S&P CAPITAL IQ

QUANTITATIVE RESEARCH
JANUARY 2012

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The authors would like to thank Victor Liu, PhD for his contributions to this effort.

Intelligent Estimates
A Superior Model of Company Earnings Surprise

As residual stakeholders, equity investors place enormous importance on a company's earnings. Analysts regularly forecast companies' future earnings. The prospects for a company's future earnings then become the basis for the price an investor will pay for a company's shares. Market participants follow sell side analysts' forecasts closely, identifying those analysts that demonstrate forecasting prowess and track those analysts' forecasts going forward.

S&P Capital IQ has developed a robust, actuarial, approach to forecasting company earnings. ***Rather than focus on the most accurate analyst, the Intelligent Estimate Model focuses on the attributes of an accurate forecast:***

- Age of Estimate – Newer estimates contain more information and represent the most complete forecast of what a company will report.
- Broker Size – The largest brokers tend to attract and retain analysts that provide more accurate forecasts.
- Forecast Horizon – Forecasts made closer to the company report date presumably will embed more information into the forecast.
- Tenure – Analysts that have been covering stocks for a long time provide more accurate forecasts.

Using these forecasts attributes the intelligent estimate model forecasts the error associated with each estimate. We then combine all the analyst forecasts for a stock with the weight inverse to the forecast error. ***The resulting weighted Intelligent Estimate forecast:***

- ***Provides a reduced median FY1 EPS forecast error of 14 and 10% over the naïve consensus within the US and internationally, respectively.***
- ***Predicts 62% of US FY1 EPS Surprises greater than 5% and 58% internationally.***

While the work of academics, as well as our own, has identified some measureable persistence in analyst skill, there are several difficulties with following the most accurate analyst:

- The most accurate forecast, by definition, must be an outlier. We show that analyst persistence is described by a handful of factors that are superior to accuracy itself.
- Analyst mortality is high, with 20% or more leaving the profession every year. This presents practical accuracy calculation problems for handling analysts with limited track records or that experience coverage changes.

Intelligent Estimate Model Results

We evaluate the Intelligent Estimate model relative to the naïve consensus for both the entire coverage universe as well as those stocks for which the Intelligent Estimate varies by more than 1,2, and 5% from the consensus. We also measure model accuracy in the US and International (developed world ex-US) universes. The Intelligent Estimate model improves the FY1 median forecast accuracy 14% and 10%, and correctly predicts 62% and 58% of the surprises that are 5% or larger in the US and internationally respectively (Figure 1).

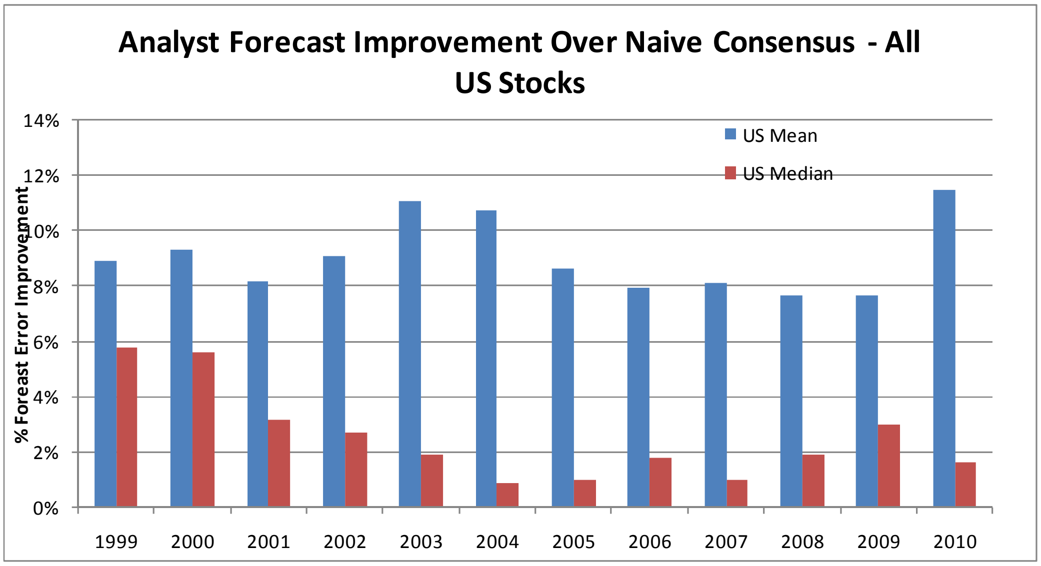
Figure 1 – Intelligent Estimate FY1 Accuracy Improvement Relative to Naïve Consensus 1999-8/2011

	US		International	
	Mean	Median	Mean	Median
All Stocks	10%	3%	7%	3%
1%+ Differences	18%	7%	10%	5%
2%+Differences	21%	9%	11%	6%
5%+ Differences	29%	14%	14%	10%

	US	International
	Hit Rate vs Naïve	Hit Rate vs Naïve
All Stocks	55%	55%
1%+ Differences	59%	56%
2%+Differences	60%	57%
5%+ Differences	62%	58%

