Are rankings of financial analysts useful to

investors?*∗*

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**Abstract**

Several institutions issue rankings of financial analysts based on the ac- curacy of their price and EPS forecasts. Given that these rankings are *ex- post* they may not be useful to investors. In this paper we show that trading strategies based on perfect foresight and on past rankings outperform a pas- sive strategy. In addition, we report that investors are better off following analysts that issue accurate price targets rather than following those with accurate EPS forecasts

*keywords*: Financial Analysts; Rankings; Target price

*JEL*:G11

**1 Introduction**

The idea that financial analysts play an important role in financial markets is rather consensual (Cowles, 1933; O’Brien, 1990). Yet there is some debate on whether following the advice of analysts brings value to investors after transaction costs (Womack, 1996; Mikhail, Walther, and Willis, 2004; Li, 2005). Related to this is the difficulty in identifying the analysts with superior stock picking skills. In this paper, we show that the rankings of financial analysts are useful to investors because strategies based upon these rankings yield positive abnormal returns.

In recent years, some institutions have been very active in publishing and sell- ing rankings of financial analysts. Some rankings are based on privately held surveys of buy-side analysts (e.g., the Institutional Investor’s rankings of the All- America Research Teams1 and Bloomberg’s America’s Best Stock Analysts2); others are based on the performance of sell-side analysts (ThomsonReuters’ top StarMine analysts3). In any of these cases, the rankings aim at identifying the top analysts. However, aside from personal acknowledgment among peers, it is still arguable whether these are useful to investors (Desai, Liang, and Singh, 2000) or are merely “popularity contests” (Emery and Li, 2009).

We show that the top ranked analysts have stock picking skills. The con- tributions of our research is fourfold. First, we develop a trading strategy that transforms the rankings of financial analysts into inputs for the Black-Litterman model (Black and Litterman, 1992). Second, we show that annualized cumulative

1 [http://www.institutionalinvestor.com/Research/4560/First-](http://www.institutionalinvestor.com/Research/4560/First-Team.html)

[Team.html](http://www.institutionalinvestor.com/Research/4560/First-Team.html)

2 [http://www.bloomberg.com/news/2013-08-14/jpmorgan-top-stock- picker-with-equities-out-of-lockstep.html](http://www.bloomberg.com/news/2013-08-14/jpmorgan-top-stock-picker-with-equities-out-of-lockstep.html)

3 <http://excellence.thomsonreuters.com/award/starmine>

returns generated by some trading strategies based upon analysts’ rankings outper- form a passive strategy (e.g., buy-and-hold the general stock market index). Third, we show that the strategy based upon the perfect foresight of rankings yields the highest cumulative annualized return. Fourth, we find that investors are better off following analysts that issue the most accurate target prices, rather than those that issue the most accurate EPS forecasts.

The paper is organized as follows: Section 2 provides motivation to use rank- ings of financial analysts; Section 3 outlines our proposed trading strategies; Sec- tion 4 describes the sample and presents some preliminary results; Section 5 presents and discusses the results; and Section 6 concludes.

**2 Industry Rankings of Financial Analysts**

In the financial literature there has been a long debate on whether financial ana- lysts produce valuable advice. Some argue that following the advice of financial analysts, translated as recommendations of buying, holding, or selling a particular stock, does not yield abnormal returns, i.e., returns that are above the required return to compensate for risk. The Efficient Market Hypothesis (Fama, 1970) states that financial markets are efficient and that any public available information regarding a stock would be immediately reflected in prices; hence, it would be impossible to generate abnormal returns based upon past information.

Yet, several authors have since stressed that there are information-gathering costs and information is not immediately reflected on prices (Grossman and Stiglitz,

1980). As such, prices may not reflect all the available information at all time because if this were the case, those who spent resources to collect and analyze

information would not have an incentive to do it, because there would not get any compensation for it.

Some authors show that financial analysts’ recommendations create value to investors (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001)4. As- suming that some analysts produce valuable advice it makes sense to rank analysts based on the accuracy of their recommendations.

StarMine rankings are based on financial analysts’ accuracy either on TP or EPS forecasts. To rank analysts based on EPS forecasts, StarMine developed a proprietary metric called a Single-stock Estimating Score (SES). This score mea- sures “... [a] relative accuracy; that is, analysts are compared against their peers. An analyst’s SES can range from 0 to 100, with 50 representing the average ana- lyst. To get a score higher than 50, an analyst must make estimates that are both significantly different from and more accurate than other analysts’ estimates”5.

As for target price ranking, StarMine’s methodology compares the portfolios

based on analysts recommendations. Portfolios are constructed as follows. For each “Buy” recommendation, the portfolio is one unit long the stock and simul- taneously one unit short the benchmark. “Strong buy” gets a larger investment of two units long the stock and two units short the benchmark. “Hold” invests one unit in the benchmark (i.e., an excess return of zero). “Sell” recommendations work in the reverse way. StarMine re-balances its calculations at the end of each month to adjust for analysts revisions (adding, dropping or altering a rating), and

4 Womack (1996) finds that post-recommendation excess returns are not mean-reverting, but

are significant and in the direction forecast by the analysts. Barber et al. (2001) finds that over the period of 1986-1996 a portfolio of stocks with the most (least) favorable consensus analyst recommendations yields an average abnormal return of 4.13 (-4.91)%.

5 [http://excellence.thomsonreuters.com/award/starmine?award=](http://excellence.thomsonreuters.com/award/starmine?award=Analyst%2BAwards&amp;award_group=Overall%2BAnalyst%2BAwards)

[Analyst+Awards&award\_group=Overall+Analyst+Awards](http://excellence.thomsonreuters.com/award/starmine?award=Analyst%2BAwards&amp;award_group=Overall%2BAnalyst%2BAwards)

when a stock enters or exits an industry grouping.

Recent evidence suggests that top ranked financial analyst affect market partic- ipants: prices seem to react more to the recommendations issued by the top-ranked analysts (Emery and Li, 2009). As such, StarMine ranking based models can be used to identify such analysts and generate superior estimates (e.g., SmartEsti- mates6).

The goal of our study is to evaluate if and how rankings add value to investors.

With this purpose, we develop several sets of active trading strategies, selecting the stocks most favored by analysts. The first strategy is based on the consensus estimate (giving equal weights to analysts’ recommendations). The second set of strategies takes in consideration the analysts’ target price and EPS accuracy ranks to form “smart estimates”. For the latter set of strategies, we analyse different time information sets to define the accuracy of the analysts.

We compare the performance of the strategies based upon two types of rank- ings (target price and EPS forecast accuracy). By doing this, we indirectly address the ongoing debate in the literature on whether analysts, when issuing the target price reports, rely on simple growth-based models or use more complex models (such as the residual income model of Ohlson (1995)). For example, Bradshaw (2004) suggests that analysts’ EPS forecasts are consistent with their price targets and that analysts use growth models based on EPS forecasts to estimate stocks target prices. Differently, Simon and Curtis (2011) argue that the most accurate analysts rely on more complex models in setting their price targets7.

