Information Ambiguity and Investor Over and Under Reactions

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Abstract

A common finding in the literature is that returns are characterised by reversals or trends exhibiting predictable behaviour. A popular explanation for this is that investors systematically over or under react to information, depending on the circumstances. Although researchers have identified behavioural factors that theoretically may lead to such behaviour, the empirical literature has not identified which (if any) of these factors actually operate in the marketplace. In a recent study Epstein and Schneider (2006), suggest a theoretical model that predicts over and under reaction based on the premise that investors are ambiguity averse. We test their hypothesis using analyst earnings forecasts and controlling for other factors for the US market. Our results confirm the predictions of the model and suggest that over and under reaction *can* become systematic amongst investors, and contribute to the documented market anomalies.

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Keywords: Information Ambiguity, Overreaction, Underreaction

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[b] We thank Kenneth French for making the company size breakpoints available on his website.

1. Introduction.

Neoclassical theories assume that investors act as Bayesians with respect to new information. This implies that prices will be unpredictable (Samuelson 1965, Fama 1970). However, a common finding in the literature is that past returns predict future ones. For example, De Bondt and Thaler (1985) document that over long horizons past losers outperform past winners, while Jegadeesh and Titman (1993) show that for shorter horizons the opposite holds. A popular explanation for these patterns is that investors sometimes overreact and sometimes underreact to new information, causing prices to, respectively, revert and trend. Such explanations require that this (mis)behaviour is systematic, and that limitations on arbitrage allow mispricings to persist (Delong at al 1990, Shleifer and Vishny, 1997).

The question of whether investor over- and under-reactions is systematic has been the source of much controversy. On the theoretical level researchers have produced models that generate both over and under reactions, based on factors identified by psychologists to be relevant (Barberis et al. 1998, Daniel et al 1998 and Odean 1998). If price predictability is driven by systematic over and under reaction as these models suggest, empirical tests should be able to identify the circumstances that lead investors to over or under use information. Until these circumstances are unmasked, the acceptance of the behavioural models is debatable.

The empirical evidence, however, is inconclusive. A large number of studies present evidence that is consistent with either over or under reaction (De Bondt and Thaler 1985, 1987, Lakonishok, Shleifer and Vishny 1994, Chan, Jegadeesh and Lakonishok 1996, Zhang 2006). However, these studies make no predictions in terms of the conditions that may cause investors to either over or under react. On this note, Fama (1998) suggests that *overreaction is as likely as underreaction* and under no circumstances do these behaviours become systematic and influence asset prices. This argument highlights that the application of behavioural theories crucially depends on empirically identifying the conditions, if any, that trigger systematic waves of under and over reactions.

A study that explicitly addresses this issue is Chan, Kothari, and Frankel (2004). They suggest that the behavioural biases of conservatism (Edwards 1968) and representativness (Kahneman and Tversky 1974) can generate over and under reactions, and seek to identify information signals that investors may (mis)treat according to these biases. Particularly they use measures of past company performance, such as sales growth, and examine whether investors exhibit systematic over and under reactions. At large their results do not suggest that investors misperceive the information signals they construct, as they find evidence mildly consistent with underraction[1]. However, the authors state that it can be the case that over and under reaction occur systematically under different circumstances, which their design did not capture. This calls for further research in terms of identifying conditions, if any, that can lead to investors systematically over or under reacting.

An innovative paper that provides evidence of both return reversals and continuations is Chan (2003). He uses a sample in which he distinguishes stocks 'with news' (any news in the media) and 'no news'. He scrutinizes the data to many different tests and concludes that the 'with news' stocks experience drifts and the 'no news' stocks, which have experienced large price swings, undergone return reversals. This paper is a breakthrough because the author produces these opposite return patterns in the same data set, which suggests that these behaviours may not be random, as suggested by Fama (1998). However, it makes no predictions of the conditions that drive over or under reaction. Therefore, an open question remains in terms of identifying the factors that may drive investors to systematically over or under react.

In a recent study Epstein and Schneider (2006), henceforth ES, construct a model that arrives at certain predictions, in terms of when to expect over or under reaction. This is an important contribution because, as highlighted, the literature is far from a consensus on whether over and under reaction is systematic. This model is based on the well known finding that people are ambiguity averse[2]. Ellsberg (1961) was the first to make this observation but since then this finding has been vastly replicated and is considered amongst psychologists to be fairly robust, (Keren and Gerritsen 1999).

In ES investors, who have recursive multiple priors utility functions (Epstein and Schneider 2003a), asses ambiguous positive and negative

[1] The drifts they report are sensitive to earnings announcements.

[2] An ambiguous situation is one where the decision maker does not have knowledge of the probability distributions that are associated with his decision. On the contrary, neoclassical theories assume that investors have knowledge of these distributions, thus make decisions in a framework of risk

information signals. Ambiguity in this set up is taken to imply that the signals have a range of possible qualities, i.e. they can be very informative or no informative at all. Being ambiguity averse investors' asses these signals by taking that their quality is the lowest implied from the set of possible 'qualities'. When the signal is negative the worst case quality is that the signal is very reliable. This leads to an overreaction towards it, as it is taken as extremely informative. On the contrary, when the signal is positive the worst case is that it is very unreliable. This leads to an underreaction as investors excessively discount it. The factors, therefore, that ES identify as drivers of systematic over and under reaction are the nature of the information signal (i.e. positive or negative) and its ambiguity.

The purpose of our paper is to empirically examine this prediction of the model. In this respect our study provides evidence on the applicability of this theory in the marketplace, as well as complements the studies of Chan et al (2004) and Kadiyala and Rau (2004) by addressing the issue raised by Fama (1998) that over and under reaction are random amongst investors and do not contribute to the documented return reversals and continuations.

In order to test the predictions of ES we require an information signal that we can identify both its nature and ambiguity. Since clear-cut indicators of these dimensions do not exist we must rely on reasonable proxies to test the predictions of the model. We suggest that analysts' earnings forecasts can be classified according to ambiguity and nature, therefore allow a reasonable test of the theory. Particularly, we use the direction of the forecast revision (i.e. downward or upward) as indicative of its nature and the magnitude of the forecast revision (vis-à-vis the analysts previous estimate) and the size of the company for which the revision is targeted as proxies for ambiguity. Section 3 explains in detail the rationale for using analyst forecast revisions and motivates the use of these proxies.

Our results confirm the predictions of ES. We show that returns after large 'surprise' downward revisions (top quintile in the distribution) exhibit significant reversals (overreaction) equal to about 30% of impact period returns. A mirror image is observed for upward forecasts, i.e. we observe significant continuations (underreaction) for large 'surprise' forecast revisions. In addition the results show that these patterns occur exclusively amongst smaller companies.

This study contributes to two lines of research. Firstly, our results complement previous attempts to identify the conditions that trigger over or under reaction, (Chan, Frankel and Kothari 2004 and Kadiyala and Rau 2004), by showing that the factors identified in a theoretical context by Epstein and Schneider (2006) are relevant. This result addresses the argument expressed by Fama (1998) by suggesting that under conditions of ambiguity over and under reaction types of behaviour have the capacity to become systematic amongst investors, and therefore may contribute to the documented price reversals and continuations. Secondly, our results have a practical dimension as well. Since analyst earnings forecasts, as noted by Dreman, (1998 p.90) "*are the major trigger for investment decisions today*", our results can be useful to investors because the point to asymmetries in post-revision returns according to revision magnitude, direction and company size.

Section 2 provides a more formal description of the ES model. Section 3 discusses how we test the prediction of the model, section 4 describes the data and the methodology, section 5 presents the results and section 6 concludes.

