Influential analyst recommendations: Are they the hidden gem?

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Abstract

Informational signals play an important role in Finance. We analyze influential recommendations changes in the US between 1993 and 2012 which accounts for 19% of the overall. We find that they depend on the magnitude of the recommendation change, concurrent earnings, and higher firm institutional ownership. Using this to predict influential recommendation in an out of sample exercise, we construct a long-short portfolio that buys positive and sells negative influential recommendation changes. We find that this strategy yields a net annualized abnormal return of 26%, an annualized Sharpe ratio of 1.23, and an annualized certainty-equivalent of 27% between 1999 and 2012, which compares well to an annualized Sharpe Ratio of 0.40 and an annualized certainty-equivalent of 6% of the CRSP equally-weighted index.

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1. Introduction

Every so often, market observers point significant share-price reaction to analyst recommendation changes. On September 1st 2009 Todd Bault, from Bernstein, issued a recommendation change (downgrade) warning investors to the fact that AIG's share could be worthless. Soon the share price fell approximately by 11%[1]. The shares of Suedzucker AG fell 12%[2] and trading volumes exceeded the previous three-month daily average[3], on September 3rd 2013, after the downgrade by Exane BNP Paribas, who predicts the end of regulated European sugar market. Nevertheless, most studies find that, on average, recommendation revisions do not generate an economically meaningful reaction after accounting for firm specific news, such as earnings announcements (Altinkilic and Hansen 2009; Chen, Francis, and Schipper 2005). However, the focus of these studies is on the average effect of stock recommendations, and foregoes recommendations that actually had an influential impact on the firm. In contrast, this study focuses on influential recommendation changes. We analyze their determinants and use this information to construct a portfolio allocation exercise. We find that a long-short portfolio conditioned on predicted influential recommendations between 1999 and 2012 has an annualized Sharpe ratio of 1.23 and an annualized certainty-equivalent (CEQ) of 27.4%. In contrast, the CRSP equally-weighted index has an annualized Sharpe ratio of 0.40 and a CEQ of 6.24%.

There is evidence that, during the period between 1965 and 1989, trading strategies long on past winners and short on past losers stocks realize significant abnormal returns (Jegadeesh and Titman, 1993). They show that this is not due to systematic risk nor attributed to delayed stock price reactions to common factors. Nevertheless, there is evidence that firm-specific information causes the delay in price reaction. Therefore, analyst recommendations,

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[1] Tibken, Shara. *The Wall Street Journal*. November 30, 2009. http://blogs.wsj.com/marketbeat/2009/11/30/aig-shares-fall-as-bernstein-cuts-price-target/

[2] Morgan, Jonathan. *Bloomberg*. September 3, 2013. http://www.bloomberg.com/news/2013-09-03/german-stocks-decline-as-thyssenkrupp-suedzucker-retreat.html

[3] Zha, Weixin. *Bloomberg Businessweek*. September 3, 2013. http://www.businessweek.com/news/2013-09-03/suedzucker-falls-as-end-to-eu-subsidies-beckons-frankfurt-mover

which are firm-specific, should be able to provide some return to investors. According to Womack (1996), recommendation changes to positive (negative) categories generate positive (negative) excess returns in the direction of the analyst's forecast predominantly during the period of one month (six months). Barber et al. (2001) find that an investment strategy based on average analyst recommendations, long on the buy recommendations and short on the sell recommendations, delivers positive returns. As a result we create three investment approaches based on (i) recommendation level consensus, (ii) recommendation change consensus, and (iii) buying positive and selling negative recommendation changes, as the recommendation is announced. Cvitanić et al. (2006) propose a dynamic portfolio allocation methodology with parameter uncertainty. They find that by using analysts' recommendations as a parameter in their model, investors are able to produce significant utility gains, compared to a naïve strategy that goes long on buy recommendations and short on sell recommendations. We benchmark these strategies to the naïve strategy (1/N) proposed by DeMiguel, Garlappi, and Uppal (2009), as they find that other portfolio allocation strategies are not necessarily better in terms of Sharpe ratio and CEQ.

Loh and Stulz (2011) find that some analyst recommendation changes cause significant alterations in firm's value, leading to large returns and turnover. They find that approximately 11.7% of the recommendation changes analyzed are influential, which they define as an analyst recommendation change that has a recognizable impact at the firm level. Therefore, we adapt the three strategies mentioned above to be conditional on influential recommendation changes. Our results show that the percentage of influential recommendations is actually greater, 19.4% for our sample. Further, they investigate what makes a recommendation change more probable to be influential. They find that analysts with larger leader-follower ratios and more accurate forecasts are more likely to be influential. Moreover, influential recommendation changes are associated with small, growth, high institutional ownership, and low analyst activity firms. Additionally, they find evidence that recommendation changes have become more influential since the introduction of the Fair Disclosure Regulation in

September 2002 by National Association of Securities Dealers (NASD). In our results we find stronger evidence, which supports that after the implementation of the Fair Disclosure Regulation analyst recommendations have a stronger impact. As we find a greater percentage of influential recommendation changes between 2003 and 2012, compared to the recommendation change during 1993 and 2002.

At a first stage, we analyze what the characteristics of influential recommendation changes are. In previous literature it is found that the timing of recommendation changes relative to earnings announcements affects the recommendations impact on stock prices (Ivkovic and Jegadeesh, 2004). Further, there is evidence that more accurate earnings forecasts facilitate analysts to issue more lucrative stock recommendations (Loh and Mian, 2006). These analysts earn considerably greater annual returns than those with poorer forecasts. However, we do not find that influential recommendation changes are issued by analysts who previously issued more accurate forecasts. Asquith, Au and Mikhail (2005) prove that the content of analyst reports when issuing a recommendation change also has an impact. Therefore, we expect that influential recommendations are accompanied by new earnings forecasts as these include more content. Jagadeesh and Kim (2010) examine whether analysts herd around the consensus when they make a new recommendation and find that the market reaction to analysts' recommendation revisions is stronger when the revised recommendations move away from the prior consensus. The herding effect is larger for downgrades than for upgrades. Consequently, we anticipate that influential recommendations deviate from the consensus and find that this is the case.

The rest of this paper is organized as follows. Section 2 describes the data and methodology applied. Section 3 discusses the results of influential recommendation changes. Section 4 considers the results of our proposed strategy. Finally Section 5 concludes.

2. Data

The stock recommendations sample is extracted from the Thomson Financial's Institutional Brokers Estimate (I/B/E/S) U.S Detail File. The sample is built starting from I/B/E/S ratings issued by individual analysts from September 1993 to December 2012, with ratings ranging from 1 (strong buy) to 5 (sell). We use an inverted ratings scale, as in Loh and Stulz (2011) (e.g., strong buy now denoted by 5).

The emphasis is on recommendation revisions and not levels, because previous research has found that recommendation changes contain more information (e.g., Jegadeesh and Kim, 2010). The recommendation change, *rec_chg*, is computed as the difference between the current rating and the previous outstanding rating by the same analyst. Rating are coded as 5 (strong buy) to 1 (sell), and the rating changes level lies between -4 and +4. We use Ljungqvist, Malloy and Marston (2009) definition that the rating has to have been confirmed by the analyst in the last twelve months and has not been stopped by the broker, for outstanding rating. Analysts coded as anonymous by I/B/E/S are removed as it is not possible to track their recommendation revisions. Also, companies that have less than five recommendations during the whole sample period and companies that have less than two years of stock price data in the CRSP are removed. This reduces the number of companies to a total of 2,700 followed by 7,553 analysts. On average, we have recommendation changes for 991 companies/year. In 1993 we start with 107 firms, as the I/B/E/S recommendation sample only starts during the 4th quarter of 1993. In 1997, we have the most companies in a year, 1,227. The sample of recommendation changes contains a total of 116,028 recommendation changes and almost 99% of these recommendation changes lay within the range of -2 to +2. In Table I the transition probabilities of the recommendation changes are plotted. We observe that recommendations are mainly in optimistic levels and one can read that prior hold ratings are more often upgraded, while the non-hold are revised to hold ratings.

We use the Recommendations Summary Statistics file from I/B/E/S to obtain the recommendation consensus. To estimate the analyst's forecast accuracy we get the one year earnings forecast (FY1) and actual earnings for the forecasted year from detailed earnings forecast file from I/B/E/S. We also retrieve the target price data from the I/B/E/S. Each target price specifies the analyst's opinion as to the stock price in the near future, which can range from a 6 months to 18 months' time horizon. We compute the target price expected return (*TPER*) as the return of the target price over the stock price at the day of the target price announcement. We end up with a total of 312,679 target price observations between January 1999 and December 2012.

From the CRSP, we obtain stock prices and dividends to compute ex dividend returns. We use the stock price and shares outstanding to compute the market capitalization. We calculate the daily turnover using the volume and shares outstanding. The book-to-market ratio is computed using the book value retrieved from COMPUSTAT and the market capitalization. The institutional ownership percentage is extracted from the Thomson Reuters stock ownership file. Finally, we extract the daily and monthly Fama-French factors and momentum factor from the Kenneth R. French database[4].