6 [http://www.starmine.com/index.phtml?page\_set=sm\_products&](http://www.starmine.com/index.phtml?page_set=sm_products&amp;sub_page_set=sm_professional&amp;topic=analytical&amp;section=accurate_estimates)

[sub\_page\_set=sm\_professional&topic=analytical&section=accurate\_](http://www.starmine.com/index.phtml?page_set=sm_products&amp;sub_page_set=sm_professional&amp;topic=analytical&amp;section=accurate_estimates)

[estimates](http://www.starmine.com/index.phtml?page_set=sm_products&amp;sub_page_set=sm_professional&amp;topic=analytical&amp;section=accurate_estimates)

7 A further major development in the theoretical accounting literature on equity valuation mod- els is the abnormal earnings growth (AEG) model of Ohlson and Juettner-Nauroth (2005), which

**3 Trading Strategies**

Our trading strategy uses the framework for active portfolio management pro- posed by Black and Litterman (1992). The model incorporates “views” in a CAPM framework, forming optimal portfolios in a mean-variance optimization setting. “Views” are expectations on individual stocks’ future performance.

While in the CAPM model expected returns are a function of systematic risk, in the BL model some stocks can be over- or under-priced and, therefore, their alphas are non-zero. The model blends the subjective views of investors about future performance of a stock with the market implicit returns given by CAPM.

Chen, Da, and Schaumburg (2015) apply the BL model and use the consensus expected returns as a proxy for views. They report that the resulting strategy outperforms a passive buy-and-hold strategy. Our approach is similar to theirs but we define views not only based on consensus estimates but also on smart estimates that account for previous analysts’ TP and EPS accuracy.

Here below we kept the notation in Black and Litterman (1992). *Q* is the vector of expected returns for the eligible stocks; Ω matrix is the confidence of *Q*. Altogether these two reflect the views of a particular analyst or a set of analysts.

To proxy expected returns we compare the analyst’ 12-month target price (TP) with today’s stock price. Confidence Ω for stock is based on variation of forecasts across analysts which is similar to the measure of dispersion in analysts’ opinions outlined in Diether, Malloy, and Scherbina (2002).

We define a trading strategy as follows (Figure 1):

1. At the beginning of quarter *t* for each stock *i*, we define *Q* and Ω (see

relates share price to the level of expected earnings per share.

Section 3.1 and Section 3.2);

2. Using the market price information available at the last day of quarter *t −* 1, we obtain the market implicit returns for each stock *i*, and the variance/co- variance matrix;

3. We apply the BL model to get optimal portfolio weights on the basis of combining views and implicit returns. We buy or sell stocks accordingly. At the beginning of *t* + 1, based on the new views, we set the new portfolio weights following steps 1–3.

**3.1 Defining** *Q*

For the consensus strategy, we use median of expected returns for a particular stock *i*:

*Qcons,i* = median *{rj,i }* (1)

where *rj,i* = *T Pj,i /Pi −* 1 is last known analyst’s *j* expected return computed using the analyst price target *T Pj,i* and stock price *Pi* 8.

For the strategies that weight the analysts’ estimates of expected return the weight of each analyst *j* is based on his/her rank such that the top analyst has the

weight of 1 and then the weights diminish as the rank increases.

*rankj,i −* min*i {rank}*

(2)

*wj,i* = 1 *−*

max*i*

*{rank}*

8 Consistent with the literature, we use stock price 3 days *ex-ante* the TP announcement. This is done to avoid any information leakage around new TP announcement day (Bonini, Zanetti, Bianchini, and Salvi, 2010)

The expected rank-weighted return is thus:

*Qrank,i* =

*j*=1 (*wj,i × rj,i* )

*j*=1 *wj,i*

*N*

*N*

(3)

*N* is the number of analysts.

As mentioned above, we use both target price and EPS accuracy rankings.

**3.1.1 Target Price ranking**

Analysts are ranked on the basis of Proportional Mean Absolute Forecast Error (PMAFE) that measures the accuracy of a forecast (Clement, 1999; Brown, 2001; Ertimur, Sunder, and Sunder, 2007). First, we define the forecast daily error *F Ej,i* as the absolute value of the difference between analyst’ target price *T Pj* and the daily stock price *P* for each stock *i*:

*j,i* = *|Pi − T Pj,i |* (4)

*F ET P*

The PMAFE is given as:

*T P T P j,i j,i*

*P M AF E* = *F E*

(5)

*F ET P*

*i*

where *F ET P*

*i*

is the average forecasting error across analysts. The target price is

fixed over the quarter unless it gets revised.

The rank that enters Equation (2) is average analyst’s *P M AF ET P* over a

particular quarter:

*P M AF ET P* = 1

*D*

) *P M AF ET P*

(6)

*j,i*

*D*

*t*=1

*j,t,i*

*rankj,i* = rank*N*

*j*=1

f*P* *M AF ET P* \ (7)

where *D* are the number of trading days in a quarter and *N* is the number of equity research firms with a valid TP. Figure 2 shows an example.

*j,i*

**3.1.2 EPS ranking**

To compute the EPS rankings, we apply the same procedure as above:

*j,i* = *|AC Ti − P REDj,i |* (8)

*F EEP S*

*EP S EP S j,i*

*P M AF E* = *F E*

*j,i*

(9)

*i*

*rankj,i* = rank*N*

*j*=1

*F EEP S*

{*P M AF EEP S* 1 (10)

*j,i*

where *AC Ti* and *P REDj,i* are the actual quarterly EPS and analyst *j*’s EPS fore- cast for stock *i*.

**3.2 Defining the confidence of expected returns** Ω

The confidence of *Q* is given by the coefficient of variation (CV) of forecasting errors. For each stock *i* is given by:

*C V* = *σi* (*F Ei* )

*i*

*F Ei*

(11)

where *σi* and *F Ei* are the standard deviation and the mean of the forecast er- rors across analysts for either TP or EPS. A low value of *C V* reflects consensual estimates of either future prices or EPS.

**3.3 Information sets to define the views**

To proceed with the trading strategy, we need to establish which information we will be using to build the rankings. These rankings will be the inputs to compute the weighted return estimates (“smart estimates”). Different analysts’ ranks are obtained if we select different time horizons. If we use only the most recent infor- mation, we will capture the recent performance of the analysts. This, of course, is more sensitive to unique episodes (e.g., a quarter which has been surprisingly good or bad). If, alternatively, we opt to incorporate the entire analyst performance, the ranking is less affected by such events, yet it may not reflect the current analyst ability. We use two information sets: the first uses only the information about the analyst’ performance in period *t −* 1; the second, uses all the available informa- tion for that particular analyst. We call the former the *recent* set and the latter the *all-time* set.

In addition to these sets, we also create a hypothetical scenario that assumes we anticipate perfectly the future analyst accuracy performance that would only be available at the end of *t*. This represents the perfect foresight strategy. The perfect foresight refers to analyst rankings not stock prices. Therefore, it serves a performance reference point to evaluate the other trading strategies. We call this

the *true* set.

Formalizing information sets considered are:

• the *true* set

*Q*�*t* = *Qt* (12)

• the *recent* set

*Q*�*t* = *Qt−*1 (13)

• the *all-time* set

1

*Q*�*t* = *T*

*T*

)

*t*=1

*Qt* (14)

where *Qt* is the analysts’ expected rank-weighted stock return (Equation (3))

**4 Data and preliminary results**

**4.1 Database and sample**

We focus on the S&P500 stocks. We extract the target price information and the EPS forecasts from ThomsonReuters I/B/E/S detailed history database. The S&P500 constituents’ list and the stock daily prices are from ThomsonReuters DataStream.

