Style investing

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Chapter 4

The drivers behind uncertainty and style migration

4.1 Introduction

US and international empirical evidence shows that on average value stocks outperform growth stocks (Fama and French, 1992, 1996, 1998, and Lakonishok, Shleifer and Vishny, 1994). Although it is becoming increasingly accepted that value stocks generate higher returns than growth stocks, the interpretation as to why they have done so is more controversial. Risk-based and error-in-expectation explanations have emerged as possible sources for the return differentials found (e.g. Fama and French, 1992, Doukas *et al.*, 2003, La Porta, 1996, and La Porta *et al.*, 1997).

Various theoretical models have been constructed to explain the empirical findings, in order to understand the mechanisms of stock pricing. Hong and Stein (1999) built a unified behavioral model, where the interaction between heterogeneous investors plays a central role. The investors can be divided into two groups, newswatchers and momentum traders. Newswatchers make forecasts based on private information and momentum traders make forecasts conditioned on past information on stock prices. The general assumption they make is that private information diffuses gradually across the newswatchers population. This is the so-called information diffusion hypothesis. When only newswatchers are active, prices adjust slowly to new information. This explains the underreaction phenomenon. Then momentum traders come into action and exploit the pricing underreaction with a simple arbitrage strategy. However, by making it profitable for momentum traders to enter the market, excessive momentum is created in prices that inevitably leads to overreaction. Hong, Lim and Stein (2000) test the information diffusion hypothesis empirically. They use two proxies for the speed of diffusion of information, size and analyst coverage, to classify stocks from high to low information diffusion. They find that stocks with slower information diffusion have more pronounced momentum, as the evidence shows that profitability of momentum strategies declines with firm size and analyst coverage.

Barberis, Shleifer and Vishny (1998) have a different approach than Hong and Stein (1999). They emphasize the psychology of the representative investor to explain the under- and overreaction mechanisms. There is a representative investor who suffers from a conservatism bias which means that he does not update his beliefs sufficiently when new public information arrives. This gives rise to underreaction in the short run. At the same time, when the investor repeatedly receives similar information, he believes that earnings follow a trend. This gives rise to overreaction. Keastner (2005) finds empirical evidence in favor of this model. He studies current and past earnings surprises and the subsequent market reaction for US companies and finds that earning surprises have predictive power for stock returns. Stocks that have experienced a string of earnings surprises show a reversal in their stock prices when a subsequent opposite earnings surprise occurs, even when the forecast error is zero. The longer the pattern of similar earnings surprises the higher the subsequent reversal of the market. Another study that examines the string of forecast errors is by Huberts and Fuller (1995). They use the average of the absolute values of three most recent annual forecast errors to show that past forecast errors persist and that historical forecast errors have predictive power for future returns.

Doukas, Kim and Pantzalis (2003) use the dispersion in analysts' earnings forecasts as a measure of uncertainty to test whether value stocks are riskier than growth stocks. They find that the value premium reflects a compensation for uncertainty, because investors are more uncertain about future earnings of value stocks in comparison with earnings forecasts of growth stocks. Combining the information diffusion hypothesis and uncertainty, one would expect that the higher the speed of information diffusion, the lower uncertainty will be. Measures that reflect the speed of information diffusion are size and analyst coverage. Doukas, Kim and Pantzalis (2004) show that analyst coverage and book-to-market ratio are negatively related to each other. Value stocks have lower analyst coverage than growth stocks. In addition, it is reasonable to expect that the higher the speed of information diffusion across the investing public, the more accuracy of estimating future earnings will increase. Lim (2001) and Doukas, and Kim and Pantzalis (2004) show that forecast errors, which they find relatively high for value stocks, decrease with analyst coverage. In addition, when analysts' earnings forecasts have been wrong in the period before, this, in itself, may lead to higher uncertainty among analysts. Ackert (1997) supports the positive relation between optimism and uncertainty. He finds that when firms are surrounded by more uncertainty, analysts are more likely to act on their incentives to release optimistic forecasts.

While these studies test the information diffusion hypothesis, the error-in-expectation hypothesis (based on representativeness) or the uncertainty hypothesis separately, they do not consider a combination of the three. The first aim of this chapter is to test whether uncertainty is related to past information and to the speed of information diffusion. Firstly, we look for evidence that uncertainty is increasing when less information about a stock is revealed. Secondly, we examine if uncertainty is increasing because investors extrapolate past information into the future. This information can be in the form of stock returns but also in the form of forecast errors. The possible influence of analysts' coverage on firm's uncertainty stems from its ability to make stock prices more informative in the sense that they more precisely reflect their fundamental values. To the extent that analyst coverage does increase the speed of information to the investment public, it is also expected that it has a better forecasting quality. If less information is available about a company, one expects that analysts are also making larger mistakes when they forecast future earnings. However, when analysts' earnings forecasts have been wrong a couple of times, this, in itself, may lead to higher uncertainty among analysts. Therefore, if the analyst coverage for a firm is low and the string of forecasts has been too optimistic, analysts may become more uncertain. In addition, when stocks have a bad past performance and analysts have been wrong in their forecasts before, uncertainty may increase.

Our results show that uncertainty is related to the extrapolation of past information and to a low diffusion of information. We follow Doukas, Kim and Pantzalis (2003) by using the dispersion in analysts' (consensus) earnings forecasts as a proxy for investor uncertainty. This is analogous to chapter 3 (e.g. Chapter 3, section 3.1), where we use analysts' (consensus) earnings forecasts as a proxy for investors expectations of future earnings. Firstly, we find that firms with higher analyst forecast errors have higher dispersion in earnings forecasts. Furthermore, we find that dispersion in analysts' earnings forecasts is increasing when analyst earnings forecast errors are large and negative two years in a row. This implies that analysts become more uncertain about future earnings when they have been too optimistic in the past. Second, we find that firms with low analyst coverage have higher dispersion in analysts' earnings forecasts, suggesting that analysts become more uncertain when less firm-specific information is available. In addition, we find that when we divide stocks on past performance and size-adjusted analyst coverage, dispersion is higher for stocks with low analyst coverage and low past performance. This suggests that investors are more uncertain about stocks with low past performance and low analyst coverage. In addition, holding one year-ahead forecast errors fixed, loser stocks have higher dispersion than winner stocks. There is a strong asymmetry, since the effect of dispersion in analysts' earnings forecasts is more pronounced for stocks for which analysts were too optimistic than for stocks for which analysts were too pessimistic. In other words, uncertainty increases more when analysts are too optimistic. This makes intuitively sense in the context where people prefer good news over bad news; analysts have to deal with their disappointment, because earnings are lower than expected. Overall, the results suggest that the less information revealed about a company, the more likely it is that too optimistic expectations and bad past performance lead to higher uncertainty.

The second aim of this chapter is to test whether it is more likely for a stock to migrate from style when investors are more uncertain about future earnings. Again following the reasoning of Doukas, Kim and Pantzalis (2003) that analysts' forecast dispersion reflects uncertainty, switching style stocks should be associated with higher dispersion in analysts' earnings forecasts than fixed-style stocks. Switching of style classification implies that investors completely revise their expectations about future earnings, whereas the expectations for fixed style stocks remain largely unchanged. The drastic change in expectations is the result of investors realizing that their expectations are too optimistic or too pessimistic. They are surprised by the results presented and change their expectations drastically in the opposite direction. In particular, surprises tend to occur for those stocks of which analysts are less informed. As is shown in chapter 3, switching-value and switching-growth stocks are the result of changes in investors' expectations regarding the future profitability of stocks. Because of the uncertainty of investors about the prospects of the value of switching-style stocks, dispersion in analysts' earnings forecasts for switching-style stocks will be higher. We apply a probit-analysis and find that dispersion in analysts' earnings forecasts is positively related to style switches. This means that the chance of a style switch increases when analysts become more uncertain.

The remainder of the chapter is organized as follows. Section 4.2 gives an overview of the data. Section 4.3 contains our main results on dispersion in analysts' earnings forecasts. In section 4.4 some robustness tests and the results of the probit-model are presented. The final section presents some concluding comments.

4.2 Data

The sample covered in this study is from January 1976 to December 2003. The universe of stocks is the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. Only common stocks are included in the sample, which means that REIT's, ADR's, closed end funds, foreign stocks and units of beneficial interest are excluded from the sample. We use COMPUSTAT to obtain annual data on the book value of equity, Tobin's q and earnings. Tobin's q is used to capture investment opportunities[10]. The book value of equity is computed as book value of equity plus deferred tax and investment tax credits minus the book value of preferred stock. Depending on the availability, we use for the book value of preferred equity the redemption value, liquidity value or par value in the order mentioned here. Earnings are defined as earnings before extraordinary items.

