RESEARCH PAPER

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DO SOME EQUITY RESEARCH ANALYSTS CONSISTENTLY MAKE MORE ACCURATE FORECASTS THAN OTHERS?

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ABSTRACT

This paper looks at forecasts made by equity research analysts on the S&P 500 companies from 2011 to 2018. First, it shows that the market takes these equity research forecasts into account when reacting to results published by companies. Then, it looks at analysts' performance in forecasting companies' earnings and shows that some analysts tend to make more accurate forecasts than others. It also shows that there is some consistency in this precision, both for skilled and less-skilled analysts. Finally, it shows that the market is probably already aware of this information, since a trading strategy based on this result would not have been profitable.

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I. INTRODUCTION

PRESENTATION OF THE TOPIC

Equity research professionals provide information and equity investment recommendations to the financial markets. Each equity research analyst, also called sell-side analyst, covers a limited number of companies, and devotes a lot of time on each of them, gathering public information, processing it, and communicating his view to his clients: the financial investors, who are also called “buy-side” investors or analysts. Even if the research process is similar to what buy-side analysts do prior to making an investment decision, the specific focus of equity research analysts on a limited and unvarying panel of stocks enables them to gain a particular expertise on their sector and on the companies under their coverage, arguably to a greater extent that buy-side analysts who usually cover a much larger number of companies or sectors. Therefore, equity research analysts are sometimes the reference point for investors considering an equity investment, and their recommendations can sometimes have a large impact on stock prices.

Part of the information analysis communicated by sell-side analysts consists in recommendations ‘buy’, ‘sell’ or ‘hold’, as well as forecasts of the different lines of the financial statements for companies they cover. The average of all analysts’ forecasts is called the consensus, and is often looked at, as an approximation of what the market expects regarding a company releasing its periodical performance. Different analysts can sometimes have a very different view on the company, which makes the question of anticipating who may be right quite interesting.

AIM OF THE RESEARCH

In this paper, I look at the forecasts made by sell-side analysts and define a model to assess their precision. I then searched for persistency in the mistake they make when forecasting, and use the results found to try to build an enhanced consensus able to beat the simple average-consensus. I then look at a possible trading strategy and measure the return it would have made over the past few years.

AN OVERVIEW OF CURRENT ANALYST PERFORMANCE MEASUREMENTS AND RESEARCH PAPERS ON THE TOPIC

Several institutions are focused on the ranking of sell-side analysts:

- The Wall Street Journal issues an annual ranking of equity analysts following US stocks, called “Best on the Street”. It measures analysts’ performance and ranks them on the basis of the return made by a portfolio built with their buy/hold/sell recommendations.

- The publisher “Institutional Investors” also provides ranking of American equity research analysts, called “All-American Research Team”. On the contrary of “Best on the Street”, this prestigious ranking is based on a survey gathering votes from buy-side investors for the best sell-side analysts and does not rely on a quantitative assessment of their performance.
- Like Institutional Investors, the Extel survey publishes every year a ranking of the best sell-side analysts per sector, based on votes from the buy-side.
- Finally, Starmine, owned by Thomson Reuters Refinitiv, has a similar approach to the Wall Street journal and looks at the return of investment recommendations from analysts, and at the precision of forecasts made by analysts.

At the end of the day, these institutions roughly use two methods: a qualitative survey to the buy-side investors, who vote for their favourite sell-side analyst, and a quantitative performance measurement of the buy/hold/sell recommendations made by sell-side analysts over the year. I think that there are two possible flaws in these approaches:

Firstly, they do not assess the effectiveness of their ranking, i.e. the prediction power they have over the next years’ performance. One of the most important warning given to retail investors in official investment documents is that “past performance is not indicative of future results”. Therefore, one should bring proof of the contrary when establishing rankings or assessment of past performance.

Secondly, their definition of performance may not be objective:

- The quantitative approach, looking at buy/sell recommendations could be biased because of the price impact that an analyst may have over the stock he covers when changing his recommendation. As a consequence, a highly-regarded analyst will have better short-term recommendations because he is listened to, and make happen to a certain extent what he has predicted. Additionally, it is difficult to assess such performance, as these recommendations are usually for long-term horizons, and should therefore be assessed over a several years of performance, over which many unpredictable factors can happen, creating a lot of noise and probably leading to a selection of the luckiest analysts instead of the most skillful, provided that skill exists.
- The survey approach may be biased by a lot of factors: some buy-side analysts may simply do not have access to all research brokers, and their views will be limited to the analysts they know. In this case, the survey would be changed into an assessment of the commercial impact of firms instead of the performance of their analysts. Some investors may also vote for their friends at the sell-side even if they do not necessarily use their research. Other may value the effectiveness of analysts on criteria such as the time they devoted to their requests, the amount of interaction they had with them, and the quality of their explanations about their companies and sector, which may not be directly related to the quality of their investment recommendations. Finally, investors may not have spent time measuring the quality of recommendations from analysts, and their opinion may therefore not matter.

Even if these rankings may not seem completely satisfactory, Fang and Yasuda (2014) found, using data from 1994 to 2009, that analysts who were top-ranked by Institutional Investors’ AA survey issued buy/hold/sell recommendations that outperformed those of the non-AA analysts, both before and after their election, by a monthly alpha of 0.6%.

This result is interesting, as it shows that even with the potential biases abovementioned for buy-side surveys, the quality of recommendations tends to matter for investors, who look at recommendation performances. This gives us a first intuition that equity research may have an impact on asset pricing, and we will investigate this topic in part III.

It also shows that there seems to be consistency in buy/sell recommendation performance, and the authors demonstrated that this performance cannot be attributed to more influence or a better access to company management after the awards, since the outperformance is of the same magnitude pre- and post-AA awards.

Mikhail, Walter and Willis (2004) also found persistency in analyst recommendations performance that generates excess returns during 3 months after the recommendation but showed that a trading strategy taking long and short positions was not profitable once taking transaction costs into account.

Sinha, Brown and Das (1997) looked at sell-side EPS forecasts, and using regressions controlling for the time delay between the forecast date and the actual date, found that analysts who outperformed for one year tend to outperform during the following year, while they found no persistency for analysts who underperformed. Brown (2001) added that a model taking into account the previous year absolute error of an analyst has the same predictive power as a 5-factor model looking at the number of years of experience of coverage of the analyst for the company, his general experience, the number of stocks and sectors it covers, and at whether the equity research company he works for is among the 10% largest.

In my paper, I measured the performance of analysts with a metric that is as objective as possible: the earnings forecasts. I didn't look at buy/sell recommendations, to avoid the noise created by the impact of such recommendations over the price and the undefined time horizon for this investment recommendation to be assessed. I did not use linear regressions like Sinha, Brown and Das (1997) did, but instead chose to model the forecasts precision and to use a statistical approach to classify analysts between 'neutral', 'good' and 'bad'. I then calculated the precision of an enhanced consensus built with the best analysts, and backtested the characteristics of a trading performance using this result.

PRESENTATION OF THE DIFFERENT PART OF THE PAPER

In Part II. I explain where the data that I used comes from, discuss its structure and disclose some choices that I made to process it.

In Part III. I show my reasoning, my computations and my results

In Part IV. I conclude and propose several perspectives that could be explored to take the analysis one step further.

II. DATA

The data I used concerns the 659 companies that were part of the S&P500 for at least one day during Jan. 1st, 2011 to Dec. 31st, 2018 (“the analysis period”) and for which I had enough data to proceed. I worked on Python 3.7.1 with the JupyterLab 0.35.3, and used the Pandas module to organise and process the data through DataFrames.

For each quarter of the period, I gathered all the available forecasts made by analysts about the 659 covered companies, for two items: the EBIT and the Net Earnings. I also gathered all the daily total shareholder returns from owning the stocks used over the analysis period.

I chose the EBIT because it is a very used metric in common valuation models, either in DCF or in valuation through multiples, and even if not an official accounting measure, it is very widely measured and forecast. I used the Net Earnings for the same reason, with the additional benefit that net earnings are more relevant for some stocks than EBIT, like the financial companies, and that they are an official accounting measure.

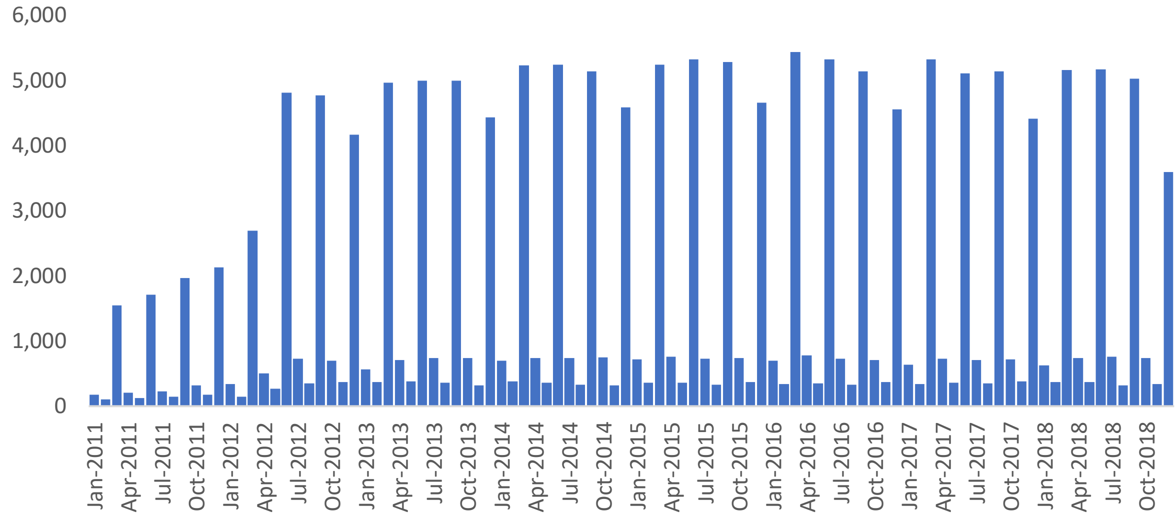
The SP500 composition comes from Compustat, the forecasts data comes from IBES and the stock returns comes from CRSP. These three data sources were accessed on the WRDS platform. Also, I gathered historical monthly returns of the S&P 500 and the US 3m Treasury yields from Yahoo finance. Once removing companies for which I have no data on IBES or CRSP, I have 559 companies left, on which my analysis is based. Please see in appendix a table with the list of companies used.

For data consistency purposes, I decided to remove too old and too recent data, i.e. forecasts that were published more than 100 days or less than 3 days before the publication of the actual. I didn’t want to have too old forecasts, that could bias my data with very imprecise measures of an analyst’s skills. On the contrary, I didn’t want to reward too much analysts who update their forecasts just before the release of the actuals, and who could benefit from too precise guidance from the company. Among the forecasts remaining, I kept the most recent one for each analyst and each quarter. Of course, changing these parameters could be quite interesting, but I didn’t try to in this paper.

The data sample focused on EBIT is made of 173,824 forecasts. The one about net earnings is made of 204,139 forecasts, after being cleaned from too old and too recent forecasts, as well as after keeping only the latest if several were available for the same period / company and analyst.

The number of forecasts made per period is presented in charts 1A and 1B. The period used is not the date at which the forecast is issued, but the ending date of the quarter to which the forecast relates.

