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Uncertainty and Financial Analysts' Optimism: A Comparison between High-Tech and Low-Tech European Firms

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Abstract: This study investigates the impact of information uncertainty on analysts' earnings forecasts for a sample of European companies from 2010 to 2019. We argue that representativeness, anchoring and adjustment, and leniency biases jointly influence analysts' forecasts and lead to optimism. We suggest that uncertainty boosts analysts' optimism as behavioral biases increase in situations of low predictability. We test analysts' optimism through the association between forecast errors and, separately, two modifications (forecast revision and forecast change) when these modifications are upwards and downwards. To examine the uncertainty effect, we implement descriptive and regression analyses for two subsamples of high-tech and low-tech firms. The evidence indicates that analysts are optimistic, as they overreact to positive prediction modifications and underreact to negative prediction modifications. The optimism is more significant for high-tech firms and increases considerably with the forecast horizon. For robustness, we utilize analysts' forecast dispersion as a second proxy for uncertainty, and we obtain comparable results.

Keywords: uncertainty; optimism; underreaction; overreaction; earnings release; forecast revision; forecast change; high-tech

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1. Introduction

The traditional finance paradigm states that the financial market is efficient and that investors and financial analysts are rational since they collect or receive all available information and their decisions and forecasts are supported by this information [1,2]. As a result, according to traditional finance, investors and analysts immediately and fully integrate new information into their judgments instead of relying on feelings. Unlike traditional finance, contemporary research has largely documented the inaccuracy and upward bias of analysts' forecasts when incorporating new information. Analysts tend to be generally optimistic instead of systematically misinterpreting available information. Several studies document the rationality of optimism. Consistent with their financial motivations, analysts prefer making optimistic forecasts in order to keep excellent ties with management and take advantage of more exclusive information [3–8]. Analysts also choose to provide forecasts only for firms showing good performance, which leads to forecast optimism [9]. Behavioral finance points out that analysts' optimism is irrational due to the influence of psychological biases. Many papers document that analysts ineffectively integrate information, primarily by examining how past earnings influence actual earnings forecasts. They demonstrate a linear association between prior and actual forecast errors [10–12]. These results indicate analysts' underreaction to new information (the earnings release). Other papers observe an overreaction [13–16].

This phenomenon of over- and underreaction is explained by the presence of cognitive biases influencing analysts' behavior. Kahneman and Tversky [17] illustrate that people's instinctive predictions are controlled by psychological biases, or rules of thumb, that consistently vary from accepted statistical norms.

Financial economics research has typically focused on the impact of a single heuristic on analyst behavior. Nevertheless, only a few studies in behavioral finance show that analysts' overreaction and underreaction are attributed to different simultaneous heuristics.

Czaczkes and Ganzach [18] illustrate the effect of representativeness and anchoring and adjustment biases on the extremity of predictions. The representativeness heuristic shows that, in the face of uncertainty, analysts are likely to assume that a firm's historically outstanding performance is "representative" of good future performance that the firm will continue to provide. The representativeness bias implies an excessively extreme forecast, or overreaction. Analysts prone to this cognitive bias overreact to salient and comparable information regarding a firm's prior performance (e.g., prior earnings). In this case, predictions are extremely low when the predictor's value is low and excessively high when the predictor's value is high. The anchoring and adjustment biases lead to regressive forecasts or underreaction. Analysts subject to this bias estimate unknown values by starting with information that is already known and adjusting until an appropriate quantity is reached. Anchoring leads analysts to anchor at a particular value (such as the previous forecast), which is related to the prediction. Campbell and Sharpe [19] suggest that analysts' anchoring to the previous forecast leads to insufficient forecast adjustment.

Amir and Ganzach [20] expand on the findings of Czaczkes and Ganzach [18] and demonstrate that, in addition to representativeness and anchoring and adjustment heuristics, leniency bias influences earnings forecasts. Leniency means that people are lenient and tend to benefit from doubt when forecasting performance, which leads to overoptimism. Amir and Ganzach [20] suggest that when analysts modify their forecasts upwards (positive modification), leniency (optimism) and representativeness (overreaction) lead to an excessive forecast that is above the current earnings, generating a significant negative forecast error, whereas anchoring and adjustment (underreaction) cause an insufficient prediction lower than the actual earnings. When analysts modify their forecasts downwards (negative modification), anchoring and adjustment (underreaction) and leniency (optimism) lead to an insufficient forecast that is above current earnings, whereas representativeness (overreaction) generates a prediction below current earnings, leading to an insignificant forecast error. As a result, analysts tend to be optimistic as forecast errors are more likely to be negative when forecast modifications are positive (optimism and overreaction effect) and negative (optimism and underreaction effect).

Amir and Ganzach [20] examine the effect of cognitive biases on forecast error. Their findings reveal an underreaction to forecast revisions (anchoring effect) and overreaction to forecast changes (representativeness effect). They also observed optimism through overreaction and underreaction, respectively, for positive and negative forecast modifications. The level of optimism increases with the forecast horizon. Marsden et al. [21] re-examine Amir and Ganzach's hypotheses on the Australian market. They study the impact of representativeness, anchoring and adjustment, and leniency biases on financial analysts' forecast errors. Their findings support analysts' optimism through their overreaction to positive forecast revisions and changes and their underreaction to negative forecast revisions and changes.

Barberis et al. [22] present a model of investor behavior when affected by representativeness and conservatism heuristics. The model demonstrates that these two behavioral biases produce overreaction in some cases and underreaction in others.

Easterwood and Nutt [23] focus on the effect of representativeness and anchoring biases on analysts' reactions to past earnings information. They find that analysts tend to be optimistic, as they overreact to good news and underreact to bad news. Gu and Xue [24] find that the overreaction to extremely good news is rational behavior. Extremely positive news is typically followed by more earnings uncertainty, which frequently results in overoptimism. Once uncertainty is controlled, analysts' overreaction to good performance decreases significantly, maintaining a general underreaction. Bessiere and Kaestner [25] find that this simultaneous phenomenon of over- and underreaction is more significant before the crash (2000–2001). A sense of caution is observed after the crash.

Bouteska and Regaieg [26] investigate the Tunisian stock market's anchoring bias. They find that financial analysts suffer from anchoring as they insufficiently adjust their predictions after earnings announcements. They also observe an overreaction to positive forecast changes and an underreaction to negative forecast changes.

If previous studies show that financial analysts' behavior is characterized by over- and underreaction and that heuristics justify these misreactions, our paper expands these contributions by studying the effect of uncertainty on analysts' behavior, as empirical evidence in psychology demonstrates that uncertainty intensifies cognitive biases [27–29]. In this context, Kahneman and Tversky [30] explain that when uncertainty is high and signals are ambiguous, people further underweight negative information and overweight positive information, leading to optimistic behavior. Hirshleifer [31] documents that psychological biases have a greater opportunity to exist when there is a lack of accurate knowledge about the fundamentals. As a result, the effect of mistaken beliefs on misvaluation should be stronger for high-uncertainty firms (low information). Daniel et al. [32] underline that mispricing due to heuristics should be greater for firms that need more judgments to assess and where the short-term feedback on the quality of these judgments is uncertain (R&D-intensive firms). Zhang [33] corroborates that uncertainty increases analysts' misinterpretation of new information: high uncertainty leads to excessive optimism after bad news and excessive pessimism after good news.

Chang and Choi [34] find that when uncertainty in financial markets is high, analysts are less likely to be sanctioned for biased forecasts and therefore provide optimistic forecasts to benefit from increased trading activity. Bessiere and Elkemali [35] examine the effect of uncertainty on financial analysts' overconfidence and find a stronger overreaction to private information and underreaction to public information when uncertainty is high. The evidence thus indicates that uncertainty exacerbates behavioral biases.

In this paper, we test analysts' optimism through their overreaction to positive information and underreaction to negative information. If uncertainty enhances optimism, these simultaneous misreactions should be more pronounced when uncertainty is larger.

When forecasting earnings, financial analysts frequently use a salient value and modify it based on new information. We start from the previous forecast and the previously announced earnings as salient values to test whether analysts react to information excessively (overreaction) or insufficiently (underreaction).

We study analysts' reactions to information through two adjustments: the forecast revision and the forecast change. We define forecast revision as the difference between the future earnings forecast and the previous forecast. We define forecast change as the difference between the future earnings forecast and the previously disclosed earnings.

We examine the sign of the forecast error when modifications are positive (positive forecast revisions and positive forecast changes) and negative (negative forecast revisions and negative forecast changes. Forecast error is measured by the difference between the forecast of future earnings and the actual earnings. When the modification is upward, analysts overreact (representativeness and leniency effects) and issue a forecast that exceeds current earnings, resulting in a significant negative forecast error (optimism). When the modification is negative, analysts underreact (leniency and anchoring effects) and issue a forecast that exceeds current earnings (optimism).

We suggest that optimistic analysts overreact to positive forecast revisions and forecast changes and underreact to negative forecast revisions and forecast changes. We expect that this optimism increases with uncertainty.

We define uncertainty by technology intensity and compare two groups: high-tech and low-tech. Considered intangible asset companies, high-tech firms are synonymous with high information uncertainty [36,37]. These firms are characterized by the high volatility of their future profits, the speed of technological development, and the low quantity and quality of information revealed to the markets concerning their R&D investments [38–40].

For more robustness, we use forecast dispersion as a second proxy for uncertainty. Higher forecast dispersion conveys higher earnings uncertainty [24,33,38,41].

Previous studies generally used three categories of proxies for earnings uncertainty. The first category is related to financial market volatility (e.g., earnings volatility, stock return volatility, and volume turnover). The second category captures firms' fundamentals (e.g., technology intensity, size, age, and risk) [42–44]. The third category focuses mainly on analysts' forecast dispersion. Recent studies find that COVID-19 (not covered by our study period) is synonymous with high uncertainty and that there is a positive association between COVID-19 disclosure and uncertainty in annual reports [45]. Our paper excludes market-based proxies because they reflect investors' opinion divergence and are not directly related to analyst activity. We follow a lot of previous research studies that have studied the association between technology intensity and analysts' predictions [24,36,38,39].

This paper examines two hypotheses related to analysts' forecasts (Figure 1). Financial analysts' forecasts are influenced by three combined heuristics: leniency, representativeness, and anchoring and adjustment. When predicting performance, the leniency bias indicates that people are tolerant and tend to profit from uncertainty, which leads to overoptimism. The representativeness bias implies overreaction. It states that, under uncertainty, people overweight good historical performance, as it is representative of good future performance that the company will continue to provide in the future. The anchoring and adjustment bias show that, when forecasting performance, people start from an initial value that is adjusted until reaching the final value. This bias implies that analysts anchor to the previous forecast when predicting future forecasts, resulting in insufficient prediction adjustment or underreaction. Therefore, when positive information is processed, one is more likely to observe overreaction since both leniency and representativeness cause this misreaction and lead to predictions exceeding current earnings (optimism). When negative information is processed, one is more likely to observe underreaction since both leniency and anchoring cause this misreaction and lead to an optimistic forecast (H1). Because cognitive biases arise in contexts requiring more judgment, we assume that the optimism describing these misreactions is greater for firms with a high uncertainty level (H2).