Monthly data on returns, market capitalization and SIC codes are obtained from CRSP. Data on analysts' earnings forecasts, expected earnings growth rates, prices and earnings are taken from the Institutional Brokers Estimates System (I/B/E/S). We select forecasts with a horizon of one year. Forecasts are defined as the median consensus forecasts reported by I/B/E/S. Forecast errors are calculated at year *t*-1, by matching the forecast F_{t-1} with the relevant realized earnings number published in I/B/E/S. We follow Doukas, Kim and Pantzalis (2003)[11] to compute the dispersion in analysts' earnings forecasts as the standard deviation of the forecasts divided by the beginning of the fiscal year stock price (year *t*). We delete firm-year observations when the stock price at the beginning of the fiscal year is below the $3. By doing this we avoid extreme ratios due to price-effects. To compute analyst coverage we select the number of analyst forecasts issued eight months prior to fiscal year-end for all stocks covered by security analysts. Following Hong, Lim and Stein (2000), we control for the influence of size on analyst coverage by regressing coverage on firm size and using the residual analyst coverage. The dependent variable is log(1+*Analyst coverage*) and is the log of the number of analysts that give a forecast in April of year *t*. The independent variable is the log(*Size*) and is

[10] *Tobin's q* is measured as: [market value of common equity+preferred stock liquidating value+bookvalue of long-term debt+(short term debt-short term assets)]/net assets.

[11] Doukas *et al.* (2003) examine alternative deflaters to construct the dispersion of analysts' forecasts, e.g. sales, book value of total assets and absolute median forecasts. They show that the results are insensitive to the choice of the scaling.

the log of the firm's market value in April of year *t*. Furthermore, we add a NASDAQ dummy (*NASD*) into the equation.[12]

Similar to our procedure in chapter 3, we divide stocks into three groups based on their book-to-market equity ratio at the end of June of each year. Growth and value stocks are determined by the breakpoints for the bottom and top 30% of the values of the book-to-market equity for NYSE stocks (we use the breakpoints available at the website of K. French[13]). The book-to-market equity ratio used to form portfolios in June of year *t* is the common book value of equity for the fiscal year ending in calendar year *t*-1, divided by its market capitalization of June *t*. Stocks with negative book values of equity are excluded. Within each portfolio, we equally weigh all the stocks and compute the average of each variable over each period. To ensure that the accounting variables are known before the returns, we match the accounting data for all fiscal year ends in calendar year *t*-1 with the style switch from July of year *t* to June of *t*+1. For each style-switching year we calculate the equally-weighted average of each variable prior to the year of the style switch. For example, the average annual return in 1979 is calculated from July 1978 to the following June in 1979.

Table 4.1 provides descriptive statistics over the period 1976 to 2003. Stocks must have at least data on the standard deviation of analysts' earnings forecasts in April of year *t* and data on book-to-market ratio, two years of monthly returns, earnings and Tobin's q at the fiscal year-end *t*-1. A total of 29,148 firm-year observations meet these requirements. The first thing that emerges from table 4.1 is the skewness in analysts' dispersion. The average dispersion is 1.2% and the median dispersion is 0.5%. Consistent with prior studies, mean and median 1-year forecast errors are negative. The average (median) forecast errors for the 26-year time period is

[12] The regression is as follows: Number of log(*Analysts*+1) = log(S*ize*)+*NASD*+residuals
[13]. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

-1.80 (-0.30). The average (median) number of analysts that cover a firm is 10 (7) and the average (median) size-adjusted analyst coverage is -0.017 (0.100).

Table 4.1: summary statistics for the period 1976 to 2003

This table reports median values of dispersion in analysts' earnings forecasts and annual returns. Portfolios are formed on the dispersion in analysts' earnings forecasts. The dispersion of the analysts' earnings forecasts ($Disp_t$) is defined as the standard deviation of the one fiscal year ahead earnings as of eight months before the fiscal year end divided by the price at the beginning of fiscal year t. The 1-year forecast errors ($FE1_{t-1}$) are defined as the difference in actual value and the 1-year forecast (8 months before the fiscal year end) divided by the price. Analyst coverage is the residual analyst coverage, where the residuals come from a regression of coverage on firm size. $Earnings_{t-1}$ is earnings before extraordinary items at fiscal year end. *Tobin's* q_{t-1} is measured as: [market value of common equity+preferred stock liquidating value+bookvalue of long-term debt+(short term debt-short term assets)]/net assets. Annual returns are calculated over the period April of year t-1 to March of year t ($R_{12,t-1}$) and over the period July of year t to June of year t+1 ($R_{12,t}$). BM_{t-1} is the book-to-market ratio and $Size_{t-1}$ is the share price time shares outstanding at fiscal year end.

	Mean	Median	Standard deviation	Min	Max
$Disp_t$	0.012	0.005	0.104	0.000	16.148
$FE1_{t-1}$	-0.018	-0.003	0.217	-28.648	3.729
Analyst coverage$_t$	9.869	7.000	7.999	3.000	48.000
Analyst coverage$_t^a$	-0.017	0.100	0.776	-2.472	1.587
$Earnings_{t-1}$ *(millions of $)*	122.904	26.428	476.457	-7987	15990
Tobin's q_{t-1}	1.195	0.806	1.674	-0.455	77.910
$Return_{t-1}$	0.074	0.107	0.460	-5.381	3.121
$Return_t$	0.036	0.090	0.480	-4.744	2.855
BM_{t-1}	0.754	0.645	1.034	0.002	105.321
$Size_t$ *(millions of $)*	2382	469.6	9585	2.105	301240

[a]Size-adjusted

4.3 Step-wise empirical analysis of analysts' forecast dispersion and style effects

In section 4.3.1, we seek evidence for the information diffusion hypothesis and the error-in-expectation hypothesis. As a proxy of uncertainty to investors we use dispersion in analysts' earnings forecasts.

The dispersion in analysts' earnings forecasts (*$Disp_t$*) is measured as the standard deviation of the one year-ahead analysts' earnings forecasts made eight months before the fiscal year end, standardized by the stock price at the beginning of the fiscal year. To test the information diffusion hypothesis, we analyze the effects of size-adjusted analyst coverage on uncertainty. Consistent with Hong, Lim and Stein (2000), it is expected that analysts' coverage has a negative influence on a firm's uncertainty, because if information diffuses more slowly and stock prices do not reflect their fundamental values, investors will be more uncertain. To test the error-in-expectation hypothesis we analyze the string of forecast errors and past performance on uncertainty. In line with Keastner (2005) who shows that investors react more heavily on a series of forecast errors, we expect that when analysts have been wrong in their earnings forecasts for a stock a couple of times, this, in itself, may lead to higher uncertainty among analysts. Furthermore, when stocks had a bad past performance and analysts have been wrong in their forecasts before, we expect uncertainty to increase.

The analysis is going to proceed as follows. We divide stocks into quintiles based on past performance, size-adjusted analyst coverage and one-year forecast errors. Next, we measure dispersion in analysts' earnings forecasts. In addition, we apply a comprehensive multivariate analysis to test whether uncertainty is increasing with low size-adjusted analyst coverage, too optimistic forecast errors and poor past performance. In section 4.3.2, we analyze whether uncertainty is increasing when analysts have been wrong in their forecasts for two consecutive years. In section 4.3.3, we analyze whether the chance of a style switch increases when analysts become more uncertain. We test whether excess size-adjusted analyst coverage, string of one-year forecast errors, and past performance have predictive power with respect to style migration. We test whether dispersion in analysts' earnings forecasts is higher for switching-style stocks than fixed-style stocks. Then we apply a multivariate probit-analysis to test whether size-adjusted analyst coverage, the string of one-year forecast errors and past performance have significant predictive power to style migration.

4.3.1 Dispersion of analysts' earnings forecasts, forecast errors, and value versus growth styles

In this section, we examine the impact of size-adjusted analyst coverage and the string of forecast errors on uncertainty. In line with the information-diffusion and error-in-expectation hypothesis, we expect that size-adjusted analyst coverage and the string of forecast errors in the past are negatively associated with the dispersion in analysts' earnings forecasts. If analyst coverage is limited and firm-specific information moves more slowly across the investing public (Hong and Stein, 1999), firms with low analyst coverage should be more vulnerable to higher forecast errors and, therefore, to higher uncertainty. In addition, firms with low analyst coverage and a string of too optimistic forecasts should display higher uncertainty relative to the firms with a string of too pessimistic forecasts.

As a proxy for uncertainty faced by investors we use dispersion in analysts' earnings forecasts. The dispersion in analysts' earnings forecasts ($Disp_t$) is measured as the standard deviation of the one year-ahead analysts' earnings forecasts made eight months before the fiscal year end, standardized by the stock price at the beginning of the fiscal year. In table 4.2, we examine the impact of size-adjusted analyst coverage and 1-year forecast errors, FE_{t-1}, on the dispersion in analysts' earnings forecasts. We sort stocks on dispersion in analysts' earnings forecasts into quintile portfolios: P1 through P5. Portfolio P1 contains the stocks with the twenty percent lowest dispersion and portfolio P5 contains the stocks with the twenty percent highest dispersion. Consistent with the hypothesis that stocks with low analyst coverage are more uncertain than stocks with high analyst coverage, the evidence in table 4.2 shows that the 1-year ahead forecast errors are a negative function of analysts' dispersion. Companies with high analysts' dispersion also have larger negative 1-year forecast errors. The difference between the portfolio with the highest and lowest dispersion in analysts' earnings forecasts is 2.28% (rounded to 2.3% in the table). The 1-year forecast errors for the lowest dispersion portfolio is 0.001 and the 1-year forecast errors for the highest dispersion portfolio is -0.032, a difference of 0.032. This implies that analyst uncertainty is increasing with the magnitude of the 1-year forecast errors in the last period. When the 1-year forecast error was high, investors will be more uncertain with respect to future earnings. These results are confirmed by Ackert (1997). In addition, the value of |P5–P3|/|P3–P1| ratio[14] reported in the last row of table 4.2 is above one for the 1-year forecast errors and for analyst coverage, suggesting that the negative relation between dispersion and forecast errors versus analyst coverage is stronger when dispersion is high than when it is low.

