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Managerial Guidance and Analysts' Underreaction*

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Abstract

Empirical investigations of analysts' forecast surveys concerning earnings realizations find significant time varying biases usually attributed to the analysts' liability to cognitive limitations. For example, a positive autocorrelation of analysts' forecast errors is commonly explained by analysts' underreaction. In this paper we develop a random dynamical system describing the evolution of analysts' forecasts and firm's prices and show that managerial guidance is capable to explain such inefficiencies in the analysts' forecasting behavior. This result is well supported by empirical tests. In particular, we find that the managers of growth firms guide stronger than the managers of value firms, which allows further conclusions on the precision and efficiency of earnings forecasts released for value and growth stocks in line with the literature.

Keywords: voluntary disclosure, managerial guidance, analysts' underreaction, inefficient forecasts

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1 Introduction

The question whether analysts' expectations are rational has been subject of several empirical studies.[1] The main finding is that analysts' forecasts can be biased and inefficient with respect to variables in the information set of the analysts, including previous forecast errors. If the analysts do not use available information efficiently when making forecasts, their forecast errors would be serially correlated. Indeed, several studies on the statistical properties of analysts' earnings forecasts by Abarbanell and Bernard (1992), Easterwood and Nutt (1999), Ali et al. (1992), Lys and Sohn (1990) and Mendenhall (1991) find evidence that the forecast errors of analysts are positively autocorrelated.

While from an empirical point of view the evidence on serially correlated forecast errors is undisputable, its theoretical explanation remains controversial. Exploring the question why forecasters make systematic forecast errors some recent studies consider the possibility that analysts underreact to information about future earnings contained in previous earnings and price realizations. For example, Mendenhall (1991), Abarbanell and Bernard (1992), and Ali et al. (1992) document evidence that analysts underreact to earnings news by underestimating the persistence of their earnings forecast errors. Further, Lys and Sohn (1990), Abarbanell (1991), and Ali et al. (1992) document evidence that analysts' forecast errors are related to past changes in the stock prices, which indicates that analysts underreact to information impounded in market prices.

This paper contributes to the literature seeking explanations for the analysts' underreaction by offering a rational economic explanation for their forecasting behavior. We assume that analysts aiming to provide precise forecasts update their expectations based on the managerial guidance regarding the future prospect of the firm. This guidance is provided by managers aiming to reduce the short–term volatility of their firm's shares, mainly driven by the behavior of noise traders. Introducing a random dynamical system compiling the demand of noise and fundamental traders adapting the earnings expectations of the guided analyst, we show that managerial guidance may increase the precision of the analysts' forecasts. However, it may also increase the effect estimated empirically as analysts' underreaction. In particular, if the manager provide guidance to analysts, their forecast errors will be positively autocorrelated. The effect is expected to differ among firms with different exposure to noise traders.

To estimate the differences in the guiding policies of the firms in our sample we use the Generalized Maximum Entropy (GME) approach suggested by Golan, Judge and Miller (1996). The results suggest that the managers of growth firms provide stronger guidance than the managers of value firms probably because the impact of noise traders is stronger for growth than for value firms. In the context of our model, this result implies that analysts forecasting the earnings of growth firms have more precise forecasts than analysts following value firms. However, their forecast are expected to be more inefficient due to the stronger guidance of the growth firm managers.

Previous studies aiming to explain the analysts' underreaction search for

[1] See Ramnath, Rock and Shane (2006) for a comprehensive overview on the analysts' decision process, the distribution of analysts' forecasts, and the informativeness and efficiency of their output.

its origins in psychological biases in individual decision making. For example, Elliot, Phalbrick, and Wiedman (1995) suggest that the observed underreaction of the analysts is due to judgemental biases, which hinders analysts to revise their forecasts sufficiently. Additionally, many experimental studies suggest circumstances where psychological biases such as conservatism and anchoring cause analysts to underreact (e.g. Maines and Hand 1996).

Other studies suggest incentive-based explanations. Based on the assumption that analysts have an asymmetric loss function with respect to their forecasting accuracy Raedy, Shane and Yang (2006) show that analysts maximizing their reputation restrain their forecast revisions so that analysts' forecasts exhibit rationally an underreaction to new information.

Our paper does not require analysts to be exposed to any behavioral biases nor to have an asymmetric loss function, which is difficult to be motivated. In our model, the analysts' underreaction is the result of the optimal guiding policy of managers aiming to minimize the short-term swings in the price of their firm's shares. If the analysts believe that the manager of the firm they follow has superior knowledge about the future prospect of the firm and does not behave strategically when disclosing this information, they will follow the guidance to increase the precision of their forecast. The manager needs to guide the analysts and influence the demand of fundamental traders in order to dampen the effect of noise traders. Specifically, after price increases (decreases), the manager needs to guide the analysts' expectations down (up) in order to decrease the volatility of the firm's price. Thus, when analysts update their forecasts in the light of increasing (decreasing) prices their forecasts may be systematically lower (higher) than the earnings realizations. However, this inefficiency of the analysts' forecasts is not irrational given that it is the result of the optimal guiding policy of the manager to analysts aiming to increase the precision of their forecasts.

The rest of the paper is organized as follows. The next section provides background on the determinants and impact of managerial guidance. Section 3 describes the model. Section 4 analyzes the impact of managerial guidance on the analysts' forecast errors in the context of our model. Section 5 describes the estimation procedure used to calibrate the model. The estimation results are presented in section 7. Section 8 discuss the results in the context of our model and section 9 concludes.

2 Determinants and Impact of Managerial Guidance

Managers release information that is not required by regulatory standards. This voluntary disclosure includes earnings estimates but also more general information such as qualitative information about market conditions, trend information that may affect the business, industry specific information, quantitative information on business measures and assumptions, or forecasts of factors that may drive future earnings. This information is usually disseminated on conference calls and has a significant impact on the forecast errors of the analysts (see for example Bowen et al., 2002). To the extent that such managers' assessments on the future performance of the firm affect the expectations of firm's outsiders, they represent managerial guidance.

To get an intuition on the managers' incentives to guide firm's outsiders, we consider the evidence of surveys analyzing managers' investors relations policies. For example, Hsieh, Koller and Rajan (2005) show that executives attribute the benefits of providing guidance to a higher valuation, lower volatility and improved liquidity. In a larger survey conducted by the National Investor Relations Institute (NIRI) in Summer 2006, 62% of the surveyed 654 managers respond that they provide guidance in order to decrease the volatility of the firm's stock price.

The volatility of stock prices is driven by the investors' demand for firm's shares. If some investors trade on changes in fundamentals but others trade on pure noise, then firm's prices will be excessively volatile (see De Long et al., 1990). This volatility is one of the main concern of firms' managers. Thus, their guiding policy is expected to be closely linked to the activities of noise traders on the stock market.

Price changes and thus stock price volatility is also closely linked to earnings surprises. This relationship is evident in empirical studies on the prominent post-earnings-announcement drift, i.e. the tendency of stock prices to drift in the same direction as the earnings surprise. Thus, managers concerned with the volatility of their stock prices need to focus on minimizing earnings surprises. This can be done either by manipulating the reported earnings and/or by managing the expectations of the analysts regarding the next period earnings. Here, we assume that the manager of the firm focuses on guiding the analysts' forecasts and does not manipulate the reported earnings.

