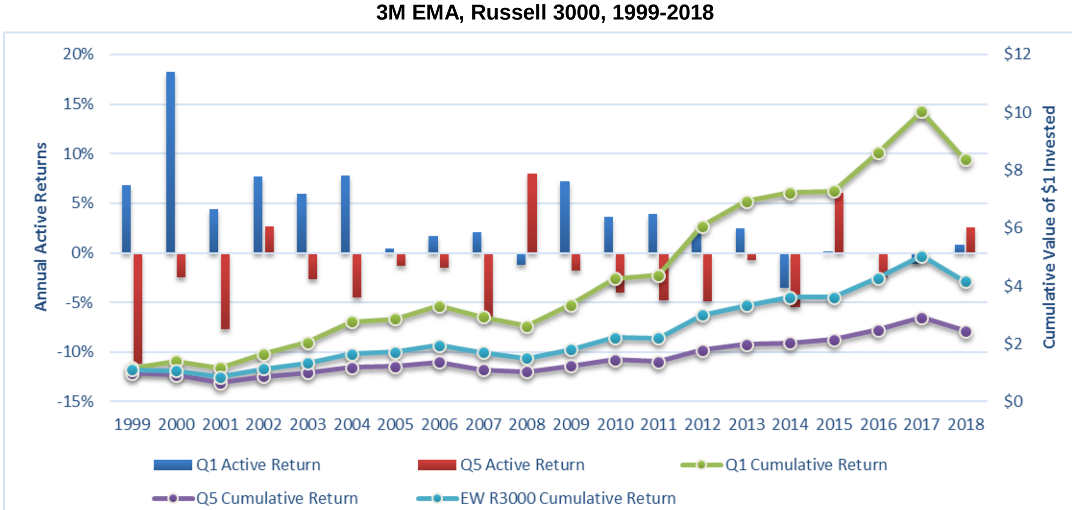
Table 1 – Buy-to-Sell Ratio Less 3-Month Exponential Moving Average, Backtest Results, Russell Indices, July 1998 – March 2019, Carhart Four-Factor Adjusted Returns

Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Russell 3000	Jul-98	486	3.65%	67.3%	1.55	5.68%	65.7%	1.43
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Russell 1000	Jul-98	185	1.24%	58.9%	0.50	2.45%	57.7%	0.55
P values			*0.023*	*0.006*		*0.013*	*0.017*	
Russell 2000	Jul-98	301	5.22%	68.5%	1.68	8.83%	69.4%	1.82
P values			*0.000*	*0.000*		*0.000*	*0.000*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results..Data as of 05/01/2019.

Active returns by year (Figure 4) for Quintile 1 of the recommendation change strategy (Russell 3000) have weakened in recent years; however, active returns for Quintile 5 have been somewhat more consistent.

Figure 4 – Q1 and Q5 Annual Market-Adjusted Active and Cumulative Total Returns, Buy-to-Sell Ratio Less 3M EMA, Russell 3000, 1999-2018



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

1.4 International Results

International results for the recommendation change strategy are strong across regions (Table 2), with significance at the 1% level across all metrics tested. In particular, Europe appears to be a standout region, with annualized long-short returns of 12%, a long-short hit rate of 84%, and an annualized long-short information ratio of 3.17 (this may be partly explained by the low volatility of market returns in general in recent years). Emerging markets results are nearly equally as strong, while Japan is the weakest region for recommendation change.

Table 2 – Buy-to-Sell Ratio Less 3-Month Exponential Moving Average, Backtest Results, International Broad Market Indices, Start Date to March 2019, Carhart Four-Factor Adjusted Returns

Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Developed Europe BMI	Jun-01	298	5.76%	79.3%	2.62	12.08%	84.0%	3.17
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Developed Asia BMI (excluding Japan)	Dec-99	129	6.13%	69.3%	1.35	11.07%	74.9%	1.84
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Japan BMI	Dec-00	138	3.12%	65.8%	0.95	5.53%	64.8%	1.15
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Emerging Markets BMI	Jan-00	258	7.71%	74.3%	1.87	15.11%	80.0%	2.84
P values			*0.000*	*0.000*		*0.000*	*0.000*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

1.5 Is Recommendation Change a Variant of EPS Revisions?

Since analyst EPS revisions is arguably the most-widely used estimate-based factor, one might ask whether the return profile of recommendation changes is simply a variant of EPS revisions. The short answer is no: Table 3 is a dependent double-sort, in which stocks are first sorted in 3-month EPS revision tertiles and within those into recommendation change tertiles. The bottom row, labeled “Row 1 – 3” shows the difference in returns, for each 3-month EPS revision column, for the top minus the bottom recommendation change tertiles. All of the “long-short” results shown in the bottom row are significant at the 1% level, indicating that recommendation change has historically had investment value independent of revisions.

Table 3 – Dependent Sort: Buy-to-Sell Ratio Less 3-month EMA by 3-month EPS Revision Tertiles, Russell 3000, January 2000 – March 2019, Carhart Four-Factor Adjusted Returns

	3-Month EPS Revisions (Most Positive to Most Negative)			
	Quantile	1	2	3
Recommendation Change (Most Positive to Most Negative)	1	3.75%***	2.71%***	2.76%***
	2	-0.07%	-0.38%	0.20%
	3	-0.10%	-1.56%**	-0.96%
	Row 1 - 3	3.85%***	4.33%***	3.76%***

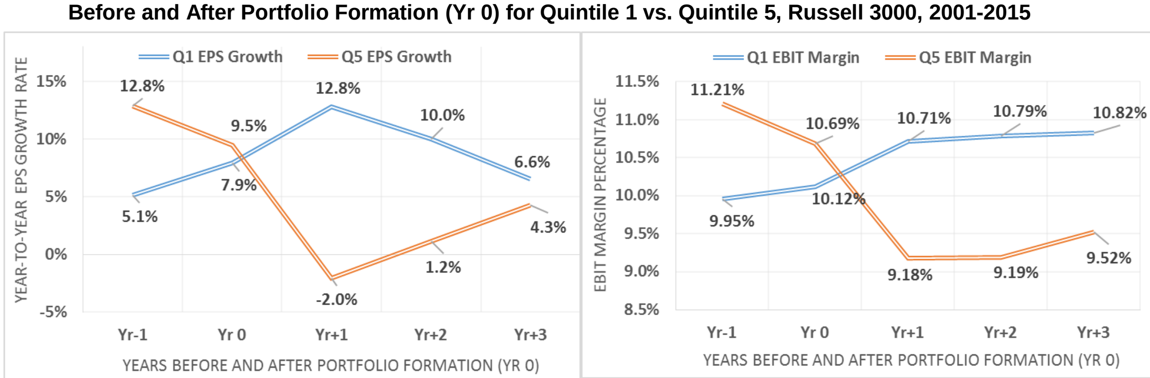
Significance: *** = at the 1% level, ** = 5% level, * = 10% level