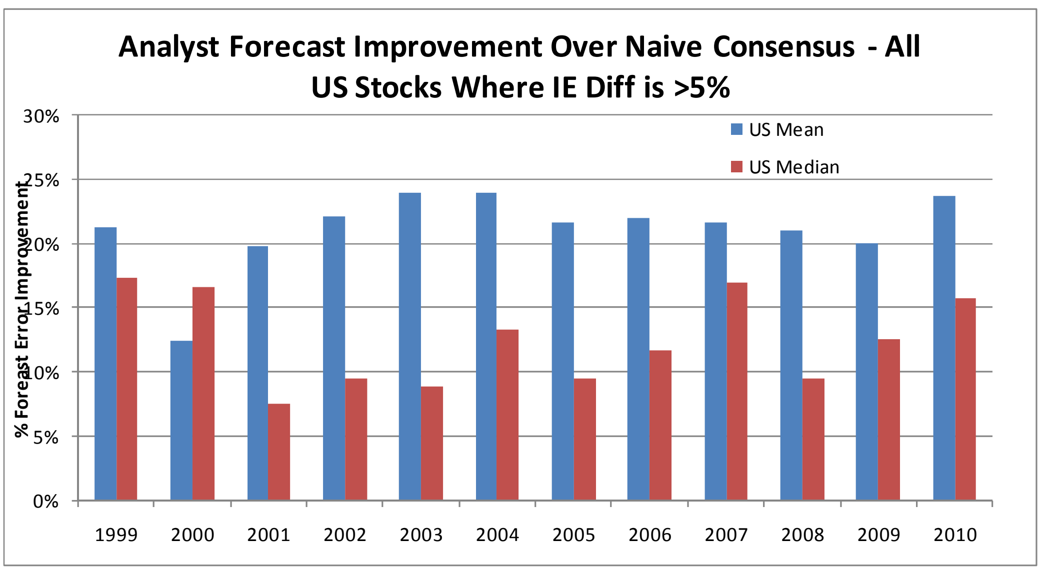
The Intelligent Estimate model provides consistent forecast error improvement in virtually every year, (on both a mean and median basis) over the naïve consensus since 1999 (Graphs 1 and 2). The mean improvement is always higher than the median indicating a positive skew in accuracy improvement, or a greater number of larger surprises that were correctly forecasted.

Graph 1 – Intelligent Estimate Improvement for US Coverage – FY1



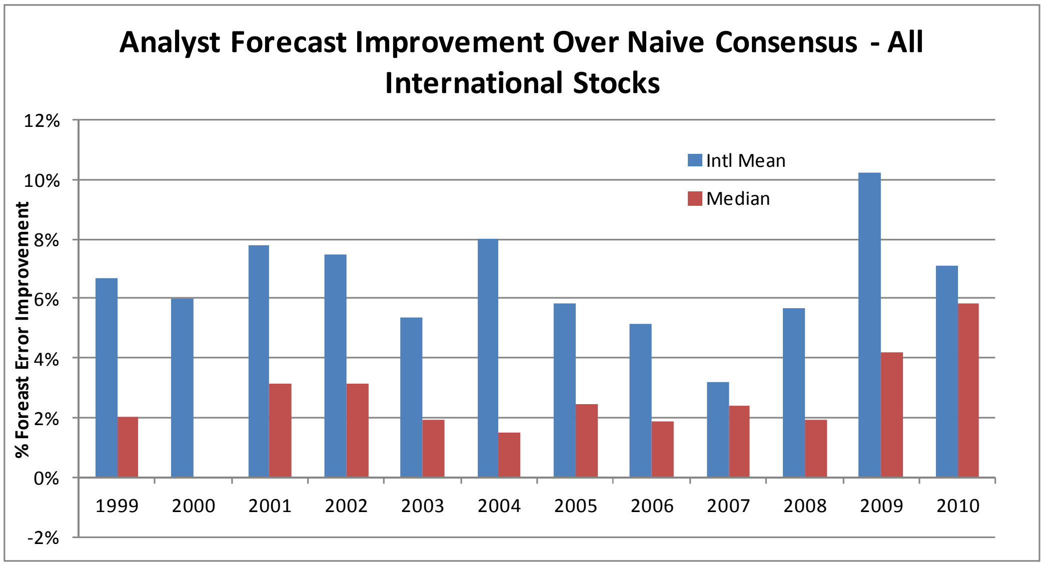
The Intelligent Estimate model shows even greater forecast error reduction where the Intelligent Estimate varies from the consensus by more than 5% (Graph2).

Graph 2 – Intelligent Estimate Improvement for US Coverage Where FY1 Intelligent Estimate Differs from Consensus by >5%

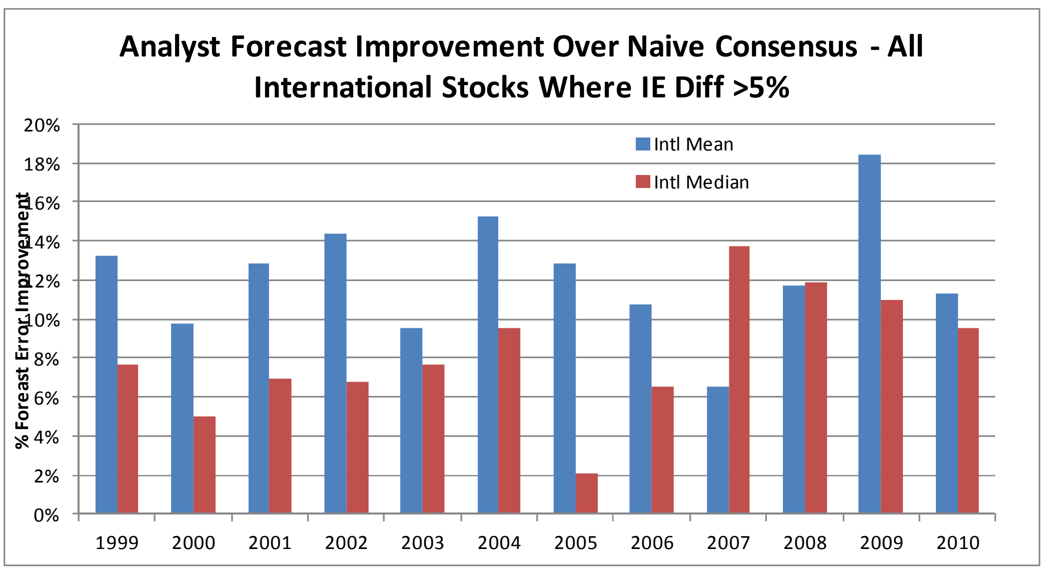


The same model efficacy is found in the broader international coverage universe. As in the US, the Intelligent Estimate model strength is improved where there are differences of opinion between the model and the consensus (Graphs 3&4).

