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EXISTENCE AND EXPLOITABILITY OF FINANCIAL ANALYSTS' INFORMATIONAL LEADERSHIP

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Abstract: This paper bridges two recent studies on the role of analysts to provide new and relevant information to investors. On the one hand, the contribution of analysts to long-term price discovery on the US market is rather low. Considering earnings per share forecasts as the main output of analysts' reports, their information share amounts to only 4.6% on average. On the other hand, trading strategies set up on these EPS forecasts are quite profitable. Self-financing portfolios yield excess returns of more than 5% p.a. over the S&P 100 index for a time period of 36 years, which is persistent after controlling for the well-known risk factors. In this paper, we discuss the link between the low information shares and the high abnormal returns. We argue that information shares of analysts cannot be higher, because otherwise their forecasts would lead to excessively profitable trading strategies which are very unlikely to persist over such a long period of time.

Keywords: analysts, informational leadership, information shares, self-financing trading strategies.

1. Introduction

The importance of financial analysts working on the sell-side of the market, providing stock forecasts to a broad audience of market participants, remains controversial. As information intermediaries, their central functions are the identification, analysis, and aggregation of information which is new to investors and the effective communication of this information as a diversity of forecasts such as target prices, buy-sell-hold-recommendations, etc. With their knowledge of macroeconomic developments, markets, industry sectors and companies, financial analysts are expected to be in informational leadership relative to other stock market participants when it comes to assessing a firm's future development and its firm value. However, according to the efficient market hypothesis (EMH) of Fama (1970), the market itself is already efficient in processing new information. If the EMH holds, all relevant information is always fully reflected by stock prices and there is no economic legitimation for information intermediaries like financial analysts.

In this paper, we analyze the actual degree of informational leadership of sell-side financial analysts in developed stock markets and discuss the degree to which individual investors can profit from analysts' leadership. We first analyze the results of Baule and Wilke (2016), who employ a direct measure of analyst's informational leadership relative to other stock market participants and quantify the empirical information share of analysts' consensus forecasts of a company's earnings per share (EPS) in the price discovery process of US S&P 100 index members. These empirical information shares turn out to be very low and vary strongly in the cross-section. In fact, analysts seem to obtain informational advantages only for a relatively small number of companies. Based on these findings, we turn to the exploitability of potential informational advantages of analysts. We show that trading strategies based on a forecast-related mispricing measure, which is provided in Baule and Wilke (2015), yield exceptionally high risk-adjusted returns and are therefore highly profitable. Thus, although financial analysts have only very limited influence on the price discovery processes in highly developed markets, this small contribution to informational efficiency translates into potentially high abnormal returns when exploited by an appropriate trading strategy.

2. Analysts' Contribution to Long-Term Price Discovery

2.1 Informational Leadership in the Context of Financial Analysts and Stock Market Investors

Informational leadership in the context of financial analysts and stock market investors describes the ability of analysts to process new information faster than the investors and vice versa. Here, processing new information involves (i) identifying new information and (ii) interpreting new information. Certain parts of information are completely processed by analysts or investors at the moment they are reflected in analyst forecasts or stock prices. Wilke (2016) distinguishes between situations in which a party (analysts, investors) processes (i) at least a single information component faster (partial informational leadership), (ii) more than the half of relevant information faster (relative informational leadership) and finally (iii) all information available faster than the respective other party (absolute informational leadership).[1]

As stock prices and analyst forecasts are subject to noise and other non-informational movements, informational leadership analysis should not involve all changes in a company's stock or an analyst's forecast. In fact, it must separate information-driven permanent changes from transitory and information-free movements, which might be due e. g. to bid-ask bounces or individual investors' demand for liquidity. Stock prices and EPS forecasts tend to be non-stationary, which means that their distribution changes over time – this enables them to grow over all bounds. Non-stationary variables can be decomposed into a non-stationary component described by a stochastic trend and a stationary component. Information-driven movements are associated with the development of the non-stationary stochastic trend component, while information-free movements are connected to the stationary component, which does not influence the stock price or the EPS forecast in the long-run.