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

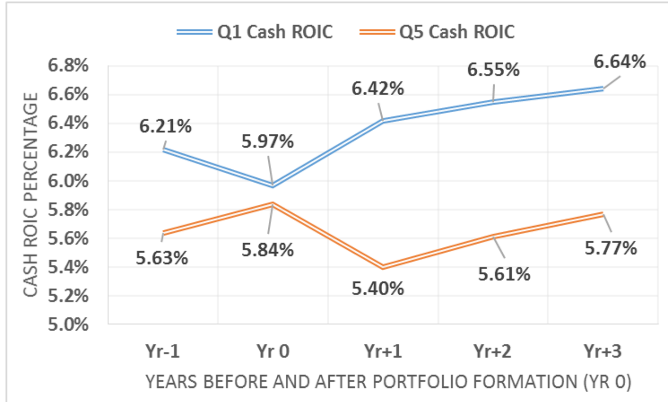
1.6 Causal Factor Analysis

Why does recommendation change work historically? It may simply be that analysts, as company and industry experts, can often identify early signs of improvement or deterioration. Figure 5 shows three fundamental ratios for Quintile 1 vs. Quintile 5 of the recommendation change strategy, from one year before (Yr-1) to three years following (Yr+3) portfolio formation (Yr 0). Following portfolio formation, year-to-year EPS growth[8] for quintile 1 (Q1 - blue line) increases (top left graph), EBIT[9] margin rises and remains elevated (top right), and cash return on invested capital (cash ROIC – bottom) also rises. The reverse is true for bottom quintile (Q5 – orange line) stocks. These studies suggest that positive recommendation changes precede fundamental improvement and negative recommendation changes precede fundamental deterioration.

Figure 5 – Why Does Recommendation Change Work? Three Fundamental Characteristics (Median Values) Before and After Portfolio Formation (Yr 0) for Quintile 1 vs. Quintile 5, Russell 3000, 2001-2015



[8] Year-to-year EPS growth excludes companies with negative prior-year EPS.
[9] Earnings before interest and taxes, represented here as operating earnings.



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

2. Target Price Revisions

> *"The price target is the piece of data produced by Wall Street least tied to reality."* – Mitch Zacks[10]

As succinctly put by Bradshaw, Huang, and Tan (2012): "Target prices convey sell-side analysts' assessments of the future value of underlying stocks."[11] However, target prices often follow market prices up and down – or are set ridiculously high – undermining their credibility with investors. Nonetheless, Brav and Lehavy (2003)[12] found a significant market reaction to target price revisions, both individually and when conditioned on recommendation and/or earnings forecast changes. We find that incorporating the "gap," or spread, between target and current market price substantially improves the historical performance of the strategy.

Figure 6 shows three forms of target price revisions: 6-month change in target price alone, 6-month change in target-price gap, and target-price gap divided by the 6-month moving average of target-price gap. All results are significant at least at the 5% level, with metrics for the latter two formulations all significant at the 1% level.

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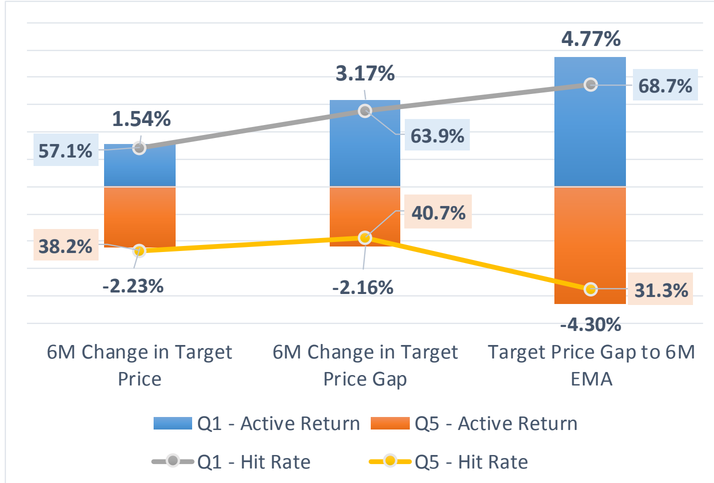
[10] Quoted in: Morgenson, G. (2001, August 5). Price Targets Are Hazardous to Investors' Wealth. *The New York Times*: *https://www.nytimes.com/2001/08/05/business/market-watch-price-targets-are-hazardous-to-investors-wealth.html*

[11] Analyst Target Price Optimism Around the World. Retrieved from: https://pdfs.semanticscholar.org/18af/640baf05193aabab6e8e8ad3f9402478defa.pdf

[12] An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics. *The Journal of Finance, 58*(5), 1933-1967.

Figure 6 – Three Methods of Calculating Target Price Change, Q1 and Q5 Active Returns and Hit Rates, Russell 3000, March 2001 – February 2019, Carhart Four-Factor Adjusted Returns



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

The target price change formula used in this paper is:

$$TgtPrcGapChg_{t0} = \frac{(Tgt_{t0} - \mathrm{Prc}_{t0})}{ABS\left|6M\ EMA(Tgt_{t-1} - \mathrm{Prc}_{t-1})\right|}$$

Where *(Tgt_{t0} – Prc_{t0})* is today's target price gap and *6M EMA(Tgt_{t-1} – Prc_{t-1})* is the exponential moving average of the past-six monthly target price gaps lagged by one month.

2.1 U.S. Results

Results for target price gap change are significant at the 1% level across the Russell indices (Table 4), unlike recommendation change, which had lower significance for Russell 1000 stocks. However, returns and information ratios are highest for the Russell 2000.

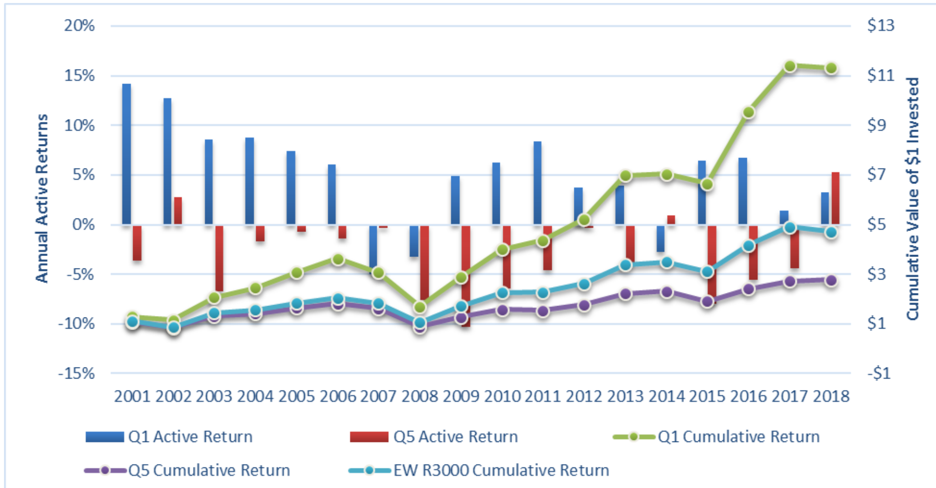
Table 4 – Target Price Gap to 6-Month EMA, Backtest Results, Russell Indices, March 2001 – March 2019, Carhart Four-Factor Adjusted Returns

Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Russell 3000	Mar-01	507	4.77%	68.7%	1.36	9.44%	68.2%	1.51
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Russell 1000	Mar-01	188	3.16%	62.7%	0.91	6.56%	65.0%	1.05
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Russell 2000	Mar-01	319	5.51%	67.3%	1.41	11.34%	71.9%	1.69
P values			*0.000*	*0.000*		*0.000*	*0.000*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

Annual active returns for the top quintile (Figure 7, Q1) by target price gap change (Russell 3000) are positive with the exception of 2007, 2008, and 2014. Bottom quintile (Q5) returns are negative except for 2002, 2014, and 2018.

