Research Article

Confirmation Biases in the Financial Analysis of IT Investments

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Abstract

This paper focuses on the optimistic and confirmation biases of experts with respect to major IT investments and their interaction with financial analysts' competencies in finance and information technology. We used an experimental design that involved asking subjects to predict the financial market's reaction to major IT investment announcements. Drawing on the literature on optimistic biases, we showed that IT and financial expertise lead to different forecasting patterns. We found that financially competent participants are more subject to confirmatory biases and have a tendency to hold on to a currently favored hypothesis throughout their analysis. IT expertise, though, mitigates the analyst's confirmatory bias, so that dual expertise leads to less optimistic biases.

Keywords: Business Value of IT, Event Study, IT Competency

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Confirmation Biases in the Financial Analysis of IT Investments

1. Introduction

Financial markets have not been indifferent to the information technology revolution. In the late 1990s with the dot-com boom and again in the early 2010s (The Economist, 2011), investors have shown great optimism about technological changes. The tech boom has been fueled by drastic reductions in computing and data storage costs, an exponential increase in use of the Internet and mobile devices, the rise of social media, and the transformational role of IT in global business. The exuberance about the IT revolution is not a new phenomenon. Historians have highlighted other major technological innovations, such as the advent of railroads and electric power, that also generated financial bubbles (for a survey, see Perez, 2002). The promises attached to major new technological innovations generated what Alan Greenspan, Chairman of the Federal Reserve of the United States from 1987 to 2006, in 1996 called an "irrational exuberance" (Greenspan, 1996). Schiller (2000), supported by a vast body of work in behavioral finance (Thaler, 1993; Tversky & Kahneman, 1974), noted that there are persistent cognitive biases in investors' behavior. This "exuberance" is evidence of investors displaying optimistic biases.

While other studies have proposed equilibrium models to explain real bubbles (Johnson, 2007; Walden & Browne, 2008), this paper explores individual decision-making and the factors that affect experts' decision processes. In the behavioral finance literature, two types of cognitive biases have been identified and extensively documented: the optimistic bias and the confirmation bias (Barberis, Shleifer & Vishny, 1998; Thaler, 1993; Tversky & Kahneman, 1974). Optimistic bias refers to the general tendency of individuals to underestimate the likelihood of negative outcomes. Confirmation bias occurs when subjects seek only the information that confirms an initial hypothesis while overlooking disconfirming information. Our focus is on how these cognitive biases are affected by expertise and competencies.

While the business and economic impact of the Internet revolution was hard to assess in the late 1990s, so too are most investments in information technologies. Evaluating investments in information systems is difficult because the majority of investments are intangible. Moreover, there is usually a considerable delay between the time of the investment and the time when profits are generated. Finally, the majority of the effects are difficult to track in a firm's financial statements (Brynjolfsson, Hitt, & Yang, 2002; Léger, 2010; Lev, 2001). As a result, IT investment projects are different from other financial events.

IT investment projects can generate considerable wealth for the investing company (and for the service providers), but they can also turn out to be gigantic white elephants. As a result of the amount of money involved, the delay between investment and profits, and the intangibility of IT investments, one can therefore see such projects as not only risky but uncertain. The financial market's reaction to major IT investments is driven by this uncertainty, which is compounded by the potentially limited understanding of the IT industry by financial analysts. Hence, this paper focuses on the optimistic and confirmation biases of experts with respect to major IT investments. In particular, we are interested in the interaction between the analysts' biases and their competencies in finance and information technology.

We use an experimental design that involves asking subjects to predict the financial market's reaction to major IT investment announcements. The experimental design was manipulated so that subjects differed in terms of their IT and financial expertise.

Not surprisingly, we found that expertise matters. And, although expertise is required to make accurate predictions, we found that it can also lead to systematically incorrect judgments. More specifically, drawing on the literature on optimistic biases, we found that IT and financial expertise lead to different forecasting patterns. We found that financial experts are more subject to confirmatory biases and have a tendency to hold on to a currently favored hypothesis throughout their analysis. IT expertise mitigated the analyst's confirmatory bias, so that dual expertise lead to less-optimistic biases.

The remainder of the paper is structured as follows. In Section 2, we present the literature on optimistic biases and develop our hypotheses. In Section 3, we present our experimental design. In Section 4, we present our results. Finally, in Section 5, we discuss our results and their implications for market participants and organizations, and draw some conclusions.

2. Competency, Prediction Accuracy, and Optimistic Bias

2.1. Predicting the Financial Impact of an IT Announcement

Several researchers have examined how financial markets assess the value of IT investments to see whether or when investment in information technology creates shareholder value. Dos Santos, Peffers, and Mauer (1993) were among the first to investigate the value of IT investments from the perspective of financial markets. To assess this particular impact of IT, they used an event study approach, a well-established methodological approach in financial economics that measures an economic event's short-term impact on the value of a firm. This approach analyzes the market return on a given stock following an unexpected and significant event for the firm by comparing the observed stock market return (following the event) to an estimated model return that one would have expected had the event not occurred (MacKinlay, 1997; McWilliams & Siegel, 1997). In their stdu, Dos Santos et al. (1993) analyzed 97 IT announcements, from 1981 to 1988, and conclude that IT projects that are innovative in nature generate a significantly abnormal stock market return in the short run. Im, Dow, and Grover (2001) expanded the Dos Santos et al. (1993) study to 238 announcements, from 1981 to 1996, and found similar effects on top of other firm-specific factors, such as firm size.

Roztocki and Weistroffer (2007) review the papers that used such an event study approach and were published in the IT literature. According to their meta-analysis, 17 articles in the top IT journals and conferences used an event study methodology. These papers cover a broad range of significant IT events such as outsourcing (Agrawal, Kishore, & Rao, 2006; Oh, Gallivan, & Kim, 2006), security (Andoh-Baidoo & Osei-Bryson, 2007; Ettredge & Richardson, 2003; Hovav & D'Arcy, 2003, 2005; Telang & Wattal, 2007), electronic commerce investments (Benbunan-Fich & Fich, 2004, 2005; Dehning, Richardson, Urbaczewski, & Wells, 2004; Subramani & Walden, 2001), enterprise systems and other infrastructure investments (Chatterjee, Pacini, & Sambamurthy, 2002; Dardan, Stylianou, & Kumar, 2006; Dehning, Richardson, & Zmud, 2003; Ranganathan & Brown, 2006), and chief information officer appointment announcements (Chatterjee, Richardson, & Zmud, 2001).