2.2 Information Shares – A Direct Measure of Analysts' Informational Leadership

Information shares as suggested by Hasbrouck (1995) provide a relative measure of informational leadership and are based on the concept of co-integration. Although

[1] See Wilke (2016), p. 73-75

non-stationary financial variables like stock prices or EPS forecasts might grow over all bounds, they tend to move together over time if they are co-integrated. Non-stationary variables are typically co-integrated, if they are driven by the same underlying fundamentals. Obviously, both stock prices and EPS forecasts related to a firm are driven by that firm's fundamental development and are therefore expected to be co-integrated. Co-integration can be illustrated for (scaled) EPS forecasts and stock prices of Walt Disney (see Figure 1).

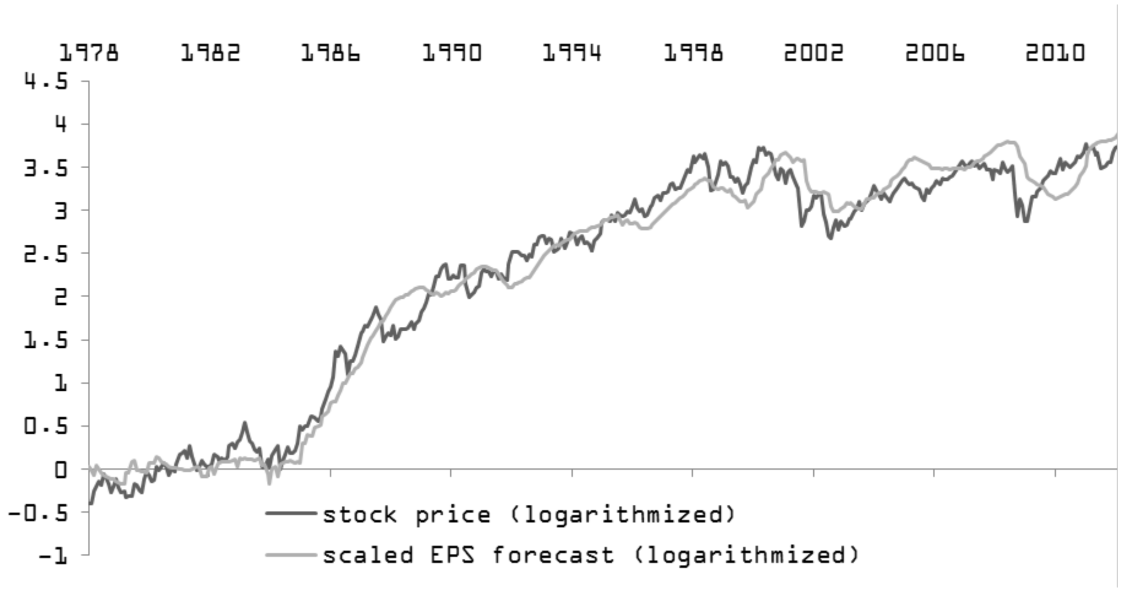

Figure 1: Co-movement of stock prices and (scaled) EPS forecasts for Walt Disney over time.

As Figure 1 shows, stock prices and (scaled) EPS forecasts develop stochastically over time. However, both series are fundamentally related, since both of them correspond to the fundamental value of the underlying company. This ties the development of prices and (scaled) forecasts together and makes them stay on a common long-term path. The common long-term path is characterized by the common stochastic trend shared by both time series. Information shares quantify the degree to which both prices and forecasts contribute to this common stochastic trend, and therefore to the common long-term development. The more EPS forecasts drive the common long-term development, the bigger is the information share of the analysts and – conversely – the lower the information share of the market participants.

2.3 Empirical Information Shares of Financial Analysts

Baule and Wilke (2016) compute empirical information shares for a highly liquid segment of the US American stock market. They analyze 75 constituents of the S&P 100 Index. The dataset is based on monthly data and spans 36 years, including monthly analyst consensus EPS forecasts and stock prices from January 1976 through March 2012. The analyst consensus forecasts are rolling twelve-month-ahead estimates. This means that every month's EPS forecast estimates the development of the respective company's earnings per share over the following one-year horizon. Market data are obtained from Thomson Reuters Datastream, forecast data are taken from the Thomson Reuters I/B/E/S database.