2. A formal description of the Epstein and Schneider (2006) model.

Assume a representative agent who sets prices[3]. This agent is interested in an objective variable, θ. He has a unique and unambiguous prior over θ, defined as $\theta \sim N(m, \sigma_\theta^2)$. This agent then receives an ambiguous information signal which

[3] The equations here appear in the ES model. The purpose of section 2 is not to be innovative but to highlight its intuition to the reader (while the subsections link our work with that of ES).

yields some new information about θ defined as $S = \theta + \varepsilon$, where $\varepsilon \sim N(0, \sigma_s^2)$, $\sigma_s^2 \in [\sigma_{s,min}^2, \sigma_{s,max}^2]$. Because the signal is ambiguous its true variance (precision) is unknown. Therefore the agent forms a family of possible variances that reflect that the signal may be very reliable ($\sigma_{s,min}^2$) or totally unreliable ($\sigma_{s,max}^2$). The agent updates in a Bayesian fashion for each different variance in the set $\sigma_s^2 \in [\sigma_{s,min}^2, \sigma_{s,max}^2]$, which results to a family of posterior distributions for the parameter θ, as shown below:

$$\theta \sim N\left(m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2}(s - m), \frac{\sigma_s^2 \sigma_\theta^2}{\sigma_s^2 + \sigma_\theta^2}\right), \qquad \sigma_s^2 \in [\sigma_{s,min}^2, \sigma_{s,max}^2]$$

Being averse to ambiguity the agent, who has a recursive multiple priors type of utility function, maximizes expected utility under the worst case belief from the above set of θ posteriors. In other words the agent maximises expected utility using as an expectation that posterior distribution that entails the lowest value of θ. This is where the asymmetric response to good and bad information derives. To illustrate, suppose that in equation 1 $s = m$. This is the case where s does not offer any new information about θ and therefore does not cause an update to expectations (or market prices). This shows that the extent to which expectations are updated depends on distance between s and m, and hence on the magnitude of m. For example, if the signal is good, $s > m$, the worst case scenario (i.e. that which entails a lower mean θ) is when $\sigma_s^2 = \sigma_{s,max}^2$. This implies that the investor believes that the good signal is unreliable. However, the actual realization of θ will on average be higher that the investor's expectation; therefore the investor systematically underreacts towards ambiguous good information. Conversely, after bad information ($s < m$) the worst case scenario is that the information signal is totally reliable, therefore expected utility is maximised under $\sigma_s^2 = \sigma_{s,min}^2$. In this case the actual realization of θ is not as bad, therefore on average the investor overreacts towards ambiguous bad information. In both cases therefore the expectation of the investor is the posterior that implies *the lowest θ value.*

3. *Empirically testing the predictions of the model*

The information signal we use to test the predictions of the ES model is revisions to analysts' earnings forecasts. The rationale for this choice is three-fold. Firstly by using analyst forecasts we have a large cross section *of the same* information signal in which ambiguity varies. Therefore, holding everything else constant, we can compare signals that differ in ambiguity and test whether and how it affects investor behaviour and asset prices. If different information signals are used (see for example Kadiyala and Rau 2004 and Chan 2003) we run the risk of capturing the effects of different factors, which makes the identification of conditions that cause systematic investor (mis)behaviour more difficult.

The main advantage of analyst earnings forecasts is that we can reasonably proxy both nature and ambiguity. In terms of the former, upward revisions can be perceived as positive news whereas downward revisions as negative news. This clear distinction is valuable because it suggests that investors homogenously classify the forecast revision as being good or bad. This, we suggest, is an improvement over previous studies which propose measures that can be interpreted in different ways by different investors. For example, Kadiyala and Rau (2004) suggest that cash financed acquisitions are good news. This depends on each particular case, i.e. what type of acquisition the company undertakes, the status of the target company etc. and is therefore to an extend subjective. Using analyst forecasts revisions allows a clear distinction between positive and negative news, which can be reasonably expected to apply to the majority of market participants. Secondly, we can characterize the ambiguity of the analyst earnings forecasts. We suggest that ambiguity with respect to analyst forecast revisions relates to at least two sources; the first is associated to the severity of the case-specific information that led the analyst to issue an earnings forecast revision. For example, revisions throughout the quarter serve two purposes; they bring new information to markets and reflect corrections to previous forecasts[4]. Small revisions probably reflect a mixture of minor information and a correction to previous forecasts. They are therefore based on the same, or marginally different, set of company fundamentals. For such revisions we argue that ambiguity, in terms of the future performance of the company and hence the forecast revision, is small. However, large revisions indicate the occurrence of important events that are likely to reflect structural breaks in the earnings capacities of companies. For example Ofer and Siegel (1987) provide evidence that analysts revise their forecasts by an amount proportional to the companies' unexpected dividend changes and Michaely et al (1995) show that such changes are strongly related to companies' fundamentals. Similarly, Krishnaswami and Subramaniam (1999) show that analyst forecast dispersion rises around spin-offs. Brous (1992) shows that analysts' revise their forecasts significantly in the presence of common stock offerings. If large revisions reflect the occurrence of such important news it can be argued that they signal a significant change to the company's fundamentals. This causes ambiguity to rise because the firm's future stream of earnings becomes more difficult to predict. Based on this rationale we suggest that since the surprise caused by the revisions indicates on the severity of the information that led to its issuance, it also relates to its ambiguity.

The second dimension of ambiguity is more general and it is related to the characteristics of the company. Zhang (2006) proposes that company size relates to the general uncertainty (ambiguity) that surrounds a company[5]. The intuition is that large companies attract a large number of media coverage (through both newsletters and analyst reports). Therefore there exists greater transparency in terms of the operations and future potential. However, smaller companies have a smaller amount of information disclosed; therefore to some degree their future potential is more ambiguous. Based on the observation of Zhang (2006) we use company size as the second measure of ambiguity. We suggest that forecast

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[4] Hong and Kubik 2003) highlight that analysts have the incentive to be accurate. Chan, Jegadeesh and Lakonishok (1996) find that as the quarter comes to a close analysts issue small revisions that aim to correct their previous forecasts.

[5] Zhang (2006) proposes a number of proxies apart from firm size but his results suggest that the size is the strongest predictor of ambiguity. In unreported results we used firm age, another variable proposed by Zhang, and the results are identical. These results are available on request.

‘surprise’ and company size relate to ambiguity in an orthogonal manner. The ambiguity that relates to the ‘surprise’ caused by the revision relates to the severity of the information that the analyst is disclosing. Therefore it is case-specific. However, company size captures a more general type of ambiguity. Using these measures in conjunction will result to a better characterization of ambiguity. However, we do not just rely on intuition when we use forecast ‘surprise’ and company size as our proxies for ambiguity. ES state that the ambiguity of information signals is related to the volatility of the objective parameter, in this case earnings. If the volatility of earnings is higher when large revisions are warranted (due to perhaps the occurrence of severe news) or when the forecasts are targeted towards smaller companies, we expect analysts to be less accurate. In other words if our intuition that revisions of larger ‘surprise’ and those targeted towards smaller companies are more ambiguous is correct, forecast errors should display a positive relationship with forecast surprise and negative with firm size. Our results strongly confirm this intuition and therefore support the claim that revision ‘surprise’ and company size are positively related to ambiguity.

3.1 The effects of prior information.

In the way we have proposed so far to test the model, we determine whether the nature of the signal is good or bad using *only* the analysts own prior forecast. For example in the above model m, which the prior expectation of the investor, is taken to equal the analysts previous forecast. In this way when the analyst issues a new forecast, s, we determine whether it is good ($s > m$) or bad ($s < m$) by calculating the difference between the two.

However, this approach can be though to be quite simplistic in an empirical sense. Investors’ prior expectation over the objective variable θ, m, probably depend on other information, besides the analysts prior earnings forecast, such as any performance indicators of the company or the market that deemed relevant. For example, suppose that the market, according to some indicator, is in a ‘good’ state and the investor believes that such good states are likely to generate higher θ's[6]. Given this belief the investor's prior expectation about θ, m, will be defined over both the analyst's prior forecast and the fact that the market is in a good state. Therefore, if an upward forecast arrives in a good state, its associated m will be *higher* when compared to the m that only takes into account the fact that the forecast is upward. In the ES equation presented in part 2, the higher m, ceteris paribus, implies a *smaller* update to expectations and prices (because $s - m$ diminishes). This analysis predicts that the update to expectations is greater when the news that arrive (i.e. upward or downward forecasts) *contradict the prior* expectations of investors. For example, if the investor using other information believes that the company is in good condition, the prior expectation, m, will be higher. Therefore, an upward forecast (good news) will have a smaller effect on the update of θ, and to market prices when compares to a case where we just assume that m equals the analyst's prior forecast. In other words 'good' news in 'bad' times cause a greater update to expectations than 'good' news in 'good' times (same applies for bad news in good times and bad news in bad times).

The second effect of prior information is that it causes a change on the posterior distribution of θ and therefore the predicted over and under reactions. For example suppose that good news arrive when the company is in a bad state. The m in this case will be lower when compared to the m that only considers the analysts prior forecast. The lower m implies, ceteris paribus, a lower posterior for θ therefore *greater* underreaction when good news arrives in 'bad' times. However, when bad news arrives in states where the company's performance is already bad, m will be lower when compared to the m that only takes into account the analysts prior forecast. This will have the effect of lowering the posterior mean θ and thus *increase* the overall overreaction.

3.2. Hypothesis development.

Based on the predictions of ES model we expect that:

[6] This is only an assumption. It could be the case that if the investor holds 'contrarian' expectations he may believe that companies which have performed poorly in the past are likely to over-perform in the future. Which scenario dominates depends on whether the average investor holds 'momentum' or 'contrarian' expectations.

H1: Greater overreaction towards highly ambiguous downward forecasts and greater under reaction towards highly ambiguous upward forecasts.

