Influential analyst recommendations:
Are they the hidden gem?

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Abstract

Informational signals play an important role in Finance. From an ex post exercise, there are 20% influential analyst recommendations in terms of impact on the price. We perform a predicting exercise to forecast influential recommendations changes. We find that ex ante these depend on the magnitude of the recommendation change, concurrent earnings forecasts issued around the recommendation change, and firm institutional ownership. From this knowledge, we construct an out of sample long-short portfolio that buys positive and sells negative influential recommendation changes' stocks. 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.

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.

There is evidence that, during the period between 1965 and 1989, trading strategies long on past winner and short on past loser stocks realize significant abnormal returns (Jegadeesh and Titman, 1993). This is not due to systematic risk and can also not be attributed to delayed stock price reactions to common factors. Still, there is evidence that firm-specific information causes the delay in price reaction. Therefore, analyst recommendations, 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.

Loh and Stulz (2011) 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. Our results show that the percentage of influential

[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

recommendations is actually greater, 19.4% for our sample. 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.

Using Loh and Stulz (2011) findings that there is a specific group of recommendation changes that has a greater impact on the market and can be described by specific characteristics, we perform a predicting exercise to forecast influential recommendations changes. We find that ex ante these depend on the magnitude of the recommendation change, concurrent earnings forecast, and firm institutional ownership. From this knowledge, we construct an out of sample long-short portfolio that buys positive and sells negative influential recommendation changes' stocks, similar to the one proposed by Womack (1996). 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.

The rest of this paper is organized as follows. Section 2 describes the data used. Section 3 discusses the predictions of influential recommendation changes. Section 4 considers the results of our proposed out of sample investment strategy and Section 5 considers various robustness checks on our results. Finally Section 6 concludes.

2. Data & Methodology

2.1. 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. The rating changes level lies between -4 and +4, as ratings are coded as 5 (strong buy) to 1 (sell). 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 the 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. The daily turnover is computed using the volume and shares outstanding. We compute the book-to-market ratio by 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].

2.2. Influential analyst recommendations

We follow Loh and Stulz (2011) to compute influential analyst recommendation revisions, and use their method 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 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:

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

$$|CAR_i| > 1.96 \times \sqrt{2} \times \sigma_{\varepsilon_i} \qquad (2)$$

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

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.

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.

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. For negative revisions the 25th and 1st percentiles have larger negative returns opposed to the positive ones. This shows that company specific news-recommendations and outliers have a strong impact on the means. Filtering the CAR means for influential recommendation changes we notice that these 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 results look like and show the statistical and economic significance of influential recommendations. Investors, who are able to successfully identify these recommendations changes when they are issued, are able to profit from significant returns.

3. Predicting influential recommendations

In this section we look at the determinants of influential recommendation changes. First we define the characteristics specific characteristics of analyst, which have been shown to have an impact on the stock price when a recommendation is issued. Then we look at how recommendation, analyst, and firm characteristics vary between influential recommendation changes and all recommendation changes. Also, we study the likelihood that a certain characteristic will result in an influential recommendation change.

3.1. The determinants

Earnings forecast accuracy: Loh and Mian (2006) show that analysts who more accurately forecast earnings also issue more profitable stock recommendations and therefore such analysts can have a larger impact on the stock price. We compute the *Earnings forecast accuracy* quintile of an analyst by sorting analysts within a firm-year into quintiles using the last unrevised FY1 forecast of the analyst, as proposed by Loh and Stulz (2011). The forecast accuracy rank (1 being the most accurate) is assigned to the analyst for the recommendations that the analyst issues during the 12-month window that overlaps three months into the next fiscal year, following Loh and Mian (2006). This allows to apply the accuracy rank during the months when the fiscal year's actual earnings are announced.

Away from consensus: Jegadeesh and Kim (2010) analyze if analysts have a tendency to take similar actions around the same time. To understand whether an analyst is not affected by this bias, implying 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).

Analyst experience: According to Mikhail, Walther, and Willis (1997) earnings forecast accuracy of analysts improve with experience. Thus, experience can be associated to the impact of influential recommendation changes. We measure analyst experience measured as the number of quarters since the analyst issued the stock recommendation on I/B/E/S. Loh and Stulz (2011) suggest to analyze analyst experience in both absolute and relative terms. *Absolute analyst experience* represents the total number of quarters that analyst appeared on I/B/E/S. While *Relative analyst experience* is the numbers of quarters the analyst has covered that specific firm minus the average experience for all analysts covering the firm.