Several empirical studies show that managers are pretty successful in managing the expectations of the analysts. In a recent study Cotter et al. (2006) explore the timing and the extent of analysts' reaction to public managerial guidance and suggest a direct connection between the management information releases and the analysts' revision. Williams (1996) studies analysts' forecast revisions in the month before and in the month after the managers' guidance and finds considerable level of revisions in the analysts' earnings forecasts. Earlier studies by Hassell, Jennings and Lasser (1988) and Baginski and Hassell (1990) provide additional evidence that analysts revise their estimates as a response to management forecasts.

The following section specifies the manager's incentives to guide firm's outsiders in a theoretical framework.

3 Model Setup

To analyze the manager's incentives for guidance we model a simple economy with one manager and many investors trading the shares of the firm. In the tradition of Brock and Hommes (1998) we assume that some of the investors judge the prospects of the firm based on its earnings potential (fundamental traders); the rest of the investors make trading decisions based on past changes in the price of firm's shares (noise traders).

The manager can influence his firm's market price only if he manages the expectations of the fundamental traders. We assume that the fundamental traders update their expectations based on the earnings estimates of the analysts following the firm. Thus, to manage the market price of his firm's shares a manager needs to influence the expectations of the analysts regarding the next period earnings.

We specify the manager's problem as a linear quadratic control problem consisting of an objective function, a state equation describing the dynamics of firm's price changes and a feedback rule governing the guidance response of the managers to previous firm's price changes. In particular, we define the manager's objective function as

$$\min_{G_t} W = E\left\{\sum_{t=1}^{\infty} \delta^t b(p_t - p_{t-1})^2\right\} \tag{1}$$

where G_t is a control variable describing manager's guidance, p_t is the price of firm's shares in period t, δ_t is a discount factor, and $b > 0$ is an unknown parameter reflecting the manager's preferences with respect to the variance of price changes.

The state equation describes the dynamics of the firm's price changes. In our model the market price of the firm is determined by the demand for firm's shares, which depends on the cumulative demand of the noise and fundamental traders. The demand of the noise traders is driven by their expectations regarding the next period price, which are defined as:

$$\mathbb{E}^N(p_{t+1} - p_t) = a(p_t - p_{t-1}) \tag{2}$$

where $a \geq 0$ is an unknown parameter describing the impact of previous price changes on the traders' demand for firm's shares. In the following, we specify the noise traders as positive feedback traders. This is consistent with the empirical evidence that the autocorrelation of returns reverse in dependence on the volatility (see Sentana and Wadhwani, 1992), which indicates the presence of positive feedback traders on the market.

To the extend that the fundamental value of the firm depends on the present value of the firm's earnings, the expectations of the fundamental traders regarding the next period price is determined by changes in their earnings expectations. The latter are assumed to be driven by changes in the consensus forecast of the analysts following the firm, i.e.

$$\mathbb{E}^F(p_{t+1} - p_t) = c\mathbb{E}^G(e_{t+1} - e_t) \tag{3}$$

The response of the fundamental traders to changes in the earnings expectations of the analysts $\mathbb{E}^G(.)$ is given by the parameter $c > 0$. If the analysts' consensus forecasts increases (decreases) by a unit, the firm's value estimated by the fundamental traders increases (decreases) as well so that their overall demand for firm's shares increases (decreases) by c units.

We implement the market clearing through Walrasian tattonnement based on the overall demand for firm's shares given by (2) and (3). Using in addition the assumption that analysts' forecasts are subject to manager's guidance as defined by the function G_t, i.e.

$$\mathbb{E}^G(e_{t+1} - e_t) = G_t \tag{4}$$

we get a dynamical system for the evolution of firm's price changes through time

$$p_{t+1} - p_t = a(p_t - p_{t-1}) + cG_t^* + \varepsilon_{1t} \tag{5}$$

where $\varepsilon_{1t} \sim N(0, \sigma^2_{\varepsilon_{1t}})$ is a noise term and G_t^* is a feedback or control rule. It describes the optimal guidance response of the manager to price changes. It is specified as

$$G_t^* = g(p_t - p_{t-1}) + \varepsilon_{2t} \tag{6}$$

where g is an unknown parameter and $\varepsilon_{2t} \sim N(0, \sigma^2_{\varepsilon_{2t}})$ is a noise term.

The manager's control problem is therefore given by the manager's objective function

$$\min_{g^*} W = E\left\{\sum_{t=1}^{\infty} \delta^t b(p_t - p_{t-1})^2\right\} \tag{7}$$

the state equation (5) and the feedback rule (6). Following Chow (1975), we get that the optimal control reaches a steady–state in the sense of having G_t invariant over time if

$$g^* = -\frac{a}{c} \tag{8}$$

and

$$b = -h + \delta(\alpha + cg)^2 h \tag{9}$$

where h is a Lagrange multiplier. The first condition states that in steady–state, the intensity of the manager's guidance must neutralize the demand of the positive feedback traders by changing the analysts' consensus forecasts, i.e. the demand of the fundamental traders. The second condition states the "pain" that the manager experiences facing the uncertainty in the price changes driven by positive feedback traders while guiding the analysts. Both relations are used together with the state equation (5) and the feedback rule (6) as consistency conditions to estimate the unknown parameters of the model.

Note that in our economy with managers guiding the expectations of the fundamental investors, firms' market prices are not predictable although there are some positive feedback traders investing systematically. The activities of these noise traders do not have any impact on the market prices, if the managers' guidance is optimal. Given the managers' objective to minimize the variance of stock price changes, their guidance needs to neutralize the impact of the positive feedback traders on the market price of the firm. In this case, firms' price changes will not be correlated over time although there are positive feedback traders on the market.

4 The Impact of Managerial Guidance on the Analysts' Forecast Errors

The specification of the manager's guiding policy in the previous section allows us to analyze its impact on the precision and the efficiency of the analysts' earnings forecasts.

Per definition, the analysts' forecast error is equal to:

$$z_t = e_t - \mathbb{E}^G(e_t) \tag{10}$$

or

$$z_t = \Delta e_t - \mathbb{E}^G(\Delta e_t) \tag{11}$$

where $\Delta e_t := e_t - e_{t-1}$.

Then, using equations (4) and (6), the forecast error of the analysts can also be written as:

$$z_t = \Delta e_t - g(\Delta p_{t-1}) \tag{12}$$

where $\Delta p_{t-1} := p_{t-1} - p_{t-2}$. Thus, analysts following the managerial guidance may increase the precision of their forecasts if the market price of the firm at the time of the forecasting falls (increases) but the trend of earnings growth is positive (negative).

Result 1. *If the current market price of the firm goes into the opposite direction as the earnings trend, the analysts following the managerial guidance produce lower forecast errors.*

Although the guidance of the manager may increase the precision of the analysts forecasts, it has a negative impact on their efficiency. In the following we show that analysts' forecasts based on the guidance by managers are positively autocorrelated.