Graph 3 – Intelligent Estimate Improvement for Intl Coverage FY1



Graph 4 – Intelligent Estimate Improvement for US Coverage Where FY1 Intelligent Estimate Differs from Consensus by >5%



When the model efficacy is examined regionally, we find strong improvements in the US and Canada. The median accuracy improvements in Asia and Europe are also strong, 5 and 7% respectively for those companies where the IE differs from the naïve consensus by 5% or more.

Figure 2 – Regional Median Accuracy Improvement By Difference Between Intelligent Estimate and Consensus 1999-2010

Intelligent Estimate Accuracy Improvement By Region

US

	IE Accuracy Improvement
Overall	2%
1% Differences	7%
2% Differences	9%
5% Differences	14%

Canada

	IE Accuracy Improvement
Overall	3%
1% Differences	5%
2% Differences	7%
5% Differences	13%

Asia

	IE Accuracy Improvement
Overall	1%
1% Differences	1%
2% Differences	2%
5% Differences	5%

Europe

	IE Accuracy Improvement
Overall	2%
1% Differences	1%
2% Differences	5%
5% Differences	7%

We observe that the Intelligent Estimate model is stronger in North America than the rest of the developed world. This may be true for two reasons. First, analysts are more timely in updating their estimates in North America. Second, analysts tend to herd to a greater degree outside the US, as guidance takes on a more important role in countries such as Japan.

The Model Specification

S&P Capital IQ has developed an earnings forecast model that focuses on the attributes of an accurate forecast rather than tracking analysts with the greatest historical skill. The model regresses the absolute de-meaned stock level forecast error against 8 predictive factors with a rolling window through time. The regression is then used to forecast the error for each analyst's forecast in the out-of-sample period. In the following sections we focus on FY1 forecasts, but the methodology is readily extended to all analyst forecasts and at all frequencies.

Abs(%Analyst Error- %Avg Error for all Analysts on that Stock)=
FH+EDiff+Age+Age2+FH2+Calendar Factor+Tenure+Broker Size

where,

FH= Forecast Horizon (+coefficient)

EDiff= Estimate Differential (+coefficient)

Age= Age of Estimate (+coefficient)

Age2= Secondary Measure of Age

FH2= Secondary Measure of Forecast Horizon

Calendar Factor = Where you are in the calendar impacts the importance of the Age of Estimate

Tenure = Tenure of Analyst (- coefficient)

Broker Size = Larger brokers tend to produce somewhat more accurate estimates (-coefficient)

For each stock, the analysts' forecasts are weighted by the inverse of the forecasted error. The resulting combination is the S&P Capital IQ Intelligent Estimate.

Figure 3 – Coefficient T-stats for S&P Capital IQ US Intelligent Estimate Model

T-Stats for US Regression - Insample

	(Intercept)	fh2	EDiff	Age	Age2	fh	Tenure	Broker Size	Calendar	R2
1/1/1999	54.1	-35.4	81.2	-9.3	4.7	6.5	-1.6	-8.2	9.6	21%
1/1/2000	190.9	-122.8	110.8	-44.3	10.3	60.2	-4.3	-24.1	49.1	15%
1/1/2001	173.4	-144.3	66.7	-34.7	12.9	105.5	-7.6	-10.4	37.2	16%
1/1/2002	172.7	-157.5	77.5	-34.9	9.6	109.5	-9.8	-11.6	42.0	18%
1/1/2003	164.0	-163.4	147.5	-26.8	10.6	134.0	-14.8	-15.7	29.7	19%
1/1/2004	215.4	-171.2	100.6	-43.1	17.1	124.3	-13.4	-20.0	39.5	17%
1/1/2005	241.5	-170.4	189.2	-48.9	19.7	104.8	-18.4	-26.1	42.0	19%
1/1/2006	247.1	-182.2	142.4	-52.3	21.5	120.2	-19.8	-15.1	46.8	18%
1/1/2007	239.7	-172.6	139.6	-52.7	21.2	116.1	-16.4	-9.2	45.2	17%
1/1/2008	253.3	-157.3	111.4	-53.3	20.8	102.3	-18.4	-12.3	46.8	17%
1/1/2009	217.3	-165.9	86.5	-31.0	12.5	145.7	-9.5	-5.2	33.9	17%
1/1/2010	179.5	-108.1	53.4	-29.6	17.7	100.3	-11.2	-12.1	16.9	14%