Over the sample period, the total number of equity research firms9 in TP

dataset is 351, covering 498 S&P500 stocks. Given the fact that financial ana- lysts commonly issue TP with the one year horizon10, we assume that analysts

9 We use words “analyst” and “equity research firm” interchangeably.

10 According to Wharton Research Data Services (WRDS), 92.33% of all price targets reported in I/B/E/S have a 12-month horizon (Glushkov, 2009).

keep their TP forecasts valid for one calendar year unless it is revised. After one year we assume that TP recommendation expires.

Consistent with other studies on analysts’ expected returns that work with price targets (Bradshaw, 2002; Brav and Lehavy, 2003; Da and Schaumburg,

2011), we truncate the sample of *T P /P −* 1 at the 5th percentile (values below

*−*0*.*114) and at the 95th percentile (values above 0.805). This is done due to oc- currence of the extreme values. Most of these extreme values are driven by mis- alignment errors found on I/B/E/S data11. To implement ranking, we require that a stock had at least three equity research firms per quarter and that a equity research firm has to be active in covering a particular stock for at least 3 years (12 quarters). After all the data requirements, our final sample number of equity research firms issued target prices is 158 covering 448 S&P500 stocks. Overall, the number of observations (Stock *×* ERF *×* Quarter) is reduced from 131 068 (initial) to 100

974 (filtered).

In the case of EPS forecasts, the initial file of quarterly EPS forecast consists of 560 ERFs covering 3517 stocks. Considering the ranking data requirement, our final sample of EPS forecasts consist of 157 ERFs covering 402 S&P500 stocks. The total number of observation is 80 185.

Given that we have two different ranking datasets (based on TP and EPS), we, further, consider S&P500 stocks that are part of both datasets. We call this sample of stocks as the *same* and the full sample of S&P500 stocks as the *all*.

Table 1 shows the distribution of the final sample of target price and EPS data. Panel A shows the number of quarterly target prices per stock. For the sample

11 We found some differences between the DataStream and I/B/E/S the databases. In some cases

the stock-splits and the dividends were not properly adjusted.

period (1999-2009), we report that each stock in the *same* and the *all* stock sets had on average of 6.915 and 6.71, respectively, quarterly target price reports. Panel B presents similar statistics of the number of EPS forecasts. The average number of quarterly forecasts for the *same* and the *all* is 6.563 and 6.571, respectively.

We apply the ranking procedure outline in Section 3.1 to the two datasets. For target price rankings, we use the average daily errors within one quarter as the measure of analysts’ forecasting ability (Equation (5)).

Table 2 and Figure 2 illustrate an example illustrate how we estimate the

*PMAFE*. Four analysts had valid target prices for Amazon for second quarter of

1999. We plot the daily Amazon price against the ERFs’ target prices. Table 2 shows the resulting TP and EPS rankings. On the bases of the average daily er- rors, LEGG is the most accurate in forecasting stock price and DLJ is the least accurate. For the EPS case (panel B), PACCREST is the most accurate in EPS forecasting and RBRTSON is the least.

**4.2 Ranking contingency results**

We consider three terciles (*top*, *medium*, *bottom*). In one particular quarter (*t*), we place analysts at one of these bins which corresponds to a tercile. We, then, check analysts position at the immediate next quarter (*t* + 1) and after one year (*t* + 4).

Beforehand, we convert the rankings into scores as follows:

*score* = *rankj,i*

*j,i* max *rank*

*i*

(15)

To get the cross-sectional values of scores across different stocks, we take the

average of *scorej,i*

1

*scorej* = *k*

*k*

)

*s*=1

*scorej,i* (16)

where *k* is number of stocks followed by a particular analyst *j*.

Table 3 shows a contingency analysis of the ranks. Panel A shows the dy- namics of each tercile for rankings based on target price accuracy. We observe that analysts exhibit strong ranking consistency as, on average, they stay at the same tercile after one quarter. For the *all* stocks, of the top (bottom) most accu- rate (inaccurate) analysts in the previous quarter 67.58% (69.37%) remain in that same tercile after one quarter. After one year the corresponding figures are lower respectively 46.568% and 40.877% for the top and bottom terciles12.

In the case of EPS ranking (panel B) 48.402% and 28.63% ( 46.687% and

32.253%) of the analysts remained in the top and bottom terciles, respectively, after one quarter (year) in the *all* stock samples.

These results are consistent with the recent findings of Hilary and Hsu (2013)

on analyst forecast consistency.

**4.3 Views: descriptive statistics**

Table 4 presents the descriptive statistics of the analysts’ expected returns condi- tional on the different information sets.

The expected returns are computed comparing TP estimates with actual prices. To form the smart strategies we compute rank-weighted estimates where weights are given either by the TP or the EPS ranks.

Bradshaw (2002) reports analyst average expected returns for the period of

12 For the case of the *same* stock sample, the results of ranking consistency analysis are similar.

2000–2009 and 206 ERFs of 24%. Da and Schaumburg (2011) report an average expected return of 40% for the period of 1996–2004. Zhou (2013) finds an average expected return of 96% for the sample period of 2000–2009. These figures suggest that analysts are overly optimistic.

Panel A of Table 4 show the statistics for the consensus expectations as defined in Equation (1). As mentioned above in Section 3.3, the consensus views have equal weights among the analysts, regardless of their ranks; thus, for the case of *true*, *recent*, and *all-time*, the median is the same regardless of knowing or not the present or past rankings (*Qcons* in Equation (1)). As such, the mean, median, and

standard deviation in the *true*, *recent*, and *all-time* information sets are the same.

For the sample of *all* stocks the mean expected return is 18.61%. However, since views also include the confidence (Equation (11)), which is based on analysts past performance, the results of the trading strategy based on consensus expectations will be different for the *recent* and *all-time* information sets.

Panel B of the table shows the TP accuracy weighted average expected returns. For the sample of *all* stocks the weighted average returns for *true*, *recent*, and *all- time* information sets are respectively 14.876%, 15.742%, and 12.459%.

Panel C shows the EPS based weighted expected return. The average return for the *true*, *recent*, and *all-time* information sets are respectively 14.689%, 14.884%, and 12.843%.

The statistics for the subsample of stocks that integrate both the TP of the EPS

samples are similar.

Overall compared to the consensus the ranked weighted expected returns (“smart estimates”) are less optimistic. The *all-time* information set shows the lowest val- ues of expected returns among all information sets. For the different stock sets,

the *same* sample of stocks has higher values of expected returns compared to the

*all* stocks.

Table Table 5 shows the number of active stocks for each of the trading strate- gies (*CONS*, *TP*, and *EPS*) conditional on considered information sets.

**5 Empirical Results**

We report the results from different trading strategies in Table Table 6. We split the table into four panels. Panel A shows the performance for the passive (market) strategy *Market*. Panels B to D compare the consensus , the TP rank weighted and the EPS rank weighted trading strategies for each of the information availability sets.

