Uncertainty and financial analysts' overconfidence:
European evidence between high-tech and low-tech firms

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Abstract

This article examines the link between uncertainty and analysts' reaction to earnings announcements for a sample of European firms during the period 1997-2007. In the same way as Daniel, Hirshleifer and Subrahmanyam (1998), we posit that overconfidence leads to an overreaction to private information followed by an undereaction when the information becomes public. Psychological findings suggest that this effect is more prominent in an uncertain environment. Our tests are based on the relationship between forecast revisions and forecast errors. When analysts excessively integrate information in their revisions (i.e. overreact), their forecast revisions are too intense, and the converse occurs when they underreact. We implement a portfolio analysis and a regression analysis for two subsamples: high-tech and low-tech, as a proxy for uncertainty. Our results support the overconfidence hypothesis. We jointly observe the two phenomena of under- and overreaction. Overreaction occurs when the information has not yet been made public and disappears just after public release. Our results also show that both effects are more important for the high-tech subsample and that the differences between high-tech and low-tech are significant. For robustness, we sort the sample using analyst forecast dispersion as a proxy for uncertainty and obtain similar results. We also document that the high-tech stocks crash in 2000-2001 moderated the overconfidence of analysts, which then strongly declined during the post-crash period.

Keywords: overconfidence, overreaction, underreaction, financial analysts, earnings announcement, earnings forecasts, high-tech.

JEL classification: G17, D89

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1 – Introduction

Experimental evidence in psychology shows that behavioral biases arise in situations which require more judgement. In particular, people exhibit a higher level of overconfidence when they are involved in non-mechanical tasks and when predictability is low and evidence ambiguous (Lichtenstein and Fischhoff (1977), Griffin and Tversky 1992)). When uncertainty is high, people tend to construct scenarios and are overconfident in the probability of their success (Kahneman and Tversky (1979)).

In the context of financial decision, Daniel and Titman (1999), Hirshleifer (2001), and Daniel, Hirshleifer and Subramanyam (1998, 2001), posit that uncertainty intensifies psychological biases[1]. They underline the role of overconfidence in producing mispricing for hard-to-value stocks and refer precisely to "*R&D-intensive firms comprised largely of intangible assets*" (Daniel et al. (2001), page 935). Daniel et al. (1998) produces a theoretical model that explains mispricing by over- and underreaction to information caused by overconfidence. The model shows that overconfident investors overreact to private information, and then underreact when information becomes public. In line with Daniel et al. (1998, 2001), this paper focuses on analysts' response to private and public information. We consider earnings announcements and two classes of assets - high-tech and low-tech firms - and we examine whether analyst forecasts reflect over- or underreaction to information.

Analysts' overconfidence receives relatively little attention from researchers, compared to that of investors and to the large body of research devoted to analysts' optimism. Many papers document the fact that analysts inefficiently incorporate information, mainly by analyzing how a current earnings forecast for a given period is influenced by earnings for the previous period. They show a serial correlation between current and past errors in forecasting (Mendenhall (1991), Abarbanell and Bernard (1992), Ali, Klein and Rosenfeld (1992)). These findings suggest that analysts underreact to new information, while the pioneer study from De Bondt and Thaler (1990) documented an overreaction. Easterwood and Nutt (1999) and Chen and Jiang (2006) show that both misreactions can be observed, and also document that analysts overreact to positive news and underreact to negative news, producing a form of

[1] For a more recent review and an extensive study about the relationship between uncertainty and behavioral biases (not exclusively related to overconfidence), see Kumar (2009).

generalized optimism. Zhang (2006a) confirms that uncertainty boosts analysts' misreactions to new information: greater uncertainty produces more optimistic forecast errors following bad news and more pessimistic forecast errors following good news He then corroborates a generalized underreaction and does not confirm the explanation provided by optimism.

Only a few papers have shown that analysts display overconfidence (Friesen and Weller (2006), Hilary and Menzly (2006), Deaves *et al*. 2010). Following Daniel et al. (1998), Friesen and Weller (2006) show that analysts overweight their private information and underweight public information. This effect is documented by implementing a model where analysts issue forecasts sequentially. Current forecasting depends on the consensus and on the precision of the private signal of the analyst who is currently issuing the new forecast. A rational (Bayesian) model produces efficient forecasts. The authors show that analysts place to much weight on their private information. Hilary and Menzly also based their analysis on forecast dynamics but in a different way. They use past success in forecast accuracy to predict the overconfidence of a given analyst. Past successes, through the mechanism of self-attribution bias[2], exacerbate overconfidence (Gervais and Odean (2001), Daniel et al. (1998)). They show that, after a short series of good predictions, analysts are more likely to be inaccurate and to take additional risks by deviating from the consensus. Overconfidence escalation, after a period of forecast accuracy, is also documented by Deaves *et al*. (2009) in their survey of German financial market practitioners[3].

In this study, we test analysts' overconfidence through the overreaction preceding a public announcement followed by an underreaction after the announcement. If overconfidence occurs, over- and underreactions should be respectively observed before and after the public announcement. If uncertainty boosts overconfidence, we predict that these two combined misreactions should be stronger when uncertainty is higher. In line with major studies devoted to investors' or analysts' reaction to information, we consider the earnings announcement to test whether analysts overreact before information becomes public and afterwards underreact. Analyst reactions to information are studied through their forecast revisions before and after the public announcement. We primarily define uncertainty according to technology intensity, and separate two types of firms: high-tech or low-tech. To make a robustness check, we then

[2] The self-attribution bias means that people attributes successful outcomes to their own ability and unsuccessful ones to external causes. When self-attribution bias occurs, people who have been successful exhibit higher overconfidence.

[3] Close to Deaves et al. study, Gloede and Menkhoff (forthcoming) also examine financial professionals' overconfidence in their forecasting performance, here applied to foreign exchange rates.

include analyst forecasts dispersion as a second proxy for uncertainty. In prior studies three categories of proxies were used to measure uncertainty about a firm's value[4]: market-based proxies which reflect investors' opinion divergence (such as bid-ask spread, volume turnover, stock return volatility), firm-based proxies which attempt to capture a firm's underlying fundamentals (such as size, age, R&D or technology intensity) and analyst-based proxies (mainly forecast dispersion). Our study is focused on fundamental-based and analyst-based proxies because they are intrinsically linked to analysts' activity. Moreover, we lean on a large body of literature that has pointed out the distinctive high-risk nature of technology based industries[5] and its impact on analysts' forecasts (Barron et al. (2002), Kwon (2002)).