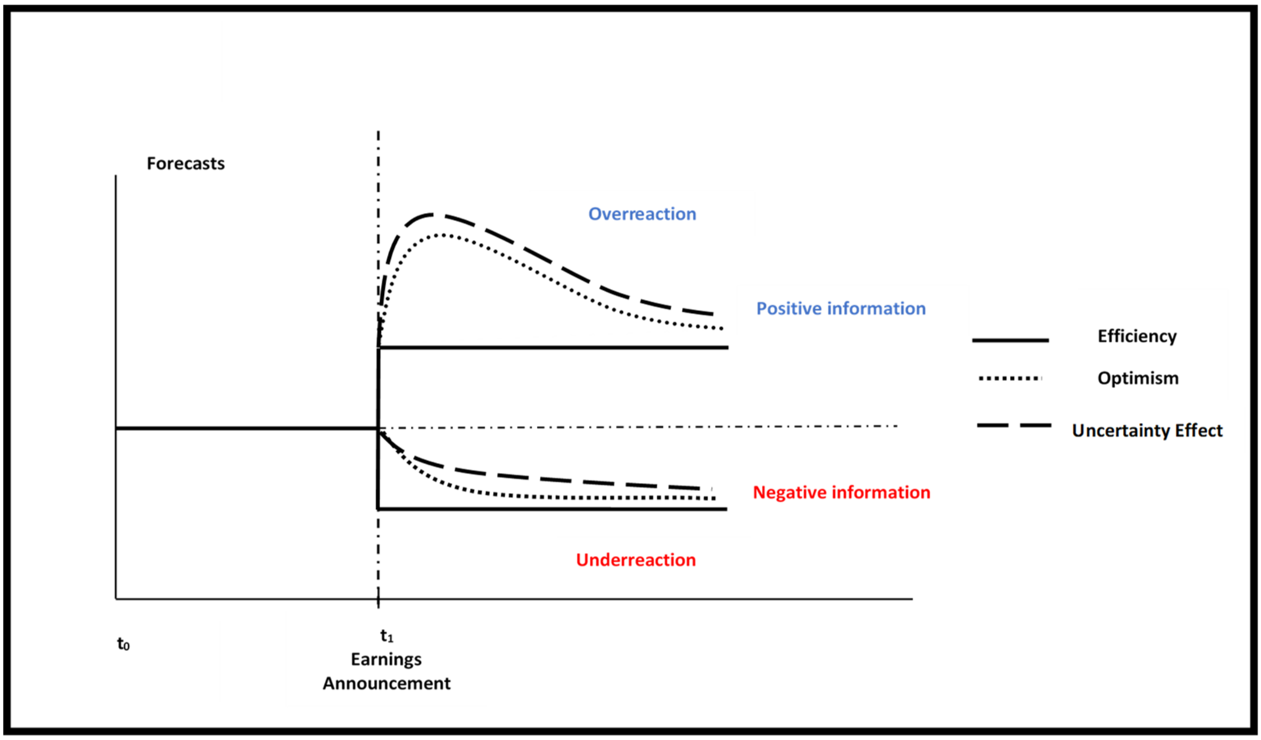

Figure 1. Nature of information and analysts 'reaction.

Hypothesis (H1). *Financial analysts exhibit optimism: they overreact to positive information and underreact to negative information.*

Hypothesis (H2). *Uncertainty boosts analysts' optimism (described in H1).*

Our findings expand previous literature contributions on analysts' overreaction and underreaction by examining these reactions in situations of high and low uncertainty since cognitive biases arise in situations of low predictability. They reveal analysts' tendency to be optimistic and confirm that uncertainty exacerbates this behavior.

This paper is important for several reasons. First, it provides a theoretical framework for the effect of combined cognitive biases, and not an isolated heuristic, on analysts' behavior. Second, it examines analysts' optimism through their overreaction and underreaction to positive and negative information when a salient value is considered and adjusted based on new information. Third, few papers have tested the relationship between technology intensity, as a proxy for uncertainty, and behavioral biases. Finally, this paper has implications for studies interested in modeling investor overreaction and underreaction phenomena.

The rest of the paper is structured as follows: Section 2 presents the data and variables. Section 3 reports the empirical results. The final section concludes the paper.

2. Sample and Variables

2.1. Sample

Our sample is covered by the Institutional Brokers Estimate Systems database (I/B/E/S) during the period of 2010–2019. The consensus forecast is defined as the mean and/or median of at least three individual analysts' forecasts published by the I/B/E/S. All analysts' forecasts exceeding, in absolute value, 200 percent of the earnings per share were deleted and considered outliers. After considering these data requirements, our final sample includes 1933 European firms with 16,942 firm-year observations.

To test the uncertainty effect on analysts' forecasts, we divided the sample into two groups based on industry codes: high-tech (HT) and low-tech (LT) firms. This industry code-based segmentation has been employed by multiple studies, such as Cooper et al. [46], Kwon [36], and Bessiere and Elkemali [35]. These authors use the OECD classification for manufacturer industries and classify service industries as low-tech, with the exception of telecommunications and computer services, which are classified as high-tech.

To make our results based on technological intensity more robust and better examine the uncertainty impact, a second decomposition according to forecast dispersion is performed. For each month and for the whole sample, we extract from I/B/E/S the standard deviation median of analyst forecasts and define two groups: high dispersion (HDISP) and low dispersion (LDISP). Firms with high forecast dispersion express a high level of uncertainty.

2.2. Variables

To test the effect of uncertainty on optimism, we define the following variables:

1. E and E_{t-1} are, respectively, the current earnings per share for year t and the prior earnings per share for year t-1.
2. F_n is the consensus forecast of current earnings E (n) months before the current earnings release month E (n = 1, 2, 3 . . . 11).
3. ERR_n is the forecast error (n) months before the actual earnings announcement month, defined as $ERR_n = (E - F_n)/|E|$. A negative forecast error ($ERR_n < 0$) expresses optimism.
4. REV_n is the forecast revision (n) months before the current earnings release month, described as $REV_n = (F_n - F_{n+1})/|F_n|$. $REV_n > 0$ expresses an upward revision for the month (*n*) due to positive information. An excessive upward forecast revision implies optimism. $REV_n < 0$ expresses a downward revision for the month (n) due to negative information. An insufficient downward forecast revision implies optimism.

5. FCH_n is the forecast change (n) months before the month of actual earnings release E, described as $FCH_n = (F_n - E_{t\text{-}1})/|F_n|$. $FCH_n > 0$ implies an upward forecast change. An excessive upward forecast change implies optimism. $FCH_n < 0$ implies a downward forecast change. An insufficient downward forecast change implies optimism.
6. HT is a dummy variable that is equal to 1 if the firm is in the high-tech subsample (HT) and otherwise 0.
7. $DISP_n$ is the forecast dispersion (n) months before the month of actual earnings release E, described as $DISP_n = Std_n/|F_n|$, where Std_n represents the standard deviation reported by I/B/E/S for the month n. The forecast change (FCH_{11}) 11 months before the month of actual earnings release E is equal to the forecast revision (REV_{11}) one month after the prior earnings announcement month $E_{t\text{-}1}$.

Table 1 provides descriptive statistics for the whole sample and both subsamples HT and LT.

Table 1. Descriptive statistics for the whole sample High- and Low-tech subsamples.

Year	Number of Firms			ERR Mean (Median)			DISP Mean (Median)		
	HT&LT	LT	HT	HT&LT	LT	HT	HT&LT	LT	HT
2010	1485	997	488	−0.489 (−0.102)	−0.341 (−0.046)	−0.732 *** (−0.208 ***)	1.117 (0.645)	0.785 (0.395)	1.408 *** (0.875 ***)
2011	1446	877	569	−0.449 (−0.095)	−0.239 (−0.033)	−0.845 *** (−0.192 ***)	1.131 (0.653)	0.801 (0.402)	1.413 *** (0.899 ***)
2012	1586	984	602	−0.487 (−0.110)	−0.333 (−0.041)	−0.611 *** (−0.176 ***)	1.054 (0.613)	0.745 (0.377)	1.398 *** (0.852 ***)
2013	1601	949	652	−0.568 (−0.125)	−0.423 (−0.039)	−0.655 *** (−0.196 ***)	1.121 (0.649)	0.755 (0.392)	1.425 *** (0.786 ***)
2014	1695	1034	661	−0.488 (−0.088)	−0.314 (−0.041)	−0.529 *** (−0.189 ***)	1.108 (0.633)	0.748 (0.411)	1.418 *** (0.764 ***)
2015	1768	1063	705	−0.334 (−0.074)	−0.212 (−0.026)	−0.469 *** (−0.145 ***)	1.092 (0.587)	0.722 (0.333)	1.363 *** (0.742 ***)
2016	1785	1083	702	−0.240 (−0.061)	−0.124 (−0.010)	−0.388 *** (−0.115 ***)	1.055 (0.542)	0.688 (0.295)	1.329 *** (0.686 ***)
2017	1812	1103	709	−0.337 (−0.094)	−0.213 (−0.035)	−0.593 *** (−0.158 ***)	1.002 (0.501)	0.673 (0.277)	1.299 *** (0.646 ***)
2018	1862	1143	719	−0.355 (−0.073)	−0.265 (−0.043)	−0.516 *** (−0.143 ***)	0.945 (0.488)	0.624 (0.254)	1.219 *** (0.602 ***)
2019	1902	1179	723	−0.248 (−0.068)	−0.189 (−0.033)	−0.409 *** (−0.138 ***)	0.966 (0.495)	0.629 (0.265)	1.242 *** (0.598 ***)
(2010–2019)	16,942	10,412	6530	−0.399 (−0.092)	−0.288 (−0.037)	−0.581 *** (−0.169 ***)	1.092 (0.602)	0.731 (0.358)	1.328 *** (0.739 ***)

Notes: The table presents the significance of mean differences (*t*-test) and median differences (Wilcoxon test) between High-tech (HT) and Low-tech (LT) subsamples at *** 1%. The table also reports, for each year, the total number of firms and the number of HT and LT firms; ERR and DISP indicate, respectively, forecast error and forecast dispersion; ERR and DISP are measured n months prior to the earnings announcement.

3. Empirical Results

This analysis tests the association between forecast error and, separately, forecast revisions and forecast changes. Depending on the positive (good information) or negative sign (bad information) of the forecast revision and forecast change, we test whether the forecast error is negative (optimism) or positive (pessimism). A negative association between positive information and the forecast error expresses overreaction, while a positive association between negative information and the forecast error implies underreaction. The overreaction and underreaction, respectively, to positive and negative information imply optimism. To examine the effect of uncertainty, we split the whole sample into two groups: HT and LT firms. Descriptive and regression analyses are performed (n) months before the actual earnings release. We also assume that uncertainty grows with the forecasting horizon. The quantity of information gathered by analysts increases as the forecast horizon deceases [47,48].

3.1. Forecast Revisions: Analysts' Anchor to Previous Forecast

3.1.1. Descriptive Analysis

This analysis focuses on the descriptive association between forecast errors and forecast revisions. We suppose that analysts start from the previous forecast as a salient value and adjust it according to new information. For the 11 months prior to the current earnings announcement, we divided the HT and LT subsamples into two subgroups of observations: upward forecast revisions (REV > 0) and downward forecast revisions (REV < 0). We removed all observations whose consensus forecast revision was equal to zero. For each month (*n*) and group, we computed the mean and median forecast errors as well as the percentage of negative forecast errors. Table 2 shows that when forecast revisions are positive (columns REV > 0), most forecast errors are negative (the percentage of negative forecast errors is more than 50%). The test statistic, Z, shows the significance of the difference between the percentages of negative forecast errors and 50%. The difference is significant at 1% for almost all 10 periods. We also observe that the mean and median forecast errors are optimistic (ERR < 0). These results confirm that when analysts upwardly revise forecasts (REV > 0), they do it excessively (overreaction) and make optimistic errors (ERR < 0).

