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Projected Earnings Accuracy and the Profitability of Stock Recommendations

D. Hess • D. Kreutzmann • O. Pucker

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Dieter Hess

Daniel Kreutzmann

Oliver Pucker*

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Abstract

Analysts providing more accurate earnings forecasts also issue more profitable recommendations. We demonstrate how investors can profit from this contemporaneous link by differentiating between “able” and “lucky” analysts. In line with previous studies, we find that past track records alone are not sufficient to identify profitable recommendations. Only skilled analysts working in a superior environment provide consistently profitable recommendations. The overall profitability of their recommendations is not driven by a post-announcement drift effect. We find that an implementable, i.e. look-ahead bias free, trading strategy based on the projected – rather than past – earnings accuracy yields substantial excess returns.

Keywords: analysts, portfolio management, profitability of recommendations

JEL classification: G14, G17, G24

* University of Cologne, Corporate Finance Seminar, Albertus-Magnus Platz, 50923 Cologne, Germany, pucker@wiso.uni-koeln.de, corresponding author.

1. Introduction

It is well known that the profitability of analysts' stock recommendations has a wide dispersion. But can investors identify ex ante those recommendations that are worth following? Intuition suggests that analysts who can predict earnings more accurately will also provide superior stock recommendations, since superior earnings forecasts should yield superior valuations. Unfortunately, earnings accuracy seems to be not persistent. By differentiating between "lucky" and "able" analysts, we show how investors can profit from the simultaneous link between earnings accuracy and profitability of recommendations. We document that analysts with superior information processing abilities – due to higher skills and a better environment – provide persistently more profitable recommendations. Following their recommendations yields substantial excess returns.

Previous evidence indicates that analysts who issue more accurate earnings forecasts also issue more profitable stock recommendations. However, this link is based on a contemporaneous relation, i.e. the accuracy of forecasts is correlated with the profitability of recommendations, but only for the same period. To profit from such a simultaneous link investors would need to know in advance which analysts will lead the rank tables at the end of a given period. Hence, this link cannot be applied directly in an investment decision process. Previous studies also indicate that looking at last years' rank tables does not help either. Our results imply that this is because last year's winners could just have been lucky, but they are unlikely to be so next time. We show that recommendations of "able" analysts, i.e. analysts with high past earnings accuracy and high expertise, generate excess returns while the recommendations of "lucky" analysts, i.e. analysts with high past earnings accuracy but low expertise, do not. Expertise is measured by looking both at characteristics of the analyst (e.g. her experience) and the working environment (e.g. the size of the broker she is working for). Our results indicate that an analyst's past earnings accuracy must be combined with characteristics that proxy for the analyst's expertise in order to identify those analysts that issue more profitable stock recommendations. Therefore, it is crucial for an investor to distinguish between "lucky" analysts, i.e. analysts that have a good track record because of random events, and "able" analysts, i.e. analysts that have a good track record because of their higher ability respectively superior working environment. Our results suggest that superior information processing abilities of some analysts are responsible for the superior profitability of their recommendations, not just a possibly misguided reputation effect.

Most closely related to our paper are the studies of Loh and Mian (2006), Ertimur, Sunder, and Sunder (2007) and Hall and Tacon (2010). Loh and Mian (2006) indicate a possible link between the accuracy of earnings projections and the profitability of recommendations. They show that following the recommendations of analysts that issue the most accurate earnings forecasts yields significant excess returns. This is plausible, since earnings forecasts and recommendations should be related, at least contemporaneously.[1] However, the trading strategy of Loh and Mian (2006) involves a look-ahead bias. In order to implement such a strategy one would need to know in advance which analysts will have issued the most accurate earnings forecasts at the end of a given period. Therefore, the trading strategy does not indicate ex ante to investors which analysts' recommendations to follow. Hall and Tacon (2010) avoid this look-ahead bias and propose an implementable trading strategy suggesting to focus on past performance, i.e. to follow only those analysts that have issued the most accurate earnings forecasts and/or the most profitable recommendations for the last period. Interestingly, their trading strategy does not yield significant excess returns. A plausible explanation for these conflicting results is that the profitability of stock recommendations is driven by the contemporaneous accuracy (and not the past accuracy) of the earnings estimates on the one hand and by the analysts' general ability on the other hand. Ertimur, Sunder, and Sunder (2007) find that analyst expertise is important in explaining the level of profitability, but they examine only the contemporaneous relation between accuracy and profitability.

In contrast to the previous studies we focus on predictability of earnings accuracy in order to analyze whether the contemporaneous link between earnings accuracy and profitability can be exploited.

[1] Earnings are an important input to generate stock recommendations (Schipper, (1991)). Asquith/Mikhail/Au (2003) find that 99.1% of analysts mention some sort of earnings multiple in their reports, while 12.8% use a Discounted Cash Flow model. Bradshaw (2004) finds that analysts use ad hoc models such as multiples rather than more sophisticated models such as residual income models.

Therefore, we examine the characteristics of analysts in addition to just the latest rank table.[2] Following analysts' recommendations based on the analysts' past earnings track record alone does not adequately differentiate between analysts that got lucky and analysts that are more able. In every period there may be some analysts whose earnings projections hit the target best just because some unforeseeable events happened. For example, an analyst who is always overly pessimistic will be relatively more accurate once a recession strikes. However, following his recommendations next year is probably not a good advice, since his higher accuracy was based on randomness and not ability. In terms of ability it proves to be important whether an analyst works in a superior environment (as indicated by the broker size), has more time for the company analysis (as indicated by the number of companies and industries covered) or whether he follows the market more closely (as indicated by the number of earnings revisions). We project the accuracy of the earnings forecast based on the analyst's characteristics when the earnings forecast is made. Therefore, we combine the predictive power of the projected higher contemporaneous earnings accuracy with predictive power of the analysts' expertise. Employing a total of eight analyst/forecast characteristics in order to project analysts' earnings accuracy enables us to differentiate between analysts with higher ability and those that just had good luck. The distinction between able and lucky analysts proves to be very important.

First, we find strong differences in the profitability of individual stock recommendations issued by able vs unable analysts. Specifically, we evaluate the returns of recommendations if we hold a recommended stock till the corresponding earnings have been announced, i.e. until the point in time when the superior (vs inferior) forecasting ability has materialized in a smaller (vs. larger) surprise. We show that "Strong Buy" and "Buy" recommendations of able analysts result in significantly higher returns than their "Sell" and "Strong Sell" recommendations, i.e. the realized returns are consistent with their recommendations. In contrast, this is not the case for the recommendations of the unable analysts, e.g. their "Sell" recommendations realize higher returns than their "Buy" recommendations. This indicates that able analysts can better differentiate between undervalued and overvalued stocks.

[2] This conclusion is also in line with the findings of Stickel (1995): Larger broker houses and analysts who have better reputations have more impact on prices.

Moreover, the “Strong Buy” and “Buy” recommendations issued by able analysts are significantly more profitable than those of unable analysts. ,

Second, the difference in profitability allows us to propose an implementable trading strategy (based on predicted accuracy rather than past accuracy), since we only use information that is available ex ante, i.e. when the investment decision is made. With our approach investors can decide at the time the recommendation is issued whether to follow it or not. We use the following methodology to project the earnings accuracy of analysts and to identify more (less) able analysts: When an analyst issues an earnings forecast for a company, we calculate the firm-specific characteristics of the analyst. Then, we project (out-of-sample) the firm-specific earnings accuracy of the analyst for the respective fiscal year. Controlling for other effects, we rank analysts according to their intrinsic firm-specific accuracy. We use the highest and the lowest projected intrinsic accuracy quintile as a criterion to discriminate between able and unable analysts. A trading strategy where investors follow the “Strong Buy” (“Buy” recommendation of able analysts yields significant excess returns of 8.61% (5.7%) p.a. in the 1994 to 2007 time period. In contrast, the corresponding recommendations of unable analysts do not add value. In order to facilitate a comparison to previous studies, we also employ a trading strategy similar to Loh and Mian (2006),[3] however, a look-ahead bias free one. As a result, we find that the long portfolio based on the recommendations of the able analysts earns excess returns of up to 11.5% per year (before transactions costs). The difference in risk-adjusted returns of the long portfolio between the able and the unable analysts is significant at the 1% level for various consensus calculation periods.[4]

Third, we show that looking at past earnings accuracy alone (without accounting for ability) does not yield excess returns. This result is in line with Hall and Tacon (2010). Overall our results suggest that expertise is important in order to distinguish between the able winners and the lucky winners.

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[3] The trading strategy used by Loh and Mian (2006) is based on the trading strategy shown by Barber et al. (2001).

[4] We use a one month, three months, six months and twelve months consensus calculation period.

Fourth, we find that the higher return of the "Strong Buy" and "Buy" recommendations is not just caused by a reputation effect, i.e. the higher overall return of these recommendations is not driven by the immediate announcement return in the first trading days after the recommendations are issued. This suggests that able analysts have stock picking abilities. Stock recommendations by able analysts have value in the investment decision process.

Finally, when comparing the realized earnings accuracy of the projected accuracy quintiles we find, in accordance with Brown (2001) and Brown and Mohd (2003), statistically significant differences, although the economic differences are relatively small: The earnings forecasts of able analysts are on average about 1.19 cent more accurate than those of unable analysts. This suggests that the profitability of stock recommendations is driven primarily by the analysts' ability.

Overall our results suggest that ability is an important criterion: Specifically, it explains differences in the profitability of analyst recommendations. Moreover, it drives the persistence of recommendations' profitability. Basically, our trading strategy exploits the fact that the profitability of able analysts' recommendations is persistent, while this not the case for unable analysts' recommendations.

The remainder of the paper is organized as follows. In Section 2, we introduce the research design. Section 3 describes the methodology and the data. Section 4 discusses the empirical results. Finally, section 5 concludes.

2. Research Design

We address the question whether analysts that are more able than their peers can be identified ex ante. When an earnings forecast is issued by an analyst we project the accuracy of the earnings forecast using analyst/forecast characteristics. We control for characteristics of the forecast in order to identify the intrinsic forecast ability of the analyst and then analyze whether analysts that have higher projected (intrinsic) earnings accuracy also issue more profitable stock recommendations (i.e. have the ability to identify undervalued or overvalued stocks).

Our approach differs from Hall and Tacon (2010) in that we employ analyst and forecast characteristics in addition to past earnings accuracy to project the earnings accuracy. Prior research based on in-sample regressions has already shown that forecast accuracy is systematically related to individual analyst characteristics as well as lagged accuracy, i.e. the analyst's earnings track record (see, e.g. Clement and Tse, (2003)). Therefore, it seems straightforward to use these characteristics as well as past earnings accuracy to identify relatively more accurate analysts and to trade on their recommendations. However, according to Brown (2001) and Brown and Mohd (2003) the out-of-sample predictive ability of individual characteristics for earnings accuracy is relatively low in economic terms. Nevertheless, O'Brien (2003) calls for analyzing individual analyst characteristics as a source for possible trading opportunities. Likewise, Ertimur, Sunder, and Sunder (2007) point out that trading strategies based on analyst accuracy might be a fruitful opportunity for future research.

We look at analyst characteristics that have been identified to be systematically related to earnings accuracy by previous studies (e.g., Jacob, Lys, and Neale (1999) and Clement and Tse (2003)) for example, size of the broker the analyst is working for, number of companies covered by the analyst and firm-specific forecast experience of the analyst. These characteristics are proxies for the analysts' ability. However, we take also into account the past earnings accuracy of an analyst. This enables us to differentiate between analysts that have provided superior forecasts in the past because they are more able than their peers and analysts that just have been lucky last time. Having identified those analysts that will most likely provide superior earnings forecasts this year we examine the value of their stock recommendations from the perspective of an investor. Therefore, we use the relationship between higher earnings accuracy and profitability as well as the association of ability and profitability. First, we analyze what returns an investor can expect on average if he follows individual recommendations provided by an analyst that is classified as "able" according to our model. We compare these to the average returns on recommendations of "unable" analysts. Second, we analyze whether an investor can profit from the superior forecasting performance of the more able analysts by implementing a trading strategy based only on information that is available ex ante (i.e. when the investment decision is made). To do so, we compute the average risk-adjusted return of following the recommendations of analysts with projected superior earnings forecast accuracy.