Figure 4 – Coefficient T-stats for S&P Capital IQ US Intelligent Estimate Model

T-Stats for International Regression - Insample

	(Intercept)	fh2	EDiff	Age	Age2	fh	Tenure	Broker Size	Calendar	R2
1/1/1999	147.6	-52.0	20.6	9.2	-10.1	31.3	2.1	8.8	25.1	3%
1/1/2000	177.0	-21.3	36.5	-29.7	-1.3	15.4	15.5	-3.7	31.3	2%
1/1/2001	190.5	-16.1	106.5	-10.0	5.5	20.4	3.5	3.5	11.3	4%
1/1/2002	177.7	-29.8	101.6	-11.7	4.9	41.6	8.7	15.0	16.8	4%
1/1/2003	194.9	-28.4	36.4	-8.3	2.3	27.7	-4.5	18.2	16.2	2%
1/1/2004	194.4	-22.5	117.6	-29.9	-2.5	22.7	3.8	7.8	36.1	5%
1/1/2005	243.4	-19.0	52.9	-29.8	10.8	7.1	-13.1	21.3	28.4	2%
1/1/2006	265.6	-26.5	108.7	-40.0	12.9	10.0	-15.4	34.6	36.8	3%
1/1/2007	267.8	-10.6	169.5	-30.3	10.0	3.9	-42.3	49.6	27.4	5%
1/1/2008	273.5	-29.1	99.8	-11.2	-2.7	26.7	-26.8	38.1	22.6	3%
1/1/2009	250.1	-34.4	84.2	-12.6	0.8	61.5	0.1	18.6	16.6	2%
1/1/2010	177.3	-23.9	87.0	-7.4	0.7	26.0	15.5	-14.0	12.3	4%

Figures 3 and 4 illustrate that the signs on the model coefficient t-stats are quite stable. The linear coefficients and t-stats have the expected signs. The in sample adjusted R-Squared's are stable and relatively strong. The real model test however will be to see how much forecast accuracy is improved from predicting forecast error in the out of sample periods.

In order of statistical significance, the forecast horizon, the boldness of the forecast, and the age of the forecast are the largest drivers of the model strength.

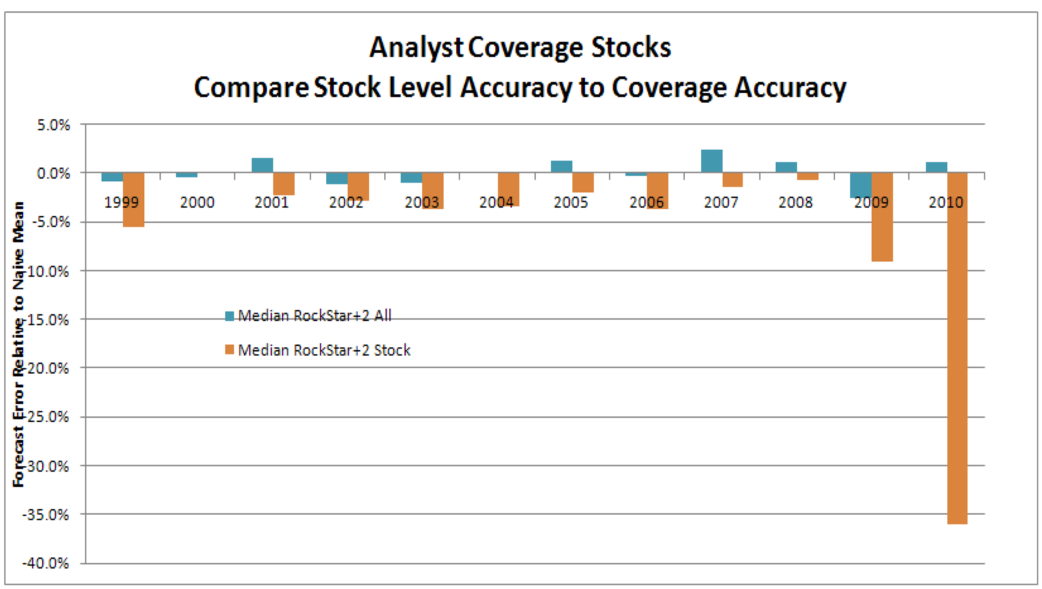
Measuring Analyst Skill– Do Analysts Cover Stocks or Their Entire Coverage?

It is a common practice to weight analyst estimates by their trailing skill, forming an accuracy weighted consensus. To the extent there is persistence in analyst skill, this accuracy weighted estimate should be closer to what a company ultimately reports than the naïve mean.

The primary question is: How does one measure accuracy? The literature commonly compares an analyst's estimate to the other analysts that cover the same stock. In this way, we subtract off the mean forecast error for every stock on every date. This relative forecast error can serve as a practical measure of analyst skill. This allows for more reasonable forecast comparisons between more challenging sectors such as technology, and more predictable sectors such as utilities.

We consider whether we should measure analyst accuracy on the individual stock level or the coverage level. Do analysts really cover one or two names, or are they equally committed to their entire assigned coverage. Graph 5 examines the median FY1 forecast error of the three best analysts in the prior year both on a stock level and coverage level relative to the forecast error of the naïve mean. The best analyst from the prior year is deemed a "Rock Star". Analyst coverage permitting, we highlight the Rock Star and the next two best analysts from the prior year. The stock level accuracy (Shown by the orange bars), consistently represents reduced forecast error when compared to the coverage level accuracy. **From this point forward, analyst accuracy refers to stock level accuracy.**