3. Influential recommendation changes

We follow Loh and Stulz (2011) to compute influential analyst recommendation revisions, and use two methods to understand how the recommendation change is reflected on the firm's stock return. The first method is based on the return impact of the firm and is computed using the cumulative buy-and-hold abnormal return (CAR) with a two-day time window

$$CAR_i = \prod_{t=0}^{1}\left(1+R_{it}\right) - \prod_{t=0}^{1}\left(1+R_{it}^{DGTW}\right) \tag{1}$$

where R_{it} is the raw return of firm i on day t, and $t = 0$ is the day of recommendation announcement, unless the announcement occurs between 4:30 pm and 11:59 pm, then $t = 0$ is the next trading day. R_{it}^{DGTW} is the return on a benchmark portfolio with the same size, book-to-market, and momentum characteristics as firm i (Daniel et al., 1997). The price momentum is computed monthly as the one year stock return. The composition of these portfolios is

[4] Kenneth R. French database: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

estimated on a monthly basis. A recommendation change is influential if simultaneously the CAR is in the same direction as the recommendation change and if the following inequality holds:

$$|CAR_i| > 1.96 \times \sqrt{2} \times \sigma_{\varepsilon_i} \tag{2}$$

where σ_{ε_i}, the idiosyncratic volatility of firm *i*, is the standard deviation of the residuals from a FF model using daily observations from the past three months that starts three months prior (t –69) and ends six days before the recommendation announcement (t –6).

The second method looks at how the stock turnover of the firm is affected by the recommendation revision. Llorente et al. (2002) find evidence that volume contains directional information about future price movements. Specifically, informed trading shows greater return continuation, while the reverse is true for stocks with low-informed trading. Therefore, we are interested in stock turnover to understand whether analyst recommendations are a hedging or speculating motive for investors. The cumulative abnormal turnover is computed as

$$CAT_i = \sum_{t=0}^{1} abturn_i \tag{3}$$

and following Llorente et al. (2002), abnormal turnover is

$$abturn_i = \log turnover_i - \overline{\log turnover}_i \tag{4}$$

where $\overline{\log turnover_i}$ is the average of daily log turnover of the past three months, and $\log turnover_i = \log(turnover_i + 0.00000255)$. A recommendation is influential in terms of cumulative abnormal turnover (CAT) if the following inequality holds:

$$CAT_i > 1.96 \times \sqrt{2} \times \sigma_{abturn_i} \tag{5}$$

where σ_{abturn_i} is the standard deviation of the stocks abnormal turnover in the past three months, which starts three months prior (t –69) and ends six days before the recommendation announcement (t –6).

To understand the predictive power of recommendation characteristics for influential recommendation changes we use a probability unit link function, also known as Probit.

$$Y_i = \begin{cases} 1 \text{ if recommendation } i \text{ is influential} \\ 0 \text{ otherwise} \end{cases} \tag{6}$$

where X_i is characteristic i of the recommendation (e.g., recommendation level, analyst experience, book-to-market,…). $Y_i | X$, $i=1,\ldots, n$ are assumed to be independent with:

$$Pr(Y_i = 1 \mid X) = \Phi(X_i\beta) \quad (7)$$

where Pr is the probability, Φ is the cumulative standard Normal distribution function, and the parameters β are estimated using a maximum-likelihood model. To determine the incremental predictability of a characteristic to forecast an influential recommendation change, we look at the marginal effect and not at the coefficient obtained from the Probit estimate. The Marginal effect shows us by how much the probability changes by changing one unit of X_i. From this we can then infer the incremental predictability of an influential recommendation change of characteristic X_i.

Table II reports the descriptive statistics of CARs for our sample of recommendation changes, grouped by the recommendation change categories from -4 to +4. All positive (negative) rating changes categories have positive (negative) CAR means and medians. This sample we filter into three other samples. This allows us to analyze differences between all recommendation change and only influential recommendation change and also how the sample changed as of 2007 with the start of the financial crisis. For negative revisions the 25th and 1st percentiles have larger negative returns opposed to the positive ones. The CARs are not normal distributed (see KS-test results in Table II) and the company specific news-recommendations and outliers have a strong impact on the means. For the period between 2007 and 2012, we do not observe any significant change.

Filtering the CAR means for influential recommendation changes we notice that they have changed and are more distant from zero but still follow the same pattern, compared to the whole sample. Regarding the 1st percentile for the positive (negative) recommendation change categories the CARs are all above (below) zero. These results describe how the tails of the non-filtered results look like and show the statistical and economic significance of influential recommendations. Therefore investors, who are able to successfully identify these recommendations changes when they are issued, are able to profit from significant returns. Filtering the influential sample for the period between 2007 and 2012, we still find similar results compared to the whole period.

Figure 1 plots the two-day CAR histogram of recommendation changes for zero-point and one point magnitude changes, as these categories include about 75% of the total recommendation changes. The top chart plots the histogram for CARs of the no recommendation change category, which mostly fall close to zero. The charts below plot the histograms for the one point downgrade and upgrade, which are negatively and positively skewed respectively. This shows that the direction of the recommendation change indicates the sign of the return obtained during the first two days after issuing the recommendation.

We find that 19.4% of the recommendation changes for the whole sample are influential in terms of abnormal return and 25.9% in abnormal turnover. While only 10.6% of the recommendation changes are influential on both. In contrast, Loh and Stulz (2011) find that 11.7% and 12.8% of recommendation revisions are influential in terms of abnormal return and turnover respectively. Further, we see that our results are higher between 2003 and 2012 (21.9% and 28.8%) but lower before 2003 (16.5% and 22.5%), which indicates that Reg_FD act had a positive impact on analyst recommendations. The fact that percentage of influential recommendation changes in CAT is higher than in CAR, shows that recommendations have a stronger impact on volume rather than on price. According to Llorent et al. (2002), stocks associated with informed trading, which had high-volume days, show return momentum. Meaning that trades performed on the basis of analyst recommendation should be seen as informed and therefore the influential recommendation changes in CAT are very helpful for investors as they have predictive power about the future stock price movement.

In Table III, we observe that influential recommendations revisions are less accurate than non-influential recommendation revisions, as the 1st quintile represents the most accurate analysts. This finding is inconsistent with Loh and Mian (2006) result that more accurate earnings forecasts generate greater annual returns. From Table IV, forecast accuracy does not provide much incremental predictability in identifying influential recommendation revisions.

Jegadeesh and Kim (2010) analyze if analyst have a tendency to take similar actions, recommendations, around the same time. This behavioral bias is also known as "herding". To understand whether an analyst is not affected by this bias, meaning that he is away from the consensus, we test if the deviation of a new recommendation is greater than the prior absolute deviation of the recommendation consensus, as suggested by Loh and Stulz (2011). We find that, on average, influential recommendation changes are further away from the consensus. In line with Jegadeesh and Kim (2010), we find that recommendation changes that are further away from the consensus are more likely to be influential (Table IV). In alignment with Mikhail, Walther, and Willis (1997), we find that analysts, who issue influential recommendation changes, tend to have more experience but do not necessarily increase the predictive power of an influential recommendation.

Kecskes, Michaely and Womack (2012) find that recommendations accompanied by earnings forecast revisions are more profitable and have larger price reactions. In line with their findings we observe in Table III that more than 60% of the influential recommendations were issued by analysts, who issued an earnings forecast between a three-day window around the recommendation announcement. Moreover, it also significantly increases the predictability of an influential recommendation (Table IV).

Conversely, Table IV shows that analysts who have been previously influential for any of the stocks they follow are more likely to produce an influential recommendation. But analysts, who issue a recommendation for a firm for which they have been influential before, have less probability of issuing an influential recommendation change.

In line with Stickel (1995), who finds that the stock-price reaction for smaller firms is greater than for larger ones, the difference in size does not change significantly for influential recommendations (Table III). Nevertheless, Table IV shows that recommendation changes for large firms have a negative marginal effect, meaning that small firms increase the predictability of an influential recommendation change. In terms of book-to-market we can observe, both in Table III and IV, that growth firms have an incremental impact on the predictability of an influential recommendation change, opposed to value firms. Comparing recommendation changes on firms related to the financial and insurance sector, we see that these are less likely to be influential. We find that influential recommendations are associated with higher institutional ownership firms. This is consistent with Kelsey et al. (2007) findings that analysts, who follow firms with higher institutional ownership, issue more accurate earnings forecast and also react faster to new information.

In Table IV, we observe that recommendation level does not increase the probability of issuing an influential recommendation change. An explanation for this is related to the fact that the recommendation level itself does not contain information about the past performance relative to the future expectations of the stock. In line with Asquith, Au and Mikhail (2005) finding that the content of recommendation has an impact, as recommendation with larger magnitudes should include more new information. The absolute recommendation change value shows a strong impact on the likelihood of issuing an influential recommendation change. Meaning that when a recommendation moves from sell (strong buy) to strong buy (sell), equal to a four-point magnitude upgrade (downgrade), a recommendation change is more likely to be influential (the bottom chart in Figure 2 plots the transition probabilities of the influential recommendation changes). Table III also shows that positive recommendation changes, *Upgrade Dummy*, are more likely to be influential. One possible reason for this is related to short selling constraints, causing negative recommendation changes to react slower. Consistent with Loh and Stulz (2011) results, we find evidence that the Regulation Fair Disclosure act from 2000, Reg FD, has a significant marginal effect in the predictability of an influential recommendation. This shows that through the introduction of Reg FD investors started to give more attention to analyst recommendations.

