Capitalizing on Analyst Earnings Estimates and Recommendation Announcements in Europe

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Abstract

Examining the market-adjusted cumulative abnormal returns associated with analyst earnings estimate and recommendation announcements in Europe, I find that both factors are significant when considered unconditionally and conditional on each other. When examining the strength of these factors during different market regime periods, however, I find that when the market or stock volatility for a given month is unusually high or dispersion between the market and stock volatilities is unusually low, the significance of both the EPS estimate and recommendation factors decrease or are non-existent. In addition, the least favorable quintile of securities – as measured by change in the earnings or recommendation factor – no longer exhibits the least favorable market-adjusted cumulative abnormal return. Since previous research has shown that volatility is somewhat persistent, modifying analyst models based on current market environments increases potential portfolio returns.

JEL classification: G11; G12; G14

Keywords: Earnings; Recommendations; Security analysts; Market regime

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1. Introduction

There are a plethora of studies suggesting that analyst factors have an impact on market returns. However, most previous research on analyst earnings and recommendations announcements focus on U.S. analyst estimates.[1] Of the papers that analyze European analyst data, most focus on consensus estimates rather than detailed estimates.[2] I have extended upon prior research on European analyst data by utilizing detailed estimates rather than just consensus estimates. By incorporating daily analyst information in this study, I overcome many of the disadvantages of limited consensus information. I also analyze both earnings estimates and analyst recommendations simultaneously, which has not to my knowledge been previously been studied in Europe.

Moreover, over the past few years investor confidence in analyst reports and analyst factors has deteriorated.[3] In an effort to prevent selective disclosure by publicly traded companies to market professionals and certain shareholders, including analysts, the Securities and Exchange Commission passed Regulation Fair Disclosure (Reg FD) in October 2000. In response, many investment banks also modified their own policies in attempts to do something about the potential conflict of interest surrounding its analysts.[4]

As a result of these changes, conclusions from previous studies analyzing earnings estimates, price targets, and recommendations, which only include time periods through 1999,[5] may no longer be an accurate reflection of the current market environment. Using a large database spanning the May 1987 through April 2004 time period, constructed from earnings estimate, recommendation, analyst, and company data from I/B/E/S and company specific data, such as market capitalization and Barra Gemm value score, from Factset, this study extends prior work by incorporating the period following the passage of Reg FD and the stock bubble burst[6] in the U.S. to determine if investors can capitalize on European analyst earnings estimates and recommendations. Consistent with previous work, I find statistically significant relationships between both percent change in earnings estimate and excess returns and level change in recommendations and excess returns both unconditionally and conditional on each other.

In addition, I examine the previously unstudied association between market returns and analyst factors during extreme volatility and dispersion environments to establish if these analyst factors perform differently during different market regime periods. Using calculated volatility and dispersion variables, I run sub-sample tests by current and 1-month lagged monthly market variables and find that the excess returns associated with analyst factors differ depending on the market environment. I find that during periods of low volatility and high dispersion, the analyst factor quintile spreads are higher than those observed during periods of high volatility and low dispersion. Since previous research has shown that volatility is somewhat persistent, modifying analyst models based on current market environments increases potential portfolio returns.

2. Prior research

Within the investment community, analyst numbers are key drivers of quantitative models and investment decisions. As a result, analyst factors have been the subject of extensive research. Much of the

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[1] A few examples include Abdel-Khalik and Ajinkya (1982), Lys and Sohn (1990), Stickel (1991), Womack (1996), Francis and Soffer (1997), Brav and Lehavy (2003), and Asquith *et al.* (2004).
[2] See Bercel (1994) and Dische and Zimmerman (1999).
[3] See Brown and Opdyke (2001), Alpert (2002), Tully (2001), and Kahn (2002).
[4] See Kurson (2001).
[5] See Brav and Lehavy (2003) and Asquith *et al*. (2004).
[6] See Hansell (2001) and Browning (2004).

literature on analyst factors, however, is concentrated within the United States.[7] Research in Europe has generally been limited to studies of specific countries or work using consensus data.[8]

Early U.S. investigations are primarily related to the market's reaction to revisions in either analysts' earnings estimates or recommendations. As a result of these studies, the market generally accepts that favorable (unfavorable) earnings estimate or recommendation revisions are followed by positive (negative) excess returns.[9]

In addition to replicating prior work testing the effect of earnings estimates and recommendations on stock returns, my work is also related to more recent research examining both earnings estimate and recommendation revisions simultaneously. Francis and Soffer (1997) find that both estimate revisions and recommendations are informative even in the presence of the other signal. Asquith *et al.* (2004) analyze both the quantitative and qualitative aspects of an analyst report. They find that when earnings estimates and recommendations are considered independently, increases (decreases) in both factors are associated with positive (negative) abnormal returns. When examining qualitative arguments, estimate revisions, recommendations, and price target changes simultaneously, however, they find that the significance of earnings estimate revisions is reduced.

In Europe, most previous research on earnings estimates has focused on consensus, rather than detailed, estimates because it is generally accepted that consensus estimates provide more accurate estimates than individual analyst estimates. While this is true, the potential excess returns associated with consensus estimates are not as large as those associated with extreme detailed estimates.

Bercel (1994) analyzes consensus estimates and revisions for seven different countries, including the United States, and five European countries. He finds that generally both changes in estimate EPS and revision score provide accurate and stable information to the market. Dische and Zimmerman (1999) examine Swiss stocks and consensus EPS revisions from January 1993 to August 1996. They find that a substantial part of the change in analyst earnings estimates is already reflected in stock process prior to the publication of the consensus and only the most favorable portfolio group exhibited any statistically significant returns a month following the announcement.

Jegadeesh and Kim (2003) examine reaction to analyst recommendations between 1993 and 2002 for a number of countries, including the United States and four European countries. They find that the reaction to recommendations in European countries such as, Britain, France, Germany, and Italy, are significant, although they are not as pronounced as the reaction in the United States.

Using a database constructed from security analyst data over the period May 1987 through April 2004, I investigate whether European earnings estimate revisions and recommendation revisions are significantly and positively associated with the market's reaction at the time this information is released. I then extend this analysis to determine if the market reaction differs depending on current or recent market conditions. To the best of my knowledge, this is the first study to look at how the market reaction to these factors changes depending on the market environment.

3. Data description

Limiting my sample to companies that make up the MSCI Europe Index, my analysis uses over 440,000 earnings estimates, released between May 1987 and April 2004, and over 220,000 recommendations, released between November 1993 and April 2004, by equity research analysts from over 500 brokerage firms and investment banks from I/B/E/S. My sample contains companies from 16 countries; Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. I also retrieved factor specific information,

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7 See Abdel-Khalik and Ajinkya (1982), Lys and Sohn (1990), Stickel (1991), Womack (1996), Francis and Soffer (1997), Brav and Lehavy (2003), and Asquith *et al.* (2004).