Table 2. Relationship between the forecast error and the forecast revision.

Month	REV > 0		REV < 0		Obs
(n)	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	49.6	0.012 *** (0.009 ***)	54.2 ***	−0.176 (−0.088)	15,248
2	51.4 *	−0.086 *** (−0.034 ***)	55.3 ***	−0.265 (−0.105)	15,108
3	52.5 **	−0.101 *** (−0.055 ***)	60.1 ***	−0.314 (−0.135)	14,556
4	54.0 ***	−0.187 *** (−0.068 ***)	65.3 ***	−0.385 (−0.144)	14,125
5	57.1 ***	−0.202 *** (−0.089 ***)	68.9 ***	−0.482 (−0.163)	13,159
6	57.4 ***	−0.227 *** (−0.092 ***)	69.5 ***	−0.490 (−0.185)	13,022
7	58.0 ***	−0.242 *** (−0.078 ***)	69.2 ***	−0.485 (−0.155)	12,908
8	59.1 ***	−0.258 *** (−0.085 ***)	70.1 ***	−0.502 (−0.203)	12,532
9	60.1 ***	−0.323 *** (−0.101 ***)	71.0 ***	−0.523 (−0.199)	11,975
10	62.1 ***	−0.326 *** (−0.125 ***)	72.1 ***	−0.545 (−0.210)	11,692

Notes: The table indicates, for positive forecast revision (REV > 0) and negative forecast revision (REV < 0) subsamples, percentage of negative forecast error (%) and mean and median forecast error n months prior to the release of earnings per share. The forecast error is defined as $ERR_n = (E - F_n)/|E|$, and the forecast revision is defined as $REV_n = (F_n - F_{n+1})/|Fn|$. ERR < 0 (ERR > 0) implies optimism (pessimism). The table also reports the statistical significance at *** 1%, ** 5%, and * 10% for the difference between the percentage of negative forecast errors and 50% (z-test), the mean differences (*t*-test), and the median differences (Wilcoxon test) between the two subsamples REV > 0 and REV < 0.

When analysts revise their forecasts downward (REV < 0), they do it insufficiently (underreaction), and their predictions remain optimistic. These results support our first hypothesis about analysts' optimism, overreaction to positive information, and underreaction to negative information.

To examine the effect of uncertainty on optimism, we distinguished between HT firms and LT firms when forecast revisions are negative and positive. Table 3 results are consistent with our second hypothesis that optimism increases with uncertainty. The percentage of negative forecast errors and the mean and median forecast errors are significantly higher for HT firms. Results also indicate that the optimism difference between HT firms and LT firms is stronger when the prediction is far from the earnings release month. As n decreases, the percentage of negative forecast errors approaches 50%, and the mean and median forecast errors approach zero. These findings specify that the effect of uncertainty on psychological biases decreases as the forecast horizon shortens.

Table 3. Relationship between the forecast error and the forecast revision for high- and low-tech subsamples.

(n)	REV > 0				REV < 0				Obs
	HT		LT		HT		LT		
	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	49.6	−0.042 ** (−0.018 ***)	49.4	0.025 (0.012)	65.7 ***	−0.336 ** (−0.188 ***)	49.7	−0.082 (−0.005)	15,248
2	51.9 **	−0.125 ** (−0.068 ***)	50.3	−0.036 (−0.016)	70.5 ***	−0.424 ** (−0.297 ***)	52.3	−0.102 (−0.036)	15,108
3	53.2 ***	−0.184 *** (−0.089 ***)	50.1	−0.082 (−0.023)	73.6 ***	−0.528 *** (−0.294 ***)	55.1	−0.148 (−0.044)	14,556
4	55.0 ***	−0.290 *** (−0.095 ***)	51.3	−0.107 (−0.036)	76.0 ***	−0.695 *** (−0.305 ***)	58.6	−0.197 (−0.059)	14,125
5	59.1 ***	−0.335 *** (−0.111 ***)	51.9	−0.152 (−0.048)	78.1 ***	−0.744 *** (−0.384 ***)	61.7	−0.277 (−0.066)	13,159
6	65.0 ***	−0.394 *** (−0.131 ***)	52.0	−0.146 (−0.060)	78.0 ***	−0.785 *** (−0.395 ***)	63.0	−0.315 (−0.062)	13,022
7	64.0 ***	−0.389 *** (−0.125 ***)	51.2	−0.135 (−0.053	77.6 ***	−0.776 *** (−0.407 ***)	62.4	−0.294 (−0.083	12,908
8	65.1 ***	−0.412 *** (−0.182 ***)	53.1	−0.167 (−0.063)	78.6 ***	−0.795 *** (−0.417 ***)	63.7	−0.325 (−0.093)	12,532
9	66.1 ***	−0.489 *** (−0.194 ***)	54.0	−0.195 (−0.071)	79.1 ***	−0.802 *** (−0.411 ***)	64.9	−0.387 (−0.102)	11,975
10	67.2 ***	−0.521 *** (−0.215 ***)	55.1	−0.228 (−0.085)	80.2 ***	−0.826 *** (−0.445 ***)	65.3	−0.369 (−0.105)	11,692

Notes: The table reports the percentage of negative errors (%) and mean and median forecast errors for the two subsamples, high and low tech, when forecast revision for month n is positive (REV > 0) and negative (REV < 0). Forecast revision is defined as $REV_n = (F_n - F_{n+1})/|F_n|$, and forecast error is defined as $ERR_n = (E - F_n)/|E|$. ERR < 0 (ERR > 0) implies optimism (pessimism). The table also reports the statistical significance at *** 1% and ** 5% for the difference between the percentage of negative forecast errors and 50% (z-test), mean differences (*t*-test), and median differences (Wilcoxon test) between the two subsamples, HT and LT, for the same REV sign.

3.1.2. Regression Analysis

The overreaction/underreaction phenomenon is also examined by regressing forecast errors on forecast revisions. Regression analysis examines not only the direction of the forecast error but also its magnitude.

$$ERR_n = \alpha + \beta\ REV_n + \zeta\ n = 1 \text{ to } 10 \tag{1}$$

where ERR_n and REV_n are the mean forecast error and mean forecast revision for the month (*n*) prior to actual earnings release, respectively, α is an intercept term, and β is the regression's slope. Lack of bias in prediction implies that both α and β equal zero. A significant relationship between the dependent and the independent variable implies biased behavior. Under rationality, no relationship must be observed, and the regression coefficient must be insignificant [11,12,14,20,23]. Overreaction (underreaction) implies a significant negative (positive) β. A significant negative (positive) α implies optimism (pessimism).

As in previous studies that examine over- and underreactions by regression analysis, we do not expect a substantial R^2 because the regression expresses biased behavior. For greater accuracy, we conducted panel regressions (Eviews software, IHS Markit, USA)

Our results reveal clear biases in analysts' forecasts. Table 4 shows analyst optimism and general underreaction as the intercept α is significantly negative and the slope β is significantly positive for almost all 10 periods. We also observe that both intercepts and slopes decrease as the earnings release month approaches (as n decreases, the forecasting horizon becomes shorter and the uncertainty decreases). These results are consistent with underreaction when previous forecasts are used as an anchor for the analysts' forecast [11,12,20].

Table 4. Relationship between forecast errors and forecast revisions n months before current earnings announcement $ERR_n = \alpha + \beta\ REV_n + \zeta$.

n	α	β	R^2	Obs
1	−0.044 (2.074 **)	0.262 (3.015 ***)	0.012	15,248
2	−0.094 (4.111 **)	0.489 (4.326 ***)	0.016	15,108
3	−0.142 (−5.011 ***)	0.618 (6.007 ***)	0.025	14,556
4	−0.188 (−8.172 ***)	0.627 (7.274 ***)	0.031	14,125
5	−0.244 (−12.074 ***)	0.893 (9.189 ***)	0.029	13,159
6	−0.222 (−11.751 ***)	0.886 (8.745 ***)	0.037	13,022
7	−0.276 (−15.112 ***)	0.973 (10.101 ***)	0.031	12,908
8	−0.345 (−18.547 ***)	1.176 (13.127 ***)	0.043	12,532
9	−0.389 (−20.187 ***)	1.345 (14.224 ***)	0.042	11,975
10	−0.436 (−25.742 ***)	1.465 (15.246 ***)	0.057	11,692

Note: Statistically significant at *** 1% and ** 5% (*t*-test). α and β report, respectively, the regression's intercept and coefficient for the whole sample.

To examine the overreaction/underreaction, we regress forecast errors on forecast revisions separately for positive (REV > 0) and negative revisions (REV < 0). The results presented in Table 5 show significant negative slopes when REV > 0 and significant positive slopes when REV < 0 for almost all 10 periods. Consequently, analysts tend to overreact to positive forecast revisions and underreact to negative revisions. The intercept α is negative for both negative and positive forecast revisions. This overreaction/underreaction and negative intercept confirm financial analysts' optimism (H1).

Another important result is that the underreaction to negative modifications appears greater than the overreaction to positive modifications (in absolute value, slopes, βs, are greater for negative forecast revisions), which explains the general underreaction observed in Table 3. The intercept α is also more negative for negative forecast revisions than for positive forecast revisions. This result suggests that analysts exhibit more optimism and anchor when the modification is negative.

To test the effect of uncertainty and quantify its magnitude and significance, we distinguished between HT and LT firms (when REV > 0 and REV < 0) and analyzed the following regression, including an interaction analysis:

$$ERR_n = \alpha_0 + \alpha_1\ HT + \beta_0\ REV_n + \beta_1\ HT.\ REV_n + \zeta\ n = 1 \text{ to } 10 \quad (2)$$

where HT is a dummy variable, which equals 1 for the HT subsample and 0 for the LT subsample. Overreaction (underreaction) implies that the coefficient $\beta_0 + \beta_1$ is negative (positive), and β_1 alone captures the additional effect of uncertainty on the relationship between forecast error and forecast revision. Moreover, a negative intercept $\alpha_0 + \alpha_1$ implies optimism, and α_1 alone shows the additional effect of uncertainty.

Tables 6 and 7 present the results of this model for HT and LT firms, respectively, when forecast revisions are negative and positive. Results show negative (positive) slopes $\beta_0 + \beta_1$ for positive (negative) forecast revisions in each of the 10 monthly regressions. The difference in slopes, β_1, is significantly negative (positive) when revisions are positive (negative). These findings confirm that the overreaction/underreaction phenomenon is far stronger for HT firms than for LT firms.