We also study how the characteristics have changed through time.[5] Figure 3 plots the estimates from a Probit model, using a 5-year monthly rolling window and an initial estimation window from 1994 to 1998, as we want to use results for an out of sample strategy. Panel A shows how the *Away_from_consensus, Influential before any stock* and *Influential before same stock* initially have an incremental effect on the predictability of an influential recommendation. However, after periods of financial bursts these characteristics lose predictive power. Looking at the *Absolute value of recommendation change*, in Panel B, we observe that this has been one of the variables with most incremental predictability for an influential recommendation. In this chart we also see that the *Upgrade Dummy* initially did not have much of an impact, however, through time it has gained more significance. One of the most volatile variables is the *Financial Dummy*, which through most of the period seems to not have had much incremental predictability for influential recommendation changes. Nevertheless, after the financial crisis we observe that the marginal effect has become negative, but slowly reverted back to no significant marginal effect. Panel C shows the evolution of one of the most important variables *Concurrent earnings forecast*, which increased in power with the boom after the dot-com bubble burst but reverted back to its initial level after the financial crisis. The third variable which shows most significance is *Institutional ownership* that remained mostly constant through time (Panel D). Price momentum had a negative marginal effect at the start of the estimation, reaching its lowest during the dot-com crisis. But since then it has been becoming non-significant, only during the financial crisis it is possible to observe a short inversion in this trend. This leads to the conclusion that the three characteristics that have the most incremental predictability of an influential recommendation change are *Absolute value of recommendation change*, *Concurrent earnings forecast*, and *Institutional ownership*. This shows that investors act more to positive recommendations, especially the ones that come from analyst who simultaneously provide new content by issuing new earnings forecasts. Moreover, the

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[5] The *Reg FD* characteristic is excluded for this analysis, as for the initial rolling window estimates the dummy variable is always equal to zero, and later it is always equal to one.

fact that *institutional ownership* is also a key characteristic shows that institutional investors are more concerned with the opinion of sell-side analysts.

4. Investment strategies

Previous literature has shown that by using analyst recommendations for investment strategies, one is able to create significant alphas. Barber et al. (2001) find that an investment strategy based on average recommendations of analysts, long (short) on the buy (sell) recommendations, yields annualized returns of 18.8% (5.8%) between 1986 and 1996 in the US. Other literature has shown that strategies based on average analyst recommendation revisions have more impact than merely on average analyst recommendations. Green (2006) finds that a strategy tracking recommendation revisions results in an average two-day return of 1.0% (1.5%) for upgrades (downgrades) after transaction costs. Barber, Lehavy and Trueman (2010) find that a strategy conditioned on recommendation levels (changes) yields an annualized abnormal return of 8.8% (9.6%). By creating a new strategy that is conditioned on both recommendation levels and changes they achieve an annualized return improvement of 3.5%. Our objective is to understand which investment strategy based on analyst data can be expected to perform well. To do this, we evaluate a range of different long-short investment approaches: (i) based on recommendation consensus of the last six months, (ii) based on average recommendation changes, and (iii) based on buying analyst recommendation changes on the day of the recommendation announcement. We include the results of the long and short portfolios in our analysis, so that it is possible to analyze how the two sides affect the long-short portfolio. This also allows identifying the best performing strategy for long-only constrained investors. We compare each of these three approaches into different kind of strategies, one that considers all recommendations and one that is only concerned by influential recommendations. According to Brav and Lehavy (2003) analysts' target price contain incremental information as there is a significant market reaction to target price revisions. Further, Asquith, Au and Mikhail (2005) find that target price revisions hold new information even in the company of stock recommendation change and earnings revisions. Huang, Mian and Sankaraguruswamy (2009) find that by combining analysts' target price revisions and consensus recommendation, they are able to improve the returns and reduce risk exposure, compared to implementing analysts' target price revisions and consensus recommendations portfolios separately. Thus, we also analyze the first two investment approaches mentioned above perform, when combined with change in consensus target price. We compare our results with the CRSP equally-weighted index (Panel A of Table V). Additionally, we construct a 1/N portfolio of our entire sample (Panel B), as it has been found that it performs as well as other portfolio allocation strategies in an out of sample analysis (DeMiguel, Garlappi and Uppal, 2009). Stocks, whose share-price is below $5 at the month end are excluded from the portfolios for the investment approaches (i) and (ii), while for investment approach (iii) we exclude the stock if the price on the recommendation announcement date (t=0) is below $5. As D'Avolio (2002) shows that it is hard to borrow stocks with a price below $5, and therefore these stocks are not suitable for strategies that involve short-selling.

Using the first baseline investment approach (i) we build two strategies. The first strategies uses all recommendations to build the consensus (Panel C), and the second one only considers recommendations that were influential (Panel D). We observe that the long-short portfolio that is conditioned to influential recommendation changes performs worse, annualized Sharpe ratio of -0.09 and CEQ of -1.1%, than its counterparty that includes all recommendation, annualized Sharpe ratio of -0.17 and CEQ of 0.2%. Hence, an investor following a strategy that is based on consensus recommendation levels can improve his return but still have a worse performance when compared to the CRSP equally-weighted index, by restricting the consensus to only include recommendations that have been influential.

For the second investment approach (ii) we similarly build two strategies, where the first one includes all recommendation (Panel E) and the second only uses influential recommendation changes for the consensus (Panel F). By using a consensus that considers the recommendation change and not the level, we note that the long-short portfolio in Panel E improves compared to the portfolio in Panel C that is based on recommendation level, the annualized Sharpe ratio increases by 0.20 and the CEQ by 2.0%. However, the long-short portfolio in Panel F, which only takes influential recommendation changes into account, has a poorer performance compared to its counterparty (Panel E). The annualized Sharpe ratio decreases by 0.40 and the CEQ by 2.7%. And also compared to the long-short portfolio (i) with all recommendations (Panel D) the annualized Sharpe ratio decreases by 0.28 and the CEQ increases by 0.6%.

Panel G shows how the third investment approach (iii) with all recommendation changes performs, while the strategy in Panel H consists only of recommendation changes that are predicted to be influential. We use the *Absolute value of recommendation change*, *Concurrent earnings forecast*, and *Institutional ownership* characteristics to predict influential recommendation changes, as we find these to be the most important in an out of sample analysis. Table V shows that the investment approach (iii) yields the best result. The two long-short portfolios in Panel G and H have a Sharpe ratio of 0.59 and 1.22 and an annualized CEQ return of 27.7% and 10.7%. Both of these strategies over-perform compared to our benchmarks, the CRSP equally-weighted index has a Sharpe ratio of 0.40 and annualized CEQ of 6.2%, while the naïve strategy has a Sharpe ratio of 0.26 and an annualized CEQ of 3.7%. The portfolios using the first and second approach have considerably poorer results. A possible reason if from consensus being formed with backward looking recommendation levels or changes, whose information is already partially incorporated in the market price. Therefore, we find that strategies that use influential recommendation changes to form a consensus perform worse than their counterparties.

Last, we consider how changes in *TPER* consensus can be used in conjunction with our stock recommendation strategies. Panel I shows the results for a strategy that is solely based on changes in *TPER* consensus. To construct the long portfolio and the short portfolio we rank the changes in *TPER* consensus into three. The long portfolio includes all stocks that have the highest changes in *TPER* consensus, while the short portfolio contains all the stocks that have the lowest changes in *TPER* consensus. Our results show that the long portfolio has an annualized Sharpe ratio of -0.68 and a CEQ 0.6%, which is similar to the naïve strategy. However, both the short and long-short portfolios have a poorer performance compared to the naïve strategy but still better than the CRSP equally-weighted index. Finally, we look at how changes in *TPER* recommendation consensus can be combined with recommendation consensus, investment approach (i), or recommendation changes consensus, investment approach (ii), considering all recommendations and only influential ones. We find that the new long portfolios for these two strategy approaches improve, while the results for the short portfolios deteriorate. This leads to new long-short portfolios, which have similar results as the portfolios that did not consider changes in *TPER* recommendation consensus and have poorer performance compared to the naïve strategy (Panels J, K, L and M of Table V). It is worth noticing that the long portfolio in Panel K, which is based on the recommendation change consensus investment approach (ii) combined with changes in *TPER* consensus, is the best performing portfolio of all that use changes in *TPER* consensus. This portfolio has a Sharpe ratio of 0.51 and annualized CEQ of 8.7%, which is better than the performance of the CRSP equally-weighted index. Similarly to our findings for investment approaches (i) and (ii) without considering changes in *TPER* consensus, we observe that the strategies, which form consensus using only influential recommendations, perform worse than their counterparties.