From the analysis in section 3.2 we expect that:

H2: Greater overreaction when highly ambiguous downward forecasts arrive in 'bad' times and greater under reaction when highly ambiguous upward forecasts in 'bad' times.

4. Methodology and data

In order to test the predictions of ES we use the following ratio to proxy the 'surprise' that each forecast revision entails:

$$S_{ijt} = \frac{F_{ijt} - F_{ijt-q}}{P_{jt-2}} \qquad 1.$$

The 'surprise' of a particular forecast revision, $S_{ijt,}$, is equal to the difference between the latest and penultimate forecast issued by analyst i for company j at time t, F_{ijt} - F_{ijt-q}, scaled by the stock price of company j two days prior to the recent forecast. A larger numerator implies that the new forecast suggests something very different to what the analyst had thought before, therefore potentially brings a substantial amount of new information in the market. The denominator is a standardising variable. Previous research, Gleason and Lee (2003), Stickel (1991) and Imhoff and Lobo (1984), has indicated that this measure is a good proxy of revision surprise. Company size is defined as the market capitalization of the company at the end of month $t-1$, where t is month that the forecast was issued[7].

The first part of the paper examines whether these variables are related to ambiguity. We believe that this relationship, if it exists, will leave its footprint

[7] In unreported results we have performed the analysis using company age (another variable proposed by Zhang (2006) as a proxy for ambiguity and the results are identical. These results are available on request.

on the behaviour of forecast errors[8]. Since forecast errors are related to the complexity of the forecasting task our intuition is that forecasts of larger 'surprise' and for smaller companies will entail larger forecast errors. In order to test this we first split the sample in quintiles based on 'surprise' and company size[9]. For forecast 'surprise', in order to avoid the problem of non-stationary distributions[10], we derive quintile breakpoints as follows: At the end of each month, *t-1*, in the sample all revisions are ranked into quintiles according to surprise. Using these breakpoints the study assigns all revisions of month *t*, i.e. the next month, into quintiles for this particular variable. For example all revision issued in January 1993 are separated into quintiles based on forecast 'surprise'. Then all revision issued in February 1993 are classified into quintiles based on the January breakpoints. The assumption here is that the structure of 'surprise' does not change significantly in the space of one month and a high (low) value in January will continue to be high (low) in February. After this is done we compare the mean absolute forecast error in the different 'surprise' and company size quintiles. If our intuition is correct absolute error should be increasing in 'surprise' and company size and the difference between the high / low quintiles should be statistically significant.

The second part of the paper tests the predictions of ES. We do this by forming equally weighted portfolios of different ambiguity (as proxied by revision 'surprise' and company size) and performing a two-stage event study, which aims to highlight whether people overreact to ambiguous bad information and underreact to ambiguous good information. Returns are risk adjusted using the modified market model, as in Fuller 2002.[11] The two stage event study is as follows: The 21 trading day period after the revision is divided into two sub-periods. The period from trading day -1 to 5, where date 0 is the date that the

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[8] Following Paudyal, Kapstaff and Rees (1995) we define mean absolute forecast error, as: $\left|\frac{\text{Forecast} - \text{Actual}}{\text{Actual}}\right|$.

[9] We thank Professor Kenneth French for making the size breakpoints available on his website.

[10] In separate analysis (not reported) we have calculated the means of 'surprise', and age in the sample for time periods 1990-1994 and 2000-2005. The means are statistically different, which suggests that the distributions are not stationary.

[11] We have also used the Brown and Warner 1985 methodology and the results are unchanged. The reason we choose these models is that, as noted by Cambell, Lo and Mackinlay (1997), such statistical models suffice when one seeks to investigate the effect of an event on asset prices.

forecast is issued[12], is called the *impact period* and measures how expectations and prices are updated in the light of analyst forecasts revisions. The second period, from trading day 6 to 20, is called the *adjustment period* and shows how prices adjust to the initial impact[13]. An efficient response requires that returns in the adjustment period are insignificant as the information content of the revision was fully and correctly incorporated in the asset price during the impact period. However, if returns continue on the same direction we can argue that the initial impact was insufficient and it takes longer for the revision to be reflected in the asset price. On the contrary if returns revert we can argue that the initial impact was excessive. These pricing patterns are consistent with the behavioural phenomena of over and under reaction in response to the analyst forecast.

We are keenly aware that out impact period is larger than conventional event studies. The reason we choose such a long period is to allow the market to absorb the information. In our framework a short window may lead to conclusions about inefficient responses where in fact the finding may be related to other factors such as market frictions, i.e. liquidity.

Our methodology has been chosen for two reasons. Firstly, Kothari and Warner (1997) and Barber and Lyon (1997) find that the statistical reliability of long-run firm specific event studies is debatable. In addition, the frequency of other earnings related information, such as forecasts by other analysts and earnings announcements is so large that it is hard to disentangle the extend to which long run returns relate to one particular forecast. A second reason for choosing a short window methodology is that previous studies have shown that in a highly liquid and deep market such as the U.S, a period of one month is sufficient for mispricings to be identified and eliminated. For example Barber and Loeffler (1993) and Liang (1999) conduct a short window event study (about one month as we do) in which they examine the price behaviour of the stocks that were included in the Dart board column of the *Wall Street Journal*. Both papers conclude that the initial impact reverses in less that one month. Therefore, it is reasonable to expect that if a mispricing occurs around publicly

[12] For date 0 the study uses the variable estdats in the IBES detail files.

[13] The study reports that it has experimented with an impact period of -2,+2 and an adjustment period of 3, 20 and the results are identical.

disclosed information, such as analyst earnings forecasts, it will not take a long time for the market to rectify it.

The second hypothesis involves testing for the effects of forecast revisions which arrive in 'good' or 'bad' states. Identifying these states is subjective. We have implemented the analysis using two different proxies that reasonably relate to the nature of the environment in which companies operate. Firstly, following Conrad, et al (2002) we use the markets de-trended P/E[14] ratio as an indicator of overall 'good' or 'bad' times. The authors state that when the ratio is high the market is experiencing a period of 'boom' which triggers a feeling of optimism amongst investors. On the contrary, when the ratio is low, the market is in a recessionary period and investors are pessimistic[15]. In unreported results we have used the company's 6-month market adjusted cumulative return ending in month t-1 where t is the revision month as a proxy for good and bad times. The rationale is that companies with a positive price run-up are experiencing 'good' times whereas companies with a negative price run-up 'bad' times. The results found are identical and are available on request[16].

In order to de-trend the P/E ratio we employ the methodology of Conrad et al (2002) where from each month's P/E we subtract the average market P/E of the preceding 12 months. The top (bottom) 30% of this time series constitutes the good (bad) times. To control for variables that according to previous research influence post-revision returns, univariate analysis is complemented by multivariate regressions. More specifically, following Clement and Tse (2003) we control for forecast horizon, the analysts' lag accuracy, the days that mediate between forecasts and broker size. The multivariate regression is of the form:

$$\begin{aligned} CAR_{ijt} &= \alpha_0 + \beta_1 \textbf{abs. surprise} + \beta_2 \ln size + \beta_3 market\ P/E \\ &+ \beta_4 lag\ error + \beta_5 time\ horizon + \beta_6 broker\ size + \beta_7 days\ elapsed + u_{ijt} \end{aligned} \qquad 2.$$

[14] The market P/E ratio is available from Datastream, code TOTMKUS datatype P/E.

[16] We have also used the companies P/E and B/M ratios but the results indicate that the market does not consider these indicators when reacting to analyst forecasts. This result is consistent with previous evidence, such as Gleason and Lee (2003).

The dependent variable, CAR, is the market adjusted abnormal return for company j at time t after the forecast revision issued by analyst i. We run the model twice, having as the dependent variable firstly the impact period returns and secondly the adjustment period returns in order to perform a joint test of how returns in the cross section are related to the variables examined. In order to avoid the problem of heteroscedasticity the study reports t-statistics calculated using the Generalised Method of Moments (GMM).

Data on quarterly[17] U.S analyst forecast revisions and actual earnings[18] are from the IBES detail files. The sample period spans from January 1990 to December 2005[19]. Prices, returns and shares outstanding data are from CRSP, while a number of filters are applied to the sample, leaving us with 300,080 earnings forecast revisions[20].