Figure 7 – Q1 and Q5 Annual Market-Adjusted Active and Cumulative Total Returns, Target Price Gap to 6-Month EMA, Russell 3000, 2001-2018



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales c cd harges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

2.2 International Results

International results (Table 5) are particularly strong in Europe, with annualized information ratios of about 1.7 and hit rates of 70% for both long and long-short portfolios. The strategy also works well in Japan and with the Emerging Markets BMI. Developed Asia (ex Japan) BMI is the weakest region for the target price gap change factor.

Table 5 – Target Price Gap to 6-Month EMA, Backtest Results, International Broad Market Indices, Start Date to March 2019, Carhart Four-Factor Adjusted Returns

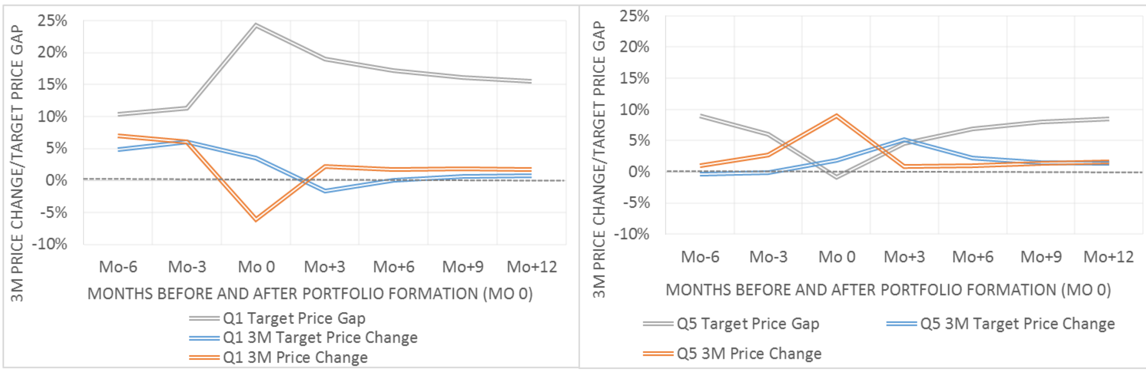
Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Developed Europe BMI	Jun-03	308	4.42%	71.6%	1.68	8.20%	70.0%	1.78
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Developed Asia BMI (excluding Japan)	Jun-03	154	3.02%	57.9%	0.71	3.71%	58.4%	0.58
P values			*0.005*	*0.031*		*0.021*	*0.021*	
Japan BMI	Jun-03	149	3.74%	64.7%	0.91	4.99%	61.1%	0.87
P values			*0.000*	*0.000*		*0.001*	*0.003*	
Emerging Markets BMI	Jun-03	316	3.89%	62.1%	0.95	6.24%	63.2%	0.98
P values			*0.000*	*0.001*		*0.000*	*0.000*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

2.3 Causal Factor Analysis

The change in target price gap strategy works as a result of both target price and market price changes prior to portfolio formation. Figure 8 shows that for Quintile 1 (left graph) target price (blue line) has been rising over the 9 months prior to portfolio formation (Mo-6, Mo-3, and Mo 0). Market price (orange line) has also been rising, but takes a sudden dip 3 months prior to portfolio formation (Mo 0). This dip creates a surge in the target price gap (gray line) which is arbitraged away by rising prices in the following 3 months (Mo+3). The reverse occurs for Quintile 5 (right graph).

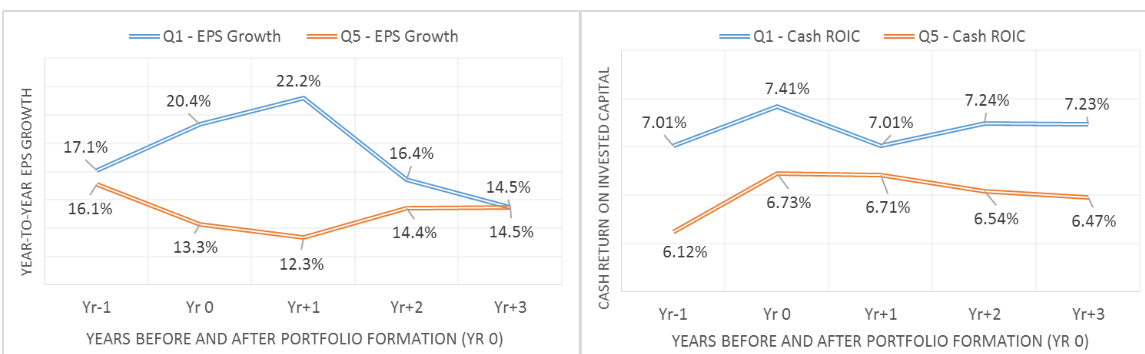
Figure 8 – Why Does Target Price Gap Change Work? Target Price Gap Analysis (Median Values), Quintile 1 (Left) vs. Quintile 5 (Right), Before and After Portfolio Formation (T 0), Russell 3000, 2001-2015



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

Price action is not the end of the story, however. Figure 9 suggests that high (Q1) and low (Q5) changes in target price gap signal differences in fundamental quality. Q1 EPS growth[13] (left graph) rises strongly in the year of portfolio formation (Yr 0) and in the following year (Yr+1), signaling these stocks have potential investment value, while Q5 EPS growth moderates. Cash return on invested capital (right graph) is also higher for Q1 than for Q5.

Figure 9 – Why Does Target Price Gap Change Work? Fundamental Analysis (Median Values), Quintile 1 vs. Quintile 5, Before and After Portfolio Formation (T 0), Russell 3000, 2001-2015



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

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[13] Year-to-year EPS growth excludes companies with negative prior-year EPS.

2.4 Does Short-Term Price Reversal Subsume Target Price Gap Change?

Given the short-term price dip that precedes portfolio formation for Q1 and the rise that precedes Q5 formation, one might ask if the target price gap factor is driven by short-term price reversal. Again, the short answer is no: Table 6 shows the results of a dependent three-by-three sort, with the first sort on 1-month price change (sorted in ascending order) and a dependent sort on target price gap change. The bottom row ("Row 1 – 3") shows "long-short" active returns for the target price gap change factor for each 2-month price change tertile. All "Row 1 – 3" results are strong and statistically significant, indicating that target price gap change is independent of short-term price reversal.

Table 6 –Dependent Sort – Target Price Gap Change by 1-Month Price Reversal Tertiles, Russell 3000, March 2001 – March 2019, Carhart Four-Factor Adjusted Returns

		1-Month Price Reversal (Low to High)		
	Quantile	1	2	3
Target Price Gap To 6M EMA (High to Low)	1	3.89%***	3.79%***	5.97%***
	2	-0.23%	0.49%	1.58%**
	3	-3.63%***	-5.48%***	-2.68%***
	Row 1 - 3	7.78%***	9.76%***	8.86%***

Significance: *** = at the 1% level, ** = 5% level, * = 10% level

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

3. Revenue Estimate Dispersion

A corollary of the stock market maxim that "markets hate uncertainty" is that they also hate instability.[14]

Analyst estimate dispersion has been the subject of a few major academic studies. Deither, Malloy, and Scherbina (2002)[15] found that stocks with higher dispersion of analyst's earnings forecasts subsequently earn lower returns, with the effect most pronounced in small and poorly-performing stocks. Min, Qiu, and Roh (2019)[16] found a link between high earnings forecast dispersion and lower profitability and vice versa. We hypothesize that high estimate dispersion indicates that companies are, for one reason or another, difficult to forecast and thus likely to be riskier/lower quality than their lower dispersion peers. We find that this effect is best captured using revenue, not earnings, estimates and (as with Diether, et al.) is most prevalent in small caps.