**5.1 Passive strategy**

The passive strategy generates an annualized cumulative return of *−*3*.*032% with a Sharpe Ratio of *−*0*.*182 over the period 1999-2001. The average number of stocks held per quarter was 499.975 and the turnover ratio was 0.053, which reflects solely the inclusion and deletions of the S&P 500 constituent list.

**5.2 Perfect foresight strategy**

Panel B presents the results for the case of the *true* information set. The annualized cumulative returns for each of the active strategies (*TP* and *EPS*) are, respectively, for the *all* stock sample: 4.325% and 0.574%. For the *same* sample of stocks these are respectively 4.549% and 0.719%. The two smart strategies outperform

the passive benchmark (*−*3*.*032%). The consensus strategy annualized returns for the *all* and the *same* sample of stocks are respectively 0.116% and 0.434%

The results show, as expected, that investors would better off if they knew in advance who the top analysts in terms of TP or EPS accuracy would be. In any case, the results suggest that the advice of analysts, as a group, are valuable.

The *TP* ranking strategy dominates also when we look at the risk-adjusted returns. The Sharpe Ratio for the *all* (*same*) stock sample is 0.294 against 0.037,

0.007, and *−*0*.*182, respectively for the *EPS*, *CONS* and the *Market* strategies. In addition, the *TP* strategy dominates the others if we consider the shorter trading periods (5 years). Table 7 shows the Sharpe Ratio for six 5-year holding periods. The *TP* strategy wins over the others in every period. The results for the subsample of stocks that integrate both the TP of the EPS datasets are similar.

While this is an hypothetical setting, given that it is not possible to know in advance which analyst will rank first, it suggests that if we can predict the rankings with some accuracy this will be a useful investment trading tool. One of the possibilities is using methods developed in the Machine Learning literature (e.g., Aiguzhinov, Soares, and Serra (2010); Brazdil, Soares, and Costa (2003)), where this type of problem (referred as a label ranking problem) has been broadly studied. For example, Aiguzhinov et al. (2010) propose a label ranking algorithm using Bayesian approach to predict the rankings.

**5.3 Feasible strategies**

Panel C of Table 6 shows the performance of the different smart strategies and the consensus strategy in the *recent* information set. We report the results of forming

portfolios with the available stocks within each dataset (*all*) and the subsample of stocks that include both the TP or the EPS datasets (*same*).

The *TP* and *CONS* active strategies outperform the *Market* (*−*3*.*032%) and show positive cumulative annualized returns for the *all* (*same*) sample of stocks of 0.282% (0.621%) and 0.116% (0.434%) respectively. The active strategy based on EPS forecasts, has negative annualized cumulative returns of *−*0*.*303% and

*−*0*.*349% for the *all* and the *same* samples respectively.

The risk-adjusted results for this information set shows that, as in the case with the *true*, the dominant trading strategy is the *TP* strategy regardless of forming portfolios with *all* stocks or with the *same* subsample. The results in panel B of Table 7 show as well that this strategy outperforms the others for all of the shorter trading periods.

Panel D of Table 6 shows interesting and slightly different findings. On one hand, when all the analyst forecast performance track record is included to set the rankings, we observe an increase in annualized cumulative returns and risk- adjusted returns for the smart strategies. Particularly in the case of the EPS strat- egy, the results suggest that strategies that weight the estimates with accuracy rankings obtained using more information show better performance: when we consider the *all* sample of stocks, the strategy based on the accuracy of EPS fore- casts outperforms the other strategies (annualized cumulative returns of 0.746%,

0.689%, 0.314%, respectively for the *EPS*, *TP*, and *CONS*). The TP strategy dom- inates when we consider the subsample of stocks that are included in both the TP and EPS datasets (0.717%, 1.056%, 0.686% respectively for the *EPS*, *TP* and *CONS* strategies) but the returns and risk-adjusted improve as well when com- pared to the figures in Panel C.

The analysis of the sub-periods performance of the *TP* and *EPS* -based strate- gies depicted in Table 7 shows that the latter outperforms the former in terms of the annualized cumulative return only for the first two periods: in 2000Q1/2004Q4

3.501% vs. 3.133% in 2001Q1/2005Q4 3.954% vs. 3.727% respectively for the *EPS* and the *TP* strategies. For the all the other sup-periods, the annualized cumu- lative returns of the *EPS* strategy are lower than those of the *TP* strategy. Table 8 shows the sub-period results when we consider only the sample of stocks that in- tegrates the TP and EPS dataset. In this setting (*same*), the *TP* strategy dominates the *EPS* and *CONS* strategies in every sub-period.

To further investigate the prevailance of the strategies based on smart estimates as opposed to consensus (and *Market*), we perform a pairwise hypothesis test with *null*-hypothesis stating that the difference between the annualized cumulative returns based on smart estimate strategies and those of the consensus strategy (and *Market*) is equal to zero. Table 9 presents t-statistic and the corresponding p-values of this test. Panel A shows the results for the case of “All vs. *Market*”. We report that all active strategies resulted in the statisitcally significant (at 1% level) prevailance over the *Market* for different information sets (*true*, *recent*, and *all-time*) as well as different stock sets (*all* and *same*).

Panel B of the table presents the t-statistic for the case of “All vs. *CONS*”. Given the results, we reject the *null*-hypothesis in all of the experiment instances (informations sets and stock sets). In terms of the positive gains, the *TP* strategy demonstrated a statistically significant positive performance over the consensus in all information sets and for both stock sets. On the other hand, the *EPS* strat- egy resulted in the statistically significant negative performance over the *CONS* strategy except for the case of *all-time* information and *all* stocks. The results of

the test confirms that the strategy based on the rankings of the analysts who issue more accurate target prices outperforms, in terms of the annualized cumulative re- turns, the strategy based on the consensus among analysts regarding stock target prices.

Figure 3 shows the graphical representation of the cumulative portfolio wealth for the passive and smart strategies in all the information sets. The *y*-axis is the dollar value of wealth and the *x*-axis is the time starting at January 2000 and ending at December 2009. The active investment management strategies in the *true* panel outperform the *Market* and the final value of the portfolio of the *TP* strategy is well above those of the other alternative strategies.

In sum the results of the feasible information sets outlined above suggest that it is worthwhile to follow the analysts, particularly the top ranked analysts, and are supportive of Desai et al. (2000) in that smart strategies based upon analyst accuracy rankings are beneficial for investors.

Further the results show that the values of the annualized cumulative returns are higher in the *all-time* information set when compared with those yield by the strategies that use only the most *recent* ranking information set. This seems to suggest that investors should estimate analysts forecasting skills over a long period of time rather than focusing on the most recent analyst accuracy performance.

Finally, the results suggest that, from an investor’s point of view, following analysts who are accurate in setting price targets is more valuable than follow- ing those that are good at forecasting EPS. This result contradicts the findings of Bradshaw (2004) and supports the argument of Simon and Curtis (2011) that stock recommendations of the most accurate analysts are not based upon simple valuation models.

**6 Conclusions**

Some institutions, such as StarMine (ThomsonReuters), rank financial analysts based on EPS and target price accuracy. These rankings are published and are rel- evant: stocks favored by top ranked analysts will probably receive more attention from investors. Therefore, there is a growing interest in understanding the relative performance of strategies based upon analysts with different forecast accuracy.