Concurrent Earnings Forecast: Stock recommendations supplemented by earnings forecast revisions have greater price movements (Kecskes, Michaely, and Womack, 2009). Hence, we include a *Concurrent earnings forecast* indicator variable specifying if the same analyst issued a FY1 forecast in the three-day window around the recommendation revision.

Influential Before: Loh and Stulz (2011) show that a recommendation change by an analyst, who has previously been influential for any stock increases the likelihood of an influential recommendation change. The likelihood further increases if the analyst had already been influential for the same stock. Therefore, we look at both analysts that had previously been influential for any stock and the same stock.

3.2. Influential versus non-influential recommendation changes

To understand the determinants of influential recommendation we analyze in table III the differences of the characteristics between regular analyst recommendations revisions and influential. While in table IV, using an in sample Probit estimation, we look at what characteristics increase the predictability of an analyst recommendation change.

In Table III, we observe that influential recommendations revisions are less accurate, in terms of earnings forecasts, 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, earnings forecast accuracy does not provide much incremental predictability. We find that, on average, influential recommendation changes are further *Away from consensus* (Table III). In line with Jegadeesh and Kim (2010), we find that recommendation changes that are further *Away from 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, 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 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). Table IV shows that analysts, who have previously been 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 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 (Table IV). 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 recommendations 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). Consistent with Loh and Stulz (2011), 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 regulatory change investors started to give more attention to analyst recommendations.

3.3. Forecast

To forecast influential recommendation changes for an out of sample investment strategy, we run, on monthly basis, a Probit regression with a five-years rolling window. The first estimation is between January 1994 and December 1998. This way we are able to account for changes in the marginal effect of the characteristics to predict influential recommendation changes for the following month.

Looking at Figure 3 we observe that *Absolute value of recommendation change*, *Concurrent earnings forecast*, and *Institutional ownership* are the main characteristics used in this strategy to predict influential recommendation changes. The greater the value of the absolute recommendation change the more likely it is that the recommendation change will be influential. We would expect this as a greater magnitude means that the analyst has come to conclusions regarding the firm, which have significantly changed his opinion concerning the prospects of the firm. A concurrent earnings forecast means that the analyst has not only considered how the firm will perform compared to its peers but also performed a deeper analysis, which led him to issue a new earnings forecast. To predict influential recommendation for the strategy we only consider earnings forecasts issued between *t*-3 and *t*, opposed to *t*-3 to *t* 3 used for the ex post analysis of influential recommendation changes. Moreover, the fact that *institutional ownership* is also a key characteristic shows that institutional investors are more concerned with the opinion of sell-side analysts. One possible explanation for this is that analysts primarily target their recommendation to institutional investors and also spend more time giving them a detailed explanation of their analysis.

We perform an analysis of how well the three most predominant characteristics, *absolute recommendation change*, *concurrent earnings forecast*, and *institutional ownership* can predict influential recommendation changes. To predict an influential recommendation change we define the critical value, on monthly basis, by looking at the mean value of the characteristic for influential recommendation changes between the starting period of our sample and the prior month. If the characteristic is above the critical value when the recommendation change is issued we forecast it to be an influential recommendation change. Using only the *absolute recommendation change* characteristic we are able correctly identify 26.6%, by the means of the *concurrent earnings forecast* characteristic 26.3%, and using *institutional ownership* characteristic a mere 21.7%. However, by combining the three characteristics we are able to accurately predict 33.6% influential recommendation changes. Figure 4 shows the evolution of the forecasted influential recommendation changes using the combination of the three recommendation characteristics against the recommendation changes that actually realized as influential between 1999 and 2012.

4. Investment strategy

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 create an out of sample investment strategy that is based on forecasting influential recommendation changes. To be able to forecast influential recommendation changes, we estimate, on a monthly basis, the marginal effects of recommendation revisions characteristics using a 5 year rolling window Probit regression. Each month we identify three characteristics, (one recommendation characteristic, one analyst characteristic and another related to the firm) with the highest marginal effect. To identify whether the recommendation change will be influential we compare the characteristics to the mean of previous influential recommendations. On the recommendation announcement date the characteristics have to be greater than the means to be include in the corresponding long or short portfolio. The position is than held for a period of one month. Additionally, we compare our results with other investment strategies that consider analyst recommendations.