Forecast errors exhibit a positive autocorrelation if:

$$\mathbb{E}_{t-1}(z_t z_{t+1}) = \mathbb{E}_{t-1}(\Delta e_t - g\Delta p_{t-1})(\Delta e_{t+1} - g\Delta p_t) > 0 \tag{13}$$

or

$$\begin{aligned}\mathbb{E}_{t-1}(z_t z_{t+1}) \quad = \quad & \mathbb{E}_{t-1}(\Delta e_t \Delta e_{t+1}) - \mathbb{E}_{t-1}(g\Delta e_t \Delta p_t) \\ & -\mathbb{E}_{t-1}(g\Delta p_{t-1}\Delta e_{t+1}) + \mathbb{E}_{t-1}(g^2 \Delta p_{t-1}\Delta p_t) > 0\end{aligned} \tag{14}$$

We assume that the firm's earnings follow a (seasonal) random walk with a drift, i.e.

$$e_t = \mu + e_{t-1} + \varepsilon_t \tag{15}$$

where $\varepsilon_t \sim N(0, \sigma_\varepsilon)$ is white noise.
The first term of the equation is equivalent to

$$\mathbb{E}_{t-1}(\Delta e_t \Delta e_{t+1}) = \mu^2$$

The second term of the equation is equivalent to

$$\mathbb{E}_{t-1}(g\Delta e_t \Delta p_t) = g\mathbb{E}_{t-1}[\Delta e_t((a + cg)\Delta p_{t-1} + \varepsilon_{t1})] = g[\mu(a + cg)]\Delta p_{t-1} = 0$$

given the optimal guidance policy $g = -\frac{a}{c}$.
The third term of the equation is

$$\mathbb{E}_{t-1}(g\Delta p_{t-1}\Delta e_{t+1}) = g\mu\Delta p_{t-1}$$

The last term is

$$g^2 \Delta p_{t-1}\mathbb{E}_{t-1}(\Delta p_t) = 0$$

since under optimal guiding $\mathbb{E}_{t-1}(\Delta p_t) = 0$. Thus, the forecast errors are positively autocorrelated if

$$\mathbb{E}_{t-1}(z_t z_{t+1}) = \mu^2 - \mu g\Delta p_{t-1} > 0 \tag{16}$$

This is true for $-\frac{|\mu|}{|g|} < \Delta p_{t-1} < \frac{|\mu|}{|g|}$.

If we focus on stocks with a positive earnings drift, i.e. $\mu > 0$, the analysts' forecast errors will be positively autocorrelated, when firm's prices increase as well. For example, in a boom market when earnings tend to increase and the market price of firm's shares increase as well, managers need to guide analysts' expectations down. As a result, analysts' forecasts will be systematically too low, i.e. the analysts underreact. If the price of the firm decreases although the earnings drift is positive, the managers need to guide the expectations of the analysts up in order to dampen the effect of the positive feedback traders betting on further decreasing prices. This guidance reduces the forecast error of the analysts as discussed above, but given that the impact of the positive feedback traders is limited and there are no large negative shocks in the economy so that the optimal guidance is not that strong, analysts' forecasts will be too low again. Thus, analysts' following the managerial guidance would have positively correlated forecast errors.

Result 2. *There is a positive autocorrelation in the analysts' forecast errors if there is a price change supporting the earnings trend. If this condition does not hold, the forecast errors of the analysts will be positively autocorrelated if the positive feedback traders do not dominate the market so that the manager does not need to guide too strongly.*

Note that if positive feedback traders dominate the market, then the manager needs to guide stronger when prices decline. Consequently, the analysts' forecasts may increase above the mean earnings growth, i.e. the analysts' forecast will be too high. Given the positive forecast error in the previous period, analysts' forecast errors will then exhibit a negative autocorrelation.

In the literature, the relationship between analysts' forecast errors and previous realizations of variables known by the analysts is used as an indicator for inefficient forecasting. Several empirical studies analyzing the properties of analysts forecasts find a significant positive relationship between the analysts' forecast errors and the firm's performance and also between the analysts' forecast errors in two subsequent periods (see Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999; Ali, Klein and Rosenfeld, 1992; Lys and Sohn, 1990 and Mendenhall, 1991). A common explanation for this empirical result is that the analysts underreact to information, i.e. analysts' systematically underestimate the trend in the firm's performance probably because of some behavioral bias. As a consequence, after a positive (negative) firm's performance the forecast error is positive (negative). The same relationship can be observed in our model as well: If the firm's performance has a positive (negative) trend, the forecast error of the analysts will be positive (negative) when the current price change supports the development of the firm's performance or if the current price decreases (increases) but only moderately, for example because of the limited impact of positive feedback traders. Note that our explanation of the observed relationship does not require analysts to be exposed to any behavioral bias. In our model, the relationship is observed because managers provide guidance to firm's outsiders in order to dampen the effect of the positive feedback traders increasing the variance of firm's price changes.

To estimate whether the proposed relationship can be explained by managerial guidance, we study the price dynamics of different firms in order to recover the unknown parameters of the problem along with the parameter of the feedback rule. We expect to see significant differences in the preferences and in the guiding policies of firms with different levels of uncertainty in their earnings and price growth. Such differences can be observed for example by growth and value stocks. To the extent that earnings are uncertain and the firm is difficult to be evaluated on the basis of fundamentals, there will be more investors evaluating the firm on the basis of its past performance. According to our model, the managers of such firms would have stronger incentives to provide guidance since it reduces the impact of the positive feedback traders on the variance of stock price changes. The implications for the analysts' forecasts is then analyzed in the context of our model.

5 Estimation Procedure

To estimate the unknown parameters of the model we propose the use of the Generalized Maximum Entropy (GME) estimation method as described by Golan, Judge and Miller (1996). The basic objective of the method is to estimate the unknown parameters with minimal distributional and sampling assumptions. This objective is similar in philosophy to other approaches as for example the Generalized Method of Moments, where the basic objective is first to search for the "natural weight" of each observation and then to use it in order to form an empirical likelihood based on some moments. In contrast, the GME does not use any moments or side–conditions a priori. Instead with the GME one maximizes the traditional entropy functional but subject to noisy moment representations, without imposing any sampling assumptions or zero moment conditions.

The principle of maximum entropy is based on the idea that when estimating the probability distribution of the model parameters from a sample one should select the distribution, which leaves the largest remaining uncertainty (maximum entropy) consistent with some constrains. Under this criterion, there are no additional assumptions or biases introduced in the estimation. Additionally, the estimation can be done without imposing assumptions on the underlying data generation process. Thus, given the linear-quadratic model in (7), (5) and (6), we estimate the unknown parameters without imposing assumptions regarding the exact relationship between sample and population moments. Assuming that the parameters and the noise terms with unknown distributions are both unknown, we aim to recover them simultaneously from the price data of a particular firm.

To achieve this goal we reformulate the unknown parameters and noise terms as discrete random variables with finite supports. Accordingly, we may write the control problem in terms of the random variables. The estimation problem is then to recover the probability distributions for the unknown parameters and noise terms that reconciles the available information with the observed sample information. At the optimum, the probabilities satisfy some consistency constraints, which are given by the state equation (5), the feedback rule (6) and the steady–state conditions (8) and (23). Given these probability distributions and the supports used in the estimation we can recover the parameters of the model. A precise description of the estimation procedure is given in the appendix.

6 Data and Descriptive Statistics

To recover the unknown parameters of the linear quadratic control problem defined in (1), (5) and (6) for different firms, we use quarterly price data from Datasteam starting in the third quarter of 2000 and ending at the forth quarter of 2006. We choose the third quarter of 2000 as a starting date since in October 2000 the SEC introduced the Regulation Fair Disclosure (Reg FD) prohibiting the private dialog between managers and analysts. We expect that after Reg FD, the market reaction to earnings forecasts and announcements changes since the dissemination of information is intensified. Previous research by Heflin et al. (2003) support this view. They observe that after Reg FD the return volatility after earnings announcements, which is part of the manager's objective function, has decreased. This result indicates that the effect of managers' guidance may differ prior and after Reg FD. We take this into account by focusing on the period after Reg FD.