Table 1: Empirical information shares of financial analysts for S&P-100 Index members. Information shares significantly larger than zero are indicated by ° (10% level), * (5% level), ** (1% level) and * (0.1% level), based on bootstrapping methods.**

Name	$IS^{Analysts}$ (%)	Name	$IS^{Analysts}$ (%)
3M	1.1	IBM	3.3
Alcoa	0.7	Intel	0.3
Altria Group	33.3*	Johnson & Johnson	0.1
American Electric Power	0.2	JP Morgan Chase & Co.	10.1°
American Express	0.0	Kraft Foods	6.5
Apache	0.0	Lockheed Martin	0.0
AT&T	0.2	Lowe's	2.5
Avon Products	0.7	McDonald's	1.6
Baker Hughes	2.4	Medtronic	0.0
Bank of America	0.0	Merck & Co.	0.0
Bank of New York	0.0	Monsanto	1.2
Baxter International	0.0	Morgan Stanley	4.3
Boeing	0.4	National Oilwell Varco	1.3
Bristol-Myers Squibb	0.0	Nike	5.1
Caterpillar	1.5	Norfolk Southern Railway	27.5*
Chevron Corporation	2.3	Occidental Petroleum	0.0
Citigroup	23.6	Oracle	0.0
Coca-Coal Company	0.0	PepsiCo	6.2
Colgate-Palmolive	0.0	Pfizer	0.0
ConocoPhillips	2.1	Procter & Gamble	0.0
CVS Caremark	2.6	Qualcomm	0.0
Dell	0.0	Raytheon	21.8*
Devon Energy	0.0	Schlumberger	0.8
Dow Chemicals	0.0	Southern Company	0.4
Emerson	5.0	Sprint Nextel	22.3*
Entergy	5.4	Target Corporation	7.5*
Exelon	7.3	Texas Instruments	0.0
Exxon Mobil	0.0	Union Pacific	15.2*
FedEx	12.9°	United Technologies Corp.	15.7*
Freeport-McMoRan	0.0	UnitedHealth	0.1
General Dynamics	13.4*	US Bancorp	0.0
General Electric	0.0	Verizon Communications	0.2
Gilead Sciences	8.8	Walt Disney	9.5°
Halliburton	0.0	Wells Fargo	15.7*
Heinz Company	0.0	Weyerhaeuser	29.1**
Hewlett-Packard	3.4	Williams Companies	0.0
Home Depot	0.0	Xerox	0.0
Honeywell International	6.9		
Mean	**4.6*** **	**Min**	**0.0**
SD (Mean)	**7.7**	1Q	0.0
SE (Mean)	**0.9**	Median	0.7
		3Q	6.2
		Max	**33.3**
Companies	**75**		
Significance at 10% level	**13**		
Significance at 5% level	**9**		
Significance at 1% level	**1**		

Table 1 shows the empirical information shares of financial analysts at the firm level. Obviously, most information is processed faster by the market itself than by financial analysts. Market prices reflect more than 95% of relevant information before they get incorporated into analyst consensus EPS forecasts. For the majority of the analyzed sample firms, investors are in absolute informational leadership compared to financial analysts. On average, the informational advantage of analysts is rather marginal; their share in price discovery is only 4.6%. Moreover, the analyst share varies considerably in the cross-section: For the broad majority of the examined firms, analysts possess no significant informational advantage at all. For single companies like Altria Group (33.3%), Norfolk Southern Railway (27.5%), Sprint Nexel (22.3%) or Weyerhaeuser (29.1%) however, analyst forecasts reflect a measurable and significant share of relevant information first. Only 13 out of 75 sample companies yield significant information shares for the analyst side. For these firms, analysts are in partial informational leadership and participate measurably in the price discovery process. Overall however, analysts appear to be pure information followers most of the time, contributing only to the price discovery process of a rather small number of firms.