Our tests are based on the relationship between forecast revisions and forecast errors. We consider forecasts for the current year, and observe their revisions encompassing the announcement of earnings for the previous year. We test whether analysts overreact before the public release and underreact after it. Overreaction implies that analysts revise their forecasts too strongly, and conversely, underreaction implies revisions that are too weak. We initially perform a portfolio analysis by grouping forecast revisions upwards and downwards and observe forecast errors for each group. To investigate the magnitude and the significance of the over- or underreaction, we then test regression models which estimate the relationship between forecast errors and forecast revisions. We study the whole sample to test whether over- and underreaction occurs globally, but our primary topic is to test whether the double phenomenon is stronger when uncertainty is high. Therefore, we conduct the analysis for two subsamples: high-tech and low-tech. For robustness, we also sort the subsamples using analyst forecast dispersion as a proxy for uncertainty[6].

Moreover, our sample period (1997-2007) allows us to investigate whether the analysts' overconfidence decline after the 2000-2001 high-tech stocks crash. So, we incorporate a dichotomy in the study between the pre-crash (1997-1999) and post-crash (2002-2007) period.

Taken together, our empirical evidence indicates that analysts exhibit overconfidence and reveal a stronger bias when uncertainty is higher. But this phenomenon, largely observed before the crash, almost completely disappeared afterwards.

[4] For discussions about uncertainty proxies, see Kumar (2009), Zhang (2006b), Kwon (2002).
[5] See Baruch Lev and coauthors in numerous articles, for instance Amir et al. (2003).
[6] Dispersion in analyst forecasts is a common proxy for uncertainty, see Barron et al. (1998, 2002), Zhang (2006a, 2006b).

This study offers interesting insights in two ways. Firstly, in the area of financial markets, it provides a test of a major over- and underreaction model (Daniel et al. (1998)) and implement it to analysts' reactions through their revisions (versus investors' reactions through stock returns). Secondly, in a broader way, it deals with the link between uncertainty and biases. Our results are consistent with the experimental evidence and extend it to a cross-sectional analysis that reinforces it as pointed out by Kumar (2009).

The rest of the paper is organized as follows. Section 2 presents hypotheses, data and methodology. Section 3 reports the empirical results for the whole period. Section 4 introduces the effect of the 2000-2001 crash on the analysis.

2 - Empirical design

2.1. Hypotheses

Our theoretical setting is derived from the Daniel et al. (1998) analysis. We consider the earnings announcement and test whether analysts overreact before and underreact after its public disclosure. We study forecast revisions (rather than stock prices as in Daniel et al.) around the public announcement. If analysts overreact, then the revision is too high. If they underreact, the revision is too small. In a previous study, Amir and Ganzach (1998) attributed such misreactions to anchoring (underreaction) or representativeness (overreaction) but did not study the impact of an announcement, that is, they did not study the revisions around a public signal. In this study we have adjusted their methodology to test how analysts react to new information.

In predicting earnings for a period *t*, analysts face an important flow of information when earnings for *t-1* are announced. Before the announcement, private information is flowing and generates adjustments in analysts' forecasts. They revise their forecasts for *t-1* and for *t*. We focus on revisions for *t* which can be analyzed before and after the public release and reveal analysts' reactions to information

Hypothesis 1: *if analysts exhibit overconfidence, they will overreact before the announcement and underreact after the announcement.*

Hypothesis 2: *if uncertainty boosts overconfidence such misreactions (described in hypothesis 1) will be greater for high-tech firms compared to low-tech firms.*

2.2. Data and sample

We drew our sample from I/B/E/S ("summary history") and extracted annual forecasts for European non-financial companies from 1997 to 2007. All monthly consensus forecasts (mean and/or median) of annual earnings per share entered the analysis if data were available for two consecutive fiscal years (*t* and *t-1*) and if at least three analysts provided estimates. From this sample, those observations for which analyst forecast was greater than 200% (in absolute value) of earnings per share were eliminated as outliers.

To categorize high-tech firms, we combined several classifications based on industry codes. Such segmentation between high-tech (HT) and low tech (LT) based on industry codes has been used in several studies devoted to analyst forecasts, for example Kwon (2002) or Cooper et al. (2001). For manufacturer industries we considered OECD classification according to their technological intensity. For service industries we refer to Kwon (2002) who classified them as low tech with the exception of communication and computer services which were integrated in high-tech subsample.

As a robustness check, we also selected two sub-subsamples based on dispersion in analysts' forecasts. High dispersion expresses high uncertainty regarding the firm. For each month of the analysis we extracted the standard deviation of analyst forecasts from I/B/E/S and defined two sub-subsamples based on the median: high dispersion (HD) and low dispersion (LD).

The final sample consists of 1742 European firms and represents 18710 firm-year observations when considering the month preceding the earnings announcement. Table 1 provides descriptive statistics for the whole sample and for HT and LT subsamples.

[insert table 1 here]

2.3. Variables

Our empirical setting is based on forecasts for the current year (year *t*) provided by analysts when the announcement of earnings for the previous year (year *t-1*) occurs. Our analysis requires consensus forecasts (*F*) of current earnings per share (*E*) provided during the several months before and after the announcement of earnings for the previous year. On the basis of these monthly forecasts for *t* we computed the forecast error (*FE*) and forecast revision (*FR*). For ease of reading we omit the reference to year *t* since all the parameters refer to the current year *t*. We denote *n* as the month where the forecast F_n is provided:

$$FR_n = (F_n - F_{n-1}) / |F_n|$$
$$FE_n = (E - F_n) / |E|$$

where for each month n, FR_n *is* the forecast revision and FE_n is the forecast error, as depicted in Figure 1. Due to those definitions FE_n>0 expresses optimism and FR_n>0 implies an upward revision during the month n. For cross-sectional analysis, we respectively standardized *FR* by the absolute value of F_n and *FE* by the absolute value of *E*. Because we are studying revisions surrounding the *t-1* earning release, *n=0* refers to the month of the announcement. We examine revisions for three months before and after the announcement.

Finally, we define forecast dispersion as follows:

$$FD_n = \sigma_n / |F_n|$$

where σ_n is the standard deviation extracted from I/B/E/S for each month n.

[Insert Fig.1 here]

3 – Empirical results

Ours tests are based on the relationship between forecast revisions and forecast errors. When analysts excessively integrate information in their revisions (i.e. overreact), they revise their forecasts too strongly. If the revision is positive (i.e. upwards), overreaction implies a negative (i.e. optimistic) forecast error. If the revision is negative (i.e. downwards), overreaction implies a positive (i.e. pessimistic) forecast error. So, *overreaction implies a negative relationship between forecast revisions and forecast errors* (whatever their signs may be), *while underreaction implies a positive relationship*. The analyses were conducted using two methodologies: a portfolio analysis and a regression analysis.