We limit our analysis on firms using the US GAAP reporting standard and choose 40 firms included in the S&P 500 Index. The selection is done based on two criteria: the firms' market capitalization as of December 2006 and the firms' fundamentals relative to their market value. We focus on the largest firms in the index to keep the group homogenous with respect to size since large firms are usually covered by more analysts than small and mid–cap firms. The market capitalization of the firms in our sample ranges between 34\$ billions and 422\$ billions.

To distinguish whether a firm is a value or a growth firm, we use the S&P500/Citigroup Growth and Value Indices. The main advantage of these indices is that firms' classification is based not only on the price-to-book ratios of the firms but also on additional variables.[2]

Table 1 provides summary statistics on the quarterly price changes of the growth firms included in our sample.

[2] The growth criteria are the five-years historical earnings per share growth rate, sales per share growth rate and the five years average annual internal growth rate. The value criteria are the book value per share to price, the sales per share to price, the cash flow per share to price, and the dividend yield.

Table 1: *Summary Statistics Growth Stocks*

The summary statistics are calculated for changes in quarterly prices. For the time period from Q1 2002 to Q4 2006 there are 26 observations. Mean and median values in italic are statistically different from zero at the 5% confidence level. The Augmented Dickey Fuller (ADF) test statistic is performed for an intercept and a trend with maximum 5 lags. The p–values are reported in parenthesis.

	Mean	Median	StDev	Skew.	Kurt.	JB-stat	ADF-test
AIG	-0.378	-0.035	9.064	0.002	1.929	1.242 (0.538)	-6.199 (0.000)
Am.Express	0.414	1.865	4.488	-0.921	3.527	3.976 (0.137)	-4.636 (0.006)
Amgen	0.812	-0.725	8.654	0.725	3.569	2.628 (0.269)	-6.832 (0.000)
Cisco	-1.604	0.070	6.749	-1.823	6.411	27.02 (0.000)	-4.765 (0.004)
Comcast	-0.067	0.175	4.402	-0.449	2.499	1.145 (0.564)	-4.693 (0.005)
Dell	1.173	1.860	3.290	-0.145	3.126	0.109 (0.947)	-6.017 (0.000)
EBay	0.496	0.013	5.668	-0.168	2.222	0.779 (0.677)	-1.004 (0.922)
Exxon	1.173	1.860	3.290	-0.145	3.126	0.109 (0.947)	-6.017 (0.000)
HomeDepot	-0.862	0.445	6.838	-1.222	4.189	8.008 (0.018)	-6.489 (0.000)
IBM	-0.805	0.715	11.093	-0.349	3.100	0.538 (0.764)	-5.549 (0.001)
J&J	1.026	1.233	5.059	-1.037	4.703	7.801 (0.020)	-6.695 (0.000)
Lowe's	0.629	0.045	3.162	0.256	2.050	1.262 (0.532)	-4.699 (0.007)
Medtronic	-0.154	0.285	4.270	-0.616	3.216	1.694 (0.429)	-7.072 (0.000)
Oracle	-0.737	0.119	3.536	-1.623	6.110	21.90 (0.000)	-6.757 (0.000)
Pepsico	1.008	1.255	4.199	-0.993	4.865	8.040 (0.018)	-6.861 (0.000)
P&G	1.201	1.123	3.123	-0.045	2.774	0.064 (0.969)	-4.663 (0.007)
Un.Health	*1.542*	*1.983*	3.291	-0.756	5.551	9.530 (0.009)	-4.608 (0.006)
Walgreen	0.532	0.760	3.921	-0.112	2.996	0.054 (0.973)	-5.767 (0.000)
Wal Mart	-0.340	-0.420	5.817	-0.293	2.687	0.479 (0.787)	-9.716 (0.000)
Yahoo	-1.452	-0.407	9.075	-3.373	15.479	217.9 (0.000)	-5.109 (0.002)

The average firms' price changes range between -1.6 and 1.5 with standard deviations between 3.1 and 11.1. The skewness and kurtosis range between -3.4 and 0.7 respectively between 1.9 and 15.5 indicating that the price changes of some firms are probably not normal distributed. However, the JB-statistic shows that the price changes of most of the firms are not statistically different from the normal distribution. Further, firms' price changes do not have a unit root according to the ADF-statistic except for one firm. This allows us to use ordinary least squares to estimate the autocorrelation of firms' price changes. The results reported in Table 2 suggest that price changes of most of the growth firms in our sample do not depend on their previous realizations. Including higher lags in the analysis does not change the conclusion that firms' quarterly price changes are not autocorrelated over time.

Table 2: *Autocorrelation in Price Changes of Growth Stocks*

$p_t - p_{t-1} = c_0 + \sum_{i=0}^{3} c_i(p_{t-i} - p_{t-i-1})$.

The Breusch–Godfrey (BG) statistic is calculated with 3 lags. P–values are reported in parenthesis.

	c_0	c_1	c_2	c_3	BG-test
AIG	-1.781 (0.350)	-0.383 (0.117)	-0.210 (0.349)	-0.007 (0.975)	0.449 (0.772)
Am.Express	0.639 (0.492)	0.072 (0.729)	-0.084 (0.684)	0.255 (0.227)	2.477 (0.099)
Amgen	0.505 (0.762)	-0.105 (0.637)	0.074 (0.737)	-0.366 (0.085)	0.917 (0.455)
Cisco	-0.248 (0.829)	0.170 (0.407)	0.423 (0.021)	-0.345 (0.056)	2.392 (0.107)
Comcast	-0.263 (0.780)	0.083 (0.726)	-0.146 (0.519)	-0.256 (0.252)	0.255 (0.856)
Dell	0.848 (0.279)	0.048 (0.838)	0.293 (0.181)	0.075 (0.733)	0.338 (0.798)
EBay	0.785 (0.561)	-0.234 (0.312)	-0.090 (0.730)	0.248 (0.368)	2.787 (0.074)
Exxon	0.848 (0.279)	0.048 (0.838)	0.293 (0.181)	0.075 (0.733)	0.338 (0.798)
HomeDepot	-0.507 (0.710)	-0.292 (0.216)	-0.041 (0.846)	-0.038 (0.846)	0.280 (0.839)
IBM	-0.922 (0.656)	0.002 (0.993)	-0.233 (0.233)	0.141 (0.481)	0.095 (0.962)
J&J	1.318 (0.244)	-0.260 (0.276)	0.082 (0.741)	-0.270 (0.255)	0.623 (0.610)
Lowe's	1.140 (0.163)	-0.431 (0.077)	0.019 (0.942)	-0.024 (0.915)	3.228 (0.050)
Medtronic	-0.321 (0.732)	-0.446 (0.065)	-0.167 (0.513)	-0.019 (0.939)	1.722 (0.203)
Oracle	-0.219 (0.794)	-0.027 (0.905)	0.375 (0.092)	-0.077 (0.738)	12.22 (0.000)
Pepsico	1.250 (0.183)	-0.433 (0.074)	-0.211 (0.398)	0.004 (0.984)	0.304 (0.822)
P&G	1.903 (0.032)	-0.366 (0.141)	-0.320 (0.187)	0.022 (0.923)	5.368 (0.009)
Un.Health	1.124 (0.376)	-0.001 (0.996)	0.032 (0.893)	0.130 (0.693)	1.146 (0.361)
Walgreen	0.431 (0.574)	-0.269 (0.231)	0.031 (0.882)	-0.354 (0.091)	1.368 (0.288)
Wal Mart	-0.166 (0.855)	-0.758 (0.005)	-0.078 (0.765)	0.099 (0.615)	0.486 (0.697)
Yahoo	0.540 (0.364)	0.189 (0.406)	0.244 (0.006)	-0.061 (0.443)	0.824 (0.500)

Summary statistics for the value firms are provided in Table 3.