We run the same analysis for a different period of time. The first period starts in 2003. We observe that the annualized Sharpe ratio decreases to 1.11, comparable to 0.66 of the naïve strategy. While in the second period, which starts in 2008, annualized Sharpe ratio has a stronger reduction to 0.62 closer to the one of the naïve strategy, 0.56. During these two periods, the CRSP equally-weighted index has a poorer performance compared to both of these strategies, a Sharpe ratio of 0.33 and 0.08 for the first sub period and the second sub period respectively.

It is possible that the results in the third investment approach (iii) that buys recommendation changes are driven by the holding period. We change this assumption to one quarter (63 trading days). In line with Stickel (1995), we observe a reduction in annualized mean returns, more importantly both long portfolios have negative Sharpe ratios. However, the long-short portfolios still have positive Sharpe ratios, 0.27 and 0.58 respectively. Compared to the CRSP equally-weighted, which has a Sharpe ratio of 0.40, the strategy using all recommendation changes becomes unattractive. Therefore, we see that increasing the holding period has a negative impact on the strategy's result, especially for an investor who is considering all recommendation changes and is constrained to long-only investments.

To incorporate trading costs (i.e. bid-ask spread, brokerage commissions, trading impact) we estimate the annualized turnover, as in Barber et al. (2001). For each stock i in portfolio p, we calculate at the close of the trading date on t-1 the new fraction of weights of the portfolio at the close of the trading date t, assuming that there was no portfolio rebalancing ($G_{i,t}$)

$$G_{i,t}= (x_{i,t-1}(1+R_{i,t}))/(\sum_{i=1}^{n_{p,t-1}} x_{i,t-1}(1+R_{i,t})) \tag{8}$$

Secondly, $F_{i,t}$, which represents the actual fraction of stock i in portfolio p, on date t taking into account any portfolio rebalancing, is subtracted from $G_{i,t}$. The turnover for firm i at time t is given by

$$U_{i,t}=\sum_{i=1}^{n_{p,t}} \max\{G_{i,t}-F_{i,t},0\} \tag{9}$$

The annual turnover is calculated by multiplying by the number of months (trading days) in a year with $U_{i,t}$. Table V shows that most long-short strategies have an annual turnover close to 100%. This means that over a period of one year the portfolio fully rotates. As expected, the two long-short portfolios in Panel G and H have significantly higher turnover, 479.8% and 412.7% respectively. Using the annual turnover we proxy transaction costs by means of the round-trip cost of the bid-ask spread estimated to be 1% [e.g. individual investors (Barber and Odean, 2000), and mutual funds (Carhart 1997)]. Looking at Table V we observe that the minimum annual transaction cost would reduce the annualized abnormal return of the long-short portfolio, which is based on all recommendations, to 15.4% (4.8% reduction), of the long-short portfolio, which acts on predicted influential recommendations, to 27.4% (4.1% reduction), and of the naïve strategy to 6.6% (0.6% reduction). This indicates that even after transaction costs the long-short portfolio conditioned to predicted influential recommendations is still a valuable strategy.

5. Conclusion

Stock analysts sell themselves to clients as experts since they are able to bring new and valuable information to them. The press has reported on several cases where stock analysts had a significant impact with their recommendation change on stock returns (e.g. AIG). Most literature is concentrated on the average market price reaction of stock recommendation changes. Following Loh and Stulz (2011), we find that approximately 20% of the recommendation changes are influential in terms of abnormal return. In terms of abnormal turnover, which can predict the direction of future stock price movements (Llorente et al., 2002), 26% of the recommendation changes are influential. The analysts who issue influential recommendation changes tend to distance their recommendation from the prior recommendation consensus, issue earnings forecasts around the period of the recommendation announcement, and have more experience as analysts. Additionally, recommendation changes for small and growth firms, with higher institutional ownership, are more likely to be influential. If a positive recommendation change is issued, the likelihood of an influential recommendation change increases. Moreover, the larger the magnitude of the recommendation changes, then more likely it is to be influential, independent of the sign of the recommendation change.

Using the three most predominant characteristics of influential recommendation revisions, *Absolute recommendation change* value, prior *Concurrent earnings forecast,* and *Institutional ownership percentage*, we construct a long-short portfolio that buys positive recommendation changes and sells negative recommendations changes from 1999 to 2012. This portfolio yields a net annualized abnormal return of 27.4% using the four factor model, a Sharpe ratio of 1.22, and a CEQ return of 27.7%. Compared to the CRSP equally-weighted index, which has a Sharpe Ratio of 0.07 and an annualized CEQ return of 0.7%, during the same period.

To conclude, we show that some recommendation changes have a greater impact on the market and that by creating a strategy based on these characteristics we achieve to construct a portfolio that has significantly better performance, compared to other strategies that have been previously studied.

References

Altinkilic, Oya, and Robert S. Hansen, 2009, On the Information Role of Stock Recommendation Revisions, *Journal of Accounting and Economics* 48, 17-36.

Asquith, Paul, Andrea S. Au, and Michael B. Mikhail, 2005, Information Content of Equity Analyst Reports, *Journal of Financial Economics* 75, 245-282.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can Investors profit from the prophets? Security analyst recommendations and stock returns, *The Journal of Finance* 56, 531 - 563.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2010, Ratings Changes, Ratings Levels, and the Predictive Value of Analysts' Recommendations, *Financial Management* 39, 533-553.

Barber, Brad M., and Terrance Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *The Journal of Finance* 55, 773-806.

Boni, Leslie, and Kent L. Womack, 2006, Analysts, Industries, and Price Momentum. *The Journal of Financial and Quantitative Analysis* 41, 85-109.

Brav, Alon, and Reuven Lehavy, 2003, An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics, *The Journal of Finance* 58, 1933-1986.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *The Journal of Finance* 52, 57-82.

Cvitanić, Jakša, Ali Lazrak, Lionel Martellini, and Fernando Zapatero, 2006, Dynamic Portfolio Choice with Parameter Uncertainty and the Economic Value of Analysts' Recommendations, *Review of Financial Studies* 19, 1113-1156.

Daniel K., M. Grinblatt, S. Titman, R. Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-based Benchmarks, *The Journal of Finance* 52, 153-193.

D'Avolio, Gene, 2002, The Market for Borrowing Stock, *Journal of Financial Economics* 66, 271–306.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal, 2009, Optimal Versus Naive Diversification: How efficient is the 1/N Strategy?, *The Review of Financial Studies* 22, 1915-1953.

Frankel, Richard, S.P. Kothari, and Joseph Weber, 2006, Determinants of the Informativeness of Analyst Research, *Journal of Accounting and Economics* 41, 29-54.

Green, T. Clifton, 2006, The Value of Client Access to Analyst Recommendations, *Journal of Financial and Quantitative Analysis* 41, 1-24.

Huang, Joshua, G. Mujtaba Mian, and Srinivasan Sankaraguruswamy, 2009, The Value of Combining the Information Content of Analyst Recommendations and the Target Prices, *Journal of Financial Markets* 12, 754-777.

Ivkovic, Zoran, and Narasimhan Jegadeesh, 2004, The Timing and Value of Forecast and Recommendation Revisions, *Journal of Financial Economics* 73, 433-463.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Loosers: Implications for Stock Market Efficiency, *The Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Woojin Kim, 2010, Do Analysts Herd? An Analysis of Recommendations and Market Reactions, *The Review of Financial Studies* 23, 901-937.

Kecskes, Ambrus, Roni Michaely, and Kent L. Womack, 2010, What Drives the Value of Analyst's Recommendations: Earnings Estimates or Discount Rate Estimates?, Working Paper, Darthmouth College.

Kelsey, D. Wei, Alexander Ljungqvist, Felicia Marston, Laura T. Starks, and Hong Yan, 2007, Conflicts of Interest in Sell-side Research and the Moderating Role of Institutional Investors, *Journal of Financial Economics* 85, 420-456.

Ljungqvist, Alexander, Christopher Malloy, and Felicia Marston, 2009, Rewriting History, *The Journal of Finance* 64, 1935-1960.

Llorente, Guillermo, Roni Michaely, Gideon Saar, and Jiang Wang, 2002, Dynamic Volume-Return Relation of Individual Stocks, *The Review of Financial Studies* 15, 1005-1047.

Loh, Roger K., and G. Mujtaba Mian, 2006, Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?, *Journal of Financial Economics* 80, 455-483.

Loh, Roger K., and René M. Stulz, 2011, When Are Analyst Recommendation Changes Influential?, *The Review of Financial Studies* 24, 593-627.

Stickel, Scott.E, 1995, The Anatomy of Buy and Sell Recommendations, *Financial Analyst Journal* 51, 25-39.

Womack, Kent L, 1996, Do Brokerage Analysts' Recommendations Have Investment Value?, *The Journal of Finance* 51, 137-167.