Another interesting pattern that emerges form table 4.2 is that firms with higher dispersion in analysts' earnings forecasts more frequently have negative earnings and lower investment opportunities, as evidenced by the lower Tobin's q. The median difference in Tobin's q between firms with low and high analysts' dispersion is 0.677 and statistically significant. The inclusion of Tobin's q is dictated by other studies that have shown that analyst coverage and Tobin's q are related (see, e.g. Doukas, Pantzalis and Kim, 2000, Doukas, Kim and Pantzalis, 2004).

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[14] This ratio shows that the bulk of the uncertainty effect seems to come from the uncertainty stocks, as opposed to low uncertainty stocks. Most of the differences come from the difference between P5-P3.

The mean difference (P1-P5) in the percentage of firms with positive earnings is 34.5% and statistically significant at the one-percent level (t-statistic=8.608). Finally, we examine whether there is a direct relation between dispersion in analysts' earnings forecasts and future returns. The two columns at the right-hand side of table 4.2 list the post formation and prior formation average annual returns. We find that the dispersion in analysts' earnings forecasts is a decreasing function of post and prior formation returns. The post formation average annual return is 8.0% for the low dispersion portfolio and the average annual ex post return for high dispersion portfolio is -1.6%, for a difference of 9.6%. Our results confirm the results of Ackert (1997) and Diether *et al.* (2002), who find abnormal returns for portfolios with lower uncertainty.

To examine whether the previous findings are driven by book-to-market effects, we perform additional tests. We divide stocks according to their book-to-market ratios into value or growth (using the methodology explained in section 4.2) and subdivide each of these two portfolios into quintile portfolios based on dispersion in analysts' earnings forecasts. Table 4.3 presents the results. The differences in uncertainty between the low and high uncertainty portfolio do not seem to deviate from each other for value and growth stocks. Uncertainty appears to deviate by almost 2.20% for value stocks between stocks with low uncertainty and high uncertainty. For growth stocks the magnitude of the difference in dispersion is 2.48%. Although the distribution is equal, the number of stocks with high uncertainty is lower for growth stocks (1328) than for value stocks (2434).
The opposite is shown for the low dispersion portfolio where the number of growth stocks is 4132 and the number of value stocks is 537. This implies that on average the future earnings of value stocks are more uncertain than for growth stocks. We find the same result when the stocks are divided on analyst dispersion scaled by its absolute 1-year forecast.

Table 4.2: Portfolios formed on dispersion in analysts' earnings forecasts

This table reports median values of dispersion in analysts' earnings forecasts and annual returns. Portfolios P1 through P5 are quintile portfolios, formed on the dispersion in analysts' earnings forecasts ($Disp_t$). The dispersion in the analysts' earnings forecasts is defined as the standard deviation of the one fiscal year ahead earnings as of eight months before the fiscal year end divided by the price. The 1-year forecast errors ($FE1_{t-1}$) are defined as the difference in actual value and the 1-year forecast (8 months before the fiscal year end) divided by the price. Analyst coverage is the residual analyst coverage, where the residuals come from a regression of coverage on firm size. $Earn_t^+$ is the fraction of stocks with positive earnings in year *t*-1. *Tobin's q* is measured as: [market value of common equity+preferred stock liquidating value+bookvalue of long-term debt+(short term debt-short term assets)]/net assets. Annual returns are calculated over the period April of year *t*-1 to March of year *t* ($R_{12,t-1}$) and over the period July of year *t* to June of year *t*+1 ($R_{12,t}$). The significance levels are presented with stars, where ** is 1% and * is 5% significance level.

Portfolios	Number of observations (n)	$Disp_t$	$FE1_{t-1}$	*Analyst coverage*	$Earn_t^+$	*Tobin's q*	$R_{12,t-1}$	$R_{12,t}$
P1 (Low)	5650	0.001	0.001	0.055	0.959	1.288	0.201	0.080
P2	5992	0.003	-0.000	0.072	0.953	0.888	0.158	0.054
P3	5985	0.005	-0.003	0.041	0.918	0.789	0.105	0.066
P4	5931	0.009	-0.011	0.003	0.834	0.699	0.032	0.033
P5 (High)	5590	0.022	-0.032	-0.014	0.614	0.611	-0.123	-0.016
Difference P5–P1		0.023	-0.032	-0.069	-0.345	-0.677	-0.324	-0.096
Kruskal-Wallis			2275.961**	2.257	8.608**[a]	2108.881**	4.932**[a]	1.472[a]
[P5–P3]/ [P3–P1]			7.308	3.915	7.415	0.357	2.375	5.857

[a] t-statistic over 26 years

The average dispersion for value stocks is 0.0093 and the average dispersion for growth stocks is 0.0071.

Table 4.3 shows similar results with respect to $Earn_t^+$ and *Tobin's q*. Firms with higher dispersion in analyst earnings forecasts more frequently have negative earnings and lower investment opportunities. Furthermore, there is a negative relation between dispersion in analysts' earnings forecasts and future returns. The difference in future returns is -13.3% for value stocks and is -19.5% for growth stocks.

To differentiate between the information diffusion hypothesis and the error-in-expectation hypothesis, we examine dispersion in analysts' earnings forecasts ($Disp_t$) and average annual returns of firms sorted on past twelve month returns and size-adjusted analyst coverage. We sort stocks based on past performance and size-adjusted analyst coverage into low (bottom 30%), medium (intermediate 40%) and high (top 30%) portfolios. The loser portfolio contains the 30% stocks that are the worst performing over the period April of year *t-1* to March of year *t*. The winner portfolio contains the 30% stocks with the best performance over the past twelve months. The results in table 4.4 panel A show that for a constant level of analyst coverage, low (high) past performance is associated with high (low) analysts' dispersion and lower (higher) future returns. The $Disp_t$ is 1.11% for the loser portfolio with low analyst coverage and $Disp_t$ is 0.75% for the loser portfolio with high analyst coverage. The $Disp_t$ is 0.35% for the winner portfolio with low analyst coverage and $Disp_t$ is 0.31% for the winner portfolio with high analyst coverage.

Similar results are obtained when we divide stocks on 1-year forecast errors ($FE1_{t-1}$) and ex ante twelve month returns (see panel B).

Table 4.3: Value and growth stocks classified into sub-portfolios based on dispersion in analysts' earnings forecasts

This table reports median values of dispersion in analysts' earnings forecasts and annual returns. Portfolios are formed on the dispersion in analysts' earnings forecasts. The dispersion of the analysts' earnings forecasts ($Disp_t$) is defined as the standard deviation of the one fiscal year ahead earnings as of eight months before the fiscal year end divided by the price. The 1-year forecast errors ($FE1_{t-1}$) are defined as the difference in 1-year forecast (8 months before the fiscal year end) and the actual value divided by the price. Analyst coverage is the residual analyst coverage, where the residuals come from a regression of coverage on firm size. $Earn^+$ is the fraction of stocks with positive earnings in year t-1. *Tobin's q* is measured as: [market value of common equity+preferred stock liquidating value+bookvalue of long-term debt+(short term debt-short term assets)]/net assets. Annual returns are calculated over the period April of year t-1 to March of year t ($R_{12,t-1}$) and over the period July of year t to June of year t+1 ($R_{12,t}$). The significance levels are presented with stars, where ** is 1% and * is 5% significance level.

Portfolios	Number of observations (n)	$Disp_t$	$FE1_{t-1}$	*Analyst coverage*	$Earn_t^+$	*Tobin's q*	$R_{12,t-1}$	$R_{12,t}$
	Value portfolios							
P1 (low)	537	0.001	-0.002	-0.068	0.912	0.380	0.074	0.174
P2	887	0.002	-0.000	0.086	0.969	0.668	0.105	0.160
P3	1396	0.004	-0.004	0.072	0.937	0.484	0.070	0.144
P4	1872	0.009	-0.018	0.016	0.873	0.399	-0.005	0.118
P5 (high)	2434	0.026	-0.045	-0.018	0.639	0.365	-0.181	0.042
Difference P5–P1		0.025	-0.043	0.050	-0.273	-0.015	-0.256	-0.133
Kruskal-Wallis			235.905**	226.338**	7.017**[a]	8.881**	3.473**[a]	2.414[a]
	Growth portfolios							
P1 (low)	4132	0.000	0.001	0.085	0.956	1.995	0.240	0.080
P2	2899	0.002	0.000	0.081	0.941	1.617	0.205	0.041
P3	2052	0.004	-0.002	0.029	0.878	1.500	0.151	0.027
P4	2899	0.008	-0.006	0.000	0.750	1.541	0.082	-0.038
P5 (high)	1328	0.022	-0.023	-0.031	0.537	1.485	-0.039	-0.115
Difference P5–P1		0.022	-0.024	-0.116	-0.420	0.510	-0.279	-0.195
Kruskal-Wallis			474.691**	507.889**	7.566**[a]	194.664**	3.763**[a]	2.793**[a]

[a] t-statistic over 26 years

Holding the level of 1-year forecast errors constant, stocks with low (high) past performance have on average higher (lower) analysts' dispersion and lower (higher) future returns. For example, the difference in $Disp_t$ between the loser portfolio with low $FE1_{t-1}$ and the loser portfolio with medium $FE1_{t-1}$ is 1.13%. The winner portfolio shows a difference in $Disp_t$ between the low and medium $FE1_{t-1}$ of 0.68%. For the portfolios with low $FE1_{t-1}$, the difference between the loser and winner portfolio is 0.74%.