Table 3: *Summary Statistics of Value Stocks*

The summary statistics are calculated for changes in quarterly prices. For the time period from Q1 2002 to Q4 2006 there are 26 observations. Mean and median values in italic are statistically different from zero at the 5% confidence level. The Augmented Dickey Fuller (ADF) test statistic is performed for an intercept and a trend with maximum 5 lags. The p–values are reported in parenthesis.

	Mean	Median	StDev	Skew.	Kurt.	JB-stat	ADF-test
AT&T	-0.408	-0.57	3.85	0.658	4.458	4.179 (0.124)	-5.216 (0.002)
Bank of America	*1.049*	1.365	2.528	-0.400	3.039	0.694 (0.707)	-6.170 (0.000)
Bristol Myers	-0.935	-0.183	5.528	-0.479	5.034	5.480 (0.065)	-5.207 (0.003)
Citigroup	0.221	0.365	4.494	-0.858	4.742	6.476 (0.039)	-5.422 (0.001)
ConocoPhilips	1.462	*1.175*	3.675	0.095	3.645	0.490 (0.783)	-3.683 (0.043)
Duke Energy	0.105	0.980	4.749	-1.147	6.285	17.39 (0.000)	-5.487 (0.001)
Du Pont	-0.231	-0.363	3.407	-0.272	2.489	0.603 (0.740)	-6.489 (0.000)
Fannie Mae	-0.224	-1.075	7.392	0.571	3.478	1.661 (0.436)	-7.080 (0.000)
Hewlett Packert	-0.590	-0.015	5.198	-0.653	3.025	1.847 (0.397)	-6.318 (0.000)
JPMorgan Chase	-0.184	-0.060	5.296	-0.154	4.087	1.383 (0.501)	-3.948 (0.029)
Merck	-0.867	0.533	6.621	0.105	3.150	0.072 (0.965)	-4.987 (0.003)
Merrill Lynch	1.257	3.390	8.035	-0.063	1.843	1.467 (0.480)	-5.598 (0.001)
Morgan Stanley	-0.093	0.735	8.146	-0.709	3.589	2.551 (0.279)	-4.437 (0.010)
Motorola	-0.385	0.330	3.881	-2.025	8.125	46.22 (0.000)	-8.236 (0.000)
Sprint Nextel	-1.429	-0.472	4.824	-2.162	7.558	42.75 (0.000)	-4.453 (0.008)
Time Warner	-1.583	-0.660	4.776	-0.195	2.719	0.250 (0.882)	-3.752 (0.042)
Tyco	-0.727	0.025	6.785	-1.750	6.867	29.47 (0.000)	-3.865 (0.030)
Verizon	-0.948	-0.050	5.099	-0.967	4.515	6.539 (0.038)	-6.103 (0.000)
Washington Mut.	0.965	1.645	3.852	-0.753	3.253	2.529 (0.282)	-6.629 (0.000)
Wells Fargo	0.571	0.763	1.650	0.011	2.351	0.457 (0.796)	-6.198 (0.000)

The average price changes of the value firms range between -1.6 and 1.5 with standard deviations between 1.6 and 8.1. The skewness and kurtosis range between -2.2 and 0.7 respectively between 1.8 and 8.1 indicating that the price changes of some firms are probably not normal distributed. However, most of the value firms have price changes that are statistically not different from the normal distribution according to the JB-statistic. Further, according to the ADF-statistic, the price changes of the value firms included in our sample do not have a unit root. This allows us to use ordinary least squares to estimate the autocorrelation of firms' price changes. The results reported in Table 4 suggest that as in the case of growth firms the price changes of most of the value firms in our sample do not depend on their previous realizations. Including higher lags in the analysis does not change the conclusion that firms' quarterly price changes are not autocorrelated over time.

Table 4: *Autocorrelation in Price Changes of Value Stocks*

$p_t - p_{t-1} = c_0 + \sum_{i=0}^{3} c_i(p_{t-i} - p_{t-i-1})$.

The Breusch–Godfrey (BG) statistic is calculated with 3 lags. P–values are reported in parenthesis.

	c_0	c_1	c_2	c_3	BG-test
AT&T	0.296 (0.617)	0.437 (0.023)	0.017 (0.906)	0.418 (0.007)	0.758 (0.534)
Bank of America	1.717 (0.033)	-0.331 (0.182)	-0.059 (0.816)	-0.021 (0.924)	2.696 (0.081)
Bristol Myers	-0.956 (0.361)	0.538 (0.025)	-0.410 (0.042)	0.196 (0.300)	0.841 (0.491)
Citigroup	-0.039 (0.970)	-0.094 (0.684)	-0.097 (0.675)	-0.004 (0.987)	0.453 (0.719)
ConocoPhilips	0.752 (0.436)	0.312 (0.196)	0.021 (0.925)	0.109 (0.630)	0.396 (0.758)
Duke Energy	-0.261 (0.776)	-0.022 (0.925)	0.356 (0.074)	-0.140 (0.493)	1.139 (0.363)
Du Pont	-0.010 (0.987)	-0.554 (0.028)	-0.479 (0.047)	-0.245 (0.263)	0.732 (0.548)
Fannie Mae	-1.152 (0.371)	-0.415 (0.083)	0.200 (0.298)	0.196 (0.292)	0.124 (0.944)
Hewlett Packert	0.681 (0.445)	-0.089 (0.688)	0.285 (0.127)	0.223 (0.211)	1.778 (0.192)
JPMorgan Chase	-0.198 (0.836)	0.138 (0.477)	0.153 (0.388)	0.037 (0.836)	1.642 (0.219)
Merck	-1.709 (0.270)	-0.014 (0.955)	-0.054 (0.798)	-0.156 (0.459)	0.416 (0.744)
Merrill Lynch	0.457 (0.798)	-0.03 (0.899)	-0.093 (0.700)	0.126 (0.585)	2.819 (0.072)
Morgan Stanley	0.162 (0.915)	0.166 (0.495)	0.352 (0.097)	-0.177 (0.395)	3.195 (0.052)
Motorola	0.331 (0.561)	-0.066 (0.779)	0.302 (0.041)	0.047 (0.761)	1.48 (0.258)
Sprint Nextel	0.026 (0.962)	-0.149 (0.519)	0.057 (0.750)	0.145 (0.282)	0.589 (0.631)
Time Warner	-0.681 (0.501)	0.177 (0.376)	0.265 (0.165)	0.105 (0.578)	2.474 (0.099)
Tyco	-1.253 (0.417)	0.277 (0.226)	-0.141 (0.545)	0.007 (0.975)	1.265 (0.320)
Verizon	-0.664 (0.553)	-0.111 (0.647)	0.005 (0.982)	-0.018 (0.929)	1.067 (0.391)
Washington Mut.	0.771 (0.368)	-0.450 (0.048)	-0.006 (0.977)	-0.005 (0.981)	1.918 (0.167)
Wells Fargo	0.932 (0.032)	-0.332 (0.118)	-0.255 (0.261)	-0.287 (0.196)	0.201 (0.894)

The missing autocorrelation of price changes of growth and value stocks is consistent with our model since optimal guidance neutralizes the effect of the positive feedback traders on the price dynamics of the firm. If the manager of the firm does not intervene against the activities of positive feedback traders, we would observe a positive autocorrelation of stock price changes. The autocorrelation would be negative if the guidance is too strong relative to the impact of the positive feedback traders on stock prices. Both guiding policies cannot be considered as rational given the manager's control problem.