4.1. Buying/selling influential recommendation changes

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). 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.

Panel C shows how the first investment approach (i) with all recommendation changes performs, while the strategy in Panel D consists only of recommendation changes that are predicted to be influential. Table V shows that the investment approach (i) yields the best result. The two long-short portfolios in Panel C and D 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%.

4.2. Comparison with other analyst recommendations strategies

Several strategies that consider analyst recommendations have previously been studied and show positive results. That is why we want to understand how our proposed strategy, in section 4.1., compares to these other strategies. Our first benchmark investment approach is based on Barber et al. (2001) and uses a recommendation consensus of the last six months. We compare this approaches into two different kinds of strategies, one that considers all recommendations and one that is only concerned by influential recommendations. The first strategy uses all recommendations to build the consensus, and the second one only considers recommendations that were influential. 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 will have a worse performance when compared to our proposed strategy of buying /selling influential recommendation changes and the CRSP equally-weighted index.

The second benchmark investment approach considers a consensus constructed on recommendation changes and not levels, as proposed by Green (2006). Similarly, we build two strategies, where the first one includes all recommendations and the second only uses influential recommendation changes for the consensus. By using a consensus that considers the recommendation changes and not the level, we note that the long-short portfolio, which considers all recommendation changes, improves compared to the portfolio in 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, which only takes influential recommendation changes into account, has a poorer performance compared to its counterparty. The annualized Sharpe ratio decreases by 0.40 and the CEQ by 2.7%. Likewise, to the previous benchmark we find that the CRSP equally weighted index and our proposed strategy that is conditional to predicted influential recommendation changes perform significantly better.

4.3. Strategy implementation

To implement our proposed strategy an investor only needs to define the characteristics of analyst recommendations, as we do in section 3. Then by running a Probit regression of a monthly basis she can establish the three most relevant recommendation change characteristics.

With this information the investor is then able to determine when a recommendation change is issued whether it is likely that this one will be influential.

Example: Analyst J. Doe issues a recommendation for stock XYZ with a strong buy rating. The previous outstanding recommendation by J. Doe for stock XYZ was a hold. The portfolio manager ran the Probit regression at the beginning of the month to define which three characteristics are important for this month. She identified *Absolute value change*, *Concurrent earnings forecast*, and *Institutional Ownership* as the ones with the most predictive power. Additionally, she knows what the average value of these characteristics for influential recommendation is, 1.5 for *Absolute value change*, 80% for *Concurrent earnings forecast*, and 65% for *Institutional Ownership*. With this information she can now examine the new recommendation change. She identifies that the recommendation change moved by two levels, which is greater than the average of 1.5. Also, that the analyst issued a new earnings forecast the day before, 80% of *Concurrent earnings forecast* means that the presence of an earnings forecast is important. Last, the percentage of institutional ownership for this stock is 67%. The portfolio manager concludes that all characteristics are above the average value and the recommendation change direction is positive. Consequently, she concludes that a buy position for this XZY should be added to her portfolio. If any of the characteristics would not have been in line with the average value of the influential recommendation change characteristics, the analyst would have disregarded this recommendation.

5. Robustness checks

As mentioned in section 4 there are several steps involved in forming the different strategies. Thus, we examine whether the performance of the main strategy, which predicts influential recommendation changes and buys or sell stock accordingly, still dominates when we modify some of the steps involved in the process. First, period of time; Second, holding period; Third; TPER; Finally, we consider how transaction costs affect the different strategies.

5.1. Period of time

As the results of our strategy may be driven by the selected time period, we run the same analysis for different periods. The first period starts in 2003. We observe that the annualized Sharpe ratio decreases to 1.03. While in the second period, which starts in 2008, annualized Sharpe ratio has a stronger reduction to 0.50. During these two periods, the CRSP equally-weighted index has a poorer performance compared to both of these strategies, a Sharpe ratio of 0.48 and 0.26 for the first sub period and the second sub period respectively.

5.2. Holding period

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 portfolio still has positive Sharpe ratio of 0.58. Compared to the CRSP equally-weighted index, 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.

5.3. Target price expected return

Additionally, we consider how changes in *TPER* consensus can be used in conjunction with our stock recommendation strategies. 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 performance of the combination of the consensus approaches with change in consensus target price.