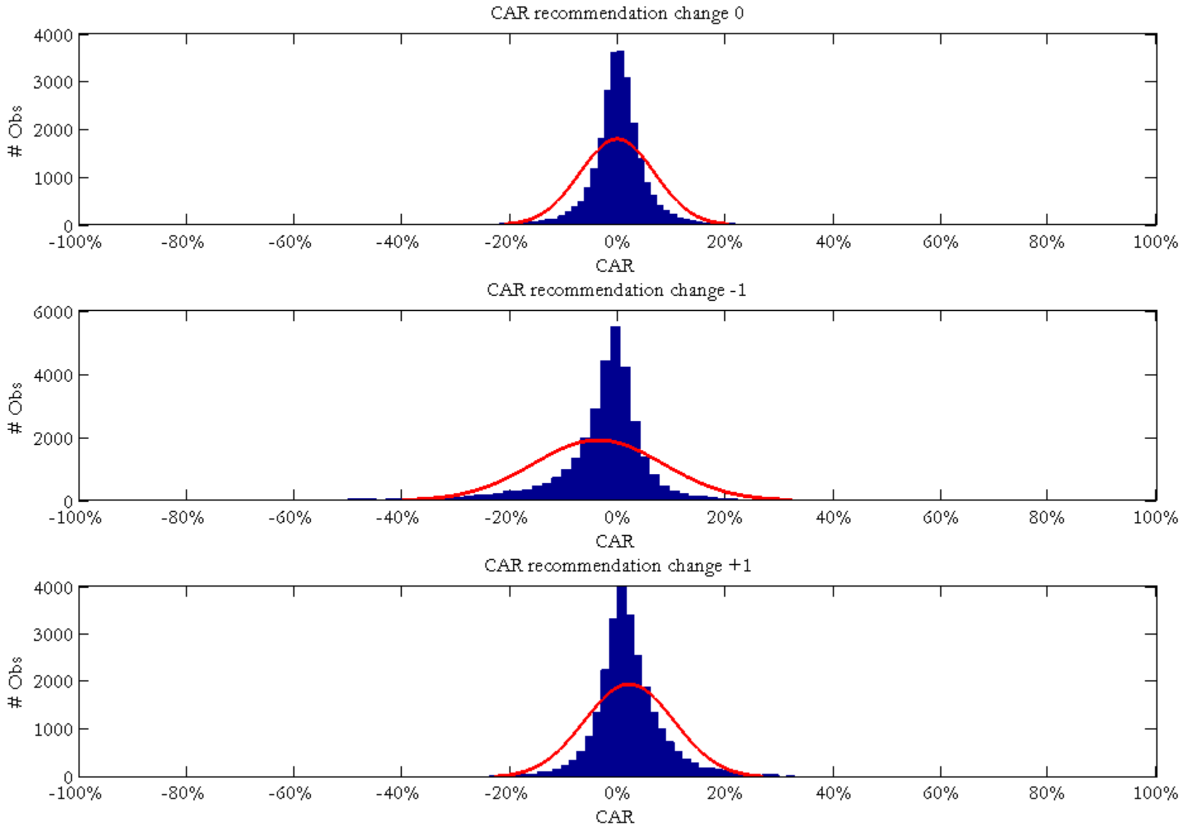

Figure 1 – Histogram of CARs for 0, -1, and +1 recommendation changes

The blue bars plot the CARs histogram of the distribution for each of the recommendation change level. The red line plots the fitted normal distribution for the CARs of each recommendation change level. The sample of recommendation changes is from the I/B/E/S Detail U.S. File in the period between 1993 and 2012. Each recommendation change is the difference between analyst's current rating and her prior rating. Analyst initiations or anonymous analysts are excluded. Rating is coded from 5 (strong buy) to 1 (sell), and the rating changes level lies between -4 and 4.

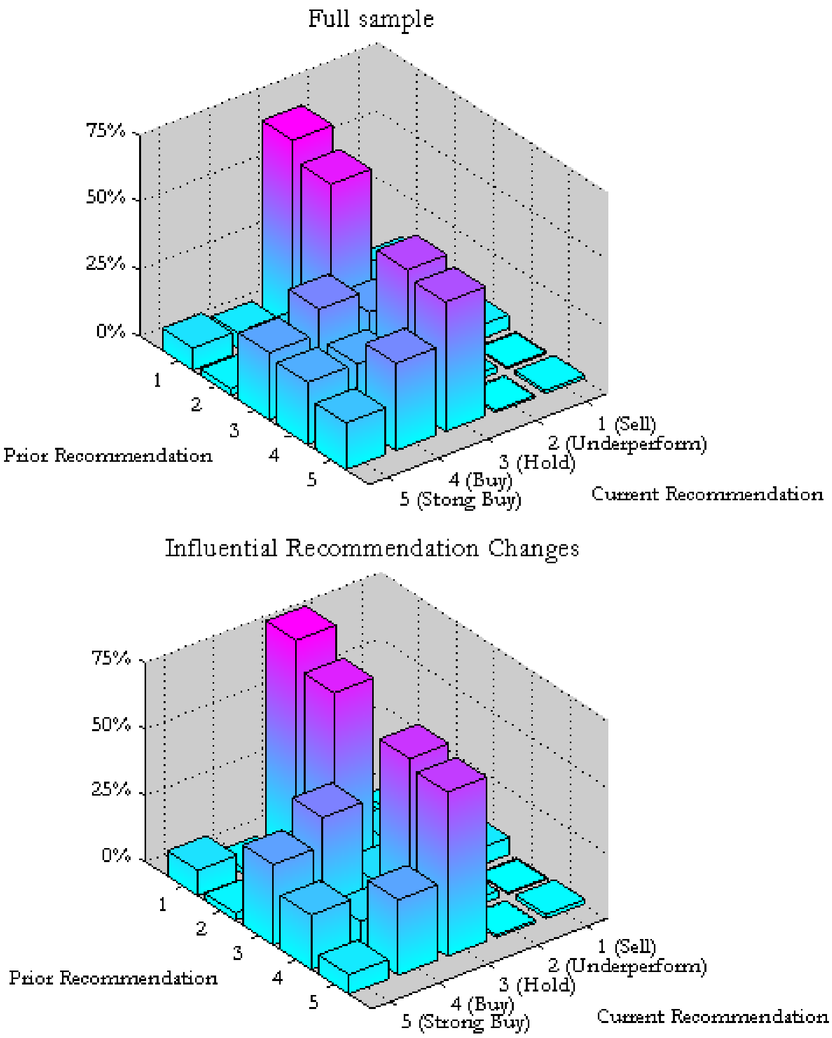

Figure 2 – Transition probabilities of recommendation changes

This chart plots the transition probabilities of recommendation changes, meaning the probability that a prior recommendation transits to any of the five rating classifications. The top chart plots the transition probabilities of the whole sample and the bottom chart the transition probabilities of influential recommendation changes. The sample of recommendation changes is from the I/B/E/S Detail U.S. File in the period between 1993 and 2012. Each recommendation change is the difference between analyst's current rating and her prior rating. Analyst initiations or anonymous analysts are excluded. Rating is coded from 5 (strong buy) to 1 (sell), and the rating changes level lies between -4 and 4.

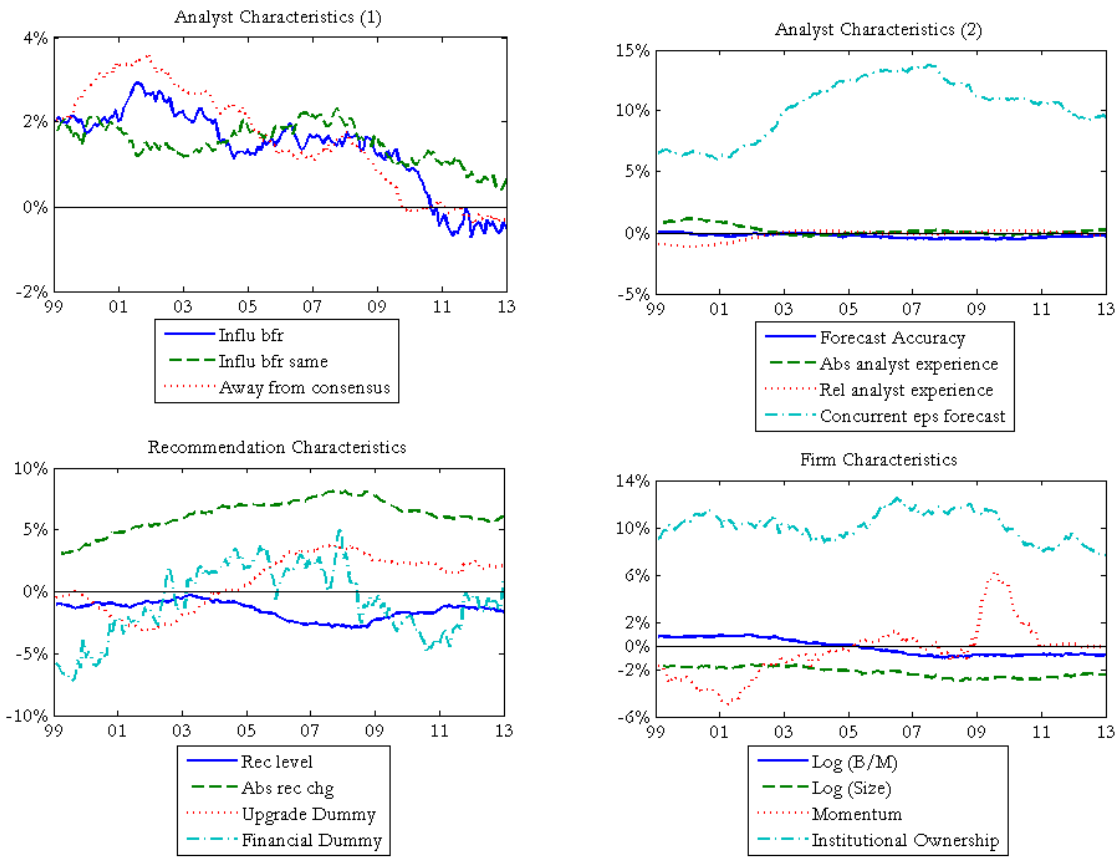

Figure 3 – Marginal effect of influential characteristics based on abnormal return