Table 5. Relationship between forecast errors and forecast revisions n months before actual earnings announcement when forecast revisions are positive and negative $ERR_n = \alpha + \beta\ REV_n + \zeta$.

n	REV > 0				REV < 0			
	α	β	R^2	Obs	α	β	R^2	Obs
1	0.011 (0.732)	−0.067 (−1.335)	0.002	6785	−0.135 (−8.782 ***)	0.489 (5.332 ***)	0.015	8463
2	−0.032 (−1.489)	−0.188 (−1.962 **)	0.004	6650	−0.281 (−10.746 ***)	0.675 (6.412 ***)	0.020	8458
3	−0.054 (−1.808 *)	−0.255 (−4.121 ***)	0.009	6270	−0.301 (−15.197)	0.894 (7.662 ***)	0.029	8286
4	−0.071 (−1.858 *)	−0.451 (−5.709 ***)	0.015	6485	−0.339 (−18.907 ***)	1.075 (9.608 ***)	0.038	7640
5	−0.065 (−1.828 *)	−0.539 (−6.192 ***)	0.020	5543	−0.444 (−20.341 ***)	1.303 (11.618 ***)	0.040	7616
6	−0.088 (−2.213 **)	−0.609 (−6.814 ***)	0.027	5006	−0.459 (−22.428 ***)	1.283 (11.486 ***)	0.049	8016
7	−0.122 (−2.328 **)	−0.701 (−7.981 ***)	0.032	5258	−0.436 (−24.741 ***)	1.418 (13.147 ***)	0.054	7650
8	−0.184 (−3.302 ***)	−0.692 (−7.638 ***)	0.038	5213	−0.568 (−25.162 ***)	1.746 (16.302 ***)	0.059	7319
9	−0.288 (−4.744 ***)	−0.787 (−8.281 ***)	0.042	4976	−0.677 (−28.315 ***)	1.947 (18.018 ***)	0.065	6999
10	−0.326 (−5.618 ***)	−0.836 (−8.474 ***)	0.037	4781	−0.728 (−29.236 ***)	2.244 (19.213 ***)	0.068	6911

Note: Statistically significant at *** 1%, ** 5%, and * 10% (*t*-test). α and β report, respectively, the regression's intercept and coefficient for positive (REV > 0) and negative (REV < 0) forecast revisions.

Table 6. Relationship between forecast errors and positive forecast revisions for high-tech (HT) and low-tech (LT) subsamples n months prior to actual earnings release. $ERR_n = \alpha_0 + \alpha_1\ HT + \beta_0\ REV_n + \beta_1\ HT.REV_n + \zeta$.

REV > 0								
	HT		LT		Difference HT vs. LT			
n	$\alpha_0 + \alpha_1$	$\beta_0 + \beta_1$	α_0	β_0	α_1	β_1	R^2	Obs
1	−0.043 (−1.598 *)	−0.129 (−2.001 **)	0.019 (0.545)	−0.015 (−1.005)	−0.062 (−1.689 *)	−0.114 (−1.954 **)	0.004	6785
2	−0.065 (−1.847 *)	−0.289 (−4.555 ***)	−0.007 (−1.289)	−0.059 (−1.643 *)	−0.058 (−1.658 *)	−0.230 (3.021 ***)	0.008	6650
3	−0.108 (−2.151 **)	−0.458 (−6.542 ***)	−0.023 (−1.408)	−0.126 (−2.821 ***)	−0.085 (−1.902 **)	−0.332 (−3.950 ***)	0.015	6270
4	−0.102 (−2.107 **)	−0.761 (−8.114 ***)	−0.046 (−1.645 *)	−0.284 (−3.519 ***)	−0.056 (−1.625 *)	−0.477 (−4.349 ***)	0.021	6485
5	−0.124 (−2.942 ***)	−0.861 (−8.525 ***)	−0.042 (−1.528 *)	−0.306 (−4.452 ***)	−0.082 (−2.124 **)	−0.555 (−5.945 ***)	0.029	5543
6	−0.209 (−3.629 ***)	−0.987 (−9.186 ***)	−0.066 (−1.878 **)	−0.359 (−5.409 ***)	−0.143 (2.625 ***)	−0.628 (−6.889 ***)	0.036	5006
7	−0.286 (−4.315 ***)	−1.065 (−10.919 ***)	−0.101 (−2.408 **)	−0.486 (−6.115 ***)	−0.185 (2.946 ***)	−0.579 (−6.112 ***)	0.038	5258
8	−0.357 (−5.162 ***)	−1.049 (−10.907 ***)	−0.137 (−3.612 ***)	−0.512 (−6.447 ***)	−0.220 (−3.002 ***)	−0.537 (−5.835 ***)	0.042	5213
9	−0.486 (−6.201 ***)	−1.174 (−11.019 ***)	−0.227 (−4.402 ***)	−0.584 (−6.888 ***)	−0.259 (−3.121 ***)	−0.590 (−6.798 ***)	0.039	4976
10	−0.516 (−6.852 ***)	−1.145 (−10.541 ***)	−0.258 (−4.618 ***)	−0.606 (−7.512 ***)	−0.258 (−3.099 ***)	−0.539 (−6.647 ***)	0.048	4781

Notes: The table reports the statistical significance at *** 1%, ** 5%, and * 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LT subsample (HT = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HT subsample (HT = 1). α_1 and β_1 capture the additional effect of technology (HT) on the relationship between forecast errors and positive forecast revisions (REV > 0).

Table 7. Relationship between forecast errors and negative forecast revisions for high-tech (HT) and low-tech (LT) subsamples n months prior to actual earnings release. $ERR_n = \alpha_0 + \alpha_1\,HT + \beta_0\,REV_n + \beta_1\,HT.REV_n + \zeta$.

	REV < 0							
	HT		**LT**		**Difference HT vs. LT**			
n	**$\alpha_0 + \alpha_1$**	**$\beta_0 + \beta_1$**	**α_0**	**β_0**	**α_1**	**β_1**	**R^2**	**Obs**
1	−0.246 (−10.212 ***)	0.814 (7.005 ***)	−0.048 (−4.311 ***)	0.298 (3.331 ***)	−0.198 (−10.252 ***)	0.516 (5.014 ***)	0.037	6122
2	−0.448 (−14.445 ***)	1.002 (9.254 ***)	−0.126 (−7.583 ***)	0.503 (5.457 ***)	−0.322 (−13.144 ***)	0.499 (4.835 ***)	0.049	5872
3	−0.549 (18.741 ***)	1.225 (10.212 ***)	−0.114 (−7.414 ***)	0.631 (5.948 ***)	−0.435 (−16.011 ***)	0.594 (6.227 ***)	0.057	5436
4	−0.624 (−22.008 ***)	1.436 (12.112 ***)	−0.188 (−9.554 ***)	0.712 (6.686 ***)	−0.436 (−17.514 ***)	0.724 (7.028 ***)	0.066	5172
5	−0.747 (−25.145 ***)	1.644 (13.358 ***)	−0.239 (−12.201 ***)	0.888 (7.334 ***)	−0.508 (−19.440 ***)	0.756 (7.648 ***)	0.062	4632
6	−0.831 (−28.117 ***)	1.527 (12.477 ***)	−0.335 (16.337 ***)	0.913 (8.221 ***)	−0.496 (−19.384 ***)	0.614 (7.104 ***)	0.079	4657
7	−0.817 (−27.114 ***)	1.954 (18.102 ***)	−0.310 (−15.287 ***)	1.011 (9.514 ***)	−0.507 (−21.461 ***)	0.943 (8.889 ***)	0.088	4546
8	−0.912 (−29.287 ***)	2.115 (18.641 ***)	−0.381 (−18.217 ***)	1.345 (10.356 ***)	−0.531 (−23.331 ***)	0.770 (8.405 ***)	0.098	4345
9	−1.025 (−31.112 ***)	2.245 (21.253 ***)	−0.447 (−21.236 ***)	1.223 (10.027 ***)	−0.578 (−25.497 ***)	1.022 (9.858 ***)	0.114	3734
10	−1.180 (−32.142 ***)	2.536 (23.015 ***)	−0.513 (−25.245 ***)	1.421 (14.235 ***)	−0.667 (−26.245 ***)	1.115 (10.022 ***)	0.125	4013

Notes: The table reports the statistical significance at *** 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LT subsample (HT = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HT subsample (HT = 1). α_1 and β_1 capture the additional effect of technology (HT) on the relationship between forecast errors and negative forecast revisions (REV < 0).

We also observe that the intercept $\alpha_0 + \alpha_1$ is negative for both positive and negative revisions and that the difference in intercepts α_1 between HT and LT is significant. This finding suggests that analysts are more optimistic when making forecasts for HT firms. The results also show that the intercept α and slope β diminish considerably as the earnings release month approaches. As the earnings announcement month approaches, analysts correct their predictions and the optimism decreases for both HT and LT firms (e.g., $\beta_0 + \beta_1$ decreases from −1.145 in month (10) to −0.129 in month (1) for REV > 0, and results are similar for αs).

Taken together, these results support analysts' optimism (H1). We jointly observe the two phenomena of overreaction to positive information and underreaction to negative information with a negative constant. This optimism is stronger for HT firms and appears more pronounced when the forecast horizon is far away. Differences between HT and LT significantly support H2.

3.2. Forecast Changes: Analysts' Anchor to Prior Earnings

In this analysis, we assume that analysts use prior earnings as "representative" information for their predictions and that the availability of this representativeness leads to a general overreaction. The overreaction is more likely to be higher in the first month after the prior earnings announcement (month 11), as analysts have not made a forecast yet for the next year's earnings. Therefore, representativeness may have a greater effect on forecasts than anchoring. The forecast change is defined not only for month 11 before the earnings announcement but also for the other 10 months. The relationship between forecast changes and forecast errors for these periods is discussed in the literature, even if earnings forecasts in these months are likely to be based on previous forecasts [12,14].

To assess analysts' optimism, we analyze the pattern of forecast error when the forecast change is positive (FCH > 0) and negative (FCH < 0). A negative relationship between positive forecast change and forecast error implies overreaction, while a positive relationship between negative forecast change and forecast error implies underreaction. The overreaction to positive forecast changes and the underreaction to negative forecast changes convey optimism.

3.2.1. Descriptive Analysis

Table 8 indicates that, for both negative and positive forecast changes, the percentage of negative forecast errors is significantly greater than 50% and the mean and median forecast errors are negative. These findings confirm analysts' overreaction to positive information and underreaction to negative information (optimism illustrated in hypothesis 1). When analysts incorporate positive information (FCH > 0), they overreact due to representativeness and leniency biases and issue an excessive forecast above the actual earnings (optimism). When analysts incorporate negative information (FCH < 0), they underreact due to the anchoring and leniency biases and issue an insufficient forecast above the actual earnings (optimism).

Table 8. Relationship between the forecast error and the sign of the forecast change.

n	FCH > 0		FCH < 0		Obs
	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	49.3	−0.032 *** (0.000 ***)	59.1 ***	−0.184 (−0.074)	16,407
2	51.8 *	−0.079 *** (−0.024 ***)	57.3 ***	−0.224 (−0.109)	16,235
3	53.4 **	−0.174 *** (−0.034 ***)	58.2 ***	−0.328 (−0.130)	16,111
4	56.5 ***	−0.218 *** (−0.0051 ***)	60.2 ***	−0.403 (−0.142)	15,805
5	57.8 ***	−0.294 *** (−0.064 ***)	58.4 ***	−0.377 (−0.132)	15,687
6	59.4 ***	−0.359 *** (−0.108 ***)	55.5 ***	−0.316 (−0.127)	15,434
7	58.3 ***	−0.331 *** (−0.114 ***)	56.4 ***	−0.328 (−0.146)	15,216
8	60.1 ***	−0.377 *** (−0.131 ***)	56.1 ***	−0.375 (−0.173)	15,112
9	62.9 ***	−0.389 *** (−0.142 ***)	57.2 ***	−0.424 (−0.214)	14,965
10	63.6 ***	−0.465 *** (−0.192 ***)	56.3 ***	−0.401 (−0.195)	14,831
11	64.4 ***	−0.446 *** (−0.178 ***)	54.2 ***	−0.355 (−0.189)	14,625

Notes: The table indicates, for positive forecast change (FCH > 0) and negative forecast change (FCH < 0) subsamples, percentage of negative forecast error (%) and mean and median forecast error n months before the release of earnings per share. Forecast change is defined for month *n* as $FCH_n = (F_n - E_{t-1})/|F_n|$. Forecast error is defined for month *n* as $ERR_n = (E - F_n)/|E|$. ERR<0 (ERR>0) implies optimism (pessimism). The table also reports the statistical significance at *** 1%, ** 5%, and * 10%, in the difference between the percentage of negative forecast errors and 50% (z-test), the mean differences (*t*-test), and the median differences (Wilcoxon test) between the two subsamples FCH > 0 and FCH < 0.