We address the following research question: Are analysts' characteristics and lagged accuracy helpful to predict which analyst will issue more accurate earnings forecasts and will these analysts also provide more profitable stock recommendations?

Therefore, we predict which analysts will issue more accurate earnings forecasts (given their past performance and their individual characteristics) and analyze the average profitability of single recommendations issued by these "able" analysts. Then we compare the profitability of their recommendations with the profitability of those stemming from analysts that are classified as "unable" according to our model. In order to analyze the influence of unforeseeable events, we differentiate between the recommendations that were not revised until the forecasted earning is actually published (i.e. until the firm announces the earnings the analyst had forecasted) and recommendations that were revised in between. Therefore, our first hypothesis becomes:

> $H_{1:}$ The difference in profitability between single recommendations of more able and less able analysts is significant if the recommendations are held until the earnings for the firm-year are published.

Under the assumption that H_1 cannot be rejected, we also want to analyze possible reasons for differences in profitability between able unable analysts: Does the market react differently to the recommendations of an able analyst than to the recommendations of an unable analyst? When does the return of the recommendation materialize? For example, assume that investors just look at the latest ranking table and follow the recommendations of the leading analysts. If excess returns associated with recommendations can be attributed to such a reputation effect, we would expect to observe a strong post announcement drift, e.g., a large positive return immediately after a past years top performer has issued a "Strong Buy" recommendation, and only moderate returns thereafter. Hence, we would expect that a relatively large fraction of the excess return associated with a recommendation is realized immediately after the recommendation was issued. Therefore, our second hypothesis becomes:

> H_2: The higher profitability of the single recommendations issued by able analysts is due to a reputation effect (i.e. most of the higher return materializes in a narrow window after the recommendation is issued).

Furthermore, we analyze the profitability of a trading strategy, where we follow all recommendations issued by able or unable analysts in a respective category, e.g. follow all “Buy” recommendations of able analysts:

> H_3: The difference in profitability between analysts that are classified as able respectively unable is significant when following the recommendations in a recommendation category.

in order to facilitate a comparison to previous studies, we also examine the profitability of a trading strategy when the consensus recommendation of single stocks is used as a trading signal. Therefore, in addition to analyzing the returns of single recommendations, we examine whether our approach to identify ex ante more able analysts can be used to assign a trading strategy similar to Loh and Mian (2006), i.e. follow the recommendations of analysts with higher intrinsic earnings forecast accuracy. However, we use only information that is available ex ante, i.e. at the time the decision to trade has to be made.

> H_4: The difference in profitability between analysts that are classified as able respectively unable is significant if the consensus recommendation of individual stocks is used as the trading signal.

Next, we analyze how lagged accuracy and the ability of an analyst are related to the profitability of stock recommendations. We differentiate analysts in regard to their track record and in regard to their ability. Therefore, we make a distinction between analysts that have a good track record and high ability, i.e. able analysts, and analysts that have a good track record and low ability, i.e. lucky analysts. Our fifth hypothesis is:

H_5: The difference in profitability between analysts that are classified as able respectively lucky is significant if the consensus recommendation of individual stocks is used as the trading signal.

Since earnings accuracy of the analysts is projected ex ante, we also want to analyze the difference in earnings accuracy ex post. Is our projection of earnings accuracy in hindsight correct? Do analysts with higher projected (intrinsic) earnings accuracy issue more accurate earnings forecasts? Therefore, our sixth hypothesis becomes:

H_6: The difference in the absolute forecast error between able and unable analysts is significant after controlling for firm-specific and time period-specific effects.

Under the assumption that our hypotheses are not rejected, we show that analysts who issue more profitable stock recommendations can be identified ex ante and that the higher profitability of their stock recommendations can be used in order to generate excess returns with an implementable trading strategy.

3. Methodology and Data

Our general approach is shown in figure 1. When an analyst issues an earnings forecast for a company we calculate the characteristics of the analyst (respectively of the earnings estimate). Using the information about characteristics available at the time the forecast is made we perform a regression analysis and project the accuracy of the earnings forecast. We use a rolling regression of the characteristics on earnings accuracy covering the last 12 months (including the month the forecast was made).[5] Then, we classify analysts as able or unable based on their intrinsic earnings accuracy. Next, we analyze the profitability of the single stock recommendations issued by able respectively unable analysts. We also measure the profitability of stock recommendations according to a trading strategy similar to Loh and Mian (2006). When an analyst is classified as able/unable for a specific company

[5] This does not imply that we use forward-looking information, i.e. incorporate a look-ahead bias, since the analysts are categorized monthly. The classification of analysts as able or unable according to our model is made for the consecutive months in the firm-year after the month in which the regression analysis was performed.

and a specific year we examine the profitability of the recommendations issued by the analyst for the company in the fiscal year after the classification.

We use the regression framework by Clement and Tse (2003) in order to calculate analyst characteristics. Our approach is based on three steps: In a first step we project the earnings accuracy of the earnings forecasts (see section 4.1. for details). In a second step (section 4.2.) we classify analysts as able respectively unable. In the third step (section 4.3.) we analyze the profitability of stock recommendations issued by able respectively unable analysts. First, we evaluate the average profitability of individual recommendations issued by analysts in the projected upper and lower accuracy quintile, differentiating between unrevised and revised recommendations (section 4.3.1.). Then, we explore whether a reputation effect could drive the results (section 4.3.2.), before we analyze the profitability of trading strategies based on the recommendations of able respectively unable analysts (section 4.4.). Next, we examine the profitability of stock recommendations of lucky and able analysts (section 4.5.). We conduct a robustness check when including/excluding one analyst characteristic in our model (section 4.6.) Finally, we discuss how large the differences in the realized accuracy of earnings forecasts are between those forecasts we have predicted to fall into the upper and lower accuracy quintile (section 4.7.)

[insert figure 1 here]

We use earnings forecasts and the corresponding actual earnings from the Institutional Brokers Estimate System (I/B/E/S). The individual analyst stock recommendations are from I/B/E/S as well. The daily stock returns and the daily market capitalization of the stocks are extracted from The Center for Research in Security Prices (CRSP). In order to calculate excess returns we extract the daily Fama/French factors and the momentum factor from the website of Kenneth French. We perform a regression analysis following Clement and Tse (2003) in order to estimate the influence of analyst characteristics on earnings accuracy. We run the OLS regression analysis for each month separately in the 1994 to 2007 time period with a rolling window of twelve months. We obtain a total of 289,979 earnings accuracy – analyst characteristics combinations for our rolling regression analysis in that time period. Based on the monthly characteristics and the coefficients of the rolling regression, we project the earnings accuracy of analysts. The able and unable analysts combined issue 54,167 recommendations in the 1994 to 2007 time period combined.

We use the following filters for the earnings forecasts that are used in the rolling regression: (1) In accordance with Clement and Tse (2003), we only use earnings forecasts that have been issued at least 30 days, but not more than one year, before the end of the fiscal year of a firm. (2) Also in accordance with Clement and Tse (2003) and other studies (e.g. Sinha, Brown, and Das (1997)) we retain only the last forecast for each analyst-firm pair during the period. (3) We only use firms for which at least two analyst have issued earnings forecasts for the respective fiscal year, since the analyst characteristics are standardized. In addition, we eliminate observations from the sample if (4) the scaled forecast revision is in the top or bottom 1% of revisions or (5) there is no corresponding Fama and French industry classification. (6) In order to control for outliers, the absolute forecast error (AFE), the number of firms covered by analyst i in period t and the difference between the actual and the preceding earnings forecast is winsorized at 1^{st} and 99^{th} percentiles. (7) If the actual values used for the standardization of ACCURACY respectively the analyst characteristics are the same, we use the value 0.5, since otherwise the observations would drop out.

We use the following filters for the calculation of the analyst characteristics that are calculated when earnings forecasts are issued: (8) We only use earnings forecasts that have not been issued more than one year before the end of the fiscal year of a firm. (9) If an analyst is employed by two or more brokers and issues several earnings forecasts for the same firm on the same day we only use the last revised earnings forecast. (10) If an analyst has issued several forecasts for a firm within a month, we only use the last forecast of the month for the more recent fiscal year.

4. Empirical Results

4.1. Projected Earnings Accuracy

When an earnings forecast is issued we project the earnings accuracy of this forecast. We use two inputs for this projection: The analyst/forecast characteristics (including the lagged accuracy) at the time the earnings estimate is made and the estimated influence of the characteristics on the earnings accuracy. The influence of the characteristics on the earnings accuracy is measured on the basis of a rolling regression following Clement and Tse (2003). At the end of each month in the 1994 to 2007 time period the economic influence of the characteristics on the earnings accuracy is estimated by performing a regression of the earnings accuracy on the characteristics. Therefore, the regression is performed 168 times. The rolling time window of the regression covers the last 12 months including the month the forecast is made.

The characteristics and the earnings accuracy are standardized in order to control for systematic differences in company years. The earnings accuracy and the characteristics used in the rolling regression are standardized relatively to other analysts who followed the firm in the respective fiscal year. In the OLS regression we use the eight analyst (respectively forecast) characteristics suggested by Clement and Tse (2003). Our model comprises three components:

(1) Five proxies for analyst ability: The size of the broker the analyst is working for (BROKER_SIZE), the frequency with which the analyst issued earnings (FOR_FREQUENCY), the time the analyst has covered the firm in the past (FIRM_EXPERIENCE), the number of companies the analyst covers (COMPANIES), and the number of industries the analyst covers (INDUSTRIES).

(2) Two characteristics of the forecast: The time elapsed since the last forecast issued by any analyst covering the firm (DAYS_ELAPSED), and the horizon of the forecast (FOR_HORIZON).

(3) Past accuracy: the analysts' earnings accuracy of the last fiscal year for the firm (LAG_ACCURACY).

Note that we take into account five additional analyst characteristics that are related to earnings accuracy in addition to past accuracy, while also controlling for two characteristics of the earnings forecast:

$$\begin{aligned} ACCURACY_{ijt-1} = \; & \alpha_0 + \alpha_1 LAG\_ACCURACY_{ijt-1} + \alpha_2 DAYS\_ELAPSED_{ijt-1} \\ & + \alpha_3 BROKER\_SIZE_{ijt-1} + \alpha_4 FOR\_FREQUENCY_{ijt-1} + \alpha_5 FIRM\_EXPERIENCE_{ijt-1} \\ & + \alpha_6 COMPANIES_{ijt-1} + \alpha_7 INDUSTRIES_{ijt-1} + \alpha_8 FOR\_HORIZON_{ijt-1} + \varepsilon_{ijt-1} \end{aligned}$$

As mentioned above we use the same analyst/forecast definitions as Clement and Tse (2003). See Appendix 1 for a more detailed description. We standardized these characteristics, i.e. a characteristic of analyst i (respectively of the forecast) for company j in time t-1 as explanatory variables is defined as:

$$CHARACTERISTIC_{ijt-1} = \frac{RAW\_CHARACTERISTIC_{ijt-1} - RAW\_CHARACTERISTIC\min_{jt-1}}{RAW\_CHARACTERISTIC\max_{jt-1} - RAW\_CHARACTERISTIC\min_{jt-1}}$$

All analyst (respectively forecast) characteristics are standardized relatively to other analysts, who have issued earnings forecasts in the same period t-1 for the same company j, to lie between 0 and 1. By using this standardization we control for systematic differences in company years (see Clement and Tse, 2003). The accuracy of the earnings forecasts is also standardized relatively to other analysts who issued earnings forecasts in the same period t-1 for the same company j:

$$ACCURACY_{ijt-1} = \frac{AFE\max_{jt-1} - AFE_{ijt-1}}{AFE\max_{jt-1} - AFE\min_{jt-1}}$$

The dependent variable ACCURACY can assume values between 0 and 1, whereby 0 is the lowest possible accuracy and 1 is the highest possible accuracy relatively to other analysts issuing earnings forecasts in period t-1 for company j.