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 our proposed approach which predicts influential recommendation changes. We also look at how changes in *TPER* recommendation consensus can be combined with recommendation consensus, investment approach (ii), or recommendation changes consensus, investment approach (iii), 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 (i) investment approach that forecasts influential recommendation changes.

5.4. Transaction costs

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 ($G_{i,t}$)

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

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.

6. 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.

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 predicts influential recommendation changes and buys positive and sells negative ones 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 0.40 and an annualized CEQ return of 6.2%, during the same period we find that our proposed strategy, which influential recommendation changes based on the three most predominant characteristics.

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.

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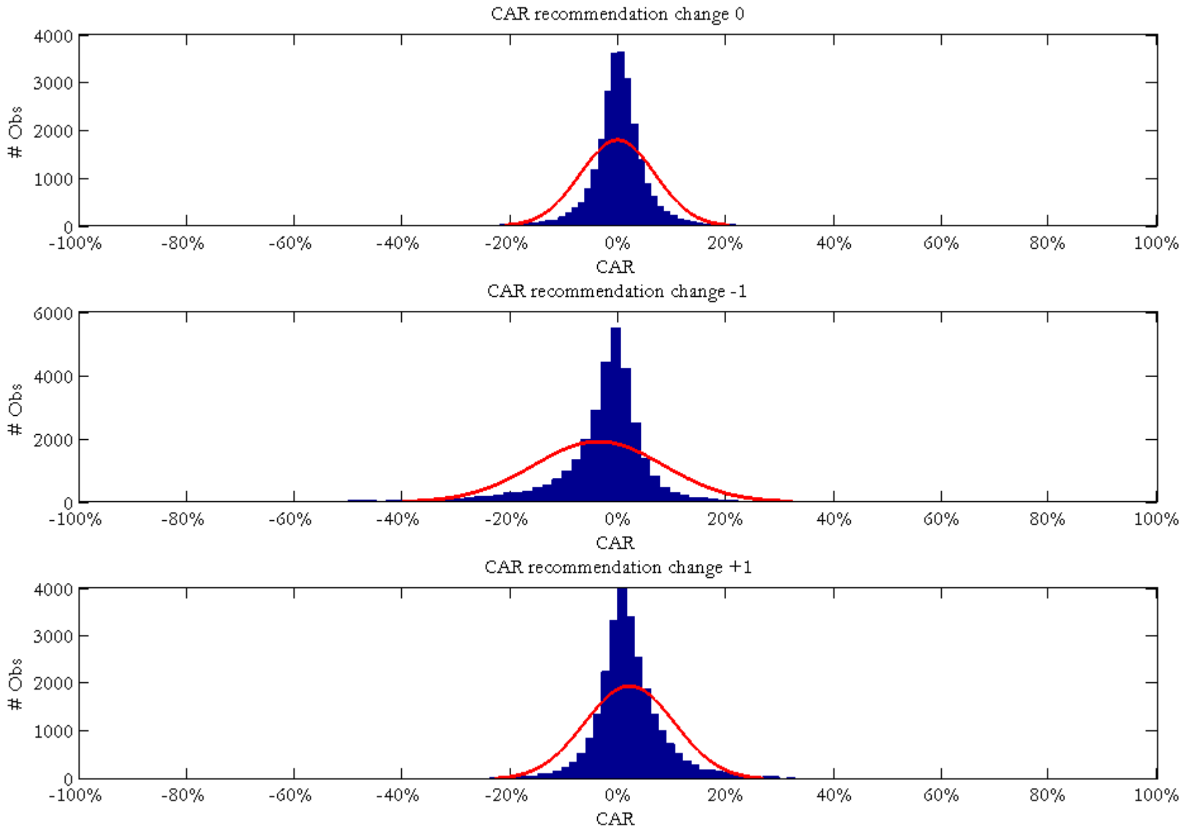

Figure 1 – Histogram of CARs for 0, -1, and +1 recommendation changes

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.