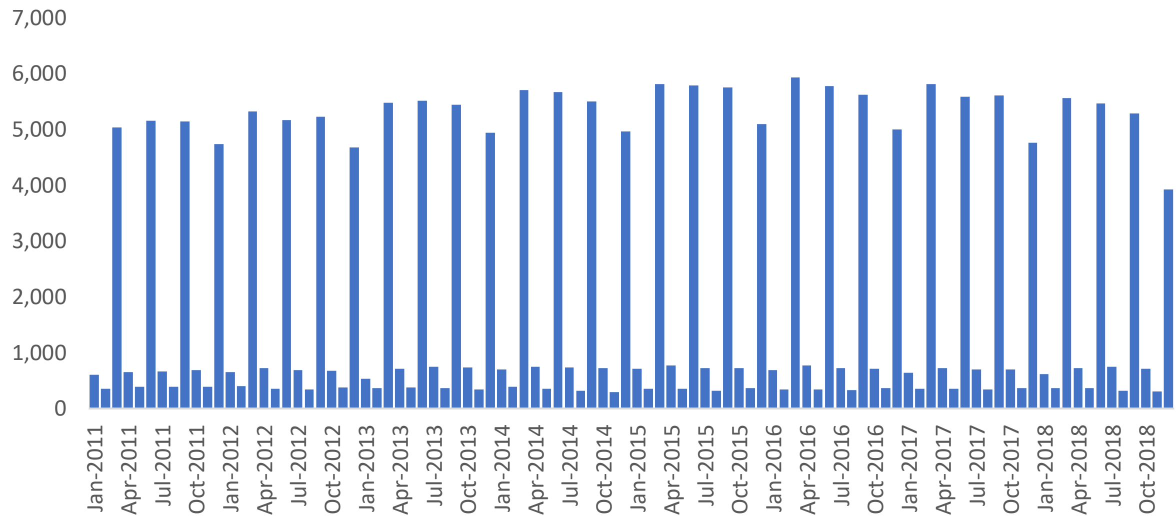
CHART1A: NUMBER OF EBIT FORECASTS KEPT PER MONTH OVER THE ANALYSIS PERIOD



The months with peaks are the months of March, June, September and December

Source: IBES, own estimates

CHART1B: NUMBER OF NET EARNINGS FORECASTS KEPT PER MONTH OVER THE ANALYSIS PERIOD



The months with peaks are the months of March, June, September and December

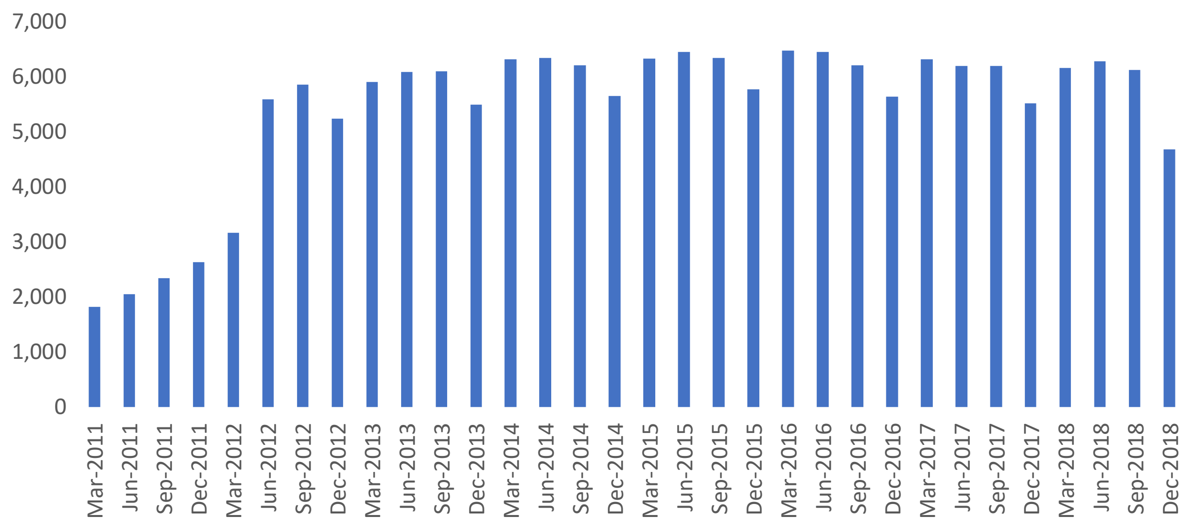
Source: IBES, own estimates

One can notice that there is a bit less data available on IBES before 2012 than after for EBIT, but since it still represents more than thousands of forecasts, I kept this period in my analysis. For net earnings, the difference is not significant.

Also, there is a big cyclicality in the data kept, for the two metrics. The peaks that can be observed correspond to the months of March, June, September and December, because the vast majority of companies report at these months.

This cyclicality logically disappears if the data is displayed by quarter:

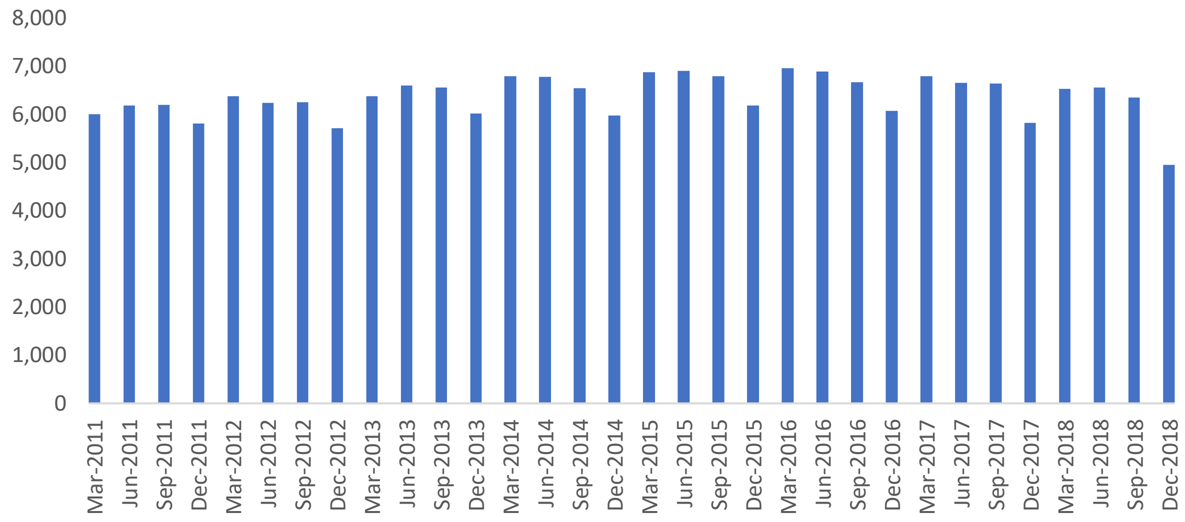
CHART2A: NUMBER OF EBIT FORECASTS KEPT PER QUARTER OVER THE ANALYSIS PERIOD



The month with systematically slightly less data is December

Source: IBES, own estimates

CHART2B: NUMBER OF NET EARNINGS FORECASTS KEPT PER QUARTER OVER THE ANALYSIS PERIOD



The month with systematically slightly less data is December

Source: IBES, own estimates

There are rarely less than 5,000 forecasts per reporting quarter, and this is once only the latest forecast per analyst and per company is kept.

There is still a cyclicality, with less forecasts available for the 4th quarter of each year. I suppose that this is probably due to some brokers publishing forecasts for the FY rather than Q4. I did not gather the FY estimate to retreat them by subtracting the Q1, Q2 and Q3 numbers to estimate their Q4 forecast.

III. ANALYSIS

A. DOES THE MARKET LOOK AT EQUITY RESEARCH?

BUY-SIDE VS SELL-SIDE CONSENSUS

The efficient-market theory states that market prices fully reflect all the available information, and that, as a consequence, share prices should only move following the release of a new information, provided that this information is a surprise for investors. A good surprise will result in the stock price rising, and a disappointing news will make the price go down.

The financial releases by companies are an important moment for investors, as they are made of information directly related to the company that can have a large impact on the price of the company. One can often notice a strong price variation on companies on the day of their quarterly results. When a company releases its financial information, investors decide if it is a positive or negative information and may place orders in consequence. The aggregation of their individual decisions makes the market dynamics. But how to decide if it is good or bad news overall? One can compare the results of the company to what was expected on average by investors: to what is often called the consensus.

When modelling the market expectations concerning companies and the release of their results, I differentiated two kind of expectations: the sell-side and the buy-side consensus.

On the one hand, the sell-side consensus (or simply "consensus") is the one obtained by taking the average (or median sometimes) of all brokers' expectations for a certain P&L item (e.g. net earnings or EBIT) of a certain a stock, for a certain period. It can easily be known and can be constantly updated since these forecasts are public, and since investment banks seek to disseminate their recommendations to as many investors as possible. But while sell-side analysts advise their buy-side counterparts on their investment choices by sending them the abovementioned forecasts, they do not invest themselves, and therefore only affect the markets in the extent to which they are listened to by buy-side investors.

On the other hand, the buy-side investors create their own expectations with their personal analysis and, maybe, with the advice they get from the sell-side analysts. These expectations, aggregated, lead to a consensus, that I would like to call the "**buy-side consensus**" in the rest of this paper. The market is, by definition, entirely based on this consensus. But, on the negative side, this consensus is not public, there is no way to know it: every investment fund, every investor will have their own expectation, on which they relied to invest or not, and they do not divulgate these expectations.

While there is no proof that the sell-side consensus is representative of what the market expects, it can only be used as a proxy of the buy-side consensus. I used the collected data to measure if it can be considered as a good proxy.

APPROACHING THE SELL-SIDE CONSENSUS

Brokers participate to IBES by sending the forecasts of their analysts on a voluntary basis. Many brokers do it and IBES is a well-furnished database, that gathers forecasts from more than 30,000 analysts over 42,000 companies in the world. I therefore assumed that enough brokers participate to it so that IBES data can be considered as representative of the sell side data.

I calculated the sell-side consensus for a certain company, for a certain period, for a certain item, by taking all the forecasts analysts had made prior to the release date for that period, company and item, and took their average. If an analyst made more than one forecast, I took the latest, and calculated the consensus three days before the release of the actual metric by the company.

CORRELATIONS BETWEEN THE SELL-SIDE CONSENSUS AND THE MARKET MOVES ON RESULTS DAY

I chose two earnings metrics, that I analysed consecutively: net earnings and EBIT. I considered these two metrics to be particularly relevant, because many analysts forecast them, because they are closely looked at by investors, and because they arguably represent the two main earnings metrics used in valuation models (DCF, DDM, and trading multiples).

For every company in my sample (559 companies), I looked at every reporting period they went through over the analysis period (2011 – 2018) and gathered two elements:

- Has the company done better or worse than the sell-side consensus expected on the metric I chose?
- Has the share price gone up or down the first day following the release?

I then counted the number of "coherent" release periods: periods for which the company did better AND the stock price went up OR for which the company did worse AND the price went down. I divided this number of coherent release periods by the total number of periods for which I have data, in order to look at the proportion. I then compare this ratio to the 50% neutral threshold: I begin with the conservative assumption that the equity research consensus is not relevant to approach the buy-side consensus, i.e. that the proportion of coherent periods shouldn't be higher than 50%. I then look at the proportion I got to decide whether I want to reject this conservative assumption or not.

Looking at the data, whether the metric chosen is net earnings or EBIT, c. 58% of observed periods with enough data show correlation between the sell-side surprise and the share price move the day of the results.

These two results are very significantly above 50%, with t-tests way above 1.96 for the statistical test assessing if the ratio obtained is significantly above 50%. We can firmly reject the conservative assumption that there is no correlation between equity research forecasts and the market expectations.

Metric observed	EBIT	Net Earnings
Number of "coherent" periods	9,537	9,863
Total number of periods with data	16,487	16,963
% "coherent" periods	57.8%	58.1%
t-test value for ratio > 50%	20	21

Source: IBES, CRSP, own estimates

I conclude that there is a statistical correlation between the reaction of the market after a release, and the surprise towards the sell side consensus at the moment of the release. If we go back to our previous distinction between sell side and buy side consensus, with the buy side consensus being just another name for what the markets expect, I see two possible conclusions:

- It is either that the buy-side investors significantly rely on equity research to form their expectations.
- Or it can be that since the buy-side and sell-side analysts have similar backgrounds, use similar estimation methods and rely on the same sources of information, they both happen to end up with similar expectations: they both approach the unknown truth the same way.

I think that The European market is an example tending to prove that the first explanation should at least be part of the answer. In Europe, the regulation MIFID II forced buy-side investors, who were until end-2017 paying for equity research indirectly (and thus without pain) through trading fees, to pay directly for the sell-side research, with the choice not to pay and no to receive this research. With a pressure on asset management fees and competition from passive investing solutions, the until-now survival of most of the equity research firms, the continuation of their costly interaction with their buy-side clients, shows that at least some of the buy-side investors consider equity research as useful and rely on the sell-side research to make their investment decisions.

B. MODELLING ANALYSTS' PERFORMANCE

We have looked so far at analysts' forecasts as an aggregate. We are now interested in each analyst and their forecast, and in assessing the performance of this analyst.

The objective of this section is to see if there are some analysts that consistently do better (worse) than the others, i.e. whose forecasts are most of the time closer (farther) to the actuals than the consensus.

WHAT DOES IT MEAN TO BE A "GOOD" ANALYST?

For practical reasons, I will call good analysts those who tend to make more precise forecasts than their peers. I have no intention of depreciating some analysts' work when I use the term "good" or "bad" analyst: it is only for the purpose of this paper, and I perfectly understand that the value of an analyst does not only depend on the precision of his forecasts.

I want to call an analyst "good" or "skilled" ("bad" or "less-skilled") if I have sufficient data to be able to say that he usually makes more precise (less precise) forecasts than his peers. A forecast is more precise than the consensus (i.e. beats the consensus) if the absolute value of its difference with the actual is lower than the absolute value of the difference between the consensus and the actual.

A forecast beats the consensus, if it is closer to the actual than the consensus is:

$$Beat = \begin{cases} yes\ if\ |F_i - A| < |C - A| \\ no\ if\ |F_i - A| \geq |C - A| \end{cases}$$

with: A the actual and C the consensus value of the item considered, F_i the forecast of analyst i.

HOW OFTEN SHOULD AN ANALYST BEAT THE CONSENSUS TO BE BETTER THAN HIS PEERS?

Even if one may have the intuition to aim for 50%, from a mathematical point of view, there is no reason for that. One can easily imagine a situation where 0% of analysts beat the consensus: for example, if there are 4 analysts, and that their forecasts are 90 – 90 – 110 – 110, and that the actual happens to be 105, the consensus will be at 100 and closer to the actual than any forecast. Actually, looking at all the data at my disposal, I measured that over the analysis period, the frequency at which analysts beat individually the consensus is on average at c.45% (45% for the EBIT data sample, and 44.5% for the Net Earnings one).