3.1. Portfolio analysis

For each month of the analysis we computed forecast revisions and divided each subsample (HT and LT) into two groups: observations with positive forecast revisions (FR>0) and observations with negative forecast revisions (FR<0). Observations for which the consensus forecast revision is zero were deleted from this analysis. We also required consecutive forecasts for the entire eight-month period surrounding the public release (according to figure 1).

The dependent measure is the mean (or median) forecast error for each group by period. Tables 2 and 3 present the results for the period preceding the announcement for which we globally expect a more pronounced overreaction in the HT subsample. For the total sample

(HT + LT) table 2 shows that when analysts revise upwards (FR>0), they do it too strongly: their errors are optimistic (FE<0). When they revise downwards (FR<0), they do it too weakly: their errors are pessimistic (FE>0).

[Insert table 2 here]

Table 3 presents the results for the two subsamples. It confirms our hypothesis that overreaction is more prominent for the high-tech sample.

[Insert table 3 here]

We conducted the same analysis for the period following the announcement, and tested here an underreaction to public information. Results for the total sample and for the two subsamples are respectively presented in tables 4 and 5. Underreaction appears when *FR* and *FE* have the same sign, which is observed in most cases reported in tables 4 and 5, and more forcefully for the HT subsample.

[Insert table 4 here]

[Insert table 5 here]

So, results of this first analysis shows that forecast revisions are too high in the pre-announcement period and too weak in the post- announcement period. This effect is more pronounced for high-tech firms.

3.2. Regression analysis

An alternative method to examine over- and underreaction is by regressing forecast errors on forecast revisions[7]. We can examine the magnitude of the relationship (and not only its sign):

$$FE_n = \alpha + \beta FR_n + \varepsilon \qquad (1)$$

where FE_n *and* FR_n are the mean forecast error and mean forecast revision for the month n as defined above (three months around the earnings release), α is the intercept and β is the slope coefficient. The lack of bias in analyst forecasts implies that both α and β equal zero. *A significant positive (negative) coefficient implies underreaction (overreaction).* A significant positive (negative) intercept implies optimism (pessimism). As in previous studies which examine over and underreactions by regression analysis (see prior footnote) we do not expect substantial R^2 because the regression expresses biased behavior. In Amir and Ganzach (1998),

[7] Regression analysis is a typical way to test under- or overreaction. Under rationality, no relationship must be observed between the dependent and the independent variable, and the regression coefficient must be insignificant. See, De Bondt and Thaler (1990), Abarbanell and Bernard (1992), Ali et al. (1992), Easterwood and Nutt (1999), Amir and Ganzach (1998)…

the adjusted R^2 are around 0.05 (depending on the period) for the same regression as our equation *(1)* but for different months. So, the test focuses on the regression slope before and after the public release and discriminates according to technology intensity. For greater accuracy, we estimate panel regressions.

Table 6 reports our estimates for the whole sample before the announcement. β are negative and significant for the first and the second month before the public release. During this period which is very close to the announcement, forecast revisions are too strong and convey analysts' overreaction.

[Insert table 6 here]

To examine the effect of uncertainty, and quantify its magnitude and significance, we analyzed the following regression, including an interaction analysis:

$$FE_n = \alpha_0 + \alpha_1 TECH + \beta_0 FR_n + \beta_1 TECH.FR_n + \varepsilon \qquad (2)$$

where *TECH* is a dummy variable which equals 1 for the high-tech subsample and 0 for the low-tech subsample. Overreaction implies that the coefficient $\beta_0+\beta_1$ is negative and β_1 alone captures the additional effect of uncertainty on the relationship between forecast error and forecast revision. Moreover, if analysts are optimistic, the intercept $\alpha_0 + \alpha_1$ will be negative and the additional effect of uncertainty will be shown by α_1.

Table 7 presents the results of this model for the period preceding the public release. For this period our hypotheses imply an overreaction, so we expect a negative slope: $\beta_0+\beta_1$ and β_1 alone are expected to be negative. The results reported in table 7 show that the overreaction analyzed in table 6 is much more pronounced for the high-tech subsample. For HT firms, the coefficient is strongly negative and highly significant for the three months. Overreaction is also observed for LT firms for the two months preceding the announcement, but with lower coefficients than those observed for HT. The analysis shows that the difference in coefficients between HT and LT is significant.

[Insert table 7 here]

We then replicated the analysis for the period following the announcement, for which we expected positive coefficients in line with the underreaction hypothesis. Tables 8 and 9 presents our estimates. In table 8, we observe an underreaction through a positive coefficient in the whole sample (except for the month +4 where β is insignificant). Table 9 confirms that the underreaction is stronger for HT firms.

[Insert table 8 here]

[Insert table 9 here]

Taken together, these results support the overconfidence hypothesis (H1). We jointly observe the two phenomena of under- and overreaction. Overreaction occurs while information has not been made public and disappears just after the public release. Our results also show that both effects are stronger for the HT subsample and that the differences between HT and LT are significant, supporting hypothesis 2.

3.3. Robustness tests

For robustness check, we assessed the dichotomy between HT and LT as a proxy for uncertainty. Even if high-tech firms have been documented as high-risk firms in numerous empirical findings, this point is clearly relevant in order to be sure that we had really tested the effect of uncertainty. So we introduced a second measure for uncertainty: dispersion in analyst forecasts. For each month of the analysis we extracted the standard dispersion in the I/B/E/S data base and constructed the subsamples according to the median. We obtained for each month a high-dispersion (high uncertainty) and a low-dispersion (low uncertainty) sample. We reproduced the portfolio and the regression analysis on these two subsamples. The results, not reported for the sake of brevity, are in line with those obtained with the HT and LT subsamples.

4 - Did overconfidence decrease during the period 1997-2007?

Finally in this section we propose a more exploratory research concerning the evolution of analysts' overconfidence during our sample period. This period gives us the opportunity to study whether a decrease could be observed after the Internet crash in 2000-2001. Following the dramatic rise and decline in high-tech stock prices, analysts were heavily criticized. The crash had aroused suspicion about their forecast accuracy which could have made them more cautious in their estimates. Then they could have produced more accurate and less biased forecasts. Overconfidence could be one of the most corrected biases because it directly deals with performance, success and even euphoria (Russo and Schoemaker (1992)).

