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 selling 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 Teams[1] and Bloomberg's America's Best Stock Analysts[2]); others are based on the performance of sell-side analysts (ThomsonReuters' top StarMine analysts[3]). 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 contributions 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 returns generated by some trading strategies based upon analysts' rankings outperform 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

[1] `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`

[3] `http://excellence.thomsonreuters.com/award/starmine`

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 rankings of financial analysts; section 3 outlines our proposed trading strategies; section 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 analysts 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]. Assuming that some analysts produce valuable advice it makes sense to rank analysts based on the accuracy of their recommendations.

[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)%.

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 measures "... [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 analyst. 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 simultaneously 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 when a stock enters or exits an industry grouping.

Recent evidence suggests that top ranked financial analyst affect market participants: 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., SmartEstimates[6]).

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

[5] `http://excellence.thomsonreuters.com/award/starmine?award=Analyst+Awards&award_group=Overall+Analyst+Awards`

[6] `http://www.starmine.com/index.phtml?page_set=sm_products&sub_page_set=sm_professional&topic=analytical&section=accurate_estimates`

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 rankings (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 targets[7].

3. Trading Strategies

Our trading strategy uses the framework for active portfolio management proposed 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

[7] A further major development in the theoretical accounting literature on equity valuation models is the abnormal earnings growth (AEG) model of Ohlson and Juettner-Nauroth (2005), which relates share price to the level of expected earnings per share.

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 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:

$$Q_{cons,i} = \text{median}\,\{r_{j,i}\} \tag{1}$$

where $r_{j,i} = TP_{j,i}/P_i - 1$ is last known analyst's j expected return computed using the analyst price target $TP_{j,i}$ and stock price P_i[8].

[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)

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.

$$w_{j,i} = 1 - \frac{rank_{j,i} - \min_i \{rank\}}{\max_i \{rank\}} \tag{2}$$

The expected rank-weighted return is thus:

$$Q_{rank,i} = \frac{\sum_{j=1}^{N} (w_{j,i} \times r_{j,i})}{\sum_{j=1}^{N} w_{j,i}} \tag{3}$$

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 $FE_{j,i}$ as the absolute value of the difference between analyst' target price TP_j and the daily stock price P for each stock i:

$$FE_{j,i}^{TP} = |P_i - TP_{j,i}| \tag{4}$$

The PMAFE is given as:

$$PMAFE_{j,i}^{TP} = \frac{FE_{j,i}^{TP}}{\overline{FE_i^{TP}}} \tag{5}$$

where $\overline{FE_i^{TP}}$ 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 $PMAFE^{TP}$ over a particular quarter:

$$\overline{PMAFE_{j,i}^{TP}} = \frac{1}{D} \sum_{t=1}^{D} PMAFE_{j,t,i}^{TP} \tag{6}$$

$$rank_{j,i} = \text{rank}_{j=1}^{N} \left\{ \overline{PMAFE_{j,i}^{TP}} \right\} \tag{7}$$

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.

3.1.2. EPS ranking

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

$$FE_{j,i}^{EPS} = |ACT_i - PRED_{j,i}| \tag{8}$$

$$PMAFE_{j,i}^{EPS} = \frac{FE_{j,i}^{EPS}}{\overline{FE_i^{EPS}}} \tag{9}$$

$$rank_{j,i} = \mathrm{rank}_{j=1}^{N} \left\{ PMAFE_{j,i}^{EPS} \right\} \tag{10}$$

where ACT_i and $PRED_{j,i}$ are the actual quarterly EPS and analyst j's EPS forecast 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:

$$CV_i = \frac{\sigma_i(FE_i)}{\overline{FE}_i} \tag{11}$$

where σ_i and $\overline{FE}_i$ are the standard deviation and the mean of the forecast errors across analysts for either TP or EPS. A low value of CV 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 information, 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 information 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

$$\widehat{Q_t} = Q_t \tag{12}$$

- the *recent* set

$$\widehat{Q_t} = Q_{t-1} \tag{13}$$

- the *all-time* set

$$\widehat{Q_t} = \frac{1}{T}\sum_{t=1}^{T} Q_t \tag{14}$$

where Q_t 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 Thomson-Reuters DataStream.