3. Exploitability of Analysts' Informational Leadership

3.1 Informational Leadership in the Context of Financial Analysts and Stock Market Investors

As shown in the previous section, empirical information shares, which provide a direct measure of analysts' informational leadership, are exceptionally low in highly developed market segments such as the S&P 100 index constituents. However, as analysts do significantly participate in the price discovery processes of single firms, we now turn to an investment and portfolio management perspective and analyze whether a stock market investor is able to exploit the small but existent informational advantages of analysts. Baule and Wilke (2015) construct a measure of a stock's temporary misevaluation, termed Q. This measure focuses on information-driven EPS forecast revisions of financial analysts, relative to the corresponding actual stock returns observed in the market. The aim of Q is to identify stocks which analysts implicitly consider as under- or overvalued – based on their forecast revision and the corresponding actual stock return. An upward revision of a company's EPS forecast can be interpreted as a signal that financial analysts expect the fundamental value of the company to be higher now than before. If the market directly reflects analysts' forecast revisions, a positive forecast revision should be associated with a positive actual stock return for the observed period of time.

Based on these ideas, Q is defined as the ratio of the gross EPS forecast revision and the corresponding gross stock return:

$$Q_t = \frac{1+r_t^A}{1+r_t^S} \tag{1}$$

with

$$r_t^A = \frac{\widehat{EPS}_t - \widehat{EPS}_{t-k}}{\widehat{EPS}_{t-k}} \tag{2}$$

and

$$r_t^S = \frac{S_t - S_{t-k}}{S_{t-k}} \tag{3}$$

$\widehat{EPS}_t$ is the consensus EPS forecast of analysts in time t, and S_t the corresponding stock price. The parameter k defines the length of the formation period in months, over which the observed stock returns and forecast revisions of analysts are compared. For this study, k is fixed at 6 months.

3.2 Implementation of Q-based Trading Strategies

How effective is the Q measure in identifying over- and undervalued stocks in the US stock market top segment, and do Q-based trading strategies outperform the market? Which Q-based returns correspond to the very low empirical information shares measured between 1976 and 2012? In this section, we will analyze the efficiency of Q and the performance of Q-based trading strategies involving the S&P 100 index members.

We analyzed the time period from February 1978 to December 2013, during which a total of 278 companies were constituents of the S&P 100 index for at least one month. The index composition is updated monthly. The main variables include monthly stock returns and the corresponding monthly EPS consensus forecast revisions of the analysts. Since sample firms might pay dividends, and since during the sample period capital increases or stock splits might occur, we use adjusted stock prices. Overall the sample data are basically the same as that used to compute the empirical information shares. Again, all company related data is provided by Thomson Reuters. For the calculation of risk-adjusted returns, monthly risk-free rates and monthly empirical risk factors suggested by Fama and French (1993), Fama and French (2015), and Carhart (1997) are employed, which are freely available in the Kenneth R. French Data Library.[2]

Since the index composition is adjusted on a monthly basis, the tradable stock universe contains only the actual S&P-100 index members on every trade date. Every month, Q is computed for all eligible stocks to determine their actual degree of misvaluation, before the stock universe is ordered by Q in decreasing order. Therefore, the first positions within the ordered stock universe are always occupied by stocks which analysts implicitly consider to be undervalued, while the last positions contain stocks which analysts see as overvalued. A quintile approach is then used to divide the stock universe into five equally weighted portfolios. In decreasing order, these quintile portfolios are then categorized as a High20 portfolio (positions 1 to 20), MidHigh20 portfolio (21 to 40), Mid20 portfolio (41 to 60), MidLow20 portfolio (61 to 80) or Low20 portfolio (81 to 100). The holding period for all quintile portfolios is the 1-month window between two consecutive EPS consensus forecasts. Based on the five quintile portfolios, we implement two self-financing trading strategies which (i) buy the High20 portfolio while short-selling the Low20 portfolio (High20 – Low20 strategy), or (ii) buy both the High20 and the MidHigh20 portfolio while short-selling the MidLow20 and the Low20 portfolio (High40 – Low40 strategy). After every portfolio rebalancing, monthly quintile portfolio returns in excess of the risk-free rate and the returns of the two self-financing

[2] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

strategies are computed. The excess returns are calculated over the exact period between the day of the current portfolio reformation and the day of the consecutive portfolio revision.