[14] The author.

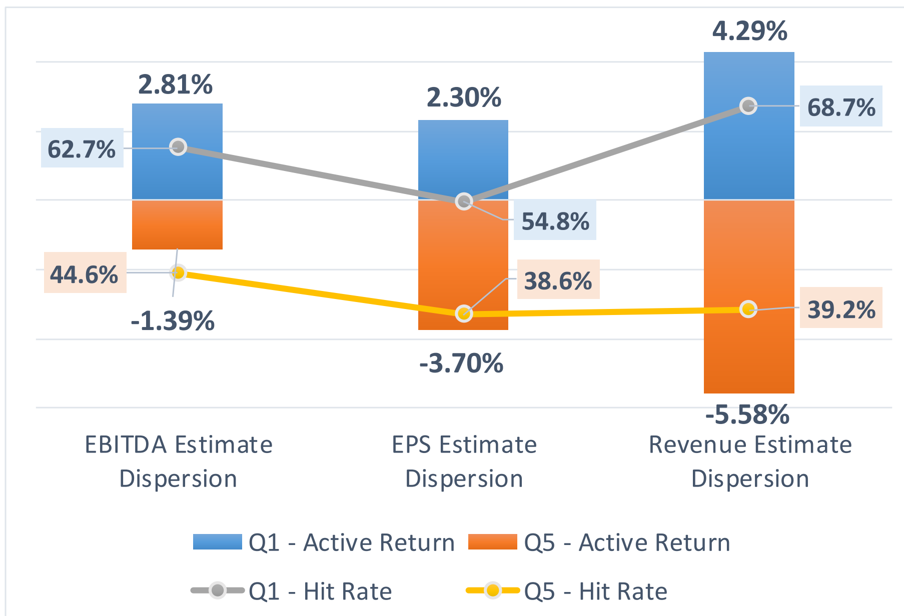
[15] "Differences of Opinion and the Cross-Section of Stock Returns," *Journal of Finance, 57:5 (Oct 2002).*

[16] What Drives the Dispersion Anomaly? Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3349929

Figure 10 shows the results of backtests on dispersion factors built for three types of quarterly analyst forecasts: EBITDA estimates, EPS estimates, and revenue estimates. Since EBITDA estimates are only available back to 2005, we begin all three tests from 2005 to aid comparison. All returns and hit rates shown are significant at the 1% level.

Why should revenue estimate dispersion produce much stronger results than EPS dispersion? We only have a hypothesis, but believe it is a sound one: Revenues are not only the source from which all profits and cash returns flow, but they are (arguably) the most stable major item on the income statement. Thus, high analyst disagreement around revenues may be a stronger signal of corporate risk/instability than is disagreement around earnings.

Figure 10 – Three Types of Consensus Estimate Dispersion, Q1 and Q5 Active Returns and Hit Rates, Russell 3000, June 2005 – March 2019, Carhart Four-Factor Adjusted Returns



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

The 1-month estimate dispersion formula used in this paper is:

$$EstDisp_{t,i} = 1 / \left(\frac{\frac{1}{22}\left(\sum_{j=0}^{22} EstStdDev_{i,t-j}\right)}{\frac{1}{22} ABS \left| \sum_{j=0}^{22} EstConsMean_{i,t-j} \right|} \right)$$

Where time (t) is in business days, *EstStdDev* is the standard deviation, and *EstConsMean* is the consensus estimate value. This formula, applied in the tests below to revenue estimates, mirrors the formula used by Diether, Malloy, and Scherbina (2002) for their research on earnings estimates. A minimum of two analyst estimates is required, and substitution of semi-annual or annual estimates is made when quarterly estimates are not available.

3.1 U.S. Results

Revenue estimate dispersion works best in the U.S. for the Russell 2000 small cap index (Table 7). However, note the high annualized information ratios of about 1.10 for the long and long-short portfolios of the Russell 3000. Russell 3000 short-only portfolio results (not shown) are also relatively strong, with an average annualized active return of -4.68% and a hit rate of 41.3%, both significant at the 1% level.

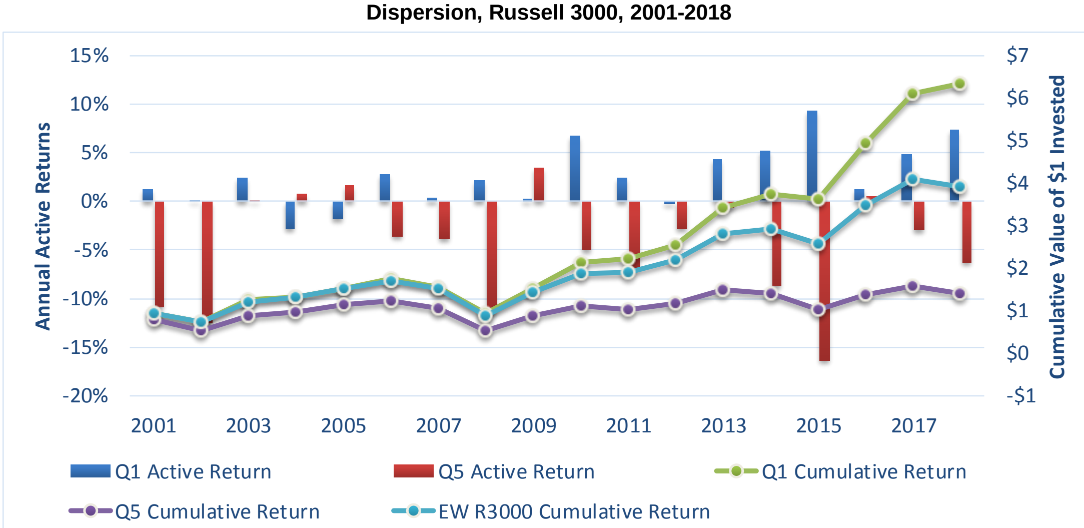
Table 7 – Revenue Estimate Dispersion, Backtest Results, Russell Indices, February 2000 – March 2019, Carhart Four-Factor Adjusted Returns

Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Russell 3000	Feb-00	454	3.25%	64.3%	1.12	8.28%	63.5%	1.09
P values			*0.000*	*0.000*		*0.000*	*0.000*	
Russell 1000	Feb-00	179	1.19%	55.2%	0.43	3.92%	57.8%	0.60
P values			*0.061*	*0.115*		*0.009*	*0.018*	
Russell 2000	Feb-00	275	3.63%	63.0%	0.94	9.40%	62.2%	0.99
P values			*0.000*	*0.000*		*0.000*	*0.000*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

Annual active returns for the top quintile (Q1) are particularly strong in the post-2009 period but not effective prior to 2009 (Figure 11 – Russell 3000). Active returns for the bottom portfolio (Q5) are strong throughout the backtest horizon, with the exception of a few years.

Figure 11 – Q1 and Q5 Annual Market-Adjusted Active and Cumulative Total Returns, Revenue Estimate Dispersion, Russell 3000, 2001-2018



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

3.2 International Results

Revenue estimate dispersion generally works well in international markets (Table 8), with information ratios highest in Europe and long-short returns highest in developed Asia. The strategy even shows some efficacy historically in Japan. Statistical significance and long-short returns are the weakest within the Emerging Markets BMI.