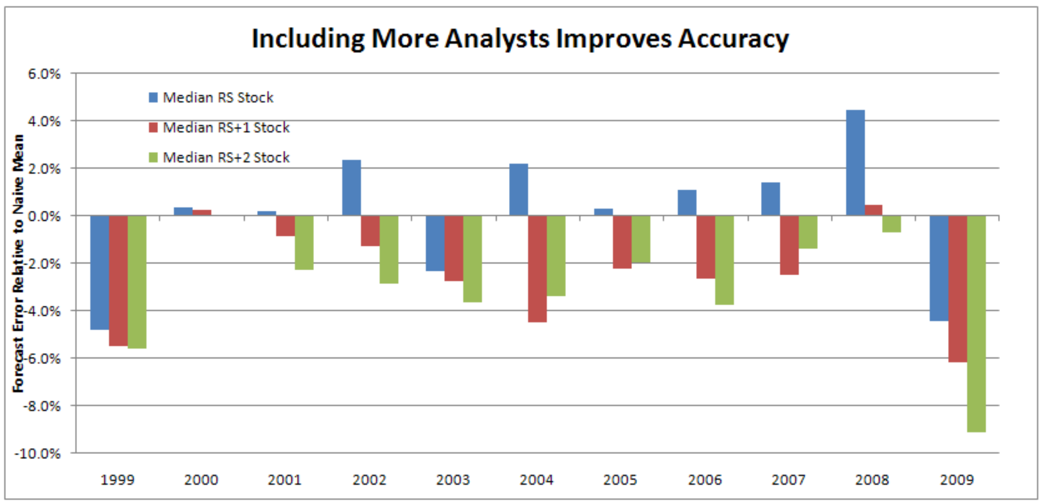
Graph 5 – US Coverage Universe 1999-2010



Further Examination of Analyst Skill– Less than Meets the Eye

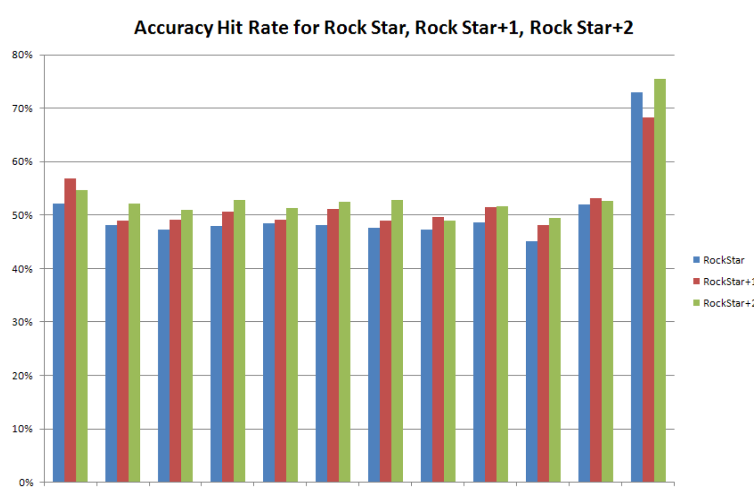
We analyze the persistence of skill by looking at the accuracy of the current Rock Stars. For most time periods the prior period Rock Star has a higher FY1 forecast error than the naïve mean. When we add the second (RS+1) and third best (RS+2) analysts the results steadily improve. This suggests that among the best analysts there may be persistence of skill as opposed to a single Rock Star. High analyst turnover among the worst analysts prevents an easy analysis of the persistence of lack of skill.

Graph 5 – US Coverage Universe 1999-2010



Testing persistence non-parametrically, a simple batting average of Rock Star performance relative to consensus, paints a similar picture. The Rock Star alone is usually unable to beat the naïve mean more than 50% of the time. When we add the second and third best analysts to form a super group, the hit rate improves, though often not significantly more than 50% of the time.

Graph 6 – US Coverage Universe 1999-2010

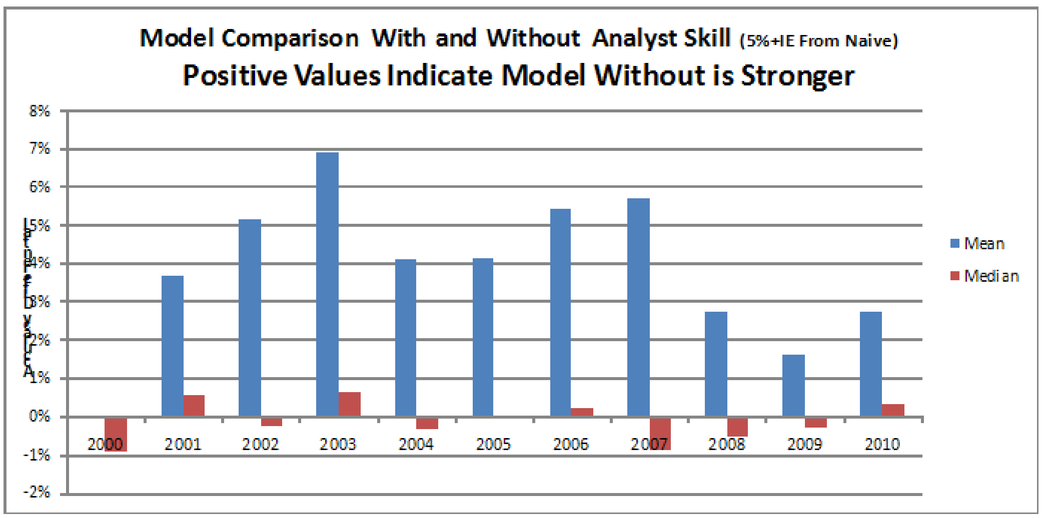


The Model–The Value Added of Analyst Accuracy

Given that analyst skill demonstrates some degree of persistence, should we include accuracy in our model? We turn our attention to the model results out of sample combining both historical analyst skill in conjunction with our 8 factor model, and our 8 factor model alone.