We provide here a simple test to examine if analysts' overconfidence decreased after the crash. We split the regression analysis[8] performed in section 3.2 according to two sub-periods

[8] We also divided the portfolio analysis (section 3.1) into pre- and post-crash periods and obtained results in line with the regression analysis. In order to be brief, this study is not reported.

surrounding the crash (2000-2001): the pre-crash period (1997-1999) and the post-crash period (2002-2007). Figure 2 presents a descriptive evolution of forecast errors over the whole period. It shows a dramatic change in 2000-2001. Before the crash, analysts were optimistic (median and mean forecast errors were negative) and they became pessimistic afterwards, with a stronger effect for high-tech firms.

[Insert figure 2 here]

Regarding overconfidence, we tested whether the double phenomenon of the overreaction to private information combined with the underreaction to public information, declined after the crash. To examine if uncertainty played a role, we combined the high- and low-tech analysis and the pre- and post-crash period. We then integrated the period into the regression *(2)*:

$$FE_n = \alpha_0 + \alpha_1 TECH + \alpha_2 K + \alpha_3 TECH.K + \beta_0 FR_n + \beta_1 TECH.FR_n + \beta_2 K.FR_n + \beta_3 TECH.K.FR_n + \varepsilon \qquad (3)$$

where K is a dummy variable which equals 1 for the post-crash period and 0 for the pre-crash period.

If analysts have become less overconfident in the post-crash period, we must observe a decrease in both the overreaction before the earnings release (less negative coefficients, or even becoming positive) and the underreaction after the earnings release (less positive coefficients, or even becoming negative). So, our primary interest is in the differences between pre- and post-crash, and between HT and LT for each sub-periods, particularly in $\beta_2+\beta_3$ which expresses the crash effect in HT subsample, that we can break down into β_2 alone (the crash effect for LT) and β_3 alone (the additional effect of the crash for HT compared to LT).

Tables 10 and 11 present the results for the period preceding and following the earnings release. To provide a quick interpretation of the model we specify below the table to which subsample and sub-period each intercept α and slope coefficient β refers to.

[Insert table 10 here]

[Insert table 11 here]

For the months before the earnings release (table 10), overreaction, namely negative coefficients, is mainly observed before the crash for the HT subsample ($\beta_0+\beta_1$) and clearly declines after the crash ($\beta_0+\beta_1+\beta_2+\beta_3$). Coefficients become even positive for month *-3* (0.219***). The differences are always significant, as shown by the coefficient $\beta_2+\beta_3$: for the

HT subsample, the crash produces a strong decline in the overreaction before the earnings release. A similar pattern, but with less intensity, is observed for the LT subsample (the most clear effect is for month -*1*, for which β_2 is significant).

For the months following the earnings release (table 11), underreaction, namely positive coefficients, is observed for the HT subsample over two months ($\beta_0+\beta_1$) with significant differences between the LT subsample (shown in β_1 alone). It declines after the crash: coefficients $\beta_0+\beta_1+\beta_2+\beta_3$ remain positive but weakly significant. The differences between pre- and post-crash are less important than those observed for the overreaction ($\beta_2+\beta_3$).

Overall, the previous analysis established in section 3.2 (without the crash effect), that showed overreaction followed by underreaction with stronger effect for the HT group, is confirmed here but seems to almost disappear after the crash. Notably, we no longer observe misreactions in the LT group, and they are declining in the HT group. We also document a decrease in optimism as shown by the evolution of the intercept and in accordance with figure 2.

We replicated the tests with analyst forecasts' dispersion as a proxy for uncertainty and obtained similar results (not reported here in order to be brief).

5 – Discussion and conclusions

Previous studies have documented overreaction (DeBondt and Thaler (1990)) and underreaction (Abarbanell and Bernard (1992)) in analysts' forecasts and provide explanations based on optimism (Easterwood and Nutt (1999)) or on representativeness and anchoring (Amir and Ganzach, 1998). Recent literature has pointed out the important role of uncertainty in explaining behavioral biases (Zhang, (2006a, 2006b), Kumar (2009)). The purpose of this study is to examine whether uncertainty strengthens overconfidence through the case of analysts' reaction to the earnings announcement.

This release conveys a significant amount of information, attested to by the abundant literature which examines price reactions at the announcement date. We consider that the period before public release produces a special competition between analysts who then try to get further information, more or less private but not public, and work with a particular intensity on the firm's forecasts. This period particularly involves the ability to generate information or to reassess the significance and the interpretation of existing data. It therefore creates special conditions for overconfidence to occur, and much more so in an uncertain environment.

Following the definition of overconfidence provided by Daniel et al. (1998), we test an overreaction to private information followed by an underreaction when the information becomes public. We consider forecasts for the current year and examine how they are revised during the period surrounding the earnings announcement of the previous year. Our tests are based on the relationship between forecast revisions and forecast errors. When analysts excessively integrate information in their revisions (i.e. overreact), they revise their forecasts too strongly. If they revise upward then the forecast error will be optimistic, and if they do it downward the forecast error will be pessimistic. We test this hypothesis for the period preceding the public release, and do the opposite for the period following it (underreaction with too weak revisions). We posit that these relationships are reinforced with uncertainty. For robustness, we check two measures of uncertainty (high-tech vs. low-tech firms and forecast dispersion). Our results are consistent with our predictions. We document a strong overreaction (underreaction) before (after) the public release for our sample of European firms during the period 1997-2007.

We may notice that uncertainty could produce a rational underreaction at the announcement due to a learning process caused by uncertainty. Brav and Heaton's model (2002) showed that fully bayesian investors place less weight on high uncertainty (low precision) signals, and thus provided a rational explanation for underreaction. Francis et al. (2007) confirmed this prediction when studying post-earnings announcement drift in a context of high or low information uncertainty. But our results do not fit this rational explanation because we observe a combined and consecutive effect – overreaction before public release and underreaction afterwards – which perfectly fit the overconfidence hypothesis.

We also propose a more exploratory research concerning the evolution of analysts' overconfidence during our sample period. This period gives us the opportunity to study whether a decrease could be observed after the Internet crash in 2000-2001. We document a strong decline in the analysts' overconfidence which completely disappears in the low-uncertainty group.