Table 8 – Revenue Estimate Dispersion, Backtest Results, International Broad Market Indices, Start Date to March 2019, Carhart Four-Factor Adjusted Returns

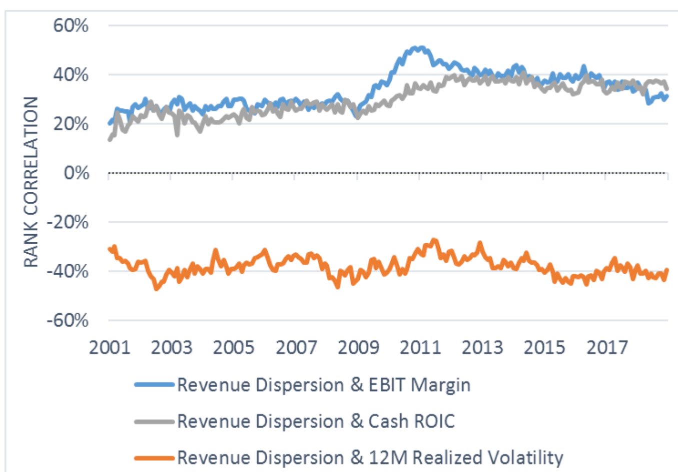
Universe	Start Date	Average Quintile Size	Annualized Long-Only Active Return	Average Long-Only Hit Rate	Annualized Long-Only Information Ratio	Annualized Long-Short Active Return	Average Long-Short Hit Rate	Annualized Long-Short Information Ratio
Developed Europe BMI	Dec-01	302	2.06%	60.1%	0.96	4.43%	62.0%	0.97
P values			*0.000*	*0.004*		*0.000*	*0.001*	
Developed Asia BMI (excluding Japan)	Dec-01	118	3.22%	57.7%	0.53	5.92%	59.1%	0.73
P values			*0.029*	*0.028*		*0.003*	*0.009*	
Japan BMI	Dec-04	172	2.68%	58.1%	0.83	4.75%	59.3%	0.75
P values			*0.002*	*0.034*		*0.005*	*0.016*	
Emerging Markets BMI	Dec-07	339	2.55%	64.0%	0.72	4.07%	55.9%	0.59
P values			*0.017*	*0.001*		*0.049*	*0.172*	

Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

3.3 Causal Factor Analysis

Revenue estimate dispersion (ranked from low to high) is positively correlated with fundamental quality and negatively correlated with price volatility. Figure 12 shows that rank correlations for EBIT margin and cash ROIC are positive over the entire test period, and the correlation with 12-month realized price volatility is highly negative.

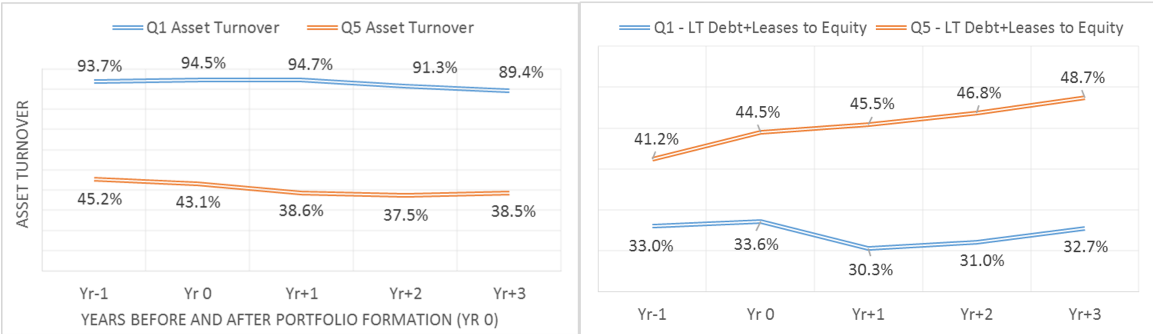
Figure 12 –Revenue Estimate Dispersion, Rank Correlations with Quality and Price Volatility, Russell 3000, 2001-2018



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

Low revenue estimate dispersion companies have better operating efficiency and lower debt than high estimate dispersion companies. Figure 13 shows that the top portfolio (Q1 – blue line) by revenue estimate dispersion has much higher asset turnover (left graph) and lower long-term debt and capital leases to equity (right graph) than the bottom portfolio (Q5 – orange line).

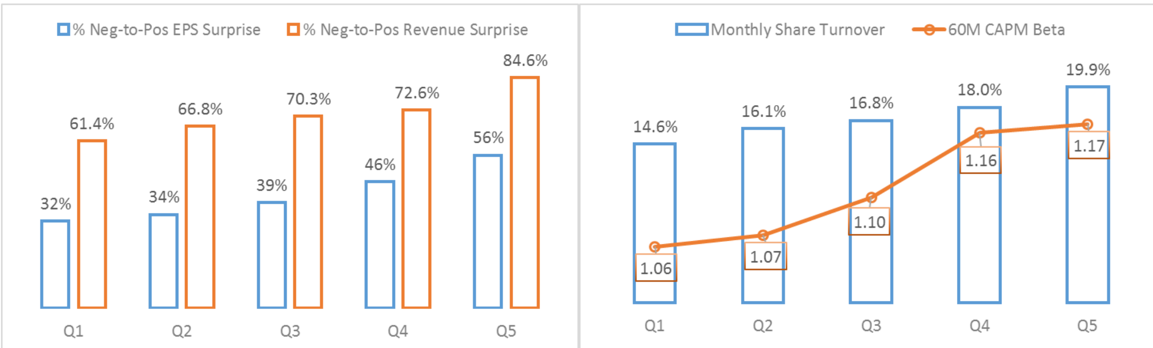
Figure 13 – Asset Turnover and Debt to Equity (Median Values) for Q1 vs. Q5 Revenue Estimate Dispersion, Before and After Portfolio Formation (Yr 0), Russell 3000, 2001-2015



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

Low revenue estimate dispersion companies (Figure 14, Q1) also have lower levels of negative EPS and revenue surprises (left graph – shows the average aggregate negative-to-positive surprise ratios) and lower share turnover and beta (right graph) than high estimate dispersion companies (Q5). EPS and Revenue surprises are captured as the average of the cross-sectional count of three-month forward negative surprises divided by the count of three-month-forward positive surprises.

Figure 14 – Forward Negative-to-Positive EPS & Revenue Surprises (Left – Aggregate Values) and Liquidity/Volatility Analysis (Right – Median Values) by Revenue Estimate Dispersion Quintiles, Russell 3000, 2001-2018