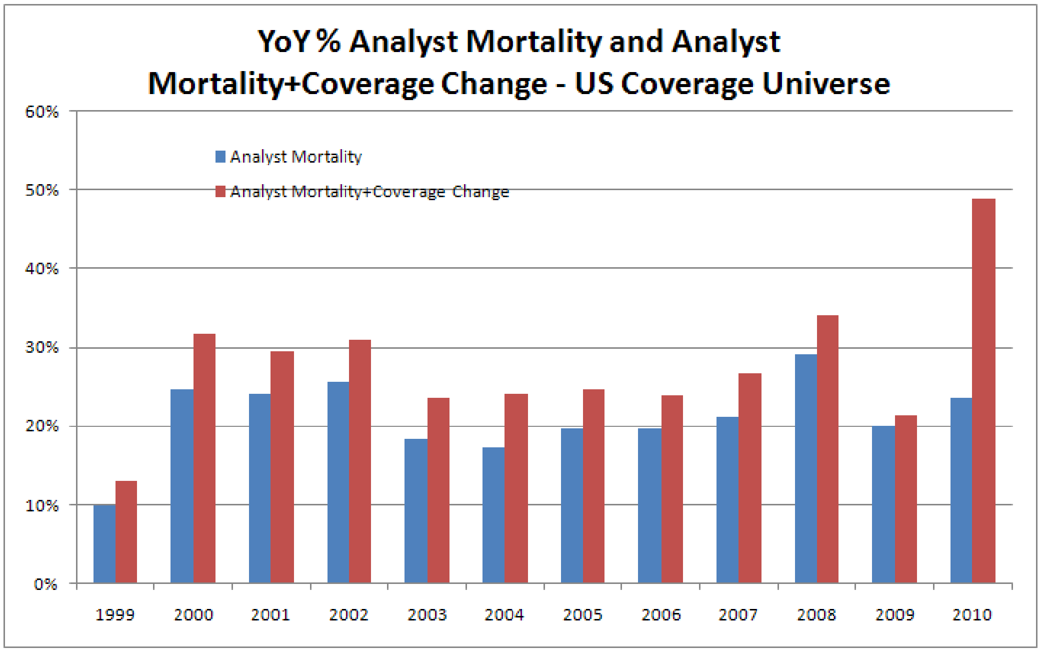
We concentrate on those stocks where the Intelligent Estimates varies widely from the consensus. We focus on the universe of stocks where the Intelligent Estimate is 5% or greater from the naïve mean (on average 15% of the stocks on a given date). Graph 7 indicates that the mean FY1 accuracy is worse for the regression model that includes analyst accuracy. The median error is more or less unchanged across the two models. This suggests that analyst accuracy is subsumed by the 8 factors listed in section 2. The observation that the mean FY1 error is worse but the median error is unchanged suggests that the 8 factor model does a better job at identifying when analysts will be wrong by a large margin. These 8 factors do a better job of separating skill from luck in outlier forecasts.

Graph 7 – Stocks For Which the Intelligent Estimate Deviates 5% or Greater from Naïve Mean 2000-2010



There is a second problem with using analyst accuracy; analysts experience a high mortality rate. On average 21% of analysts leave the industry every year. This effect is more pronounced at the stock level. With so many analysts leaving and new analysts joining at any given point in time, it renders a large portion of the forecasts unusable. Analyst attrition rises to 28% at the stock level as this mortality measure now incorporates coverage changes.

Graph 8 – US Coverage Universe 1999-2010



S&P Capital IQ Analyst Estimate Data

The Intelligent Estimate model has been constructed using S&P Capital IQ's industry leading analyst detail database. An advantage to using Capital IQ detail data is the manner in which it is collected and stored. S&P Capital IQ organizes data at the broker level rather than then analyst level as most of our competitors do. This means that S&P Capital IQ always has one active estimate per broker. This allows us to automatically ignore the analyst estimates for those analysts that have undergone coverage changes. Competitors that collect and store data at the analyst level will have more than one estimate per broker, storing the prior analysts estimate as active, until it is expired. As with competing offerings, the S&P Capital IQ analyst detail database is subject to historical changes given contributor and other updates. At the time of this publication, S&P Capital IQ is working on extending its estimates database into a point-in-time format, an advance which, as researchers, we fully support.

S&P Capital IQ provides a full selection of global estimates, bolstering our internationally recognized fundamental research and analytics offerings with vital financial forecasting measures. The addition of a competitive estimates offering underlines S&P Capital IQ's deep commitment to providing the most accurate and transparent financial information in the marketplace alongside industry leading functionality. By continuing to employ numerous accuracy checks, proactive surveillance, and proven methodology, S&P Capital IQ is now a preferred source of estimates for thousands of the world's top buy-side and sell-side industry professionals.

The S&P Capital IQ Estimates database covers over 21,000 companies in over 100 countries. History goes back to 1999 in the US and 1996 Internationally. S&P Capital IQ currently collects data from over 700 contributors and stores over 45 unique data points. Current coverage includes 100% of the S&P 500, 99.6% of the MSCI World, 100% of the MSCI Asia Mid Cap, and 100% of the FTSE indices.

Conclusions

There is a natural tendency in all aspects of human performance to look to those specialists that have historically demonstrated skill in their area. Equity analysts are no exception. Given real world complexities surrounding analyst attrition and the inherent difficulty of forecasting itself, S&P Capital IQ introduces a model for determining forecast accuracy independent of historical skill.

Rather than focus on analyst track records, we turn our attention to those attributes of a forecast that tend to lead to the greatest degree of accuracy. Namely, we look at 8 factors comprising of Estimate Age, Forecast Horizon, Analyst Tenure and Broker Size. The Intelligent Estimate model improves median forecast accuracy in every calendar year since 1999 an average of 10-14%, and also improves accuracy over a model that includes historical analyst skill.