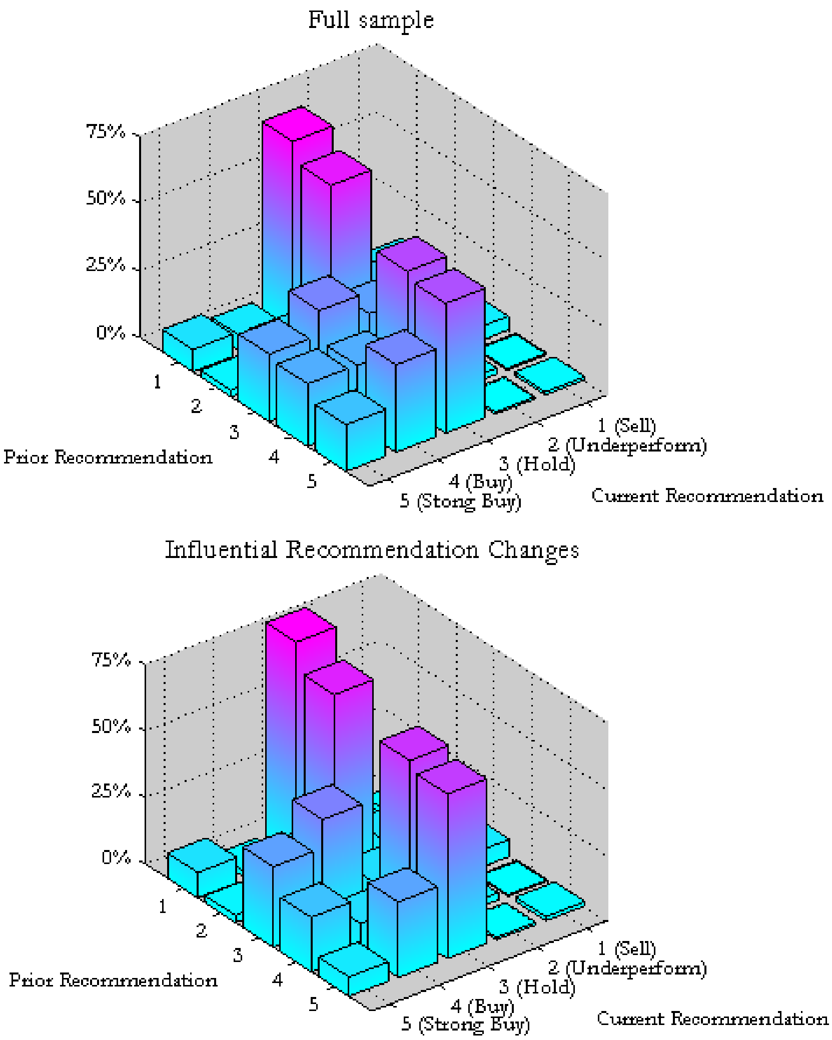

Figure 2 – Transition probabilities of recommendation changes

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.