8 See Bercel (1994) and Dische and Zimmerman (1999).

9 See Abdel-Khalik and Ajinkya (1982), Lys and Sohn (1990), Stickel (1991), or Womack (1996).

such as the announcement dates, broker, and fiscal period, from the same source. I retrieved company identifiers, such as the country, currency, market capitalization in USD (MKTCAP), and Barra Gemm value score (VALUE), from Factset.

My empirical analysis required me to calculate several variables. First, I compute the percent change in an analyst's earnings estimate for a company (EPS_CHNG) as $(EST_t - EST_{t-1}) / |EST_{t-1}|$ where EST_t is the earnings estimate at time t. In order to determine the previous earnings estimate, I use the data point immediately preceding the current estimate by the same broker for the same company and forecast period. In terms of recommendations, I/B/E/S assigns a recommendation number that corresponds to each recommendation level. In this study I quantify strong buy as 1, buy as 2, hold as 3, sell as 4, and strong sell as 5. I calculate the level change in recommendation (REC_CHNG) as previous recommendation minus current recommendation by a given broker for a given company.

Next, I measure the market's reaction to the release of analyst reports with market-adjusted cumulative abnormal returns (CAR) from the report release date. The index returns were calculated using the equal-weighted returns of all of the companies in our sample. The market-adjusted returns were computed as the difference between the security and index cumulative returns for 5, 10, 20, 40, and 60 calendar days before and after the estimate announcement date. I focus my analysis on longer term 60-day (CAR(60)) cumulative abnormal returns and find, consistent with my expectations and prior research, statistically significant 60-day mean returns for the most favorable and least favorable earnings estimate and recommendation changes by quintile.

Finally, in order to perform analysis on the viability of the earnings estimate and recommendation signals, I calculated three market factors – index volatility, stock volatility, and the dispersion between the stock and index volatilities. The monthly index volatility (IDX_VOL) is the standard deviation of the daily index returns for a given month. The monthly stock volatility (STK_VOL) is the equally weighted standard deviations of daily company stock returns for a given month. The dispersion between the stock and index volatilities (DISPER) is calculated as (STK_VOL – IDX_VOL) / IDX_VOL.

4. Empirical results

4.1. Effect of analyst and company-specific factors

In this section I examine the overall effects of earnings estimates and recommendations on abnormal returns. Table 1 presents the Spearman and Pearson correlations between EPS_CHNG, REC_CHNG, logMKTCAP, VALUE, and different abnormal return windows, CAR(20) and CAR(60). As expected, both the Spearman and Pearson correlations between cumulative abnormal returns and factor changes and revision scores are highly significant. Comparing Spearman correlations between change in factor with abnormal returns, correlations between REC_CHNG and returns, both CAR(20) and CAR(60), are similar to comparable correlations between EPS_CHNG and returns. This result indicates that percent change in earnings estimate and change in recommendation provide similar information signals to the market. Returns are also positively correlated with market capitalization and negatively correlated with value score, suggesting that higher returns are associated with higher market capitalization or larger companies and lower value or growth companies.

TABLE 1: Pearson / Spearman Correlation Coefficients for Analyst Factors

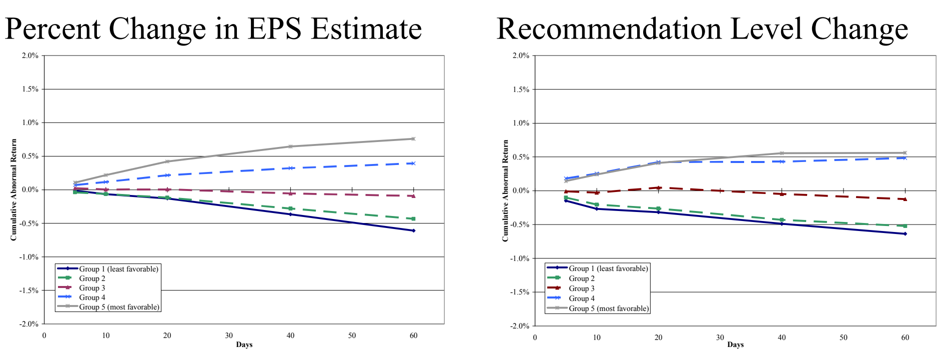
Spearman Correlation	Pearson Correlation: EPS_CHNG	REC_CHNG	logMKTCAP	VALUE	CAR(20)	CAR(60)
EPS_CHNG		6.32% *** <.0001	8.15% *** <.0001	1.24% *** <.0001	1.35% *** <.0001	1.77% *** <.0001
REC_CHNG	15.39% *** <.0001		2.07% *** <.0001	-3.94% *** <.0001	3.56% *** <.0001	3.22% *** <.0001
logMKTCAP	10.82% *** <.0001	2.04% *** <.0001		-9.16% *** <.0001	2.47% *** <.0001	1.42% *** <.0001
VALUE	-7.25% *** <.0001	-3.83% *** <.0001	-8.60% *** <.0001		-3.70% *** <.0001	-0.36% ** 0.0149
CAR(20)	3.57% *** <.0001	4.23% *** <.0001	3.76% *** <.0001	-3.28% *** <.0001		
CAR(60)	4.92% *** <.0001	3.96% *** <.0001	2.36% *** <.0001	0.30% ** 0.0432		

Notes to table 1: This table presents the Pearson (upper triangle) and Spearman (lower triangle) correlations for the following variables for company j at time t: EPS_CHNG$_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)]; REC_ CHNG$_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation); logMKTCAP$_{j,t}$ = log of market capitalization; VALUE$_{j,t}$ = Barra Gemm value score; and CAR (X)$_{j,t}$ = market-adjusted cumulative abnormal return for X days starting on the report release date t. P-values are listed below the correlation numbers. *one-tailed probability < 0.10; **one-tailed probability < 0.05; ***one-tailed probability < 0.01.

In order to illustrate the relationship between EPS_CHNG and CAR, I separated the dataset into quintile portfolios by EPS_CHNG and graphed the portfolio returns for the different abnormal return periods. I repeated this analysis for REV_CHNG.

Figure 1 presents the excess returns over time for quintile portfolios grouped by EPS_CHNG and REC_CHNG. As expected, in general the more favorable the change, the higher the excess returns following its announcement.

FIGURE 1: Cumulative Abnormal Returns by Change in Factor



Notes to figure 1: These graphs illustrate the cumulative abnormal return from the date of the factor announcement. For the EPS Estimate and Recommendation graphs the sample is broken up into quintile portfolios by EPS_CHNG and REC_CHNG. The variable calculations for company j at time t are: EPS_CHNG$_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)] and REC_ CHNG$_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation); Statistics for the portfolios can be found on Table 2.

Table 2 summarizes the descriptive characteristics of the portfolios illustrated in Figure 1. When comparing the statistics for the quintile portfolios, one key trend stands out. In agreement with the correlation analysis results, for both EPS_CHNG and REC_CHNG, VALUE is generally smaller for more favorable quintiles. That is, growth stocks seem to make up a greater portion of the more favorable quintile portfolios. There is no clear pattern for MKTCAP.