3.3 Results and Discussion of the Q-based Strategies

Figure 2 shows cumulated excess returns for the High20 portfolio (black line) and the Low20 portfolio (grey line). Also included as a benchmark are the cumulated excess returns of the market (dotted line), i.e. the excess returns of the S&P-100 Index. The High20 portfolio clearly outperforms the market, while the Low20 portfolio underperforms.

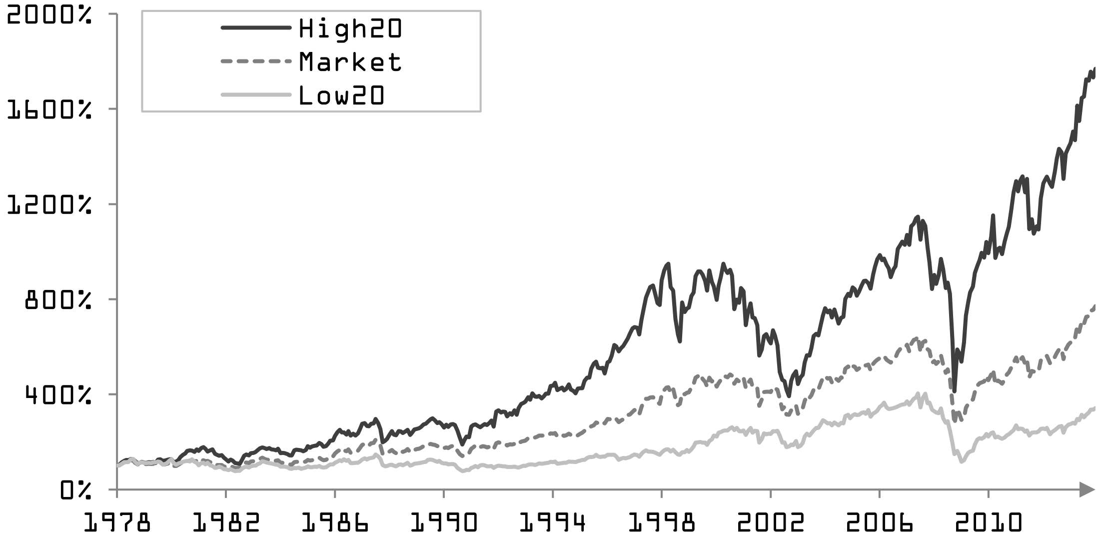

Figure 2: Performance of the Q-based extreme portfolios and the market.

Table 2 gives an overview over the performance of the quintile portfolios and the two self-financing strategies. Also included is the excess return of the market as a benchmark. Reported are monthly excess returns over the risk-free rate.

Table 2: Monthly excess returns of the Q-based quintile portfolios, the Q-based self-financing strategies and the market.

Portfolio	Mean excess return (%)	Std. Err. (%)
High20	0.886 **	0.317
MidHigh20	0.612 *	0.252
Mid20	0.571 **	0.218
MidLow20	0.494 *	0.221
Low20	0.439 °	0.263
S&P-100 Index (Market)	0.598 *	0.237
High20 – Low20	0.446 *	0.214
High40 – Low40	0.282 °	0.149

° p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

The High20 portfolio yields monthly excess returns of 0.89%, the Low20 portfolio only 0.44%. Moreover, the mean excess returns decrease monotonically between both extreme portfolios. Obviously, Q is capable of identifying over- and undervalued stocks effectively. As a consequence, both self-financing strategies generate significantly positive returns: Buying the 20 (40) most undervalued stocks while short-selling the 20 (40) most overvalued stocks yields monthly returns of 0.45% (0.28%).