Overall, the results in tables 4.3 and 4.4 demonstrate that future returns decline with increasing uncertainty. This is true even after controlling for analyst coverage and 1-year forecast errors, respectively, indicating that firms with higher uncertainty tend to be firms with low past performance. These results show invariably that dispersion in analysts' earnings forecasts is increasing when analyst coverage is low, forecast errors are high and negative and past returns are low in the year before. The change in uncertainty is consistent with the information diffusion hypothesis and the error-in-expectation hypothesis.

4.3.2 Dispersion of analysts' earnings forecasts and the multiple of forecast errors

The previous results show that dispersion in analysts' earnings forecasts are negatively related to 1-year forecast errors and analyst coverage. The magnitude of the forecast errors may be the result of low analyst coverage (Doukas, Kim and Pantzalis, 2004). The lower the analyst coverage of a stock, the higher the forecast error will be. Another reason for high analysts' dispersion is that analysts become uncertain about a stock, when they have been wrong more than once in succession with their earnings forecasts of that stock. Huberts and Fuller (1995), and Keastner (2005) find that earning surprises have predictive power with respect to stock returns.

Table 4.4: Analysts' dispersion and portfolios formed on 1-year forecast errors, analyst coverage and past performance

This table reports median values of dispersion in analysts' earnings forecasts and annual returns (between brackets). Portfolios are formed on twelve-month lagged raw returns (into 'loser', 'medium' and 'winner'), analyst coverage (P_L, P_M and P_H) and 1-year forecast errors (FE_L, FE_M and FE_H). The 1-year forecast errors are defined as the difference between the actual and forecast of the one-year fiscal earnings as eight months before the fiscal year end scaled by price. The dispersion of the analysts' earnings forecasts is defined as the standard deviation of the one fiscal year earnings as of eight months before the fiscal year end divided by the price. Annual returns are calculated over the period April of year *t*-1 to March of year t and over the period July of year *t* to June of year *t+1*. The significance levels are presented with stars, where ** is 1% and * is 5% significance level.

Panel A: Portfolios formed on past performance and size-adjusted analyst coverage

Portfolios	Low cov. (P_L)	Medium (P_M)	High cov. (P_H)	Difference $P_L – P_H$	Kruskal-Wallis
Loser	0.011 (-0.057)	0.0102 (-0.045)	0.008 (-0.026)	0.004 (-0.031)	62.125**
Medium	0.005 (0.069)	0.0046 (0.069)	0.0034 (0.069)	0.001 (0.000)	19.372**
Winner	0.004 (0.057)	0.0034 (0.063)	0.003 (0.068)	0.000 (-0.011)	11.024**
Difference Loser–Winner	0.008 (-0.114**)	0.007 (-0.117)	0.004 (-0.094)		
Kruskal-Wallis	702.633**	1316.544**	622.519**		

[Table 4.4 continued]

Panel B: Portfolios formed on past performance and 1-year forecast errors					
Portfolios	Low $FE_{L,t-1}$	Medium $FE_{M,t-1}$	High $FE_{H,t-1}$	Difference $FE_{L,t-1} - FE_{M,t-1}$	Difference $FE_{H,t-1} - FE_{M,t-1}$
Loser	0.017 (-0.065)	0.005 (-0.032)	0.007 (-0.005)	0.011 (1262.667**)	0.002 (39.460**)
Medium	0.011 (0.053)	0.003 (0.079)	0.004 (0.084)	0.008 (2610.773**)	0.001 (190.254**)
Winner	0.009 (0.053)	0.003 (0.073)	0.003 (0.089)	0.007 (1239.557**)	0.001 (143.496**)
Difference Loser–Winner	0.007 (-0.118**)	0.003 (-0.105)	0.004 (-0.094)		
Kruskal-Wallis	260.572**	600.472**	237.749**		

Keastner (2005) finds that stocks that have experienced a string of earnings surprises show a reversal in their stock prices when a subsequent opposite earnings surprise occurs, even when the subsequent earnings equals the analysts' estimates. In table 4.5 we show that uncertainty and two consecutive forecasts errors with the same sign are related.

The methodology is as follows. Firstly, each stock is assigned according to the 1-year forecast errors into low (bottom 30%), medium (intermediate 40%) and high (top 30%) portfolios. The bottom 30% are stocks with negative forecast errors and is labeled as optimistic, P(opt). The top 30% are stocks with positive 1-year forecast errors and is labeled as pessimistic, P(pess). Subsequently, within each of the three portfolios we assigned each stock to one of the three portfolios according to the next year 1-year forecast-error. For example, P(opt,opt) is the portfolio with two subsequent years of too optimistic forecasts and P(pess,pess) is the portfolio with two subsequent years of too pessimistic forecasts. As can be seen from Panel A of table 4.5, dispersion is a decreasing function of the 1-year forecast errors. The median value of dispersion is 0.015 for the portfolio with two consecutive years of too optimistic forecast errors (portfolio P(opt,opt)) and the median value is 0.007 for the portfolio with a too optimistic in year 1 and a too pessimistic forecast error in year 2, P(opt,pess). The median value of dispersion is 0.012 for the portfolio with the first year too pessimistic and second year too optimistic forecast errors (portfolio P(pess,opt)) and the median value is 0.004 for portfolio P(pess,pess). This indicates that analysts are more uncertain when they have been wrong in their earnings forecasts two years in a row. Another result that comes up is that the more pessimistic analysts are about stocks, the higher the returns will be the year after. For example, the average annual return is 0.04% for P(opt,opt) (in the table rounded to 0.000) and the average annual return for portfolio P(pess,pess) is

10.1%, for a rounded difference of -10.1% which is significant at 5% level (see table 4.5).

Table 4.5: Two consecutive years of forecast errors and uncertainty

Portfolios are formed on two subsequent years (t-2 and t-1) of 1-year forecast errors. First we divide stocks into three portfolios from negative to positive forecast errors: P(opt), P(med) and P(pess). Thereafter we form portfolios based on two subsequent years of 1-year forecast errors. For example, P(opt,opt) is the portfolio with two subsequent years of the lowest forecast errors. P(med,opt) is the portfolio with stocks that belongs in the first year in the portfolio with medium forecast errors and stocks belong in the second year to the portfolio with the lowest forecast errors. $Disp_t$ is the median of dispersion in analysts' earnings forecasts in April of year t. $R_{12,t}$ is the average annual return for July of year t to June of year t+1. Kruskal-Wallis tests are performed to test whether the median differences in $Disp_t$ are significant; ** is 1% significance level, * is 5% significance level. T-tests are performed to test whether mean differences in $Disp_t$ are significant.

	Panel A: all stocks		**Panel B: value stocks**		**Panel C: growth stocks**	
Portfolios	$Disp_t$	$R_{12,t}$	$Disp_t$	$R_{12,t}$	$Disp_t$	$R_{12,t}$
P(opt,opt)	0.015	0.000	0.020	0.004	0.013	-0.002
P(opt,med)	0.007	0.036	0.010	0.092	0.005	-0.049
P(opt,pess)	0.007	0.062	0.009	0.095	0.005	0.057
P(opt,opt)–P(opt,pess)	0.008**	-0.062**	0.011**	-0.091**	0.008**	-0.059**
P(med,opt)	0.010	0.043	0.012	0.022	0.008	0.002
P(med,med)	0.003	0.088	0.004	0.085	0.002	0.070
P(med,pess)	0.003	0.091	0.005	0.118	0.002	0.056
P(med,opt)–P(med,pess)	0.006**	-0.048**	0.007**	-0.096**	0.005**	-0.054**
P(pess,opt)	0.012	0.035	0.016	0.051	0.008	0.028
P(pess,med)	0.003	0.066	0.005	0.099	0.002	0.046
P(pess,pess)	0.004	0.101	0.007	0.161	0.003	0.069
P(pess,opt)–P(pess,pess)	0.008**	-0.066**	0.009**	-0.110**	0.005**	-0.041**
P(opt,opt)–P (pess,pess)	0.012**	-0.101**	0.012**	-0.157**	0.011**	-0.071**

In addition, we have also controlled our analysis for the impact of the book-to-market ratio, see panels B and C of table 4.5. Here the subsamples of value stocks and growth stocks each contain 30% of the total stock sample, according to the methodology that has been explained in section 4.2. The dispersion in analysts' earnings forecasts is more extreme for value stocks than for growth stocks. When analysts were too optimistic two years in a row, the dispersion for value stocks is 0.020 and the dispersion in analysts' earnings forecasts for growth stocks is 0.013, yielding a difference of 0.006.