The results of these studies suggest that financial markets do not react arbitrarily to the announcement of IT projects. Although not all IT investments lead to abnormal stock returns, the market nevertheless seems to recognize the value of certain types of IT investments when they are made in a specific business context. For instance, Dehning et al. (2003) suggest that markets react positively to transformational IT investments in the sense that they found evidence of abnormal stock returns following IT investments that can give thea firm a sustainable competitive advantage in its industry because the investment enables a business transformation. Along the same lines, Oh, Kim, and Richardson (2006) suggest that a firm's characteristics have a moderating effect on the nature of IT investments. Not only did they find evidence that the growth in sales, the uncertainty of the product market, and the strategic role of IT have a significant direct effect on the stock market return for firms that announce a major investment in IT, but they also found a significant interaction effect between the transformational nature of the investments and the level of uncertainty in the industry.

None of the aforementioned studies provide any evidence as to how individual investors assess the intrinsic value of new IT investment announcements. Our study fills that gap by focusing on the individual behavior of market participants in assessing the market value of IT projects.

2.2. Competency and Confirmation Bias

The interest in how analysts behave and how individual reactions affect the market can be traced back to Brown (1993) and Schipper (1991), both of whom have called for more research to understand analysts' decision processes in determining stock price forecasts. On the topic of analysts' expertise, Maines, McDaniel, and Harris (1997) and Clement (1999) emphasize that field experience plays an important role in predicting the impact of earnings. Koehler, Brenner, and Griffin (2002) also found that competent individuals are generally more accurate in their predictions than novices. However, they also report that financial and economic forecasters tended to be systematically over-optimistic in making predictions.

Optimistic biases—the general impression by individuals that they are less likely to be victims of unfortunate future events than other people are—are pervasive and generalized phenomena. This impression of invulnerability, which has been observed and reported consistently in the decision-making, health psychology, and marketing literature, is often referred to as self-positivity bias, unrealistic optimism, or optimistic bias (Weinstein & Klein, 1996). Because they play a role in protecting one's self-image, optimistic biases are widespread and hard to circumscribe (Kreuter & Strecher, 1995; Weinstein & Klein, 1995). Thus, our first prediction is as follows:

> **H1:** *Optimistic biases in predicting the market response to IT investments will be observed.*

This systematic optimism is partly attributed to a confirmation bias (Madsen, 1994), which is defined as an inclination by individuals to retain a currently favored hypothesis throughout their decision process (Klayman, 1995). Under the confirmation bias framework, analysts investigate each IT investment announcement in a hypothetico-deductive manner. First, they pay attention to a limited set of information in order to generate a focal hypothesis about the market's likely reaction to the announcement of the IT investment. Analysts will then test their focal hypothesis with the remaining information. If the hypothesis cannot be supported, a new hypothesis will be generated and the process will be repeated. Thus, the confirmation bias framework implies that optimism originates in the hypothesis generation phase of the evaluation process. This optimistic outlook is then theorized to be confirmed by individuals in the hypothesis testing phase of the process.

When an IT investment is announced, at least two types of information are available: financial and IT information. Financial information, due in part to legal obligations, tends to be presented in a standardized manner. This information is also largely quantitative. In contrast, the IT information that is available often describes intangible features that may or may not be relevant to evaluate the investment.

The evaluation of an IT investment requires an assessment of risk exposure. This risk is a function of two main components: the probability of occurrence of undesirable outcomes, and the impact of these outcomes on the investment's performance (Boehm, 1991). A vast literature explores the risk factors that are likely to increase the probability of occurrence of these undesirable outcomes (Barki, Rivard, & Talbot, 1993, 2001; Han & Huang, 2007; Wallace, Keil, & Rai, 2004). These risk factors are related to elements such as the size of the investment, its technological newness, the application's complexity, the lack of team expertise, the lack of user support, and the lack of organizational support. This type of information is likely to vary in its availability and to be presented in a non-standardized way.

As Figure 1 shows, competent analysts will tend to pay attention initially to their area of expertise. Financially competent analysts will first focus on financial information and will then confirm their focal hypothesis with the IT information. IT-competent individuals are more likely to do the reverse: generate their focal hypothesis on the grounds of IT information and then support it with financial information.
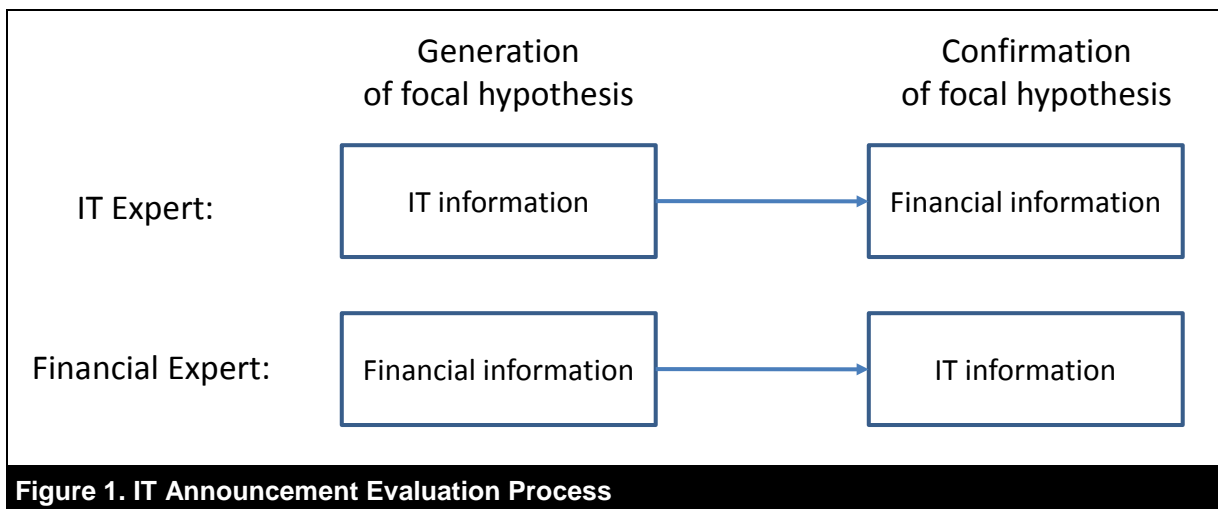
	Generation of focal hypothesis	Confirmation of focal hypothesis
IT Expert:	IT information	Financial information
Financial Expert:	Financial information	IT information