We use the Black-Litterman model. The views are TP or EPS rank-weighted means of analysts forecasted returns. We developed simulations of trading strate- gies using different information sets to compute the ranks. If we consider that only the information known prior to time *t* is used to obtain the ranks, investors would be better off following the strategy that weights more heavily the estimates issued by the most accurate TP forecast analysts and considering the whole performance tracking record of the of the analysts.

For future work we will developed new methods to forecast analysts rankings so as to get closer to the upper bound of perfect foresight of rankings.

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Table 1: Sample Statistics

This table shows the average number of target prices (panel A) and EPS forecasts

(panel B) per stock per quarter. Stocks in the *all* sample are subsamples of the

S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets.

Min Mean Median Max Std.dev

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | *all* | *same* | *all* | *same* | *all* | *same* | *all* | *same* | *all* | *same* |
| **Panel** | **A: TP** |  |  |  |  |  |  |  |  |  |
| 1999 | 3 | 3 | 4.286 | 4.326 | 4 | 4 | 11 | 11 | 1.657 | 1.668 |
| 2000 | 3 | 3 | 4.873 | 4.944 | 4 | 4 | 14 | 14 | 2.009 | 2.017 |
| 2001 | 3 | 3 | 5.537 | 5.691 | 5 | 5 | 16 | 16 | 2.453 | 2.481 |
| 2002 | 3 | 3 | 6.411 | 6.611 | 6 | 6 | 19 | 19 | 3.108 | 3.145 |
| 2003 | 3 | 3 | 7.021 | 7.252 | 6 | 6 | 21 | 21 | 3.524 | 3.573 |
| 2004 | 3 | 3 | 7.477 | 7.728 | 7 | 7 | 22 | 22 | 3.671 | 3.726 |
| 2005 | 3 | 3 | 7.667 | 7.946 | 7 | 7 | 24 | 24 | 3.736 | 3.744 |
| 2006 | 3 | 3 | 7.754 | 8.037 | 7 | 7 | 22 | 22 | 3.561 | 3.532 |
| 2007 | 3 | 3 | 7.394 | 7.691 | 7 | 7 | 22 | 22 | 3.494 | 3.429 |
| 2008 | 3 | 3 | 6.708 | 6.973 | 6 | 6 | 18 | 18 | 3.023 | 2.964 |
| 2009 | 3 | 3 | 5.510 | 5.627 | 5 | 5 | 19 | 19 | 2.412 | 2.433 |
| Total | 3 | 3 | 6.710 | 6.915 | 6 | 6 | 24 | 24 | 3.336 | 3.356 |
| **Panel B: EPS** | | | | | | | | | | |
| 1999 | 3 | 3 | 5.673 | 5.643 | 5 | 5 | 17 | 17 | 2.991 | 2.936 |
| 2000 | 3 | 3 | 5.433 | 5.426 | 5 | 5 | 17 | 17 | 2.774 | 2.733 |
| 2001 | 3 | 3 | 6.020 | 6.048 | 5 | 5 | 18 | 18 | 2.972 | 2.987 |
| 2002 | 3 | 3 | 6.338 | 6.357 | 5 | 5 | 21 | 21 | 3.264 | 3.274 |
| 2003 | 3 | 3 | 6.523 | 6.532 | 6 | 6 | 24 | 24 | 3.430 | 3.443 |
| 2004 | 3 | 3 | 6.947 | 6.978 | 6 | 6 | 22 | 22 | 3.749 | 3.771 |
| 2005 | 3 | 3 | 7.205 | 7.216 | 6 | 6 | 24 | 24 | 3.774 | 3.777 |
| 2006 | 3 | 3 | 7.494 | 7.467 | 7 | 7 | 26 | 26 | 3.843 | 3.820 |
| 2007 | 3 | 3 | 7.134 | 7.091 | 6 | 6 | 21 | 21 | 3.532 | 3.489 |
| 2008 | 3 | 3 | 6.378 | 6.353 | 6 | 6 | 22 | 22 | 3.062 | 3.039 |
| 2009 | 3 | 3 | 5.811 | 5.773 | 5 | 5 | 20 | 20 | 2.783 | 2.753 |
| Total | 3 | 3 | 6.571 | 6.563 | 6 | 6 | 26 | 26 | 3.423 | 3.412 |

Table 2: Example of ranking

This table shows target prices (panel A) and EPS forecasts (panel B) rankings

for Amazon (AMZN) for the second quarter of 1999. We apply (Equation (7))

*T P*

to obtain the ranks of the ERFs. *TP* are target prices; *P M AF E*

is the daily

average proportional mean adjusted TP error. For the EPS case, *P RED* are the EPS forecasts issued by the analysts; *P M AF EEP S* is the proportional mean- adjusted forecast error of quarterly EPS forecasts.

**Panel A: TP**

*T P*

ERF/Analyst *TP P M AF E*

*rankT P*

|  |  |  |  |
| --- | --- | --- | --- |
| LEGG | 58.50 | 0.05 | 1.00 |
| MONTSEC | 87.50 | 0.46 | 2.00 |
| KAUFBRO | 125.00 | 1.65 | 3.00 |
| DLJ | 140.00 | 1.97 | 4.00 |
| **Panel B: EPS** | | | |
| ERF/Analyst | *P RED* | *P M AF EEP S* | *rankEP S* |
| MONTSEC | -0.120 | 0.023 | 1.000 |
| BEAR | -0.130 | 0.068 | 2.500 |
| PACCREST | -0.130 | 0.068 | 2.500 |
| BACHE | -0.135 | 0.091 | 4.000 |
| RBRTSON | -0.140 | 0.114 | 5.000 |
| FBOSTON | -0.145 | 0.137 | 6.000 |

Table 3: Analysts’ accuracy consistency

This contingency table shows changes in analysts’ *top*, *middle*, *bottom* ranking

bins. Panel A (Panel B) depicts the dynamics of the analysts’ ranks based on the accuracy in target prices (EPS forecasts). Stocks in the *all* sample are subsamples of the S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *top* |  | *middle* | *bottom* | *Sum* |
| *all* | *same* | *all same* | *all same* | *all same* |

**Panel A: TP** *t* + 1

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| *top* | 67.6 | 67.7 | 22.2 | 22.0 | 10.3 | 10.2 | 100.0 | 100.0 |
| *middle* | 30.5 | 29.7 | 47.8 | 48.4 | 21.7 | 21.9 | 100.0 | 100.0 |
| *bottom* | 13.7 | 13.4 | 16.9 | 17.0 | 69.4 | 69.6 | 100.0 | 100.0 |
| *t* + 4 | | | | | | | | |
| *top* | 46.6 | 46.3 | 27.9 | 28.2 | 25.6 | 25.5 | 100.0 | 100.0 |
| *middle* | 39.0 | 39.1 | 29.1 | 29.1 | 31.9 | 31.7 | 100.0 | 100.0 |
| *bottom* | 32.7 | 32.1 | 26.4 | 26.5 | 40.9 | 41.4 | 100.0 | 100.0 |
| **Panel B: EPS** *t* + 1 | | | | | | | | |
| *top* | 48.4 | 48.4 | 26.1 | 26.1 | 26.0 | 26.0 | 100.5 | 100.5 |
| *middle* | 48.1 | 48.2 | 26.3 | 26.2 | 25.9 | 25.8 | 100.4 | 100.2 |
| *bottom* | 46.5 | 46.3 | 25.7 | 25.9 | 28.6 | 28.5 | 100.8 | 100.6 |
| *t* + 4 | | | | | | | | |
| *top* | 46.7 | 46.8 | 28.4 | 28.3 | 26.1 | 26.0 | 101.1 | 101.2 |
| *middle* | 45.4 | 45.5 | 27.1 | 27.0 | 28.1 | 28.1 | 100.6 | 100.6 |
| *bottom* | 42.8 | 42.7 | 27.7 | 27.6 | 32.3 | 32.4 | 102.7 | 102.7 |