BERNOULLI TRIAL DEPENDING ON AN UNKNOWN PARAMETER p_0

I assumed that at every quarter, a given analyst has a certain probability to beat the consensus. This probability is specific to this certain analyst, and to make things simpler, constant over time. It means that I assume that analysts have a certain expertise, a certain skill, that doesn't improve or deteriorate through time, and that we will try to approach, looking at past data. Since this skill does not evolve through time, past data are relevant to forecast future performance of the analysts. Of course, this assumption could be relaxed, introducing, for example, a factor taking into account the experience of the analyst, which I did not do in this paper.

I can model the event "the analyst beats the consensus this quarter" as the result of a Bernoulli trial, with the unknown parameter p_0 that I try to estimate. The higher this p_0, the better the analyst, because the more likely he is to issue more precise forecasts than the consensus.

USING PAST DATA TO KEEP OR REJECT THE CONSERVATIVE ASSUMPTION:

I will use statistics over past data to infer the p_0 of each analyst. I will start from the conservative assumption for analyst i, which I call $H_{0,i}$, that this analyst has a p_0 of 0.45 and I will then see if the data enables me to reject this hypothesis, whether because p_0 is probably higher or lower.

At any moment in the past, I am able to look at the data prior this moment, and to give each analyst a score that represents the number of times they did beat the consensus over the previous reporting periods. By dividing their score by the number of forecasts they made, I get an observed proportion $\widehat{p_{0,\iota}}$ that I now want to compare to their assumed $p_{0,i}$ (45%).

I write $(X_i = k)$ the event "the analyst i had a score of k over the past period"

For each analyst, I will decide if I keep or reject the conservative assumption stating that all analysts have a p_0 at 45% if the probability of reaching their observed score is very unlikely.

I assumed that at every quarter, beating or not the consensus is an event that is independent of previous periods' result. Since a series of independent Bernoulli trials follows a Binomial distribution, I know that for any score k over a series of n forecasts, the probability of having this score k, conditionally on p_0 is:

$$P(X_i = k) = \binom{n}{k} * {p_0}^k * (1 - p_0)^{n-k}$$

If $\widehat{p_{0,\iota}}$ is above the assumed $p_{0,i}$, I want $P(X_i \geq k)$ sufficiently low (I chose below 10%) to reject $H_{0,i}$

Similarly, if $\widehat{p_{0,\iota}}$ is below the assumed $p_{0,i}$, I want $P(X_i \leq k)$ sufficiently low (below 10%) to reject $H_{0,i}$

I do not want to look only at $P(X_i = k)$, as the results would not be comparable between analysts with a long track-record of forecasts (i.e. a large n) and those with a smaller n, as for the same k, $P(X = k)$ is lower if n is larger.

We have:

$$P(X_i \geq k) = \sum_{j=k}^{n} P(X_i = j) = \sum_{j=k}^{n} \binom{n}{j} * {p_0}^j * (1 - p_0)^{n-j}$$

And:

$$P(X_i \leq k) = \sum_{j=0}^{k} P(X_i = j) = \sum_{j=0}^{k} \binom{n}{j} * {p_0}^j * (1 - p_0)^{n-j}$$

If the calculated probability is below 10%, we reject $H_{0,i}$, which means that we do not consider the analyst to have an average skill, but a superior (inferior) one if $\widehat{p_{0,i}}$ is higher (lower) than the threshold used (45%).

We know that we have only a 10% probability of wrongly rejecting $H_{0,i}$ (i.e. advancing that the analyst does not have an average skill while he has).

In the cases where the probability was above 10%, we don't reject $H_{0,i}$ and keep the analyst in the "average" category. We have no clue on the probability of being wrong when doing so: it is a type II error.

C. CREATING AN ENHANCED CONSENSUS AND TRADING STRATEGY

CREATING A CONSENSUS STAR WITH THE BEST ANALYSTS

To see if there is consistency in analysts' ability to form accurate forecasts, I want to see if taking only the analysts who outperformed in the past enables me to beat the consensus.

At each quarter during our analysis period, I carry the analysis described above, and detect analysts who can be considered to perform well, only based on data prior this quarter (to avoid in-sampling effects). I then create an "enhanced consensus" or "star consensus", only taking these analysts.

I then calculate if this star consensus beats the basic consensus (using the same definition as before, i.e. if it is closer to the actual than the consensus is). It is the case 61.2% of the time over the analysis period for the EBIT sample, and 57.4% of the time for the Net Earnings one. More detailed results are presented below on table 1:

These two ratios are statistically significantly above 50% (with t-tests from 12 to 18). This is the proof that analysts who outperformed tend to keep on outperforming by releasing more accurate forecasts than their less-skilled peers.

CREATING A CONSENSUS STAR WITHOUT THE WORST ANALYSTS

Similarly, I measured the success of an enhanced consensus that would remove analysts that I can consider less skilled than their peers, based on past data. This estimate also outperforms the basic consensus, both on EBIT and Net Earnings: 60.9% of the time for the EBIT data sample, 58.4% for the Net Earnings one.

TABLE 1: HOW OFTEN DOES THE ENHANCED CONSENSUS BEAT THE CLASSICAL ONE?

Metric observed Version	EBIT taking good analysts	EBIT removing bad analysts	NE taking good analysts	NE removing bad analysts
number of periods with data	6,504	7,911	7,019	8,150
# periods enhanced consensus beats consensus	3,979	4,814	4,031	4,759
% beats	61.2%	60.9%	57.4%	58.4%
t-test value for ratio > 50%	18	19	12	15

Source: IBES, CRSP, own estimates

These results are very significantly above 50%. I can therefore conclude that it is possible to forecast a company's earnings with more precision than the sell-side consensus does. I now want to measure if a trading strategy would be profitable.

TRADING STRATEGY

Based on this result, one could think of a first trading strategy, that would consist in inserting this enhanced consensus in classical valuation models (trading multiples or DCF for example), to compute a valuation for the company considered, and trade on this information: on the comparison between the value calculated and the market value. This strategy is a bit cumbersome to set up as it requires to gather market data, such as the multiples on the peer companies, or to derive from the EBIT the FCF for the DCF. It is however quite interesting to think about it if deriving the FCF from an enhanced FCF estimate, or from a series of enhanced metric: EBIT, CAPEX, etc, for which the advantage acquired over the consensus could cumulate.

A second strategy, much simpler to put in place, is to trade every time we have enough data to create an enhanced consensus, and place orders depending on where our enhanced consensus stands compared to the sell-side consensus. If the enhanced consensus is above, we expect the company to release better results than expected, and thus, we expect investors to be positively surprised and the share price to rise. So, if our enhanced consensus is above the consensus, we want to buy the stock before the release and sell it after, and if the enhanced consensus is below, we want to sell.

I used the historical total returns for the companies under coverage from CRSP to simulate a strategy buying or shorting the stocks at the closing price the last market day before the release and taking the opposite position at the next closing price. This assumes that there is no leak of information prior the release, and that once released, the markets are sufficiently liquid and efficient to react to the news in one day.

The date and time at which companies released their results comes from IBES

Everyday:

- If there is no company releasing its quarterly result on the next trading day, or if I don't have an enhanced consensus (e.g. if there was not enough data for it, for example) for that publication, I do nothing. I am not invested in the S&P500 when I don't trade
- If there is a company reporting the next trading day, and if I have sufficient data to predict an enhanced consensus, I take positions at the closure price (long if my calculated consensus is above the market consensus, short if not) the day before the results announcement, and exit this position (buy if I had shorted, sell if I had bought) at the closure price of the release date. This is of course in the case where the company releases its financials pre-market, when the company does so after closure, I delayed the process by one day: place the order at closure on the day of release, a few minutes / hours before the announcement, and close the position at the next closure. The positions that I take involve 100% of my remaining capital. If it is a short, I take an exposure that is worth all my capital (and do not use it as a leverage).
- If there are more than just one company reporting the same day, I do the same process, but spit my capital equally for each trade, and do not use the shorts to leverage other trades.

I simulated such a strategy beginning with an initial capital of 100, and assuming no trading fees at all.

For simplicity, let's use the following names for the four strategies:

- The one investing on the EBIT metric, using the best analysts will be called EBIT – good
- The one investing on the EBIT metric, removing the less-skilled analysts will be called EBIT – bad
- The one investing on the Net Earnings metric, using the best analysts will be called NE – good
- The one investing on the Net Earnings metric, removing the less-skilled analysts will be called NE – bad

For all the graphs, the sources are IBES, Compustat, CRSP and own estimates

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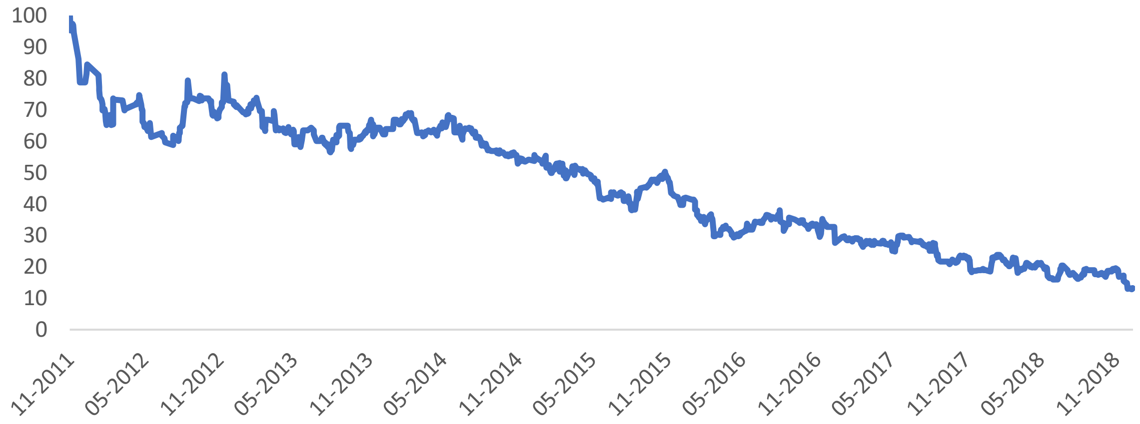
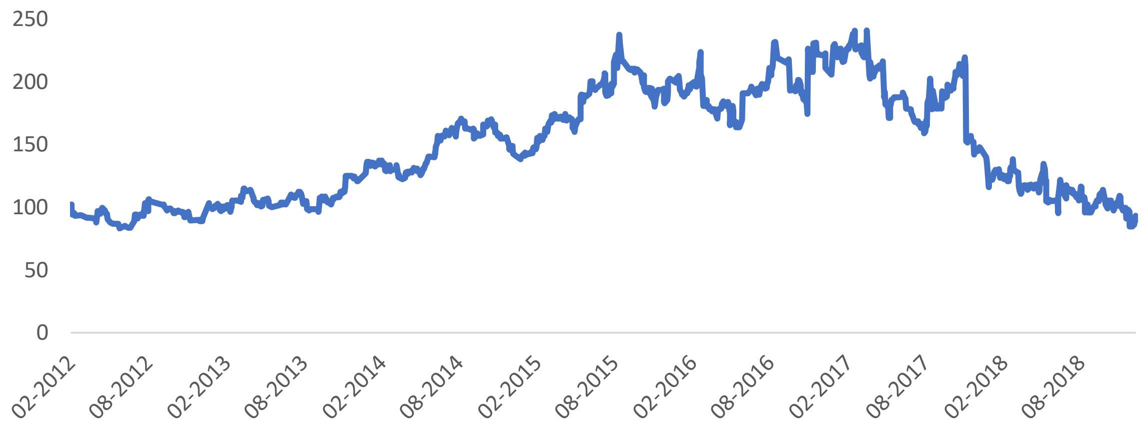
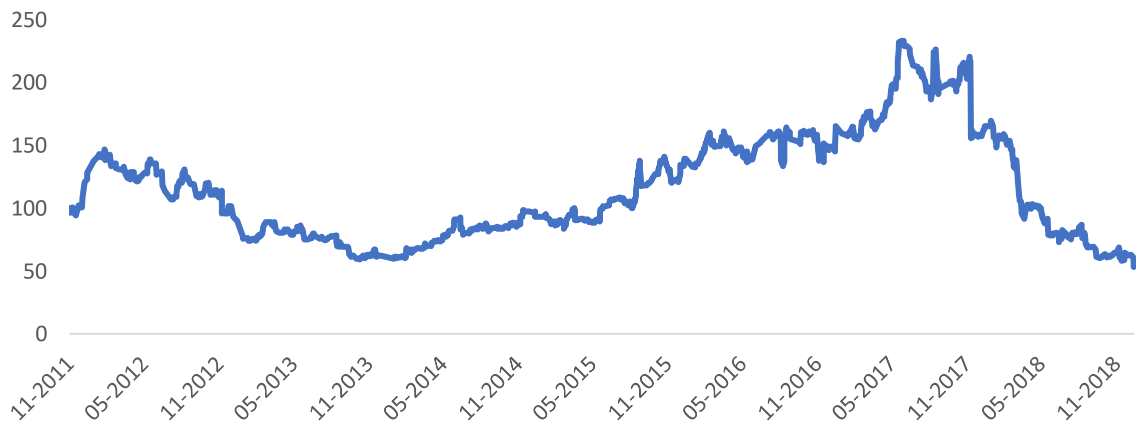
GRAPH 3: EBIT – GOOD. THE FINAL CAPITAL IS AT 13.1, WE LOST 77% OF OUR CAPITAL