Figure 1. IT Announcement Evaluation Process

This difference in the locus of information needed to generate the focal hypothesis will lead to different optimistic outcomes. Because IT information shows greater variability in its format and content, it is likely to elicit more confirmation biases than financial information. Indeed, Klayman (1995) indicates that "vague and ambiguous data are fertile ground for confirmation bias, because when faced with such evidence, people tend to give the hypothesis the benefit of the doubt" (p. 394).

Thus, financially competent analysts are more likely to display confirmation biases, especially when more IT information is presented. The more information is available, the more an analyst will be likely to identify information that confirms the focal hypothesis. In turn, greater confirmation biases should decrease an analyst's prediction accuracy. We predict that:

> **H2**: *For more financially competent analysts, the more IT information provided in an announcement, (a) the lower the accuracy, and (b) the higher the optimism will be.*

Conversely, IT-competent analysts will anchor their focal hypothesis with IT information. Confirming their focal hypothesis with a set of secondary financial information will be harder since this information is presented in a standardized fashion. Consequently, we predict that:

> **H3**: *For more IT-competent analysts, the more IT information provided in an announcement, (a) the higher the accuracy, and (b) the lower the optimism will be.*

Finally, dual competence is likely to buffer an analyst from confirmation biases. Dual competence should allow individuals to generate their focal hypothesis from a more diverse set of information, avoiding the confirmation of a focal hypothesis with IT information. Therefore:

> **H4**: *IT competence will mitigate the negative effects of financial competence on of (a) accuracy and (b) optimism.*

3. Experimental Design

To test our hypotheses, we used an experimental design in which participants are put in a situation, not identical but similar to that of stock market traders, to see how they reacted to press releases on major IT investments. We collected data on (1) the subjects' self-assessed IT and financial experience, (2) their perception of the IT investment based on the information contained in the press release and on the investing firm's financial reports, and (3) their expectation regarding the stock market's reaction to the press release.

The highlights of the experimental design for the two experiments are as follows (the Appendix provides more details on this methodology). Subjects were students in an AACSB institution. Each

participant was asked to evaluate six or eight press releases that were selected at random from a possible set of 15[1]. From this set of real announcements, five had been followed by a positive abnormal return, five by a negative abnormal return and five by a normal return.

Subjects were provided with the content of the press release and basic financial information on the company. They had to review a number of press releases and anticipate whether the stock market return of the company making the IT investment would be higher, lower, or the same as the average market return following the issuance of the press release. Monetary incentives were provided so that subjects who accurately anticipated the market's reaction to the IT investment would earn more. Overall, 300 evaluations were performed, which represents an average of 20 evaluations per press release. All 44 participants were asked to self-evaluate their competence in IT and finance using a questionnaire.

We tested our hypotheses by developing a construct of financial competency based on the experimental subjects' self-assessed knowledge of finance and on whether they considered the investing company's available financial information (the financial information was provided as an appendix to the press release). This construct allowed us to separate financially experienced subjects from non-financially experienced subjects. As for IT competency, we used a construct of the subjects' self-assessed IT competence based on the one developed by Bassellier, Benbasat, and Reich (2003). The amount of IT information presented in each announcement was measured by counting the number of words used in describing the announcement.

The dependent variables were the anticipation capacity. Both were binary variables equal to 1 if the subject was able to correctly anticipate the market reaction and 0 if not. Table 1 summarizes the variables in this study.

Table 1. List of Research Variables		
Variable	**Measurement**	**Implementation**
Anticipation	Binary variable	1 if the subject was capable of successfully anticipating financial market reaction and 0 otherwise
Financial competence	20 items (Alpha = 0.98)	Adapted from Basselier et al (2003)
IT competence	18 items (Alpha = 0.97)	Basselier et al (2003)
IT information (abstract length)	Measured	Number of words used in describing the investment

4. Results

4.1 Preliminary Analysis

Table 2 shows the raw results for participants' capacity to accurately predict the outcome of IT investment announcements. Of the 300 forecasted outcomes, 83 (27.7%) were accurately predicted. Negative outcomes (12/102 or 11.8%) were predicted with less accuracy than neutral (43/109 or 39.4%) or positive outcomes (28/89 or 31.5%). A simple chi-square test confirms that a participant's capacity to predict outcomes accurately depends on the valence of the outcome; $\chi^2(2) = 27.71$, p<.0001. A closer examination of Table 2 suggests that participants displayed a general optimistic

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[1] Participants could evaluate the six or eight press releases in any chosen order. They could examine a press release early and revise their answers later. Hence, we have no way to track whether analysts get worse or better over time, or if their performance has decreased due to fatigue. This could be the subject of future research.

bias. When we compare the lower off-diagonal with the upper off-diagonal, we see that participants tended to be optimistic: we have 149 optimistic predictions and 68 pessimistic predictions. A statistical comparison of the two off-diagonals, corresponding to Bhapkar's test (Agresti, 1990), shows that an optimistic bias is present: $\chi^2(2) = 37.15$, p<.0001. This result supports H1.