TABLE 2: Statistics for Quintile Portfolios

	n	Change	MKTCAP	VALUE
EPS Estimate		**EPS_CHNG**		
Group 1 (least favorable)	88096	-57.32%	5468.64	0.23
Group 2	88097	-6.94%	7617.48	0.32
Group 3	88096	-1.34%	10523.15	0.19
Group 4	88097	2.47%	10448.40	0.14
Group 5 (most favorable)	88096	30.75%	8012.28	0.05
Recommendation		**REC_CHNG**		
Group 1 (least favorable)	33476	-2.17	8045.51	0.24
Group 2	42333	-1.00	10166.65	0.24
Group 3	38909	0.00	9981.54	0.19
Group 4	39436	1.00	10487.23	0.15
Group 5 (most favorable)	31798	2.18	8471.14	0.13

Notes to table 2: This table presents quintile portfolio statistics for the following variables for company j at time t: $EPS\_CHNG_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)]; $REC\_CHNG_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation); $MKTCAP_{j,t}$ = market capitalization in thousands; and $VALUE_{j,t}$ = Barra Gemm value score.

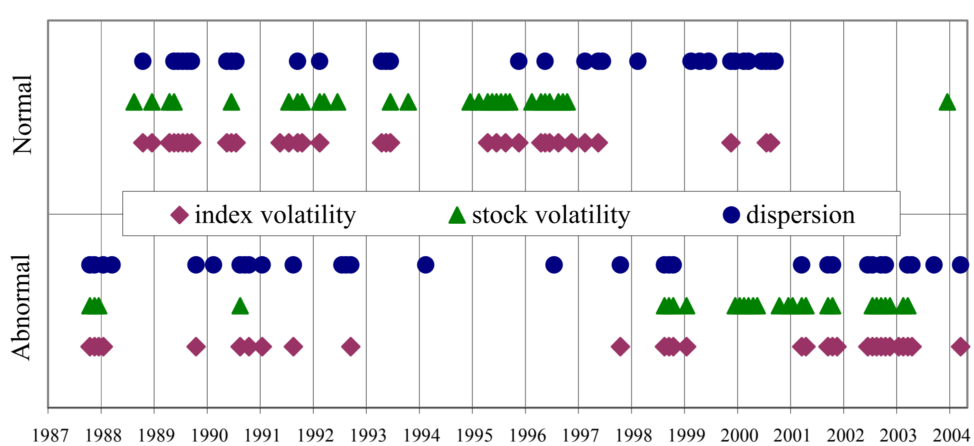
4.2. Effect of contemporaneous market factor signals

Finally, I analyze the impact of the market environment on the informativeness of analyst factors. Since previous research has shown that volatility is somewhat persistent,[10] extreme volatility sub-sample results may be useful in forecasting the accuracy of the analyst factor models. Using the market variables, IDX_VOL, STK_VOL, and DISPER, I create different sub-samples representing different market environments and run two sub-sample tests for each market factor, monthly index volatility, stock volatility, and dispersion.

The first group, low volatility or dispersion, consist of data points where IDX_VOL, STK_VOL, or DISPER is in the bottom 15% of the total sample. The second group, high volatility, consisted of data points where the IDX_VOL, STK_VOL, or DISPER is in the top 15% of the total sample. Refer to Figure 4 for time periods covered in each sub-sample group.

FIGURE 4: Clustering of Extreme Market Factors over Time

Panel A: Earnings Estimate Time Period (May 1987 – April 2004)

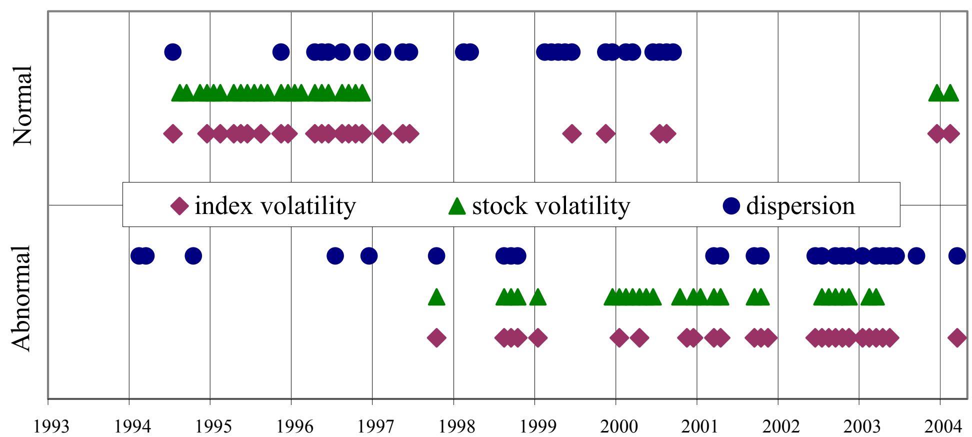


Notes to figure 4: This graph illustrates clustering of extreme market factor numbers over time where for a given month t: IDX_VOL_t = standard deviation of the daily index returns; STK_VOL_t = market capitalization weighted standard deviations of the daily stock returns; $DISPER_t$ = (STK_VOL_t – IDX_VOL_t. Abnormal market factor periods include high IDX_VOL, high STK_VOL, and low DISPER. Normal market factor periods include low

[10]See Schwert, 1989.

IDX_VOL, low STK_VOL, and high DISPER.

Panel B: Recommendation Time Period (November 1993 – April 2004)



Through simple linear regression calculations, I document market reaction to earnings estimate and recommendation revisions at the time of release. Market reaction is measured by 60-day market-adjusted returns from the announcement date. Table 5 provides results of the following regression estimation using ordinary least squares:

$$CAR(60)_{j,t} = \alpha_0 + \alpha_1 EPS\_CHNG_{j,t} + \alpha_2 REC\_CHNG_{j,t} + \alpha_3 logMKTCAP_{j,t} + \alpha_4 VALUE_{j,t} + \varepsilon_{j,t} \quad (1)$$

where the variable calculations for company j at time t are:

$CAR\ (60)_{j,t}$	market-adjusted cumulative abnormal return for 60 days;
$EPS\_CHNG_{j,t}$	percent change in the analyst's earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)]
$REC\_\ CHNG_{j,t}$	level change in the analyst's recommendation computed as (previous recommendation) – (current recommendation)
$logMKTCAP_{j,t}$	log of market capitalization
$VALUE_{j,t}$	Barra Gemm value score

The *EPS Estimate* and *Recommendation* groups in Table 3 present the results from estimating regressions for earnings estimate revisions and recommendation revisions individually. Consistent with prior research, I find that the coefficients on EPS_CHNG and REC_CHNG are both positive and statistically significant, suggesting that increases (decreases) in earnings estimates and recommendation upgrades (downgrades) are associated with positive (negative) abnormal returns. The *Both Factors* group in Table 3 presents the results from estimating regressions for earnings estimate and recommendation revisions conditional on each other. Consistent with prior research, I find that both factors are still positive and statistically significant, suggesting that each factor provides information to the market beyond what is contained in the other factor.