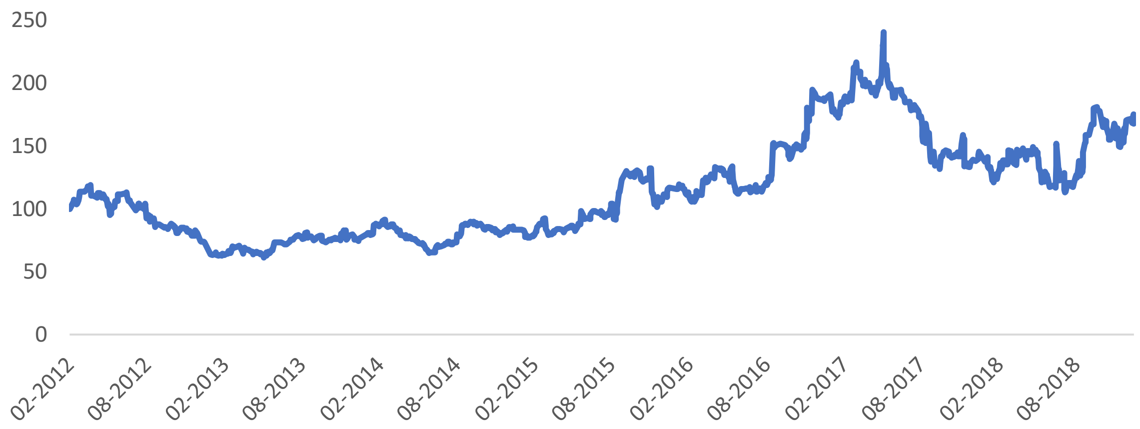
GRAPH 4: EBIT – BAD. THE FINAL CAPITAL IS AT 89.6, WE LOST 10% OF OUR CAPITAL



GRAPH 5: NE – GOOD. THE FINAL CAPITAL IS 53.2, WE LOST 47% OF OUR CAPITAL



GRAPH 6: NE – BAD. THE FINAL CAPITAL IS 168.1, WE MADE +68% RETURN



Note: even if the data starts in 01-2011, the trading strategies begin a bit later (between 11-2011 and 02-2012), because the algorithm needs to have enough data to build enhanced consensus. The EBIT – Good and NE – Good strategies begin a bit before (11-2011) the EBIT – Bad and the NE – Bad strategies (02-2012), because our p_0 is a bit below 50%. This means that in the extreme cases (i.e. if the analyst has always done better or worse than the consensus over past data), it takes more forecasts for an analyst to be considered bad than to be considered good (i.e. to have a probability as defined in section III. B that is below 10%). For example, with 3 past forecasts in the data, if the analyst was better than the consensus three times, his probability to do so while having a p_0 as low as 0.45 is only 9%, so the algorithm classifies him as considered good. However, if he did worse 3 times, the probability of doing so while having a p_0 as high as 0.45 is of 17% > 10%, and we can't consider him as a bad analyst: we need one more observation at least. The gap between 11-2011 and 02-2012 is one quarter, i.e. one forecast in the data.

Investing following our enhanced consensus made either by taking the best analysts or by removing the less-skilled ones does seem to lead to a quite random performance. Out of the four strategies, three made losses when back-testing them, and only one, the NE – bad strategy, gives a +68% total return, after peaking at c.250 early-2017. My guess here is that this result is just luck, and I wouldn't consider investing in this strategy for the future.

CUMULATED SUM OF RETURNS

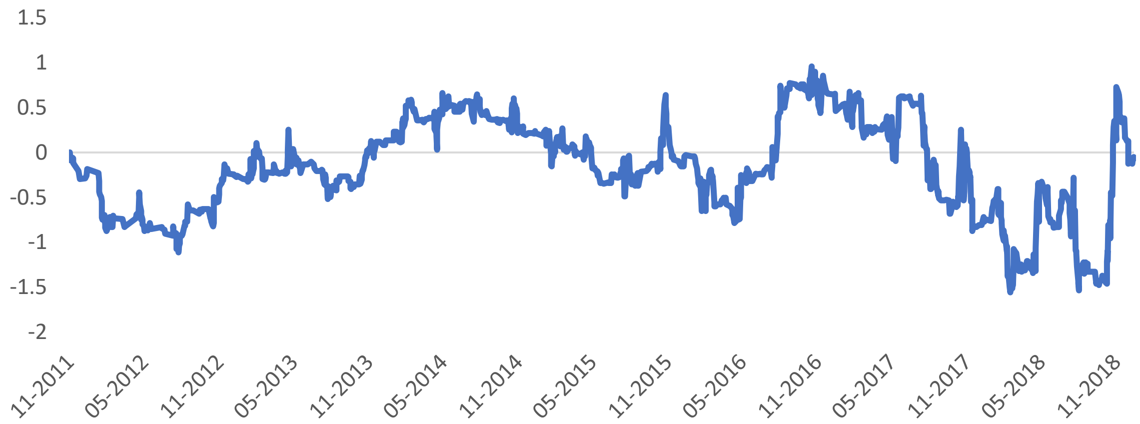
Even If these strategies do not seem profitable, the results may be a bit harsh due to the compounding effect, which distorts the performance. It could be quite useful to look at cumulated returns, to have a less biased vision of when performance happens, without the distorting effect of compounding.

This is an example to show what I mean with the 'distorting effect of compounding': if my fund has a return of -50% and then +60% with an initial capital of 100, the final capital will be at 100*(1-50%)*(1+60%) = 80, i.e. -20%, but the cumulated return is -50% + 60% = 10%

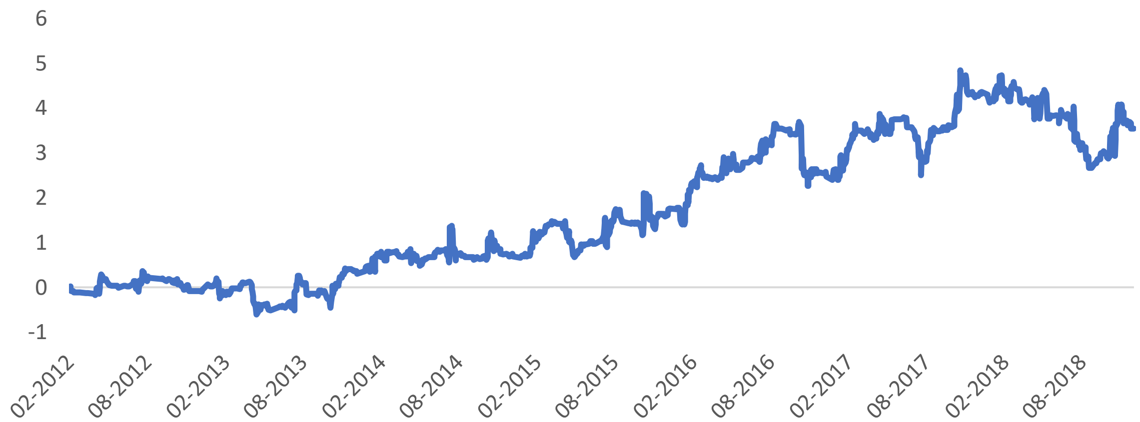
This difference between -20% and +10% is due to the fact that the +60% is applied to a lower basis than the -50% was.

Therefore, I also calculated the cumulated sum of the returns. This is equivalent as assuming that I borrow at a 0% rate $1 for each trade idea, invest it according to my strategy, take the resulting cash amount, and give back the $1, allowing my portfolio to go below zero.

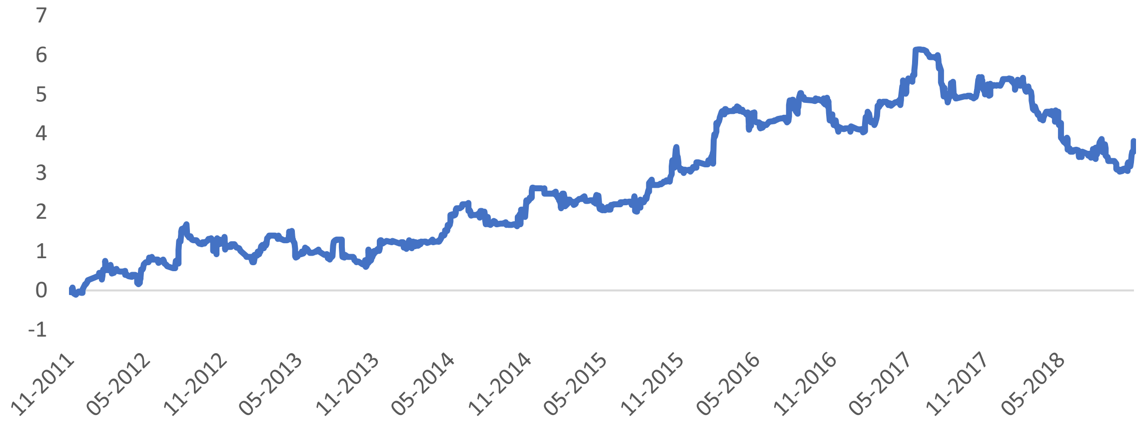
GRAPH 7: EBIT – GOOD, THE CUMULATED SUM OF RETURNS IS AT -0.1



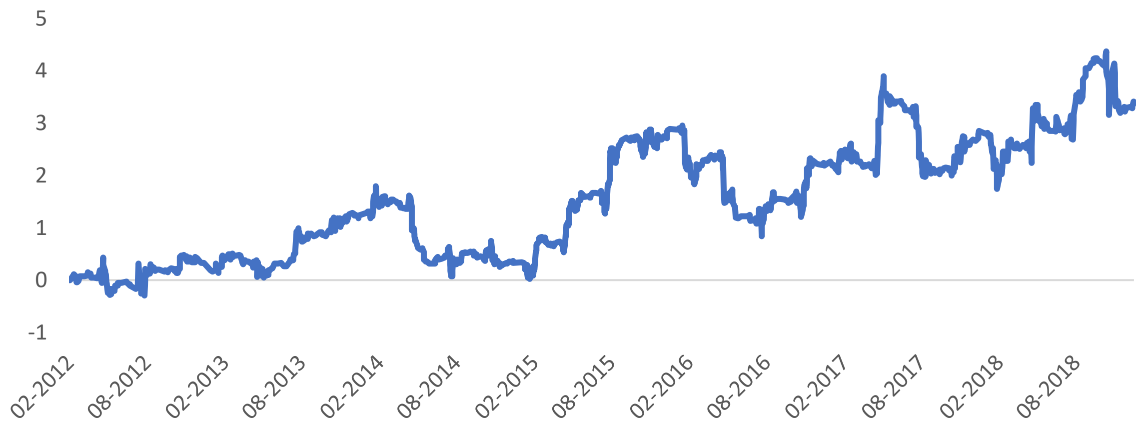
GRAPH 8: EBIT – BAD, THE CUMULATED SUM OF RETURNS IS AT 3.8



GRAPH 9: NE – GOOD, THE CUMULATED SUM OF RETURNS IS AT 3.7



GRAPH 10: NE – BAD, THE CUMULATED SUM OF RETURNS IS AT 3.4

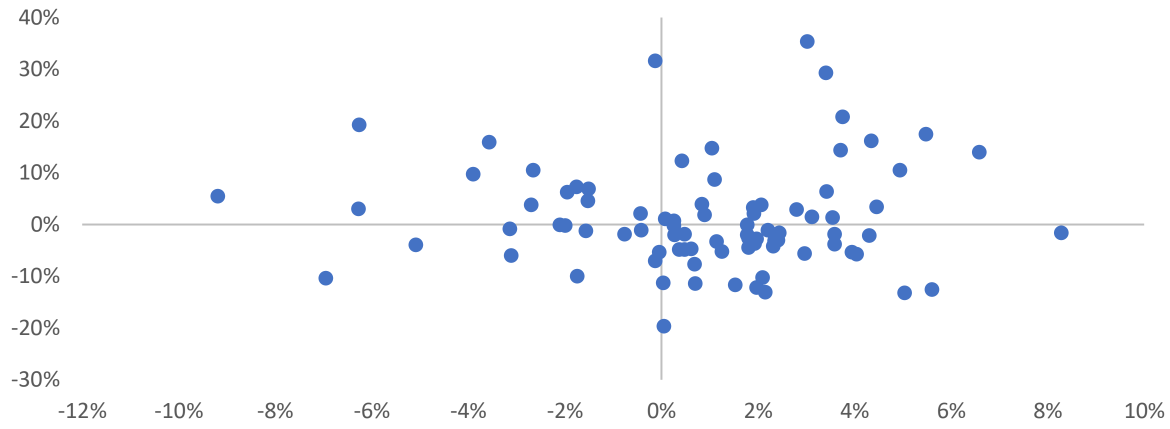


Source: IBES, Compustat, CRSP, own estimates

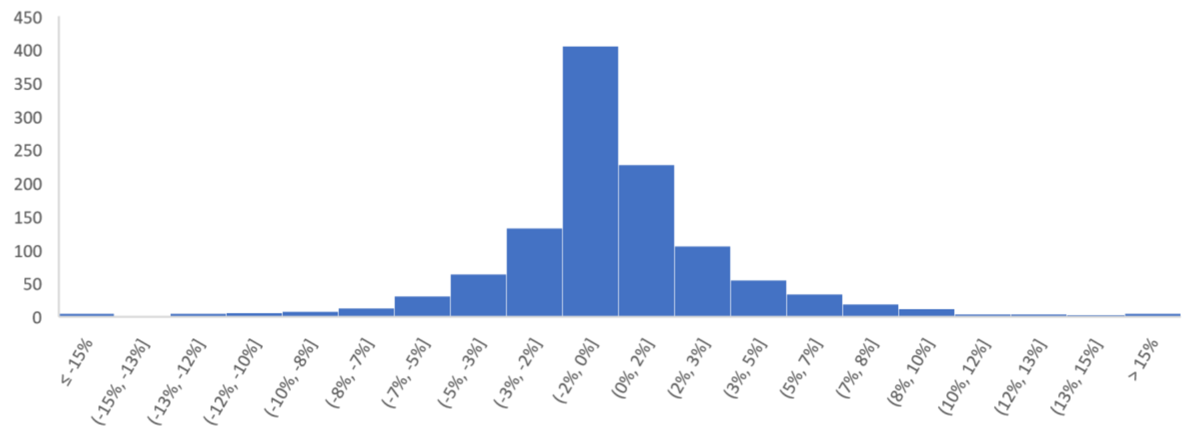
Looking at the returns without compounding effect, the result is better. Three out of our four strategies made positive cumulated returns. These returns are, however quite low.