Table 2. Participants' Capacity to Predict Outcomes Accurately					
		Outcome			
		Negative	**Neutral**	**Positive**	**Total**
Prediction	**Negative**	12	7	21	40
	Neutral	46	43	40	129
	Positive	44	59	28	131
	Total	102	109	89	300

The remaining hypotheses are generated on the basis of a confirmation bias framework. We conjecture that IT-competent analysts would focus more on the IT information and that financially competent analysts would focus predominantly on financial information. This differential focus is hypothesized to lead to distinctive types of confirmatory biases.

To verify this assumption, we asked each analyst to indicate the extent to which they relied on IT information and financial information for each announcement. Since the measures of information reliance were repeated 6 to 8 times per participant, we apply a repeated-measures analysis using the PROC MIXED procedure from the SAS 9.2 statistical package. A heterogeneous compound symmetry structure was assumed for the variance-covariance matrix. As expected, we found that IT-competent analysts reported that they relied more on IT information to make their predictions. The measure for IT competence was positively associated to reliance on IT information (β=.16, SE=0.08, t(41)=1.94, p<.05, one-tailed). Similarly, financially competent analysts reported that they relied more on financial information (β=.20, SE=0.11, t(41)=1.88, p<.05, one-tailed).

4.2. Prediction Accuracy

Generalized estimating equations (GEE) are suitable for modeling the accuracy of predictions as a function of IT and financial competence. A GEE model is in fact the appropriate statistical procedure for three reasons. First, a binary outcome can be used as a dependent variable and the parameters can be interpreted in the same fashion as a logistic regression. In this case, accuracy of the prediction is a binary outcome equal to 1 when an accurate prediction is made and 0 otherwise. Second, GEE accounts for the non-independence of observations that originate from the same subjects (Diggle, Liang, & Zeger, 2002). Because each subject made repeated predictions, it is important to take this non-independence into account. Third, our data collection procedure created a pattern of intermittent missing data in which the subjects were randomly exposed to 6 or 8 out of 15 possible IT announcements. PROC GENMOD, from the SAS 9.2 statistical package, allows one to control and correct for this type of missing data.

A logit link function was used for the model specification. A probit link function was tested to assess the robustness of the model. It led to analogous results. The probit estimations are not presented for the sake of brevity.

Thus, a GEE regression was performed on the binary outcome of prediction accuracy with (1) the valence of the final outcome (coded as dummy variables for positive and negative outcomes), (2) IT information, (3) IT competence, (4) financial competence, and (5) the predicted interactions. Continuous predictors were mean centered to facilitate interpretation. Due to the relatively limited size of the sample, we assumed the covariance among the repeated outcomes to be exchangeable or identical for every pair of measurements from the same subject.

As Table 3 shows, results of the GEE model suggests that analysts are less accurate in their predictions of negative outcomes (β=-1.609, SE=0.372, $\chi^2(1)$ = *18.67, p<.0001*, one-tailed) and of positive outcomes (β=-.433, SE=0.241, $\chi^2(1)$ = *3.22, p<.05*, one-tailed) as compared to neutral outcomes. The large beta for the dummy variable describing negative outcomes is consistent with the preliminary analyses that showed that accuracy was lowest for negative outcomes.

Table 3. Prediction Accuracy as a Function of IT Information, IT Competence and Financial Competence

Parameter	Estimate	Standard error
Intercept	-0.452 **	0.172
Positive events	-0.433 *	0.241
Negative events	-1.609 **	0.372
IT information (A)	-0.006	0.010
IT competence (B)	0.022	0.083
Financial competence (C)	0.003	0.070
A x B	0.013 *	0.007
A x C	-0.011 *	0.005
B x C	0.078 *	0.045
*p < .05, one-tailed, **p < .01		

IT information, and IT and financial competence as simple effects, were not significant predictors of accuracy (*p>.10*). However, the three predicted interactions were significant. As Table 3 shows, the interaction of IT information and financial competence (the A x C term) wass negative and significant: β=-.011, SE=0.005, $\chi^2(1)$ = *4.30, p<.05*, one-tailed. Figure 2 illustrates this interaction. Since the two independent predictors were continuous, we plotted the effect of IT information at specific levels of financial competence. Following Aiken and West's (1991) recommendation, we used values at one standard deviation below the mean as the low financial competence reference and one standard deviation above the mean as the high financial competence reference. As Figure 2 shows, an increase in IT information was associated with a decrease in prediction accuracy for individuals with high financial competence (one standard deviation over the mean). A test of this simple slope for high financial competence reveals that the beta was negative (β=-.025, SE=0.013) and significant ($\chi^2(1)$ = *-1.87, p<.05*, one-tailed). For individuals with less financial competence, the beta was positive albeit non-significant; β=.012, SE=0.014, $\chi^2(1)$ = *.88, p>.05*. This result supports H2a in that more financially competent analysts become less accurate for announcements where more IT information is available.
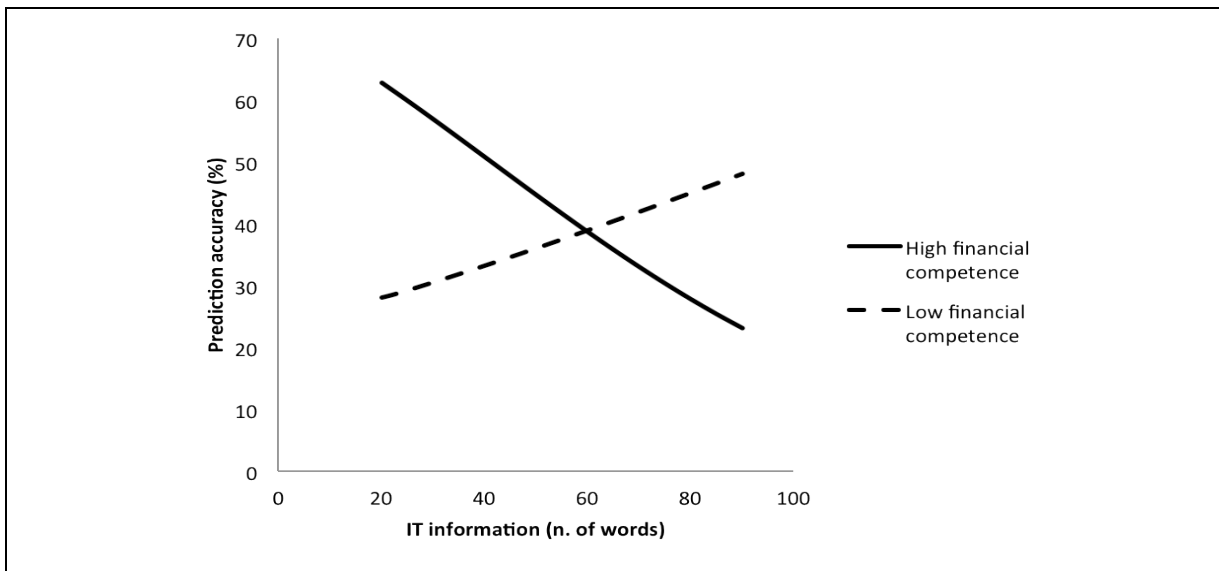
Figure 2. Prediction Accuracy as a Function of IT Information and Financial Competence