Moreover, when comparing results in normal periods (low index volatility, low stock volatility, and high dispersion) to those of abnormal periods (high index volatility, high stock volatility, and low dispersion), we see that the significance of both the EPS estimate and recommendation factors decrease or are non-existent. This stark difference in factor significance during abnormal sub-sample periods clearly indicates that the relationship between factor signals and abnormal returns are different depending on the market environment.

TABLE 3: Regression Analysis for Contemporaneous Market Factor Sub-Samples

	Total Sample	Low Index Volatility	High Index Volatility	Low Stock Volatility	High Stock Volatility	High Dispersion	Low Dispersion
EPS Estimate							
Intercept	-0.0071 ***	-0.0174 ***	0.0073 **	-0.0311 ***	-0.0001	-0.0057 *	0.0059
	-6.4800	*-6.2000*	*2.0300*	*-12.6000*	*-0.0300*	*-1.8400*	*1.6000*
EPS_CHNG	0.0038 ***	0.0056 ***	-0.0008	0.0049 ***	0.0008	0.0066 ***	-0.0005
	10.9400	*6.7300*	*-0.6100*	*7.3900*	*0.6200*	*6.4800*	*-0.4200*
logMKTCAP	0.0010 ***	0.0029 ***	-0.0007 *	0.0045 ***	0.0003	0.0012 ***	-0.0004
	7.5200	*8.2900*	*-1.6600*	*14.3000*	*0.7100*	*3.2300*	*-0.9200*
VALUE	-0.0005 **	-0.0080 ***	-0.0044 ***	-0.0034 ***	-0.0040 ***	-0.0036 ***	-0.0062 ***
	-2.5500	*-16.8500*	*-6.1400*	*-8.3000*	*-5.5000*	*-6.5100*	*-8.7900*
n	417,102	55,298	60,788	60,414	57,519	57,530	61,574
Adjusted R2	0.0005	0.0075	0.0006	0.0057	0.0005	0.0018	0.0012
Recommendation							
Intercept	-0.0106 ***	-0.0185 ***	0.0042	-0.0177 ***	-0.0058	-0.0099 *	0.0056
	-6.1800	*-3.9100*	*0.6200*	*-4.7900*	*-0.9800*	*-1.6700*	*0.8500*
REC_CHNG	0.0032 ***	0.0028 ***	-0.0001	0.0014 ***	0.0021 **	0.0030 ***	-0.0002
	14.4400	*5.5700*	*-0.0700*	*3.9600*	*2.2300*	*4.2600*	*-0.2200*
logMKTCAP	0.0013 ***	0.0027 ***	0.0003	0.0024 ***	0.0013 *	0.0011	0.0002
	5.9300	*4.6500*	*0.3800*	*5.1500*	*1.8000*	*1.5500*	*0.2200*
VALUE	0.0014 ***	-0.0023 ***	0.0007	-0.0019 ***	-0.0034 ***	0.0034 ***	-0.0021 *
	4.4200	*-3.0400*	*0.5100*	*-3.3300*	*-2.9300*	*3.2800*	*-1.6700*
n	177,978	18,627	18,413	26,020	24,279	18,410	18,615
Adjusted R2	0.0014	0.0034	-0.0001	0.002	0.0007	0.0014	0.0000
Both Factors							
Intercept	-0.0027	-0.0136 *	0.0127	-0.0258 ***	0.0061	-0.0264 ***	0.0189 **
	-0.9900	*-1.6500*	*1.6000*	*-3.9800*	*0.6900*	*-3.0600*	*2.1900*
EPS_CHNG	0.0023 ***	0.0037	-0.0047 *	0.0042 **	0.0002	0.0138 ***	-0.0033
	2.7700	*1.4100*	*-1.8600*	*2.2100*	*0.0700*	*4.4900*	*-1.2200*
REC_CHNG	0.0033 ***	0.0030 ***	0.0010	0.0013 **	0.0006	0.0043 ***	-0.0005
	9.9000	*3.5600*	*0.8800*	*2.0800*	*0.5300*	*4.3400*	*-0.4800*
logMKTCAP	0.0005	0.0024 **	-0.0010	0.0037 ***	0.0003	0.0033 ***	-0.0016
	1.5400	*2.3900*	*-1.0700*	*4.6000*	*0.2900*	*3.3300*	*-1.5300*
VALUE	-0.0006	-0.0078 ***	0.0005	-0.0022 **	-0.0020	0.0000	-0.0012
	-1.1400	*-5.8800*	*0.3400*	*-2.2000*	*-1.1900*	*-0.0200*	*-0.7300*
n	72,672	7,054	12,710	8,748	12,841	8,970	11,229
Adjusted R2	0.0015	0.0081	0.0001	0.0040	-0.0001	0.0057	0.0001

Notes to table 3: This table presents regression estimates using ordinary least squares: $CAR(60)_{j,t} = \alpha_0 + \alpha_1 EPS\_CHNG_{j,t} + \alpha_2 REC\_CHNG_{j,t} + \alpha_3 logMKTCAP_{j,t} + \alpha_4 VALUE_{j,t} + \varepsilon_{j,t}$. The variable calculations for company j at time t are: $EPS\_CHNG_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)]; $REC\_CHNG_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation); $logMKTCAP_{j,t}$ = log of market capitalization; $VALUE_{j,t}$ = Barra Gemm value score; and $CAR(60)_{j,t}$ = market-adjusted cumulative abnormal return for 60 days. T-statistics are listed below the coefficients. *one-tailed probability < 0.10; **one-tailed probability < 0.05; ***one-tailed probability < 0.01.

Table 4 presents 60-day cumulative abnormal returns by quintile group for the total sample and each of the sub-samples. For EPS Estimates, during low market return, low volatility, and high dispersion periods, the extreme portfolio spreads are all between 1.9% and 2.1%. In contrast, during high market return, high volatility, and low dispersion periods, the spreads are all below 0.2%. For recommendations the contrast between market periods is not as large as they are for EPS estimates. With the exception of stock volatility, however, the spreads for low volatility and high dispersion periods, are larger than for high volatility and low dispersion periods.