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Appendix – US FY1 Intelligent Estimates Stats By Sector

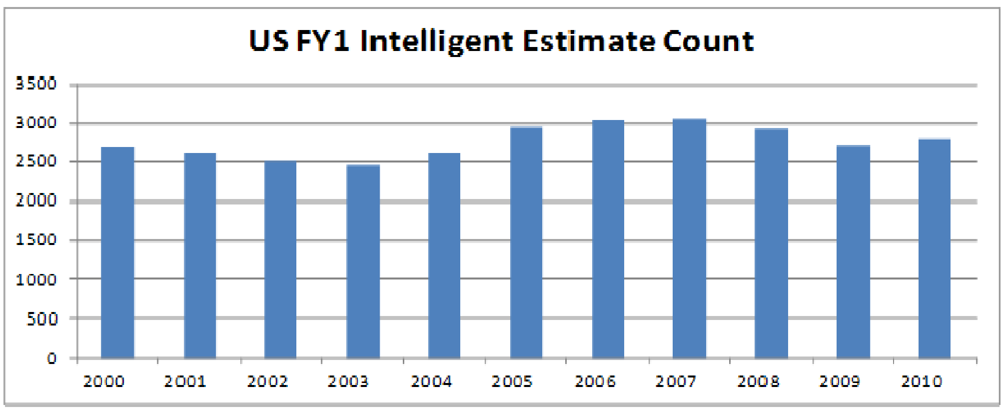
Accuracy Improvement of Intelligent Estimates for Various Levels of Disagreement
US Universe - 1999 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	6%	6%	4%	5%	8%	19%	7%	6%	8%	4%
2%	7%	7%	6%	10%	12%	15%	7%	8%	14%	0%
5%	15%	10%	12%	15%	9%	19%	11%	14%	14%	7%

Disagreement is defined as the absolute percentage difference between Intelligent Estimates and Consensus

Percentage of the time (Hit Rate) That Intelligent Estimate is Closer than Consensus for Various Levels of Disagreement
US Universe - 1999 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	59%	60%	59%	59%	56%	57%	59%	59%	60%	56%
2%	60%	61%	60%	61%	59%	59%	59%	60%	63%	56%
5%	63%	63%	64%	63%	63%	61%	61%	63%	65%	59%



Appendix – International FY1 Intelligent Estimates Stats By Sector

Accuracy Improvement of FY1 Intelligent Estimates for Various Levels of Disagreement
Canada Universe - 1999 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	6%	10%	-3%	5%	-3%	13%	-3%	8%	31%	-3%
2%	11%	13%	0%	6%	9%	12%	1%	11%	46%	-9%
5%	23%	22%	4%	13%	27%	14%	0%	26%	21%	-3%

Disagreement is defined as the absolute percentage difference between Intelligent Estimates and Consensus

Accuracy Improvement of FY1 Intelligent Estimates for Various Levels of Disagreement
Europe Universe - 1996 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	4%	11%	3%	5%	0%	6%	0%	9%	5%	1%
2%	5%	14%	4%	7%	-1%	6%	1%	9%	5%	5%
5%	22%	16%	5%	5%	5%	7%	-2%	9%	13%	5%

Disagreement is defined as the absolute percentage difference between Intelligent Estimates and Consensus

Accuracy Improvement of FY1 Intelligent Estimates for Various Levels of Disagreement
Asia Universe - 1996 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	8%	-1%	4%	2%	12%	3%	-2%	0%	8%	5%
2%	10%	2%	5%	3%	12%	10%	-3%	10%	16%	3%
5%	9%	5%	1%	7%	22%	24%	-4%	40%	31%	0%

Disagreement is defined as the absolute percentage difference between Intelligent Estimates and Consensus

Percentage of the Time (Hit Rate) That Intelligent Estimate is Closer than Consensus for Various Levels of Disagreement
Canada Universe - 1999 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	59%	61%	57%	57%	56%	57%	51%	60%	58%	47%
2%	60%	62%	57%	59%	55%	57%	54%	63%	67%	47%
5%	61%	65%	56%	63%	55%	59%	57%	66%	73%	50%

Percentage of the Time (Hit Rate) That Intelligent Estimate is Closer than Consensus for Various Levels of Disagreement
Europe Universe - 1999 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	60%	61%	57%	58%	55%	56%	57%	60%	58%	53%
2%	61%	62%	57%	59%	55%	56%	57%	61%	58%	54%
5%	66%	65%	57%	59%	53%	57%	56%	62%	60%	53%

Percentage of the Time (Hit Rate) That Intelligent Estimate is Closer than Consensus for Various Levels of Disagreement
Asia Universe - 1996 Through 2011

Disagreement	Energy	Materials	Industrials	Consumer Disc	Consumer Stpls	Health Care	Financials	Technology	Telecom	Utilities
1%	58%	58%	57%	59%	57%	59%	53%	61%	58%	53%
2%	59%	60%	58%	60%	57%	61%	54%	63%	60%	53%
5%	63%	62%	57%	60%	61%	62%	55%	63%	62%	52%

Our Recent Research

December 2011: Factor Insight – Residual Reversal
Many investors employ price reversal strategies (strategies that buy "losers" and sell "winners" based on short-term price changes) in their stock selection decisions. One popular reversal strategy is constructed as the change in 1-month stock price over the most recent month. This report compares the performance of this factor to a "residual reversal" signal proposed by Blitz, Huij, Lansdorp and Verbeek in their 2011 paper, "Short-Term Residual Reversal".