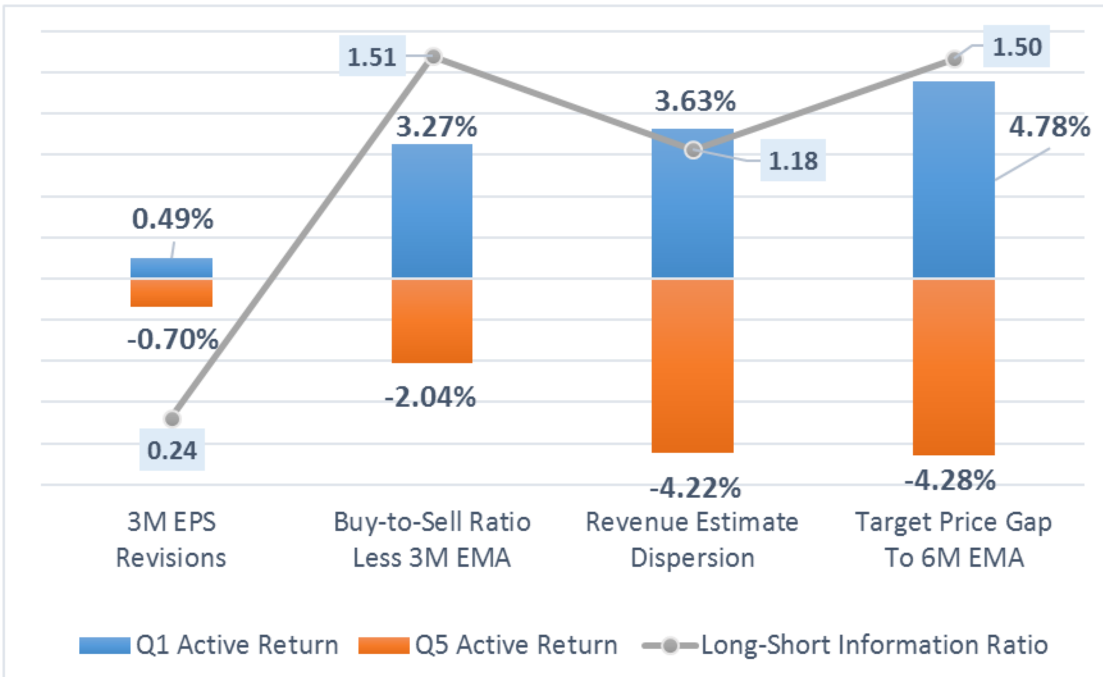


Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

4. Analyst Estimate/Revision Factor Comparison

How do the three strategies presented above compare with each other and how do they compare with traditional EPS estimate revisions? Figure 15 shows that the three estimate/revision-related strategies presented in this paper all have higher long- and short-portfolio returns and information ratios than those for EPS revisions[17]. All returns shown are significant at the 1% level, except those for EPS revisions, which are not significant.

Figure 15 – Factor Comparison: Analyst Estimate/Revision Strategies, Top Quintile (Q1) and Bottom Quintile (Q5) Returns & Long-Short Information Ratios, Russell 3000, March 2001-April 2019, Carhart Four Factor Adjusted Returns



Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

[17] For 3M EPS revisions, we use the 3-month change in the consensus mean estimate for FY1 (current fiscal year) divided by market price.

Figure 16 shows rank and return correlations for the four factors shown in Figure 15, above. Both types of correlations are moderately positive or negative across the board. Correlations among revenue estimate dispersion and all other revision factors are particularly low.

Figure 16 – Factor Rank and Return Correlations, Russell 3000, March 2001-April 2019

RANK CORRELATION		Rec Chg	TPG Chg	RE Disp	EPS Rev
Recommendation Change	Rec Chg	1			
Target Price Gap Change	TPG Chg	0.116141	1		
1M Revenue Estimate Dispersion	RE Disp	0.017833	0.013858	1	
3M EPS Revisions	EPS Rev	0.081627	-0.00684	0.070005	1

LONG-SHORT RETURN CORRELATION		Rec Chg	TPG Chg	RE Disp	EPS Rev
Recommendation Change	Rec Chg	1			
Target Price Gap Change	TPG Chg	0.188375	1		
1M Revenue Estimate Dispersion	RE Disp	0.07766	-0.22758	1	
3M EPS Revisions	EPS Rev	0.195543	-0.00136	0.043464	1

Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

5. Data, Methodology, and Terminology

S&P Global Estimates is a comprehensive, standardized database of global, real-time financial forecasting measures on upgrades/downgrades, target price revisions, market-moving news or significant developments for public companies worldwide, and estimates based on the projections, models, analysis, and research of analysts, brokers, and the companies themselves. Data is collected for annual, quarterly, and semi-annual time periods. Estimates and company guidance are sourced from research reports, research contributors, and news releases (guidance). Both consensus and detail data is available for company financial estimates, target prices, and recommendations.

Except as noted, all returns are adjusted for four widely-recognized risk factors: market beta, book-to-market ratio (value), market capitalization (size), and price momentum (labelled "Carhart Four-Factor Adjusted Returns"). Backtests are rebalanced monthly, and all returns include dividends and cash distributions ("total returns"). *Hit rates,* defined as the percentage of times that monthly portfolio excess returns are positive, measure the consistency of a strategy in producing excess returns over time. *Information ratio,* the ratio of average excess returns to the standard deviation of excess returns, provides another measure of strategy consistency/volatility.

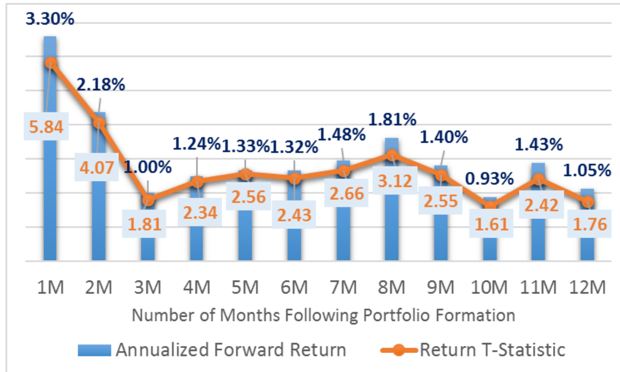
Conclusion

As experts on the companies and industries they cover, sell-side equity analysts produce some of the most in-depth company research available. Although analyst compensation is generally not based on the success or failure of their stock recommendations, many analysts take pride in making key "calls" that generate profitable trades for investors. Our research indicates that, although neither recommendation nor target price *levels* generate significant excess returns, both target price and recommendation *revisions* do generate excess returns historically. We show that the direction of recommendation and target price revisions is positively related to the level and direction of future profits and cash flows. In addition, we show that changes in the target price gap, or the spread between target price and market price, help investors take advantage of temporary price dislocations. Finally, this report demonstrates that analyst estimate dispersion has been a historically profitable phenomenon linked to both fundamental quality and price volatility (lower estimate dispersion is associated with *higher* fundamental quality and with *lower* price volatility than is higher estimate dispersion). Specifically, we show that revenue estimate dispersion provides a better measure of uncertainty than EPS estimate dispersion, perhaps because of revenue's lower inherent volatility and more primal position on the income statement.

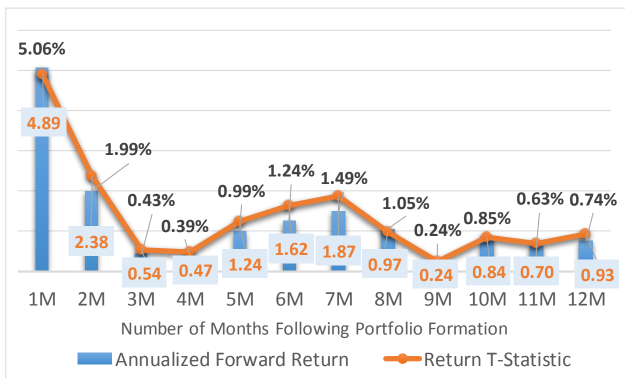
Appendix A – Factor Decay

Note: Factor decay is calculated by lagging the factor by 1 month to 11 months before calculating one-month forward returns. I.e., "1M" represents unlagged forward returns, "2M" represents forward returns for 1-month-lagged portfolios, etc.