Marginal effects from a 5-year rolling window Probit model estimated monthly, starting in 1999, using characteristics of influential recommendation as the explanatory variable. The binary dependent variable is 1 if the recommendation is influential and 0 otherwise. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability the independent variable change by one standard deviation (from 0 to 1). Influential recommendations have been defined in two different manners. First, a recommendation change is influential on abnormal returns when $|CAR_i|>1.96 \times\sqrt{2}\times\sigma_{\varepsilon_i}$. *Forecast accuracy* is the analysts' prior quintile (lower rank represents greater accuracy). *Away from consensus* is one when the new recommendation has a higher absolute deviation than the absolute deviation of the prior recommendation consensus. *Absolute analyst experience* is the number of quarters an analyst is in the I/B/E/S prior to the recommendation and *Relative analyst experience* is the difference between the *Absolute analyst experience* and the mean *Absolute analyst experience* of other analysts for the same company. *Financial Dummy* is one if the recommendation is for a firm in the financial and insurance sector. *Concurrent earnings forecast* is one if the analyst issues an earnings forecast (FY1) in a three-day window around the recommendation.

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Table I – Transition probabilities of recommendation changes

	Current Recommendation					
	1	2	3	4	5	
Prior Recommendation	(Sell)	(Underperform)	(Hold)	(Buy)	(Strong Buy)	Total
1 (Sell)	241	194	2,120	166	245	2,966
	8.1%	6.5%	71.5%	5.6%	8.3%	100%
2 (Underperform)	239	1,073	3,761	632	139	5,844
	4.1%	18.4%	64.4%	10.8%	2.4%	100%
3 (Hold)	2,226	4,193	11,206	14,775	10,852	43,252
	5.1%	9.7%	25.9%	34.2%	25.1%	100%
4 (Buy)	226	793	18,397	8,299	8,419	36,134
	0.6%	2.2%	50.9%	23.0%	23.3%	100%
5 (Strong Buy)	311	208	13,428	9,060	4,825	27,832
	1.1%	0.7%	48.2%	32.6%	17.3%	100%
Total	3,243	6,461	48,912	32,932	24,480	116,028

Reports the transition probabilities of recommendations changes (e.g. in column 5 when the prior recommendation is a sell, it has a probability of 8.9% of moving to a strong buy in the next quarter). The sample of recommendation changes is from the I/B/E/S Detail U.S. File in the period between 1993 and 2012. Each recommendation change is the difference between analyst's current rating and her prior rating. Analyst initiations or anonymous analysts are excluded. Rating is coded from 5 (strong buy) to 1 (sell), and the rating changes level lies between -4 and 4.

Table II – Descriptive statistics of CARs

Filtered Samples	Mean	Mode	% CAR +	Skewness	Kurtosis	KS test	Percentiles 99%	75%	Median	25%	1%	# Obs
						Recommendation Change = -4						
1) Full Sample	-6.551	2.620	36.334	-4.77	41.00	0.424 ***	23.01	1.39	-2.335	-9.48	-74.76	311
2) Influential	-24.196	-3.445	0.000	1.15	21.57	0.510 ***	-2.47	-10.22	-14.848	-28.39	-170.92	87
3) 2007-2012	-10.418	2.620	-4.272	0.95	27.46	0.431 ***	32.62	1.17	-5.502	-12.13	-156.22	105
4) Influential 2007-2012	-27.998	-5.957	0.000	2.50	14.40	0.514 ***	-3.44	-10.40	-14.596	-26.57	-201.14	40
						Recommendation Change = -3						
1) Full Sample	-3.779	-0.281	36.636	-1.86	11.62	0.404 ***	27.40	1.69	-1.120	-5.47	-59.70	434
2) Influential	-24.110	-8.111	0.000	-1.46	5.03	0.509 ***	-2.44	-10.41	-19.990	-29.39	-86.42	83
3) 2007-2012	-4.655	0.512	29.231	-3.17	18.22	0.428 ***	27.47	0.59	-2.110	-5.31	-83.33	65
4) Influential 2007-2012	-22.092	-8.250	0.000	-2.037	6.21	0.510 ***	-2.59	-9.90	-14.622	-25.36	-88.38	14
						Recommendation Change = -2						
1) Full Sample	-4.250	-0.044	34.438	-3.56	31.51	0.426 ***	20.73	1.14	-1.602	-6.02	-62.60	16,447
2) Influential	-17.915	-3.216	0.000	-3.16	17.72	0.506 ***	-2.57	-6.70	-11.363	-20.87	-101.84	4,237
3) 2007-2012	-3.318	0.701	35.232	-4.34	51.54	0.417 ***	26.79	1.44	-1.672	-5.94	-54.73	5,864
4) Influential 2007-2012	-14.842	-2.781	0.000	-4.814	36.24	0.506 ***	-2.40	-5.99	-9.373	-16.03	-102.99	1621
						Recommendation Change = -1						
1) Full Sample	-3.661	-0.468	36.429	-3.30	29.45	0.429 ***	18.25	1.39	-1.393	-5.58	-54.29	31,889
2) Influential	-17.248	-3.351	0.000	-2.95	17.00	0.506 ***	-2.56	-6.72	-11.497	-20.98	-83.52	7,191
3) 2007-2012	-2.619	1.592	37.483	-4.16	55.33	0.419 ***	23.61	1.52	-1.286	-5.09	-40.82	8,892
4) Influential 2007-2012	-13.898	-2.769	0.000	-5.027	43.05	0.506 ***	-2.29	-5.85	-9.367	-15.71	-80.35	2110
						Recommendation Change = 0						
1) Full Sample	-0.141	0.334	50.542	-2.62	56.52	0.430 ***	17.03	2.44	0.042	-2.30	-21.02	25,644
2) Influential	9.134	2.617	100.000	4.60	51.09	0.505 ***	39.38	10.92	6.861	4.56	2.08	2,188
3) 2007-2012	0.039	0.405	51.353	-1.42	108.82	0.434 ***	15.84	2.45	0.102	-2.22	-16.01	8,204
4) Influential 2007-2012	8.110	2.219	100.000	7.544	109.58	0.505 ***	33.05	9.76	6.315	4.19	1.90	923

(continued)

Table II – Continued

Filtered Samples	Mean	Mode	% CAR +	Skewness	Kurtosis	KS test	Percentiles 99%	75%	Median	25%	1%	# Obs
						Recommendation Change = +1						
1) Full Sample	2.085	-0.188	63.431	1.27	40.11	0.429 ***	27.57	4.96	1.374	-1.37	-18.94	27,149
2) Influential	11.293	2.893	100.000	5.21	62.81	0.507 ***	44.47	13.85	8.769	5.73	2.57	5,583
3) 2007-2012	1.823	-0.690	62.029	2.18	47.31	0.427 ***	27.18	4.75	1.265	-1.61	-19.95	8,272
4) Influential 2007-2012	10.661	2.847	100.000	6.309	69.86	0.507 ***	41.80	12.82	8.139	5.36	2.35	1895
						Recommendation Change = +2						
1) Full Sample	2.065	2.655	63.717	-2.94	174.62	0.431 ***	26.14	4.90	1.436	-1.26	-19.30	13,604
2) Influential	10.725	2.783	100.000	6.31	89.58	0.506 ***	39.98	13.15	8.438	5.61	2.38	3,087
3) 2007-2012	2.335	-0.818	64.253	3.21	69.87	0.428 ***	28.58	5.25	1.666	-1.29	-20.38	5,399
4) Influential 2007-2012	10.839	2.524	100.000	7.844	109.36	0.506 ***	41.53	12.97	8.548	5.60	2.29	1430
						Recommendation Change = +3						
1) Full Sample	1.125	-0.770	54.754	1.17	13.25	0.421 ***	27.26	3.68	0.414	-1.95	-22.66	305
2) Influential	13.742	2.793	100.000	2.16	8.56	0.511 ***	56.08	16.32	11.625	7.09	2.79	40
3) 2007-2012	0.595	-1.071	49.206	1.68	9.99	0.448 ***	29.38	2.31	-0.089	-2.88	-18.26	63
4) Influential 2007-2012	12.582	2.793	100.000	0.801	2.20	0.511 **	30.04	19.12	9.976	4.81	2.79	8
						Recommendation Change = +4						
1) Full Sample	1.922	3.124	62.449	-2.25	31.08	0.441 ***	20.38	4.85	1.458	-1.25	-17.81	245
2) Influential	9.572	3.948	100.000	0.83	2.85	0.506 ***	24.25	11.68	8.365	5.23	1.60	52
3) 2007-2012	3.140	0.711	64.444	1.06	12.28	0.452 ***	36.02	6.37	1.780	-0.77	-24.87	90
4) Influential 2007-2012	9.775	8.749	100.000	0.582	2.44	0.506 ***	20.18	12.21	9.448	5.27	1.57	24