Since the reported earnings must be known in order to calculate earnings accuracy, we use earnings forecasts for which the earnings report dates already took place. We use earnings forecasts for which the corresponding earnings have been reported in the respective 12 month including the month the forecast is made.

For example, the regression analysis performed at the end of December of 2006 (the 156th month in our sample) uses all earnings forecasts of which the corresponding earnings have been reported in the January of 2006 to December of 2006 time period. By using a relatively small time window of 12 months we are able to account for non time stable relationships between characteristics and earnings accuracy.[6]

The average coefficients of the OLS rolling regression, the range of the coefficients and the absolute t-statistics of the coefficients are shown in table 1:

[insert table 1 here]

Table 1 shows that the accuracy of analyst i's earnings forecast for firm j in the previous year (LAG_ACCURACY) and the forecast frequency (FOR_FREQUENCY) had a significant positive impact on the earnings accuracy in all time windows, while the number of days elapsed since the last forecast (DAYS_ELAPSED), the number of industries covered by the analyst (INDUSTRIES), and the forecast horizon (FOR_HORIZON) had a significant negative impact in nearly all time windows on the earnings accuracy. These results are in line with Clement and Tse (2003).[7] Our results differ to those of Clement and Tse (2003) in respect to Broker size (BROKER_SIZE), the number of companies covered (COMPANIES) and the firm experience (FIRM_EXPERIENCE). In our sample period these characteristics do not have a time stable impact on earnings accuracy. Possible reasons for changes in the relationship between characteristics and earnings accuracy are regulatory changes. For example, broker size and firm-specific experience lose their explanatory power for analysts' relative accuracy after Regulation FD (Findlay and Mathew, 2006). Therefore, differences to Clement and Tse

[6] Possible reasons for changes in the relationship between characteristics and earnings accuracy are regulatory changes. For example broker size and firm-specific experience lose their explanatory power for analysts' relative accuracy after Regulation FD (Findlay/Mathew, 2006).

[7] Note, however, that we report the arithmetic mean of the coefficients based on 168 rolling regressions, while Clement and Tse (2003) perform the regression for the whole sample period.

(2003) might be explained by the fact that our sample period also covers earnings forecasts made after Regulation FD.

The second input required in order to project the earnings accuracy are the characteristics of the analyst respectively the forecast that are calculated when a forecast is made.[8] The definitions of the characteristics that are calculated when a forecast is made are the same as in the rolling regression. However, the characteristics of the analyst respectively of the forecast are standardized according to the forecasts made in the respective 12 months including the month of the forecast. The “rolling” standardization of the monthly characteristics enables us to incorporate recent changes in analyst characteristics. If the characteristics would be standardized according to the fiscal year, the standardization would only be possible yearly instead of monthly. The accuracy of an earnings forecast is projected according to the characteristics of the analyst respectively of the forecast and the coefficients of the rolling regression:

$$\begin{aligned}\widehat{ACCURACY}_{ijt} = {} & \widehat{\alpha_0} + \widehat{\alpha_1} LAG\_ACCURACY_{ijt} + \widehat{\alpha_2} DAYS\_ELAPSED_{ijt} \\ & + \widehat{\alpha_3} BROKER\_SIZE_{ijt} + \widehat{\alpha_4} FOR\_FREQUENCY_{ijt} + \widehat{\alpha_5} FIRM\_EXPERIENCE_{ijt} \\ & + \widehat{\alpha_6} COMPANIES_{ijt} + \widehat{\alpha_7} INDUSTRIES_{ijt} + \widehat{\alpha_8} FOR\_HORIZON_{ijt}\end{aligned}$$

As an example, consider how the accuracy is projected for an earnings forecast that was issued in August of 2006 for a firm with a fiscal year end in December of 2006: If an analyst issues an earnings forecast in August of 2006, the firm-specific characteristics of the analyst respectively of the forecast are calculated for August of 2006. Furthermore, we use the coefficients of the regression in the September of 2005 to August of 2006 time period. The earnings accuracy (for the fiscal year end) is projected by combining the analyst’s characteristics of August 2006 with the coefficients of the regression performed over the September of 2005 to August of 2006 time period.

[8] Note that we only use earnings forecasts which have not been issued more than one year before the end of the fiscal year.

4.2. Identification of Able and Unable Analysts

We use the projected earnings accuracy in order to identify able respectively unable analysts. The projected earnings accuracy is also driven by the forecast horizon (i.e. a forecast that is made in August of 2006 for the end of December of 2006 is likely to be less accurate than a forecast made in November of 2006 for the same fiscal year end) and the time elapsed since the last forecast made by any analyst. However, because the forecast horizon and the time elapsed since the last forecast are not intrinsic characteristics of the analyst, we have to control for these two characteristics of the forecast in order to identify the projected intrinsic ability of the analysts:

$$\widehat{\text{INTRINSIC\_ACCURACY}}_{ijt} = \widehat{\text{ACCURACY}}_{ijt} - \widehat{\alpha}_0 - \widehat{\alpha}_2 \text{DAYS\_ELAPSED}_{ijt} - \widehat{\alpha}_8 \text{FOR\_HORIZON}_{ijt}$$

In every month we rank analysts according to their projected intrinsic earnings accuracy. The projected intrinsic accuracy is based on the past earnings accuracy as well as five additional analyst characteristics that are related to earnings accuracy. Therefore, we take into account the track record as well as additional information about the analyst in order to differentiate between analysts that got lucky in the last period and analysts that show characteristics which are systematically related to earnings accuracy.

We classify analysts as able (unable) if they belong to the upper (lower) intrinsic accuracy quintile of the respective month. This procedure is carried out for every month within the 1994 to 2007 time period (168 months). The classification is firm-specific. That means an analyst can be classified as able for one company while being classified as unable for another company at the same time. The firm-specific classification of an analyst is effective till the end of the fiscal year of the firm the forecast is issued for respectively till the classification changes. For example, the analyst could be classified as neither able nor unable according to his first earnings forecast for the firm and as able according to the second earnings forecast made by him for the same company year (e.g. because he moves to another broker).

4.3 Profitability of Single Recommendations

4.3.1. Single Recommendations –All Recommendations

Thus far we have classified analysts as able (i.e. high projected intrinsic earnings accuracy) respectively unable (i.e. low projected intrinsic earnings accuracy). Next, we address the question whether recommendations are more (less) profitable if they are issued by an able (unable) analyst. For the respective recommendation categories ("Strong Buy" to "Strong Sell") we analyze the return of single recommendations issued by able (unable) analysts. For example, if an analyst has been identified as an able analyst for a firm-year based on a forecast made in April 2005, we analyze the profitability of the recommendations issued by the analyst in that firm-year.[9] We measure the return of single recommendations in the time window (i.e. holding period) beginning one trading day after recommendation issuance and ending five trading days after the earnings report date. We hold the recommendation till five trading days after the earnings report date, since the analyst is classified as able (unable) based on his earnings forecast made prior in the fiscal year. Therefore, the report date is the information event in terms of the analyst classification.

[insert figure 2 here]

The discrete raw returns of the respective recommendations categories are shown in table 2: [10]

[insert table 2 here]

Figure 3 illustrates the difference in returns between the recommendations issued by the able respective by the unable analysts. The holding period covers one trading day after recommendation announcement till five trading days after the earnings report date (as shown in Column 7):

[insert figure 3 here]

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[9] If the classification changes based on another forecast made by the analyst for the same firm year, the subsequent recommendations are either not regarded (if the classification changes to neither able not unable) or they are analyzed as recommendations issued by unable analysts (if the classification changes to unable).

[10] Note that the raw returns are not annualized.

Table 2 shows that able analysts in general are superior in predicting stock returns: Following the “Strong Buy” and “Buy” recommendations issued by an able analysts yields higher returns than following the “Strong Buy and “Buy” recommendations of unable analysts. Also, following “Sell” recommendations issued by able analysts yields lower returns than following “Sell” recommendations by unable analysts.

As shown in figure 3, the difference in returns of 3.42% for “Strong Buy” recommendations as well as the difference of 1.61% for “Buy” recommendations is statistically significant at a 1% (5%) level. However, the difference in returns for the other recommendation categories is not statistically significant. Our results indicate that able analysts have the skill to identify undervalued stocks.[11] Therefore, our first hypothesis cannot be rejected. The difference in profitability between single recommendations of more able and less able analysts is significant if the recommendations are held until the earnings for the firm-year (plus five trading days) are published. Table 3 shows the correlation coefficients between our intrinsic accuracy measure respectively the analyst characteristics and the realized returns. The intrinsic accuracy measure is positively correlated to the realized returns for all holding periods.

[insert table 3 here]

4.3.2. When does the return materialize?

Able analysts issue more profitable “Strong Buy” and “Buy” recommendations. We want to analyze to what extent the higher return is due to the forecasting skills of the able analysts: Are the higher returns a consequence of the fact that the market follows the able analyst more intensely, i.e. investors buy the stock when the recommendations are issued? Or does the higher return materialize over a longer time window? We separate the total time window from the trading day after the recommendation issuance date to the earnings report date plus trading five trading days into three different time windows (see also figure 2): (1) The time window covering the recommendation announcement return, which is our

[11] Interestingly, Cohen, Frazzini and Malloy (2010) come to a similar result when differentiating between analysts in respect to their school ties: analysts` buy recommendations on school-tied stocks outperform buy recommendations on non-tied stocks, while sell recommendations do not.

proxy for a reputation effect, (2) the time window covering the earnings announcement return, which is our proxy for the earnings announcement effect, and (3) the time window in between (1) and (2). The time window covering the recommendation announcement begins at the trading day after the recommendation announcement and ends five trading days later. The time window covering the earnings announcement return starts five trading days before and ends five trading days after the report date.

As shown in table 2 the higher profitability of the "Strong Buy" ("Buy") recommendations issued by able analysts is neither due to a reputation effect nor to an earnings announcement effect. Both are economically insignificant in comparison to the total return over the holding period: For example the recommendation announcement return of a "Strong Buy" recommendation issued by an able analyst is on average about 0.76%, while the earnings announcement return is about 1.35%. Both effects combined only account for about 19%[12] of the total return over the total holding period. This indicates that the stock picking ability of the able analysts is real: The "Strong Buy" and "Buy" recommendations by able analysts earn higher returns because they anticipate the trend of the underlying stock. A plausible explanation is that able analysts anticipate favorable firm news which lead to higher returns.

Overall, our second hypothesis can be rejected. Able analysts issue significantly more profitable "Strong Buy" and "Buy" recommendations. However, the higher return is not driven by a reputation effect. This indicates that the higher returns of the "Strong Buy" and "Buy" recommendations is not due to the fact that market participants just blindly follow able analysts. The fact that the large majority of the return of the "Strong Buy" and "Buy" recommendations is realized over a longer time window indicates that the stock picking ability of able analysts is real.

[12] (0.76%+1.35%)/11.12% = (Recommendation Announcement Return + Earnings Announcement Return)/Total Holding Period = 19%

4.3.3. Individual Recommendations – Revised/Not Revised

Next, we differentiate between recommendations that are revised (not revised) by the same analyst in order to account for unexpected adverse information events for the respective recommendation. For example, an analyst with an outstanding “Buy” recommendation might need to revise the recommendation after a financial crisis strikes. Similarly, an analyst with an outstanding “Sell” recommendation might need to revise the recommendation after macroeconomic conditions improve unexpectedly.