Since the NE – bad strategy is the one displaying the best results so far, I present in the two following graphs some results about the returns through which this strategy goes:

GRAPH 11: DISTRIBUTION OF MONTHLY RETURNS FOR THE NE – BAD STRATEGY (Y-AXIS) VS S&P500 (X-AXIS)



GRAPH 12: DISTRIBUTION OF DAILY RETURNS FOR THE NE – BAD STRATEGY



There are here two noticeable facts:

Firstly, there is no correlation between the returns of the NE – bad strategy and those of the S&P 500.

Secondly, even if the cumulated returns are slightly positive, most returns are negative, and it is only thanks to a few positive ones that the average is maintained above 0 (at 0.05%). This reinforces the initial thought that this strategy is not viable.

Additionally, this strategy would be very costly to set up, as it involves a lot of trading that would have a cost (the strategies trade on average 1,000 times per year). This cost was not taken into account in the measurement of the performance, suggesting that a more realistic result would be even lower. Actually, adding a 10bps transaction fee through the period would take all the cumulated returns into negative territory: -6.4, -3.9, -3.2 and -4.5 respectively.

TABLE 2: SUMMARY OF THE FOUR INVESTMENT STRATEGIES

	EBIT - Good	EBIT - Bad	NE - Good	NE - Bad
final capital	13	90	53	168
cumulated returns	-0.05	3.78	3.66	3.36
min return	-30%	-29%	-34%	-29%
max return	28%	30%	30%	30%
# of trades	6,345	7,665	6,818	7,908

STATISTICAL SIGNIFICANCE OF RETURNS

The following tables present, for the four strategies, the average return over the investment period, as well as the t-stat for the statistical test looking if the returns are strictly positive.

The test statistic used is $\sqrt{number\ of\ trades} * \frac{(average\ return\ per\ trade - 0)}{stdev\ of\ the\ returns}$

The tables show the returns and the t-stat for the four strategies and across several parameters:

- "min gap" designates the gap between the consensus and the enhanced consensus. Top 20% means that we only trade if the gap is among the top 20% largest gaps (in absolute value) over the investment period. This uses of course data that didn't exist at the trading time, since there was no way to know in 2013 what threshold would be required for the gap to be among the top 20% of all the gaps between 2012 and 2018, but this is for the sake of the statistical analysis.
- Days X before, Y after shows what happens if I decide to start trading X days before the release day, or if I want to close my position Y days after the trading day.
- For example, I had used so far a min gap at 0 and the trading days were 1 before and 0 after.

TABLE 3: AVERAGE RETURNS OF THE EBIT – GOOD STRATEGY

EBIT - Good		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.00%	-0.03%	0.03%	-0.18%
	3 before, 0 after	-0.03%	-0.01%	0.02%	-0.23%
	1 before, 3 after	-0.10%	-0.09%	-0.01%	-0.25%
	3 before, 3 after	-0.09%	-0.08%	-0.02%	-0.31%

TABLE 4: T-STATS FOR THE RETURNS OF THE EBIT – GOOD STRATEGY

EBIT - Good		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	(0.03)	(0.32)	0.25	(0.94)
	3 before, 0 after	(0.34)	(0.14)	0.15	(1.14)
	1 before, 3 after	(1.17)	(0.93)	(0.07)	(1.13)
	3 before, 3 after	(1.00)	(0.75)	(0.16)	(1.32)

TABLE 5: AVERAGE RETURNS OF THE EBIT – BAD STRATEGY

EBIT - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.06%	0.01%	-0.01%	0.14%
	3 before, 0 after	0.04%	0.03%	0.03%	0.09%
	1 before, 3 after	0.06%	0.03%	0.09%	0.20%
	3 before, 3 after	0.06%	0.05%	0.13%	0.14%

TABLE 6: T-STATS FOR THE RETURNS OF THE EBIT – BAD STRATEGY

EBIT - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.90	0.09	(0.11)	0.98
	3 before, 0 after	0.60	0.36	0.28	0.58
	1 before, 3 after	0.81	0.37	0.82	1.11
	3 before, 3 after	0.72	0.59	1.10	0.78

TABLE 7: AVERAGE RETURN OF THE NET – GOOD STRATEGY

NE - Good		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.06%	-0.04%	-0.02%	0.12%
	3 before, 0 after	0.05%	-0.02%	-0.01%	-0.02%
	1 before, 3 after	0.05%	-0.01%	0.02%	0.22%
	3 before, 3 after	0.09%	0.01%	0.03%	0.08%

TABLE 8: T-STATS FOR THE RETURNS OF THE NET – GOOD STRATEGY

NE - Good		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.92	(0.49)	(0.21)	0.71
	3 before, 0 after	0.67	(0.19)	(0.07)	(0.10)
	1 before, 3 after	0.63	(0.10)	0.14	1.10
	3 before, 3 after	1.00	0.13	0.22	0.39

TABLE 7: AVERAGE RETURN OF THE NET – BAD STRATEGY

NE - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.05%	0.15%	0.15%	0.36%
	3 before, 0 after	0.02%	0.13%	0.11%	0.34%
	1 before, 3 after	0.05%	0.13%	0.12%	0.40%
	3 before, 3 after	0.01%	0.11%	0.08%	0.38%

TABLE 8: T-STATS FOR THE RETURNS OF THE NET – BAD STRATEGY

NE - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	0.78	2.16	1.61	2.26
	3 before, 0 after	0.36	1.67	1.12	2.01
	1 before, 3 after	0.66	1.58	1.10	2.06
	3 before, 3 after	0.08	1.20	0.72	1.88

Note: t-stats above 1.96 are highlighted in green

Once again, the Net Earnings strategy removing bad analysts is the one delivering the best results. But this performance was obtained without trading fees, and by comparing the returns to a threshold of 0 to test their significance, while investors usually want to beat the stock market, i.e. a 10% average return for the S&P500 over the period. I present below the same tables for the NE – Bad strategy, which was the best so far, to show that once adding 10bps of trading fees and comparing the return to an expected annual return of 10% (0.038% per day), the strategy is not interesting anymore:

TABLE 9: AVERAGE RETURN OF THE NET – BAD STRATEGY WITH TRADING FEES

NE - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	-0.03%	0.05%	0.05%	0.26%
	3 before, 0 after	-0.08%	0.03%	-0.04%	0.24%
	1 before, 3 after	-0.05%	0.03%	0.02%	0.30%
	3 before, 3 after	-0.09%	0.01%	-0.02%	0.28%

TABLE 9: T-STATS FOR THE EXCESS RETURNS OF THE NET – BAD STRATEGY WITH TRADING FEES

NE - Bad		min gap			
		all	top80%	top50%	top20%
days	1 before, 0 after	(1.12)	0.21	0.15	1.38
	3 before, 0 after	(2.77)	(1.15)	(1.77)	0.74
	1 before, 3 after	(2.71)	(1.42)	(1.14)	0.75
	3 before, 3 after	(4.10)	(2.53)	(2.06)	0.25

The test statistic used is $\sqrt{number\ of\ trades} * \frac{(average\ return\ per\ trade - 0.038\% * number\ of\ days)}{stdev\ of\ the\ returns}$

TO CONCLUDE ON THE TRADING STRATEGY:

The trading results are disappointing, as the strategy implemented does not provide financial performance over the analysis period. Even if the average return made on trades is positive, it is not good enough to lead to financial performance once calculated with the compounding effect. From a statistical point of view, none of the four strategies is able to deliver significant excess returns after trading fees.

There is however a positive correlation between the returns and the gap between the enhanced consensus and the consensus. The larger the gap, the better the returns.

Another cost to take into account would be the access to a very wide sample of equity research houses, so as to gather the forecasts and conduct the analysis I made on up-to-date and non-anonymised data. This research has a consequent cost that should be added to the fixed costs of implementing this strategy.

The fact that this strategy does not provide financial performance suggests that the market is already aware of the results showed in this paper, and that prices have adjusted to an extent so that there is no excess return available after trading fees.

Even if getting this info is useful to beat statistically the sell-side consensus, it is not to beat the market.

IV. CONCLUSION

SUMMARY OF THE RESULTS

In this paper, I showed the following results:

- Investors tend to look at equity research forecasts when they form their expectations
- Some equity research analysts are more skilled than others (and some are less), and there is consistency in this discrepancy. It is possible to use past performance to create an alternative forecast that beats c.60% of the time the sell-side consensus.
- Even if equity research forecasts have an impact on prices and if there is consistency in their out- and underperformance, a simple trading strategy using this result wouldn't have delivered positive returns over the period 2011 – 2018.
- The combination of the results showing that investors look at equity research, and the inefficiency of the trading strategy suggest that the market is already aware of this result and includes them in its asset pricing.

LIMITATIONS TO MY RESEARCH AND ADDITIONAL PERSPECTIVES

My results could be criticised and improved for several reasons:

On the one hand, because of choices that I made in my research process:

- I kept forecasts that have different degree of recency. Even if I always kept the latest forecast made by each analyst, some may have been issued 5 days before the results, while others may date from more than two months. My window was -100 to -3 days prior to result day, these parameters could be changed.
- Some companies provide guidance that may favour significantly the analysts who just update their forecasts with the guidance. Then my model doesn't capture skill but certain practices, that rely on the investor relation team's policy on guidance. For example, if an analyst constantly updates his forecasts with the guidance provided by the company just before the results, he is likely to have a better precision than his peers who kept the forecast they made based only on their personal estimate. In this case, my model would reward guidance instead of forecasts.
- All analysts are not focusing all their efforts on beating the consensus in their forecasts. Some value that they bring to clients is qualitative, and not quantitative, for example when they give an insight of the industry or describe the particularity of a stock they cover. Even on the quantitative aspect of their task, the next quarter EBIT and Net Earnings are of moderate interest compared to the generally longer-term forecasts they use for their valuation models.
- I assumed that the two most looked at metrics are the EBIT and the Net Earnings, but one could try to see if the results would be more significant with other metrics, such as sales. It may also be interesting to focus on a single industry and look at the adapted metrics.
- I considered in my approach that the same analyst following two different companies was actually two different analysts, because I did not want to assume that forecast skill is transferable from one company under coverage to another. It would be interesting to see if an

approach considering the performance of the analysts over all of their companies under coverage would lead to different results.

- My strategy was based on buying and selling just before and just after the result. One could imagine investing a few days before, to try to avoid the noise from guidance from companies.
- I used a threshold of 45% to decide whether the analyst is skilled or not, but the estimation of this threshold was made after looking at all past data in my sample, and I applied it to all my periods, as an in-sample parameter. I assumed that since 45% is reasonably close to 50%, it would not have a significant impact on the final result.

On the other hand, because of limitations in the data that I couldn't make up for:

- There is a lot of turnover in the data. Only 40% of analysts made more than 10 forecasts in the sample (and 25% more than 25, this figure is similar for the EBIT and NE files). This limits the potential of the analysis, since larger forecasts sample enable to evaluate with a better precision the skill of the analyst.
- The data is anonymised by IBES (each analyst making a forecast is protected under a code), which means that I had no way to check the data with other sources
- I had only access to c. 8 years of data on IBES, which limits a little bit the scope of my research.
- I don't know what proportion of the data existent was captured by IBES (e.g. which proportion of all the forecasts made by sell-side brokers was reported to IBES). This means that my sell-side consensus may be a rough estimate of the real consensus.