Table 4.6 presents the change in dispersion ($\Delta Disp$) for each of the nine portfolios which are similar to the ones in table 4.5. To control for changes in price effects, the dispersion in analysts' earnings forecasts is scaled by the price of year *t-1*. Independent of the forecast errors of last year ($FE1_t$), analysts' dispersion is higher for stocks with too optimistic earnings forecasts the year before ($FE1_{t-1}$) compared to stocks with too pessimistic forecasts the year before. For example, dispersion in analysts' earnings forecasts is 0.014 for P(opt,opt), 0.007 for P(med,opt) and 0.011 for P(pess,opt). In addition, uncertainty is increasing when past forecast errors are high the last year ($FE1_t$) and decreasing when past forecast errors were low. For example, portfolio P(pess,opt) shows an increase in dispersion of 0.002. Also, when past forecast errors were too optimistic in the first year and too pessimistic in the second year, dispersion is decreasing by 0.003. These findings are consistent with Keastner (2005) in the sense that investors react more heavily to a series of surprises. The change in dispersion seems to be asymmetric. The portfolios with medium 1-year forecast errors in the first year, P(med,..), show an increase of 0.001 in analysts' dispersion when analysts become too optimistic and a change of 0.001 in dispersion when analysts became too pessimistic in the year after. The results indicate that bad news leads to higher uncertainty compared to good news.

To control for book-to-market effects, we also examine the change in analysts' dispersion for value and growth stocks (see panels B and C of table 4.6). In the case of value stocks, the dispersion in analysts' earnings forecasts increases with 0.003 when the forecast errors are extremely positive the first year and too negative the second year (P(pess,opt)). This implies that analysts become more nervous when forecasts are too optimistic. When the forecast error increases from negative to positive P(opt, pess), dispersion in analysts' earnings forecasts decreases with 0.001. Growth stocks, on the other hand, show that the change from positive forecast errors to negative forecast errors (P(pess,opt)) leads to an increase in uncertainty of 0.001. The change from extreme negative forecast errors to positive forecast errors in the subsequent year (P(opt,pess)) leads to a decrease in uncertainty of 0.0002 (in table 4.6 rounded to 0.000). For value stocks, dispersion in analysts' earnings forecasts seems to be more sensitive to negative changes in 1-year forecast errors than in the case of growth stocks.

The results of the previous section 4.3.1 have shown that uncertainty is negatively related to analyst coverage and 1-year forecast errors. The outcomes in tables 4.5 and 4.6 of the present section show that a string of forecast errors has impact on analysts' forecast dispersion. In summary, the evidence suggests that information and past earnings surprises play an important role in explaining analysts' uncertainty, measured in terms of dispersion in analysts' earnings forecasts. Moreover, our results may imply that low analyst coverage and a string of too optimistic forecasts lead to higher uncertainty among analysts and to lower returns in the future.

Table 4.6: Two consecutive years of forecast errors and the change in dispersion in analysts' earnings forecasts

Portfolios are formed similar to table 5. $Disp_t$ is the median dispersion in analysts' earnings forecasts in April of year t and t-1. $\Delta Disp$ is the difference in analysts' dispersion of year t-1 and year t. Kruskal-Wallis tests are performed to test whether the median differences in $Disp_t$ are significant; ** is 1% significance level, * is 5% significance level.

	Panel A: all stocks			Panel B: value stocks			Panel C: growth stocks		
Variables	$Disp_{t-1}$	$Disp_t$	$\Delta Disp$	$Disp_{t-1}$	$Disp_t$	$\Delta Disp$	$Disp_{t-1}$	$Disp_t$	$\Delta Disp$
Portfolios									
P(opt,opt)	0.015	0.014	-0.000	0.015	0.015	-0.001	0.013	0.013	0.000
P(opt,med)	0.008	0.007	-0.002**	0.010	0.008	-0.002*	0.008	0.006	-0.001**
P(opt,pess)	0.015	0.011	-0.003**	0.014	0.011	-0.003	0.010	0.008	-0.001
P(opt,opt)-P(opt,pess)	0.000	0.003**	0.004**	0.002**	0.004**	0.002**	0.004**	0.005**	0.001
P(med,opt)	0.006	0.008	0.001**	0.007	0.009	0.001**	0.005	0.006	0.001*
P(med,med)	0.003	0.003	0.000**	0.004	0.004	0.000	0.002	0.002	0.000**
P(med,pess)	0.004	0.004	0.001**	0.005	0.005	0.000	0.003	0.003	0.001**
P(med,opt)-P(med,pess)	0.003**	0.003**	0.001**	0.002**	0.004**	0.001**	0.002**	0.003**	0.001
P(pess,opt)	0.008	0.010	0.002**	0.009	0.012**	0.003**	0.007	0.008	0.001
P(pess,med)	0.003	0.003	0.000**	0.004	0.004	0.001**	0.002	0.002	0.000**
P(pess,pess)	0.004	0.005	-0.001**	0.006	0.008	-0.001**	0.003	0.003	-0.000**
P(pess,opt)-P(pess,pess)	0.003**	0.006**	0.003**	0.003**	0.005**	0.005**	0.004**	0.005**	0.001

4.3.3 Dispersion of analysts' earnings forecasts and style migration

In the previous sections we showed that analysts' dispersion can predict future returns even after controlling for book-to-market ratio. In this section we test whether dispersion in analysts' earnings forecasts can explain style migration. In doing so, we explicitly use the underlying assumption that the dispersion of analysts' forecasts proxies investor uncertainty regarding stock's future earnings (see section 4.1). While superior returns of value stocks have been shown by, a.o. Lakonishok, Shleifer and Vishny (1994) and Fama and French (1992), we have shown in the previous chapter 3 that the value premium is primarily driven by the migration of stocks from one style to another. This is the result of drastic changes in expectations of investors. It implies that at the time portfolios are formed, investors perceive relatively high uncertainty about future earnings for stocks that switch in the year after formation. We therefore also examine whether the ambiguity of investors about future performance of 'style-switchers' is greater in comparison to 'fixed-style' stocks.

Before we analyze whether style migration is the result of uncertainty, we first examine whether the switching nature of stocks is driven by a small number of industries. To this end we check the two-digit Standard Industrial Classification code of each stock. The two-digit SIC grouping is based on Boudoukh and Richardson (1994) and Moskowitz and Grinblatt (1999). Table 4A.1 in the appendix presents an overview of the number of stocks that belong to each industry, distinguished among value and growth stocks and the subdivision of switching- versus fixed-style stocks.

The average number of value, switching-value and fixed-value stocks per industry is 1404, 505 and 898, respectively. The average numbers for growth, switching-growth and fixed- growth stocks are 1635, 541 and 1094. The lowest number of stocks belonging to an industry for both stocks is the railroads industry. We perform an F-test to test the hypothesis that the mean percentages for switching- and fixed style stocks within each industry are equal. The F-test shows that the hypothesis of equal means cannot be rejected. This implies that the mean percentages of stocks in a particular industry are essentially equal for switching or fixed-style stocks for both value and growth stocks. This suggests that there is little cross-sectional variance in the mean percentages of stocks across industries, meaning that the switching behavior is not industry-dependent.

As we mentioned above, in this section we test whether the ambiguity of investors about the future performance of style-switchers is larger in comparison with fixed-style stocks. The results are reported in table 4.7. They show that the dispersion of analysts' earnings forecasts is larger for switching-style stocks than for fixed-style stocks, indicating that the future growth prospects of switching-style stocks are subject to greater uncertainty. The results also show that for value stocks the book-to-market ratio and the dispersion of analysts' earnings forecasts are not positively related. The book-to-market ratio of switching-value stocks is lower in comparison to the book-to-market ratio of fixed-value stocks (difference of -0.119), whereas the scaled dispersion measures are higher (difference of 0.001). The difference in dispersion is for both measures statistically significant at a 1% level. On the other hand, fixed-growth stocks have a higher book-to-market ratio than switching-growth stocks.

Table 4.7: Dispersion in analyst earnings forecasts for switching and fixed-style stocks

This table reports median values of dispersion in analysts' earnings forecasts and of book-to-market ratio's (*BM*). *N* is the number of observations. The dispersion in analysts' earnings forecasts ($Disp_t$) are scaled by price *P* and by absolute 1-year forecasts (F_1).

	Value stocks				Growth stocks			
	N	*BM*	$Disp_t/P$	$Disp_t/\|F_1\|$	*N*	*BM*	$Disp_t/P$	$Disp_t/\|F_1\|$
Switching	2361	1.178	0.010	0.099	4294	0.330	0.004	0.056
Fixed	3579	1.297	0.009	0.089	9820	0.261	0.002	0.039
Difference Switching–Fixed		-0.119	0.001	0.011		0.069	0.002	0.017
Kruskal-Wallis			23.447**	16.406**			284.388**	192.401**

In order to refine our analysis further, we correct for size-effects (consistent with the findings by Lakonishok, Sleifer and Vishny, 1994, and Fama and French, 1992). We examine whether the median values of dispersion of analysts' earnings forecasts change when we divide switching and fixed-style stocks into size-portfolios. Each stock is classified into one of the three portfolios (30-40-30%) depending on its size. The results reported in table 4.8 indicate that small stocks have a higher dispersion of analysts' earnings forecasts than large caps (in all cases the dispersion difference 'small-large' is positive). This means that analysts are more uncertain about the future earnings of small caps as compared to future earnings of large caps. These results are consistent with Fama and French (1992) and Doukas, Kim and Pantzalis (2003), who show that the superior returns of size portfolios are based on risk.