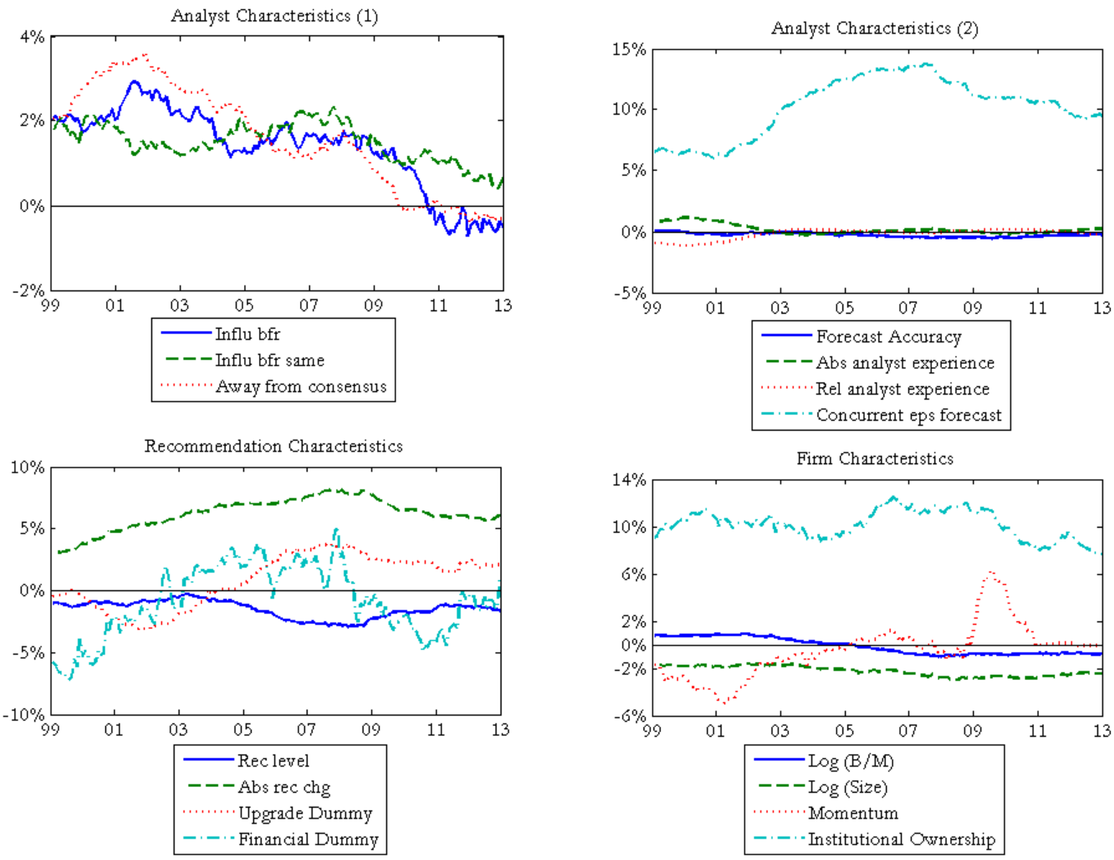

Figure 3 – Marginal effect of influential characteristics based on abnormal return

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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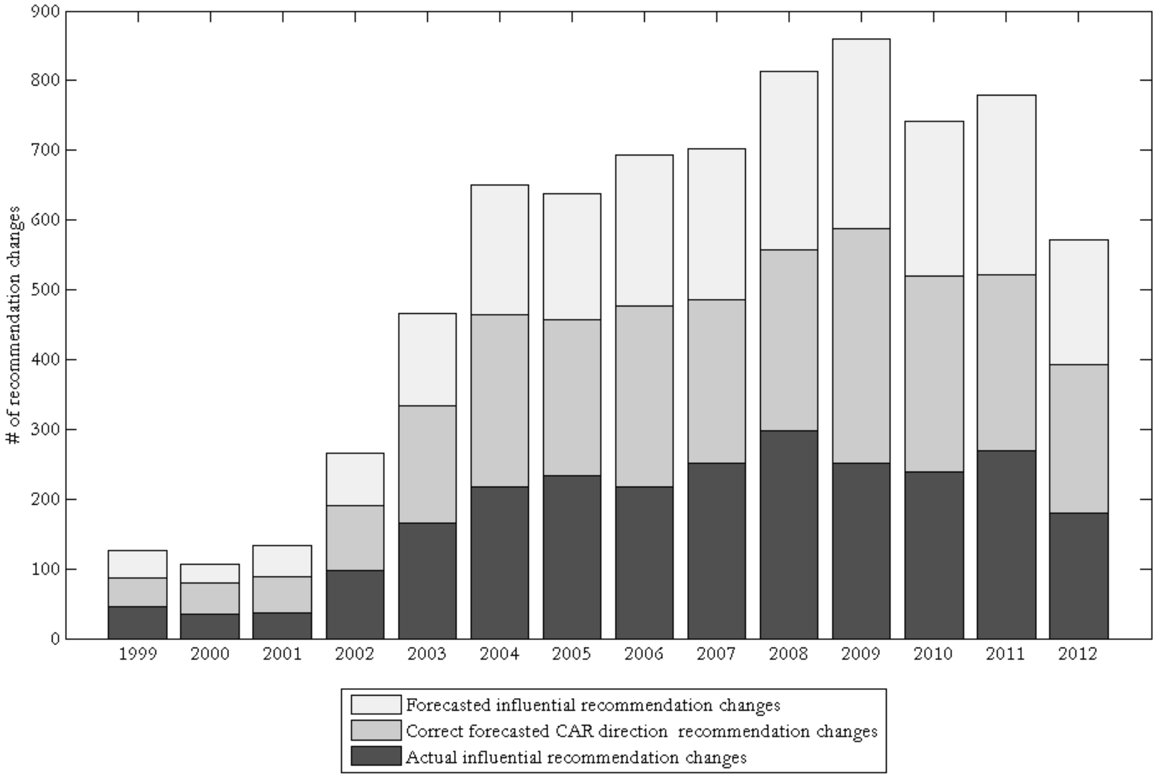

Figure 4 – Forecasted versus actual influential recommendation changes

Plots the total number of forecasted influential recommendation changes between 1999 and 2012 against the forecasted ones with the same CAR direction as the recommendation changes, and also the forecasted ones that actually concretized as influential recommendation changes. A recommendation change is forecasted as influential using the three most predominant characteristics in terms of marginal effect determined by a monthly 5 years rolling window Probit starting in 1994. The characteristic values of the recommendation change have to be above the means of influential recommendation changes issued until the new recommendation change.