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Fig. 1: Over- and underreaction around EPS announcement – Test based on the relation between forecast revision and forecast error

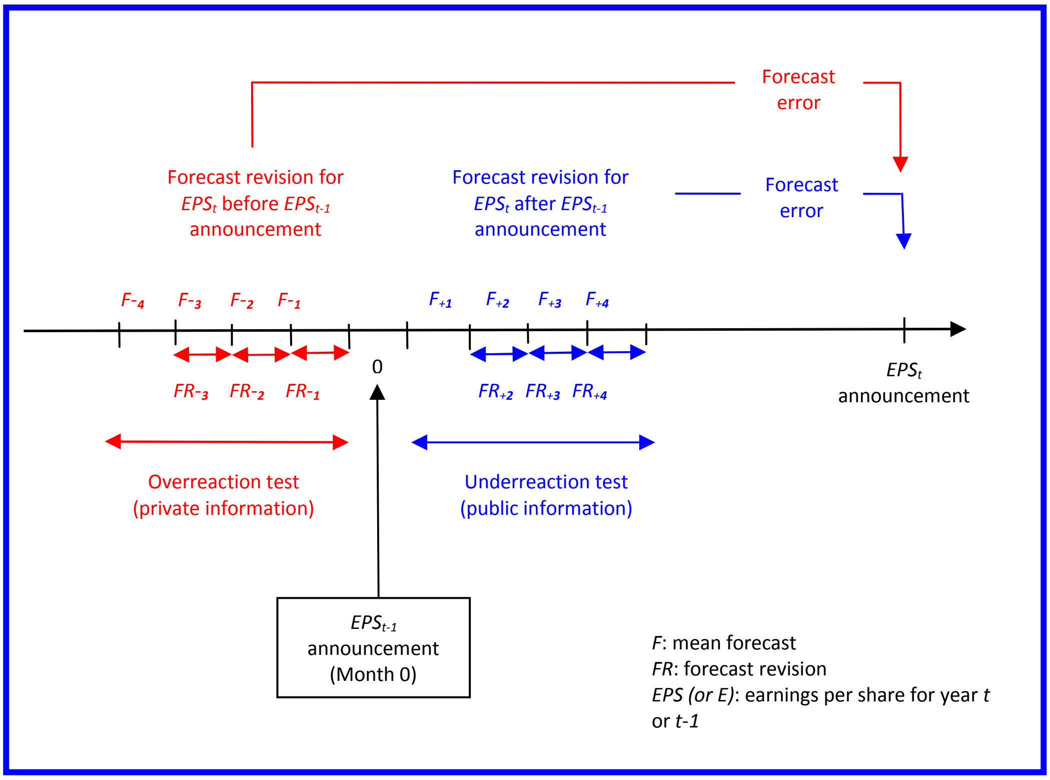
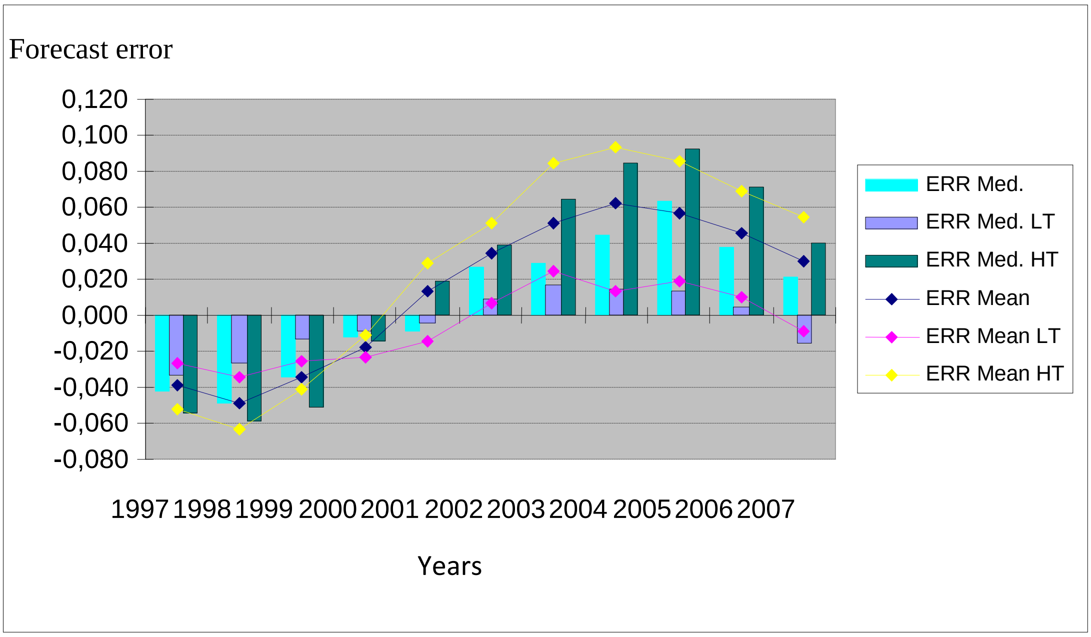


Fig. 2: Evolution of the mean and median forecast error



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Forecast error is measured as $FE_n = (E - F_n) / |E|$, based on the mean or the median forecast F_n. F_n is measured the month preceding the earnings announcement

Table 1 :
Samples - descriptive statistics

Years	Number of firms			MEAN FE			MEDIAN FE			MEAN FD			MEDIAN FD		
	N	**LT**	**HT**	**HT&LT**	**LT**	**HT**	**HT&LT**	**LT**	**HT**	**HT&LT**	**LT**	**HT**	**HT&LT**	**LT**	**HT**
1997	1568	986	582	-0,039	-0,027	-0,052***	-0,043	-0,033	-0,054*	0,290	0,112	0,388***	0,218	0,157	0,389***
1998	1646	1019	627	-0,049	-0,034	-0,063***	-0,049	-0,027	-0,059**	0,156	0,098	0,411***	0,112	0,061	0,411***
1999	1681	1008	673	-0,034	-0,026	-0,041*	-0,034	-0,013	-0,051***	0,254	0,123	0,327***	0,201	0,112	0,523***
2000	1697	1028	669	-0,018	-0,023	-0,011	-0,012	-0,009	-0,014	0,121	0,067	0,276***	0,152	0,082	0,412***
2001	1712	1038	674	0,014	-0,014	0,029***	-0,009	-0,004	0,019**	0,133	0,085	0,258***	0,172	0,109	0,281***
2002	1730	1044	686	0,034	0,006	0,052***	0,027	0,009	0,039***	0,112	0,104	0,263***	0,218	0,143	0,306***
2003	1722	1051	671	0,051	0,024	0,084***	0,029	0,017	0,064***	0,105	0,058	0,199***	0,294	0,117	0,368***
2004	1739	1056	683	0,062	0,013	0,093***	0,045	0,015	0,084***	0,132	0,072	0,249***	0,219	0,132	0,333***
2005	1733	1041	692	0,057	0,019	0,086***	0,063	0,013	0,093***	0,221	0,124	0,319***	0,371	0,201	0,416***
2006	1740	1055	685	0,046	0,009	0,069***	0,038	0,005	0,071***	0,241	0,142	0,342***	0,254	0,162	0,324***
2007	1742	1053	689	0,030	-0,008	0,055***	0,021	-0,015	0,040***	0,261	0,109	0,401***	0,351	0,189	0,489***
(1997-2007)	**18710**	**11379**	**7331**	**0,011**	**-0,010**	**0,032*****	**0,018**	**-0,006**	**0,022******	**0,196**	**0,095**	**0,271*****	**0,212**	**0,121**	**0,325*****