The results reported in panel A of table 4.8 show that the median dispersion in analysts' earnings forecast is the highest (0.013) for small switching-value stocks, while the corresponding median values for large fixed-value stocks is the lowest (0.006). Growth stocks appear to show the same results (see panel B), although, small caps show slightly higher dispersion for the fixed-growth stocks than for the switching growth stocks. The difference in forecast dispersion among analysts for small caps is not significant in the case of growth stocks. Although we find size-effects as important inputs for uncertainty among investors, not all uncertainty is explained by size. In each size-portfolio the differences in median values of switching versus fixed style stocks (except small growth stocks) are significant at 5% level (see right-hand column). These results provide evidence that investors are more uncertain about the future earnings of switching-style stocks than of fixed-style stocks. In addition, investors are more uncertain about small-cap stocks than about large- and medium-cap stocks.

Table 4.8: Dispersion in analysts' earnings forecasts of switching versus fixed-style stocks and of size sorted stock portfolios

Size portfolios are formed on market capitalization of March in year *t*. Switching stocks are stocks that belong one year to the same style. Fixed-style stocks belong two or more consecutive years to the same style. *N* is the number of observations. The dispersion in analysts' earnings forecasts ($Disp_t$) are scaled by price. Kruskal-Wallis tests are performed to test whether the median differences in $Disp_t$ are significant; ** is 1% significance level, * is 5% significance level.

Panel A: Value stocks						
	Switching		Fixed		Difference	
Size Portfolios	*N*	$Disp_t/P$	*N*	$Disp_t/P$	switching-fixed	Kruskal-Wallis
Small	1240	0.013	1766	0.011	0.002	18.204**
Medium	710	0.008	1121	0.008	0.001	1.169**
Large	410	0.007	692	0.006	0.001	4.587*
Difference Small–Large		0.005		0.005		
Kruskal-Wallis		72.029**		89.444**		
Panel B: Growth stocks						
Size Portfolios	*N*	$Disp_t/P$	*N*	$Disp_t/P$	switching-fixed	Kruskal-Wallis
Small	1594	0.004	2452	0.005	-0.000	1.180
Medium	1767	0.003	3998	0.003	0.001	71.442**
Large	933	0.003	3370	0.002	0.002	180.855**
Difference Small–Large		0.001		0.003		
Kruskal-Wallis		32.826**		498.138**		

In summary, a first important finding is that information and past earnings surprises play an important role in explaining analysts' uncertainty, measured in terms of dispersion in analysts' earnings forecasts. Uncertainty increases more when analysts are too optimistic for two consecutive years. In addition, our findings show that uncertainty is negatively related to bad past performance in stock returns. These findings are consistent with the error-in-expectation hypothesis. Furthermore, the results suggest that if less information is revealed about a company (low size-adjusted analyst coverage), uncertainty will be higher. This is in line with the information diffusion hypothesis of Hong and Stein (1999). The second important finding is that analysts are more uncertain about the prospects of earnings of switching-style stocks compared to fixed-style stocks.

4.4 Robustness tests

In the previous sections, we have identified a number of variables that are related to uncertainty. In this section we test which of these variables are significant in a multiple regression. In section 4.4.1, we apply a comprehensive multivariate analysis and in section 4.4.2, we apply a probit regression analysis to test whether these variables have significant power to predict the style switch of a stock the year after portfolio formation.

4.4.1 Comprehensive multivariate analysis of analysts' forecast dispersion

In this section we apply a comprehensive multivariate analysis to test for the simultaneous impact of the relevant variables and test which of these variables are statistically significant. We examine whether dispersion in analysts' earnings forecasts ($Disp_{i,t}$) is related to the following variables: 1-year forecasts errors ($FE_{i,t-1}$), the string of forecast errors (measured by dummy variables $d_{1,i}$, $d_{2,i}$ and $d_{3,i}$), size-adjusted analyst coverage ($Cov_{i,t-1}$), Tobin's q ($Tobinq_{i,t-1}$), annual return ($R_{12,i,t-1}$), a dummy for positive/negative earnings ($Earn^{+}_{i,t-1}$), book-to-market ratio ($BM_{i,t}$) and the log of market capitalization ($Size_{i,t}$). The effect of the string of forecast errors on dispersion is measured by three dummies. The dummy represents the interaction between the 1-year forecast error in periods t-2 and t-1, where $d_{1,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=1)$, $d_{2,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=2)$ and $d_{3,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=3)$[15]. The equation we estimate is as follows:

$$\begin{aligned} Disp_{i,t} = \beta_0 + \beta_1 FE_{i,t-1} + \beta_2 d_{1,i} + \beta_3 d_{2,i} + \beta_4 d_{3,i} + \beta_5 Cov_{i,t} + \beta_6 Tobinq_{i,t} + \\ \beta_7 R_{12,i,t-1} + \beta_8 Earn^{+}_{i,t-1} + \beta_9 BM_{i,t} + \beta_{10} Size_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4.1}$$

The regression controls for the impact that growth opportunities, measured as $Tobinq_{i,t}$, have on analysts' forecast dispersion and the impact that negative earnings have on analysts' forecast dispersion. The inclusion of $Tobinq_{i,t}$ is dictated by other studies that have shown that analyst coverage and $Tobinq_{i,t}$, are related (see, e.g. Doukas, Kim and Pantzalis, 2000, and Doukas, Pantzalis and Kim, 2004). A dummy for positive earnings, $Earn^{+}_{i,t-1}$, is included, because the study by Ali, Klein and Rosenfeld (1992) shows that the degree of overestimation is most evident for firms with negative earnings. Furthermore, the regression controls for book-to-market and size effects.

Table 4.9 shows the time-series averages of the coefficients from year-to-year Fama and MacBeth regressions of the cross-section of analysts' dispersion on the variables mentioned in equation 4.1. Following the procedure of Fama and MacBeth (1973), we run a regression separately for each year in which the dependent variable is the analysts' forecast dispersion on stock i and the independent variables are the characteristics of stocks i (i.e. independent variables in (4.1)) observed at the beginning of the year. In our analysis, we have 26 portfolio formation periods (1976-2001) and therefore we run 26 separate cross-sectional regressions.

[15] According to the 1-year forecast errors each stock is assigned into low (bottom 30%), medium (intermediate 40%) and high (top 30%) portfolios.

Table 4.9: OLS regressions on analysts' forecast dispersion

The average slope is the time-series average of the annual regression slopes, and the *t*-statistic is the average slope divided by its time-series standard error. We use Newey-West correction to adjust the standard errors for autocorrelation and heteroskedasticity. The independent variables are 1-year forecasts errors ($FE1_{i,t-1}$), string of 1-year forecast errors (, $d_{1,i}$, $d_{2,i}$ and $d_{3,i}$), size-adjusted analyst coverage ($cov_{i,t-1}$), Tobin's q ($Tobinq_{i,t-1}$), past 12-month return ($R_{12,I,t-1}$), positive/negative earnings ($Earn^{+}_{i,t-1}$), book-to-market ($BM_{i,t}$) and the log of market capitalization ($size_t$). We use three dummies, $d_{1,i}$, $d_{2,i}$ and $d_{3,i}$ for the string of 1-year forecast errors. The dummy represents the interaction between the 1-year forecast error in period *t*-2 and *t*-1, where $d_{1,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=1)$, $d_{2,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=2)$ and $d_{3,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=3)$. Each stock is assigned according to the 1-year forecast errors into low (bottom 30%), medium and high (top 30%) portfolios. Stars present significant levels: * 5% significance, ** 1% significance

Variables:	I	II	III	IV
Intercept	0.027** (7.961)	0.068** (4.155)	0.053** (4.917)	0.051** (10.519)
$FE1_{i,t-1}$	-0.101** (-3.406)			-0.095** (-3.103)
$d_{1,i}$	0.005** (3.639)			0.004** (4.264)
$d_{2,i}$	0.000 (0.415)			0.001 (0.716)
$d_{3,i}$	0.009** (4.033)			0.010** (4.249)
$Cov_{i,t}$		-0.002** (-2.423)		-0.001** (-5.768)
$Tobinq_{i,t}$	-0.001** (-2.115)	-0.003** (-2.205)	-0.003** (-2.040)	-0.006** (-3.571)
$R_{12,i,t-1}$			-0.013** (-3.043)	-0.001** (-1.999)
$Earn^{+}_{i,t-1}$	-0.014** (-3.414)	-0.034** (-4.065)	-0.030** (-3.947)	-0.012** (-3.126)
$BM_{i,t}$	-0.001 (-0.262)	-0.003 (-0.798)	-0.003 (-0.869)	-0.001 (-0.454)
$Size_{i,t}$	-0.001** (-4.809)	-0.003** (-3.105)	-0.001** (-6.296)	-0.002** (-10.114)
Avg. Adj. R-squared	0.392	0.260	0.249	0.413
# of obs.	27494	27494	27494	27494
Average # of firms	1058	1058	1058	1058

The reported coefficients are the time-series averages of the coefficients obtained for each year. The *t*-statistics are computed using the standard error of the estimates for each year. We use Newey-West correction to adjust the standard errors for possible serial correlation and heteroskedasticity. Supporting to the results in tables 4.2 and 4.3, the regressions in table 4.9 show that $FE1_{i,t-1}$, $d_{1,i,}$, $d_{2,i}$, $d_{3,i}$, $Cov_{i,t}$, $R_{12,i,t-1}$, $Earn^{+}_{i,t-1}$ and $size_{t-1}$ explain the cross-section in analysts dispersion.