Panel A of table one presents descriptive statistics of the variables used. In general the means are different from the medians indicating that the distributions are skewed. The average revision, as a percentage of the previous forecast, is -2.19%, which means that on average revisions are small and downward. The average forecast error in the sample is -0.079 which suggests that analysts on average under predict by a small amount. In terms of company size we observe that the mean size decile rank (using end of previous month breakpoints) for the firms in the sample is 6.6, which indicates that the sample is slightly tilted towards large companies. This is a common finding when IBES data are used because large companies have larger analyst coverage. However the sample does include small firms as 25% percent are below a decile rank of 4. The book to market and momentum mean values reveal that the sample is tilted

[17] Kothari (2001) states that, due to timeliness, quarterly data are better measures of market expectations.
[18] Livnat and Mendenhall (2006) report that the earnings reported by IBES reflect better the EPS that the market observed when the announcement took place.
[19] The choice of 1990 as the breakpoint is based on Clement and Tse (2003) and related to the inaccuracy of the issuance date in the IBES files of forecasts made prior to 1990.
[20] A company must have data from both CRSP and IBES. If the estimation date (variable estdats) is after the announcement date the observation is deleted. Following Capstaff, Paudyal and Rees (1995) all revisions which entail an error in excess of 100% of the actual earnings are deleted. Also the revisions which imply a 100% or more change to the forecasted EPS in comparison to the previous forecast by the same analyst for the same company and quarter/year are deleted. The authors state that these observations are likely to be erroneous. Consistent with other studies, Clement and Tse (2003), Clement (1999), O'Brien (1990) only the last forecast issued by each analyst-firm pair for each quarter is retained.

towards growth and high momentum stocks, as analysts usually prefer to follow such stocks which are more likely to generate reactions from investors.

Panel B presents the distribution of company size in each ‘surprise’ quintile. We observe that most of the revisions are for larger companies, which reflects that the sample is mostly comprised of larger stocks. However, we have a large number of large revisions for small companies, therefore the tests we propose have power. Panel C of table 1 represents Pearson’s (above) and Spearman (below) correlation coefficients for the variables used. The first observation is that revisions surprise and company size are positively and negatively related to absolute forecast error. This provides an early indication that our intuition that these variables relate to ambiguity is correct.

Please insert Table 1 about here

5. Results.

5.1. Forecast error analysis.

In this first part of the paper we examine the relationship between absolute forecast error and forecast surprise and company size. If our intuition is confirmed that these attributes are related to ambiguity, they should have explanatory power over the forecast error. Table 2 presents a two way classification of forecast errors. Firstly we assign forecasts in quintiles based on surprise and on size. Each surprise quintile is then subdivided into 5 size groups according to the initial classification. Panel A includes upward forecasts and panel B downward forecasts. The results support our intuition. Particularly, forecasts errors within particular ‘surprise’ quintiles decrease with company size. This suggests that analysts are less accurate when predicting the earnings of smaller companies, which gives support to the notion that company size relates to ambiguity. In addition, within particular size quintiles, we observe that larger ‘surprise’ revisions also entail larger absolute forecast errors. This indicates that holding size constant, the size of the revision relates to the difficulty of the forecasting task and supports our intuition that larger forecasts are ceteris paribus more ambiguous. Overall, as the differentials are all significant in the 1% level, the variables we propose capture significant variation in absolute error therefore are informative in terms of the difficulty of the forecasting task. Table 2, also shows the standard deviation (the bracketed term) of each surprise / size combination as well as an F-statistic that shows whether the standard deviation of the low / high groups is statistically different. What is evident is that in most cases the higher ambiguity groups (i.e. smaller company or larger surprise) entail statistically (significant at the 1% level of confidence) larger standard deviations. This suggests that the variables proposed affect both the first and second moment of the forecast error distribution. This provides further support that they are positively related to ambiguity.

Please insert Table 2 about here

4.2. Impact and adjustment period returns by forecast surprise and company size.

Table 3 presents market adjusted abnormal returns for equally weighted portfolios formed according to forecast 'surprise' and company size quintiles for the impact (trading days -1, 5) and the adjustment (trading days 6, 20) periods. Panel A (B) presents returns after upward (downward) forecasts. The left side of the table groups revisions according to 'surprise' and the right according to company size. The first result observed, which relates to impact period returns, is that larger surprise revisions and those targeted for smaller companies trigger larger initial market reactions. The former is an intuitive conclusion and it is consistent with the ES model. Larger revisions cause a larger discrepancy between s and m in the equation in section 2 and therefore trigger a larger initial update to the objective parameter. The latter is consistent with Stickel (1992) and highlights that investors rely less on analysts to value large companies. This reflects that large companies are more transparent and allow access to good quality information, i.e. accounting reports, profit history etc. The fact that forecasts for smaller companies entail a much larger response shows that the market does not have much information about them and relies heavily on analysts to form an opinion.

In order to test the validity of the predictions of the ES model we turn towards the behaviour of adjustment period returns. Particularly, we expect that investors underreact to ambiguous positive information and overreact to ambiguous negative information. Our analysis in table 2 has shown that larger surprise forecasts and forecasts targeted for smaller companies are more ambiguous; therefore we expect that greater continuations (reversals) will occur after larger 'surprise' upward (downward) forecasts and after forecasts issued for smaller companies. Adjustment period returns confirm this prediction. For upward forecasts, we observe that the continuations increase in forecast surprise and that the differential between the high low surprise portfolios is of significant economic and statistical magnitude. Same results are derived when company size is used as proxy for ambiguity, i.e. smaller companies are associated with much larger continuations. A mirror image is produced when we consider downward forecasts. Particularly we observe that larger surprise downward revisions and revisions targeted towards smaller companies entail statistically and economically larger reversals. The results however suggest that company size, in the sense of ES, is a better proxy for ambiguity as the differentials of adjustment period returns between small / large companies are significantly greater than those between low / high surprise portfolios (1% difference). In addition the large company size quintile, does not exhibit significant continuations or reversals. This again highlights that ambiguity for large companies is small if not non-existent. On the contrary the results show that ambiguity is maximal for small companies, where future potential is much more subjective.

Please insert Table 3 about here

Table 4 presents a two-way classification of the adjustment period abnormal returns by surprise and company size. Table 2 has shown that absolute errors are larger (and more volatile) when both forecast surprise is large and company size small. Based on this finding we expect that reversals and continuations will be the largest in the high surprise quintiles and small company subgroups. Table 4 confirms this intuition. Firstly the differentials, between small and large surprise portfolios (for given size quintiles) are in most cases significant in the direction predicted by the ES model, i.e. larger surprise revisions cause greater continuations (upward forecasts) and reversals (downward). The same is observed when we compare, for given surprise quintiles, post-forecast returns for small and large companies, i.e. larger continuations / reversals when the companies are smaller. The largest continuations / reversals are observed in the high surprise / small company portfolio, where as shown by table 2, both the mean and standard deviation of the forecast errors are the largest. These results confirm the predictions of the ES model because they show that where ambiguity is the largest, investors over and under react to greater extend. However, in the large company quintiles (4 and 5) the differentials between low / high surprise revisions are insignificant. This provides support to the claim that large companies are not ambiguous in the sense of ES. This result is consistent with Zhang (2006) and shows that the bulk of continuations / reversals occur amongst small / medium size companies.

Please insert Table 4 about here

4.3. Impact and adjustment period returns by forecast surprise, company size and market P/E ratio.

In section 2.2 of the paper we suggested that prior information affects the definition of m and therefore can affect both the initial response of the market as well as the over and under reactions. Particularly, in terms of the former, we suggest that upward forecasts (good news) that arrive when the company is in a bad state will have a greater effect than if the company is in a good state. Similarly, downward forecasts (bad news) that arrive in good states will trigger a larger response than bad news in bad states.

Prior information also affect the value of the posterior θ. Recall that the ES predictions are based on the notion that the investor takes action by having as an expectation the posterior of θ with the lowest value. If, therefore, good news arrive in bad states all posteriors of θ *will be* lowered. This will trigger large underreaction. On the contrary when good news arrive in good states, the posteriors of θ increase, which reduces overreaction. Similarly, when bad news arrive in bad times, posterior values of θ decrease because m is defined over a larger information set and therefore is lower when compared to the m that just reflects the analysts prior forecast. This induces larger overreaction in comparison to bad news in good times (where m, and therefore θ are higher).For a more detailed discussion of these predictions refer to section 2.2.

Table 5 shows the results when we classify good and bad times, using the de-trended market P/E ratio proposed by Conrad et al (2002). Low values of this ratio reflect 'bad' times and high values 'good' times. Panel A presents market adjusted abnormal returns for impact and adjustment period using forecast surprise as the proxy for ambiguity and panel B using company size. The first striking result is that the market responds differently to otherwise identical surprise and company size analyst forecasts, depending on the overall P/E ratio of the market. For upward forecasts, as predicted, the market reacts more strongly when the P/E ratio is *low*. This is shown by both Panels A and B and captures the fact that prior of the market of earnings, m, are not only defined over the analysts previous forecast but over a larger information set.