By contrast, the interaction of IT information and IT competence (the A x B interaction in Table 3) was positive and significant; β=-.013, SE=0.007, $\chi^2(1) = 3.73$, p<.05, one-tailed. Applying the same plotting procedure as in Figure 2, Figure 3 suggests that, for high IT competence individuals, an increase in IT information lead to greater prediction accuracy (β=.013, SE=0.012) than for low IT competence (β=-.025, SE=0.016). It should be underlined that the two slopes for these two levels of IT expertise are not significant (p>.10). However, the interaction coefficient presented in Table 3 is a sufficient test of whether IT competence and IT information interact in the expected direction (Aiken & West, 1991, p. 21). Thus, this set of results supports H3a: more IT-competent analysts tend to be more accurate in their predictions when more IT information is presented in the announcement.
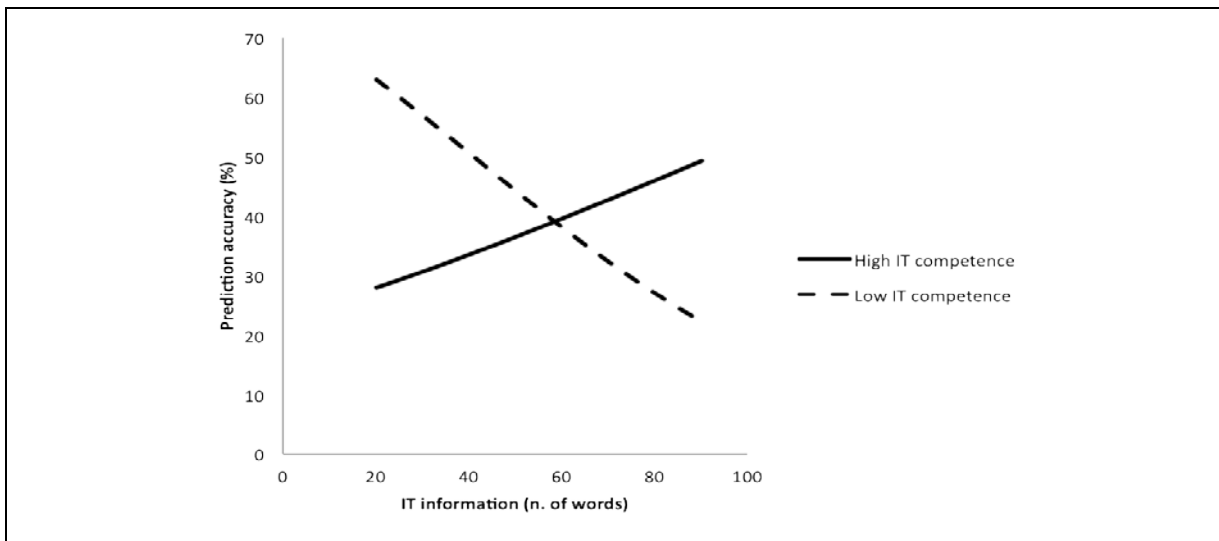

Figure 3. Prediction Accuracy as a Function of IT Information and IT Competence

Finally, the interaction of financial competence and IT competence (the B x C in Table 3) supports H4a. IT competence mitigated the negative effects of financial competence on prediction accuracy: β=-.078, SE=0.045, $\chi^2(1) = 3.03$, p<.05, one-tailed. As Figure 4 shows, high IT competence (one standard deviation over the mean) allowed finance competence to be associated to increasing

prediction accuracy (β=-.118, SE=0.098) when compared to low IT competence (β=.112, SE=0.094). Again, these two slopes are not significantly different from zero, but the interaction coefficient in Table 3 indicates that they are statistically different from one another.
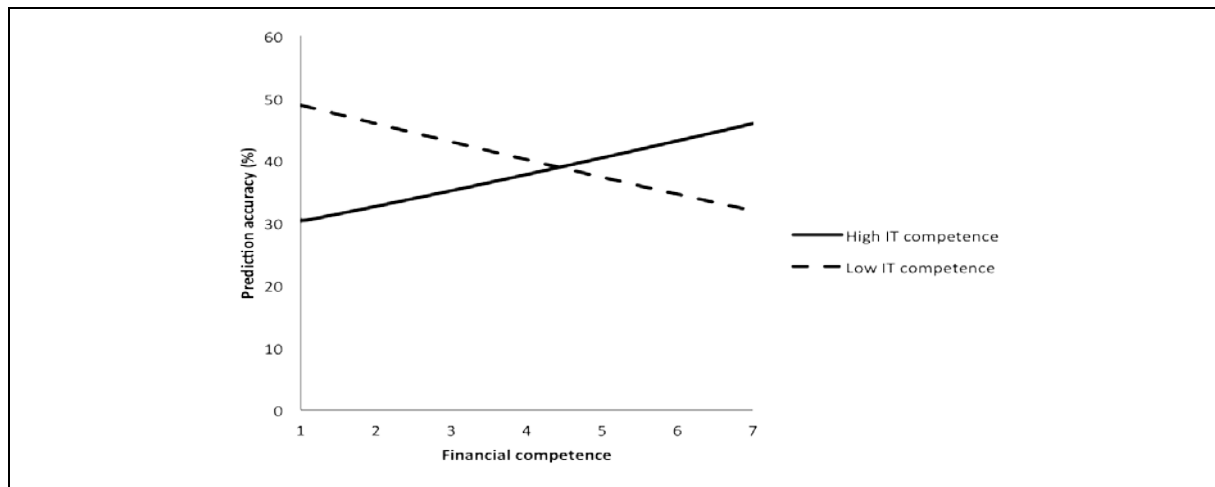