*t*

*t*

Table 4: Descriptive statistics of views

This table shows the descriptive statistics of views (expected returns) based on

the consensus (median) among the analysts (panel A); target price rankings (panel B); and EPS forecasts rankings (panel C). Stocks in the *all* sample are subsamples of the S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets.

|  |  |  |  |
| --- | --- | --- | --- |
| Mean (in %) | Median (in %) | Std.dev |  |
| *all same* | *all same* | *all* | *same* |

**Panel A: Consensus**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| *true* | 18.610 | 18.985 | 16.889 | 17.185 | 0.120 | 0.119 |
| *recent* | 18.610 | 18.985 | 16.889 | 17.185 | 0.120 | 0.119 |
| *all-time* | 18.610 | 18.985 | 16.889 | 17.185 | 0.120 | 0.119 |
|  |  |  | **Panel B: TP** |  |  |  |
| *true* | 14.876 | 15.191 | 13.380 | 13.604 | 0.096 | 0.096 |
| *recent* | 15.742 | 16.102 | 14.314 | 14.541 | 0.098 | 0.098 |
| *all-time* | 12.459 | 12.714 | 10.591 | 10.798 | 0.089 | 0.089 |
|  |  |  | **Panel C: EPS** |  |  |  |
| *true* | 14.689 | 14.769 | 13.214 | 13.252 | 0.101 | 0.102 |
| *recent* | 14.884 | 14.959 | 13.392 | 13.420 | 0.103 | 0.103 |
| *all-time* | 12.843 | 12.916 | 11.410 | 11.439 | 0.089 | 0.089 |

Table 5: Number of active stocks

This table shows number of active stocks in each of the trading strategies conditional on

different information sets: *true* (panel A), *recent* (panel B) and *all-time* (panel C). Stocks in the *all* sample are subsamples of the S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Year | *CONS*  *all* | *same* | *TP*  *all* | *same* | *EPS*  *all* | *same* |
| **Panel A: *true*** |  |  |  |  |  |  |
| 1999 | 71 | 67 | 71 | 67 | 42 | 42 |
| 2000 | 257 | 235 | 253 | 232 | 191 | 191 |
| 2001 | 310 | 281 | 302 | 273 | 244 | 244 |
| 2002 | 360 | 321 | 353 | 316 | 289 | 289 |
| 2003 | 374 | 334 | 369 | 330 | 299 | 299 |
| 2004 | 385 | 341 | 375 | 331 | 318 | 318 |
| 2005 | 401 | 352 | 395 | 347 | 337 | 337 |
| 2006 | 415 | 358 | 403 | 351 | 337 | 337 |
| 2007 | 421 | 361 | 418 | 359 | 351 | 351 |
| 2008 | 422 | 360 | 413 | 353 | 339 | 339 |
| 2009 | 405 | 351 | 346 | 306 | 306 | 306 |
| Total | 442 | 378 | 442 | 378 | 375 | 375 |
| **Panel B: *recent*** | | | | | | |
| 1999 | 71 | 67 | 71 | 67 | 41 | 41 |
| 2000 | 257 | 235 | 257 | 235 | 185 | 186 |
| 2001 | 310 | 281 | 310 | 281 | 247 | 247 |
| 2002 | 360 | 321 | 360 | 321 | 287 | 287 |
| 2003 | 374 | 334 | 374 | 334 | 307 | 307 |
| 2004 | 385 | 341 | 385 | 341 | 318 | 318 |
| 2005 | 401 | 352 | 401 | 352 | 337 | 337 |
| 2006 | 415 | 358 | 415 | 358 | 343 | 343 |
| 2007 | 421 | 361 | 421 | 361 | 352 | 352 |
| 2008 | 422 | 360 | 422 | 360 | 349 | 349 |
| 2009 | 405 | 351 | 405 | 351 | 321 | 321 |
| Total | 442 | 378 | 442 | 378 | 376 | 376 |
| **Panel C: *all-time*** | | | | | | |
| 1999 | 71 | 67 | 71 | 67 | 51 | 51 |
| 2000 | 257 | 235 | 257 | 235 | 204 | 204 |
| 2001 | 310 | 281 | 310 | 281 | 261 | 261 |
| 2002 | 360 | 321 | 360 | 321 | 302 | 302 |
| 2003 | 374 | 334 | 374 | 334 | 317 | 317 |
| 2004 | 385 | 341 | 385 | 341 | 332 | 332 |
| 2005 | 401 | 352 | 401 | 352 | 344 | 344 |
| 2006 | 415 | 358 | 415 | 358 | 353 | 353 |
| 2007  2008 | 421  422 | 361  360 | 34021  422 | 361  360 | 358  359 | 358  359 |
| 2009 | 405 | 351 | 405 | 351 | 350 | 350 |
| Total | 442 | 378 | 442 | 378 | 377 | 377 |

Table 6: Trading strategies performance: entire period

This table shows the performance statistics of the different trading strategies.

Panel A presents the results for the passive strategy. Panels B, C, and D show the results for the perfect foresight scenario (*true*), and, respectively, the scenarios for which we use the most recent (*recent*) and all ranking history of analysts (*all-time*) to weight the TP/EPS estimates. Within each panel, we show the strategy results of three views regarding expected return: *CONS* uses the median of the analysts estimates; *TP* is based upon TP accuracy ranking; and *EPS* is based upon EPS accuracy ranking. Stocks in the *all* sample are subsamples of the S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets. The trading period goes from 2000Q1 until 2009Q4.

Strategy Annualized return (in

%)

Annualized Std. dev (in %)

Sharpe ratio

Average num. stock

Average turnover rate

**Panel A**

*Market* -3.032 16.654 -0.182 499 0.053

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel B**  *CONS* | **: *true***  *all*  0.116 | *same*  0.434 | *all*  15.948 | *same*  15.995 | *all*  0.007 | *same*  0.027 | *all*  283 | *same*  251 | *all*  0.256 | *same*  0.251 |
| *TP* | 4.325 | 4.549 | 14.697 | 14.794 | 0.294 | 0.307 | 283 | 251 | 0.345 | 0.327 |
| *EPS* | 0.574 | 0.719 | 15.528 | 15.505 | 0.037 | 0.046 | 205 | 205 | 0.496 | 0.494 |
| **Panel C: *recent*** | | | | | | | | | | |
| *CONS* | 0.116 | 0.434 | 15.948 | 15.995 | 0.007 | 0.027 | 283 | 251 | 0.256 | 0.251 |
| *TP* | 0.282 | 0.621 | 15.662 | 15.682 | 0.018 | 0.040 | 284 | 251 | 0.264 | 0.256 |
| *EPS* | -0.303 | -0.349 | 16.088 | 16.096 | -0.019 | -0.022 | 206 | 206 | 0.410 | 0.408 |
| **Panel D: *all-time*** | | | | | | | | | | |
| *CONS* | 0.314 | 0.686 | 15.773 | 15.825 | 0.020 | 0.043 | 283 | 251 | 0.228 | 0.223 |
| *TP* | 0.689 | 1.056 | 15.565 | 15.485 | 0.044 | 0.068 | 284 | 251 | 0.256 | 0.248 |
| *EPS* | 0.746 | 0.717 | 15.444 | 15.481 | 0.048 | 0.046 | 245 | 245 | 0.256 | 0.256 |

Table 7: Trading strategies performance: sub-periods, *all* sample This table presents the annualized return (in %) and the Sharpe ratio of each of the trading strategies: the passive (*Market*) and the active (consensus and smart estimates) calculated for different holding periods. Panel A represents the perfect foresight information set; panels B and C show, respectively, the results of the strategies using the most recent and all history analysts’ performance.