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APPENDICES

APPENDIX 1: HOW TO GET THE DATA FROM IBES, COMPUSTAT AND CRSP

From IBES (the forecasts from the analysts, the actuals and dates of release):

Go to WRDS > IBES > Detail History > Detail

- Date variable: Forecast Period End Date
- Date range: from "2011-01" to "2018-12"
- Company codes: I put the CUSIP from a .txt file
- Measures: took EBIT (Non Per Share, EBI) or NE (Net Income, Non Per Share, NET)
- Forecast Period Indicator: ask for Quarter 1 (6), Quarter 2 (7), Quarter 3 (8) and Quarter 4 (9)
- Query variables: ask for:
    - I/B/E/S Ticker
    - CUSIP
    - Forecast Period End Date SAS Format
    - Estimator
    - Analyst Code
    - Announce Date, SAS Format
    - Estimate Value
    - Announce Date of the Actual, from the Detail Actuals File, SAS Format
    - Announce Time of the Actual, from the Detail Actuals File, SAS Format
    - Actual Value, from the Detail Actuals File
- Output format: "tab-delimited text (*.txt)",
- Compression type: "zip (*.zip)"
- Date format: "DDMMYY10"

From Compustat (for the list of companies in the SP500):

Go to WRDS > Compustat Capital IQ > North America - Daily > Index Constituents

- Date range: from "2011-01" to "2018-12"
- Company codes: the code I used for the S&P 500 is "i0003", under the category 'TIC'
- Query Variables: CUSIP
- Output Format: "tab-delimited text (*.txt)"
- Date Format: "DDMMYY10"
- Compression type: "zip (*.zip)"

In the resulting file, the columns 'from' and 'thru' are respectively the dates of entrance and exit of the company from the S&P 500

From CRSP: the shareholder's return for the stocks

Go to WRDS > CRSP > Stock / Security Files > Daily Stock File

- Date range: from "2011-01" to "2018-12"
- Company codes: I put the CUSIP from a .txt file
- Query variables: CUSIP, Holding Period Return
- Output Format: "tab-delimited text (*.txt)"
- Date Format: "DDMMYY10"
- Compression type: "zip (*.zip)"

APPENDIX 2: TABLE OF ALL COMPANIES USED, WITH THEIR CUSIP 8, NAME, OFFICIAL TICKER AND IBES TICKER

Company Name	CUSIP 8	Ticker	IBES Ticker	Company Name	CUSIP 8	Ticker	IBES Ticker
ARISTA NETWORKS	04041310	ANET	004W	INGERSOLL RAND	G4779110	IR	IR
KEYSIGHT TECH	49338L10	KEYS	00C6	INTUITIVE SURGIC	46120E60	ISRG	ISRG
ARCONIC	03965L10	ARNC	AA	ILL TOOL WORKS	45230810	ITW	ITW
APPLE INC	03783310	AAPL	AAPL	LIFE TECHNOLOGIE	53217V10	LIFE	IVGN
ADVANCE AUTO	00751Y10	AAP	AAPS	INVESCO LTD	G491BT10	IVZ	IVZ
ABBVIE	00287Y10	ABBV W	ABBV	HUNT JB TRANSP	44565810	JBHT	JBHT
ABIOMED INC	00365410	ABMD	ABD	JABIL CIRCUIT	46631310	JBL	JBIL
ABBOTT LABS	00282410	ABT	ABT	JC PENNEY	70816010	JCP	JCP
AUTODESK INC	05276910	ADSK	ACAD	JACOBS ENG	46981410	JEC	JEC
MOLSON COORS	60871R20	TAP	ACCO	JACK HENRY & ASS	42628110	JKHY	JKHY
CHUBB LTD CH	H1467J10	CB	ACL1	JOHNSON & JOHNSN	47816010	JNJ	JNJ
ACCENTURE PLC	G1151C10	ACN	ACNT	JUNIPER NETWORKS	48203R10	JNPR	JNPR
ADOBE SYS INC	00724F10	ADBE	ADBE	JOY GLOBAL INC	48116510	JOYG	JOYG
ANALOG DEVICES	03265410	ADI	ADI	KELLOGG CO	48783610	K	K
ARCH-DAN-MIDLAND	03948310	ADM	ADM	EVERGY	30034W10	EVRG	KAN
ADT CORP	00101J10	ADT WI	ADTT	MONDELEZ INT	60920710	MDLZ	KFT
NABORS INDS LTD	G6359F10	NBR	AEL	KRAFT HEINZ	50075410	KHC	KHC
AMERN ELEC PWR	02553710	AEP	AEP	KIMCO REALTY COR	49446R10	KIM	KIM
AES CORP	00130H10	AES	AESC	KLA-TENCOR CORP	48248010	KLAC	KLAC
AETNA INC	00817Y10	AET	AET	KIMBERLY CLARK	49436810	KMB	KMB
AFLAC INC	00105510	AFL	AFL	KINDER MORGAN	49456B10	KMI	KMI
AIRGAS INC	00936310	ARG	AGA	SEARS HOLDINGS	81235010	SHLD	KMRT
AGL RESOURCES	00120410	GAS	AGLT	CARMAX INC.	14313010	KMX	KMX
ALLERGAN INC	01849010	AGN	AGN	COCA-COLA CO	19121610	KO	KO
SKYWORKS SOLUT	83088M10	SWKS	AHA	KROGER	50104410	KR	KR
HESS CORP	42809H10	HES	AHC	KRAFT FOODS GROU	50076Q10	KRFT	KRFT
AMERN INTL GROUP	02687478	AIG	AIG	KOHLS CORP	50025510	KSS	KSS
ASSURANT INC	04621X10	AIZ	AIZI	KANSAS CITY SO	48517030	KSU	KSU
GALLAGHER, ART J	36357610	AJG	AJGC	LYONDELLBASELL I	N5374510	LYB	LALL
AKAMAI TECH	00971T10	AKAM	AKAM	LEGGETT & PLATT	52466010	LEG	LEG
AK STEEL HOLDING	00154710	AKS	AKST	LENNAR CP	52605710	LEN	LEN
ALBEMARLE CORP.	01265310	ALB	ALB1	LOCKHEED MARTIN	53983010	LMT	LK
HONEYWELL INTL	43851610	HON	ALD	LKQ CORP	50188920	LKQX	LKQX
ALLEGION PLC	G0176J10	ALLE	ALEE	L3	50241310	LLL	LLL
ALIGN TECH	01625510	ALGN	ALGN	LSI CORP	50216110	LSI	LLSI
ALASKA AIR GROUP	01165910	ALK	ALK	LINEAR TECH	53567810	LLTC	LLTC
ALLSTATE CP	02000210	ALL	ALL1	ELI LILLY	53245710	LLY	LLY
ALLEGHENY TECH	01741R10	ATI	ALS1	LEGG MASON INC	52490110	LM	LM
ALTERA CP	02144110	ALTR	ALTR	LINCOLN NATL	53418710	LNC	LNC
ALEXION PHARM	01535110	ALXN	ALXN	RANGE RESOURCES	75281A10	RRC	LOMK

Company Name	CUSIP 8	Ticker	IBES Ticker
APPLD MATERIALS	03822210	AMAT	AMAT
BEAM INC	07373010	BEAM	AMB
PROLOGIS	74340W10	PLD	AMBP
ADV MICRO DEVICE	00790310	AMD	AMD
TIME WARNER INC	88731730	TWX	AMER
AFFILIATED MGRS	00825210	AMG	AMG
AMGEN	03116210	AMGN	AMGN
AMERIPRISE FINAN	03076C10	AMP	AMPW
AMERICAN AIRLINE	02376R10	AAL	AMR
ENVISION HLTHCR	29414D10	EVHC	AMSG
AMER TOWER CP-A	03027X10	AMT	AMT2
AMAZON.COM INC.	02313510	AMZN	AMZN
ABERCROM & FITCH	00289620	ANF	ANF
ALPHA NATURAL RE	02076X10	ANR	ANRI
ANSYS INC	03662Q10	ANSS	ANSS
BROADCOM	11135F10	AVGO	AOVG
APACHE CP	03741110	APA	APA
ANADARKO PETE CO	03251110	APC	APC
AIR PROD & CHEM	00915810	APD	APD
AMPHENOL CORP	03209510	APH	APH1
APOLLO GROUP	03760410	APOL	APOL
ALEX RE EQUITIES	01527110	ARE	ARE1
ALLIANCE DATA	01858110	ADS	ASD1
AMRISRCEBERGEN	03073E10	ABC	ASHC
AGILENT TECH	00846U10	A	AT1
ANTHEM	03675210	ANTM	ATHI
AUTO DATA	05301510	ADP	AUD
AVALONBAY COMM	05348410	AVB	AVN
AVON PRODS INC	05430310	AVP	AVP
ACTIVISION BLIZZ	00507V10	ATVI	AVSN
AVERY DENNISON	05361110	AVY	AVY
AMERICAN WATER	03042010	AWK	AWKC
AMERN EXPRESS	02581610	AXP	AXP
ACUITY BRANDS IN	00508Y10	AYI	AYI
AUTOZONE INC	05333210	AZO	AZO
PINNACLE WST CAP	72348410	PNW	AZP
BOEING CO	09702310	BA	BA
BAXTER INTL	07181310	BAX	BAX
BED BATH & BEYON	07589610	BBBY	BBBY
BROADRIDGE FINA	11133T10	BR	BBFS
BEST BUY INC	08651610	BBY	BBUY
ROBERT HALF INTL	77032310	RHI	BCMP
C R BARD	06738310	BCR	BCR
BECTON DICKINSON	07588710	BDX	BDX
VERIZON COMM	92343V10	VZ	BEL
BROWN-FORMAN	11563720	BFB	BFD1
CONSTELLATION EN	21037110	CEG	BGE
BRIGHTHOUSE	10922N10	BHF	BHFWV
BAKER HUGHES GE	05722G10	BHGE	BHI1
THE BANK OF NEW	06405810	BK	BK
BERKSHIRE HATHAW	08467070	BRK.B	BKHT/1
BLACKROCK INC	09247X10	BLK	BLKI
BALL CP	05849810	BLL	BLL
BMC SOFTWARE	05592110	BMC	BMCS
BEMIS INC	08143710	BMS	BMS
BRISTOL-MYERS SQ	11012210	BMY	BMY
BROADCOM CP CL A	11132010	BRCM	BRCM
BOSTON SCIENTIFI	10113710	BSX	BSX
BORGWARNER INC	09972410	BWA	BWA

Company Name	CUSIP 8	Ticker	IBES Ticker
LOWES CO	54866110	LOW	LOW
LAM RESEARCH	51280710	LRCX	LRCX
L BRANDS INC	50179710	LTD	LTD
LOEWS CP	54042410	L	LTR
JEFFERIES FINCL	47233W10	JEF	LUK
SOUTHWEST AIRLS	84474110	LUV	LUV
LEVEL 3 COMM	52729N30	LVLT	LVLT
LAMB WESTON	51327210	LW	LW
LEXMARK INTL INC	52977110	LXK	LXK
MID-AMER APART	59522J10	MAA	MAA
MASTERCARD	57636Q10	MA	MAAA
MACERICH	55438210	MAC	MACC
MASCO CP	57459910	MAS	MAS
MATTEL INC	57708110	MAT	MAT
AMETEK INC	03110010	AME	MATS
MCCORMICK & CO	57978020	MKC	MCCR
MCDONALDS CP	58013510	MCD	MCD
MICROCHIP TECH	59501710	MCHP	MCHP
MCKESSON CORP	58155Q10	MCK	MCK
MEREDITH	58943310	MDP	MDP
MEDTRONIC	G5960L10	MDT	MDT
MOODY'S CORP.	61536910	MCO	MDY
CVS CAREMARK COR	12665010	CVS	MES
METLIFE INC	59156R10	MET	METL
MGM RESORTS INTE	55295310	MGM	MGMG
S&P GLOBAL	78409V10	SPGI	MHP
MARRIOTT INTL	57190320	MAR	MHS
MEDCO HEALTH SOL	58405U10	MHS	MHSI
MEAD JOHNSON NUT	58283910	MJN	MJN
MARTIN MAR MATLS	57328410	MLM	MLM
MARSH & MCLENNAN	57174810	MMC	MMC
MOTOROLA MOBILIT	62009710	MMI	MMIW
3M CO	88579Y10	MMM	MMM
MALLINCKRODT PLC	G5785G10	MNK	MNKP
ALTRIA GROUP INC	02209S10	MO	MO
MOHAWK INDS INC	60819010	MHK	MOHK
MOLEX	60855410	MOLX	MOLX
MONSANTO CO/NEW	61166W10	MON	MONN
MOSAIC CO	61945C10	MOS	MOSC
MOTOROLA SOLUTIO	62007630	MSI	MOT
MARATHON PETROLE	56585A10	MPC	MPCW
MARSHALL& ILSLEY	57183710	MI	MRIS
MERCK & CO	58933Y10	MRK	MRK
IHS MARKIT	G4756710	INFO	MRKT
MARATHON OIL CP	56584910	MRO	MRO1
MICROSOFT	59491810	MSFT	MSFT
ENTERGY CP	29364G10	ETR	MSU
METTLER-TOLEDO	59268810	MTD	MTD
MURPHY OIL CP	62671710	MUR	MUR
MSCI INC	55354G10	MSCI	MXB
MAXIM INTEGRATED	57772K10	MXIM	MXIM
MYLAN	N5946510	MYL	MYLN
NAVIENT	63938C10	NAVI	NAVIV
NOBLE ENERGY	65504410	NBL	NBL
BANK OF AMERICA	06050510	BAC	NCB
NORWEGIAN CRUISE	G6672110	NCLH	NCLH
NASDAQ OMX GROUP	63110310	NDAQ	NDAQ
NOBLE CORPORATIO	G6543110	NE	NDCO
NEWMONT MINING	65163910	NEM	NEM