November 2011: Research Brief: Return Correlation and Dispersion – All or Nothing

October 2011: The Banking Industry
Investors can improve model and portfolio risk adjusted returns using various approaches, including incorporating new alpha signals in an existing investment process. In this research piece, we build on our earlier work (See "Is your Bank Under Stress? Introducing our Dynamic Bank Model", November 2010), to determine if bank specific data provided by financial institutions regulatory bodies (FFIEC standardized data), can yield alpha signals orthogonal to those found in most stock selection models.

September 2011: Methods in Dynamic Weighting
In this report, we introduce a powerful discovery tool in Alphaworks and provide a pragmatic survey covering the identification and potential dynamic techniques to handle financial regimes and security level context. With increasingly volatile factor performance, the ability to implement adaptive strategies is paramount in maximizing factor efficacy.

September 2011: Research Brief: Return Correlation and Dispersion - Tough Times for Active Managers

July 2011: Research Briefs- A Topical Digest of Investment Strategy Insights
Investors must sort through a constant stream of information in order to identify opportunities, structural changes, and market risks. Wading through information quickly and efficiently is critical as investors must understand how their strategy and exposures are impacted. Typical classes of questions include: What strategy should I use in response to a regime shift? How do I invest in a specific industry? Do other markets behave differently than the US market? In this report we highlight several classes of questions that investors are routinely interested in and share our thoughts on these topics.

June 2011: A Retail Industry Strategy: Does Industry Specific Data tell a different story?
Investors are on a constant quest for new investment insights. A more complete understanding of the dynamics that shape an industry is integral to this search. As S&P Capital IQ's quantitative research begins a more thorough examination industry specific sources of alpha, we turn our attention first to the retail industry utilizing the Compustat database. Many of the strategies validate common investor best practice when looking at the retail space. In this paper we develop several new retail specific factors and use them to construct a 6-factor retail specific model.

May 2011: Introducing S&P Capital IQ's Global Fundamental Equity Risk Models
Global investors invest in assets across multiple countries. Building on the success of S&P Capital IQ's release of our U.S. Fundamental Equity Risk models we use similar building blocks viz. the best of breed point-in-time S&P Capital IQ data, state of the art Alphaworks alpha factor library, GICS global industry classification system and an open and robust risk estimation methodology to construct the S&P Capital IQ Global Fundamental Equity Risk Model.

May 2011: Topical Papers That Caught Our Interest
Favorite Papers on a Few Favorite Topics – Regime Switching and Minimum Variance
Two current topics of significant interest and frequent discussion to investors are regime switching, or a strategy's sensitivity to the current environment, and minimum variance portfolios.

In this piece our team highlights academic articles of note on each of these two topics. We found these papers to provide unique insights that would be of broad interest to practitioners. We provide analyst notes for each article which summarize the main points. Our hope is that by sharing this with you, you may gain new perspective and generate new ideas that will help you as much as this research has helped us. For each research piece we provide a link to the article, the abstract, and a brief summary and discussion of why the article was chosen, and the analyst notes highlighting key insights in the work.

April 2011: Can Dividend Policy Changes Yield Alpha?
Investors are acutely sensitive to changes in dividend policy. Literature suggests that dividend change announcements provide information about management's assessment of companies' prospects, and therefore are predictive of future stock returns. The implication for investors is worth noting. In the first quarter of 2011 alone, 105 of the 384 dividend paying S&P 500 companies (27.3%) increased their dividends, while only 1 (0.26%) decreased dividends.

In this paper, we analyze the market reaction to different types of dividend policy changes, specifically initiation, increase, decrease and suspension of dividends.

April 2011: CQA Spring 2011 Conference Notes

March 2011: How Much Alpha is in Preliminary Data?
Companies often report financials twice: first, through a preliminary press release and again in their official, i.e., final, SEC filings. In theory, there should be no difference between the numbers reported in a company's preliminary financial filings and their final filings with the SEC. In practice, often significant difference can occur between the preliminary and final filings. In this month's research report, we focus on these observed differences within the S&P Capital IQ Point-In-Time database in order to ascertain the nature and exploitability of these differences.

February 2011: Industry Insights – Biotechnology: FDA Approval Catalyst Strategy
Biotechnology is a challenging sector for investors due to the binary nature of the product cycle. Indeed many biotechnology firms' futures rest upon the success of a single product. A critical stage in the product life-cycle is the FDA approval process. In this report we look at the exploitability of a strategy centered on FDA filings.

January 2011: US Stock Selection Models Introduction
In this report, we launch our four US Stock Selection models — Value, Growth, Quality, and Price Momentum. Built using S&P Capital IQ's robust data and analytics, these four models are the culmination of over two years of research and development. Each model is intended to be employed as the basis for a stand-alone stock selection strategy or integrated into an existing systematic process as an overlay or new component.

January 2011: Variations on Minimum Variance
Various explanations for why risk is mispriced have been offered; the most common one is that leverage restrictions incite some investors to chase volatility at the individual issue level. In this paper, we explore various methodologies for construction of minimum variance portfolios of US listed equities and analyze the features of these portfolios.

January 2011: Interesting and Influential Papers We Read in 2010
As researchers, we spend a large amount of time trying to generate new ideas. In order to discover and refine these ideas, we find ourselves in a continuous quest for innovative and interesting articles and papers from academics, analysts, and other researchers. There is such a large body of information out there that it can be difficult to wade through all the material to find what is truly of value and interest to us. To assist in sifting through all this information, our group recently took the time to find and discuss articles that recently struck us.

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