Period *Market CONS TP EPS*

Ann.ret SR Ann.ret SR Ann.ret SR Ann.ret SR

**Panel A: *true***

2000Q1/2004Q4 -3.401 -0.201 2.663 0.167 5.844 0.395 1.890 0.124

2001Q1/2005Q4 -1.539 -0.093 2.669 0.170 6.119 0.425 3.945 0.270

2002Q1/2006Q4 2.567 0.196 5.734 0.447 9.124 0.757 5.877 0.492

2003Q1/2007Q4 7.919 0.925 9.548 1.106 14.715 1.915 10.681 1.364

2004Q1/2008Q4 -5.667 -0.435 -4.708 -0.343 0.908 0.070 -3.133 -0.232

2005Q1/2009Q4 -2.662 -0.158 -2.367 -0.146 2.827 0.189 -0.725 -0.045

All period -3.032 -0.182 0.116 0.007 4.325 0.294 0.574 0.037

**Panel B: *recent***

2000Q1/2004Q4 -3.401 -0.201 2.663 0.167 2.620 0.168 1.172 0.074

2001Q1/2005Q4 -1.539 -0.093 2.669 0.170 3.266 0.214 2.659 0.171

2002Q1/2006Q4 2.567 0.196 5.734 0.447 6.075 0.490 5.485 0.455

2003Q1/2007Q4 7.919 0.925 9.548 1.106 10.068 1.248 9.337 1.155

2004Q1/2008Q4 -5.667 -0.435 -4.708 -0.343 -4.148 -0.305 -4.541 -0.332

2005Q1/2009Q4 -2.662 -0.158 -2.367 -0.146 -2.003 -0.125 -1.757 -0.106

All period -3.032 -0.182 0.116 0.007 0.282 0.018 -0.303 -0.019

**Panel C: *all-time***

2000Q1/2004Q4 -3.401 -0.201 3.102 0.197 3.133 0.205 3.501 0.232

2001Q1/2005Q4 -1.539 -0.093 3.016 0.194 3.727 0.249 3.954 0.264

2002Q1/2006Q4 2.567 0.196 5.410 0.417 5.793 0.464 5.712 0.468

2003Q1/2007Q4 7.919 0.925 9.419 1.071 10.335 1.245 10.002 1.202

2004Q1/2008Q4 -5.667 -0.435 -4.860 -0.358 -3.941 -0.289 -4.223 -0.309

2005Q1/2009Q4 -2.662 -0.158 -2.398 -0.149 -1.697 -0.105 -1.936 -0.121

All period -3.032 -0.182 0.314 0.020 0.689 0.044 0.746 0.048

Table 8: Trading strategies performance: sub-periods, *same* subsam- ple

This table presents the annualized return (in %) and the Sharpe ratio of each of the

trading strategies for the *same* set of stocks: the passive (*Market*) and the active (consensus and smart estimates) calculated for different holding periods. Panel A represents the perfect foresight information set; panels B and C show, respec- tively, the results of the strategies using the most recent and all history analysts’ performance.

Period *Market CONS TP EPS*

Ann.ret SR Ann.ret SR Ann.ret SR Ann.ret SR

**Panel A: *true***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 2000Q1/2004Q4 | -3.401 | -0.201 | 3.378 | 0.213 | 6.609 | 0.451 | 2.116 | 0.139 |
| 2001Q1/2005Q4 | -1.539 | -0.093 | 2.825 | 0.180 | 6.226 | 0.432 | 4.161 | 0.286 |
| 2002Q1/2006Q4 | 2.567 | 0.196 | 5.836 | 0.468 | 8.985 | 0.768 | 5.827 | 0.486 |
| 2003Q1/2007Q4 | 7.919 | 0.925 | 9.417 | 1.100 | 14.249 | 1.891 | 10.672 | 1.361 |
| 2004Q1/2008Q4 | -5.667 | -0.435 | -4.826 | -0.349 | 0.398 | 0.030 | -3.126 | -0.232 |
| 2005Q1/2009Q4 | -2.662 | -0.158 | -2.426 | -0.148 | 2.528 | 0.166 | -0.658 | -0.041 |
| All period | -3.032 | -0.182 | 0.434 | 0.027 | 4.549 | 0.307 | 0.719 | 0.046 |
| **Panel B: *recent***  2000Q1/2004Q4 | -3.401 | -0.201 | 3.378 | 0.213 | 3.331 | 0.216 | 1.073 | 0.067 |
| 2001Q1/2005Q4 | -1.539 | -0.093 | 2.825 | 0.180 | 3.523 | 0.231 | 2.598 | 0.167 |
| 2002Q1/2006Q4 | 2.567 | 0.196 | 5.836 | 0.468 | 6.218 | 0.516 | 5.436 | 0.450 |
| 2003Q1/2007Q4 | 7.919 | 0.925 | 9.417 | 1.100 | 9.972 | 1.244 | 9.325 | 1.153 |
| 2004Q1/2008Q4 | -5.667 | -0.435 | -4.826 | -0.349 | -4.252 | -0.311 | -4.552 | -0.332 |
| 2005Q1/2009Q4 | -2.662 | -0.158 | -2.426 | -0.148 | -2.019 | -0.124 | -1.752 | -0.105 |
| All period | -3.032 | -0.182 | 0.434 | 0.027 | 0.621 | 0.040 | -0.349 | -0.022 |
| **Panel C: *all-time***  2000Q1/2004Q4 | -3.401 | -0.201 | 3.909 | 0.250 | 3.852 | 0.257 | 3.470 | 0.230 |
| 2001Q1/2005Q4 | -1.539 | -0.093 | 3.254 | 0.210 | 4.014 | 0.271 | 3.919 | 0.261 |
| 2002Q1/2006Q4 | 2.567 | 0.196 | 5.461 | 0.433 | 5.915 | 0.488 | 5.686 | 0.465 |
| 2003Q1/2007Q4 | 7.919 | 0.925 | 9.297 | 1.067 | 10.199 | 1.253 | 9.988 | 1.199 |
| 2004Q1/2008Q4 | -5.667 | -0.435 | -4.979 | -0.364 | -4.091 | -0.299 | -4.241 | -0.310 |
| 2005Q1/2009Q4 | -2.662 | -0.158 | -2.437 | -0.150 | -1.665 | -0.102 | -1.963 | -0.122 |
| All period | -3.032 | -0.182 | 0.686 | 0.043 | 1.056 | 0.068 | 0.717 | 0.046 |