TABLE 4: Portfolio Spreads for Contemporaneous Market Factor Sub-Samples

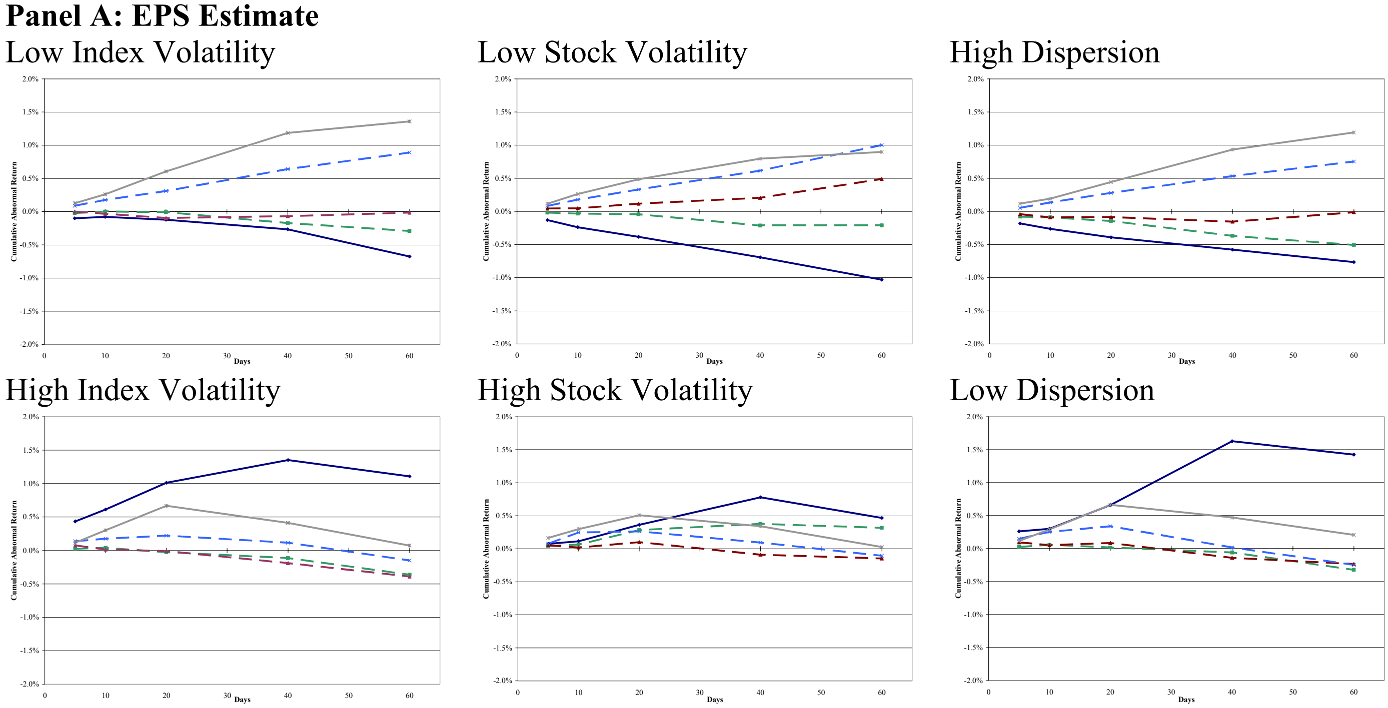
	Total Sample	Low Index Volatility	High Index Volatility	Low Stock Volatility	High Stock Volatility	High Dispersion	Low Dispersion
EPS Estimates							
P5 - P1	1.37%	2.04%	-1.03%	1.93%	-0.44%	1.96%	-1.22%
P4 - P2	0.82%	1.18%	0.21%	1.21%	-0.42%	1.26%	0.07%
P5 - P2	1.19%	1.65%	0.44%	1.11%	-0.29%	1.70%	0.53%
Recommendations							
P5 - P1	1.20%	1.17%	0.13%	0.37%	0.58%	1.93%	-0.51%
P4 - P2	1.01%	1.07%	0.24%	0.68%	0.67%	0.74%	-0.30%
P5 - P2	1.08%	1.30%	-0.01%	0.58%	0.82%	1.40%	-0.71%

Notes to table 4: This table presents the 60-day cumulative returns and spreads between the quintile portfolios for the sub-samples as shown in Figure 6. P5-P1 = the difference between excess returns of the group 5 (most favorable) and group 1 (least favorable) portfolios. P4-P2 = the difference between excess returns of the group 4 and group 2 portfolios. P5-P2 = the difference between excess returns of the group 5 (most favorable) and group 2 portfolios

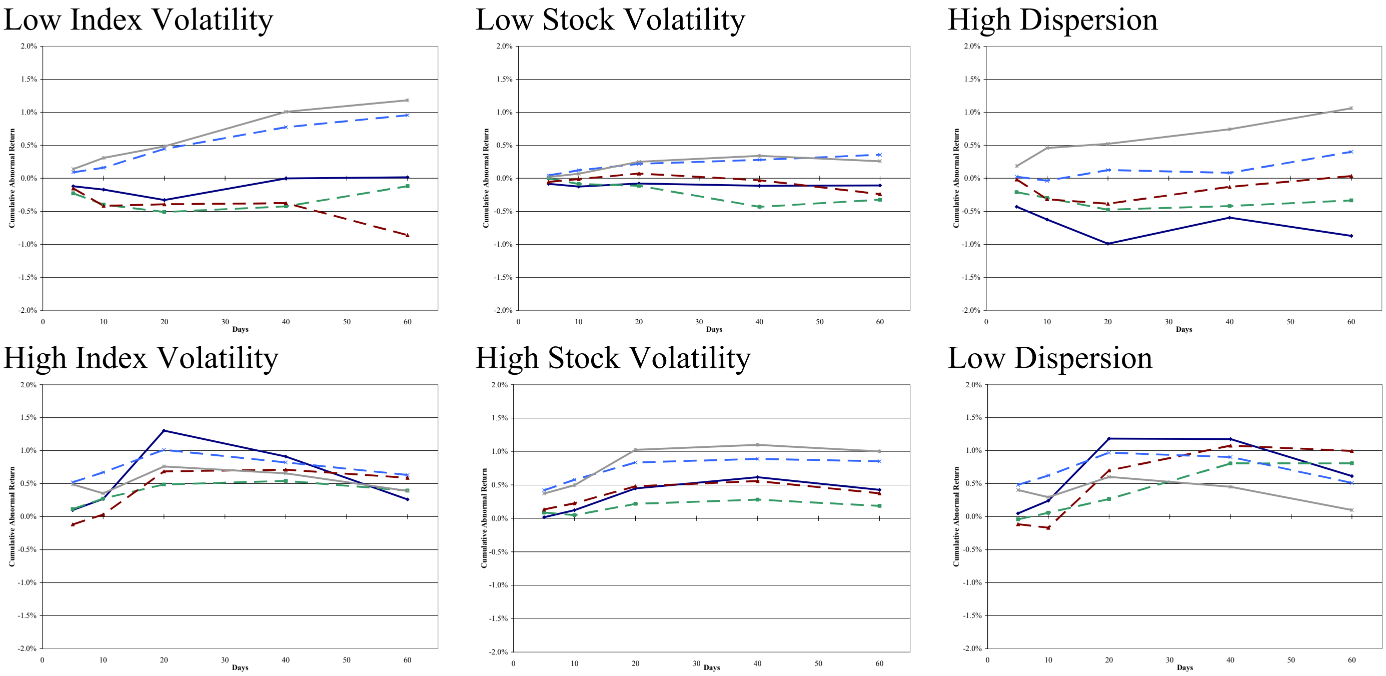
Figure 5 illustrates the cumulative abnormal returns for the sub-sample quintile portfolios. These graphs clearly show that during normal market periods (Panels A and B, top row), the quintile returns are larger for more favorable factor changes. In contrast, during abnormal market periods (Panels A and B, bottom row), the returns for the least favorable quintile, Group 1, are surprisingly not the most negative. In fact, for EPS estimates in particular, Group 1 exhibits the highest positive returns. Forecasting the market periods during which these factors are likely to reverse would likely increase portfolio returns and reduce potential losses.