When separating between HT and LT companies for the two groups of FCH > 0 and FCH < 0 (Table 9), we notice that the mean and median forecast errors are significantly more negative and that the percentage of negative forecast errors is greater for HT firms than for LT firms. These findings confirm that uncertainty exacerbates optimism (H2). This optimism decreases gradually as n decreases, which indicates that as the earnings release month becomes shorter, the effect of uncertainty on psychological biases decreases.

3.2.2. Regression Analysis

In this analysis, we regress forecast errors on forecast changes:

$$ERR_n = \alpha + \beta\ FCH_n + \zeta\ n = 1 \text{ to } 11 \tag{3}$$

where ERR_n and FCH_n are, respectively, the mean forecast error and mean forecast change for the month (n) prior to earnings release.

For the full sample (Table 10), results reveal negative intercepts αs and slopes βs. These results confirm the optimism and general overreaction observed by many authors such as DeBondt and Thaler [13] and Amir and Ganzach [20]. The optimism ($\alpha = -0.325$) and overreaction ($\beta = -0.658$) are higher for the first month (period 11) following the previous earnings release and decline as the forecast horizon is shortened. These results confirm the effect of cognitive biases on analysts' optimism and that this effect declines as the earnings announcement month approaches. The representativeness leads to a stronger overreaction in the first month after the prior earnings release as no previous forecast was made for the next year's earnings (the anchoring effect is low). As n decreases, the effect of representativeness bias decreases, and hence the overreaction declines.

Table 9. Relationship between the forecast error and the sign of the forecast change for high- and low-tech subsamples.

n	FCH > 0				FCH <0				Obs
	HT		LT		HT		LT		
	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	55.7 **	−0.119 ** (−0.052 ***)	48.5	0.039 (0.007)	63.3 ***	−0.236 *** (−0.188 ***)	55.8	−0.076 (−0.035)	16,407
2	57.9 ***	−0.215 ** (−0.089 ***)	50.6	−0.047 (−0.025)	64.7 ***	−0.284 *** (−0.099 ***)	55.2	−0.095 (−0.024)	16,235
3	58.2 ***	−0.377 *** (−0.122 ***)	51.1	−0.096 (−0.071)	62.6 ***	−0.345 *** (−0.143 ***)	53.1	−0.118 (−0.042)	16,111
4	63.4 ***	−0.490 *** (−0.182 ***)	53.4	−0.144 (−0.092)	64.4 ***	−0.439 *** (−0.215 ***)	54.8	−0.138 (−0.091)	15,805
5	62.5 ***	−0.441 *** (−0.168 ***)	54.7	−0.136 (−0.086)	63.1 ***	−0.389 *** (−0.168 ***)	52.5	−0.152 (−0.072)	15,687
6	64.0 ***	−0.524 *** (−0.197 ***)	56.1	−0.124 (−0.091)	62.3 ***	−0.365 *** (−0.152 ***)	51.9	−0.107 (−0.052)	15,434
7	63.8 ***	−0.568 *** (−0.210 ***)	56.3	−0.112 (−0.099)	61.6 ***	−0.412 *** (−0.208 ***)	51.3	−0.138 (−0.069)	15,216
8	65.9 ***	−0.546 *** (−0.193 ***)	55.2	−0.144 (−0.122)	60.4 ***	−0.489 *** (−0.245 ***)	50.6	−0.114 (−0.056)	15,112
9	67.2 ***	−0.662 *** (−0.279 ***)	56.8	−0.202 (−0.157)	60.1 ***	−0.543 *** (−0.288 ***)	51.6	−0.151 (−0.099)	14,965
10	68.1 ***	−0.758 *** (−0.361 ***)	57.5	−0.245 (−0.194)	56.9 ***	−0.525 *** (−0.274 ***)	50.9	−0.205 (−0.115)	14,831
11	68.4 ***	−0.728 *** (−0.334 ***)	57.8	−0.368 (−0.201)	56.2 ***	−0.495 *** (−0.296 ***)	50.3	−0.196 (−0.108)	14,625

Notes: The table reports the percentage of negative errors (%) and mean and median forecast error for the two subsamples, high and low tech, when forecast change for month n is positive (FCH > 0) and negative (FCH < 0). Forecast change is defined for month n as $FCH_n = (F_n - E_{t-1})/|F_n|$. Forecast error is defined as $ERR_n = (E - F_n)/|E|$. ERR < 0 (ERR > 0) implies optimism (pessimism). The table also reports the statistical significance at *** 1% and ** 5% in the difference between the percentage of negative forecast errors and 50% (z-test), mean differences (*t*-test), and median differences (Wilcoxon test) between the two subsamples, HT and LT, for the same FCH sign.

To complete the analysis, we ran the same regression for the positive and negative forecast change groups. Table 11 reports negative βs for positive forecast changes and positive βs for negative forecast changes, a finding consistent with our first hypothesis about analysts' optimism through the overreaction to positive modifications and the underreaction to negative modifications. Results also show that analysts' underreaction for negative forecast changes is much lower than that observed for negative forecast revisions, indicating that the previous forecast is more powerful than previous earnings when the modification is negative. The intercept α is more negative for negative forecast changes than for positive forecast changes. These findings suggest that analysts exhibit more optimism when modifying their forecasts downward. Leniency tends to intensify the anchor when the forecast is negative.

To examine the effect of uncertainty, we use the following regression:

$$ERR_n = \alpha_0 + \alpha_1\, HT + \beta_0\, FCH_n + \beta_1\, HT.\, FCH_n + \zeta \quad n = 1 \text{ to } 11 \qquad (4)$$

The interpretation of intercepts and slopes is similar to that of regression (2). Tables 12 and 13 present results for HT and LT firms when forecast changes are, respectively, positive and negative. For HT firms, we observe that (β_0 + β_1) is strongly negative (positive) and highly significant when forecast changes are positive (negative), confirming that the overreaction (underreaction) observed in Table 11 is more pronounced for high-uncertainty firms (e.g., for month 11 (FCH > 0), HT's slope $\beta_0 + \beta_1 = -1.125$ while LT's slope $\beta_0 = -0.511$). The difference in slopes β_1 between HT and LT firms is significant for all 11 periods. The intercepts (α_0 + α_1) of HT firms are clearly more negative than those of LT firms (α_0), with a significant negative difference (α_1) between these subsamples (for month 11 (FCH > 0), HT firms intercept $\alpha_0 + \alpha_1 = -0.294$ while LT firms intercept $\alpha_0 = -0.113$). As shown in previous tables, intercepts and slopes decrease as the forecast horizon declines. Taken together, these results support the high effect of uncertainty on optimism (H2).

Table 10. Relationship between forecast errors and forecast changes n months before the actual earnings announcement. $ERR_n = \alpha + \beta\ FCH_n + \zeta$.

n	α	β	R^2	Obs
1	−0.088 (−3.126 ***)	−0.028 (−1.566 *)	0.000	16,407
2	−0.101 (−3.949 ***)	−0.019 (−1.453)	0.007	16,235
3	−0.096 (−3.884 ***)	−0.078 (−1.947 **)	0.008	16,111
4	−0.128 (−4.657 ***)	−0.176 (−3.101 ***)	0.021	15,805
5	0.138 (−5.114 ***)	−0.296 (−3.414 ***)	0.036	15,687
6	−0.173 (−6.118 ***)	−0.328 (−4.854 ***)	0.038	15,434
7	−0.190 (−7.114 ***)	−0.389 (−5.446 ***)	0.043	15,216
8	−0.214 (−8.724 ***)	−0.481 (−6.424 ***)	0.054	15,112
9	−0.255 (−10.548 ***)	−0.587 (−7.825 ***)	0.057	14,965
10	−0.287 (−12.247 ***)	−0.613 (−8.653 ***)	0.062	14,831
11	−0.325 (−13.454 ***)	−0.658 (−8.425 ***)	0.063	14,625

Notes: Statistically significant at *** 1%, ** 5%, and * 10% (*t*-test). α and β report, respectively, the regression's intercept and coefficient for the whole sample.

3.3. Robustness Tests

Previous studies have documented that technological intensity is synonymous with high uncertainty, and in order to make our results more robust, we have reproduced previous portfolio and regression analyses based on a second measure of informational uncertainty: the dispersion of analyst forecasts (analyst-based proxy). For each month, we determined two subsamples of high and low dispersion according to the median. Firms with forecast dispersion above the median are considered high-uncertainty firms (high dispersion), while firms with forecast dispersion below the median represent low-uncertainty firms (low dispersion). The results are reported in the Appendix in Tables A1–A7. They are in line with those obtained for the HT and LT subsamples (reported in Tables 1, 3, 6, 7, 9, 12, and 13).

Table 11. Relationship between forecast errors and forecast changes *n* months before the actual earnings announcement when forecast changes are positive and negative. $ERR_n = \alpha + \beta\ FCH_n + \zeta$.

	FCH > 0				FCH < 0			
n	**α**	**β**	**R^2**	**Obs**	**α**	**β**	**R^2**	**Obs**
1	−0.045 (−2.110 **)	−0.108 (−2.835 ***)	0.024	9745	−0.186 (−8.241 ***)	0.089 (2.002 **)	0.001	6662
2	−0.084 (−3.219 ***)	−0,148 (−3.122 ***)	0.039	10,087	−0.246 (−9.701 ***)	0.096 (2.912 ***)	0.001	6148
3	−0.061 (−2.901 ***)	−0.183 (−4.120 ***)	0.044	10,359	−0.211 (−8.105 ***)	0.107 (3.002 ***)	0.005	5752
4	−0.073 (−3.112 ***)	−0.286 (−4.624 ***)	0.053	10,662	−0.245 (−9.817 ***)	0.115 (4.447 ***)	0.008	5143
5	−0.092 (−3.616 ***)	−0.415 (−5.002 ***)	0.062	10,763	−0.294 (−10.141 ***)	0.214 (5.774 ***)	0.011	4924
6	−0.084 (−3.416 ***)	−0.576 (−7.331 ***)	0.075	11,012	−0.322 (−10.824 ***)	0.291 (6.455 ***)	0.019	4422
7	−0.117 (−3.917 **)	−0.685 (−8.794 ***)	0.084	10,886	−0.385 (−12.892 ***)	0.308 (7.156 ***)	0.022	4330
8	−0.123 (−4.121 ***)	−0.745 (−10.081 ***)	0.091	11,546	−0.315 (−14.922 ***)	0.391 (7.754 ***)	0.029	3566
9	−0.161 (−4.402 ***)	−0.804 (−11.851 ***)	0.104	11,225	−0.367 (−15.787 ***)	0.487 (8.001 ***)	0.039	3740
10	−0.154 (−4.211 ***)	−0.841 (−12.125 ***)	0.121	11,145	−0.355 (−15.333 ***)	0.543 (8.147 ***)	0.042	3686
11	−0.176 (−4.889)	−0.869 (−12.556 ***)	0.125	10,980	−0.382 (−15.773 ***)	0.566 (8.847 ***)	0.049	3645

Notes: Statistically significant at *** 1% and ** 5% (*t*-test). α and β report, respectively, the regression's intercept and coefficient for positive (FCH > 0) and negative forecast changes (FCH < 0).