7 Estimation Results

The estimation procedure described in section 5 and in the appendix is applied to estimate the unknown parameters of the optimal control problem that the managers of different value and growth firms need to solve when deciding their guiding strategies. The GME approach requires to specify the support of each of the unknowns in order to reflect prior knowledge about the parameters. Since our model does not provide specific restrictions on the upper and lower bounds on the parameter space, we run the estimation for a variety of plausible bounds. For each combination of bounds we estimate the coefficients and calculate the corresponding entropy.

We choose six supports in equidistant fashion for each of the parameters subject to estimation. We first use broad supports and then refine them while evaluating changes in the corresponding entropy. For the parameter a we choose the supports

$$\begin{aligned} z^a &= (0.1, 0.3, 0.5, 0.7, 0.9, 1.0) \\ z^a &= (0.05, 0.1, 0.15, 0.2, 0.25, 0.3) \\ z^a &= (0.4, 0.5, 0.6, 0.7, 0.8, 1.0) \end{aligned}$$

The parameter g is estimated over the supports

$$\begin{aligned} z^g &= (-1, -0.9, -0.7, -0.5, -0.3, -0.1) \\ z^g &= (-0.3, -0.25, -0.2, -0.15, -0.1, -0.05) \\ z^g &= (-1, -0.8, -0.7, -0.6, -0.5, -0.4) \end{aligned}$$

For the parameters b and h we use the supports

$$\begin{aligned} z^b &= (0.1, 0.3, 0.5, 0.7, 0.9, 1) \\ z^b &= (0.5, 1, 1.5, 2, 2.5, 3) \\ z^h &= (-1, -0.9, -0.7, -0.5, -0.3, -0.1) \\ z^h &= (-3, -2.5, -2, -1.5, -1, -0.5) \end{aligned}$$

The supports for both noise terms are chosen symmetrically around zero, i.e.

$$v^e = (-0.5, -0.25, -0.1, 0.1, 0.25, 0.5)$$

The parameter c reflecting the demand response of the fundamental traders to the earnings estimates of the guided analysts is set to be equal to 1. This assumption is not restrictive given that the manager knows how the fundamental traders respond to the provided guidance. In this case the manager can adjust his guidance policy captured by the parameter g and take into account the expectations of the fundamental traders in order to influence the next period price.

Combining the different support sets, we get eighteen different coefficient estimates with corresponding entropies for each firm in the sample. The coefficients estimates with the lowest entropy for the growth and value stocks in our sample are reported in Table 5 respectively in Table 6.[3] For focus is on

[3]The full sample of estimates is available upon request.

the coefficients g and b since according to the steady–state conditions of the problem and the assumption that $c = 1$, $a = -g$ and $h = -b$.

The estimated coefficients for the growth and value stocks are reported in Tables 5 and 6 respectively. Figures 1 and 2 illustrate the estimation results graphically.

Table 5: *Coefficient Estimates for Growth Stocks*

	g	b	H
AIG	-0.205	0.500	1.153
American Express	-0.282	0.227	4.197
Amgen	-0.057	0.776	3.718
Cisco	-0.057	0.776	6.015
Comcast	-0.300	0.744	6.450
Dell	-0.429	0.774	5.226
EBay	-0.282	0.227	7.841
Exxon	-0.100	0.752	1.514
Home Depot	-0.225	0.282	5.026
IBM	-0.208	0.500	3.386
J&J	-0.057	0.752	5.724
Lowe's	-0.192	0.500	6.446
Medtronic	-0.429	0.772	7.333
Oracle	-0.150	0.776	6.554
Pepsico	-0.225	0.500	6.824
P&G	-0.100	0.752	4.911
United Health	-0.434	0.752	4.833
Walgreen	-0.220	0.500	7.201
Wal Mart	-0.438	0.752	5.637
Yahoo	-0.205	0.500	3.509
Mean	-0.230	0.606	
Median	-0.214	0.748	
St.Dev.	0.127	0.196	

Table 6: *Estimated Coefficients for Value Stocks*

	g	b	H
AT&T	-0.050	0.205	3.386
Bank of America	-0.100	0.776	6.047
Bristol Myers	-0.500	1.042	3.875
Citigroup	-0.411	0.752	3.682
ConocoPhilips	-0.100	0.227	8.608
Duke Energy	-0.300	0.773	4.745
Du Pont	-0.057	0.764	4.559
Fannie Mae	-0.050	0.227	3.773
Hewlett Packert	-0.100	0.773	1.832
JPMorgan Chase	-0.196	0.500	6.565
Merck	-0.400	0.201	4.367
Merrill Lynch	-0.200	0.720	1.337
Morgan Stanley	-0.057	0.772	6.486
Motorola	-0.427	0.774	9.796
Sprint Nextel	-0.050	0.205	8.340
Time Warner	-0.050	0.213	9.461
Tyco	-0.100	0.500	7.804
Verizon	-0.057	0.776	4.319
Washington Mutual	-0.300	0.683	4.103
Wells Fargo	-0.192	0.500	8.522
Mean	-0.178	0.554	
Median	-0.100	0.702	
St.Dev.	0.154	0.280	

Figure 1: Estimated Guidance Policies of Growth and Value Stocks

The box portion of the boxplot represents the first and third quartiles. The median is depicted using a line through the center of the box, while the mean is drawn using a symbol. The shaded region displays approximate confidence intervals for the median. The bounds of the shaded area are defined by the median $+/-1.57 * IQR/\sqrt{N}$, where IQR is the difference between the first and third quartile and N is the number of observations.

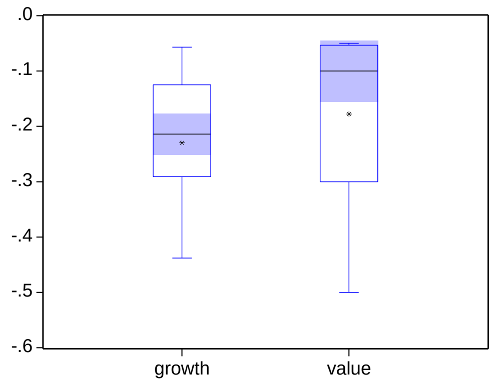

Figure 2: Estimated Preferences of Growth and Value Managers

The box portion of the boxplot represents the first and third quartiles. The median is depicted using a line through the center of the box, while the mean is drawn using a symbol. The shaded region displays approximate confidence intervals for the median. The bounds of the shaded area are defined by the median $+/-1.57 * IQR/\sqrt{N}$, where IQR is the difference between the first and third quartile and N is the number of observations.