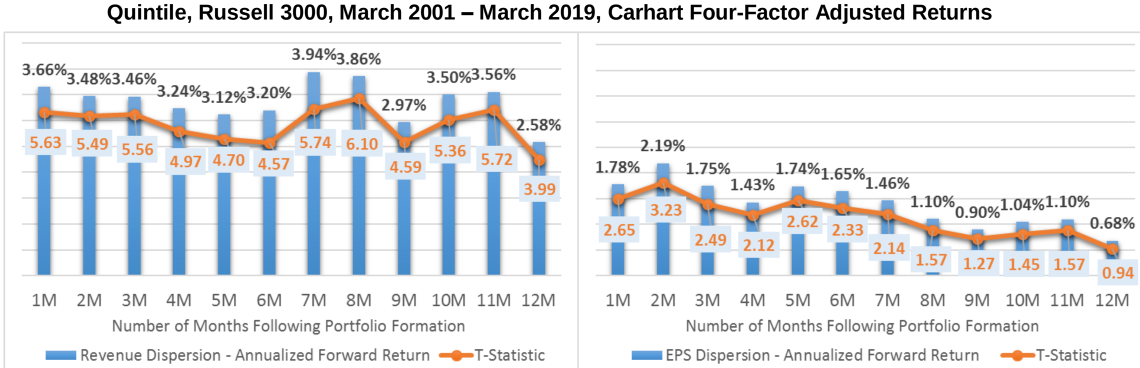
Buy-to-Sell Ratio Less 3M EMA, Factor Decay Horizon, Top Quintile, Russell 3000, July 1998 - March 2019, Carhart Four-Factor Adjusted Returns



Target Price Gap to 6M EMA, Factor Decay Horizon, Top Quintile, Russell 3000, March 2001 – March 2019, Carhart Four-Factor Adjusted Returns



Revenue Estimate Dispersion (Left) vs. EPS Estimate Dispersion (Right), Factor Decay Horizon, Top Quintile, Russell 3000, March 2001 – March 2019, Carhart Four-Factor Adjusted Returns

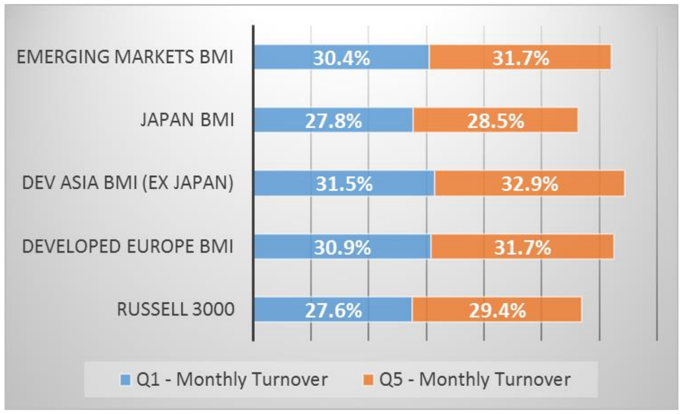


Source: S&P Global Market Intelligence Quantamental Research. All returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as of 05/01/2019.

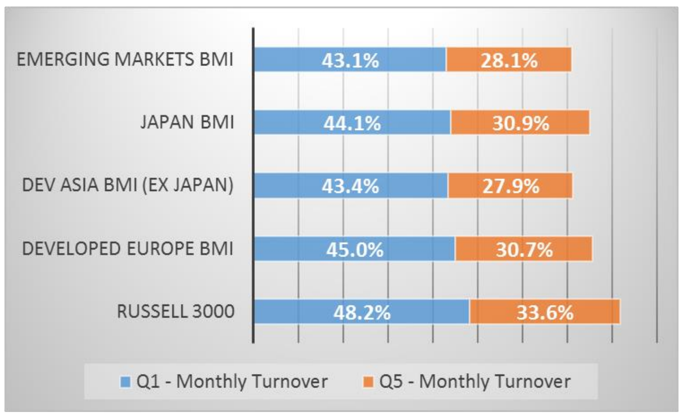
Appendix B – Portfolio Turnover

Note: Turnover is calculated as the percentage of stocks at time t_0 that weren't in the portfolio at time t_{-1}. Turnover shown below is calculated on a monthly basis.

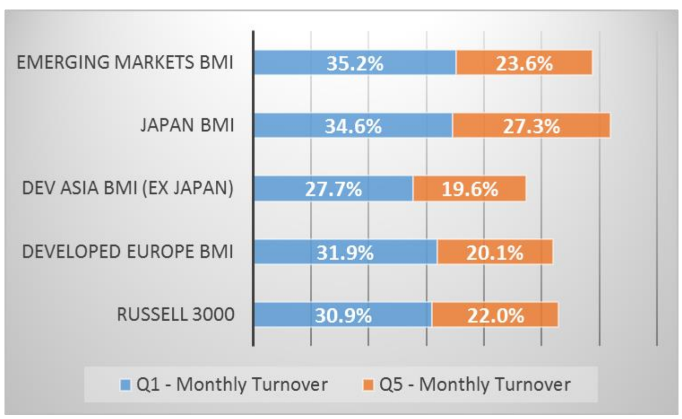
Buy-to-Sell Ratio Less 3M EMA, Q1 and Q5 Monthly Turnover by Index, Average over Complete Backtest Horizon for Each Index



Target Price Gap to 6M EMA, Q1 and Q5 Monthly Turnover by Index, Average over Complete Backtest Horizon for Each Index



Revenue Estimate Dispersion, Q1 and Q5 Monthly Turnover by Backtest Index, Average Over Complete Backtest Horizon



Source: S&P Global Market Intelligence Quantamental Research. Data as of 05/01/2019.

References

Agrawal, A., & Chadha, S. (2004). Corporate Governance and Accounting Scandals. *The Journal of Law & Economics, 48*(2), 371-406.

Asquith, P., Mikhail, M. B., & Au, A. S. (2002). *Information Content of Equity Analyst Reports*. Retrieved from National Bureau of Economic Research : https://www.nber.org/papers/w9246.pdf

Barber, B., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can Investors Profit from the Prophets? Security Recommendations and Stock Returns. *The Journal of Finance, 56*(2), 531-563.

Boni, L., & Womack, K. L. (2006). Industries and Price Momentum. *The Journal of Financial and Quantitative Analysis, 41*(1), 85-109.

Bradshaw, M. T. (2011). *Analysts' Forecasts: What Do We Know After Decades of Work?* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1880339

Bradshaw, M. T., & Brown, L. D. (2006). *Do Sell-Side Analysts Exhibit Differential Target Price Forecasting Ability? Work in progress.* Retrieved from https://www8.gsb.columbia.edu/faculty-research/sites/faculty-research/files/accounting/BRADSHAW.pdf

Bradshaw, M., Huang, A. G., & Tan, H. (2012). *Analyst Target Price Optimism around the World.* Retrieved from https://pdfs.semanticscholar.org/18af/640baf05193aabab6e8e8ad3f9402478defa.pdf

Brav, A., & Lehavy, R. (2003). An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics. *The Journal of Finance, 58*(5), 1933-1967.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2014). *Inside the "Black Box" of Sell-Side Financial Analysts.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2228373

Chen, j., Hong, H., & Stein, J. C. (2001). *Breadth of Ownership and Stock Returns.* Retrieved from National Bureau of Economic Research: https://www.nber.org/papers/w8151.pdf

Da, Z., Hong, K. P., & Lee, S. (2016). What Drives Target Price Forecasts and Their Investment Value? *Journal of Business Finance & Accounting, 43*(3,4), 487-510.