Figure 3 illustrates the development of the High20 – Low20 strategy returns within the analyzed period. Reported are both cumulated (black line, left axis) and not cumulated (grey bars, right axis) monthly strategy returns.

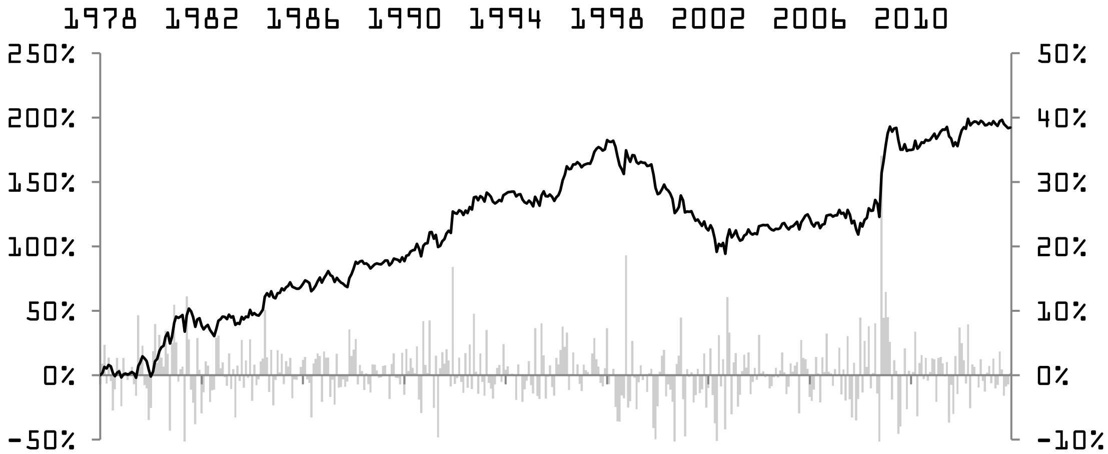

Figure 3: Performance of the Q-based extreme portfolios and the market.

Figure 3 shows that the Q-based strategy of buying undervalued stocks while short-selling overvalued stocks yielded positive monthly returns most of the time. However, analysts did not foresee the dotcom bubble, which was building up around the turn of millennium. Their informational advantage decreased significantly in the years between 1998 and 2002 and even turned into a relative informational disadvantage, which is reflected in the preponderantly negative returns throughout this period. In contrast, analysts were able to increase their informational edge in the turbulent first decade of the new millennium. Especially, they did not seem to lose their advantage in the course of the 2007 financial crisis. Indeed, the High20 – Low20 strategy generated an ongoing series of extremely high monthly returns in the recovery period around 2009. Overall, analysts seem to have withstood the decade’s turbulences better than the market.

3.4 Q-based Strategy Performance after Adjusting for Risk

The foregoing analysis concentrated on monthly returns in excess of the risk-free rate, which did not take into account that stocks differ in their risk-return characteristics. The observed high returns of the High20 portfolio might therefore simply be due to an increase in the riskiness of the portfolio investment. After all, are the discussed Q-based strategies systematically picking high-risk stocks to boost their performance? In the following, we therefore focus on risk-adjusted returns. We employ an empirical expansion of the CAPM which includes all well-established risk factors: the market factor (MKT), the two traditional Fama and French (1993) factors of firm size “small minus big” (SMB) and book-to-market ratio “high minus low” (HML), the Carhart (1997) momentum factor (MOM), and the two new Fama and French (2015) factors of profitability "robust minus weak" (RMW) and investment behavior "conservative minus aggressive" (CMA):

$$ER_t = \alpha + \beta_{MKT}\, MKT_t + \beta_{SMB}\, SMB_t + \beta_{HML}\, HML_t + \beta_{CMA}\, CMA_t + \beta_{RMW}\, RMW_t + \beta_{MOM}\, MOM_t + \varepsilon_t. \tag{4}$$

ER_t denotes the excess return of the Q-based portfolios over the risk-free rate in month t.