A revision is defined as a change in recommendation to another category, where the first category includes “Strong Buy” and “Buy” recommendations, the second category includes “Hold” recommendations and the third category included “Sell” and “Strong Sell” recommendation. For example, a “Strong Buy” recommendation issued by an able analyst on August 15th, 2006, is held from August 16th, 2006, till January 5th, 2007 (if the firm year end at December 31th, 2006), as long as the analyst does not revise the recommendation before the report date. If the analyst revises the recommendation because of an unexpected information event, the recommendation is held till the revision date. Table 4 shows the profitability of single stock recommendations that are not revised, while table 5 shows the profitability of stock recommendations that have been revised:

[insert table 4 here]

Table 4[13] shows that the “Strong Buy” and “Buy” recommendations that are not revised earn slightly higher returns compared to the total sample of recommendations (e.g. 12.07% vs. 11.12% in category “Strong Buy – Return till Report Date +5”). At the same time, sell recommendations have lower returns (e.g.:3.6% vs. 6.62% in category “Strong Sell – Return till Report Date +5”). Therefore, controlling for unexpected adverse information events leads to more predictive power of recommendations. The results indicate that analysts process information that is relevant for the stock price and base their investment advice on economic rationale.

[13] Note that the returns shown in table 3 are based on recommendations that are not revised. Therefore, they contain a look-ahead bias. Also note that the returns are not annualized.

[insert table 5 here]

Table 5 shows that the overall return of the “Strong Buy” and “Buy” recommendations is economically marginal in the time window between the recommendations issuance and the revision. This indicates that analysts revise their recommendations if the outlook for a firm has changed, i.e. analysts process relevant information.

After the revision is made “Strong Buy” recommendations by able analysts that have been revised outperform “Strong Buy” recommendations by unable analysts that have been revised (e.g. 4.41% vs 1.57%). However, since the overall return of the “Strong Buy” recommendations that are revised is relatively low, the revision is still economically meaningful. For “Buy” recommendations the difference is very small (e.g.: 1.80% vs 1.52%), while “Strong Sell” recommendations of able that have been revised outperform “Strong Sell” recommendations of unable that have been revised. Overall, the differences are marginal. This suggests that able analysts are superior in their stock recommendation regarding private information. An unexpected event provoking a revision of recommendation is observable by an able as well as an unable analyst. Thus, we observe while controlling for unexpected events that the difference between an able and an unable analyst decreases. The dominance of able analysts seems to be a consequence of their access to private information and therefore their reputation.

4.4 Profitability of Trading Strategies

4.4.1 Trading Strategy – Recommendation Categories

So far, we have analyzed the profitability of single stock recommendations. A trading strategy yields the advantage that we can analyze excess returns and therefore study, whether recommendations add value in the investment decision process. We perform the trading strategy separately based on the recommendations issued by the able analysts respectively based on the recommendations issued by the unable analysts in each recommendation category, i.e. we perform the trading strategy a total of ten times. We separately analyze for the able and unable analysts each of the five recommendation categories, e.g. we perform the trading strategy for “Strong Buy” recommendations of able analysts.

Our trading signal is the issuance of a recommendation by an able or unable analyst, i.e. we follow every recommendation in the analyzed recommendation category. If there are several recommendations in a category for a firm, we assign the stock each time to the portfolio ρ. Each recommendation is assigned to the portfolio on the next trading day τ after issuance in order to prevent a look-ahead bias.[14] The stocks which have been assigned to the portfolio are equally weighted. Each stock in the portfolio is hold till the respective earnings report date plus five trading days.

The daily excess return of the respective portfolio is calculated according to Carhart’s (1997) 4-factor-model:[15]

$$R_{\rho\tau} - rf_{\tau} = \alpha_{\rho} + \beta_{\rho}(Rm - rf_{\tau}) + s_{\rho}SMB_{\tau} + h_{\rho}HML_{\tau} + m_{\rho}UMD_{\tau} + \varepsilon_{\rho\tau}$$

The results of the trading strategy are shown in table 6:

[insert table 6 here]

Our results show that investors can earn excess returns by following “Strong Buy” and “Buy” recommendations of able analysts. The other recommendation categories and all recommendations issued by unable analysts do not add value in the investment decision process. The difference in the daily excess return is significant for the “Strong Buy” recommendation category: Able analysts issue more profitable “Strong Buy” recommendations than unable analysts. Our results are in line with the profitability of single stock recommendations (table 2): Able analysts issue more profitable “Strong Buy” and “Buy” recommendations, however, from an investors perspective it is not beneficial to follow the recommendations of the other three categories.

[14] Since the recommendation announcement return is economically insignificant in our sample, we could also assign each stock later (e.g. two trading days) to the portfolio.

[15] We use the daily FF-factors retrieved from the website of Kenneth French. Also see Fama and French (1993).

4.4.2 Trading Strategy – Consensus Recommendation

We also perform a trading strategy similar to Loh and Mian (2006) using ex ante information. Therefore, the trading strategy is implementable. In line with Loh and Mian (2006) we calculate the consensus recommendation of a stock based on the recommendations issued in the respective last six months.[16] We also use alternative consensus recommendation calculation periods of one month/three months/twelve months. We perform the trading strategy separately based on the recommendations issued by the able analysts respectively based on the recommendations issued by the unable analysts.

The consensus recommendation $\overline{A}$ for firm j is calculated at the end of the trading day $\tau - 1$ based on the recommendations issued for the respective firm within the last six months (alternatively one month/three months/twelve months). The single recommendations A assume values between 1 and 5, where a rating of 1 reflects a "Strong Buy" recommendation, 2 a "Buy", 3 a "Hold", 4 a "Sell" and 5 a "Strong Sell". For example, if for firm j one "Strong Buy" recommendation and one "Buy" recommendation has been issued within the last six months, the current consensus recommendation for firm j would be 1.5.

$$\overline{A}_{j\tau-1} = 1/n_{j\tau-1} \sum_{i=1}^{n_{j\tau-1}} A_{ij\tau-1}$$

We assign each stock on the following trading day according to the consensus recommendation either (1) into the long portfolio, (2) into the short portfolio or (3) none of both. The investment decision is made one trading day after the stock recommendation was issued in order not to trade before the recommendation was available. A stock is assigned into the long portfolio if $\overline{A}_{j\tau-1} \leq 2$ (implying that the consensus recommendation is at least "Buy"), while the stock is assigned to the short portfolio if $\overline{A}_{j\tau-1} > 2.5$. The portfolio classifications are the same as in Loh and Mian (2006).

The stocks which have been assigned to the long- or short portfolio ρ are weighted according to the market capitalization on the prior trading day. $x_{j\tau-1}$ is the market value of equity for firm j as of the

[16] According to Womack (1996) the post-recommendation drift lasts up to six months.

close of trading on date $\tau - 1$ divided by the aggregate market capitalization of all firms in portfolio ρ as of the close of trading on that date. $R_{j\tau}$ is the return of firm j's common stock on date τ and $n_{\rho\tau-1}$ is the number of firms in portfolio ρ at the close of trading on date $\tau - 1$:

$$R_{\rho\tau} = \sum_{j=1}^{n_{\rho\tau-1}} x_{j\tau-1} R_{j\tau}$$

The daily excess return of the long- and short portfolio is calculated according to Carhart's (1997) 4-factor-model:

$$R_{\rho\tau} - rf_{\tau} = \alpha_{\rho} + \beta_{\rho}(Rm - rf_{\tau}) + s_{\rho} SMB_{\tau} + h_{\rho} HML_{\tau} + m_{\rho} UMD_{\tau} + \varepsilon_{\rho\tau}$$

The results of the trading strategy based on the consensus recommendation as trading signal are shown in table 7. Figure 4 illustrates the returns of the long portfolio:

[insert table 7 here]

[insert figure 4 here]

Our results shows that a trading strategy similar to Loh and Mian (2006) yields significant excess returns for the long portfolio based on the recommendations of the able analysts. The higher return of the individual stock recommendations also translates into a higher profitability of a trading strategy. The daily excess return of the long portfolio based on the recommendations of the able analysts is statistically significant at the 1% level for different consensus calculation periods (one month, three months, six months and twelve months). For example, the excess return for the one month consensus calculation period is 11.5% annually before transactions costs. In contrast, the excess return of the long portfolio based on the recommendations of the unable analysts is not significant for any consensus calculation period. The excess return for the one month consensus calculation period is only 1.3% annually and not statistically significant. The difference in profitability of the long portfolio between the able and unable analysts is significant at the 1% level for all consensus calculation periods.

Therefore, our results show that a trading strategy similar to Loh and Mian (2006) can be successfully implemented when differentiating between able and unable analysts. Investors can actually profit from the documented contemporaneous link between earnings accuracy and recommendation profitability, if the analyst ability is also taken into account. Based on these results we cannot reject our fourth hypothesis: Analysts who are classified as able issue on average more profitable stock recommendations for the respective firm if the consensus recommendation of an individual stock is used as the trading signal and the consensus recommendation is "Buy" or higher.

It should also be noted that the excess return of the short portfolio based on the recommendations of the unable analysts is not statistically significant for any consensus calculation period. The difference in profitability of the short portfolio between the able and unable analysts is not significant for any consensus calculation period, either. Our results are in line with the profitability of single stock recommendations (table 2) and the analysis of the trading strategy for every recommendation category: Able analysts issue more profitable "Strong Buy" and "Buy" recommendations, therefore, they add value in the investment decision process.

Our results also indicate that a shorter holding period leads to higher returns: While the reputation effect is economically insignificant in comparison to the total earning return, as pointed out by the analysis of the individual recommendations, the post recommendation announcement drift is stronger in the first couple of weeks. Therefore, in order to maximize return, an investor should hold the recommendation only a short period of time. The long portfolio of the trading strategy similar to Loh and Mian (2006) and the 30 day consensus recommendation period lead to higher returns than only following the "Strong Buy" recommendations of the able analysts and holding the recommendations till five trading days after the earnings announcement day.