Over the sample period, the total number of equity research firms[9] in TP dataset is 351, covering 498 S&P500 stocks. Given the fact that financial analysts commonly issue TP with the one year horizon[10], we assume that analysts 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 $TP/P-1$ at the 5^{th} percentile (values below -0.114) and at the 95^{th} percentile (values above 0.805). This is done due to occurrence of the extreme values. Most of these extreme values are driven by misalignment errors found on I/B/E/S data[11]. 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 $\times$ ERF $\times$ 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

[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).

[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.

sample 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 errors, 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:

$$score_{j,i} = \frac{rank_{j,i}}{\max rank_i} \tag{15}$$

To get the cross-sectional values of scores across different stocks, we take the average of $score_{j,i}$

$$\overline{score_j} = \frac{1}{k} \sum_{s=1}^{k} score_{j,i} \tag{16}$$

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 dynamics 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 accurate (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 terciles[12].

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 conditional 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 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 (Q_{cons} in equation (1)). As such, the mean, median, and standard deviation in the *true*, *recent*, and *all-time* information

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

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 values 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 strategies (*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 strategy, 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 forecasts outperforms the other strategies (annualized cumulative returns of 0.746%, 0.689%, 0.314%, respectively for the *EPS*, *TP*, and *CONS*). The TP strategy dominates 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 compared to the figures in Panel C.

The analysis of the sub-periods performance of the *TP* and *EPS* -based strategies 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 cumulative 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 integrates 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* strategy 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 returns, 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 following 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 relevant: 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 strategies 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)) to obtain the ranks of the ERFs. TP are target prices; $\overline{PMAFE}^{TP}$ is the daily average proportional mean adjusted TP error. For the EPS case, $PRED$ are the EPS forecasts issued by the analysts; $PMAFE^{EPS}$ is the proportional mean-adjusted forecast error of quarterly EPS forecasts.

Panel A: TP

ERF/Analyst	TP	$\overline{PMAFE}^{TP}$	$rank^{TP}$
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	$PRED$	$PMAFE^{EPS}$	$rank^{EPS}$
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
					$t+4$				
t	*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
					$t+4$				
t	*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

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*		*TP*		*EPS*	
	all	*same*	*all*	*same*	*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	421	361	421	361	358	358
2008	422	360	422	360	359	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: *true*										
	all	*same*	*all*	*same*	*all*	*same*	*all*	*same*	*all*	*same*
CONS	0.116	0.434	15.948	15.995	0.007	0.027	283	251	0.256	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* subsample

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, 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	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 information 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		*same*	
	t value	$\Pr(>\lvert t\rvert)$	t value	$\Pr(>\lvert t\rvert)$
Panel A: *Market*				
true				
CONS	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
recent				
CONS	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
all-time				
CONS	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
recent				
TP	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
EPS	10.492	0.000	-3.008	0.005
Market	-15.858	0.000	-17.456	0.000

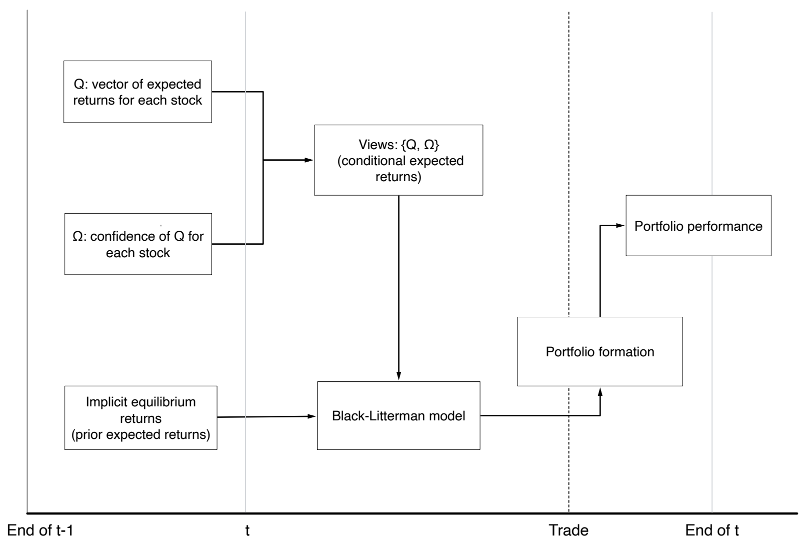

Figure 1: Trading strategy timeline
Black-Litterman model inputs are at the beginning of t we apply the BL model and form the active portfolio. At the end of t, we evaluate performance.