For each year, the table reports the number of firms (N) and the number of high-tech (HT) and low-tech (LT) firms. FE, FR, SD, indicate forecast error, forecast revision and forecast dispersion. FE, FR and SD are measured the month preceding the earnings announcement. ***, **and * indicate statistical significance of 1%, 5% and 10%, respectively, in mean differences (t-test) and median differences (Wilcoxon test) between HT and LT.

Table 2

Relation between the sign of the forecast revision and the forecast error before the public announcement of *t-1* earnings

Month	FR>0		FR<0		Obs
	MEAN FE	MED FE	MEAN FE	MED FE	
-1	-0,103***	-0,034***	0,052***	0,021*	11578
-2	-0,099***	-0,018*	0,068***	0,014	11507
-3	-0,102***	-0,026**	0,077***	0,029**	9985

The table indicates mean and median forecast error when mean forecast revision for a given month is positive (upwards revisions) or negative (downwards revisions). Each variable refers to the current year *t* and is measured for respectively one, two and three months before the month *0*. The month *0* is the month when earnings for the prior year (*t-1*) are announced. For each month *n*, forecast revision is measured as $FR_n = (F_n - F_{n-1}) / |F_n|$, based on the mean forecast F_n and forecast error is measured as $FE_n = (E - F_n) / |E|$, based on the mean or the median forecast F_n. (with *E* as actual earnings per share). *FE<0* (*FE>0*) indicates optimism (pessimism). ***,** and * indicate statistical significance of 1%, 5% and 10%, respectively, in mean differences (t-test) and median differences (Wilcoxon test) between the two groups based on FR sign.

Table 3

Relation between the sign of the forecast revision and the forecast error before the public announcement of *t-1* earnings for high-tech and low-tech subsamples

Month	FR>0				FR<0				Obs
	HT		LT		HT		LT		
	MEAN FE	MED FE	MEAN FE	MED FE	MEAN FE	MED FE	MEAN FE	MED FE	
-1	-0,188***	-0,100***	-0,068***	-0,011	0,092***	0,040***	0,024**	0,014	11578
-2	-0,126***	-0,078***	-0,072***	-0,017	0,109***	0,022*	0,052***	0,013	11507
-3	-0,227***	-0,114***	-0,094***	-0,024*	0,128***	0,049***	0,069***	0,020*	9985

The table indicates for the high-tech (HT) and low-tech (LT) subsample, mean and median forecast error when mean forecast revision for a given month is positive (upwards revisions) or negative (downwards revisions). Each variable refers to the current year *t* and is measured for respectively one, two and three months before the month *0*. The month *0* is the month when earnings for the prior year (*t-1*) are announced. For each month *n*, forecast revision is measured as $FR_n = (F_n - F_{n-1}) / |F_n|$, based on the mean forecast F_n and forecast error is measured as $FE_n = (E - F_n) / |E|$, based on the mean or the median forecast F_n. (with *E* as actual earnings per share). *FE<0* (*FE>0*) indicates optimism (pessimism). ***,** and * indicate statistical significance of 1%, 5% and 10%, respectively, in mean differences (t-test) and median differences (Wilcoxon test) between the two groups based on FR sign.

Table 4

Relation between the sign of the forecast revision and the forecast error after the public announcement of *t-1* earnings

Month	FR>0		FR<0		Obs
	MEAN FE	MED FE	MEAN FE	MED FE	
+2	0,015	0,020*	-0,095***	-0,030**	11001
+3	0,030**	0,012	-0,083***	-0,021*	11124
+4	-0,016	-0,004	-0,037***	-0,014	11570

The table indicates mean and median forecast error when mean forecast revision for a given month is positive (upwards revisions) or negative (downwards revisions). Each variable refers to the current year *t*. Forecasts are measured for respectively one, two and three months after the month *0*, which induces forecast revisions for two, three and four months after the month *0*, and corresponding forecast errors. The month *0* is the month when earnings for the prior year (*t-1*) are announced. For each month *n*, forecast revision is measured as $FR_n = (F_n - F_{n-1}) / |F_n|$, based on the mean forecast F_n and forecast error is measured as $FE_n = (E - F_n) / |E|$, based on the mean or the median forecast F_n. (with *E* as actual earnings per share). *FE<0* (*FE>0*) indicates optimism (pessimism). ***,** and * indicate statistical significance of 1%, 5% and 10%, respectively, in mean differences (t-test) and median differences (Wilcoxon test) between the two groups based on FR sign.

Table 5

Relation between the sign of the forecast revision and the forecast error after the public announcement of *t-1* earnings for high-tech and low-tech subsamples

Month	FR>0				FR<0				Obs
	HT		LT		HT		LT		
	FE MOY	FE MED	FE MOY	FE MED	FE MOY	FE MED	FE MOY	FE MED	
+2	0,066***	0,036***	-0,027**	0,000	-0,170***	-0,069***	-0,032**	0,010	11001
+3	0,048***	0,021*	0,019*	0,002	-0,149***	-0,042***	-0,024*	0,012	11124
+4	-0,021*	0,006	-0,011	0,005	-0,068***	-0,017	-0,008	0,006	11570

The table indicates for the high-tech (HT) and low-tech (LT) subsample, mean and median forecast error when mean forecast revision for a given month is positive (upwards revisions) or negative (downwards revisions). Each variable refers to the current year *t*. Forecasts are measured for respectively one, two and three months after the month *0*, which induces forecast revisions for two, three and four months after the month *0*, and corresponding forecast errors. The month *0* is the month when earnings for the prior year (*t-1*) are announced. For each month *n*, forecast revision is measured as $FR_n = (F_n - F_{n-1}) / |F_n|$, based on the mean forecast F_n and forecast error is measured as $FE_n = (E - F_n) / |E|$, based on the mean or the median forecast F_n. (with *E* as actual earnings per share). *FE<0* (*FE>0*) indicates optimism (pessimism). ***,** and * indicate statistical significance of 1%, 5% and 10%, respectively, in mean differences (t-test) and median differences (Wilcoxon test) between the two groups based on FR sign.