4.5. Differentiating between Lucky and Able Analysts

We want to further analyze the relationship between lagged accuracy and the ability of an analyst (as defined by our model). As a reminder our model comprises three sets of variables: (1) Proxies for analyst ability, (2) characteristics of the forecast, and (3) lagged earnings accuracy: In this section we analyze the additional value of the proxies for analyst analysts: We differentiate between analysts according to lagged accuracy and according to ability. First, we form quintiles according to our standard model without lagged accuracy (all three sets of variables are included):

$$
\begin{aligned}
ACCURACY_{ijt-1} = {} & \alpha_0 + \alpha_1 DAYS\_ELAPSED_{ijt-1} \\
& + \alpha_2 BROKER\_SIZE_{ijt-1} + \alpha_3 FOR\_FREQUENCY_{ijt-1} + \alpha_4 FIRM\_EXPERIENCE_{ijt-1} \\
& + \alpha_5 COMPANIES_{ijt-1} + \alpha_6 INDUSTRIES_{ijt-1} + \alpha_7 FOR\_HORIZON_{ijt-1} + \varepsilon_{ijt-1}
\end{aligned}
$$

$$
\begin{aligned}
\widehat{ACCURACY}_{ijt} = {} & \widehat{\alpha_0} + \widehat{\alpha_1} DAYS\_ELAPSED_{ijt} \\
& + \widehat{\alpha_2} BROKER\_SIZE_{ijt} + \widehat{\alpha_3} FOR\_FREQUENCY_{ijt} + \widehat{\alpha_4} FIRM\_EXPERIENCE_{ijt} \\
& + \widehat{\alpha_5} COMPANIES_{ijt} + \widehat{\alpha_6} INDUSTRIES_{ijt} + \widehat{\alpha_7} FOR\_HORIZON_{ijt}
\end{aligned}
$$

$$
\begin{aligned}
\widehat{INTRINSIC\_ACCURACY}_{ijt} = {} & \widehat{ACCURACY}_{ijt} - \widehat{\alpha_0} \\
& - \widehat{\alpha_1} DAYS\_ELAPSED_{ijt} - \widehat{\alpha_7} FOR\_HORIZON_{ijt}
\end{aligned}
$$

In the next step, independent of the first step, we form quintiles according to our standard model, however, we only include lagged accuracy (only variable set (2) and (3) are included):

$$
\begin{aligned}
ACCURACY_{ijt\text{-}1} = {} & \alpha_0 + \alpha_1 LAG\_ACCURACY_{ijt\text{-}1} + \alpha_2 DAYS\_ELAPSED_{ijt\text{-}1} \\
& + \alpha_3 FOR\_HORIZON_{ijt\text{-}1} + \varepsilon_{ijt\text{-}1}
\end{aligned}
$$

$$
\begin{aligned}
\widehat{ACCURACY}_{ijt} = {} & \widehat{\alpha_0} + \widehat{\alpha_1} LAG\_ACCURACY_{ijt} + \widehat{\alpha_2} DAYS\_ELAPSED_{ijt} \\
& + \widehat{\alpha_3} FOR\_HORIZON_{ijt}
\end{aligned}
$$

$$
\begin{aligned}
\widehat{INTRINSIC\_ACCURACY}_{ijt} = {} & \widehat{ACCURACY}_{ijt} - \widehat{\alpha_0} \\
& - \widehat{\alpha_1} DAYS\_ELAPSED_{ijt} - \widehat{\alpha_7} FOR\_HORIZON_{ijt}
\end{aligned}
$$

We receive five quintiles for every model, i.e. a total of 25 quintiles. For every quintile we perform the trading strategy described in section 4.4.2. (consensus recommendation as a trading signal). We only focus on the long portfolio, since the short portfolio does not generate excess returns. The results are shown in table 8:

[insert table 8 here]

Table 8 shows that (for the 3-month and the 6-month consensus calculation period) the earnings track record of an analyst is generally not sufficient in order to differentiate between “able” and “unable” analysts. However, in combination with our standard model, analysts who issue more profitable stock recommendations can be identified. Therefore, the track record is one important characteristic of an analyst that needs to be considered together with other analyst characteristics when making investment decisions. On a standalone basis, however, lagged accuracy is not sufficient. This result also indicates why the trading strategy in Hall and Tacon (2010) does not generate excess returns.

Therefore, analysts that just got lucky, i.e. have a high lagged accuracy but a low ability according to our model, do in general not issue profitable stock recommendations for the 3-month and 6-month consensus calculation period. The recommendations of analysts that are classified as unable and have a low lagged accuracy (“unable losers”) have in some cases even negative investment value for the 3-month consensus calculation period. Our fifth hypothesis cannot be rejected.

4.6. Robustness Check – Identifying Able and Unable Analysts Based on One Characteristic Only

As a robustness check, we differentiate between able and unable analysts based on only one characteristic such as lagged accuracy or broker size. Therefore, we test whether one characteristic is sufficient in order to differentiate between analysts that issue more (less) profitable recommendations. We use the same approach as described in section 4.1 and 4.2, however, we only include one characteristic in the regression analysis. The robustness check is influenced by Hall and Tacon (2010), since they show that past earnings accuracy is not sufficient in order to differentiate between able and unable analysts. The results are shown in table 9:

[insert table 9 here]

The results in table 9 show that one characteristic is not sufficient in order to differentiate between able and unable analysts. The difference in returns is generally not statistically significant at the 1% level for any characteristic and any consensus calculation period. As a reminder, the difference in returns is statistically significant at the 1% level for every consensus calculation period when using all six analyst characteristics. This also shows why the approach of Hall and Tacon (2010) is not sufficient in order to differentiate between analysts, since they use only the track record of an analyst.

Interestingly, the returns are statistically significant at a 10% level for the 3-month and the 6-month consensus calculation period when using only lagged accuracy and controlling for the number of days elapsed. Therefore, in contrast to Hall and Tacon (2010), we obtain at least weak empirical evidence that past earnings accuracy can be used in order to differentiate between able and unable analysts. This different result is likely to be the consequence of our methodology: First, we control more exactly for the forecast horizon by calculating the number of days till the end of the fiscal year, while Hall and Tacon (2010) compare the last forecasts issued by analysts in the 1 April to 30 June time window. Also, we standardize the characteristics in order to control for time and firm period specific effects.

Furthermore, we use a regression approach and control for non time-stable relationships between analyst characteristics and earnings accuracy by using a rolling regression window

The results in table 9 show that in general the statistical significance in returns between the able and unable analysts decreases when one characteristic is excluded. Therefore, the results indicate that our model is the correct one in order to identify analysts that issue more profitable stock recommendations. The statistical significance of the difference in returns decreases in particular if the lagged accuracy or the forecast frequency is excluded. Since both characteristics have at least some predictive power when used as a single characteristic, it seems to be that both principally drive our results.

4.7. Difference in Ex Post Realized Accuracy between Able and Unable Analysts

Do analysts that have been identified ex ante as able (unable) also issue more (less) accurate earnings forecasts? In order to test our sixth hypothesis, we compare the ex post accuracy of earnings forecast issued by analysts that have been identified as either able or unable. We only use earnings forecasts that have been issued no more than one year before the end of the fiscal year of a firm. Therefore, we analyze short-term accuracy of the able and unable analysts.

We compare earnings forecasts which have been issued in the same week, for the same firm and for the same fiscal year.[17] Therefore, there must be at least one earnings estimate of an able respectively of an unable analyst that has been issued in the same week, for the same firm and for the same fiscal year. If there is more than one earnings forecast issued by able or unable analysts we calculate the arithmetic mean of the forecasts. For example, if there are two able analysts that issue an earnings forecast in the same week, for the same firm and for the same fiscal year and one unable analyst, we compare the arithmetic mean of the two forecasts of the two able with the one forecast of the unable analyst. The results are shown in table 10:

[17] Therefore, we control for firm-specific and period-specific effects respectively for the age of the forecast.

[insert table 10 here]

The able analysts issue earnings forecast with an absolute forecast error (AFE) that is 1.19 cent lower. The winsorized AFE is 1.71 cent lower for the able analysts. The t-test shows that the difference in post realized accuracy between the highest and the lowest projected accuracy quintile is statistically significant at the 10% (1%) level for the AFE (winsorized AFE). Able analysts issue earnings forecasts that are ex post more accurate than the earnings forecasts issued by the unable analysts.

The economic significance of the difference between the highest and the lowest accuracy quintile is debatable. Therefore, we conclude that there is a statistically significant difference in the ex post realized accuracy between the able and the unable analysts, while the economic difference is very small. Similar evidence is found by Brown (2001) and Brown and Mohd (2003): Analyst characteristics, while descriptive in-sample, are not predictive in respect to earnings accuracy out-of-sample (O'Brien (2003)). However, we disagree with O'Brien (2003) who argues that "Thus, the theoretical relations, while useful for informing out notions of how the world works, are probably not useful for identifying profit opportunities". Our analysis of the profitability of stock recommendations points out that able analysts issue more profitable recommendations. The combination of a relatively low higher earnings accuracy and higher ability has predictive power for the profitability of stock recommendations. This interpretation is in line with the results of Ertimur, Sunder, and Sunder (2007) who point out that the profitability of recommendations is associated with earnings accuracy as well as analyst ability. Our results indicate that the projected intrinsic earnings accuracy is a general performance measure of analysts: Our model can be used in order to identify analysts that issue at least statistically more accurate earnings forecasts and statistically as well as economically more profitable recommendations.

5. Conclusion

We use analyst characteristics that are proxies for analyst ability in addition to lagged earnings accuracy in order to differentiate between able and unable analysts. Our approach enables us to differentiate between analysts that have a good track record because they got lucky and analysts that have a good track record because of their higher intrinsic ability.

We find that only “Strong Buy” and “Buy” recommendations of able analysts add value in the investment decision process. In contrast, unable analysts do not issue recommendations in any recommendation category that yield excess returns. Interestingly, the higher returns of the recommendations issued by able analysts are not driven by a reputation effect, i.e. a high recommendation announcement return in the first trading days after issuance. The higher return materializes rather over a longer time window. This indicates that the stock picking ability of the able analysts is real. Our results imply that at least some analysts have the ability to discriminate between over- and undervalued stocks.

The long portfolio based on the recommendations of the able analysts earns excess returns of up to 11.5% per year before transactions costs in the 1994 to 2007 time period. We show that investors can hence improve their trading strategy based on stock recommendations by focusing on analyst with characteristics that are systematically related to earnings accuracy. While analyst characteristics have economically small predictive power for the accuracy of earnings forecasts they have economically significant predictive power for the profitability of stock recommendations. We show that analyst characteristics are useful for identifying profit opportunities. Stock recommendations, earnings forecasts and analyst characteristics do have value in the investment decision process from an investor’s perspective.

Appendix 1:

Definitions of the analyst/forecast characteristics:

$ACCURACY_{ijt-1}$ - a measure of analyst i's forecast accuracy for firm j in year t-1. It is calculated as the maximum absolute forecast error for analysts who follow firm j in year t-1 minus the absolute forecast error of analyst i following firm j in year t-1, with this difference scaled by the range of absolute forecast errors for analysts following firm j in year t-1;

$LAG\_ACCURACY_{ijt-1}$ - a measure of analyst i's past forecast accuracy for firm j. It is calculated as the maximum ACCURACY for analysts who follow firm j in year t – 2 minus the ACCURACY for analyst i following firm j in year t – 2, with this difference scaled by the range of ACCURACY for analysts following firm j in year t -2;

$DAYS\_ELAPSED_{ijt-1}$ - a measure of the days elapsed since the last forecast by any analyst following firm j in year t-1. It is calculated as the days between analyst i's forecast of firm j's earnings in year t-1 and the most recent preceding forecast of firm j's earnings by any analyst, minus the minimum number of days between two adjacent forecasts of firm j's earnings by any two analysts in year t-1, with this difference scaled by the range of days between two adjacent forecasts of firm j's earnings in year t-1;

$BROKER\_SIZE_{ijt-1}$ - a measure of the analyst's broker size. It is calculated as the number of analysts employed by the broker employing analyst i following firm j in year t-1 minus the minimum number of analysts employed by following firm j in year t-1, with this difference scaled by the range of brokerage size for analysts brokers for analysts following firm j in year t-1;

$FOR\_FREQUENCY_{ijt-1}$ - a measure of analyst i's forecast frequency for firm j. It is calculated as the number of firm j forecasts made by analyst i following firm j in year t-1 minus the minimum number of firm j forecasts for analysts following firm j in year t-1, with this difference scaled by the range of number of firm j forecasts issued by analysts following firm j in year t-1;

$FIRM\_EXPERIENCE_{ijt-1}$ - a measure of analyst i's firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year t-1 minus the minimum number of years of firm-specific experience for analysts following firm j in year t-1, with this difference scaled by the range of years of firms-specific experience for analysts following firm j in year t-1;

$COMPANIES_{ijt-1}$ - a measure of the number of companies analyst i follows in year t-1. It is calculated as the number of companies followed by analyst i following firm j in year t-1 minus the minimum number of companies followed by analysts who follow firm j in year t-1, with this difference scaled by the range in the number of companies followed by analysts following firm j in year t-1;

$INDUSTRIES_{ijt-1}$ - a measure of the number of industries analyst i follows in year t-1. It is calculated as the number of industries covered by analyst i following firm j in year t-1 minus the minimum number of industries followed by analysts who follow firm j in year t-1, with this difference scaled by the range in the number of industries followed by analysts following firm j in year t-1. We use the Fama and French industry classification;

$FOR\_HORIZON_{ijt-1}$ - a measure of the time from the forecast date to the end of the fiscal period. It is calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm j in year t-1 minus the minimum forecast horizon for analysts who follow firm j in year t-1, with this difference scaled by the range of forecast horizons for analysts following firm j in year t-1;

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7. Tables

Table 1: Summary Statistics of the Rolling Regression

Table 1 shows the summary statistics of the rolling regression performed in the 1994 to 2007 time period. The regression analysis was performed 168 times. The definitions of the characteristics can be found above. Column 2 shows the coefficient's arithmetic mean based on the 168 coefficients. Column 3 shows the percentage of the 168 coefficients that are positive, column 4 shows the standard deviation of the coefficients, column 5 shows the average absolute t-value, column 6 and 7 show the minimum respectively the maximum value of the coefficient.