Table 3 shows the risk-adjusted performance of Q-based portfolios, based on the 6-factor model. The model fit is quite good, which is indicated by an adjusted R^2 ranging between 80% and 90% for the quintile portfolios. The portfolio alphas decrease significantly between both extreme quintile portfolios (High20, Low20). The High20 portfolio significantly outperforms the 6-factor model by 0.48% per month, while the Low20 portfolio gets outperformed by the model and yields a negative alpha of –0.22% per month. As a consequence, both self-financing strategies remain profitable even after adjusting for risk. The High20 – Low20 strategy generates a monthly alpha of 0.70% in excess of the 6-factor model; the High40 – Low40 strategy still outperforms the model by 0.49% per month. Notably, the High20 portfolio and the Low20 portfolio do not differ in terms of systematic market risk.

Table 3: Risk-adjusted performance of the Q-based quintile portfolios and the Q-based self-financing strategies.

n = 431	α	β_{MKT}	β_{SMB}	β_{HML}	β_{CMA}	β_{RMW}	β_{MOM}	R^2
High	**+0.484*** (0.13)**	+1.081*** (0.35)	+0.199*** (0.05)	–0.046 (0.06)	–0.181° (0.09)	+0.030 (0.16)	–0.274 (0.04)	0.88
MidHigh20	**+0.035 (0.10)**	+1.017*** (0.03)	–0.088* (0.04)	–0.047 (0.05)	–0.038 (0.06)	–0.035 (0.05)	+0.030 (0.03)	0.90
Mid20	**–0.052 (0.08)**	+0.907*** (0.02)	–0.072* (0.04)	–0.037 (0.04)	+0.104° (0.06)	+0.077° (0.04)	+0.050* (0.02)	0.89
LowMid20	**–0.237** (0.09)**	+0.946*** (0.02)	–0.108** (0.04)	+0.039 (0.05)	+0.127* (0.06)	+0.107** (0.04)	+0.121*** (0.03)	0.88
Low20	**–0.215° (0.13)**	+1.017*** (0.04)	+0.060 (0.05)	+0.093 (0.07)	–0.022 (0.08)	–0.111* (0.06)	+0.094* (0.04)	0.82
High20–Low20	**+0.699*** (0.21)**	**+0.064 (0.07)**	**+0.139° (0.08)**	**–0.139 (0.12)**	**–0.159 (0.15)**	**+0.081 (0.10)**	**–0.368*** (0.07)**	**0.19**
High40–Low40	**+0.486*** (0.15)**	**+0.068 (0.05)**	**+0.079 (0.05)**	**–0.112 (0.06)**	**–0.162 (0.09)**	**–0.030 (0.07)**	**–0.230*** (0.05)**	**0.21**

4. Conclusion: Low Level of Informational Leadership but High Level of Exploitability

How do the results of low information shares and high abnormal returns relate to each other? In the first part of this paper we found that analysts exercised only marginal informational leadership on highly developed stock markets. On average, equity analysts tend to be information followers rather than information leaders. However, since analysts do possess temporary informational advantages for a small number of firms, they do take part in the price discovery process of the overall market. In the second part of the paper, we discussed the misvaluation measure Q as a vehicle to identify stocks which analysts implicitly consider over- or undervalued. The results show that Q is quite successful in determining the current level of a stock's misvaluation. Putting both results together, individual investors could exploit analysts' informational edges systematically and generate highly significant returns on their investment – even though the empirical informational leadership of analysts is relatively marginal.

Are these results implausible? Is the empirical information share of analysts "too small" or the corresponding individual profit "too high"? Neither one nor the other. If the information shares of analysts were considerably larger, they would be able to make much better predictions about stock market movements for mid-term investments, meaning we would observe even larger abnormal returns from trading strategies such as constructed by the Q measure. Much larger abnormal returns, however, are hardly likely to continue over such a long period of time. Thus, it is quite plausible that information shares of analysts are quite low, because otherwise obvious trading strategies following analysts' EPS forecasts would lead to implausibly high abnormal returns.

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