Tableau 6

Relation between forecast revision and forecast error before the public announcement of *t-1* earnings

$$FE_n = \alpha + \beta FR_n + \varepsilon$$

Month	α	β	R^2	Obs
-1	-0,064	-0,144	0,002	11578
	(17,184***)	(-5,171***)		
-2	-0,133	-0,046	0,001	11507
	(-35,633***)	(-2,603***)		
-3	-0,073	0,042	0,000	9985
	(-22,219***)	(1,426)		

The table reports the intercept and the slope coefficient of the regression model for the whole sample. *** indicates statistical significance of 1% (t-test).

Table 7

Relation between forecast revision and forecast error before the public announcement of *t-1* earnings for high-tech and low-tech subsamples

$$FE_n = \alpha_0 + \alpha_1 TECH + \beta_0 FR_n + \beta_1 TECH.FR_n + \varepsilon$$

Month	HT		LT		Difference HT vs. LT		R^2	Obs
	$\alpha_0 + \alpha_1$	$\beta_0+\beta_1$	α_0	β_0	α_1	β_1		
-1	-0,180	-0,356	-0,078	-0,166	-0,102	-0,190	0,014	11578
	(-30,551***)	(-7,761***)	(-17,006***)	(-4,893***)	(-13,661***)	(-3,333***)		
-2	-0,190	-0,139	-0,092	-0,061	-0,098	-0,078	0,012	11507
	(-32,492***)	(-3,979***)	(-19,101***)	(-3,013***)	(-12,969***)	(-1,926*)		
-3	-0,230	-0,090	-0,067	0,036	-0,163	-0,126	0,041	9985
	(-42,733***)	(-2,380**)	(-17,146***)	(0,994)	(-24,339***)	(-2,383**)		

The table reports the intercept α_0 and the coefficient β_0 for the LT subsample (TECH=0) and $\alpha_0+\alpha_1$ and $\beta_0+\beta_1$ for the HT subsample (TECH=1). α_1 and β_1 capture the additional effect of technology (TECH) on the relationship between forecast error and forecast revision. ***,** and * indicate statistical significance of 1%, 5% and 10%, respectively (t-test).

Table 8

Relation between forecast revision and forecast error after the public announcement of *t-1* earnings

$$FE_n = \alpha + \beta FR_n + \varepsilon$$

Month	α	β	R^2	Obs
+2	-0,062	0,096	0,001	11001
	(-16,362***)	(3,880***)		
+3	-0,048	0,082	0,001	11124
	(-13,728***)	(4,623***)		
+4	-0,029	-0,009	0,000	11570
	(-12,360***)	(-1,329)		

The table reports the intercept and the slope coefficient of the regression model for the whole sample. *** indicates statistical significance of 1% (t-test).

Table 9

Relation between forecast revision and forecast error after the public announcement of *t-1* earnings for high-tech and low-tech subsamples

$$FE_n = \alpha_0 + \alpha_1 TECH + \beta_0 FR_n + \beta_1 TECH.FR_n + \varepsilon$$

Month	HT		LT		Difference HT vs. LT		R^2	Obs
	$\alpha_0 + \alpha_1$	$\beta_0+\beta_1$	α_0	β_0	α_1	β_1		
+2	-0,181	0,260	-0,079	0,101	-0,102	0,159	0,015	11001
	(-32,132***)	(8,214***)	(-16,268***)	(2,656***)	(-13,661***)	(3,230***)		
+3	-0,136	0,141	-0,071	0,052	-0,065	0,089	0,007	11124
	(-24,652***)	(3,536***)	(-16,277***)	(2,643***)	(-9,188***)	(2,014**)		
+4	-0,024	-0,013	-0,071	-0,036	0,047	0,023	0,007	11570
	(-6,748***)	(-1,751*)	(-23,712***)	(-2,063**)	(10,299***)	(1,253)		

The table reports the intercept α_0 and the coefficient β_0 for the LT subsample (TECH=0) and $\alpha_0+\alpha_1$ and $\beta_0+\beta_1$ for the HT subsample (TECH=1). α_1 and β_1 capture the additional effect of technology (TECH) on the relationship between forecast error and forecast revision.***, ** and * indicate statistical significance of 1%, 5% and 10%, respectively (t-test).

Table 10
Relation between forecast revision and forecast error before the public announcement of *t-1* earnings for high-tech and low-tech subsamples: Pre- and post-crash analysis

$$FE_n = \alpha_0 + \alpha_1 TECH + \alpha_2 K + \alpha_3 TECH.K + \beta_0 FR_n + \beta_1 TECH.FR_n + \beta_2 K.FR_n + \beta_3 TECH.K.FR_n + \varepsilon$$

Month	HT		LT		Difference HT vs. LT			
	Pre-crash							
	$\alpha_0 + \alpha_1$	$\beta_0+\beta_1$	α_0	β_0	α_1	β_1		
-1	-0,175	-0,286	-0,078	-0,090	-0,097	-0,196		
	(-15,026***)	(-6,793***)	(-8,562***)	(-4,190***)	(-6,611***)	(-4,740***)		
-2	-0,187	-0,153	-0,092	-0,067	-0,095	-0,086		
	(-15,315***)	(-5,909***)	(-10,019***)	(-1,679*)	(-6,525***)	(-3,726***)		
-3	-0,232	-0,030	-0,069	0,048	-0,163	-0,078		
	(-20,172***)	(-1,266)	(-8,651***)	(0,748)	(-11,623***)	(-2,631***)		
	Post-crash							
	$\alpha_0+\alpha_1+\alpha_2+\alpha_3$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\alpha_0 + \alpha_2$	$\beta_0+\beta_2$	$\alpha_1+ \alpha_3$	$\beta_1+\beta_3$		
-1	-0,056	-0,052	-0,001	-0,054	-0,055	0,002		
	(-6,996***)	(-2,261**)	(-0,701)	(-1,694*)	(-4,382***)	(0,894)		
-2	-0,069	0,077	-0,021	-0,021	-0,048	0,098		
	(-4,573***)	(1,590*)	(-4,910***)	(-0,754)	(-5,319***)	(2,702***)		
-3	-0,094	0,219	-0,003	0,024	-0,091	0,195		
	(-12,825***)	(5,005***)	(-0,595)	(2,376**)	(-9,019***)	(4,028***)		
	Difference pre-crash vs. post-crash							
	$\alpha_2+\alpha_3$	$\beta_2+\beta_3$	α_2	β_2	α_3	β_3	R^2	**Obs**
-1	0,119	0,234	0,077	0,036	0,042	0,198	0,014	9485
	(8,468***)	(6,870***)	(7,107***)	(4,142***)	(3,042***)	(5,211***)		
-2	0,118	0,230	0,071	0,046	0,047	0,184	0,011	9426
	(10,091***)	(2,818***)	(3,841***)	(0,941)	(3,162***)	(4,817***)		
-3	0,138	0,249	0,066	-0,024	0,072	0,273	0,030	8170
	(10,074***)	(7,301***)	(6,776***)	(-1,487)	(3,521***)	(5,781***)		