4.4.2 Probit analysis of style-switching behavior

The previous analyses have identified a variety of variables that are related to uncertainty. In section 4.3.3, we have shown that uncertainty is higher for switching-style stocks than for fixed-style stocks. In this section, we test which of these variables are significant in a probit analysis. We use a probit model where the dependent variable, y_i, is a dummy variable representing the occurrence of an event. In this case the event is the style switch a stock may make the year after formation. The goal is to quantify the relationship between individual stock characteristics and the probability of a stock switching from style. The dependent variable, $y_{i,}$ takes only two values, zero and one.

$$y_i = \begin{cases} 1 & \text{if stock } i \text{ switches from style} \\ 0 & \text{otherwise} \end{cases}$$

Firstly, we test whether high dispersion in analysts' earnings forecasts leads to a higher probability that the stock under consideration migrates from style. The following regression is considered:

$$y_{i,t} = \beta_0 + \beta_1 Disp_{i,t} + \varepsilon_{i,t}, \tag{4.2}$$

where $y_{i,t}$ is a dummy with value one when stock i switches from style the year after formation and zero otherwise (the style-switch year is from July of year t to June of year t+1). To test against the null-hypothesis that the slope coefficients are all equal to zero, we use the likelihood ratio test:

$$Lratio = 2[L(a,\beta) - L(a,0)] \xrightarrow{a} \chi^2(k-1),$$

where $L(a,\beta)$ is the maximized value of the log-likelihood of the model being estimated, $L(a,0)$ is the value of the log-likelihood for a probit with only a constant term and k-1 is the number of slope coefficients. We improve the efficiency of the estimator by taking into account the serial correlation in the error term. Therefore, we estimate the standard errors using a generalized linear model (GLM) method (McCullagh and Nelder, 1989).

Table 4.10 presents the outcomes of the probit for each stock with the characteristics of stocks that we have identified. We run the cross-sectional regressions, in which the dependent variable is one when a stock switches from style in the next period and zero otherwise. The independent variable is dispersion in analysts' earnings forecasts in April of year t, $Disp_{t.}$ As we can see from the likelihood ratio (*Lratio*), the null hypothesis that the slope coefficients are equal to zero, is rejected. The coefficients of dispersion in analysts' earnings forecasts, $Disp_t$, are positive for value and growth stocks. This implies that the likelihood of switching increases with analysts' uncertainty regarding future earnings. The Mac-Fadden R^2, which is analogous to the R^2 of linear regressions, is low with 0.003 and 0.005 respectively.

In table 4.9, we have shown that the dispersion in analysts' earnings forecast is related to 1-year forecast errors, analyst coverage and past performance in stock returns.

Table 4.10: Probit with dispersion in analysts' earnings forecasts

At the end of June between 1977 and 2002 we compute for every stock in the sample whether it behaves as a switcher or not in the next period. We then estimate equation 4.2. The dependent variable is a dummy with value one when the stock switches from style and zero otherwise. The independent variable is the dispersion in analysts' earnings forecast, $Disp_t$. Growth and value stocks are determined by the breakpoints for the bottom and top 30% of the values of the book-to-market equity for NYSE stocks (we use the breakpoints available at the website of K. French). GLM-method is used to estimate the standard errors. Stars present significant levels: * 5% significance, ** 1% significance.

	Value stocks	**Growth stocks**
Constant	-0.281** (-16.056)	-0.539** (-21.318)
$Disp_{i,t}$	1.100** (3.802)	4.649** (4.085)
Mac-Fadden R^2	0.003	0.005
Lratio	19.553**	80.484**
Variance Factor estimate	1.001	1.522
# of obs. with dep.=zero	3008	8922
# of obs. with dep.=one	2023	3795

To test whether these variables have significant power to predict the style switch of a stock we apply the following regressions:

$$y_{i,t} = \beta_0 + \beta_1 Cov_{i,t-1} + \beta_2 Tobinq_{i,t-1} + \beta_3 Earn^{+}_{i,t-1} + \beta_4 Size_{i,t-1} + \varepsilon_{i,t} \quad (4.3)$$

$$y_{i,t} = \beta_0 + \beta_1 FE_{i,t-1} + \beta_2 d_{1,i} + \beta_3 d_{2,i} + \beta_4 d_{3,i} + \beta_5 Tobinq_{i,t-1} + \beta_6 Earn^{+}_{i,t-1} + \beta_7 Size_{i,t-1} + \varepsilon_{i,t} \quad (4.4)$$

$$y_{i,t} = \beta_0 + \beta_1 R_{12,i,t-1} + \beta_2 Tobinq_{i,t-1} + \beta_3 Earn^{+}_{i,t-1} + \beta_4 Size_{i,t-1} + \varepsilon_{i,t} \quad (4.5)$$

Table 4.11 presents the outcomes of the regression where the 1-year forecast error, $FE1_{i,t-1}$, the string of forecast errors in the two years preceding the year of the style switch ($d_{1,i}$, $d_{2,i}$ and $d_{3,i}$), past annual return, and the size-adjusted analyst coverage are the independent variables. The results of estimating (4.3) are in column I, the results of estimating (4.4) are in column II and the results of estimating (4.5) are in column III. The first result (column I) that comes up is that the coefficient of the size-adjusted analyst coverage has a positive sign for value stocks. Given the outcomes of table 4.2 and 4.3, we expect a negative relation between analyst coverage and uncertainty, because uncertainty increases when analyst coverage is low. On the other hand, the coefficient for growth stocks has the expected sign. However, the coefficients are not statistically significant and therefore not reliable. Another measure that reflects the rate of information diffusion is size. To detect size-effects in the style-switching behavior of stocks within a style, we add market capitalization in the regression (see: $Size_{i,t}$). Coefficients show negative signs, which means that the lower the market capitalization, the higher the chance will be that a stock switches from style. This may imply that the smaller the firm, the lower the rate of information diffusion and the higher uncertainty will be. The *t*-statistics show that size is statistically significant for value and growth stocks (except for the outcomes in column III). Hong, Lim and Stein (2004) use size as a proxy for the rate of information diffusion across the investing public and show that the profitability of momentum strategies declines with firm size. This implies that the slower firm-specific information diffusion, the more difficult it is to predict future earnings and, therefore, the higher uncertainty will be.

The results in column II show that the coefficients for the 1-year forecast errors have opposite signs for value and growth stocks. This means that the 1-year forecast errors seem to be higher for fixed-value stocks than for switching-value stocks the year before the style switch. Growth stocks show the opposite, the lower the forecast error in the period for the style-switch the higher the chance that the stock switches from style. For value stocks, the coefficients for the 1-year forecast errors, $FE1_{i,t-1}$, are not significant. In addition, it emerges from the table that the forecast errors made in April of year *t*-2 and *t*-1 for December of year *t*-2 and December *t*-1 (style switch from first July of year *t* to end of June year *t*+1) have significant predictive power for switching dynamics of growth stocks ($d_{1,i}$, $d_{2,i}$ and $d_{3,i}$). If analysts are too optimistic two years in a row, the chance of a style switch is higher. Value stocks show negative (equation 4.4) but not significant coefficients for $d_{1,i}$, $d_{2,i}$ and $d_{3,i}$. This means that the more optimistic the analysts were in the two years before the style-switch, the lower the chance that a value stock switches from style next year.

Column III presents the regression with past annual return as independent variable. The estimated coefficients are negative and significant for value stocks and growth stocks, which suggests that if value or growth stocks had negative returns in the year of formation, the chance of a style switch will be higher. The sign of the coefficients for the growth stocks are in line with Jegadeesh and Titman (1993), who find momentum in the short run. Value stocks on the other hand show contrarian effects. Looking at the log likelihood ratio, the results become better for the value portfolio after adding momentum in the probit analysis.

In addition, we add other variables (Tobin's q and a dummy for positive earnings and) in the regression, to test whether this has predictive power to style-switching. The first result emerging is that positive earnings and Tobin's q have predictive power for the style switch the year after formation for both value and growth stocks. The coefficients for Tobin's q show opposite signs, the coefficients of value stocks are positive and the coefficients of growth stocks are negative. This implies that if a value stock has many growth opportunities, the chance will be higher that a value stocks switches from style the next year. Overall then, table 4.10 provides further evidence that uncertainty is higher for stocks that switches from style. Table 4.11 provides evidence that past returns and the interaction between two consecutive years of forecast errors have significant power to predict style-switching the next year.