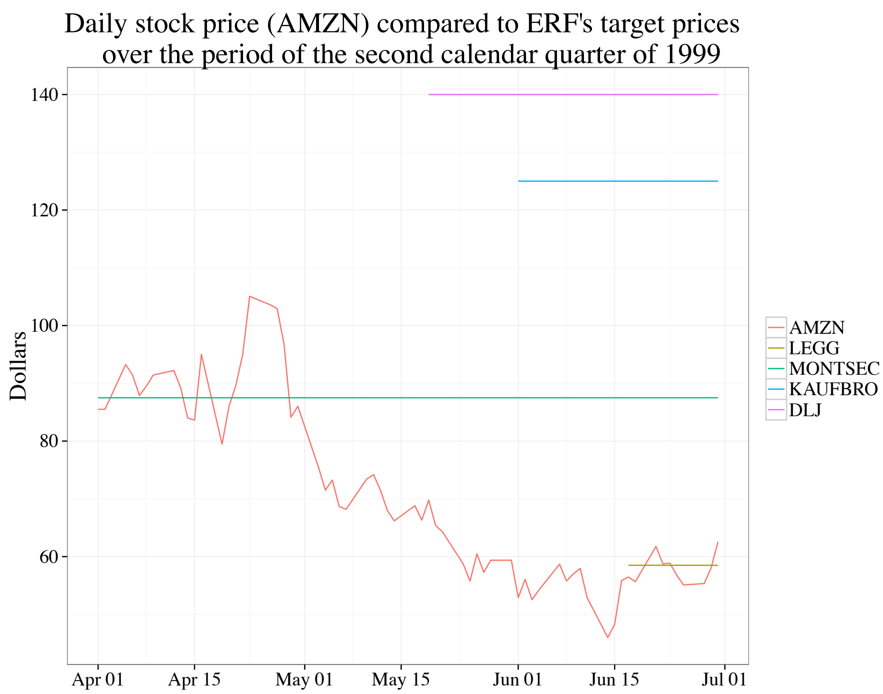

Figure 2: Amazon daily stock price and ERFs target prices

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

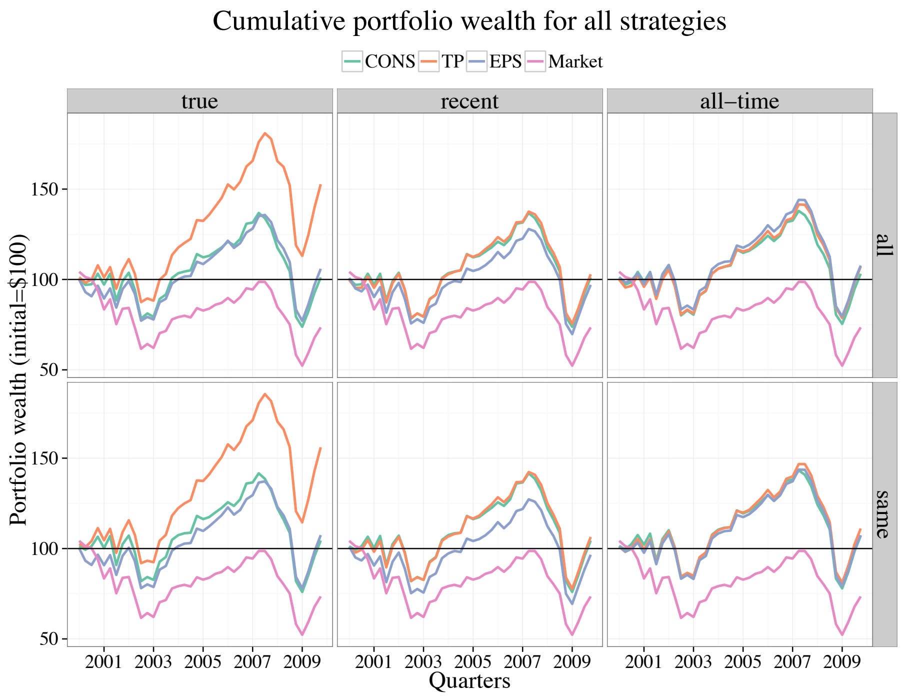

Figure 3: Performance of the BL model

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 information 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.