Table 12. Relationship between forecast errors and positive forecast changes for high- (HT) and low-tech (LT) subsamples n months before the actual earnings announcement. $ERR_n = \alpha_0 + \alpha_1\ HT + \beta_0\ FCH_n + \beta_1\ HT.FCH_n + \zeta$.

	FCH > 0							
	HT		LT		Difference HT vs. LT			
n	**$\alpha_0 + \alpha_1$**	**$\beta_0 + \beta_1$**	**α_0**	**β_0**	**α_1**	**β_1**	**R^2**	**Obs**
1	−0.096 (−2.110 **)	−0.191 (−3.801 ***)	−0.015 (−1.441)	0.041 −1.119	−0.081 (−2.731 ***)	−0.232 (−3.925 ***)	0.042	9745
2	−0.102 (−2.798 ***)	−0.233 (−4.779 ***)	−0.026 (1.773 *)	−0.069 (−1.317)	−0.076 (−2.625 ***)	−0.164 (−3.845 ***)	0.062	10,087
3	−0.096 (−3.168 ***)	−0.376 (−6.445 ***)	−0.053 (−2.441 **)	−0.115 (−1.661 *)	−0.043 (−1.625 *)	−0.261 (−4.585 ***)	0.074	10,359
4	−0.085 (−3.005 ***)	−0.509 (−8.225 ***)	−0.024 (−1.917 **)	−0.204 (−1.727 *)	−0.061 (−2.325 **)	−0.713 (−9.217 ***)	0.083	10,662
5	−0.112 (−3.275 ***)	−0.688 (−9.524 ***)	−0.036 (−2.720 ***)	−0.356 (−2.339 **)	−0.076 (−2.803 ***)	−0.332 (−4.975 ***)	0.094	10,763
6	−0.122 (−3.848 ***)	−0.857 (−10.202 ***)	−0.041 (−2.776 ***)	−0.434 (−2.890 ***)	−0.081 (−3.127 ***)	−0.423 (−5.874 ***)	0,095	11,012
7	−0.165 (−4.113 ***)	−0.997 (−13.761 ***)	−0.063 (−3.127 ***)	−0.552 (−3.202 ***)	−0.102 (−3.475 ***)	−0.445 (−6.874 ***)	0.102	10,886
8	−0.193 (−5.614 ***)	−0.971 (−11.632 ***)	−0.076 (−3.421 ***)	−0.492 (−3.007 ***)	−0.117 (−4.827 ***)	−0.479 (−7.012 ***)	0.105	11,546
9	−0.235 (−6.214 ***)	−1.010 (−12.698 ***)	−0.089 (−3.719 ***)	−0.610 (−3.442 ***)	−0.146 (−5.423 ***)	−0.400 (−6.129 ***)	0.118	11,225
10	−0.275 (−6.889 ***)	−1.104 (−13.536 ***)	−0.105 (−4.211 ***)	−0.525 (−3.221 ***)	−0.170 (−6.124 ***)	−0.579 (−8.545 ***)	0.121	11,145
11	−0.294 (−7.111 ***)	−1.125 (−14.309 ***)	−0.113 (−4.617 ***)	−0.511 (−4.112 ***)	−0.181 (−6.554 ***)	−0.614 (8.869 ***)	0.129	10,980

Notes: The table reports the statistical significance at *** 1%, ** 5%, and * 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LT subsample (HT = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HT subsample (HT = 1). α_1 and β_1 capture the additional effect of technology (HT) on the relationship between forecast errors and positive forecast changes (FCH > 0).

Table 13. Relationship between forecast errors and negative forecast revisions for high-tech (HT) and low-tech (LT) subsamples n months before the actual earnings announcement. $ERR_n = \alpha_0 + \alpha_1$ HT + β_0 $FCH_n + \beta_1$ HT.$FCH_n + \zeta$.

	FCH < 0							
	HT		LT		Difference HT vs. LT			
n	$\alpha_0 + \alpha_1$	$\beta_0 + \beta_1$	α_0	β_0	α_1	β_1	R^2	Obs
1	−0.202 (−8.312 ***)	0.129 (2.357 **)	−0.062 (−2.317 **)	0.024 −1.461	−0.140 (−5.381 ***)	0.105 (2.865 ***)	0.005	6662
2	−0.296 (−10.867 ***)	0.167 (2.745 ***)	−0.087 (−2.832 ***)	0.026 −1.120	−0.209 (−6.421 ***)	0.141 (3.172 ***)	0.007	6148
3	−0.303 (−11.832 ***)	0.231 (3.156 ***)	−0.096 (−3.423)	0.057 (2.050 **)	−0.207 (−6.898 ***)	0.174 (3.647 ***)	0.009	5752
4	−0.335 (−13.410 ***)	0.271 (3.813 ***)	0.125 (−4.404 ***)	0.087 (2.995 ***)	−0.460 (−8.585 ***)	0.184 (4.581 ***)	0.011	5143
5	−0.325 (−13.216 ***)	0.324 (4.778 ***)	−0.114 (−4.267 ***)	0.127 (3.567 ***)	−0.211 (−6.42 ***5)	0.197 (4.315 ***)	0.021	4924
6	−0.395 (−14.661 ***)	0.489 (5.124 ***)	−0.191 (−6.476 ***)	0.197 (4.043 ***)	−0.204 (−6.318 ***)	0.292 (5.345 ***)	0.032	4422
7	−0.413 (−15.295 ***)	0.585 (5.456 ***)	0.164 (6.150 ***)	0.227 (4.753 ***)	−0.577 (−11.205 ***)	0.358 (6.228 ***)	0.047	4330
8	−0.489 (−16.426 ***)	0.626 (6.751 ***)	−0.203 (−7.938 ***)	0.298 (5.970 ***)	−0.286 (−7.369 ***)	0.328 (5.875 ***)	0.058	3566
9	−0.458 (−15.754 ***)	0.662 (7.227 ***)	−0.196 (−6.746 ***)	0.329 (6.175 ***)	−0.262 (−7.425 ***)	0.333 (6.047 ***)	0.054	3740
10	−0.509 (−16.332 ***)	0.736 (8.725 ***)	−0.247 (−8.767 ***)	0.385 (6.872 ***)	−0.262 (−7.741 ***)	0.351 (7.258 ***)	0.069	3686
11	−0.524 (−16.825 ***)	0.879 (9.343 ***)	−0.211 (−8.515 ***)	0.413 (7.108 ***)	−0.313 (−9.369 ***)	0.466 (6.648 ***)	0.065	3645

Notes: The table reports the statistical significance at *** 1% and ** 5% (*t*-test), the intercept α_0 and the coefficient β_0 for the LT subsample (HT = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HT subsample (HT = 1). α_1 and β_1 capture the additional effect of technology (HT) on the relationship between forecast errors and negative forecast changes (FCH < 0).

4. Discussions and Conclusions

Prior studies have documented that financial analysts are optimistic. Some studies provide evidence that analysts rationally and intentionally build an optimistic bias into forecasts for strategic purposes such as maintaining a good relationship with management or selecting to forecast only firms with relatively good prospects. Other studies show that psychological biases affect analysts' optimism and lead to irrational behavior of overreaction to positive information and underreaction to negative information. Experimental evidence in psychology shows that cognitive biases arise in situations of low predictability and ambiguous evidence.

The purpose of this paper is to examine the effect of uncertainty on analysts' optimism through overreaction and underreaction to positive and negative information. Following Amir and Ganzach [20], we argue that there are three psychological biases that affect analysts' forecasts: leniency, representativeness, and anchoring and adjustment.

Leniency indicates that people are more tolerant and lenient in their evaluations, and such behavior leads to overoptimistic predictions. Representativeness bias classifies events as typical or representative and overstates them, leading to excessive predictions, or overreaction. Anchoring and adjustment involve people anchoring at some salient outcome value and adjusting based on predictive information, leading to insufficient predictions, or underreaction.

The effect of representativeness, anchoring, and adjustments on analysts' behavior depends on the sign of forecast modification and the value used as the basis for this modification (salience of the anchor). We suggest that both previous forecasts and previously announced earnings can serve as anchors, and then we test whether analysts incorporate information excessively (overreaction) or insufficiently (underreaction). We suppose that the previous forecast is more salient than the previous earnings.

Analysts' reactions are studied through two modifications: forecast revision and forecast change. Our paper investigates the relationship between forecast errors and, separately, forecast revisions and forecast changes when modifications are positive and negative. If analysts are optimistic (forecast above actual earnings), they overreact to positive modifications and underreact to negative modifications. When positive information is processed, leniency and representativeness lead to an overreaction, while when negative information is processed, leniency, anchoring, and adjustment lead to an underreaction. We posit that this optimism is reinforced by uncertainty. For robustness, we check two proxies of uncertainty (high-tech vs. low-tech firms and high vs. low forecast dispersion). The results are consistent with our hypotheses.

Using descriptive and regression analyses, we document a general underreaction to forecast revisions and overreaction to forecast changes in our sample of European firms during the period of 2010–2019. When dividing the whole sample according to the modification sign, we find an overreaction to positive information and an underreaction to negative information. The underreaction to negative forecast revision is greater than the underreaction to negative forecast change, which confirms that the previous forecast is more salient than the previous earnings. Together, these are consistent with the conclusions of Amir and Ganzach [20] and Easterwood and Nutt [23] and suggest that analysts interpret information optimistically and do not systematically overreact or underreact. We also find that analysts' optimism is more pronounced for high-uncertainty firms (high-tech firms or high-forecast-dispersion firms) and increases with the prediction horizon, suggesting that the longer the forecast horizon, the higher the uncertainty and the lower the predictability. Therefore, uncertainty reinforces cognitive biases and leads to an excess of optimism, manifested by a strong overreaction to positive information and a strong underreaction to negative information for high-uncertainty firms compared to low-uncertainty firms.

This study is interesting for several reasons. First, it contributes to the literature on analyst forecast optimism through the simultaneous phenomena of overreaction and underreaction. Second, while previous literature has generally focused on the effect of an isolated heuristic on earnings forecasts, few papers have tested the impact of combined heuristics on analysts' optimism. Third, more broadly, it deals with the relationship between information uncertainty and psychological biases. Finally, in the real world, investors can clearly see from the study how optimistic analysts' predictions are for businesses with high uncertainty, such as high-tech firms.

As our study period ends in 2019 due to a lack of data, further research is needed to examine the effect of heuristics on analysts' behavior during and after the COVID-19 pandemic. Further research is needed to examine whether our findings about the effect of uncertainty on optimism are specific to financial analysts or whether this behavior is typical to investors in general.

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Appendix A. Forecast Dispersion as a Second Proxy for Uncertainty

Table A1. Descriptive statistics for the whole sample High- and Low-forecast-dispersion subsamples (in relation to main text Table 1).