Each panel reports summary statistics for the two-day (0,1) buy-and-hold CAR (in percent) of a recommendation change category. Daily abnormal return is the raw return less the daily return of the corresponding DGTW portfolio. The sample of recommendation changes is from the I/B/E/S Detail U.S. File in the period between 1993 and 2012. Each recommendation change is the difference between analyst's current rating and her prior rating. Analyst initiations or anonymous analysts are excluded. Rating is coded from 5 (strong buy) to 1 (sell), and the rating changes level lies between -4 and 4. KS test is the Kolmogorov-Smirnov D statistic testing for the normality of the sample distribution where *, **, *** denote the significance levels of 10%, 5%, and 1%, respectively for the rejection of the null hypothesis of normality.

Table III – Analyst and firm characteristics around the recommendation event

	Influential based on firm's							
	Abnormal return				*Abnormal turnover*			
Characteristics	Non Influential	Influential	Difference	*t*-stat	Non Influential	Influential	Difference	*t*-stat
Panel A: Analyst characteristics								
Number of recommendation changes	93,480	22,548			85,955	30,073		
		19.43%				25.92%		
Forecast accuracy quintile	2.463	2.488	0.025 ***	(6.14)	2.466	2.473	0.007 **	(1.65)
Away from consensus	0.502	0.562	0.060 ***	(40.66)	0.503	0.544	0.041 ***	(27.61)
Absolute analyst experience (# Qtrs)	18.937	20.878	1.941 ***	(42.43)	18.923	20.433	1.510 ***	(33.01)
Relative analyst experience	7.626	8.523	0.896 ***	(22.79)	7.660	8.201	0.540 ***	(13.74)
Concurrent earnings forecast	0.444	0.602	0.158 ***	(107.49)	0.438	0.578	0.140 ***	(95.62)
Influential before (any stock)	0.708	0.772	0.063 ***	(47.99)	0.708	0.757	0.050 ***	(37.72)
Influential before (same stock)	0.297	0.348	0.051 ***	(37.63)	0.296	0.338	0.042 ***	(31.32)
Panel B: Firm characteristics prior to recommendation								
B/M ratio	0.302	0.206	-0.095 ***	(-3.58)	0.252	0.294	-0.042 *	(-1.6)
Size ($m)	11053.686	10863.568	-190.118 **	(-2.03)	11001.953	11059.007	57.054	(0.61)
Institutional ownership (%)	61.687	65.770	4.083 ***	(52.91)	61.181	66.196	5.015 ***	(64.99)

Comparison of non-influential recommendation changes with influential ones, influential recommendation changes are defined either on abnormal return or turnover. A recommendation change is influential on abnormal returns when $|CAR_i|>1.96 \times\sqrt{2}\times\sigma_{\varepsilon}$. A recommendation change is influential on abnormal turnover when $CAT_i>1.96 \times\sqrt{2}\times\sigma_{abturn_i}$. Abnormal *turnover$_i$* is log *turnover$_i$*- $\overline{\log turnover}_i$, where log *turnover$_i$* = log(*turnover$_i$* + 0.00000255). *, **, *** denote the significance levels of 10%, 5%, and 1%, respectively. Panel A compares analyst characteristics between non-influential recommendation changes versus influential ones. *Past Forecast accuracy quintile* is the analysts' prior quintile (lower ranks represent greater accuracy). *Away from consensus* is one when the new recommendation has a higher absolute deviation than the absolute deviation of the prior recommendation consensus. *Absolute analyst experience* is the number of quarters an analyst is in the I/B/E/S prior to the recommendation and *Relative analyst experience* is the *Absolute analyst experience* minus mean *Absolute analyst experience* of other analysts for the same company. *Concurrent earnings forecast* is one if the analyst issues an earnings forecast (FY1) in a three-day window around the recommendation. *Influential before (any stock)* look at whether the analyst issuing the recommendation has previously been influential for any stock he follows, while *Influential before (same stock)* only considers the same stock as for the recommendation the analyst issuing. Panel B compares firm characteristics, such as *B/M ratio*, *Size* and percentage of shares hold by institutions (*Institutional ownership*), between non-influential recommendation change and influential ones, prior to the recommendation announcement.

Table IV – Characteristics of influential recommendation changes

	Influential based on firm's					
	Abnormal return			*Abnormal turnover*		
Explantory Variable	Coefficient		Marginal Effect	Coefficient		Marginal Effect
Influential before (any stock)	0.102	***	2.711	0.065	***	2.071
	(8.72)			(5.99)		
Influential before (same stock)	0.042	***	1.122	0.041	***	1.307
	(4.12)			(4.25)		
Recommendation level	-0.042	***	-1.118	-0.044	***	-1.392
	(-7.31)			(-8.13)		
Absolute value of recommendation change	0.224	***	5.959	0.185	***	5.903
	(34.61)			(30.54)		
Upgrade Dummy	0.054	***	1.440	0.028	**	0.887
	(4.53)			(2.49)		
Reg FD Dummy	0.073	***	1.949	0.065	***	2.068
	(5.37)			(5.08)		
Financial Dummy	-0.060		-1.592	-0.024		-0.766
	(-1.09)			(-0.48)		
Past forecast accuracy quintile	0.000		0.010	-0.009	***	-0.286
	(0.12)			(-3.08)		
Away from consensus	0.082	***	2.176	0.047	***	1.503
	(9.28)			(5.72)		
Absolute analyst experience	0.005	***	0.124	0.005	***	0.150
	(4.53)			(4.86)		
Relative analyst experience	-0.004	***	-0.109	-0.005	***	-0.163
	(-3.75)			(-4.96)		
Concurrent earnings forecasts	0.331	***	8.814	0.310	***	9.893
	(38.11)			(38.2)		
Log (B/M)	-0.028	***	-0.732	-0.004		-0.118
	(-10.99)			(-1.58)		
Log (Size)	-0.044	***	-1.159	-0.075	***	-2.398
	(-10.69)			(-19.71)		
Price Momentum	-0.004		-0.110	-0.003		-0.091
	(-1.02)			(-0.73)		
Log (Institutional ownership)	0.221	***	5.887	0.286	***	9.102
	(12.19)			(16.61)		

This table presents Probit models estimates and t-statistics in brackets below the coefficients. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability the independent variable change by one standard deviation (from 0 to 1). The binary dependent variable is one if the recommendation is influential, and zero otherwise. Influential recommendations have been defined in two ways. First, a recommendation change is influential on abnormal returns when $|CAR_i| > 1.96 \times \sqrt{2} \times \sigma_{\varepsilon_i}$. Second, a recommendation change is influential on abnormal turnover when $CAT_i > 1.96 \times \sqrt{2} \times \sigma_{abturn_i}$. Abnormal turnover is $\log turnover_i - \overline{\log turnover_i}$ where $\log turnover_i = \log(turnover_i + 0.00000255)$. *, **, *** denote the significance levels of 10%, 5%, and 1%, respectively. *Influential before (any stock)* look at whether the analyst issuing the recommendation has previously been influential for any stock he follows, while *Influential before (same stock)* only considers the same stock as for the recommendation the analyst issuing. *Past Forecast accuracy quintile* is the analysts' prior quintile (lower ranks represent greater accuracy). *Away from consensus* is one when the new recommendation has a higher absolute deviation than the absolute deviation of the prior recommendation consensus. *Absolute analyst experience* is the number of quarters an analyst is in the I/B/E/S prior to the recommendation and *Relative analyst experience* is the *Absolute analyst experience* minus mean *Absolute analyst experience* of other analysts for the same company. *Financial Dummy* is one if the recommendation is for a firm in the financial and insurance sector. *Concurrent earnings forecast* is one if the analyst issues an earnings forecast (FY1) in a three-day window around the recommendation.