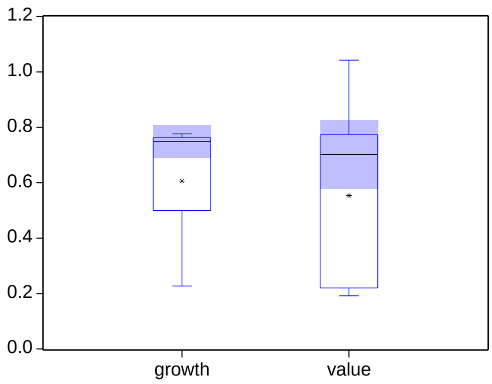

Table 7: *Significance Tests*

	g	b
F-Test (variances)	1.462	2.049
	(0.415)	(0.125)
Levene Test	1.846	6.604
	(0.1823)	(0.014)
T-Test (means)	-1.165	-0.680
	(0.126)	(0.250)
Wilcoxon Mann-Whitney Test	133.5	219.5
	(0.036)	(0.306)
Kolmogorov-Smirnov Test	0.350	0.200
	(0.076)	(0.348)

The average guidance coefficient estimated for the sample of growth firms is equal to -0.230, which is greater in absolute terms compared to the corresponding average for the sample of value firms equal to -0.178. Additionally, the standard deviation of the estimated guidance of growth firm is lower than the corresponding statistic in the value sample. These difference indicate that the growth firms guide on average stronger than value firms and the guiding policies of the growth firms is more homogenous than the guiding policies of the value firms included in our sample.

To verify the significance of this result we first apply the F–Test and the Levene Test to test the null hypothesis that the variances of both samples are homogenous. Both tests indicate that we cannot reject the null hypothesis under a reasonable level of risk. Thus, we can apply the Student t-test to derive conclusions whether the observed differences in the average estimates of both samples are statistically significant. We can reject the null hypothesis that the means of the value and growth samples of estimates are equal under the risk of 12.6%. We also apply two additional non–parametric tests to relax the assumption that the differences between the samples are normally distributed. With the Wilcoxon Mann-Whitney statistic we test whether the locations of the distribution with growth estimates is on the right side of the distribution with value estimates. We can reject the null hypothesis of identical distribution functions under the risk of 3.6%. With the Kolmogorov-Smirnov-one-tailed test we extend the analysis to compare any part of both distributions. We can reject the null-hypothesis that the distribution of estimates in the growth sample is not significantly lower than the distribution of estimates in the value sample under the risk that it is true of 7.59%. Overall, we may conclude that the heterogeneity of the guiding policies of the firms in the growth and value sample is similar, but most of the growth firms guide stronger than the value firms.

Differences between value and growth firms are also observed with respect to the managers' variance aversion. Comparing the variance of the estimated coefficients in each group, we find significant differences between the managers' preferences in the growth and value sample, i.e the group of the growth managers is more homogeneous than the group of the value managers. These managers have also a higher aversion to variances in price changes than the value stocks managers. Though, this difference is not statistically significant according to the applied non–parametric tests.

8 Discussion of the Estimation Results

The estimation results presented in the previous section suggest that growth firms provide stronger guidance to the analysts. In our model, the motivation for their guiding policy can either be driven by their preferences or by the power of positive feedback traders increasing the variance of firm's price changes. We do not observe significant differences in the preferences of the value and growth managers with respect to the variance of the firm's price changes. Thus, the observation that growth firms' managers guide stronger than value firms' managers can be explained with the stronger demand of positive feedback traders.

Positive feedback traders are expected to be more active in trading growth stocks because growth stocks are usually more difficult to evaluate since most of their assets are intangible. To the extent that the value and profitability of firm's assets is uncertain, investors trading the shares of the firm would be more willingly to base their decisions on previous prices than on earnings forecasts of the analysts. This is, the future market price of the firm would be dominated by the expectations of the positive feedback traders and the impact of the fundamental investors would be limited. This motivates variance-averse managers to intervene against the positive feedback traders by providing stronger guidance to the analysts that in turn influence the expectations of the fundamental traders.

The managerial guidance has a significant impact on the precision and efficiency of analysts' forecasts. Our first result in section 4 states that the stronger the provided guidance the smaller is the analysts' forecast error, given that the current price grows in the opposite direction as the earnings drift, ceteris paribus. For example, if the current price decreases (increases) although the firm's earnings tend to increase (decrease), the manager's guidance increases the precision of the analysts' forecasts, see equation (12). We can use this result in the context of our estimations to derive a proposition on the relative impact of guidance on the forecast errors of analysts following value and growth stocks. If we assume that the earnings of value and growth stocks have both either a positive or a negative drift, we propose that the forecast errors of the analysts following growth firms should be lower than the forecast errors of the analysts following value firms since according to our estimates, growth managers guide stronger than value managers. Doukas, Kim and Penzalis (2002) provide empirical evidence supporting our proposition.

The estimated differences in the guiding policies of value and growth managers have additional implications for the efficiency of analysts' forecasts as stated in our second result in section 4. In a bull (bear) market when earnings drift and current price changes are positive (negative), stronger guidance means also a higher degree of autocorrelation of subsequent forecast errors, see equation (16). Hence, we can expect that the inefficiency of forecasts observed in the empirical literature would be more pronounced for analysts following growth firms than for analysts estimating the earnings of value firms. Testing this proposition is a subject of further research.

9 Conclusion

In this paper we estimate the guiding policy of different managers as the solution of an optimal control problem, in which managers minimize the variance of their firms' price changes. We use our model to derive conclusions on the properties of analysts' forecasts errors. In particular, we show that optimal guidance may explain why analysts' forecast errors are correlated with previous forecast errors or with past observations of the firm's performance as observed by other empirical studies. A common explanation for the observed inefficiency is that analysts underreact to new information. In our model, the inefficiency occurs as a response to guidance provided by managers minimizing the uncertainty in the firm's market prices. According to our model, the stronger the guidance provided by the manager, the stronger is the autocorrelation of the analysts' forecast errors.

The manager's guiding policy and its implications for the analysts' forecast errors are analyzed in a linear dynamic system with control. We assume that the price of firm's shares is basically determined by positive feedback traders increasing the variance of firm's price changes and fundamental investors following the forecasts of the analysts. To minimize the variance of firm's price changes, the firm's manager guides the earnings expectations of the analysts following the firm. The parameters of the manager's objective function, the state equation governing the price changes and the feedback rule are recovered simultaneously by using the GME estimating procedure. The results suggest that the managers of growth firms provide stronger guidance to the analysts than the managers of value firms since the market price of growth firms is more likely to be determined by positive feedback traders than by fundamental investors. Using this result in the context of our model, we propose that contrary to the error-in-expectations hypothesis analysts following growth stocks should have more precise forecasts than analysts following value stocks. However, we expect that due to the differences in the optimal guiding policies of value and growth firms, the forecast errors of the analysts following growth firms will exhibit stronger autocorrelation than the forecast errors of the analysts following value firms. Since the analysts operate in an economy with managers aiming to reduce the volatility in the their firm's price deviations, we may conclude that the observed autocorrelation is desirable and thus rational.