Characteristic 1	Average Coefficient 2	% of Coeff. > 0 3	Standard Deviation 4	Average abs. t-value 5	Min. Coefficient 6	Max. Coefficient 7
LAG_ACCURACY	0.060	100.00%	0.015	7.641	0.030	0.094
DAYS_ELAPSED	-0.033	0.60%	0.015	4.879	-0.063	0.001
BROKER_SIZE	-0.005	47.62%	0.017	1.850	-0.042	0.029
FOR_FREQUENCY	0.056	100.00%	0.012	6.705	0.022	0.093
FIRM_EXPERIENCE	-0.001	43.45%	0.017	2.070	-0.030	0.034
COMPANIES	-0.009	29.17%	0.022	2.075	-0.056	0.037
INDUSTRIES	-0.033	0.00%	0.016	3.882	-0.069	-0.005
FOR_HORIZON	-0.383	0.00%	0.058	45.570	-0.513	-0.306
_cons	0.753	100.00%	0.030	76.687	0.702	0.837

Table 2: Profitability of Single Stock Recommendations (All Recommendation)

Table 2 shows the profitability of single stock recommendations. The respective holding periods are displayed in figure 2. Column 1 shows the category of the recommendation. Column 2 shows the number of recommendations issued in the specific category. Column 3 shows the number of trading days till the earnings report date. Column 4 shows the discrete raw return in the five trading days prior to the recommendation announcement day (mean/median). Column 5 shows the discrete raw return in the five trading days after to the recommendation announcement day (excluding the return of the announcement day (mean/median). Column 6 shows the discrete raw return in the period one trading after the recommendation announcement till five trading days before report date (mean/median). Column 7 shows the discrete raw return in the period one trading day after the recommendation announcement till five trading days after report date (mean/median). Column 8 shows the discrete raw return in the period five trading days after the recommendation announcement till five trading days before report date (mean/median). Column 9 shows the discrete raw return in the period five trading days before the earnings report date till five trading days after the earnings report date (mean/median).

			Return Analysis					
Recommendation	# of rec.	Trading Days Till Report Date	Return -5	Return +5	Return till Report Date-5	Return till Report Date+5	Return Intermediate	Return Report Date -5 till +5
1	2	3	4	5	6	7	8	9
Able Analysts - All								
Strong Buy	6117	130.1	0.22%	0.76%	9.56%	11.12%	8.65%	1.35%
			0.00%	0.45%	5.30%	6.18%	4.79%	1.02%
Buy	7738	129.9	0.11%	0.23%	7.59%	8.45%	7.21%	0.85%
			0.00%	0.00%	4.34%	5.01%	3.99%	0.59%
Hold	11335	126.6	-1.33%	-0.64%	6.58%	7.08%	7.10%	0.56%
			-0.24%	-0.29%	3.31%	3.97%	3.69%	0.25%
Sell	1292	126.9	-0.87%	-0.98%	7.90%	7.15%	9.23%	-0.84%
			-0.39%	-0.68%	3.38%	2.99%	3.39%	-0.79%
Strong Sell	801	128.1	-0.76%	-0.75%	6.49%	6.62%	6.82%	0.29%
			0.00%	-0.66%	3.49%	4.46%	3.40%	0.55%
Unable Analysts - All								
Strong Buy	5971	131.7	0.26%	0.97%	7.15%	7.66%	6.06%	0.53%
			0.00%	0.57%	4.36%	4.69%	3.40%	0.43%
Buy	7673	128.3	-0.14%	0.26%	6.47%	6.89%	6.29%	0.54%
			0.00%	0.00%	2.98%	3.66%	2.82%	0.35%
Hold	11055	127.6	-1.43%	-0.74%	6.62%	7.02%	7.33%	0.47%
			-0.29%	-0.30%	3.62%	3.58%	4.00%	0.16%
Sell	1417	126.0	-2.18%	-0.38%	10.23%	9.40%	10.49%	-0.78%
			-0.56%	-0.19%	5.20%	4.21%	5.59%	-0.50%
Strong Sell	768	121.3	-1.16%	-1.11%	6.16%	6.40%	7.18%	0.23%
			0.00%	-0.72%	2.82%	1.60%	2.32%	-0.30%

Table 3: Correlation Coefficients between Characteristics and Returns

Table 3 shows the correlation coefficients between the raw returns of different holding periods and the intrinsic accuracy respectively the individual characteristics. Column 2 shows the correlation between the characteristics and the discrete raw return in the five trading days prior to the recommendation announcement day. Column 3 shows the correlation between the characteristics and the discrete raw return in the five trading days after to the recommendation announcement day. Column 4 shows the correlation between the characteristics and the discrete raw return in the period one trading after the recommendation announcement till five trading days before report date. Column 5 shows the correlation between the characteristics and the discrete raw return in the period one trading day after the recommendation announcement till five trading days after report date. Column 6 shows the correlation between the characteristics and discrete raw return in the period five trading days after the recommendation announcement till five trading days before report date. Column 7 shows the correlation between the characteristics and the discrete raw return in the period five trading days before the earnings report date till five trading days after the earnings report date.

1	Return -5 2	Return +5 3	Return till Report Date-5 4	Return till Report Date+5 5	Return Intermediate 6	Return Report Date -5 till +5 7
INTRINSIC_ACC	0.0089	0.0005	0.0116	0.0156	0.0105	0.0138
LAG_ACCURACY	0.0113	-0.0041	0.0094	0.0099	0.0091	0.0021
DAYS_ELAPSED	-0.005	-0.008	0.0101	0.0062	0.011	-0.0131
BROKER_SIZE	-0.0097	-0.008	0.006	0.0048	0.0073	-0.0039
FOR_FREQUENCY	-0.0087	-0.0033	0.0013	0.003	0.0009	0.0062
FIRM_EXPERIENCE	-0.0069	-0.0023	-0.0038	-0.0018	-0.0048	0.0062
COMPANIES	-0.0036	-0.0021	0.0156	0.0112	0.0174	-0.0158
INDUSTRIES	-0.0129	-0.0005	-0.0053	-0.0066	-0.0038	-0.0061
FOR_HORIZON	-0.0028	-0.0028	0.0425	0.0408	0.0436	-0.005

Table 4: Profitability of Single Stock Recommendations (Not Revised Recommendations)

Table 4 shows the profitability of single stock recommendations. The respective holding periods are displayed in figure 2. Column 1 shows the category of the recommendation. Column 2 shows the number of not revised recommendations issued in the specific category and the relation to the total number of issued recommendations. Column 3 shows the number of trading days till the earnings report date. Column 4 shows the discrete raw return in the five trading days prior to the recommendation announcement day (mean/median). Column 5 shows the discrete raw return in the five trading days after to the recommendation announcement day (excluding the return of the announcement day (mean/median). Column 6 shows the discrete raw return in the period one trading after the recommendation announcement till five trading days before report date (mean/median). Column 7 shows the discrete raw return in the period one trading day after the recommendation announcement till five trading days after report date (mean/median). Column 8 shows the discrete raw return in the period five trading days after the recommendation announcement till five trading days before report date (mean/median). Column 9 shows the discrete raw return in the period five trading days before the earnings report date till five trading days after the earnings report date (mean/median).

			Return Analysis					
Recommendation	# of rec. (% Total)	Trading Days Till Report Date	Return -5	Return +5	Return till Report Date-5	Return till Report Date+5	Return Intermediate	Return Report Date -5 till +5
1	2	3	4	5	6	7	8	9
Able Analysts - Not Revised								
Strong Buy	5248	126.0	0.27%	0.83%	10.53%	12.07%	9.60%	1.30%
	85.8%		0.14%	0.51%	5.90%	6.61%	5.20%	1.00%
Buy	6562	125.1	0.21%	0.29%	8.59%	9.49%	8.22%	0.83%
	84.8%		0.00%	0.00%	4.52%	5.43%	4.34%	0.64%
Hold	9259	120.4	-1.47%	-0.73%	5.39%	5.84%	6.00%	0.59%
	81.7%		-0.31%	-0.34%	2.94%	3.44%	3.32%	0.23%
Sell	989	118.2	-0.91%	-0.86%	6.85%	6.16%	8.06%	-0.75%
	76.5%		-0.57%	-0.67%	2.63%	2.60%	2.59%	-0.84%
Strong Sell	509	116.7	-0.62%	-0.34%	3.37%	3.60%	3.41%	0.16%
	63.5%		-0.13%	-0.51%	2.66%	3.46%	2.78%	0.23%
Unable Analysts - Not Revised								
Strong Buy	5328	128.7	0.31%	0.95%	7.67%	8.16%	6.59%	0.51%
	89.2%		0.00%	0.60%	4.36%	4.71%	3.39%	0.38%
Buy	6699	124.7	-0.07%	0.29%	7.15%	7.62%	6.98%	0.62%
	87.3%		0.00%	0.00%	3.37%	3.97%	3.16%	0.34%
Hold	9430	122.9	-1.53%	-0.70%	5.89%	6.31%	6.58%	0.47%
	85.3%		-0.31%	-0.26%	3.30%	3.44%	3.70%	0.15%
Sell	1149	120.4	-1.97%	-0.32%	10.03%	8.86%	10.20%	-1.14%
	81.1%		-0.55%	-0.11%	4.62%	3.83%	5.30%	-0.74%
Strong Sell	603	114.4	-1.22%	-0.89%	6.15%	6.15%	7.00%	0.03%
	78.5%		0.00%	-0.62%	3.14%	1.60%	2.42%	-0.36%

Table 5: Profitability of Single Stock Recommendations (Revised Recommendations)

Table 5 shows the profitability of single stock recommendations. The respective holding periods are displayed in figure 2. Column 1 shows the category of the recommendation. Column 2 shows the number of revised recommendations issued in the specific category and the relation to the total number of issued recommendations. Column 3 shows the number of trading days till the revision. Column 4 shows the discrete raw return in the five trading days prior to the recommendation announcement day (mean/median). Column 5 shows the discrete raw return in the five trading days after to the recommendation announcement day (excluding the return of the announcement day (mean/median). Column 6 shows the discrete raw return in the period one trading after the recommendation announcement till the revision date (mean/median). Column 7 shows the discrete raw return in the period five trading days after the recommendation announcement till the revision date (mean/median). Column 8 shows the discrete raw return in the period from the date of revision till the report date plus five trading days (mean/median).