Figure 4. Prediction Accuracy as a Function of IT and Financial Competence

4.3. Optimistic Biases

In this section, we determine whether there is a systematic pattern of outcome misprediction. A value of 1 was assigned to a positive outcome, 0 to a neutral one, and -1 to a negative one. Similarly, a value of 1 was assigned to a positive prediction, 0 to a neutral one, and -1 to a negative one. The biases were then calculated by subtracting the real outcome value from the prediction. Consequently, the possible range on the bias measure was between -2 and 2; with positive valence representing an optimistic bias.

We performed a repeated-measures analysis with the bias measure using the MIXED procedure from the SAS 9.2 statistical package. Allowing the bias measure to be considered as a continuous outcome allows for a more flexible and easily interpretable model. The MIXED procedure, like the GENMOD procedure, accommodates missing data and several covariance structures. Primary analyses revealed that the heterogeneous compound symmetry covariance structure provided the best fit. A compound symmetry model, where we estimated the covariance between IT announcement evaluations, provided a better fit than a variance component model: $\Delta\chi^2 = 20.1$, $df=1$, $p<.001$. The significance of the covariance parameter shows that the repeated observations were not independent. Furthermore, the heterogeneous compound symmetry structure, where a covariance parameter and a distinct variance parameter for each announcement are estimated, fit the data better than the compound symmetry structure: $\Delta\chi^2 = 781.31$, $df=14$, $p<.001$.

The final model, presented in Table 4, confirms once again that a general optimistic bias existed in our participants. The significant and positive intercept indicates that prediction errors were systematically optimistic: $\beta_0=.638$, SE=0.029, $t(40) = 21.63$, $p<.0001$, one-tailed. This further supports H1. In general, IT information reduced the magnitude of optimistic biases: $\beta=-.011$, SE=0.003, $t(40) = -3.57$, $p<.001$, one-tailed. This result was not predicted in our hypotheses. Another result not among our hypotheses is that financial competence tended to increase optimistic biases: $\beta=.029$, SE=0.018, $t(40) = 1.65$, $p=.05$, one-tailed.

Table 4. Optimistic Bias as a Function of IT Information, IT Competence and Financial Competence

Parameter	Estimate	Standard error
Intercept	0.638 **	0.029
IT information (A)	-0.011 **	0.003
IT competence (B)	0.019	0.020
Financial competence (C)	0.029 *	0.018
A x B	-0.004 *	0.002
A x C	0.003 *	0.002
B x C	-0.004	0.012
*p < .05, one-tailed, **p < .001		

As Table 4 shows, the interaction of IT information and financial competence (A x C) was positive and significant: $\beta=.003$, SE=0.002, $t(253) = 1.65$, $p<.05$, one-tailed. As Figure 5 shows, more IT information reduced optimistic biases for low financial competence individuals: $\beta=-.016$, SE=0.004, $t(253) = -3.61$, $p<.01$, one-tailed. For high financially competent individuals, the un-biasing effect of IT information subsided: $\beta=.006$, SE=0.004, $t(253) = -1.41$, $p>.10$. This result supports H2b in that more financially competent analysts are expected to display more optimistic bias about announcements where more information was available.
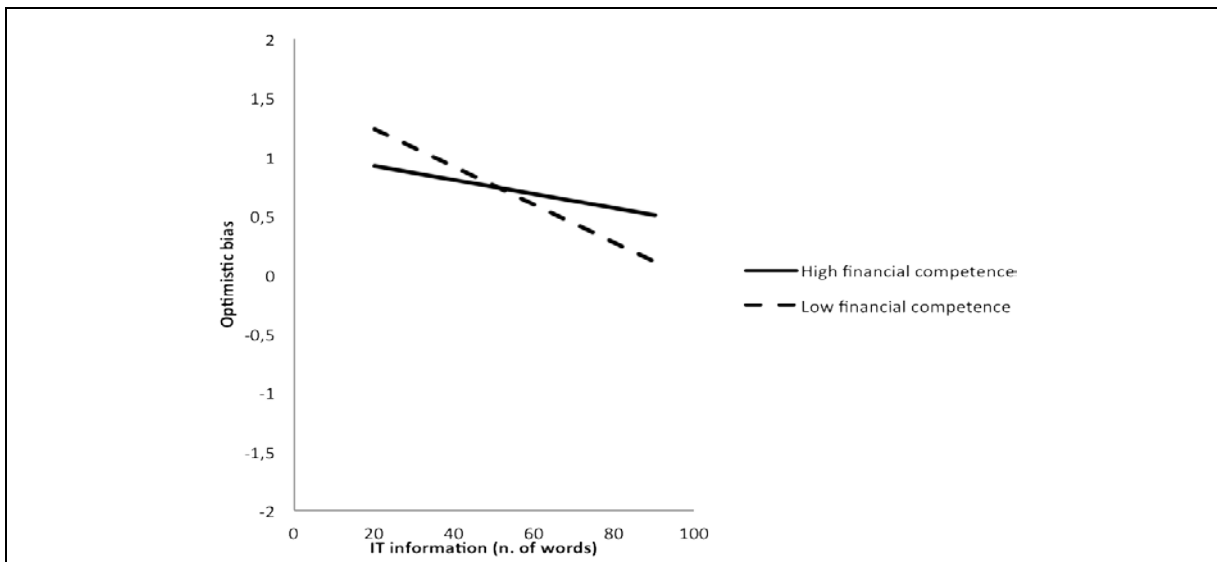