Company Name	CUSIP 8	Ticker	IBES Ticker
BAXALTA	07177M10	BXLT W	BXLT
BOSTON PROP	10112110	BXP	BXP
CONAGRA FOOD INC	20588710	CAG	CAG
CA INC	12673P10	CA	CASI
CATERPILLAR INC	14912310	CAT	CAT
CHUBB CP	17123210	CB	CB
CBRE GROUP INC	12504L10	CBG	CBCG
COOPER INDUSTRIE	G2414010	CBE	CBE
CBOE HOLDINGS	12503M10	CBOE	CBOH
CITIGROUP INC.	17296742	C	CCC2
COCA-COLA EURO	G2583910	CCE	CCE
CARNIVAL CP	14365830	CCL	CCL
CHARTER COMMNS	16119P10	CHTR	CCMM
COSTCO WHOLESALE	22160K10	COST	CCS1
CONSTELLAT BRAN	21036P10	STZ	CDG2
CARDINAL HEALTH	14149Y10	CAH	CDIC
CELGENE CP	15102010	CELG	CELG
CEPHALON INC	15670810	CEPH	CEPH
CELANESE	15087010	CE	CEPU
CERNER CP	15678210	CERN	CERN
FIDELITY NATNL I	31620M10	FIS	CEY
CF INDUSTRIES	12526910	CF	CFF
CITIZENS FINANCI	17461010	CFG	CFG
LORILLARD INC	54414710	LO	CGLC
JPMORGAN CHASE	46625H10	JPM	CHL
C.H. ROBINSON WW	12541W20	CHRW	CHRW
CHEVRON	16676410	CVX	CHV
CIGNA	12552310	CI	CI
CINN FINANCIAL	17206210	CINF	CINF
FRONTIER COMMN	35906A30	FTR	CIT1
COLGATE PALMOLVE	19416210	CL	CL
CLEVELAND-CLIFFS	18589910	CLF	CLF
CLOROX CO	18905410	CLX	CLX
COMERICA INC MI	20034010	CMA	CMCA
COMCAST CORP	20030N10	CMCSA	CMCS
COMCAST CORP	20030N20	CMCSK	CMCS/2
CME GROUP INC	12572Q10	CME	CME
CHIPOTLE MEXICAN	16965610	CMG	CMG
CMS ENERGY CORP	12589610	CMS	CMS
BIG LOTS INC	08930210	BIG	CNS
CENTENE	15135B10	CNC	CNTE
CNX RESOURCES	12653C10	CNX	CNX
CAPITAL ONE FINL	14040H10	COF	COF
CABOT OIL & GAS	12709710	COG	COG1
TAPESTRY	87603010	TPR	COH2
ROCKWELL COLLINS	77434110	COL	COLS
COTY INC	22207020	COTY	COTY
COVIDIEN PLC	G2554F11	COV	COV
CAMPBELL SOUP	13442910	CPB	CPB
COLUMBIA US	19828010	CPGX W	CPGX
PROGRESS ENERGY	74326310	PGN	CPL
COPART INC	21720410	CPRT	CPRT
COMPUWARE CORP	20563810	CPWR	CPWR
CHURCH & DWIGHT	17134010	CHD	CRCH
CAREFUSION CORP	14170T10	CFN	CRFS
SALESFORCE.COM I	79466L30	CRM	CRMN
CAMERON INTL	13342B10	CAM	CRON
DXC TECH	23355L10	DXC	CSC
CISCO SYS INC	17275R10	CSCO	CSCO

Company Name	CUSIP 8	Ticker	IBES Ticker
NETFLIX INC.	64110L10	NFLX	NFLX
NEWFIELD EXPLORA	65129010	NFX	NFX
LABORATORY CORP	50540R40	LH	NHLI
NISOURCE INC	65473P10	NI	NI
NIKE INC	65410610	NKE	NIKE
NIELSEN HOLDINGS	G6518L10	NLSN	NLSN
TENET HEALTHCARE	88033G40	THC	NME
WELLS FARGO	94974610	WFC	NOB
NORDSTROM INC	65566410	JWN	NOBE
NORTHROP GRUMMAN	66680710	NOC	NOC
NATIONAL OILWELL	63707110	NOV	NOI
NOVELL INC	67000610	NOVL	NOVL
NRG ENERGY INC.	62937750	NRG	NRGE
NORFOLK SOUTHERN	65584410	NSC	NSC
DENBURY RESOURCE	24791620	DNR	NSC1
NATL SEMICON	63764010	NSM	NSM
XCEL ENERGY INC	98389B10	XEL	NSP
NETAPP INC	64110D10	NTAP	NTAP
NORTHN TRUST	66585910	NTRS	NTRS
EVERSOURCE	30040W10	ES	NU
NUCOR CP	67034610	NUE	NUE
NVIDIA CORP	67066G10	NVDA	NVDA
NOVELLUS SYSTEMS	67000810	NVLS	NVLS
NEWELL RUBBER	65122910	NWL	NWL
NEWS CORP	65249B10	NWSA	NWSV
NYSE EURONEXT	62949110	NYX	NYX
FIRSTENERGY CORP	33793210	FE	OEC
OWENS ILLINOIS	69076840	OI	OI1
ONEOK INC	68268010	OKE	OKE
ORACLE CORP	68389X10	ORCL	ORCL
O'REILLY AUTO	67103H10	ORLY	ORLY
OCCIDENTAL PETE	67459910	OXY	OXY
CONOCOPHILLIPS	20825C10	COP	P
PAYCHEX	70432610	PAYX	PAYX
PEOPLES UNITED F	71270410	PBCT	PBCT
PITNEY/BOWES	72447910	PBI	PBI
PACCAR INC	69371810	PCAR	PCAR
P G & E CORP	69331C10	PCG	PCG
PLUM CREEK TIMBE	72925110	PCL	PCL2
BOOKING HLDG	09857L10	BKNG	PCLN
PRECISION CSTPTS	74018910	PCP	PCST
PATTERSON COMPAN	70339510	PDCO	PDCO
PIONEER NAT RES	72378710	PXD	PDP
EXELON CORP	30161N10	EXC	PE
PEABODY ENERGY	70454920	BTU	PEAB
PUB SVC ENTERS	74457310	PEG	PEG
PEPSICO INC	71344810	PEP	PEP
PETSMART INC	71676810	PETM	PETM
PFIZER INC	71708110	PFE	PFE
PRINCIPAL FINANC	74251V10	PFG	PFGA
PROCT & GAMBL	74271810	PG	PG
PARKER HANNIFIN	70109410	PH	PH
PULTEGROUP INC	74586710	PHM	PHM
PACKAGING CORP	69515610	PKG	PKG
PALL CP	69642930	PLL	PLL
AON CP	G0408V10	AON	PMA
PHILIP MORRIS IN	71817210	PM	PMW
PNC FIN SER	69347510	PNC	PNCF
PENTAIR PLC	G7S00T10	PNR	PNTA

Company Name	CUSIP 8	Ticker	IBES Ticker
CHESAPEAKE ENERG	16516710	CHK	CSPK
CSRA	12650T10	CSRA	CSRAW
CSX CP	12640810	CSX	CSX
CINTAS CP	17290810	CTAS	CTAS
CENTURYLINK INC	15670010	CTL	CTL
COGNIZANT TECH	19244610	CTSH	CTSH
CITRIX SYSTEMS	17737610	CTXS	CTXS
CUMMINS INC	23102110	CMI	CUM
CABLEVISION SYS	12686C10	CVC	CVC
COVENTRY HLTH	22286210	CVH	CVTY
CONCHO RESOURCES	20605P10	CXO	CXO
DOMINION RES INC	25746U10	D	D
DELTA AIR LINES	24736170	DAL	DAL
DISCOVERY COMMUN	25470F10	DISCA	DCHA
DISCOVERY COMMUN	25470F30	DISCK	DCHA/2
E I DUPONT	26353410	DD	DD
DEERE & CO	24419910	DE	DE
DELL INC	24702R10	DELL	DELL
DISCOVER FINANCI	25470910	DFS	DFSV
QUEST DIAGNOSTIC	74834L10	DGX	DGX
TARGET CORP	87612E10	TGT	DH
WALT DISNEY CO	25468710	DIS	DIS
DISH NETWORK COR	25470M10	DISH	DISH
DIGITAL REALTY T	25386810	DLR	DLRN
DOLLAR TREE INC	25674610	DLTR	DLTR
DANAHER CP	23585110	DHR	DMG
DUN&BRADSTRT	26483E10	DNB	DNB
RR DONNELLEY	25786720	RRD	DNY
DIAMOND OFFSHORE	25271C10	DO	DO
DOLLAR GENERAL	25667710	DG	DOLR
DOVER CP	26000310	DOV	DOV
OMNICOM GROUP	68191910	OMC	DOYL
DR PEPPER SNAPPL	26138E10	DPS	DPSG
MICRON TECH	59511210	MU	DRAM
DUKE REALTY	26441150	DRE	DRE
D R HORTON INC	23331A10	DHI	DRHI
DARDEN REST INC	23719410	DRI	DRI
DTE ENERGY	23333110	DTE	DTE
DUKE ENERGY CORP	26441C20	DUK	DUK
FLOWSERVE CORP	34354P10	FLS	DURI
DEVON ENERGY COR	25179M10	DVN	DVN
ADTALEM GLO EDU	00737L10	ATGE	DVR1
MORGAN STANLEY	61744644	MS	DWD
EBAY INC	27864210	EBAY	EBY1
CADENCE DES SYS	12738710	CDNS	ECAD
ECOLAB INC	27886510	ECL	ECON
CONSOLIDATED EDI	20911510	ED	ED
EQUIFAX INC	29442910	EFX	EFX
PERKINELMER INC	71404610	PKI	EGG
E*TRADE FINANCIA	26924640	ETFC	EGRP
ESTEE LAUDER COS	51843910	EL	EL
EMC CP MASS	26864810	EMC	EMCS
EASTMAN CHEMICAL	27743210	EMN	EMN
EMERSON ELECTRIC	29101110	EMR	EMR
ENDO INTERNATION	G3040110	ENDP	ENDP
EOG RESOURCES	26875P10	EOG	EOG
EL PASO CO	28336L10	EP	EPG
EQUINIX	29444U70	EQIX	EQIX
EQUITY RESID	29476L10	EQR	EQR

Company Name	CUSIP 8	Ticker	IBES Ticker
PEPCO HOLDINGS	71329110	POM	POM
PPG INDS	69350610	PPG	PPG
PP&L CORP	69351T10	PPL	PPL
PERRIGO CO	G9782210	PRGO	PRGO
PROGRESSIVE OHIO	74331510	PGR	PROG
PRUDENTIAL FIN	74432010	PRU	PRU
EVEREST RE GRP	G3223R10	RE	PRUD
PHILLIPS 66	71854610	PSX	PSXX
T ROWE GROUP	74144T10	TROW	PTRW
PVH CORP	69365610	PVH	PVH
QUANTA SERVICES	74762E10	PWR	PWR1
PAYPAL HLDG	70450Y10	PYPLV	PYPLV
QUALCOMM INC	74752510	QCOM	QCOM
QEP RESOURCES IN	74733V10	QEP	QEP
QLOGIC CORP	74727710	QLGC	QLGC
IQVIA HLDG	46266C10	IQV	QQUN
QORVO	74736K10	QRVO	QRVO
RALPH LAUREN COR	75121210	RL	RAL1
SIGNET JEWELERS	G8127610	SIG	RATN
ROYAL CARIBBEAN	V7780T10	RCL	RCL
ROWAN COS	G7665A10	RDC	RDC
RYDER SYS	78354910	R	RDR
REGENCY CENTERS	75884910	REG	REG
REGENERON PHARMA	75886F10	REGN	REGN
RESMED INC	76115210	RMD	RES2
RED HAT INC	75657710	RHT	RHAT
TRANSOCEAN LTD	H8817H10	RIG	RIG
RAY JAMES FINL	75473010	RJF	RJFN
REYNOLDS AMERICA	76171310	RAI	RJRW
WESTROCK	96145D10	WRK	RKTN
REALTY INCOME CP	75610910	O	RLTY
ROCKWELL AUTO	77390310	ROK	ROK
ROLLINS INC	77571110	ROL	ROL
ROPER INDS INC	77669610	ROP	ROPR
ROSS STORES INC	77829610	ROST	ROST
REPUBLIC SERVICE	76075910	RSG	RSG
RAYTHEON CO	75511150	RTN	RTN
AUTONATION INC.	05329W10	AN	RWIN
LEIDOS HOLDINGS	52532710	LDOS	SAIC
SBA COMMNS	78410G10	SBAC	SBAC
AT&T INC	00206R10	T	SBC
STARBUCKS CORP	85524410	SBUX	SBUX
EDISON INTL	28102010	EIX	SCE
SCANA CP	80589M10	SCG	SCG
CHARLES SCHWAB	80851310	SCHW	SCH
SEMPRA ENERGY	81685110	SRE	SDO
SEAGATE TECH	G7945M10	STX	SEAA
SEALED AIR CP	81211K10	SEE	SEE
PUBLIC STORAGE	74460D10	PSA	SEQ
SPECTRA ENERGY	84756010	SE	SEWI
SHERWIN-WMS	82434810	SHW	SHW
SIGMA-ALDRICH	82655210	SIAL	SIAL
SVB FINANCIAL	78486Q10	SIVB	SIVB
SMUCKER, JM 'A'	83269640	SJM	SJM
SCHLUMBERGER LTD	80685710	SLB	SLB
HILLSHIRE BRANDS	43258910	HSH	SLE
SL GREEN REALTY	78440X10	SLG	SLG
AO SMITH	83186520	AOS	SMC
SNAP-ON INC	83303410	SNA	SNA