FIGURE 5: Cumulative Abnormal Returns for Contemporaneous Market Factor Sub-Samples

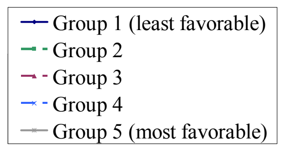
Panel A: EPS Estimate



Panel B: Recommendations



Notes to figure 5: These graphs illustrate CAR from the date of the announcement of an earnings estimate (Panel A) and recommendation (Panel B), broken up into quintile portfolios by EPS_CHNG and REC_CHNG, respectively. The variable calculations for company j at time t are: $EPS\_CHNG_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)] and $REC\_CHNG_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation).



4.3. The effects of 1-month lagged market factor signals

Volatility is fairly persistent over time.[11] As seen in Table 5, the correlations between the current month's market factors and the previous month's numbers are all highly significant. The Pearson and Spearman correlations between STK_VOL in the current and previous months are 74.44% and 80.97%, respectively. The correlations between IDX_VOL months, 46.44% and 53.69% and DISPER months, 46.72% and 42.03%, are not quite as high but are still positive and statistically significant. DISPER is negatively correlated with both IDX_VOL and STK_VOL, reinforcing the notion that generally high dispersion can be found during periods of low index and stock volatility.

[11] See Schwert, 1989.

TABLE 5: Pearson / Spearman Correlation Coefficients for Market Factors

	Pearson Correlation					
Spearman Correlation	**IDX_VOL(t)**	**SKT_VOL(t)**	**DISPER(t)**	**IDX_VOL(t-1)**	**SKT_VOL(t-1)**	**DISPER(t-1)**
IDX_VOL(t)		81.55% ***	-65.53% ***	46.44% ***	46.83% ***	-23.21% ***
		<.0001	*<.0001*	*<.0001*	*<.0001*	*0.0009*
STK_VOL(t)	79.06% ***		-24.08% ***	49.43% ***	74.44% ***	-4.39%
	<.0001		*0.0005*	*<.0001*	*<.0001*	*0.5337*
DISPER(t)	-82.79% ***	-36.07% ***		-31.18% ***	-8.54%	46.72% ***
	<.0001	*<.0001*		*<.0001*	*0.2256*	*<.0001*
IDX_VOL(t-1)	53.69% ***	54.48% ***	-34.27% ***			
	<.0001	*<.0001*	*<.0001*			
STK_VOL(t-1)	56.41% ***	80.97% ***	-15.24% **			
	<.0001	*<.0001*	*0.03*			
DISPER(t-1)	-33.51% ***	-13.85% **	42.03% ***			
	<.0001	*0.0487*	*<.0001*			

Notes to table 5: This table presents the Pearson (upper triangle) and Spearman (lower triangle) correlations for the following variables for month t: IDX_VOL_t = standard deviation of the daily index returns; STK_VOL_t = equal weighted standard deviations of the daily stock returns; $DISPER_t = (STK\_VOL_t – IDX\_VOL_t) / IDX\_VOL_t$. P-values are listed below the correlation numbers. *one-tailed probability < 0.10; **one-tailed probability < 0.05; ***one-tailed probability < 0.01.

In this section, I examine the effect of using the previous month's market factor signals to determine my sub-sample groups and find similar results as those obtained using contemporaneous market factor signals. Testing sub-samples based on the previous month's market signal determines if investors can increase the effectiveness of analyst factors by altering strategies based on the most recent market environment. Table 6 replicates the regressions shown in Table 3, by using sub-sample groups based on 1-month lagged market factor numbers rather than contemporaneous numbers. Consistent with the contemporaneous results, the coefficients on EPS_CHNG and REC_CHNG are both individually positive and statistically significant. When both factors are considered together, EPS_CHNG is only slightly significant in low index and low stock volatility periods.

TABLE 6: Regression Analysis for 1-Month Lagged Market Factor Sub-Samples

	Total Sample	Low Index Volatility	High Index Volatility	Low Stock Volatility	High Stock Volatility	High Dispersion	Low Dispersion
EPS Estimate							
Intercept	-0.0071 ***	-0.0317 ***	-0.0059 *	-0.0334 ***	0.0144 ***	-0.0079 ***	0.0040
	-6.4800	*-12.2300*	*-1.8800*	*-13.5800*	*4.1100*	*-2.6300*	*1.1900*
EPS_CHNG	0.0038 ***	0.0037 ***	-0.0018 *	0.0047 ***	-0.0019	0.0034 ***	0.0023 **
	10.9400	*4.4900*	*-1.6900*	*6.9100*	*-1.5300*	*3.3100*	*2.0400*
logMKTCAP	0.0010 ***	0.0045 ***	0.0008 **	0.0046 ***	-0.0018 ***	0.0013 ***	-0.0003
	7.5200	*13.9000*	*2.1500*	*14.7100*	*-4.2600*	*3.4900*	*-0.7900*
VALUE	-0.0005 **	-0.0037 ***	-0.0007	-0.0013 ***	-0.0027 ***	-0.0008	-0.0028 ***
	-2.5500	*-8.3000*	*-1.2100*	*-3.3000*	*-3.9500*	*-1.4200*	*-4.2800*
n	417,102	60,951	60,995	60,364	57,625	57,452	63,985
Adjusted R2	0.0005	0.0051	0.0001	0.0048	0.0005	0.0004	0.0003
Recommendation							
Intercept	-0.0106 ***	-0.0434 ***	0.0119	-0.0303 ***	0.0248 ***	-0.0307 ***	-0.0030
	-6.1800	*-10.5900*	*1.5200*	*-8.0800*	*3.2000*	*-3.3600*	*-0.5900*
REC_CHNG	0.0032 ***	0.0017 ***	0.0031 ***	0.0014 ***	0.0022 **	0.0036 ***	0.0039 ***
	14.4400	*3.8400*	*2.7700*	*3.7500*	*2.0400*	*3.3200*	*5.2300*
logMKTCAP	0.0013 ***	0.0057 ***	-0.0009	0.0040 ***	-0.0023 ***	0.0041 ***	0.0003
	5.9300	*11.2000*	*-0.9800*	*8.4900*	*-2.5900*	*3.8600*	*0.4900*
VALUE	0.0014 ***	0.0006	-0.0006	0.0010 *	-0.0048 ***	0.0015	-0.0013
	4.4200	*0.9400*	*-0.3800*	*1.6700*	*-3.2400*	*0.9500*	*-1.3100*
n	177,978	25,219	11,915	25,461	13,610	8,497	24,718
Adjusted R2	0.0014	0.0054	0.0005	0.0033	0.0012	0.0027	0.0011
Both Factors							
Intercept	-0.0027	-0.0687 ***	0.0132 *	-0.0212 ***	0.0240 ***	-0.0312 ***	0.0130 *
	-0.9900	*-9.2200*	*1.6600*	*-3.5100*	*3.0600*	*-3.4100*	*1.7400*
EPS_CHNG	0.0023 ***	-0.0047 *	0.0029	-0.0041 **	-0.0020	-0.0022	0.0027
	2.7700	*-1.9100*	*1.1600*	*-2.5300*	*-0.7700*	*-0.6400*	*1.1100*
REC_CHNG	0.0033 ***	0.0030 ***	0.0030 ***	0.0024 ***	0.0023 **	0.0036 ***	0.0031 ***
	9.9000	*3.9000*	*2.6800*	*4.1800*	*2.0900*	*3.3400*	*3.1000*
logMKTCAP	0.0005	0.0089 ***	-0.0010	0.0032 ***	-0.0023 **	0.0041 ***	-0.0013
	1.5400	*10.0400*	*-1.0900*	*4.3500*	*-2.5000*	*3.9000*	*-1.5300*
VALUE	-0.0006	-0.0033 ***	-0.0006	0.0004	-0.0048 ***	0.0016	-0.0004
	-1.1400	*-2.5900*	*-0.4200*	*0.4200*	*-3.2100*	*0.9800*	*-0.3200*
n	72,672	8,066	11,915	9,684	13,610	8,497	11,887
Adjusted R2	0.0015	0.0161	0.0005	0.0038	0.0011	0.0026	0.0008