Figure 5. Optimistic Bias as a Function of IT Information and Financial Competence

By contrast, the interaction of IT information and IT competence (A x B in Table 4) was negative and significant: $\beta=-.004$, SE=0.002, $t(253) = -2.10$, $p<.05$, one-tailed. As Figure 6 shows, for low IT-competent individuals, more IT information did not lead to decreased optimism; $\beta=-.004$, SE=0.004, $t(253) = -1.00$, $p>.10$. However, for highly IT-competent individuals, more IT information lead to decreased optimistic biases: $\beta=-.018$, SE=0.004, $t(253) = -4.03$, $p<.01$, one-tailed. This result supports H3b because IT-competent analysts tend to be less optimistic in their predictions when more IT information is presented in the announcement. Finally, the interaction of financial competence and IT competence was not significant: $p>.10$. Thus, H4b is not supported.
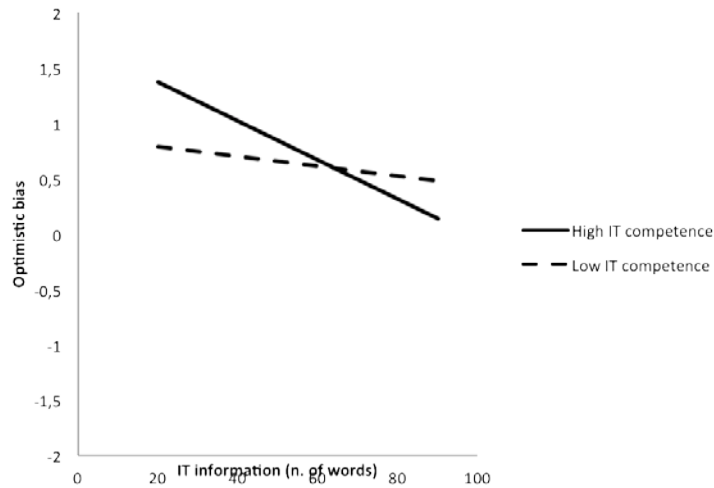
Figure 6. Optimistic Bias as a Function of IT Information and IT Competence

5. Conclusion

In this study, we found that prediction accuracy about market reactions to IT investments was hampered by confirmation biases. Financially competent analysts were particularly subject to such confirmation biases, especially when information about information technology is plentiful. By contrast, we found that IT-competent analysts were less prone to this confirmation bias. Finally, IT competence buffered confirmation bias for financially competent analysts. This set of findings supports the assertion that analysts attribute more weight to information in which they have some expertise. Although confirmation biases have been reported in a business setting (Klayman, 1995), this article is, to our knowledge, the first to test this bias using individuals who have diverse competencies and who need to analyze a heterogeneous set of information. The results of our research suggest that, from an analyst's point of view, more information is not always better. The pitfalls of over-information have recently been extended to the area of confidence judgments. Tsai, Klayman, and Hastie (2008), also using an experimental approach, found that more information leads to over-confidence without improving judgment accuracy.

Future research could extend to other types of biases such as the preference for extremity: a tendency to overestimate particularly rare or frequent events (Koehler et al., 2002). Another possible venue for future research would be to look for feature-positive effects (Klayman, 1995) and opportunities for bias reduction. Individuals tend to be better at learning from the presence of a feature rather than its absence. Training analysts, especially in a studying the cases of IT successes and failures, by emphasizing the possible biasing properties of information could reduce confirmation biases by drawing on feature-positive effects. Another promising avenue for future research would be to control for fundamental individual characteristics when comparing their investment decisions. For example, Barnea, Cronqvist, and Siegel (2010) found that one-third of the variance in stock market participation and asset allocation can be explained by a genetic factor. Additionally, Cronqvist and Siegel (2012) found that genetic variation explains also about a third of the variation in savings behavior across individuals (see also Cronqvist & Siegel, 2013). Considering the recent advances in NeuroIS (Loos, Riedl, Müller-Putz, vom Broke, Davis, Banker, & Léger, 2010), we feel that future research should build on the new evidence to see if, over and above the individual's genetic differences, IT competency still explains the effect we have found in our paper.

The development of expertise is central to the education of professionals in information technology. The results of this study explore the limits to expertise by examining the bias one develops when becoming an expert. Our results open a new area of investigation in the study of expertise in information technology. The findings reported in this article should not be interpreted as a plea for

blissful ignorance. Rather, they represent a call for more diversified training for analysts and managers so that they can grasp contextual information and reduce the likelihood of confirmation biases. Indeed, research suggests that taking time to consider the opposite view and that admitting that the information could contradict one's initial beliefs tend to have corrective effect on one's conclusion (Lord, Lepper, & Preston, 1984). A "consider-the-opposite" pedagogical strategy in an introductory MIS class for non-IT students could mean using counter-intuitive teaching cases that force them to carefully evaluate alternative positions. In sum, these proposals could be particularly timely in light of the current downward trend in IT course development in North American universities (Street, Wade, Bjørn-Andersen, Ives, Venable, & Zack, 2008) and could provide support to include information technologies in general business programs, such as MBA.

In addition, this article deals with analyses that were produced by individuals in isolation. The diversity of competencies that was found to be bias-reducing could also be found at the team level. It could be argued that most financial analyses are done in a group setting. This type of diversity in a team's expertise, described as variety by Harrison and Klein (2007), could thus reduce confirmation biases and help improve prediction accuracy.

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Appendix

Subjects

Subjects participating in the experiment were all graduate and undergraduate students in a large AACSB school in North America. Our main objective was not to clone market investors, analysts, and traders; rather, it was to see how knowledge and experience matter in assessing market reaction to IT investment. Drawing subjects from a student population allowed us to select students who had a diverse set of skills, experiences, and backgrounds. We sought two specific types of students: some were chosen for their interest in finance and financial analysis, while others were chosen for their experience in IT implementation.