Surprisingly, for downward forecasts we observe a much less consistent picture. In panel A the results show that the market reacts more strongly to downward forecasts issued in good periods, as predicted. In addition in Panel B for large companies the market reacts more strongly to forecasts issued in bad times. However, results change when we consider large surprise revisions (quintiles 4 and 5) and forecasts issued for small companies (quintiles 1 and 2). Particularly the market responds more strongly to large surprise downward forecasts issued in bad times and downward forecasts issued for small companies. This result is at odds with our prediction and provides an interesting account of how ambiguity interacts with bad and good information. When the forecast is upward the market always reacts more strongly when the P/E ratio is low, regardless of ambiguity. However, for downward forecasts the results show that for high ambiguity forecasts (large surprise and small companies) the market reacts more strongly when the P/E ratio is low whereas for low ambiguity (small revision and large companies) when it is high. This reflects that when ambiguous bad news arrives in bad environments, investors become overly pessimistic and act more strongly.

In terms of adjustment period returns, our predictions are that bad news in bad times will trigger larger overreaction that bad news in good times and that good news in bad times larger underreaction that good news in good times.

In terms of upward revisions the results show that the bulk of continuations shows in table 3 occur for 'bad' time portfolios. In panel A, surprise quintiles 4 and 5, which experience the continuations, show that bad times adjustment period returns significantly exceed good times (1.37% and 0.82% compared to 0.32% and 0.39% respectively). Panel B confirms this result as continuations for small companies are much stronger for bad times portfolios. These results confirm our prediction that continuations will be larger when good news arrives in bad times. In terms of downward forecasts, the pattern is much more consistent. In Panel A the results show that reversals for the high surprise portfolios are solely concentrated in 'bad' times portfolios. Same results are shown in panel B, i.e. the reversals that follow revisions for small / medium companies occur in 'bad' times' portfolios. These results confirm our predictions that bad news in bad times spur greater overreaction.

Two things stand out from the analysis of adjustment period returns. Firstly, large companies do not appear to involve any ambiguity. They do not entail continuations or reversals as predicted by the ES model, which suggests that the market responds relatively efficiently towards them. This finding is consistent with existing evidence that large stocks display less predictability (Hong and Stein 2000, Zhang 2005, De Bondt and Thaler 1985). On the other hand given the ambiguous nature of small firms and the findings that a) they are preferred by the 'behaviourally' prone individual investors (Reinganum 1983, Barber and Odean 2000 Odean 1999, Malmendier and Shanthikumar 2007) and b) that they involve higher arbitrage costs, (D'Avolio 2002), the mispricings observed are not so surprising.

The second point that stands out from the analysis of adjustment period returns is that the reversals documented relate to the way investors use the P/E ratio information when they receive downward forecasts. Impact period returns show that for downward forecasts, the influence of the market P/E ratio is conditional on ambiguity. For low ambiguity signals (large company / small surprise) the market reacts more strongly to forecasts issued in 'good' times. On the contrary, for high ambiguity portfolios the market responds more strongly when times are bad. The adjustment period returns show that this change of attitude is suboptimal as the high ambiguity portfolios experience significant reversals. We suggest that this result is consistent with our predictions and the ES model, that bad news in bad times spur greater overreaction.

Table 6 presents the results in a multivariate setting where impact and adjustment period returns are regressed on 'forecast surprise', company size, market P/E and a number of control variables that previous research finds to influence post-revision returns, (Clement and Tse 2003). Panels A and B (C and D) present impact and adjustment period returns for downward (upward) forecasts. To address the problems of heteroscedasticity and autocorrelation the t-statistics are derived using GMM. Overall, the results are consistent with the univariate analysis. Impact period returns for upward forecasts decrease with company size and P/E ratio. A very interesting finding is that forecast surprise, when all factors are considered jointly, is insignificant, suggesting that markets when assessing upward forecasts do not consider surprises to carry substantive information. A different picture emerges for downward forecasts, where forecast surprise is highly significant and negatively related to returns. In addition, returns increase (i.e. less impact) with company size. The P/E ratio is not significant, however this is not surprising when we consider that it is used in a different manner for high and low ambiguity forecasts. For adjustment period returns upward forecasts (Panel D) the P/E ratio is not significant. Ideally it should have been negative and significant, because we predicted higher under reaction in low P/E ratio times. Company size is negatively related to adjustment period returns. In addition, forecast 'surprise' is also highly significant and positively related top adjustment period returns. These loadings suggest that upward revisions of large surprise and those targeted for smaller companies involve larger return continuations, supporting the predictions of ES that greater ambiguity triggers larger underreaction. Turning attention to downward forecasts (panel C), adjustment period returns are negatively related to company size and market P/E ratio and positively to forecast surprise. This translates to greater overreaction to high ambiguity forecasts (large surprise and small companies) as predicted by the model of ES. The negative relationship between the P/E ratio and adjustment period returns confirm our prediction that overreaction is higher in 'bad' times.

Please insert Tables 5 and 6 about here

6. Conclusion

The literature identifies that returns exhibit positive correlation over time horizons of 1 month to 1 year and negative correlation in 3-5 year time periods. Various explanations have been put forward including that investors systematically over and underreact to information. On the theoretical level researchers have identified various conditions that may cause investors to over or under react, (Barberis et al 1998, Daniel et al 1998). However the empirical evidence is mixed. Fama (1998) reviews the literature on return predictability and suggests that over reaction is as likely as underreaction. Therefore he suggests that the phenomena of return drifts and reversals are due to other reasons, other than behavioural. This tension in the literature is the focus of this study. Our objective is to implement an empirical test of a theoretical model by ES which predicts that investors underreact to ambiguous good information and overreact to ambiguous bad information.

We have used analyst earnings forecasts to test the predictions of the model, because by doing so we can reasonably proxy the factors that ES as drivers of over and under reaction, namely information nature (i.e. good or bad) and ambiguity. In terms of the former the partition is straight forward because upward forecasts are good news and downward forecasts bad news. For ambiguity we use two proxies. The first is the surprise caused by the revision. Information that requires large revisions indicates a shock to the operations of the company. Therefore, it signals a change in the fundamentals which make the revision more ambiguous. The second proxy is company size. Smaller companies are less transparent and more difficult to value. This makes them more ambiguous. In the first part of the paper we demonstrate that large surprise forecasts and forecasts targeted for smaller companies are less accurate, which confirms the use of these variables as proxies for ambiguity.

Our results confirm the predictions of the ES model. Particularly we observe greater continuations for large surprise revisions and revisions targeted towards and small size companies. A mirror image is produced when we consider downward forecasts, i.e. larger reversals for large surprise revisions and revisions targeted for small companies. These results demonstrate that, as ES predict, over and under reaction have the capacity to become systematic amongst investors and therefore may contribute to the arousal of return reversals and continuations. In addition the results suggest that these patterns are mainly confined in 'bad' market periods, as captured by the market P/E ratio. This suggests that in periods of negative sentiment investors take bad news even more seriously and discount good news even more heavily.

A long standing debate is whether over and under reaction types of behaviour are systematic enough to affect asset prices. Fama (1998) suggests that such behaviours are randomly distributed and on average prices are set rationally. The empirical evidence thus far has not conclusively challenged this view. This is a drawback of behavioural explanations, because ultimately empirical tests refute or validate theories. Our paper addresses this issue and provides evidence that in certain measurable conditions such behaviours are systematic and influence asset prices. These results suggest that price predictability may be partly driven by behaviour inconsistent with expected utility. Such findings are important because they demonstrate that 'alternative' theories play a role in financial markets and help piece together the puzzle of price formation. Future research can identify in what other situations information ambiguity plays a role as well as attempt to unveil other factors that may trigger systematic over and under reaction.

References.

Barber B., Loffler D., 1993, "The 'dartboard' column: second-hand information and price pressure", *Journal of Financial and Quantitative Analysis*, 28, 273-284.

Barber B., Lyon J., 1997, "Detecting long-run abnormal stock returns: The empirical power and specification of test statistics", *Journal of Financial Economics,* 43, 341-372.

Barber B., Odean T., 2000, "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors", *Journal of Finance* 55, 773–806.

Barberis N., Shleifer A., Vishny R., 1998, "A model of investor sentiment", *Journal of Financial Economics*, 49, 307-343.

Barberis N., Thaler R., 2002, "A Survey of Behavioural Finance", in the Handbook of the Economics and Finance, edited by G.M. Constantinides, M. Harris and R. Stultz.

Brous, P. A., 1992, "Common Stock Offerings and Earnings Expectations: A Test of the Release of Unfavorable Information", *Journal of Finance,* 47, 1517-36.

Brown S., Warner J., 1985, "Using daily stock returns: The case of event studies", *Journal of Financial Economics*, 14, 3-31.

Capstaff J., Paudyal K., Rees W., 1995, "The accuracy and rationality of earnings forecasts by UK analysts, *Journal of Business, Finance and Accounting*, 22, 67-85.