Table 4.11: Probit-analysis with dispersion in analysts' earnings forecasts

At the end of June between 1977 and 2002 we compute for every company in the sample whether it as a switcher or not the next period. We then estimate equation 4.3 to 4.5. The dependent variable is a dummy with value one when the stock switches from style and zero otherwise. The independent variables are 1-year forecasts errors ($FE1_{i,t-1}$), string of 1-year forecast errors ($d_{1,i}$, $d_{2,i}$ and $d_{3,i}$), size-adjusted analyst coverage ($Cov_{i,t-1}$), Tobin's q ($Tobinq_{i,t-1}$), past annual return ($R_{12,t-1}$), positive/negative earnings ($Earn_{I,t-1}^{+}$), book-to-market ($BM_{i,t}$) and the log of market capitalization ($Size_{i,t}$). We use three dummies, $d_{1,i}$, $d_{2,i}$ and $d_{3,i}$ for the string of 1-year forecast errors. The dummy represents the interaction between the 1-year forecast error in period t-2 and t-1, where $d_{1,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=1)$, $d_{2,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=2)$ and $d_{3,i}$ is $(FE1_{i,t-2}=1)*(FE1_{i,t-1}=3)$. Each stock is assigned according to the 1-year forecast errors into low (bottom 30%), medium and high (top 30%) portfolios. GLM-method is used to estimate the standard errors. Stars present significant levels: * 5% significance, ** 1% significance.

	I		II		III	
	Value	Growth	Value	Growth	Value	Growth
Constant	0.383 (1.385)	0.239** (5.043)	0.295 (1.141)	0.134* (2.174)	-0.071 (-0.271)	0.248** (3.862)
$FE_{i,t-1}$			-0.073 (-0.878)	0.0020 (0.672)		
$d_{1,i}$			-0.045 (-0.875)	0.129* (2.215)		
$d_{2,i}$			-0.000 (-0.000)	0.253** (3.616)		
$d_{3,i}$			0.059 (0.767)	0.241** (3.742)		
$Earn^{+}_{i,t-1}$	-0.281** (-6.588)	-0.116** (-2.859)	-0.289** (-6.481)	-0.088* (-2.194)	-0.209** (-4.611)	-0.087* (-1.962)
$R_{12,i,t-1}$					-0.176** (-4.846)	-0.144** (-4.039)
$Tobinq_{i,t-1}$	0.332** (6.186)	-0.060** (-7.626)	0.332** (6.115)	-0.058** (-7.774)	0.268** (4.832)	-0.058** (-6.892)
$Size_{i,t}$	-0.028** (-2.097)	-0.090** (-9.441)	-0.023* (-1.961)	-0.083** (-9.107)	-0.010 (-0.794)	-0.092** (-8.932)
$Cov_{i,t}$	0.030 (0.929)	-0.007 (-0.349)				

[Table 4.11 continued]

Mc-Fadden R^2	0.014	0.024	0.014	0.027	0.020	0.027
Lratio	94.774**	378.721**	96.710**	422.324**	117.588**	410.877**
Variance Factor estimate	1.001	1.721	1.002	1.553	1.001	2.008
# of obs. with dep.=zero	3008	8922	3008	8922	3008	8922
# of obs. with dep.=one	2023	3795	2023	3795	2023	3795

4.5 Summary and conclusion

The first objective of this chapter is to seek evidence for the information diffusion hypothesis and the error-in-expectation hypothesis. As a proxy of uncertainty of investors we use dispersion in analysts' earnings forecasts. The dispersion in analysts' earnings forecasts reflects the analysts' divergence of opinion in predicting future earnings. The more uncertain analysts are about future earnings of a company, the larger the divergence in opinion will be. The dispersion in analysts' earnings forecasts ($Disp_t$) is measured as the standard deviation of the one-year-ahead analysts' earnings forecasts made eight months before the fiscal year end, standardized by the stock price at the beginning of the fiscal year.

To test the information diffusion hypothesis, we examine uncertainty in relation with size-adjusted analyst coverage. Our findings support that if the analyst coverage is low, uncertainty will increase. This is in line with the information diffusion hypothesis of Hong and Stein (1999). To test the error-in-expectation hypothesis, we examine two consecutive years of forecast errors and past performance in stock returns. We draw several conclusions from the evidence reported in the tables. First, our findings support that if analysts' earnings forecasts have been wrong for two subsequent years, uncertainty will increase. This is in line with Keastner (2005) in the sense that investors react more heavily to a series of surprises. Second, after holding analyst coverage and 1-year forecast errors fixed, past performance in stock returns has a negative impact on analysts' forecast dispersion. These findings are consistent with the results of Ackert (1997) and Diether *et al.* (2002), who show abnormal returns for portfolios with low uncertainty. Summarized, our findings demonstrate that firms with low analysts' coverage, too optimistic earnings forecasts and low past performance have higher analysts' dispersion. Hence, the evidence supports that uncertainty is consistent with the extrapolation and information diffusion hypotheses. Our empirical results also appear to hold after applying a comprehensive regression on the different variables with the dispersion in analysts' earnings forecasts.

The second objective of this chapter is to investigate whether it is more likely for a stock to migrate from style when investors are more uncertain about future earnings. The results indicate that there are differences in the dispersion in analysts' earnings forecasts between switching and fixed-style stocks. Switching-style stocks show higher dispersion in analysts' earnings forecasts. Hence the results support the contention that earnings uncertainty is higher for switching-style stocks than for fixed-style stocks. The results are confirmed by applying a multivariate probit-analysis. We conclude that dispersion in analysts' earnings forecasts is positive related to style switching.

Appendix 4A

Table 4A.1: Description of industries for fixed versus switching-style stocks

Stocks are divided into different industries based on the two-digit Standard Industrial Classification code. Between brackets are the percentages of stock in the specific industry relative to the total number of stocks in the style portfolio. In the bottom panel, an F-statistic is performed to test whether the average percentages of the different industries are equal to each other.

Industry	SIC Codes	Average Number of stocks					
		Value			**Growth**		
		All	Switch	Fixed	All	Switch	Fixed
1. Mining	10-14	1452 (5.2%)	542 (5.4%)	910 (5.1%)	1275 (3.9%)	512 (4.7%)	763 (3.5%)
2. Food	20	571 (2.0%)	169 (1.7%)	402 (2.2%)	880 (2.7%)	215 (2.0%)	665 (3.0%)
3. Apparel	22-23	679 (2.4%)	202 (1.7%)	477 (2.2%)	293 (0.9%)	124 (1.1%)	169 (0.8%
4. Paper	26	316 (1.1%)	93 (0.9%)	223 (1.2%)	224 (0.7%)	68 (0.6%)	156 (0.7%)
5. Chemical	28	854 (3.0%)	398 (3.9%)	456 (2.5%)	3668 (11.2%)	844 (7.8%)	2824 (12.9%)
6. Petroleum	29	221 (0.8%)	63 (0.6%)	158 (0.9%)	140 (0.4%)	45 (0.4%)	95 (0.4%)
7. Construction	32	260 (0.9%)	76 (0.8%)	184 (1.0%)	143 (0.4%)	55 (0.5%)	88 (0.4%)
8. Prim. Metals	33	721 (2.6%)	190 (1.9%)	531 (3.0%)	281 (0.9%)	99 (0.9%)	182 (0.8%)
9. Fab. Metals	34	609 (2.2%)	218 (2.2%)	391 (2.2%)	501 (1.5%)	200 (1.8%)	301 (1.4%)
10. Machinery	35	1776 (6.3%)	740 (7.3%)	1036 (5.8%)	2447 (7.5%)	858 (7.9%)	1589 (7.3%)
11. Electrical Eq.	36	1909 (6.8%)	860 (8.5%)	1049 (5.8%)	3279 (10.0%)	1127 (10.4%)	2152 (9.8%)

[Table 4A.1 continued]

12. Transport Eq.	37	542 (1.9%)	203 (2.0%)	339 (1.9%)	453 (1.4%)	183 (1.7%)	270 (1.2%)
13. Manu-facturing	38-39	1648 (5.9%)	696 (6.9%)	952 (5.3%)	3110 (9.5%)	948 (8.8%)	2162 (9.9%)
14. Railroads	40	137 (0.5%)	37 (0.4%)	100 (0.6%)	21 (0.1%)	11 (0.1%)	10 (0.0%)
15. Other transport	41-47	737 (2.6%)	245 (2.4%)	492 (2.7%)	426 (1.3%)	179 (1.7%)	247 (1.1%)
16. Utilities	49	2768 (9.9%)	592 (5.9%)	2176 (12.1%)	354 (1.1%)	142 (1.3%)	212 (1.0%)
17. Dept. Stores	53	279 (1.0%)	94 (0.9%)	185 (1.0%)	220 (0.7%)	58 (0.5%)	162 (0.7%)
18. retail	50-52, 54-59	3469 (12.4%)	1200 (11.9%)	2269 (12.6%)	3296 (10.1%)	1169 (10.8%)	2127 (9.7%)
19. Financial	60-69	2918 (10.4%)	895 (8.9%)	2023 (11.3%)	1708 (5.2%)	581 (5.4%)	1127 (5.2%)
20. Others	Other	6207 (22.1%)	2596 (25.7%)	3611 (20.1%)	9975 (30.5%)	3402 (31.4%)	6573 (30.0%)
Total number		28073	10109	17964	32694	10820	21874
Average numbers		1404 (4.1%)	505 (3.9%)	898 (4.2%)	1635 (3.7%)	541 (3.6%)	1094 (3.7%)
F-statistic (is equal)		0.000			0.000		