Year	Number of Firms			ERR Mean (Median)			DISP Mean (Median)		
	HDISP&LDISP	LDISP	HDISP	HDISP&LDISP	LDISP	HDISP	HDISP&LDISP	LDISP	HDISP
2010	1485	743	742	−0.489 (−0.102)	−0.379 (−0.079)	−0.712 *** (−0.197 ***)	1.117 (0.645)	0.816 (0.411)	1.401 *** (0.848 ***)
2011	1446	723	723	−0.449 (−0.095)	−0.265 (−0.052)	−0.659 *** (−0.178 ***)	1.131 (0.653)	0.825 (0.423)	1.396 *** (0.861 ***)
2012	1586	793	793	−0.487 (−0.110)	−0.368 (−0.072)	−0.591 *** (−0.152 ***)	1.054 (0.613)	0.782 (0.389)	1.367 *** (0.828 ***)
2013	1601	801	800	−0.568 (−0.125)	−0.452 (−0.085)	−0.615 *** (−0.181 ***)	1.121 (0.649)	0.773 (0.372)	1.395 *** (0.763 ***)
2014	1695	848	847	−0.488 (−0.088)	−0.341 (−0.076)	−0.501 *** (−0.166 ***)	1.108 (0.633)	0.762 (0.423)	1.402 *** (0.741 ***)
2015	1768	884	884	−0.334 (−0.074)	−0.229 (−0.054)	−0.434 *** (−0.129 ***)	1.092 (0.587)	0.739 (0.354)	1.341 *** (0.711 ***)
2016	1785	893	892	−0.240 (−0.061)	−0.156 (−0.025)	−0.362 *** (−0.104 ***)	1.055 (0.542)	0.705 (0.303)	1.301 *** (0.664 ***)
2017	1812	906	906	−0.337 (−0.094)	−0.243 (−0.049)	−0.547 *** (−0.136 ***)	1.002 (0.501)	0.698 (0.292)	1.276 *** (0.623 ***)
2018	1862	931	931	−0.355 (−0.073)	−0.287 (−0.056)	−0.506 *** (−0.125 ***)	0.945 (0.488)	0.676 (0.279)	1.208 *** (0.591 ***)
2019	1902	951	951	−0.248 (−0.068)	−0.197 (−0.041)	−0.387 *** (−0.117 ***)	0.966 (0.495)	0.659 (0.284)	1.227 *** (0.562 ***)
(2010–2019)	16,942	8473	8469	−0.399 (−0.092)	−0.295 (−0.065)	−0.545 *** (−0.139 ***)	1.092 (0.602)	0.766 (0.375)	1.226 *** (0.717 ***)

Notes: The table presents the significance of mean differences (*t*-test) and median differences (Wilcoxon test) between high-dispersion (HDISP) and low-dispersion (LDISP) subsamples at *** 1%. The table also reports, for each year, the total number of firms and the number of HDISP and LDISP firms. ERR and DISP indicate, respectively, forecast error and forecast dispersion; ERR and DISP are measured n months prior to the earnings announcement.

Table A2. Relationship between the forecast error and the forecast revision for high- and low-forecast-dispersion subsamples (in relation to main text Table 3).

n	REV > 0				REV < 0				Obs
	HDISP		LDISP		HDISP		LDISP		
	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	49.4	−0.031 ** (−0.022 ***)	49.6	0.016 (0.008)	65.2 ***	−0.314 ** (−0.167 ***)	49.9	−0.091 (−0.024)	15,248
2	51.5 **	−0.105 ** (−0.053 ***)	50.5	−0.053 (−0.025)	70.1 ***	−0.411 ** (−0.263 ***)	52.7	−0.122 (−0.059)	15,108
3	53.1 ***	−0.162 *** (−0.076 ***)	50.6	−0.094 (−0.035)	73.3 ***	−0.509 *** (−0.271 ***)	55.5	−0.164 (−0.062)	14,556
4	54.9 ***	−0.271 *** (−0.085 ***)	51.8	−0.119 (−0.042)	75.8 ***	−0.675 *** (−0.288 ***)	58.9	−0.217 (−0.071)	14,125
5	58.8 ***	−0.315 *** (−0.101 ***)	52.2	−0.158 (−0.059)	77.6 ***	−0.731 *** (−0.362 ***)	61.9	−0.294 (−0.079)	13,159
6	64.7 ***	−0.377 *** (−0.117 ***)	52.4	−0.153 (−0.075)	77.7 ***	−0.749 *** (−0.371 ***)	63.3	−0.334 (−0.083)	13,022
7	63.8 ***	−0.371 *** (−0.114 ***)	51.6	−0.148 (−0.067)	77.3 ***	−0.752 *** (−0.389 ***)	62.6	−0.311 (−0.095)	12,908
8	65.0 ***	−0.402 *** (−0.171 ***)	53.5	−0.179 (−0.077)	78.4 ***	−0.771 *** (−0.397 ***)	64.0	−0.338 (−0.098)	12,532
9	65.8 ***	−0.476 *** (−0.185 ***)	54.3	−0.205 (−0.085)	78.8 ***	−0.788 *** (−0.402 ***)	65.3	−0.394 (−0.117)	11,975
10	66.9 ***	−0.499 *** (−0.203 ***)	55.5	−0.243 (−0.092)	79.9 ***	−0.811 *** (−0.425 ***)	65.7	−0.378 (−0.129)	11,692

Notes: The table reports the percentage of negative errors (%) and mean and median forecast error for the two subsamples, high (HDISP) and low (LDISP) forecast dispersion, when forecast revision for month n is positive (REV > 0) and negative (REV < 0). Forecast revision is defined as $REV_n = (F_n - F_{n+1})/|F_n|$, and forecast error is defined as $ERR_n = (E - F_n)/|E|$. ERR < 0 (ERR > 0) implies optimism (pessimism). The table also reports the statistical significance at *** 1% and ** 5% in the difference between the percentage of negative forecast errors and 50% (z-test), mean differences (*t*-test), and median differences (Wilcoxon test) between the two subsamples, HDISP and LDISP, for the same REV sign.

Table A3. Relationship between forecast errors and positive forecast revisions for high- (HDISP) and low-forecast-dispersion (LDISP) subsamples n months prior to actual earnings release. $ERR_n = \alpha_0 + \alpha_1$ HDISP + β_0 REV_n + β_1 HDISP.REV_n + ζ (in relation to main text Table 6).

REV > 0								
	HDISP		LDISP		Difference HDISP vs. LDISP			
n	$\alpha_0 + \alpha_1$ **(t)**	$\beta_0 + \beta_1$ **(t)**	α_0 **(t)**	β_0 **(t)**	α_1 **(t)**	β_1 **(t)**	R^2	**Obs**
1	−0.034 (−1.415)	−0.115 (−1.979 **)	0.009 (0.488)	−0.034 (−1.315)	−0.043 (1.919 **)	−0.081 (−2.897 ***)	0.07	6785
2	−0.057 (−1.547 *)	−0.276 (−4.345 ***)	−0.035 (−1.319)	−0.068 (−1.741 *)	−0.022 (−1.559 *)	−0.208 (−3.791 ***)	0.011	6650
3	−0.062 (−1.634 *)	−0.442 (−6.147 ***)	−0.049 (−1.584 *)	−0.139 (−2.869 ***)	−0.013 (−1.413)	−0.303 (−4.647 ***)	0.020	6270
4	−0.091 (−2.087 **)	−0.744 (−7.585 ***)	−0.059 (−1.621 *)	−0.302 (−3.625 ***)	−0.032 (−1.605 *)	−0.442 (−6.497 ***)	0.025	6485
5	−0.109 (−2.857 ***)	−0.815 (−8.147 ***)	−0.062 (−1.579 *)	−0.338 (−4.252 ***)	−0.047 (−1.952 **)	−0.477 (−5.278 ***)	0.031	5543
6	−0.197 (−3.584 ***)	−0.954 (−9.021 ***)	−0.079 (−2.078 **)	−0.384 (−5.514 ***)	−0.118 (−2.651 ***)	−0.570 (−5.663 ***)	0.038	5006
7	−0.274 (−4.286 ***)	−1.015 (−10.714 ***)	−0.125 (−2.442 **)	−0.502 (−6.185 ***)	−0.149 (−2.981 ***)	−0.513 (−5.890 ***)	0.039	5258
8	−0.349 (−5.087 ***)	−0.948 (−10.715 ***)	−0.141 (−3.832 ***)	−0.538 (−6.546 ***)	−0.208 (−4.324 ***)	−0.410 (−6.099 ***)	0.044	5213
9	−0.473 (−6.114 ***)	−1.126 (−11.158 ***)	−0.235 (−4.395 ***)	−0.597 (−6.941 ***)	−0.238 (−4.236 ***)	−0.529 (−6.748 ***)	0.047	4976
10	−0.508 (−6.651 ***)	−1.105 (−10.349 ***)	−0.264 (−4.604 ***)	−0.634 (−7.681 ***)	−0.244 (−4.445 ***)	−0.471 (−6.549 ***)	0.052	4781

Notes: The table reports the statistical significance at *** 1%, ** 5%, and * 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LDISP subsample (HDISP = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HDISP subsample (HDISP = 1). α_1 and β_1 capture the additional effect of forecast dispersion (HDISP) on the relationship between forecast errors and positive forecast revisions (REV > 0).

Table A4. Relationship between forecast errors and negative forecast revisions for high- (HDISP) and low-forecast-dispersion (LDISP) subsamples n months prior to actual earnings release. $ERR_n = \alpha_0 + \alpha_1$ HDISP + β_0 REV_n + β_1 HDISP.REV_n + ζ. (in relation to main text Table 7).

REV < 0								
	HDISP		LDISP		Difference HDISP vs. LDISP			
n	$\alpha_0 + \alpha_1$	$\beta_0 + \beta_1$	α_0	β_0	α_1	β_1	R^2	**Obs**
1	−0.218 (−10.096 ***)	0.793 (6.841 ***)	−0.082 (−4.654 ***)	0.325 (4.586 ***)	−0.136 (−10.058 ***)	0.468 (5.267 ***)	0.041	6122
2	−0.436 (−14.175 ***)	0.982 (8.141 ***)	−0.136 (−7.754 ***)	0.489 (5.104 ***)	−0.300 (−12.869 ***)	0.493 (5.183 ***)	0.054	5872
3	−0.531 (18.649 ***)	1.015 (9.845 ***)	−0.164 (−8.214 ***)	0.678 (6.057 ***)	−0.367 (−13.458 ***)	0.337 (4.967 ***)	0.061	5436
4	−0.617 (−22.215 ***)	1.128 (10.991 ***)	−0.215 (−10.454 ***)	0.784 (6.897 ***)	−0.402 (−14.829 ***)	0.344 (5.238 ***)	0.068	5172
5	−0.725 (−25.345 ***)	1.259 (11.128 ***)	−0.268 (−11.587 ***)	0.928 (7.661 ***)	−0.457 (−16.114 ***)	0.331 (6.895 ***)	0.069	4632
6	−0.815 (−26.109 ***)	1.443 (13.280 ***)	−0.358 (16.584 ***)	0.996 (8.561 ***)	−0.457 (−16.549 ***)	0.447 (7.596 ***)	0.086	4657
7	−0.898 (−26.857 ***)	1.725 (16.529 ***)	−0.369 (−15.542 ***)	1.142 (9.782 ***)	−0.529 (−18.227 ***)	0.583 (8.769 ***)	0.098	4546
8	−0.925 (−29.421 ***)	1.913 (18.471 ***)	−0.410 (−18.526 ***)	1.373 (10.551 ***)	−0.515 (−17.864 ***)	0.540 (9.854 ***)	0.105	4345
9	−0.992 (−31.024 ***)	2.105 (19.813 ***)	−0.486 (−21.415 ***)	1.286 (10.426 ***)	−0.506 (−18.782 ***)	0.819 (10.534 ***)	0.118	3734
10	−1.124 (−31.652 ***)	2.321 (21.606 ***)	−0.602 (−25.649 ***)	1.518 (15.326 ***)	−0.522 (−19.225 ***)	0.803 (10.238 ***)	0.124	4013

Notes: The table reports the statistical significance at *** 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LDISP subsample (HDISP = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HDISP subsample (HDISP = 1). α_1 and β_1 capture the additional effect of forecast dispersion (HDISP) on the relationship between forecast errors and negative forecast revisions (REV < 0).