Chan W.S., 2003, "Stock price reaction to news and no-news: drift and reversal after headlines", *Journal of Financial Economics*, 70, 223-260.

Chan, W., Kothari, S., Frankel, R., 2004, "Testing Behavioural Finance Theories Using Trends and Consistency in Financial Performance", *Journal of Accounting and Economics* 38, 3-50.

Clement M., Tse S., 2003, "Do investors respond to analysts' forecast revisions as if accuracy is all that matters?", *The Accounting Review*, 78, 227-249.

Clement M., 1999, "analyst forecast accuracy: Do ability, resources and portfolio complexity matter?", *Journal of Accounting and Economics*, 27, 285-303.

Conrad J., Cornell B., landsman W., 2002, "When is bad news really bad news?", *Journal of Finance*, 57, 2507-2532.

Daniel K., Hirshleifer D., Subrahmanyam A., 1998, "Investor psychology and security market under-and overreactions", *Journal of Finance*, 53, 1839-1885.

DeBondt W., Thaler R., 1985, "Does the Stock Market overreact?", *Journal of Finance*, 40, 793-808.

De Long B., Shleifer A., Summers L., Waldmann R., 1990, "Noise trader risk in financial markets", Journal of Political Economy, 98, 703-738.

Dreman D., 1998, "Contrarian Investment Strategies: The Next Generation", Simon & Schuster, New York.

Ellsberg D., 1961, "Risk, Ambiguity and the Savage Axioms", *Quarterly Journal of Economics*, 75, 643-669.

Epstein L., Scheider M., 2003, "Recursive Multiple Priors", Journal of Economic Theory, 113, 1-31 .

Epstein L., Schneider M., "Ambiguity, information quality and asset pricing," *forthcoming in Journal of Finance.*

Fama Eugene, 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance.*

Fama E., 1998, "Market efficiency, long-term returns and Behavioural Finance", *Journal of Financial Economics*, 49, 283-306.

Fuller K., Netter J., Stegemoller M., 2002, "What Do Returns to Acquiring Firms Tell Us? Evidence from Firms That Make Many Acquisitions", *Journal of Finance* 57, 1763–1793.

Gleason C., Lee C., 2003, "Analyst forecast revisions and market price discovery", *The Accounting Review*, 78, 1, 193-225.

Hong H., Lim N.,Stein J.,2000, "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies", *The Journal of Finance,* 55, 265–295.

Hsu M., Bhatt M., Adolphs R., Tranel D., Camerer C., 2005, "Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making, *Science,* 310, 1680-1683.

Imhoff E., Lobo G., 1984, "Information content of analysts' composite forecast revisions", *Journal of Accounting Research*, 22, 541-554.

Jegadeesh N., Titman S., 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency", Journal of Finance, 48, 65-91.

Kadiyala P., Rau R., 2004, "Investors reaction to corporate events announcements: Underreaction or Overreaction?" *Journal of Business*, 77, 357-386.

Keren G., Gerritsen L., 1999, "On the robustness and possible accounts of ambiguity aversion", *Acta Psychologica*, 103, 149-172.

Kothari S.P., Warner J., 1997, "Measuring long-horizon security price performance", *Journal of Financial Economics, 43,* 301-339.

Kothari, S., 2001, Capital Markets Research in Accounting, *Journal of Accounting & Economics* 31, 105-231.

Krishnaswami S., Subramaniam V., 1999, "Information asymmetry, valuation, and the corporate spin-off decision2, *Journal of Financial Economics*, 53, 73-112.

Liang B., 1999, "Price Pressure: Evidence from the Dart-Board column", *Journal of Business*, 72, 119-134.

Livnat J., Mendenhall R., 2006, "Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts", *Journal of Accounting Research*, 44, 177-205.

Malmendier U., Shanthikumar D., 2007, "Are small investors naive about incentives?", *Journal of Financial Economics, 85,* 457-489.

Michaely R., Thaler R., Womack K., 1995, "Price reactions to dividend initiations and omissions: Overreaction or Drift?", Journal of Finance, 50, 573-608.

O'Brien P., 1990, "Forecast accuracy of individual analysts in nine industries", *Journal of Accounting Research*, 28, 286-304.

Ofer A., Siegel D., 1987, Corporate Financial Policy, Information, and Market Expectations: An Empirical Investigation of Dividends", *Journal of Finance*, 42, 889-911.

Reinganum, Marc R., "The anomalous stock market behaviour of small firms in January: Empirical tests for tax-loss selling effects", *Journal of Financial Economics*, 12, 89-104.

Samuelson Paul, 1965, "Properly anticipated prices fluctuate randomly", *Industrial Management Review.*

Shleifer A., Vishny R., 1997, "The Limits of Arbitrage", *Journal of Finance*, 52, 35-55.

Stickel S., 1991, "Common stock returns surrounding earnings forecasts revisions: More puzzling evidence", *The Accounting Review*, 66, 402- 416.

Stickel S., 1992, "Reputation and performance among security analysts", *Journal of Finance*, 47, 1811-1836.

Sorescu S., Subrahmanyam A., "The cross section of analyst recommendations", *Journal of Financial and Quantitative Analysis*, 41, 1, 139-168.

Zhang F., 2006, "Information Uncertainty and Stock Returns, *Journal of Finance*, 55, 105-136.

Table 1: Descriptive statistics. Panel A presents the general characteristics of the sample. Panel B presents the number of revisions in each surprise and size combination. Panel C presents correlation coefficients of the variables used. Surprise is defined as New forecast by analyst i for firm j and quarter t minus the previous forecast by the same analyst for the same company and quarter scaled by the stock price of company j two days prior to the forecast. Surprise quintiles are derived by sorting all revisions in the sample by surprise for each month t-1. The breakpoints from these distributions are then used to assign revisions in month t into surprise quintiles. Company size is the market capitalization of company j at the end of month t-1 where t is the month that an analyst forecast is issued. The size quintile breakpoints are from Kenneth French's website. Momentum is the 6 month market adjusted cumulative return for company j from month t-6 to month t-1 where t is the month that analyst i issues a forecast for company j. In order to derive breakpoints for momentum all NYSE stocks were each month t-1 sorted into deciles based on their market adjusted cumulative return from months t-6 to t-1. These breakpoints where then used to classify the stocks of the sample in month t into momentum deciles. The winners group corresponds to the top 30 % of this distribution, the neutral to the middle 40% and the losers to the bottom 30%.

Panel A: General Sample characteristics

Variable	Units of measurement	Mean	Q1	Median	Q3
Surprise	(New forecast- old forecast)/price	0.0025	0.0004	0.001	0.0025
Size	Size decile rank at time of forecast	6.6	4	7	9
Forecast error	(Forecast- actual EPS)/ actual EPS	-0.079	-0.095	-0.023	0.028
Percentage revisions	[(New forec.-Old forec.)/Old forec.] *100	-2.19%	-10.40%	-1.90%	5.80%
Momentum	6 month market adjusted CAR	0.04	-0.11	0.03	0.19
Book to market	book value / market value	0.41	0.18	0.32	0.51

Panel B: Two-way classification according to revisions surprise and company size

		Surprise quintile				
R = 0 = 5,291		1	2	3	4	5
	Mean Surprise	0.0003	0.0007	0.0014	0.0028	0.0105
	Size quintile					
Rev < 0 = 210,131	1	854	2730	3840	5160	8762
	2	3,296	5,463	6,121	7,330	8,172
	3	5754	7012	7484	8192	7822
	4	10389	10557	10308	9592	8113
	5	23240	16285	13652	11168	8835
	Total	43533	42047	41405	41442	41704
	Mean Surprise	0.0002	0.0004	0.0007	0.0015	0.0063
	Size quintile					
Rev > 0 = 164,668	1	325	1530	2583	3462	5932
	2	1603	4083	4851	5502	5864
	3	3527	5792	6090	6380	5879
	4	6425	8951	8810	8306	7208
	5	16887	14284	12151	10216	8027
	Total	28767	34640	34485	33866	32910

Panel C: Pearson (above) and Spearman (below) correlation coefficients

	Error	Surprise	Size	Horizon	Momentum
Absolute error	1	0.0582	-0.0517	0.2227	0.0418
		<0.0001	<0.0001	<0.0001	<0.0001
Surprise	0.1722	1	-0.0496	-0.0157	-0.1385
	<0.0001		<0.0001	<0.0001	<0.0001
Company size	-0.1473	-0.3094	1	-0.0131	0.023
	<0.0001	<0.0001		<0.0001	<0.0001
Momentum	0.0411	-0.155	0.0831	0.0281	1
	<0.0001	<0.0001	<0.0001	<0.0001	

Table 2. Absolute Forecast error analysis by revision direction, surprise and company size. Surprise is defined as New forecast by analyst i for firm j and quarter t minus the previous forecast by the same analyst for the same company and quarter scaled by the stock price of company j two days prior to the forecast. Surprise quintiles are derived by sorting all revisions in the sample by surprise for each month t-1. The breakpoints from these distributions are then used to assign revisions in month t into surprise quintiles. Company size is the market capitalization of company j at the end of month t-1 where t is the month that an analyst forecast is issued. The size quintile breakpoints are from Kenneth French's website. The bracketed term is the standard deviation of the absolute forecast error in each size/surprise group. The table provides a t-statistic which is adjusted for the equality of variances. A folded F –statistic is provided, testing whether the variances for the two subgroups are equal.