			Return Analysis				
Recommendation	# of rec.	Trading Days Till Report Date	Return -5	Return +5	Return till Revision	Return Intermediate	Return from Revision till report date +5
1	2	3	4	5	6	7	8
			Able Analysts - All				
Strong Buy	869	47.3	-0.02%	0.27%	0.42%	0.30%	4.14%
	14.2%		0.00%	0.07%	0.67%	0.55%	0.96%
Buy	1176	52.2	-0.52%	0.06%	0.19%	0.00%	1.80%
	15.2%		-0.15%	0.01%	0.37%	0.29%	1.07%
Hold	2076	45.6	-0.69%	-0.24%	1.08%	1.32%	10.59%
	18.3%		0.00%	0.00%	0.13%	0.15%	6.46%
Sell	303	48.2	-0.76%	-1.31%	-2.32%	-0.95%	11.04%
	23.5%		-0.09%	-0.69%	-1.11%	-0.32%	6.40%
Strong Sell	292	32.4	-0.76%	-1.66%	-2.57%	-0.69%	15.03%
	36.5%		0.00%	-0.85%	-0.41%	-0.35%	8.76%
			Unable Analysts - All				
Strong Buy	643	55.7	-0.10%	1.08%	1.85%	0.87%	1.57%
	10.8%		0.00%	0.47%	2.37%	1.86%	2.27%
Buy	974	53.2	-0.52%	-0.04%	-0.31%	-0.18%	1.52%
	12.7%		-0.25%	0.13%	0.29%	0.00%	0.13%
Hold	1625	49.8	-0.81%	-0.93%	0.12%	1.08%	10.45%
	14.7%		-0.13%	-0.60%	-0.51%	0.00%	6.39%
Sell	268	42.6	-2.97%	-0.79%	0.02%	0.90%	11.41%
	18.9%		-0.62%	-0.61%	-1.61%	-0.36%	9.35%
Strong Sell	165	45.4	-1.09%	-1.61%	-3.73%	-2.19%	10.06%
			-0.53%	-1.03%	-3.94%	-1.96%	5.75%

Table 6: Results of the Trading Strategy (Recommendation Category)

Table 6 shows the results of the trading strategy in the 1994 to 2007 time period, if the issuance of a recommendation is used as a trading signal, i.e. we follow every recommendation in the analyzed recommendation category. Column 1 shows the recommendation category. Column 2 shows the number of recommendations in the respective category. Column 3 shows the daily excess return if the returns are risk-adjusted with the FF-4-factor model. Columns 4 to 7 show the FF-coefficients. Column 7 shows the annualized daily excess return. Column 8 shows the annualized daily excess return. Column 9 shows the difference in daily FF-Alpha between the able and unable analysts. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Recommendation	# of rec.	Daily FF Alpha 1994-2007	Coefficient of FF-4-Factor Model 1994-2007: Rm-rf	SMB	HML	UMD	Yearly Excess Return for 1994-2007	Daily Alpha Able - Unable 1994-2007
1	2	3	4	5	6	7	8	9
Able Analysts - All								
Strong Buy	6,117	0.0003305***	1.17***	0.55***	0.09***	-0.22***	8.61%	0.0002361***
Buy	7,738	0.0002218***	1.16***	0.55***	0.09***	-0.29***	5.70%	0.00014
Hold	11,335	0.00002	1.12***	0.58***	0.24***	-0.38***	0.48%	0.00005
Sell	1,292	0.00003	1.08***	0.60***	0.32***	-0.43***	0.85%	0.00034
Strong Sell	801	-0.00018	1.10***	0.70***	0.39***	-0.57***	-4.41%	-0.00007
Unable Analysts - All								
Strong Buy	5,971	0.00009	1.10***	0.63***	0.18***	-0.17***	2.39%	
Buy	7,673	0.00009	1.09***	0.64***	0.18***	-0.24***	2.18%	
Hold	11,055	-0.00003	1.07***	0.66***	0.30***	-0.32***	-0.75%	
Sell	1,417	-0.00030	1.12***	0.74***	0.45***	-0.41***	-7.27%	
Strong Sell	768	-0.00011	1.07***	0.69***	0.40***	-0.20***	-2.75%	

Table 7: Results of the Trading Strategy (Consensus Recommendation)

Table 7 shows the results of the trading strategy in the 1994 to 2007 time period, if the consensus recommendation is used as the trading signal. Column 2 shows the daily excess return if the returns are risk-adjusted with the FF-4-factor model (t-statistics below). Columns 3 to 6 show the FF-coefficients. Column 7 shows the annualized daily excess return. Column 8 shows the difference in daily FF-Alpha between the able and unable analysts. t-statistics appear below the respective values. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Portfolio	Daily FF Alpha 1994-2007	Coefficient of FF-4-Factor Model 1994-2007				Yearly Excess Return for 1994-2007	Daily Alpha (a)-(c) und (b)-(d) 1994-2007
		Rm-rf	SMB	HML	UMD		
1	2	3	4	5	6	7	8
1-Month Consensus Calculation Period							
Q5 (high accuracy)							
Long-Portfolio (a)	0.043%	1.041	-0.103	-0.121	-0.109	11.46%	0.038%
	3.96***	74.67***	-5.11***	-4.86***	-7.69***		2.42***
Short-Portfolio (b)	-0.022%	1.067	-0.052	0.170	-0.158	-5.31%	0.001%
	-1.46	56***	-1.9*	4.99***	-8.19***		0.04
Q1 (low accuracy)							
Long-Portfolio (c)	0.005%	1.016	-0.054	-0.195	-0.025	1.32%	
	0.46	70.45***	-2.59***	-7.56***	-1.69*		
Short-Portfolio (d)	-0.023%	1.057	-0.002	0.174	-0.151	-5.51%	
	-1.75*	64.29***	-0.09	5.90***	-9.07***		
3-Month Consensus Calculation Period							
Q5 (high accuracy)							
Long-Portfolio (a)	0.027%	1.039	-0.121	-0.121	-0.089	7.10%	0.027%
	4.03***	119.79***	-9.65***	-7.78***	-10.14***		2.78***
Short-Portfolio (b)	-0.016%	1.058	-0.080	0.055	-0.127	-3.98%	-0.004%
	-1.52	77.86***	-4.06***	2.24**	-9.27***		-0.31
Q1 (low accuracy)							
Long-Portfolio (c)	0.000%	1.001	-0.079	-0.161	-0.032	0.03%	
	0.02	113.05***	-6.18***	-10.16***	-3.59***		
Short-Portfolio (d)	0.012%	1.020	0.026	0.164	-0.042	3.02%	
	-1.39	93.48***	1.64	8.38***	-3.77***		
6-Month Consensus Calculation Period							
Q5 (high accuracy)							
Long-Portfolio (a)	0.022%	1.036	-0.126	-0.093	-0.048	5.59%	0.026%
	4.30***	160.77***	-13.54***	-8.01***	-7.37***		3.53***
Short-Portfolio (b)	-0.012%	1.041	-0.131	0.164	-0.152	-2.85%	0.001%
	-1.50	106.09***	-9.25***	9.32***	-15.29***		0.09
Q1 (low accuracy)							
Long-Portfolio (c)	-0.004%	0.999	-0.078	-0.117	-0.001	-1.07%	
	-0.82	148.94***	-8.05***	-9.69***	-0.10		
Short-Portfolio (d)	-0.012%	1.039	-0.053	0.183	-0.046	-3.08%	
	-1.72*	112.02***	-3.92***	11.01***	-4.85***		
12-Month Consensus Calculation Period							
Q5 (high accuracy)							
Long-Portfolio (a)	0.016%	1.039	-0.128	-0.085	-0.004	4.10%	0.019%
	3.99***	202.51**	-17.21***	-9.20***	-0.72		3.23***
Short-Portfolio (b)	-0.007%	1.020	-0.108	0.182	-0.144	-1.62%	-0.009%
	-1.02	125.32***	-9.21***	12.51***	-17.52***		-1.01
Q1 (low accuracy)							
Long-Portfolio (c)	-0.003%	0.998	-0.100	-0.073	-0.018	-0.75%	
	-0.70	183.08***	-12.72***	-7.47***	-3.34***		
Short-Portfolio (d)	0.002%	1.024	-0.026	0.194	-0.109	0.56%	
	0.38	137.26***	-2.45**	14.51***	-14.40***		

Table 8: Lucky and Able Analysts – Annual Excess Returns (Long Portfolio)

Table 8 shows the results of the trading strategy similar to Loh and Mian (2006) in the 1994 to 2007 time period, if we differentiate according to lagged accuracy only and according to our standard model (as proxy for ability) without lagged accuracy. The table shows the annualized excess returns of the long portfolio. Column 1 to 5 shows the annual excess returns for different consensus calculation periods. The row on the left shows the quintiles according to our standard model without lagged accuracy. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Quintiles according	Quintiles according to Lagged Accuracy Only				
to Ability Only	Q5	Q4	Q3	Q2	Q1
1-Month Consensus Calculation Period					
Q5	10.354%	9.047%	11.464%	4.647%	9.890%
	1.62	1.92*	2.25**	0.90	1.62
Q4	12.569%	5.865%	17.839%	7.936%	12.569%
	1.85*	1.36	3.71***	1.57	2.12**
Q3	5.306%	9.680%	3.094%	-5.085%	8.591%
	0.84	2.06**	0.69	-1.06	1.59
Q2	-1.734%	6.136%	5.079%	-1.720%	5.581%
	-0.29	1.31	1.09	-0.34	1.08
Q1	11.747%	6.649%	8.215%	8.012%	-0.253%
	1.88*	1.23	1.53	1.62	-0.05
3-Month Consensus Calculation Period					
Q5	11.322%	8.474%	7.982%	3.889%	2.108%
	2.72***	2.94***	2.47**	1.21	0.54
Q4	2.518%	5.343%	5.037%	3.301%	0.683%
	0.59	1.94*	1.64	1.07	0.19
Q3	5.618%	8.175%	2.753%	-1.475%	4.100%
	1.16	2.86***	0.98	-0.49	1.10
Q2	3.159%	2.828%	-0.670%	0.043%	-6.288%
	0.85	0.96	-0.23	0.01	-1.89**
Q1	2.717%	2.996%	1.622%	4.968%	-3.526%
	0.68	0.95	0.46	1.60	-0.98
6-Month Consensus Calculation Period					
Q5	6.764%	8.498%	5.496%	2.506%	3.581%
	2.07**	3.81***	2.29**	1.11	1.09
Q4	3.003%	5.097%	3.941%	2.013%	0.710%
	0.99	2.49**	1.71*	0.89	0.26
Q3	0.007%	4.771%	1.847%	-3.040%	3.343%
	0.00	2.29**	0.88	-1.34	1.22
Q2	1.693%	1.019%	0.981%	0.534%	-0.865%
	0.61	0.49	0.46	0.24	-0.34
Q1	-0.578%	3.730%	0.599%	1.765%	-6.264%
	-0.19	1.58	0.23	0.73	-2.08***

Table 9: Differentiation based on only one characteristic

Table 9 shows the results of the trading strategy in the 1994 to 2007 time period, if one analyst characteristic is included respectively excluded. Column 1 shows the included (excluded) characteristic, columns 2 and 4 show the difference in annualized excess return between the able and unable analysts for the long portfolio if one characteristic is included. Column 3 and 5 show the difference in annualized excess return between the able and unable analysts for the short portfolio if one characteristic is included. Column 6 and 7 show the difference in annualized excess return between the able and unable analysts for the long and the short portfolio if one characteristic is excluded. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