Appendix

To calibrate the model, we first need to reformulate the unknown parameters summarized in the vector β and noise terms summarized in the vector e so that they have the properties of probabilities. In particular, we treat each of the unknowns as a random variable with a compact support and $2 \leq M \leq \infty$ respectively $2 \leq J \leq \infty$ possible outcomes. Let the vector $z = z_1, ..., z_M$ be a set of M points spanning the possible unknown value of the vector of parameters β and the vector $v = v_1, ..., v_J$ be a set of J points spanning the possible values of the vector of noise terms ε. Then, each of the k parameters can be written as

$$\beta^k = \sum_{m=1}^{M} p_m^k z_m^k \tag{17}$$

and each of the n noise terms can be written as

$$e^n = \sum_{j=1}^{J} w_j^n v_j^n \tag{18}$$

with $\sum_{m=1}^{M} p_k^m = 1$ and $\sum_{j=1}^{J} w_n^j = 1$. The estimation problem is to recover the probability distributions for the unknown parameters and error terms that reconcile the available prior information with the observed sample information.

Using the reparameterized unknowns and the steady–state conditions of the linear-quadratic control problem we propose a GME solution to the problem that selects the probabilities p^k with $k = a, b, c, g, h$ where h is a Lagrange multiplier and w^n with $n = \varepsilon_1, \varepsilon_2$ to maximize

$$H(p^k, w^n) = -\sum_k \sum_M p_m^k \ln(p_m^k) - \sum_n \sum_J w_j^n \ln(w_j^n) \tag{19}$$

subject to

$$y_t = \sum_{m=1}^{M} p_m^a z_m^a y_{t-1} + G_t + \sum_{j=1}^{J} w_j^{\varepsilon_1} v_j^{\varepsilon_1} \tag{20}$$

$$G_t = \sum_{m=1}^{M} p_m^g z_m^g y_{t-1} + \sum_{j=1}^{J} w_j^{\varepsilon_2} v_j^{\varepsilon_2} \tag{21}$$

where $y_t = p_t - p_{t-1}$,

$$\sum_{m=1}^{M} p_m^g z_m^g = -\sum_{m=1}^{M} p_m^a z_m^a / \sum_{m=1}^{M} p_m^c z_m^c \tag{22}$$

$$\sum_{m=1}^{M} p_m^b z_m^b = -\sum_{m=1}^{M} p_m^h z_m^h + \delta(\sum_{m=1}^{M} p_m^a z_m^a + \sum_{m=1}^{M} p_m^c z_m^c \sum_{m=1}^{M} p_m^g z_m^g)^2 \sum_{m=1}^{M} p_m^h z_m^h \tag{23}$$

$$\sum_{m=1}^{M} p_k^m = 1 \text{ where } k = a, b, c, g, h \tag{24}$$

$$\sum_{j=1}^{J} w_n^J = 1 \text{ where } n = \varepsilon_1, \varepsilon_2 \tag{25}$$

Here, the objective function is the Shannon entropy (1948) of the distribution of probabilities. Equations (20), (21) together with the reparameterized steady–state conditions of the control problem (22) and (23) represent consistency relations. Equations (24) and (25) are additivity or normalization constraints.

References

[1] Ali, A., A. Klein and J. Rosenfeld, 1992, Analysts' Use of Information About Permanent and Transitory Earnings Components in Forecasting Annual EPS. The Accounting Review 67 (1), 183–198.

[2] Abarbanell, J., 1991, Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes. Journal of Accounting and Economics 14 (2), 147–165.

[3] Abarbanell, J. and V. Bernhard, 1992, Test of Analysts Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behaviour. The Journal of Finance 47, 1181–1207.

[4] Cotter, J., I. Tuna and P. Wysocki, 2006, Expectations Management and Beatable Targets: How Do Analysts React to Explicit Earnings Guidance? Contemporary Accounting Research 23 (3), 593-624.

[5] Baginski, S. and J. Hassell, 1990, The market interpretation of management earnings forecasts as a predictor of subsequent analyst forecast revisions. The Accounting Review 65 (1), 175–190.

[6] Brock, W. and C. Hommes, 1998, Heterogeneous beliefs and routes to chaos in a simple asset pricing model, Jornal of Economic Dynamics and Control 22, 1235–1274.

[7] Bowen, M., A. Davis and D. Matsumoto, 2002, Do Conference Calls Affect Analysts' Forecasts? The Accounting Review 77 (2), 285–316.

[8] Chow, G., 1975, Analysis and Control of Dynamic Economic Systems (Wiley, New York).

[9] DeLong, J., A. Shleifer, L. Summers and R. Waldmann, 1990, Noise Trader Risk in Financial Markets. Journal of Political Economy 98 (4), 703–738.

[10] Doukas, J., Ch. Kim and Ch. Pantzalis, 2002, A Test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts. Journal of Finance 57 (5), 2143–2165.

[11] Easterwood, J. and S. Nutt, 1999, Inefficiency in Analysts Earnings Forecasts: Systematic Misreaction or Systematic Optimism? Journal of Finance 54, 1777–1797.

[12] Elliott, J., D. Philbrick and C. Wiedman, 1995, Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions. Contemporary Accounting Research 11, 919-938.

[13] Golan, A., G. Judge and D. Miller, 1996, Maximum Entropy Economics: Robust Estimation with Limited Data. John Wiley&Sons.

[14] Hassell, J., R. Jennings and D. Lasser, 1988, Management earnings forecasts: their usefulness as a source of firm-specific information to security analysts. The Journal of Financial Research 11, 303–319.

[15] Hsieh, P., T. Koller and S. Rajan, 2006, The Misguided Practice of Earnings Guidance. The McKinsey Quarterly, March 2006.

[16] Heflin, F., K. Subramanyam and Y. Zhang, 2003, Regulation FD and the Financial Information Environment: Early Evidence. The Accounting Review 78 (1), 1–37.

[17] Lys, T. and S. Sohn, 1990, The Association between Revisions of Financial Analysts Earnings Forecasts and Security-Price Changes, Journal of Accounting and Economics 13, 341–363.

[18] Maines, L. and J. Hand, 1996, Individuals Perceptions and Misperceptions of Time Series Properties of Quarterly Earnings. Accounting Review 71 (3), 317-336.

[19] Mendenhall, R., 1991, Evidence on the Possible Underweighting of Earnings- Related Information. Journal of Accounting Research. Spring, 170–179.

[20] National Investor Relation Institute (NIRI), 2006, Corporate Disclosure Practice Survey, March 2006.

[21] Ramnath, S., S. Rock and Ph. Shane, 2006, A Review of Research Related to Financial Analysts' Forecasts and Stock Recommendations. Available at SSRN: http://ssrn.com/abstract=848248.

[22] Raedy, J., P. Shane and Y. Yang, 2006, Horizon-Dependent Underreaction in Financial Analysts' Earnings Forecasts. Contemporary Accounting Research 23 (1), 219–322.

[23] Shannon, C.E., 1948, A Mathematical Theory of Communication. Bell System Technical Journal 27, 379–423.

[24] Sentana, E. and S. Wadhwani, 1992, Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data. Economic Journal 102, 415–425.

[25] Trueman, B. and S. Titman, 1988, An Explanation for Accounting Income Smoothing. Journal of Accounting Research 26-Suppl, 127–139.

[26] Williams, P., 1996, The relation between a prior earnings forecast by management and analyst response to a current management forecast. The Accounting Review 71 (1), 103–115.