Dechow, P. M., & You, H. (2018). *Understanding the Determinants of Analyst Target Price Forecasts.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2412813

Dechow, P. M., & You, H. (n.d.). *Understanding the Determinants of Analyst Target Price Forecasts.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2412813

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance, 57*(5), 2113-2141.

Easterwood, J. C., & Nutt, S. R. (1999). Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism? *The Journal of Finance, 54*(5), 1777-1797.

Elgers, P. T., Lo, M. H., & Pfeiffer, R. J. (2001). Delayed Security Price Adjustments to Financial Analysts' Forecasts of Annual Earnings. *The Accounting Review, 76*(4), 613-632.

Feldman, R., Livnat, J., & Zhang, Y. (2012). Analysts' Earnings Forecast, Recommendation, and Target Price Revisions. *The Journal of Portfolio Management, 38*(3).

Ho, M. J., & Harris, R. S. (1998). Market Reactions to Messages from Brokerage Ratings Systems. *Financial Analyst Journal, 54*(1), 49-57.

Hsieh, J., Ng, L., & Wang, Q. (2005). *How Informative are Analyst Recommendations and Insider Trades.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=687584

Huberts, L. C., & Fuller, R. J. (1995). Predictability Bias in the U.S. Equity Market. *Financial Analysts Journal, 51*(2), 12-28.

Jegadeesh, N., Kim, J., Krische, S. D., & Lee, C. M. (2004). Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance, 59*, 1083-1124.

Kadan, O., Maduriera, L., Wang, R., & Zach, T. (2008). Conflicts of Interest and Stock Recommendations: The Effects of the Global Settlement and Related Regulations. Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=568884

Kolaskinski, A. C., & Kothari, S. P. (2008). Banking and Analyst Objectivity: Evidence from Analysts Affiliated with Mergers and Acquisitions Advisors. *The Journal of Financial and Quantitative Analysis, 43*(4), 817-842.

McClellan, S. T. (2008). *Full of Bull: Do What Wall Street Does, Not What It Says, To Make Money in The Market.* Upper Saddle River: FT Press.

Min, B. K., Qiu, B., & Tai-Yong, R. (2019). *What Drives the Dispersion Anomaly?* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3349929

Morgenson, G. (2001, August 5). Price Targets Are Hazardous to Investors' Wealth. *The New York Times*.

Morgenson, G. (2005, July 27). An Analyst Receives a Time Out From Altera. *The New York Times*, p. C1.

Nutt, S. R., Easterwood, J. C., & Easterwood, C. M. (1999). New Evidence on Serial Correlation in Analyst Forecast Errors. *Financial Management, 28*(4), 106-117.

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting, 24*, 34-75.

Stickel, S. E. (1995). The Anatomy of the Performance of Buy and Sell Recommendations. *Financial Analysts Journal, 55*, 25-39.

Womack, K. L. (1996). Do Brokerage Recommendations Have Investment Value? *Journal of Finance, 51*(1).

Our Recent Research

February 2019: U.S. Stock Selection Model Performance Review
Despite volatile market conditions and index declines, the four long-short factor models tracked by S&P Global Market Intelligence did well in 2018. The models (Growth, Value, Quality and Price Momentum) benefited from the multifactor approach used in the selection process while the live, out-of-sample results for the four were all positive on both a long-only and long-short return basis. This report examines each of the four U.S. Stock selection model performances in 2018.

February 2019: International Small Cap Investing: Unlocking Alpha Opportunities in an Underutilized Asset Class
Institutional investors typically overlook or underweight small cap equities in global mandates for a number of reasons, including a higher risk level (relative to large caps), a lack of operational history, liquidity, and information/data gaps which make it challenging to make informed investment decisions. However, investors who are willing to embrace the risk in small cap investing also stand to reap the benefits of allocating to this asset class – potentially earning higher risk-adjusted performance and portfolio diversification. In this report, we examine international small cap performance across various themes and provide actionable insights for both fundamental and quantitative investors, by identifying key drivers of small cap stock performance.

January 2019: Value and Momentum: Everywhere, But Not All the Time
"Momentum" and "Value" strategies have had well-documented return premia in multiple geographies and asset classes. Average monthly returns to momentum are larger than average returns to value, caveated by large pullbacks ("crashes") in the momentum portfolio. Practitioners often include both approaches in their investment strategy.

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

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

- Lower latency, higher frequency and finer granularity vs. financial data: Insights into corporate activity can be enhanced with Panjiva's Supply chain data which can be updated as often as on a daily basis - well ahead of, and at a higher frequency than - financial reports at a high level of product granularity. Examples include the underperformance vs. consensus earnings by UPS and LG Electronics in Q3 2018 as well as the near-term impact of solar panel duties.

- Detection of anomalous activity: Spikes in imports can indicate inventory build, new products introductions, attempts to boost market share or even capital markets events. Honda's accelerated imports ahead of new tariffs, Sony's launch of the "PlayStation Classic", Target's aim to replace Toys'R'Us and PepsiCo's bid for Sodastream are all examples of this use case.

Risk event impact assessment: Panjiva's supply chain graph includes geographical references for corporate entities, allowing the rapid assessment of the impact of natural disasters and geopolitical actions such as border closures.

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

Highlights include:

- Sentiment-based signals: Firms whose executives and analysts exhibited the highest positivity in sentiment during earnings calls outperformed their counterparts. Firms with the largest year-over-year positive sentiment change and firms with the strongest positive sentiment trend outperformed their respective counterparts.
- Behavioral-based signals: Firms whose executives provided the most transparency by using the simplest language and by presenting results with numbers outperformed their respective counterparts.
- Sentiment- and behavioral-based signals are not subsumed by commonly used alpha and risk signals.
- Positive language from the unscripted responses by the executives during the Q&A drove the overall predictability of the positive sentiment signal.
- The sentiment of CEOs has historically been more important than the sentiment of other executives.
- The aggregate sentiment of analysts historically enhanced the predictability of the 3-month FY1 EPS analyst revision signal.

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

Highlights include:

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

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

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

May 2018: Buying the Dip: Did Your Portfolio Holding Go on Sale?
'Buy the Dip' ("BTD"), the concept of buying shares after a steep decline in stock price or market index, is both a Wall Street maxim, and a widely used investment strategy. Investors pursuing a BTD strategy are essentially buying shares at a "discounted" price, with the opportunity to reap a large pay-off if the price drop is temporary and the stock subsequently rebounds. BTD strategies are especially popular during bull markets, when a market rally can be punctuated by multiple pullbacks in equity prices as stock prices march upwards.

March 2018: In The Money: What Really Motivates Executive Performance?
CEO compensation has soared over the past four decades, aided by consultants, compensation committees, the CEOs themselves, and an extended bull market (1982- 1999). "Pay for performance" has become dogma and large equity grants de rigueur. But there is a cost to such largesse. Figure 1 shows that realized pay1 for a company's top five executives can approach 6%-11% of earnings before interest and taxes (EBIT), on the index level, for small and mid-cap firms. What types of compensation motivate top executives to boost shareholder returns? And what are the fundamental characteristics of companies in which executives are motivated to boost stock performance?

February 2018: The Art of (no) Deal: Identifying the Drivers of Cancelled M&A Deals

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