Panel A: Two-way sort of Upward revisions forecast error by forecast 'surprise' and company size

	Low	Revision surprise			High					
Company Size	1	2	3	4	5	Dif (Low-High)	t- stat	Prob t	F-stat	Prob F
1(small)	0.144***	0.138***	0.150***	0.192***	0.243***	**-0.099*****	**-8.46**	<0.0001	1.35	0.0004
	[0.203]	[0.177]	[0.175]	[0.204]	[0.236]					
2	0.155***	0.133***	0.154***	0.174***	0.202***	**-0.0471*****	**-7.76**	< 0.0001	1.03	0.5343
	[0.213]	[0.181]	[0.192]	[0.202]	[0.215]					
3	0.149***	0.123***	0.142***	0.155***	0.178***	**-0.0284*****	**-6.2**	< 0.0001	1.27	< 0.0001
	[0.224]	[0.176]	[0.191]	[0.192]	[0.198]					
4	0.140***	0.126***	0.138***	0.147***	0.183***	**-0.0432*****	**-11.62**	< 0.0001	1.21	< 0.0001
	[0.225]	[0.188]	[0.194]	[0.189]	[0.205]					
5 (Big)	0.126***	0.121***	0.130***	0.137***	0.165***	**-0.0385*****	**-13.57**	< 0.0001	1.29	< 0.0001
	[0.227]	[0.204]	[0.106]	[0.187]	[0.200]					
Dif (Small-Big)	**0.017**	**0.016*****	**0.02*****	**0.055*****	**0.077*****					
t- stat	**1.52**	**3.47**	**5.15**	**14**	**20.46**					
Probt	0.1297	0.0005	<0.0001	<0.0001	<0.0001					
F-stat	1.25	1.33	1.27	1.18	1.4					
Prob F	0.0075	<0.0001	<0.0001	<0.0001	<0.0001					

Panel B:Two-way sort of Downward revisions forecast errors by forecast 'surprise' and company size

	Low	Revision surprise			High					
Company Size	1	2	3	4	5	Dif (Low-High)	t- stat	Prob t	F-stat	Prob F
1(small)	0.135***	0.146***	0.176***	0.195***	0.221***	**-0.0851*****	**-12.29**	<0.0001	1.42	< 0.0001
	[0.189]	[0.182]	[0.200]	[0.212]	[0.225]					
2	0.124***	0.135***	0.154***	0.166***	0.187***	**-0.0625*****	**-15.81**	< 0.0001	1.33	< 0.0001
	[0.183]	[0.179]	[0.190]	[0.198]	[0.211]					
3	0.116***	0.128***	0.139***	0.155***	0.157***	**-0.0403*****	**-12.68**	< 0.0001	1.21	< 0.0001
	[0.175]	[0.175]	[0.181]	[0.190]	[0.192]					
4	0.108***	0.110***	0.130***	0.152***	0.163***	**-0.0548*****	**-19.6**	< 0.0001	1.27	< 0.0001
	[0.176]	[0.160]	[0.175]	[0.188]	[0.198]					
5 (Big)	0.092***	0.104***	0.120***	0.135***	0.138***	**-0.0453*****	**-19.96**	< 0.0001	1.12	< 0.0001
	[0.174]	[0.158]	[0.167]	[0.175]	[0.184]					
Dif (Small-Big)	**0.043*****	**0.041*****	**0.055*****	**0.060*****	**0.082*****					
t- stat	**6.56**	**11.29**	**15.63**	**17.84**	**26.65**					
Probt	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001					
F-stat	1.18	1.33	1.44	1.46	1.5					
Prob F	0.0005	< 0.0001	< 0.0001	< 0.0001	< 0.0001					

*,**,*** denote statistical significance at the 10, 5 and 1 % confidence levels respectively

Table 3. One-way classification of market adjusted abnormal returns for impact (trading days -1, 5) and adjustment (trading days 6,20) periods. Panel A presents returns after upward forecasts and Panel B of downward. The left side of the table classifies forecasts by forecast 'surprise', where 'surprise' is defined as New forecast by analyst i for firm j and quarter t minus the previous forecast by the same analyst for the same company and quarter scaled by the stock price of company j two days prior to the forecast. The right side of the table groups forecasts by Company size defines as the market capitalization of company j (price x shares outstanding) at the end of month t-1 where t is the month of the forecast by analyst i for company j. Size decile breakpoints were derived from Kenneth French's website.

Panel A: Upward revisions

Surprise quintile	Impact	Adjustment	N	Company size	Impact	Adjustment	N
1 (low)	0.599***	-0.18***	28767	1 (Small)	2.70***	1.77***	13832
2	1.32***	0.007	34640	2	2.68***	0.18**	21903
3	1.65***	0.10**	34485	3	2.22***	0.31***	27668
4	2.37***	0.38***	33866	4	1.65***	0.14**	39700
5 (High)	2.44***	0.71***	32910	5 (Large)	0.93***	-0.12	61565
Dif 1-5 (Low-High)	-1.841***	-0.89***		Dif 1-5 (Small-Large)	1.77***	1.89***	
t-statistic	-25.36	-10.59		t-statistic	16.43	15.22	

Panel B: Downward revisions

Surprise quintile	Impact	Adjustment	N	Company size	Impact	Adjustment	N
1	-0.67***	-0.22***	43533	1 (Small)	-2.49***	1.16***	21346
2	-1.02***	-0.11***	42047	2	-2.17***	0.54***	30382
3	-1.64***	0.08	41405	3	-1.93***	0.44***	36264
4	-2.39***	0.35***	41442	4	-1.41***	0.17***	48959
5	-2.67***	0.88***	41704	5 (Large)	-1.32***	-0.34***	73180
Dif 1-5 (Low-High)	2.00***	-1.1***		Dif 1-5 (Small-Large)	-1.17***	1.5***	
t-statistic	29.6	-15.11		t-statistic	-12.24	15.28	

*,**,*** denote statistical significance at the 10, 5 and 1 % confidence levels respectively

Table 4. Two-way classification of average market adjusted abnormal returns for adjustment period. The left side of the tables presents the results for upwards and the right for downward revisions. Surprise is calculated as analysts *i's* latest forecast for company j minus his previous forecast for the same company and quarter divided by the stock price two days prior to the forecast. Company size is defines as market capitalization of company j (price x shares outstanding) at the end of month t-1 where t is the month of the forecast by analyst *i* for company j. Decile breakpoints were derived from Kenneth French's website. Group 1 contains the smaller companies whereas group 5 the largest.

Rev > 0	Forecast Surprise							**Rev < 0** Forecast surprise						
Size	1	2	3	4	5	**D1 - D5**	t stat.	1	2	3	4	5	**D1 - D5**	t stat.
1 (Low)	-0.9	0.66**	1.30***	1.02**	2.86***	**-3.76*** **	-8.71	0.05	0.76***	0.44*	0.92***	1.86***	**-1.81*** **	-5.6
2	-0.06	0.2*	0.36**	0.18	0.06	**0**	-0.53	0.38*	0.4*	0.40*	0.59**	0.77***	**-0.39* **	-1.86
3	-0.4**	-0.01	0.23*	0.90***	0.75**	**-1.15*** **	-6.41	-0.29*	0.08	0.33*	0.62**	1.23***	**-1.52*** **	-8.52
4	0.05	0.1	-0.21*	0.22*	0.56**	**-0.51*** **	-3.15	-0.02	-0.14	0.23*	0.47***	0.42	**-0.45*** **	-3.08
5 (High)	-0.26*	-0.12*	-0.09	0.09	-0.29*	**0.03**	0.85	-0.39***	-0.50***	-0.41***	-0.34*	0.14	**-0.53*** **	-5.06
D1-D5	**0.53* **	**0.78*** **	**1.39*** **	**0.93*** **	**3.15*** **			**0.44* **	**1.27*** **	**0.85*** **	**1.25*** **	**1.72*** **		
t-stat.	1.79	3.59	8.10	4.81	12.24			1.65	6.86	4.79	6.80	8.33		

*,**,*** denote statistical significance on the 10, 5 and 1 % confidence levels respectively

Table 5. Two-way classification of impact and adjustment period market adjusted abnormal returns by forecast surprise/company size and market P/E ratio. Panel A presents results when forecast surprise is used as a proxy for ambiguity and panel B when company size is used. Surprise is calculated as analysts *i's* latest forecast for company j minus his previous forecast for the same company and quarter divided by the stock price two days prior to the forecast. Company size is defines as market capitalization of company j (price x shares outstanding) at the end of month t-1 where t is the month of the forecast by analyst *i* for company j. Decile breakpoints were derived from Kenneth French's website. Group 1 contains the smaller companies whereas group 5 the largest. Market P/E is calculates as

$$P/E_t = \frac{\sum_{1}^{n}(P_t * N_t)}{\sum_{1}^{n}(E_t * N_t)}$$

where P_t is the stock price of company t at the end of month t multiplied by the shares outstanding divided by the earnings per share that correspond to the end of month t multiplied by the shares outstanding, where n is the number of constituents of the index. In order to differentiate between high and low values each months market P/E is subtracted by the average market for the preceding 12 months. Then this standardised time series is ranked and the top 30% corresponds to the high values, the middle 40% to the neutral and the bottom 30% to the low.