Table 9: Significance of cumulative returns

The table demonstrates a pairwise statisitical test in difference of the cumulative returns of all strategies vs. *Market* (Panel A) and vs. *CONS* strategy (Panel B). Case of *true* shows the known future information; *recent* is the case of ranking information know at *t −* 1, and the *all-time* is the case of using all ranking infor- mation for up to *t −* 1. *TP* is the strategy with rankings based on the accuracy in target prices, *CONS* is the strategy based on the consensus among the analysts regarding a stock’s expected return. *EPS* is the strategy with rankings based on the accuracy of EPS forecasts. Stocks in the *all* sample are subsamples of the S&P

500, stocks in the *same* sample integrate both the EPS and TP datasets.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | | | *all*  t value | Pr(*> |t|*) | *same*  t value | Pr(*> |t|*) |
|  | **Panel A: *Market*** |  |  |
| *CONS* | ***true*** | | 15.247 | 0.000 | 16.857 | 0.000 |
| *TP* |  | | 12.661 | 0.000 | 13.799 | 0.000 |
| *EPS* |  | | 11.664 | 0.000 | 12.001 | 0.000 |
| *CONS* | ***recent*** | | 15.247 | 0.000 | 16.857 | 0.000 |
| *TP* |  | | 14.015 | 0.000 | 15.481 | 0.000 |
| *EPS* |  | | 12.655 | 0.000 | 12.640 | 0.000 |
| *CONS* | ***all-time*** | | 15.858 | 0.000 | 17.456 | 0.000 |
| *TP* |  | | 14.314 | 0.000 | 15.833 | 0.000 |
| *EPS* |  | | 15.625 | 0.000 | 15.690 | 0.000 |
|  |  | |  | **Panel B: *CONS*** |  |  |
|  | ***true*** | |  |  |  |  |
| *TP* |  | 9.284 | | 0.000 | 9.625 | 0.000 |
| *EPS* |  | -2.352 | | 0.024 | -6.358 | 0.000 |
| *Market* |  | -15.247 | | 0.000 | -16.857 | 0.000 |
| *TP* | ***recent*** | 2.032 | | 0.049 | 1.706 | 0.096 |
| *EPS* |  | -20.130 | | 0.000 | -27.074 | 0.000 |
| *Market* |  | -15.247 | | 0.000 | -16.857 | 0.000 |
| ***all-time*** | | | | | | |
| *TP* |  |  | 3.182 | 0.003 | 2.892 | 0.006 |

*... continued next page*

*all same*

t value Pr(*> |t|*) t value Pr(*> |t|*)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *EPS* |  | 10.492 | 0.000 | -3.008 | 0.005 |
| *Market* |  | -15.858 | 0.000 | -17.456 | 0.000 |
|  |  |  | **Panel C: *TP*** |  |  |
| *CONS* | ***true*** | -9.284 | 0.000 | -9.625 | 0.000 |
| *EPS* |  | -12.876 | 0.000 | -15.090 | 0.000 |
| *Market* |  | -12.661 | 0.000 | -13.799 | 0.000 |
| *CONS* | ***recent*** | -2.032 | 0.049 | -1.706 | 0.096 |
| *EPS* |  | -17.847 | 0.000 | -23.272 | 0.000 |
| *Market* |  | -14.015 | 0.000 | -15.481 | 0.000 |
| ***all-time*** | | | | | |
| *CONS* |  | -3.182 | 0.003 | -2.892 | 0.006 |
| *EPS* |  | 18.770 | 0.000 | -14.975 | 0.000 |
| *Market* |  | -14.314 | 0.000 | -15.833 | 0.000 |

Table 10: Dunn Test

The table presents the Dunn test

Pairs Z-stat p-value

**Panel A: *true***

|  |  |  |
| --- | --- | --- |
| *CONS* - *TP* | -3.04 | 0.00 |
| *CONS* - *EPS* | 0.85 | 0.20 |
| *TP* - *EPS* | 3.89 | 0.00 |
| *CONS* - *Market* | 5.59 | 0.00 |
| *TP* - *Market* | 8.62 | 0.00 |
| *EPS* - *Market* | 4.73 | 0.00 |
| **Panel B: *recent***  *CONS* - *TP* | 0.03 | 0.49 |
| *CONS* - *EPS* | 2.27 | 0.01 |
| *TP* - *EPS* | 2.24 | 0.01 |
| *CONS* - *Market* | 6.35 | 0.00 |
| *TP* - *Market* | 6.32 | 0.00 |
| *EPS* - *Market* | 4.07 | 0.00 |
| **Panel C: *all-time***  *CONS* - *TP* | -0.18 | 0.43 |
| *CONS* - *EPS* | 0.28 | 0.39 |
| *TP* - *EPS* | 0.45 | 0.33 |
| *CONS* - *Market* | 6.40 | 0.00 |
| *TP* - *Market* | 6.58 | 0.00 |
| *EPS* - *Market* | 6.12 | 0.00 |

Q: vector of expected returns for each stock

Views: {Q, Ω} (conditional expected returns)

Ω: confidence of Q for each stock

Portfolio performance

Portfolio formation

Implicit equilibrium returns

(prior expected returns)

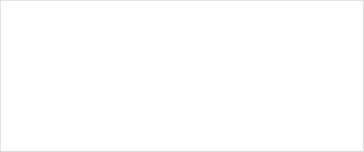
Black-Litterman model

End of t-1

t Trade

End of t

Figure 1: Trading strategy timeline



Black-Litterman model inputs are at the beginning of *t* we apply the BL model and form the active portfolio. At the end of *t*, we evaluate performance.

140

Daily stock price (AMZN) compared to ERF's target prices over the period of the second calendar quarter of 1999

120

100

Dollars

80

AMZN LEGG MONTSEC KAUFBRO DLJ

60

Apr 01 Apr 15 May 01 May 15 Jun 01 Jun 15 Jul 01

Figure 2: Amazon daily stock price and ERFs target prices

Target price and actual prices for Amazon the second quarter of 1999.

Cumulative portfolio wealth for all strategies

CONS TP EPS Market

true recent all−time

150

100

all

Portfolio wealth (initial=$100)

50

150

100

same

50

2001 2003 2005 2007 2009 2001 2003 2005 2007 2009 2001 2003 2005 2007 2009

Quarters

Figure 3: Performance of the BL model

Quarterly performance of the cumulative portfolio wealth for all strategies. Panel *true* shows the case of the known future information; *recent* is the case of ranking information know at *t −* 1, and the *all-time* is the case of using all ranking infor- mation for up to *t −* 1. *TP* is the strategy with rankings based on the accuracy in target prices, *CONS* is the strategy based on the consensus among the analysts regarding a stock’s expected return. *EPS* is the strategy with rankings based on the accuracy of EPS forecasts. Stocks in the *all* sample are subsamples of the S&P 500, stocks in the *same* sample integrate both the EPS and TP datasets. The trading period ranges from 2000Q1 until 2009Q4.