Table V – Investment strategies

Portfolio	Mthly avg # firms	Avg mkt cap ($m)	Ann mean (%)	Ann std dev (%)	Skewness	Kurtosis	Ann Sharpe ratio	Ann CEQ (%)	Ann Turnover (%)	Coefficient estimates for the four factor model: Ann Intercept (%)	Rm-Rf	SMB	HML	UMD	Adjusted R^2	$Corr_{long,short}$
Panel A: CRSP equally weighted index																
			10.73	21.17	-0.08	4.35	0.40	6.24		2.85 *	0.89 ***	0.67 ***	0.08 *	-0.22 ***	0.91	
Panel B: Portfolio formed on the basis of naïve long-only strategy (1/N)																
Long	1,279	5,175.43	7.39	19.27	-0.06	4.49	0.26	3.67	49.60	-0.71	0.88 ***	0.55 ***	0.21 ***	-0.12 ***	0.88	
Panel C: Equally weighted portfolios formed on the basis of changes in consensus recommendation																
Long	879	6,584.25	6.53	19.67	0.00	4.50	0.22	2.66	49.05	-1.26	0.90 ***	0.51 ***	0.20 ***	-0.14 ***	0.86	
Short	69	4,584.85	5.63	21.46	0.49	5.69	0.16	1.03	46.96	-1.85	0.84 ***	0.48 ***	0.37 ***	-0.30 ***	0.76	
Long-Short	948	6,438.19	0.89	8.25	-1.35	7.59	-0.17	0.21	96.00	-1.69	0.07 *	0.03	-0.17 ***	0.16 ***	0.26	0.92
Panel D: Equally weighted portfolios formed on the basis of influential changes in consensus recommendation																
Long	633	8,611.82	6.11	20.15	0.08	4.52	0.19	2.05	48.66	-1.33	0.93 ***	0.46 ***	0.19 ***	-0.16 ***	0.85	
Short	26	5,886.52	5.13	25.73	0.88	8.91	0.11	-1.49	44.07	-1.98	0.68 ***	0.75 ***	0.16	-0.48 ***	0.64	
Long-Short	659	8,503.99	0.97	14.36	-1.67	16.51	-0.09	-1.09	92.73	-1.63	0.25 ***	-0.29 ***	0.02	0.32 ***	0.19	0.83
Panel E: Equally weighted portfolios formed on the basis of changes in consensus recommendation change																
Long	550	6,615.13	7.23	19.73	-0.04	4.45	0.25	3.34	49.42	-0.80	0.93 ***	0.50 ***	0.20 ***	-0.09 ***	0.86	
Short	338	6,826.13	4.81	20.37	0.20	4.78	0.12	0.66	48.70	-2.46	0.88 ***	0.50 ***	0.19 ***	-0.24 ***	0.85	
Long-Short	887	6,695.46	2.41	4.69	-0.61	5.52	0.03	2.19	98.12	-0.62	0.05 **	0.01	0.01	0.14 ***	0.34	0.97
Panel F: Equally weighted portfolios formed on the basis of influential changes in consensus recommendation change																
Long	377	9,275.26	5.72	19.90	0.06	4.35	0.17	1.76	48.43	-1.49	0.96 ***	0.40 ***	0.14 ***	-0.11 ***	0.84	
Short	151	8,955.40	5.79	22.15	0.32	4.88	0.16	0.88	50.21	-1.44	0.91 ***	0.55 ***	0.15 **	-0.30 ***	0.85	
Long-Short	528	9,183.60	-0.07	6.34	-0.04	7.50	-0.37	-0.47	98.64	-2.33 *	0.04	-0.15 ***	-0.01	0.19 ***	0.38	0.96
Panel G: Equally weighted portfolios formed on the basis buying all recommendations (holding period 20 days)																
Long	349	10,528.55	5.72	23.46	-0.73	4.47	0.15	0.21	236.25	-2.32	1.19 ***	0.43 ***	0.18 ***	-0.14 ***	0.91	
Short	257	9,623.48	-17.51	24.31	-0.87	5.17	-0.81	-23.42	243.51	-25.01 ***	1.15 ***	0.44 ***	0.13 **	-0.23 ***	0.87	
Long-Short	607	10,144.43	17.24	25.55	1.14	5.77	0.59	10.71	479.76	20.20 ***	-1.20 ***	-0.44 ***	-0.13 *	0.24 ***	0.85	0.97

(continued)

Table V – Continued

Portfolio	Mthly avg # firms	Avg mkt cap ($m)	Ann mean (%)	Ann std dev (%)	Skewness	Kurtosis	Ann Sharpe ratio	Ann CEQ (%)	Ann Turnover (%)	Coefficient estimates for the four factor model: Ann Intercept (%)	Rm-Rf	SMB	HML	UMD	Adjusted R^2	$Corr_{long,short}$
Panel H: Equally weighted portfolios formed on the basis buying predicted influential recommendations (holding period 20 days)																
Long	35	8,128.79	17.20	27.28	-0.29	3.90	0.55	9.76	195.55	8.27 *	1.13 ***	0.32 ***	0.58 ***	-0.10	0.56	
Short	38	6,716.31	-16.35	32.50	0.21	5.38	-0.57	-26.92	217.17	-24.41 ***	1.37 ***	0.41 ***	0.08	-0.12	0.59	
Long-Short	72	7,392.95	34.86	26.79	1.60	10.79	1.22	27.68	412.72	31.15 ***	-0.31 **	0.02	0.52 ***	0.04	0.09	0.67
Panel I: Equally weighted portfolios formed on the on the basis of TPER consensus change																
Long	678	4,738.78	6.40	19.02	-0.01	5.03	0.22	2.78	45.30	5.39	0.18 *	-0.22 *	-0.16	0.03	0.01	
Short	137	8,824.02	4.15	13.88	-0.32	11.05	0.13	2.22	15.87	2.07	0.18 **	-0.17 *	-0.05	0.13 **	0.03	
Long-Short	816	5,426.19	0.68	2.36	0.62	10.92	-0.68	0.63	61.17	-1.49 **	-0.01	0.00	0.00	-0.02 *	0.00	0.71
Panel J: Equally weighted portfolios formed on the basis of TPER consensus change and changes in consensus recommendation																
Long	201	4,811.06	10.87	22.33	-0.02	4.46	0.22	5.88	52.81	10.03 *	0.24 **	-0.24	-0.18	-0.01	0.02	
Short	20	5,169.42	3.00	15.79	0.22	11.13	0.04	0.51	15.08	0.81	0.23 ***	-0.21 *	-0.03	0.15 **	0.04	
Long-Short	221	4,843.74	4.44	6.56	-1.26	15.75	0.33	4.01	67.88	2.37	-0.06	0.04	-0.05	-0.03	0.00	0.63
Panel K: Equally weighted portfolios formed on the basis of TPER consensus change and changes in consensus recommendation change																
Long	244	4,104.85	13.22	21.32	0.00	4.58	0.51	8.67	54.13	11.91 **	0.28 **	-0.21	-0.15	0.00	0.03	
Short	32	6,048.25	4.68	15.80	0.29	11.06	0.15	2.18	14.95	2.58	0.20 **	-0.20 *	-0.04	0.16 **	0.04	
Long-Short	276	4,330.18	2.50	5.35	0.50	10.34	0.04	2.21	69.08	0.14	0.00	0.04	-0.01	-0.02	-0.01	0.63
Panel L: Equally weighted portfolios formed on the basis of TPER consensus change and influential changes in consensus recommendation																
Long	150	7,919.70	10.33	22.59	0.23	4.40	0.36	5.23	49.32	9.70	0.21 *	-0.26 *	-0.18	-0.01	0.02	
Short	5	8,320.77	2.28	19.12	2.84	24.00	0.00	-1.38	12.22	-0.09	0.21 **	-0.19	0.05	0.11	0.01	
Long-Short	154	7,931.54	3.18	11.57	-2.48	25.51	0.08	1.85	61.54	1.01	-0.03	0.04	-0.07	-0.01	-0.02	0.52
Panel M: Equally weighted portfolios formed on the basis of TPER consensus change and influential changes in consensus recommendation change																
Long	127	6,564.56	8.61	21.20	0.11	4.44	0.30	4.12	47.61	8.33	0.22 *	-0.31 **	-0.22	0.00	0.03	
Short	9	7,991.90	7.47	19.82	2.25	22.65	0.26	3.54	15.74	6.49	0.19 *	-0.30 **	-0.17	0.15 *	0.03	
Long-Short	136	6,658.42	-0.80	9.60	-4.18	41.53	-0.32	-1.72	63.35	-3.96	-0.01	0.10	0.10	-0.02	0.00	0.61

This table reports the monthly average number of firms in a portfolio, the average market capitalization of the firms in each portfolio, annualized mean return (in percent), annualized standard deviation (in percent), skewness, kurtosis, annualized Sharpe ratio, annualized CEQ return (in percent, and annualized turnover of the Buy and Sell portfolios for the Naïve, Analyst Consensus, and Influential Analyst Consensus Strategies between 1999 and 2012. The certainty equivalent is computed using the power utility function with a risk aversion of 2. We estimate the four factor model using the Fama and French and Momentum factors. $Corr_{long,short}$ is the correlation between the long and short portfolios for each strategy. *, **, *** denote the significance levels of 10%, 5%, and 1%, respectively.