Company Name	CUSIP 8	Ticker	IBES Ticker
EQT CORP	26884L10	EQT	EQT
ELECTRONIC ARTS	28551210	ERTS	ERTS
EXPRESS SCRIPTS	30219G10	ESRX	ESRX
ESSEX PPTY TRUST	29717810	ESS	ESS
EATON CORP	G2918310	ETN	ETN
EDWARDS LIFESC	28176E10	EW	EW
EXPEDITORS INTL	30213010	EXPD	EXPD
EXPEDIA INC	30212P30	EXPE	EXPE
EXTRA SPACE	30225T10	EXR	EXRN
COOPER COS INC	21664840	COO	EYE
FORD MOTOR CO	34537086	F	F
REGIONS FINL COR	7591EP10	RF	FABC
DIAMONDBACK ENER	25278X10	FANG	FANG
FASTENAL CO	31190010	FAST	FAST
FORTUNE BRANDS H	34964C10	FBHS	FBHS
FACEBOOK INC	30303M10	FB	FBK
FRPT MCMO COPPER	35671D85	FCX	FCX
MACY'S INC	55616P10	M	FD
FAMILY DLR STORS	30700010	FDO	FDO
FEDEX CORP	31428X10	FDX	FDX
M & T BANK CORP	55261F10	MTB	FEMP
F5 NETWORKS INC	31561610	FFIV	FFIV
FEDERATED INVEST	31421110	FII	FII
FISERV INC	33773810	FISV	FISV
5TH 3RD BCP OH	31677310	FITB	FITB
FLIR SYSTEMS	30244510	FLIR	FLIR
MASSEY ENERGY	57620610	MEE	FLR
FLUOR CORP	34341210	FLR	FLR1
FLEETCOR TECHNOL	33904110	FLT	FLTT
FMC CP	30249130	FMC	FMC2
US BANCORP	90297330	USB	FNAC
FOSSIL GROUP INC	34988V10	FOSL	FOSL
NEXTERA ENERGY I	65339F10	NEE	FPL
FRANKLIN RES INC	35461310	BEN	FRRI
FED RLTY INV	31374720	FRT	FRT
FOREST LABS	34583810	FRX	FRX
FIRST SOLAR	33643310	FSLR	FSLR
FIRST HORIZON	32051710	FHN	FTEN
TECHNIPFMC	G8711010	FTI	FTI
FMC TECH	30249U10	FTI	FTI1
FORTINET INC	34959E10	FTNT	FTNT
FORTIVE	34959J10	FTV	FTVWI
GARTNER	36665110	IT	GART
NICOR INC	65408610	GAS	GAS
TEGNA	87901J10	TGNA	GCI
GEN DYNAMICS	36955010	GD	GD
GEN ELECTRIC US	36960410	GE	GE
GILEAD SCIENCES	37555810	GILD	GIL1
GEN MILLS INC	37033410	GIS	GIS
CORNING INC.	21935010	GLW	GLW
DIRECTV	25490A30	DTV	GM12
KEURIG GREEN MTN	49271M10	GMCR	GMCR
GAMESTOP CORP	36467W10	GME	GME
GENERAL MOTORS	37045V10	GM	GNM
GENWORTH FINANCI	37247D10	GNW	GNWD
ALPHABET	02079K30	GOOGL	GOOG
ALPHABET	02079K10	GOOG	GOOG/1
GENUINE PARTS	37246010	GPC	GPC
GLOBAL PAYMENTS	37940X10	GPN	GPN

Company Name	CUSIP 8	Ticker	IBES Ticker
BB&T CP	05493710	BBT	SNAT
SANDISK CORP	80004C10	SNDK	SNDK
SCRIPPS NETWORKS	81106510	SNI	SNIW
SYNOPSYS INC	87160710	SNPS	SNPS
SOUTHN CO	84258710	SO	SO
KEYCORP	49326710	KEY	SOCI
STAPLES INC	85503010	SPLS	SPLS
SIMON PROPERTY	82880610	SPG	SPPG
STERICYCLE INC.	85891210	SRCL	SRCL
STATE STREET	85747710	STT	STBK
SUNTRUST BKS GA	86791410	STI	STI
ST JUDE MEDICAL	79084910	STJ	STJM
TRAVELERS COS IN	89417E10	TRV	STPL
STRYKER CP	86366710	SYK	STRY
SUNOCO INC	86764P10	SUN	SUN
JANUS CAPITAL	47102X10	JNS	SV
SUPERVALU	86853630	SVU	SVU
STANLEY BLACK	85450210	SWK	SWK
SOUTHWSTN ENERGY	84546710	SWN	SWN
SAFEWAY INC	78651420	SWY	SWY
DEAN FOODS CO	24237020	DF	SWZA
SYNCHRONY FINCL	87165B10	SYF	SYF
SYMANTEC CORP	87150310	SYMC	SYMC
SYSCO CP	87182910	SYY	SYY
TERADATA	88076W10	TDC	TDC
TECO ENERGY INC	87237510	TE	TE
TE CONNECTIVITY	H8498910	TEL	TELW
TERADYNE INC	88077010	TER	TER
TRANSDIGM GROUP	89364110	TDG	TGD
TIFFANY AND COMP	88654710	TIF	TIF
TITANIUM METALS	88833920	TIE	TIMT
TELLABS	87966410	TLAB	TLAB
TORCHMARK CP	89102710	TMK	TMK
THERMO FISHER SC	88355610	TMO	TMO
MONSTER WORLDWID	61174210	MWW	TMPW
TRIPADVISOR INC	89694520	TRIPV	TRAD
DAVITA INC	23918K10	DVA	TRL
TRACTOR SUPPLY	89235610	TSCO	TSCO
ANDEAVOR US	03349M10	ANDV	TSO
TOTAL SYSTEM SVC	89190610	TSS	TSYS
TAKE-TWO INT SFT	87405410	TTWO	TTWO
TIME WARNER CABL	88732J20	TWC	TWCA
TWITTER INC	90184L10	TWTR	TWEE
CROWN CASTLE	22822V10	CCI	TWRS
TEXAS INSTRUMENT	88250810	TXN	TXN
TEXTRON	88320310	TXT	TXT
JOHNSON CNTRLS	G5150210	JCI	TYC
TYSON FOODS INC	90249410	TSN	TYSN
UNITED CONTINENT	91004710	UAL	UAL
UNDER ARMOUR	90431110	UA	UARM
UNDER ARMOUR	90431120	UA.C	UARM/1
UDR INC	90265310	UDR	UDRT
AMEREN CP	02360810	AEE	UEP
UNVL HEALTH SVCS	91390310	UHS	UHSI
ULTA SALON COSME	90384S30	ULTA	ULTA
UNITEDHEALTH GRP	91324P10	UNH	UNIH
UNUM GROUP	91529Y10	UNM	UNM
UNION PACIFIC CP	90781810	UNP	UNP
VIAVI SOLUTIONS	92555010	VIAV	UNPH

Company Name	CUSIP 8	Ticker	IBES Ticker
GAP INC	36476010	GPS	GPS
GOODRICH CORP	38238810	GR	GR
GARMIN	H2906T10	GRMN	GRMN
GOLDMAN SACHS	38141G10	GS	GSG
GOODYEAR TIRE	38255010	GT	GT
WW GRAINGER	38480210	GWW	GWW
HALLIBURTON	40621610	HAL	HAL
MONSTER BEVERAGE	61174X10	MNST	HANS
HASBRO INC.	41805610	HAS	HAS
HUNTINGT BCSH OH	44615010	HBAN	HBAN
HANESBRANDS INC	41034510	HBI	HBI
HCA HOLDINGS INC	40412C10	HCA	HCAZ
HUDSON CITY BANC	44368310	HCBK	HCBC
WELLTOWER	95040Q10	HCN	HCN
HCP INC	40414L10	HCP	HCP
HOME DEPOT INC	43707610	HD	HD
HARLEY-DAVIDSON	41282210	HOG	HDI
HARTFORD FIN SVC	41651510	HIG	HIGW
HARMAN INTL INDS	41308610	HAR	HIII
HUNTINGTON INGAL	44641310	HII	HIIW
HILTON WORLDWIDE	43300A20	HLT	HLTT
HOST HOTELS & RE	44107P10	HST	HMT1
HJ HEINZ	42307410	HNZ	HNZ
HOLLYFRONTIER CO	43610610	HFC	HOC
HOLOGIC INC	43644010	HOLX	HOLX
STARWOOD H&R	85590A40	HOT	HOT
CENTERPOINT ENER	15189T10	CNP	HOU
HELMERICH &PAYNE	42345210	HP	HP
HEWLETT PACKARD	42824C10	HPE	HPEWI
APTIV	G6095L10	APTV	HPLD
H&R BLOCK	09367110	HRB	HRB
HORMEL FOODS CP	44045210	HRL	HRL
HARRIS CP	41387510	HRS	HRS
HENRY SCHEIN	80640710	HSIC	HSIC
HOSPIRA	44106010	HSP	HSPI
HERSHEY	42786610	HSY	HSY
HUMANA INC	44485910	HUM	HUM
HP	40434L10	HPQ	HWP
INTL BUS MACH	45920010	IBM	IBM
INTERCONTINENTAL	45866F10	ICE	ICEI
BIOGEN IDEC INCO	09062X10	BIIB	IDPH
IDEXX LABS INC	45168D10	IDXX	IDXX
INTL FLAV & FRAG	45950610	IFF	IFF
INTL GAME TECH	45990210	IGT	IGAM
ITT	45073V10	ITT	IIN
ILLUMINA INC	45232710	ILMN	ILMN
IRON MOUNTAIN	46284V10	IRM	IMTN
NEKTAR	64026810	NKTR	INHL
INTEL CP	45814010	INTC	INTC
INTUIT	46120210	INTU	INTU
INTL PAPER CO	46014610	IP	IP
INTERPUBLIC GRP	46069010	IPG	IPG
IPG PHOTO	44980X10	IPGP	IPGP
INCYTE CORP	45337C10	INCY	IPI

Company Name	CUSIP 8	Ticker	IBES Ticker
UTD PARCEL SVC	91131210	UPS	UPS
URBAN OUTFITTERS	91704710	URBN	URBN
UNITED RENTALS	91136310	URI	URI1
WASTE MGMT. INC	94106L10	WM	USAS
SPRINT NEXTEL	85206110	S	UT
UTD TECH	91301710	UTX	UTX
VARIAN MED SYS	92220P10	VAR	VAR
WINDSTREAM HLDG	97382A30	WIN	VCGI
VENTAS INC	92276F10	VTR	VCOR
VF CP	91820410	VFC	VFC
CBS CORP	12485720	CBS	VIA
VIACOM INC	92553P20	VIA.B	VIAB
VISA INC	92826C83	V	VISA
VALERO ENERGY CP	91913Y10	VLO	VLO
VULCAN MATLS CO	92916010	VMC	VMC
VORNADO RLTY TR	92904210	VNO	VNO
VERISK ANALYTICS	92345Y10	VRSK	VRSK
VERISIGN INC	92343E10	VRSN	VRSN
VERTEX PHARMACEU	92532F10	VRTX	VRT1
WALGREENS BOOTS	93142710	WBA	WAG
WATERS CORP	94184810	WAT	WAT
ALLERGAN	G0177J10	AGN	WATS
WELLCARE HEALTH	94946T10	WCG	WCGI
WESTN DIGITAL	95810210	WDC	WDC
WHOLE FOODS MKT	96683710	WFMI	WFMI
SUNEDISON INC	86732Y10	SUNE	WFR
WHIRLPOOL CP	96332010	WHR	WHR
WILLIAMS COS	96945710	WMB	WMB
WAL-MART STRS	93114210	WMT	WMT
WEC ENERGY GROUP	92939U10	WEC	WPC
ALLIANT ENER	01880210	LNT	WPL
GRAHAM HOLDINGS	38463710	GHC	WPO
INTEGRYS ENERGY	45822P10	TEG	WPS
WPX ENERGY INC	98212B10	WPX	WPX
WILLIS TOWERS	G9662910	WLTW	WSH
WESTERN UNION CO	95980210	WU	WUN
WEYERHAEUSER CO	96216610	WY	WY
WYNN RESORTS	98313410	WYNN	WYNN
WYNDHAM WORLDWID	98310W10	WYN	WYNW
US STEEL CORP	91290910	X	X
CIMAREX ENERGY	17179810	XEC	XEC
XL GRP	G9829410	XL	XL
XILINX	98391910	XLNX	XLNX
EXXON MOBIL CORP	30231G10	XOM	XON
DENTSPLY SIRONA	24906P10	XRAY	XRAY
XEROX	98412160	XRX	XRX
XYLEM INC	98419M10	XYL	XYL
YUM! BRANDS INC	98849810	YUM	YUM
FOOT LOCKER INC	34484910	FL	Z
ZIONS BANCORP	98970110	ZION	ZION
ZIMMER HOLDINGS	98956P10	ZMH	ZMH
ZOETIS INC	98978V10	ZTS	ZOTS
TJX COS INC	87254010	TJX	ZY