The pre-crash period is 1997-1999 and the post-crash period is 2002-2007. The table reports the results of the regression model for the high-tech (TECH=1) and the low-tech (TECH=0) subsample and for the pre- (K=0) and post-crash (K=1) period. The intercepts and the slope coefficients are interpreted as follows:

- α_0 and β_0 are for the low-tech subsample before the crash,
- $\alpha_0+\alpha_1$ and $\beta_0+\beta_1$ are for the high-tech subsample before the crash (α_1 and β_1 show the difference between HT and LT),
- $\alpha_0+\alpha_2$ and $\beta_0+\beta_2$ are for the low-tech subsample after the crash,
- $\alpha_0+\alpha_1+\alpha_2+\alpha_3$ and $\beta_0+\beta_1+\beta_2+\beta_3$ are for the high-tech subsample after the crash,
- $\alpha_1+\alpha_3$ and $\beta_1+\beta_3$ show the additional effect of technology after the crash (they show the difference between HT and LT),
- $\alpha_2+\alpha_3$ and $\beta_2+\beta_3$ show the additional effect of the crash for the high-tech subsample (they show the difference between the two periods for HT),
- α_2 and β_2 show the additional effect of the crash for the low-tech subsample,
- α_3 and β_3 show the combined additional effect of the crash and the technology.

***, ** and * indicate statistical significance of 1%, 5% and 10%, respectively (t-test).

Tableau 11

Relation between forecast revision and forecast error after the public announcement of *t-1* earnings for high-tech and low-tech subsamples: Pre- and post-crash analysis

$$FE_n = \alpha_0 + \alpha_1 TECH + \alpha_2 K + \alpha_3 TECH.K + \beta_0 FR_n + \beta_1 TECH.FR_n + \beta_2 K.FR_n + \beta_3 TECH.K.FR_n + \varepsilon$$

Month	HT		LT		Difference HT vs. LT			
	Pre-crash							
	$\alpha_0+\alpha_1$	$\beta_0+\beta_1$	α_0	β_0	α_1	β_1		
+2	-0,177	0,208	-0,084	0,059	-0,093	0,149		
	(-15,743***)	(3,299***)	(-8,671***)	(0,909)	(-6,281***)	(3,749***)		
+3	-0,137	0,155	-0,070	0,049	-0,066	0,106		
	(-12,716***)	(3,101***)	(-8,227***)	(1,266)	(-4,848***)	(2,652***)		
+4	-0,025	-0,015	-0,071	-0,046	0,046	0,031		
	(-3,809***)	(-1,104)	(-12,311***)	(-1,541*)	(5,201***)	(0,929)		
	Post-krach							
	$\alpha_0+\alpha_1+\alpha_2+\alpha_3$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\alpha_0+\alpha_2$	$\beta_0+\beta_2$	$\alpha_1+\alpha_3$	$\beta_1+\beta_3$		
+2	-0,027	0,080	0,001	0,039	-0,028	0,041		
	(-3,604***)	(1,845*)	(0,803)	(0,684)	(-3,777***)	(2,373**)		
+3	-0,017	0,046	0,002	0,027	-0,019	0,019		
	(-2,211**)	(1,721*)	(0,378)	(0,979)	(-2,778***)	(1,672*)		
+4	-0,005	-0,055	-0,011	-0,016	0,006	-0,039		
	(-0,946)	(-1,912*)	(-2,611***)	(-1,732*)	(1,641*)	(-1,833*)		
	Difference pre-crash vs. post-crash							
	$\alpha_2+\alpha_3$	$\beta_2+\beta_3$	α_2	β_2	α_3	β_3	R^2	**Obs**
+2	0,150	-0,128	0,085	-0,020	0,065	-0,108	0,017	8985
	(10,974***)	(-1,672*)	(7,134***)	(-0,230)	(5,621***)	(-2,024**)		
+3	0,120	-0,109	0,072	-0,022	0,048	-0,087	0,015	9112
	(9,171***)	(-2,018**)	(6,936***)	(-0,472)	(4,213***)	(-1,721*)		
+4	0,020	-0,040	0,060	0,030	-0,040	-0,070	0,008	9210
	(2,431**)	(-1,889*)	(8,230***)	(2,290**)	(-3,425***)	(-1,652*)		

The pre-crash period is 1997-1999 and the post-crash period is 2002-2007. The table reports the results of the regression model for the high-tech (TECH=1) and the low-tech (TECH=0) subsample and for the pre- (K=0) and post-crash (K=1) period. The intercepts and the slope coefficients are interpreted as follows:

α_0 and β_0 are for the low-tech subsample before the crash,
$\alpha_0+\alpha_1$ and $\beta_0+\beta_1$ are for the high-tech subsample before the crash (α_1 and β_1 show the difference between HT and LT),
$\alpha_0+\alpha_2$ and $\beta_0+\beta_2$ are for the low-tech subsample after the crash,
$\alpha_0+\alpha_1+\alpha_2+\alpha_3$ and $\beta_0+\beta_1+\beta_2+\beta_3$ are for the high-tech subsample after the crash,
$\alpha_1+\alpha_3$ and $\beta_1+\beta_3$ show the additional effect of technology after the crash (they show the difference between HT and LT),
$\alpha_2+\alpha_3$ and $\beta_2+\beta_3$ show the additional effect of the crash for the high-tech subsample (they show the difference between the two periods for HT),
α_2 and β_2 show the additional effect of the crash for the low-tech subsample,
α_3 and β_3 show the combined additional effect of the crash and the technology.

***, ** and * indicate statistical significance of 1%, 5% and 10%, respectively (t-test).