Notes to table 6: This table presents regression estimates using ordinary least squares: $CAR(60)_{j,t} = \alpha_0 + \alpha_1 EPS\_CHNG_{j,t} + \alpha_2 REC\_CHNG_{j,t} + \alpha_3 logMKTCAP_{j,t} + \alpha_4 VALUE_{j,t} + \varepsilon_{j,t}$. The variable calculations for company j at time t are: $EPS\_CHNG_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)]; $REC\_CHNG_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation); $logMKTCAP_{j,t}$ = log of market capitalization; $VALUE_{j,t}$ = Barra Gemm value score; and $CAR(60)_{j,t}$ = market-adjusted cumulative abnormal return for 60 days. T-statistics are listed below the coefficients. *one-tailed probability < 0.10; **one-tailed probability < 0.05; ***one-tailed probability < 0.01.

Table 7 replicates portfolio spread calculations shown in Table 4. During low volatility and high dispersion periods, the extreme portfolio spreads for EPS estimates are between 1% and 2%. In contrast, during high volatility and low dispersion periods, the spreads very low or negative. The contrast between market periods is not as significant for recommendations. In fact, 60-day spreads during low volatility and high dispersion periods, are slightly smaller than for high volatility and low dispersion periods.

TABLE 7: Portfolio Spreads for 1-Month Lagged Market Factor Sub-Samples

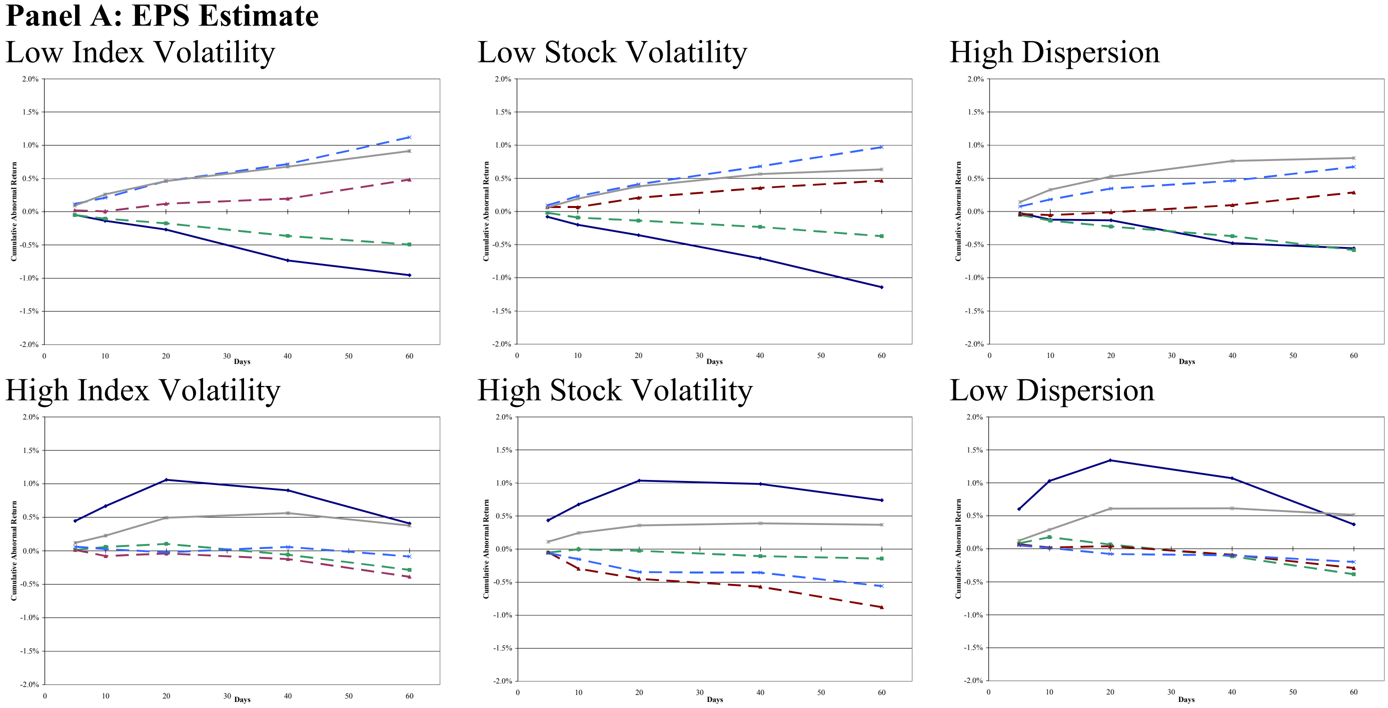
	Total Sample	Low Index Volatility	High Index Volatility	Low Stock Volatility	High Stock Volatility	High Dispersion	Low Dispersion
EPS Estimates							
P5 - P1	1.37%	1.87%	-0.03%	1.78%	-0.37%	1.36%	0.14%
P4 - P2	0.82%	1.61%	0.20%	1.34%	-0.42%	1.25%	0.19%
P5 - P2	1.19%	1.41%	0.66%	1.01%	0.51%	1.39%	0.90%
Recommendations							
P5 - P1	1.20%	0.75%	1.38%	0.64%	0.71%	1.06%	1.47%
P4 - P2	1.01%	0.46%	1.46%	0.42%	1.15%	0.80%	1.38%
P5 - P2	1.08%	0.25%	1.30%	0.31%	1.04%	0.97%	1.16%