Table A5. Relationship between the forecast error and the sign of the forecast change for high- and low-forecast-dispersion subsamples (in relation to main text Table 9).

n	FCH >0				FCH < 0				Obs
	HDISP		LDISP		HDISP		LDISP		
	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	%	ERR Mean (Median)	
1	56.3 ***	−0.109 *** (−0.045 ***)	49.1	−0.015 (−0.007)	63.1 ***	−0.222 ** (−0.168 ***)	56.2	−0.092 (−0.049)	16,407
2	57.5 ***	−0.202 *** (−0.067 ***)	50.9	−0.062 (−0.038)	64.2 ***	−0.265 ** (−0.101 ***)	55.6	−0.102 (−0.034)	16,235
3	57.9 ***	−0.358 *** (−0.101 ***)	52.2	−0.114 (−0.079)	62.4 ***	−0.345 *** (−0.138 ***)	53.9	−0.124 (−0.056)	16,111
4	63.2 ***	−0.474 *** (−0.163 ***)	54.6	−0.143 (−0.095)	63.9 ***	−0.427 *** (−0.201 ***)	55.1	−0.152 (−0,0084)	15,805
5	62.1 ***	−0.429 *** (−0.151 ***)	55.1	−0.158 (−0.088)	62.5 ***	−0.369 *** (−0.151 ***)	52.8	−0.149 (−0.079)	15,687
6	63.6 ***	−0.501 *** (−0.184 ***)	56.4	−0.142 (−0.098)	62.1 ***	−0.351 *** (−0.138 ***)	52.2	−0.124 (−0.064)	15,434
7	63.5 ***	−0.552 *** (−0.196 ***)	56.7	−0.131 (−0.105)	61.3 ***	−0.401 *** (−0.197 ***)	51.8	−0.152 (−0.084)	15,216
8	65.4 ***	−0.530 *** (−0.184 ***)	55.6	−0.167 (−0.139)	60.1 ***	−0.472 *** (−0.234 ***)	51.5	−0.135 (−0.078)	15,112
9	66.7 ***	−0.641 *** (−0.259 ***)	57.3	−0.232 (−0.167)	59.9 ***	−0.532 *** (−0.281 ***)	51.9	−0.181 (−0.111)	14,965
10	67.6 ***	−0.732 *** (−0.342 ***)	57.8	−0.259 (−0.201)	56.5 ***	−0.517 *** (−0.262 ***)	51.2	−0.225 (−0.121)	14,831
11	67.9 ***	−0.715 *** (−0.318 ***)	58.2	−0.385 (−0.221)	55.6 ***	−0.484 *** (−0.288 ***)	50.8	−0.212 (−0.124)	14,625

Notes: The table reports the percentage of negative errors (%) and mean and median forecast error for the two subsamples, high and low tech, when forecast change for month n is positive (FCH > 0) and negative (FCH < 0). Forecast change is defined for month n as $FCH_n = (F_n - E_{t-1})/|F_n|$. Forecast error is defined for month n as $ERR_n = (E - F_n)/|E|$. ERR < 0 (ERR > 0) implies optimism (pessimism). The table also reports the statistical significance at *** 1% and ** 5% in the difference between the percentage of negative forecast errors and 50% (z-test), mean differences (*t*-test), and median differences (Wilcoxon test) between the two subsamples, HDISP and LDISP, for the same FCH sign.

Table A6. Relationship between forecast errors and positive forecast changes for high- (HDISP) and low-forecast-dispersion (LDISP) subsamples *n* months before the actual earnings announcement. $ERR_n = \alpha_0 + \alpha_1$ HDISP $+ \beta_0\, FCH_n + \beta_1$ HDISP.$FCH_n + \zeta$ (in relation to main text Table 12).

	FCH > 0							
	HDISP		LDISP		Difference HDISP vs. LDISP			
n	$\alpha_0 + \alpha_1$	$\beta_0 + \beta_1$	α_0	β_0	α_1	β_1	R^2	Obs
1	−0.074 (−2.224 **)	−0.177 (−3.622 ***)	−0.028 (−1.606 *)	0.059 −1.049	−0.046 (−4.511 ***)	−0.236 (−4.217 ***)	0.055	9745
2	−0.094 (−2.698 ***)	−0.211 (−4.451 ***)	−0.042 (2.161 **)	−0.078 (−1.287)	−0.052 (−3.971 ***)	−0.133 (−3.948 ***)	0.068	10,087
3	−0.084 (−3.066 ***)	−0.341 (−6.108 ***)	−0.067 (−2.328 **)	−0.154 (−1.591 *)	−0.017 (−2.885 ***)	−0.187 (4.057 ***)	0.079	10,359
4	−0.069 (−2.945 ***)	−0.492 (−7.854 ***)	−0.047 (−2.748 **)	−0.239 (−1.787 *)	−0.022 (−3.421 ***)	−0.253 (−4.562 ***)	0.079	10,662
5	−0.107 (−3.105 ***)	−0.641 (−9.111 ***)	−0.058 (−2.889 ***)	−0.379 (−2.925 ***)	−0.049 (−3.987 ***)	−0.262 (−5.334 ***)	0.088	10,763
6	−0.116 (−3.541 ***)	−0.827 (−10.432 ***)	−0.062 (−3.019 ***)	−0.458 (−3.587 ***)	−0.054 (−4.110 ***)	−0.369 (−5.117 ***)	0.093	11,012
7	−0.148 (−4.101 ***)	−0.974 (−11.563 ***)	−0.086 (−3.415 ***)	−0.586 (−4.145 ***)	−0.062 (−4.471 ***)	−0.388 (−5.849 ***)	0.106	10,886
8	−0.174 (−5.303 ***)	−0.957 (−11.423 ***)	−0.088 (−3.554 ***)	−0.526 (−3.584 ***)	−0.086 (−4.225 ***)	−0.431 (−6.247 ***)	0.107	11,546
9	−0.219 (−5.917 ***)	−1.031 (−12.714 ***)	−0.096 (−3.852 ***)	−0.636 (−3.605 ***)	−0.123 (5.474 ***)	−0.395 (−6.853 ***)	0.115	11,225
10	−0.262 (−6.457 ***)	−1.056 (−13.415 ***)	−0.128 (−4.824 ***)	−0.559 (−3.846 ***)	−0.134 (−6.214 ***)	−0.497 (−7.254 ***)	0.118	11,145
11	−0.281 (−6.847 ***)	−1.099 (−14.121 ***)	−0.145 (−5.227 ***)	−0.545 (−4.778 ***)	−0.136 (−5.841 ***)	−0.554 (−7.802 ***)	0.123	10,980

Notes: The table reports the statistical significance at *** 1%, ** 5%, and * 1% (*t*-test), the intercept α_0 and the coefficient β_0 for the LDISP subsample (HDISP = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HDISP subsample (HDISP = 1). α_1 and β_1 capture the additional effect of forecast dispersion (HDISP) on the relationship between forecast errors and positive forecast changes (FCH > 0).

Table A7. Relationship between forecast errors and negative forecast changes for high- (HDISP) and low-forecast-dispersion (LDISP) subsamples n months before the actual earnings announcement. $ERR_n = \alpha_0 + \alpha_1$ HDISP $+ \beta_0$ $FCH_n + \beta_1$ $HDISP.FCH_n + \zeta$ (in relation to main text Table 13).

FCH < 0								
	HDISP		LDISP		Difference HDISP vs. LDISP			
n	$\alpha_0 + \alpha_1$ (t)	$\beta_0 + \beta_1$ (t)	α_0 (t)	β_0 (t)	α_1 (t)	β_1 (t)	R^2	Obs
1	−0.191 (−8.121 ***)	0.108 (2.124 **)	−0.077 (−2.388 **)	0.038 −1.105	−0.114 (−7.659 ***)	0.070 (3.138 ***)	0.007	6662
2	−0.296 (−10.867 ***)	0.152 (2.658 ***)	−0.098 (−2.994 ***)	0.044 −1.289	−0.198 (−8.883 ***)	0.108 (4.002 ***)	0.010	6148
3	−0.265 (−11.427 ***)	0.214 (3.008 ***)	−0.117 (−3.676)	0.079 (2.165 **)	−0.148 (−8.774 ***)	0.135 (3.954 ***)	0.013	5752
4	−0.299 (−12.840 ***)	0.264 (3.545 ***)	−0.157 (−4.687 ***)	0.112 (2.884 ***)	−0.456 (−9.649 ***)	0.152 (4.127 ***)	0.019	5143
5	−0.311 (−13.187 ***)	0.334 (4.145 ***)	−0.165 (−5.008 ***)	0.154 (3.450 ***)	−0.146 (−8.802 ***)	0.180 (4.528 ***)	0.031	4924
6	−0.410 (−14.552 ***)	0.447 (4.978 ***)	−0.225 (−6.847 ***)	0.186 (4.111 ***)	−0.185 (−9.648 ***)	0.261 (5.437 ***)	0.039	4422
7	−0.401 (−14.384 ***)	0.564 (5.756 ***)	−0.185 (−6.425 ***)	0.264 (5.099 ***)	−0.586 (−12.547 ***)	0.300 (6.648 ***)	0.051	4330
8	−0.452 (−15.122 ***)	0.604 (6.547 ***)	−0.235 (−7.627 ***)	0.319 (6.228 ***)	−0.217 (−9.894 ***)	0.285 (6.245 ***)	0.063	3566
9	−0.433 (−14.605 ***)	0.645 (6.958 ***)	−0.215 (−7.845 ***)	0.354 (6.756 ***)	−0.218 (−10.277 ***)	0.291 (4.975 ***)	0.059	3740
10	−0.489 (−15.615 ***)	0.692 (8.168 ***)	−0.286 (−9.374 ***)	0.424 (7.107 ***)	−0.203 (−10.618 ***)	0.268 (5.319 ***)	0.068	3686
11	−0.513 (−15.954 ***)	0.845 (9.127 ***)	−0.244 (−9.175 ***)	0.474 (8.259 ***)	−0.269 (−10.527 ***)	0.371 (6.659 ***)	0.072	3645

Notes: The table reports the statistical significance at *** 1% and ** 5% (*t*-test) the intercept α_0 and the coefficient β_0 for the LDISP subsample (HDISP = 0), and $\alpha_0 + \alpha_1$ and $\beta_0 + \beta_1$ for the HDISP subsample (HDISP = 1). α_1 and β_1 capture the additional effect of forecast dispersion (HDISP) on the relationship between forecast errors and negative forecast changes (FCH < 0).

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