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
					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
					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
					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
					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

(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
					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
					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
					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

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

Characteristics	Non Influential	Influential	Difference		*t*-stat
Panel A: Analyst characteristics					
Number of recommendation changes	93,480	22,548			
		19.43%			
Forecast accuracy quintile	2.463	2.488	0.025	***	(6.14)
Away from consensus	0.502	0.562	0.060	***	(40.66)
Absolute analyst experience (# Qtrs)	18.937	20.878	1.941	***	(42.43)
Relative analyst experience	7.626	8.523	0.896	***	(22.79)
Concurrent earnings forecast	0.444	0.602	0.158	***	(107.49)
Influential before (any stock)	0.708	0.772	0.063	***	(47.99)
Influential before (same stock)	0.297	0.348	0.051	***	(37.63)
Panel B: Firm characteristics prior to recommendation					
B/M ratio	0.302	0.206	-0.095	***	(-3.58)
Size ($m)	11053.686	10863.568	-190.118	**	(-2.03)
Institutional ownership (%)	61.687	65.770	4.083	***	(52.91)

Comparison of non-influential recommendation changes with influential ones, influential recommendation changes are defined in terms abnormal return. A recommendation change is influential on abnormal returns when $|CAR_i|>1.96\times\sqrt{2}\times\sigma_\varepsilon$. *, **, *** 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

Explantory Variable	Coefficient		Marginal Effect
Influential before (any stock)	0.102	***	2.711
	(8.72)		
Influential before (same stock)	0.042	***	1.122
	(4.12)		
Recommendation level	-0.042	***	-1.118
	(-7.31)		
Absolute value of recommendation change	0.224	***	5.959
	(34.61)		
Upgrade Dummy	0.054	***	1.440
	(4.53)		
Reg FD Dummy	0.073	***	1.949
	(5.37)		
Financial Dummy	-0.060		-1.592
	(-1.09)		
Past forecast accuracy quintile	0.000		0.010
	(0.12)		
Away from consensus	0.082	***	2.176
	(9.28)		
Absolute analyst experience	0.005	***	0.124
	(4.53)		
Relative analyst experience	-0.004	***	-0.109
	(-3.75)		
Concurrent earnings forecasts	0.331	***	8.814
	(38.11)		
Log (B/M)	-0.028	***	-0.732
	(-10.99)		
Log (Size)	-0.044	***	-1.159
	(-10.69)		
Price Momentum	-0.004		-0.110
	(-1.02)		
Log (Institutional ownership)	0.221	***	5.887
	(12.19)		

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. A recommendation change is influential on abnormal returns when $|CAR_i|>1.96 \times\sqrt{2}\times\sigma_{\varepsilon_i}$. *, **, *** 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	$Corr_{long,short}$
Panle 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: 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
Panle D: 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

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.

Online Appendix to "Influential recommendation changes: Are they the hidden gem?"

This appendix presents additional figures and tables to accompany the paper "Influential recommendation changes: Are they the hidden gem?"