Notes to table 7: This table presents the 60-day cumulative returns and spreads between the quintile portfolios for the sub-samples as shown in Figure 7. P5-P1 = the difference between excess returns of the group 5 (most favorable) and group 1 (least favorable) portfolios. P4-P2 = the difference between excess returns of the group 4 and group 2 portfolios. P5-P2 = the difference between excess returns of the group 5 (most favorable) and group 2 portfolios

Figure 6 replicates Figure 5, illustrating the cumulative abnormal returns for the sub-sample quintile portfolios. During normal market periods (Panels A and B, top row), the quintile returns all as expected. In contrast, during abnormal market periods (Panels A and B, bottom row), the returns for the least favorable quintile, Group 1, remain the high and positive following EPS estimate signals (Panel A). Returns for Group 1 are also positive in the shorter term for recommendations (Panel B) but seem to ultimately underperform in the longer term. These results clearly illustrate that modifying analyst factor models based on the current market environment increases potential returns.

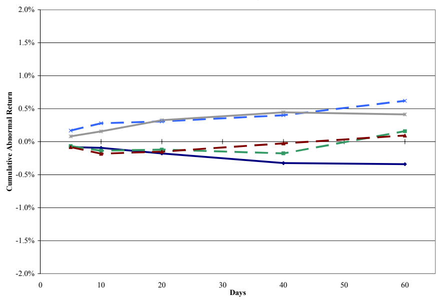
FIGURE 6: Cumulative Abnormal Returns for 1-Month Lagged Market Factor Sub-Samples

Panel A: EPS Estimate

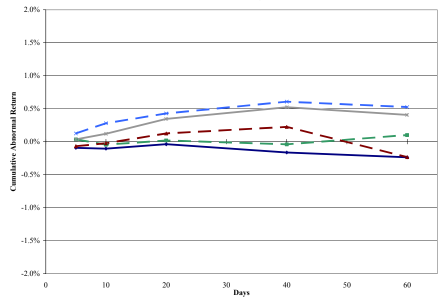


Panel B: Recommendations

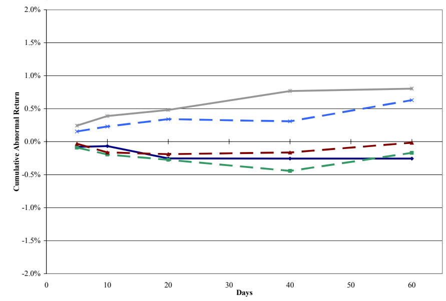
Low Index Volatility



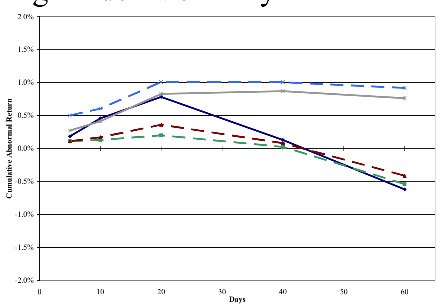
Low Stock Volatility



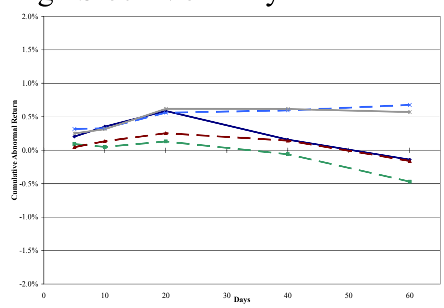
High Dispersion



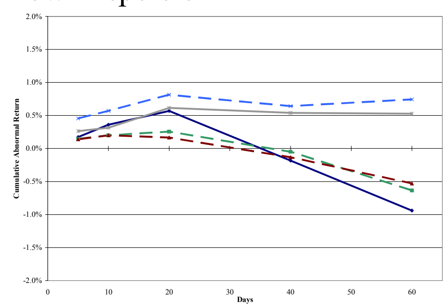
High Index Volatility

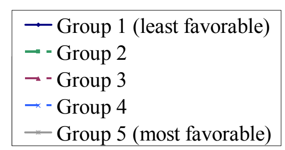


High Stock Volatility



Low Dispersion





Notes to figure 6: These graphs illustrate CAR from the date of the announcement of an earnings estimate (Panel A) and recommendation (Panel B), broken up into quintile portfolios by EPS_CHNG and REC_CHNG, respectively. The variable calculations for company j at time t are: $EPS\_CHNG_{j,t}$ = percent change in earnings estimate computed as [(earnings estimate at time t – earnings estimate at time t-1) / (absolute value of earnings estimate at time t-1)] and $REC\_CHNG_{j,t}$ = level change in recommendation computed as (previous recommendation) – (current recommendation).

5. Conclusion

This paper examines the reaction of the market to analyst earnings estimate and recommendation changes. Using a database constructed from analyst data over the period May 1987 through April 2004, I extend prior work by incorporating the period following the passage of Reg FD and the stock bubble burst in the U.S. and find that earnings estimate and recommendation revisions in Europe are significantly and positively associated with the market's reaction at the time an analyst's estimate and recommendation are announced.

Using the calculated market variables, I run sub-sample tests by current and 1-month lagged monthly market variables – volatility and dispersion. I find that the excess returns associated with analyst factors differ depending on the market environment.

EPS estimates exhibited the greatest difference in spreads depending on market environment. In general, during normal market periods, characterized by low market index volatility, low stock volatility, and high dispersion, the earnings estimate signal works as expected. That is, the higher the change in the earnings estimates, the larger the associated excess returns and spreads between the most favorable and least favorable quintiles. In contrast, during abnormal market periods, characterized by high market index volatility, high stock volatility, and low dispersion, the quintile spreads are relatively low and, at times, negative.

Recommendation returns also seem to trend differently depending on market environment. In the shorter term the spreads between the most favorable and least favorable quintiles during normal market periods are higher than that of abnormal periods. In the longer term the differences depending on market environment is not as pronounced.

Both factors consistently exhibit larger quintile spreads during low dispersion periods as opposed to high dispersion periods. High dispersion periods likely yield stronger results due to the fact that if stock volatility and market volatility are similar, thus leading to low dispersion, there is less room for analysts to add value and for investors to make money. These results suggest that altering models based on the current market environment increases potential returns and allows for maximum capitalization of earnings estimate and recommendation factors.

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