Panel A: Classification by forecast surprise market P/E										
REV > 0										
Surprise		Impact					Adjustment			
	Low	Med	High	L-H	t- stat	Low	Med	High	L-H	t-stat
1 (low)	0.99***	0.55***	0.23***	**0.76*** **	6.90	-0.56***	0.02	-0.07	**-0.49*** **	-3.88
2	1.79***	1.31***	0.86***	**0.93*** **	8.70	-0.31***	0.25***	0	**-0.31*** **	-2.58
3	2.15***	1.64***	1.15***	**1.00*** **	8.68	0.02	0.20***	0.05	**-0.03**	-0.26
4	2.97***	2.36***	1.78***	**1.19*** **	9.40	0.82***	0.1	0.32***	**0.5*** **	3.72
5 (High)	2.52***	2.67***	2.02***	**0.5*** **	2.95	1.37***	0.50***	0.39***	**0.98*** **	5.09
L-H	**-1.53*** **	**-2.12*** **	**-1.79*** **			**-1.93*** **	**-0.48*** **	**-0.46*** **		
t-statistic	-9.93	-20.47	-13.53			-10.84	-3.91	-3.14		
REV < 0										
1	-0.44***	-0.75***	-0.78***	**0.33*** **	3.72	-0.01	-0.24***	-0.39***	**0.38*** **	3.81
2	-0.73***	-0.97***	-1.40***	**0.67*** **	6.34	0.34***	-0.21***	-0.45***	**0.79*** **	6.87
3	-1.60***	-1.48***	-1.87***	**0.27** **	2.29	0.66***	0.1	-0.52***	**1.18*** **	9.66
4	-2.75***	-2.20***	-2.26***	**-0.49*** **	-3.72	1.11***	0.38***	-0.51***	**1.62*** **	12.24
5	-3.12***	-2.62***	-2.58***	**-0.5*** **	-3.20	2.03***	0.67***	-0.03	**2.06*** **	12.55
L - H	**2.68*** **	**1.87*** **	**1.8*** **			**-2.04*** **	**-0.91*** **	**-0.36*** **		
t-statistic	18.45	18.50	14.25			-13.70	-8.41	-2.93		
Panel B: Classification by company size and market P/E										
REV > 0										
Company size										
1 (Small)	2.93***	2.96***	1.91***	**1.02*** **	3.44	2.71***	1.56***	0.90***	**1.81*** **	5.42
2	3.03***	2.99***	1.82***	**1.21*** **	6.51	0.14	0.39***	-0.07	**0.21**	1.07
3	2.86***	2.18***	1.61***	**1.25*** **	8.60	0.71***	0.19**	0.04	**0.67*** **	4.19
4	2.09***	1.60***	1.28***	**0.81*** **	7.4	0.05	0.12*	0.24***	**-0.19***	-1.69
5 (Large)	1.19***	0.89***	0.75***	**0.44*** **	6.06	-0.37***	-0.08	0.07	**-0.44*** **	-5.29
S - L	**1.74*** **	**2.07*** **	**1.16*** **			**3.08*** **	**1.66*** **	**0.83*** **		
t-statistic	7.91	14.07	5.58			11.82	9.68	3.70		
REV < 0										
1 (Small)	-3.10***	-2.01***	-2.50***	**-0.6*** **	-2.28	2.48***	1.04***	-0.28*	**2.76*** **	10.60
2	-2.74***	-1.93***	-1.86***	**-0.9*** **	-4.96	1.09***	0.51***	-0.02	**1.12*** **	6.55
3	-2.04***	-1.65***	-2.22***	**0.16**	1.1	1.18***	0.32***	-0.17*	**1.35*** **	9.25
4	-1.46***	-1.31***	-1.48***	**0.02**	0.16	0.90***	0.09	-0.43***	**1.34*** **	12.08
5 (Large)	-0.91***	-1.47***	-1.53***	**0.61*** **	8.36	-0.01	-0.39***	-0.61***	**0.6*** **	7.55
S-L	**-2.19*** **	**-0.54*** **	**-0.97*** **			**2.49*** **	**1.44*** **	**0.33***		
t-statistic	-11.01	-4.49	-5.07			11.97	10.63	1.87		

*,**,*** denote statistical significance at the 10, 5 and 1 % confidence levels respectively

Table 6. Impact/adjustment period returns are regressed on surprise, company size, market P/E ratio and various control variables as found in Clement and Tse (2003). Surprise is defined as the new forecast by analyst i for firm j and quarter t minus the previous forecast by the same analyst for the same company and quarter scaled by the stock price of company j two days prior to the forecast. Company size is the natural logarithm of the market capitalization of company j at the end of month t-1 where t is the month that an analyst forecast is issued, refer to table 5 for a definition of market P/E ratio. Lag error is the absolute error for the last forecast issued by analyst i for company j for the previous quarter, forecast horizon is the days that separate the forecast of analyst i for company j and the earnings announcement of company j, broker size measures the amount of analysts employed by the brokerage house in which analyst j is employed in the given quarter, days elapsed measures the days that separate the forecast by analyst i for company j quarter q with a previous forecast by any analyst for company j and quarter q. t-statistics are derived using deriving standard errors from GMM estimation. The model estimated is:

$$CAR_{ijt} = \alpha_0 + \beta_1 \mathbf{abs.\,surprise} + \beta_2 \ln size + \beta_3 market\ P/E$$
$$+ \beta_4 lag\ error + \beta_5 time\ horizon + \beta_6 broker\,size + \beta_7 days\ elapsed + u_{ijt}$$

Panel A:Impact Period returns/ Downward revisions					***Panel C:Adjust. Period ret./ Downward rev.***		
Variable	Parameter	Estimate	t-stat *(GMM)*	Pr > ¦t¦	Estimate	t-stat *(GMM)*	Pr > ¦t¦
Constant	α	-0.0341***	-16.2	<0.0001	0.008	3.16***	0.0016
Surprise	B_1	-0.334***	-3.85	<0.0001	0.3744	1.82*	0.0683
ln_size	B_2	0.0021***	8.68	<0.0001	-0.0013	-4.84***	<0.0001
Market P/E ratio	B3	0.0003	0.15	0.8779	-0.0024	-11.32***	<0.0001
Lag error	B_4	0.014***	7.92	<0.0001	0.0083	4.13***	<0.0001
Time horizon	B_5	0.0003	0.74	0.4611	0.00001	4.06***	<0.0001
Broker size	B_6	-0.00005***	-4.99	<0.0001	0.0009	0.96	0.3366
Days elapsed	B7	0.00008***	8.16	<0.0001	-0.00006	-5.72***	<0.0001
Panel B:Impact Period returns/ Upward revisions					***PanelD:Adjust. Period returns/ Upward rev.***		
Constant	α	0.0416***	20.05	<0.0001	0.0098	4.32***	<0.0001
Surprise	B_1	0.0014	0.01	0.9905	0.4108	2.3**	0.0216
ln_size	B_2	-0.0033***	-13.78	<0.0001	-0.0014	-5.64***	<0.0001
Market P/E ratio	B3	-0.0015***	-7.06	<0.0001	-0.0002	-0.97	0.3318
Lag error	B_4	0.0107***	5.79	<0.0001	0.0133	5.93***	<0.0001
Time horizon	B_5	-0.0003	-0.03	0.923	0.0005	1.67*	0.094
Broker size	B_6	0.00002**	2.34	0.0192	0.001	1.32	0.1845
Days elapsed	B7	-0.0007***	-7.27	<0.0001	-0.0001	-0.1	0.918

*,**,*** denote statistical significance at the 10, 5 and 1 % confidence levels respectively