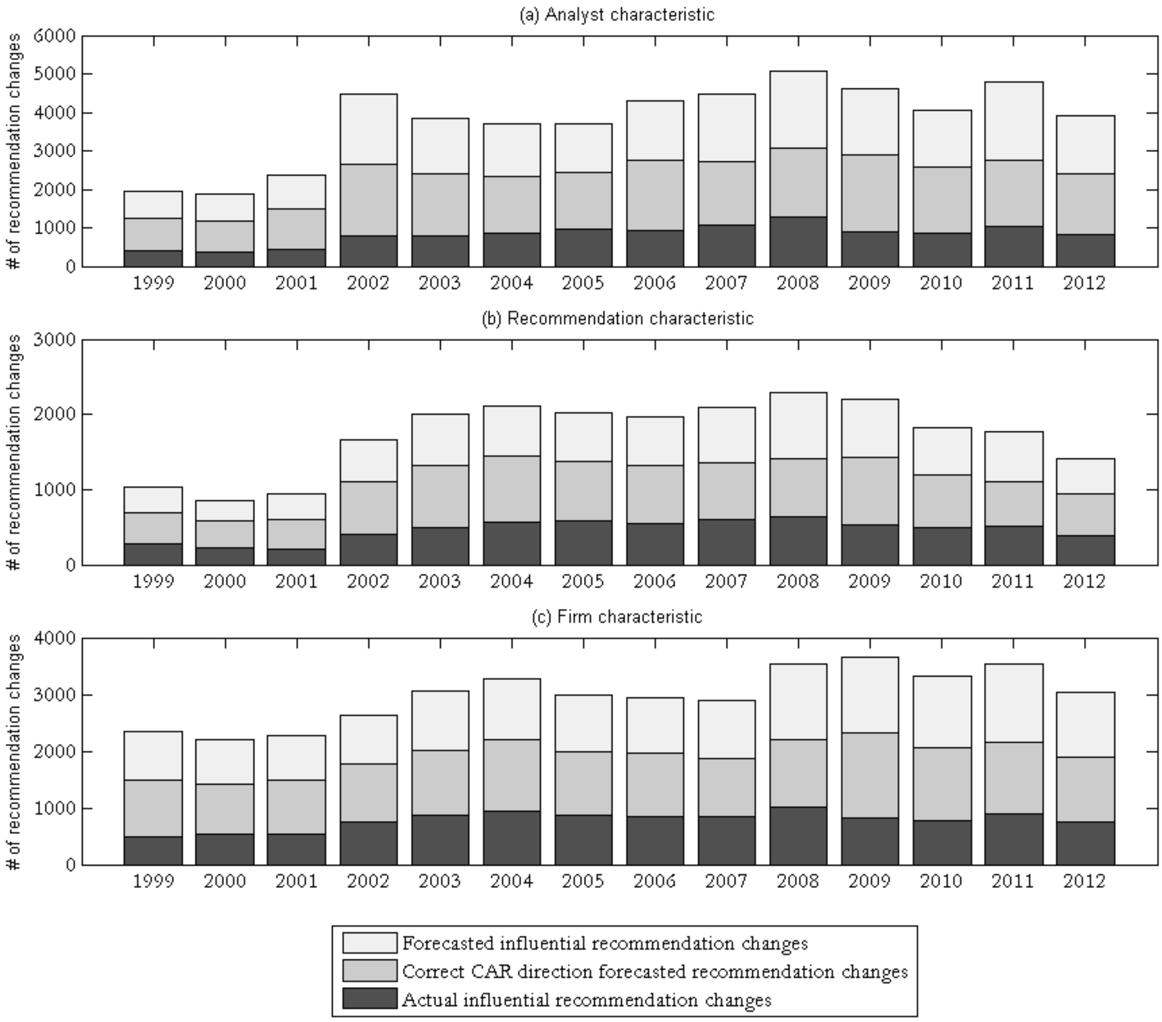

Figure 1 – Forecasted versus actual influential recommendation changes by type of characteristic

Plots the total number of forecasted influential recommendation changes between 1999 and 2012 against the forecasted ones with the same CAR direction as the recommendation changes, and also the forecasted ones that actually concretized as influential recommendation changes. A recommendation change is forecasted as influential using the three most predominant characteristics in terms of marginal effect determined by a monthly 5 years rolling window Probit starting in 1994. The characteristic values of the recommendation change have to be above the means of influential recommendation changes issued until the new recommendation change.

Table I – Descriptive statistics of CARs including filters for the period between 2007 and 2012

							Percentiles					
Filtered Samples	Mean	Mode	% CAR +	Skewness	Kurtosis	KS test	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 I – 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 II – Analyst and firm characteristics around the recommendation event in terms of abnormal return and turnover

	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 VII – Characteristics of influential recommendation changes in terms of abnormal return and turnover

	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 IV – Complete investment strategies results

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 IV – Continued

Portfolio	Mthly avg # firms	Avg mkt cap ($m)	Ann mean (%)	Ann std dev (%)	Skewness	Kurtosis	Ann Sharpe ratio	Ann CEQ (%)	Ann Turnover (%)	Ann Intercept (%)	Rm-Rf	SMB	HML	UMD	Adjusted R^2	$Corr_{long,short}$
										Coefficient estimates for the four factor model						
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.