	Included Variable without days elapsed		Included Variable with days elapsed		Excluded Variable with days elapsed	
	Q5 - Q1 Long-Portfolio	Q5 - Q1 Short-Portfolio	Q5 - Q1 Long-Portfolio	Q5 - Q1 Short-Portfolio	Q5 - Q1 Long-Portfolio	Q5 - Q1 Short-Portfolio
Characteristic 1	2	3	4	5	6	7
1-Month Consensus Calculation Period						
LAG_ACCURACY	2.65%	6.51%	2.05%	6.62%	1.68%	-3.60%
	0.620	1.290	0.490	1.310	0.410	-0.720
BROKER_SIZE	1.48%	-1.23%	0.53%	-3.05%	11.63%	4.11%
	0.340	-0.220	0.120	-0.540	2.81***	0.810
FOR_FREQUENCY	5.76%	-2.70%	6.90%	-5.08%	2.49%	7.07%
	1.360	-0.500	0.000	0.000	0.590	1.320
FIRM_EXPERIENCE	1.11%	-5.18%	0.93%	-5.97%	7.65%	4.27%
	0.270	-1.010	0.230	-1.160	1.88*	0.860
COMPANIES	-1.06%	3.49%	-1.40%	3.57%	8.10%	-3.90%
	-0.230	0.640	-0.310	0.650	1.96**	-0.780
INDUSTRIES	3.23%	-1.37%	-0.75%	-0.97%	7.76%	-0.48%
	0.710	-0.260	-0.170	-0.180	1.89*	-0.090
3-Month Consensus Calculation Period						
LAG_ACCURACY	4.98%	1.29%	5.24%	-0.11%	4.65%	-2.60%
	1.86*	0.370	1.94*	-0.030	1.82*	-0.740
BROKER_SIZE	0.02%	3.55%	-1.02%	3.28%	7.48%	-0.50%
	0.010	0.880	-0.350	0.800	2.96***	-0.150
FOR_FREQUENCY	4.48%	-3.71%	3.94%	-5.65%	3.94%	0.81%
	1.7*	-0.990	1.500	-1.500	1.480	0.230
FIRM_EXPERIENCE	2.74%	0.64%	2.48%	1.89%	6.86%	0.51%
	1.040	0.170	0.950	0.480	2.73***	0.150
COMPANIES	2.17%	-0.09%	2.19%	-0.17%	5.94%	-3.78%
	0.710	-0.020	0.720	-0.040	2.39**	-1.070
INDUSTRIES	-0.56%	-4.86%	-0.24%	-6.90%	6.81%	-3.69%
	-0.200	-1.300	-0.090	-1.850	2.78***	-1.030
6-Month Consensus Calculation Period						
LAG_ACCURACY	3.11%	1.34%	3.93%	0.09%	4.94%	-2.59%
	1.520	0.480	1.9*	0.030	2.5**	-1.040
BROKER_SIZE	2.99%	3.34%	2.06%	2.52%	5.69%	-0.24%
	1.310	1.180	0.900	0.870	2.99***	-0.090
FOR_FREQUENCY	4.19%	-2.79%	4.42%	-3.94%	3.47%	1.14%
	2.07**	-0.980	2.1**	-1.380	1.71*	0.440
FIRM_EXPERIENCE	0.67%	1.78%	0.73%	1.20%	5.69%	0.43%
	0.340	0.570	0.370	0.380	2.97***	0.160
COMPANIES	1.68%	-2.01%	1.65%	-2.05%	5.62%	-1.96%
	0.660	-0.660	0.650	-0.670	3.05***	-0.730
INDUSTRIES	1.42%	-3.11%	1.13%	-4.24%	6.40%	-2.59%
	0.680	-1.020	0.540	-1.390	3.44***	-1.000

Table 10: Differences in Ex Post Realized Earnings Accuracy

Table 10 shows the differences in ex post realized accuracy of the analysts within the two projected accuracy quintiles. Column 2 shows the ex post realized absolute forecast error (AFE) and column 3 shows the winsorized AFE. Column 4 shows the difference in AFE between the highest and the lowest projected accuracy quintile and the respective t-value of the difference (mean-comparison test). Column 5 shows the difference in the winsorized AFE between the highest and the lowest projected accuracy quintile and the respective t-value of the difference (mean-comparison test). t-statistics appear below the respective values. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

Analysts 1	AFE 2	AFE_winsor 3	Difference in AFE (Q5-Q1) 4	Difference in AFE winsorized (Q5-Q1) 5
Comparison of the Ex Post Realized Accuracy				
Able	0.3828	0.3148	-0.0119	-0.0171
			-1.5144*	-3.8940***
Unable	0.3947	0.3319		

8. Figures

Figure 1: Employed Three-Step Approach

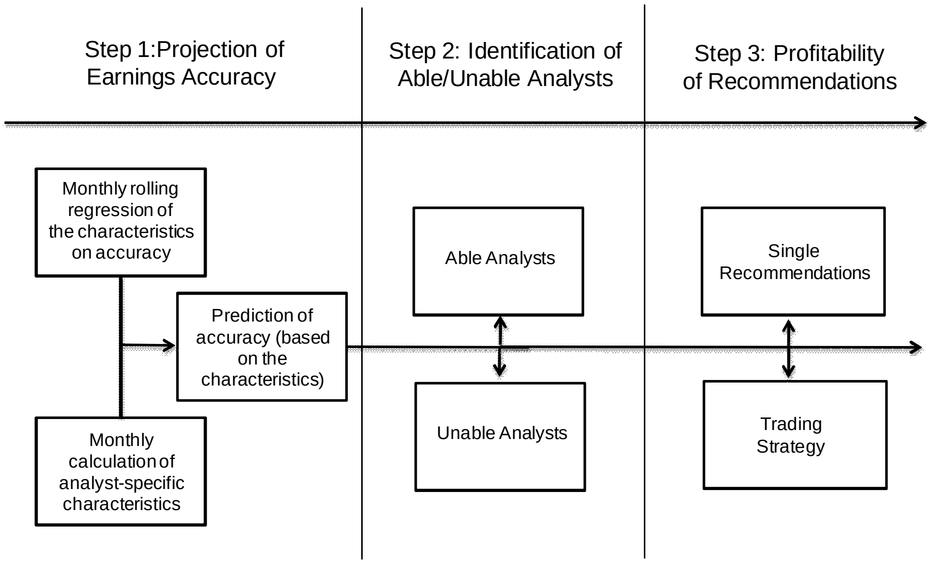


Figure 2: Holding Periods of Individual Recommendations

Figure 2 shows holding periods that are analyzed. There are a total of six holding periods, the corresponding column in table 4 and 5 is shown in parentheses.

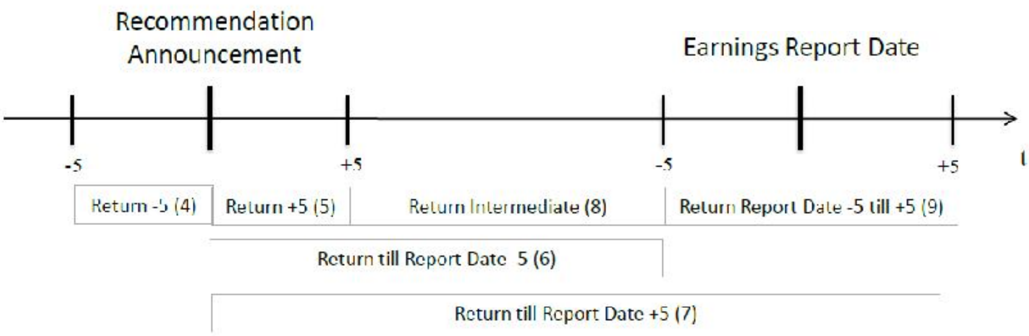


Figure 3: Difference in Profitability of Single Stock Recommendations (All Recommendations)

Figure 3 shows the difference in profitability of single stock recommendations (ordinate) between the able and the unable analysts. The corresponding t-value is shown above each bar. Significance levels are indicated as follows: *** 1% significance, ** 5% significance, * 10% significance.

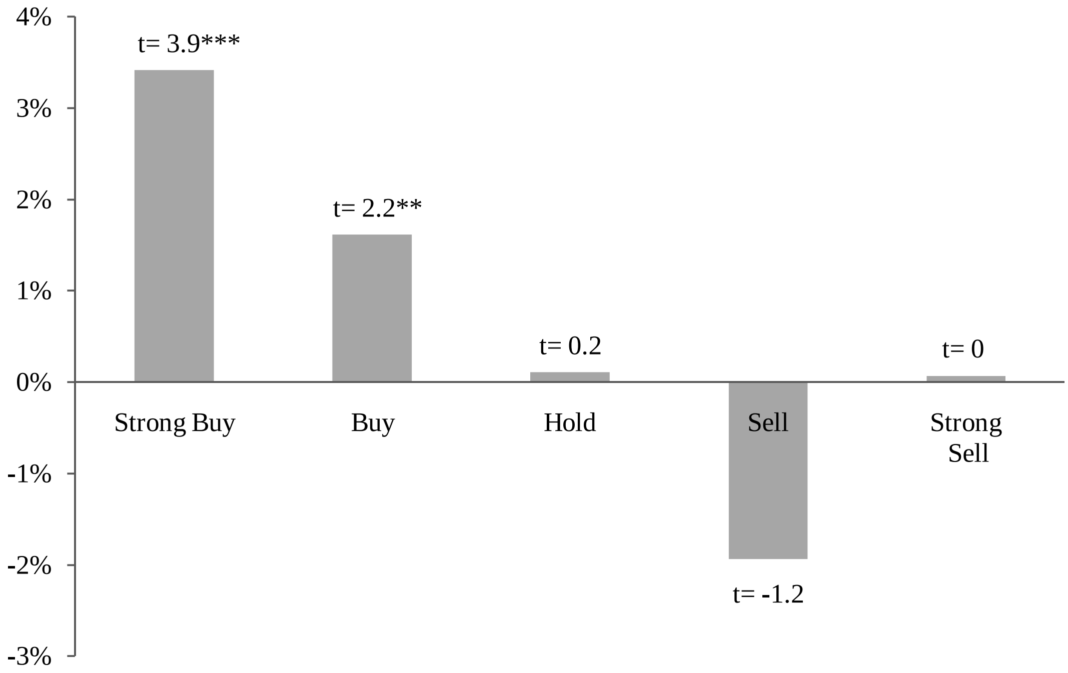
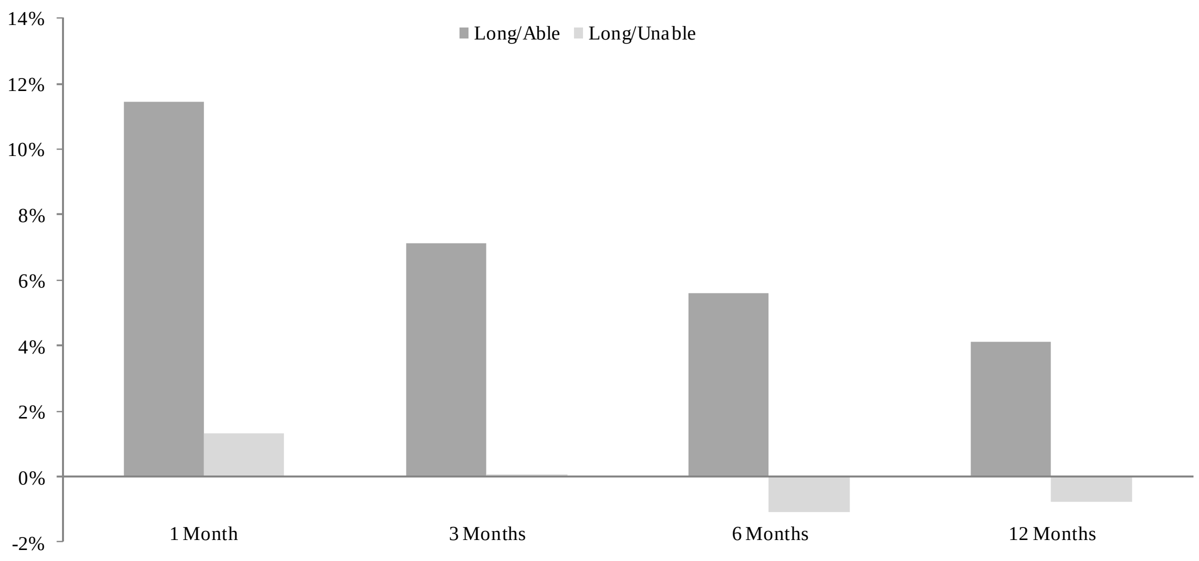


Figure 4: Returns of the Long-Portfolio



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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de