Students in the first group were members of an investment club composed of approximately 30 undergraduate students who major in finance. The club met regularly to review the portfolio return, analyze the performance of publicly traded corporations, and make stock trading decisions. It was coached and supervised by finance faculty members and industry professionals. Members of the club often had working experience in the financial industry as junior analysts. The second group of subjects was recruited among graduate students in IT. Most of these students had IT implementation experience (for instance, reengineering of business processes, implementation of ERP systems, etc). Short of using active professionals, we made an effort to select business majors and graduate students with as much experience as possible in their respective fields.

Selection of IT Investments

We selected 15 press releases for the purpose of this study. Building on McWilliams and Siegel (1997), the selection process included many steps. We looked for:

- Initial press releases concerning significant IT investments
- Investments made by publicly traded companies
- Investments likely to have a significant impact on the stock market value of the investing company, and
- No other major external event (such as an earnings announcement, dividend payment or new debt issuance) that could bias the market at the time of the press release.

Press releases were taken from the PR-Newswire produced by Thomson Dialog®. In 2004, most significant IT investments were related to enterprise systems, so we have searched the 2004 database for the following key words: "SAP", "Peoplesoft", "Oracle", "J.D. Edwards", "Siebel", "ERP", "CRM", or "SCM", and "selects", "chooses", "selected", or "adopts". A total of 1,086 press releases were identified.

From those 1,086 releases, we randomly selected 30 releases over a series of iterations. We verified that each release was about a publicly traded company, that it referred to a significant IT investment, and that it was the first release issued about this particular event. Releases that did not satisfy these criteria were eliminated. Next, we conducted event studies using Eventus® software to estimate whether the market return was higher, lower, or not significantly different than the market return expected by a one-factor CAPM model. We then verified that no other major event had occurred for this company at the time of the release. These event studies included announcements of other investments, mergers or acquisitions, dividend payments, releases of new products, or major commercial deals. We consulted the A1 summary page of the *Wall Street Journal* three days prior to and after the press release date to control for events that might have had a confounding effect on stock returns.

Finally, we used a quota sampling technique to obtain an equal distribution of all cases: five announcements followed by a positive abnormal return, five followed by a negative abnormal return and five followed by a normal return. Following recommendations by MacKinlay (1997), we used an investment window of plus and minus one day and plus and minus three days from the day of the event. Of the initial 1,086 press releases, 796 releases were investigated to create our balanced sample of 15 cases.

Table A-1 lists the cases used for the experiment. A return was classified as abnormal if the market return for the plus and minus one-day or three-day window was significantly different from zero; that is, the null hypothesis can be accepted with a probability of less than 10 percent. All press releases were gathered in 2004.

Table A-1. List of the Companies, Date of the Release and Abnormal Stock Martket Returns Associated with the Press Releases Used in the Experiment				
Company announcing the IT investment	**Market index of reference**	**Press release date**	**Abnormal market return (one-factor model)**	
			(-1,+1) z-value	**(-3,+3) z-value**
Aspect Comm. Corporation	NASDAQ	27/01/2004	12.45% 3.522***	5.16% 0.935
Graco	DJINDUS	04/10/2004	3.03% 2.095**	2.45% 1.104
ICU Medical Inc.	NASDAQ	15/01/2004	10.10% 2.562***	16.44% 2.731***
Rural Cellular	NASDAQ	19/05/2004	7.72% 1.499*	17.26% 2.192**
SIG Holding	DJSTOXX50	29/06/2004	6.64% 2.375***	12.76% 2.990***
Autodesk	NASDAQ	17/05/2004	-4.82% -2.073**	-12.21% -3.451***
Berry Petroleum	DJINDUS	03/08/2004	-7.76% -1.568*	-5.31% -0.901
Entegris	NASDAQ	26/01/2004	-9.47% -3.616***	-11.26% -2.852***
Logitech	DJSTOXX50	08/03/2004	-2.16% -0.776	-6.55% -1.545*
Select Comfort	NASDAQ	28/01/2004	-2.82% -0.856	-11.15% -2.187**
Aceto Corporation	NASDAQ	29/07/2004	-0.21% -0.052	-4.98% 0.824
BG Group	DJSTOXX50	28/01/2004	-2.76% -0.875	-3.27% -0.698
Devry Inc.	DJINDUS	18/05/2004	-0.37% -0.075	-3.00% -0.406
McClatchy Co.	DJINDUS	02/06/2004	-0.20% -0.111	-0.56% -0.205
Nvidia	NASDAQ	19/072004	0.05% 0.010	-0.93% -0.093
Calculations of abnormal return were done using a one-factor market model beta (using the index of reference as the market return) and then subtracting the predicted return from the observed return. The z-value for the abnormal return appears below the coefficient. Abnormal returns identified by * are significant at the 10% level, by ** at the 5% level and by *** at the 1% level.				

For each case, we prepared an information sheet containing the full text of the press release and some basic financial information. In a pre-trial, we asked the subjects what additional information would be useful in order to make their decisions and used this information to build our final announcement sheet. The final information sheet included the following items: (1) the reference

market index and the company's three-month alpha and beta coefficients from the CAPM model; (2) basic balance sheet and profit and loss account items (total assets, shareholders' equity, operating revenues/turnover, net income, market capitalization, number of employees, and median value for the 20 closest companies); and (3) key ratios (return on shareholders' equity, profit margin, return on total assets, and current solvency and price-earnings ratios).

Survey Instruments

Financial competence (20 items)

What is your level of knowledge of (from low to high, 7-point Likert scale) :

- Generally accepted accounting principles?
- Items figuring in the balance sheet of a company?
- Items figuring in the profit and loss statement of a company?
- Items figuring in the cash flow statement?
- The consequences of the dividend policy on the value of the company?
- Net present value evaluation models?
- Scenario analysis techniques?
- Top down approach in the evaluation of financial securities?
- The market efficiency theory?
- Market inefficiencies and irregularities?
- The concept of earnings per share?
- The concept of price/earnings ratio (P/E)?
- The concept of cash flow?
- The concept of credit rating?
- The concept of expected growth (g)?
- The concept of the required yield?
- How change of the credit rating affect the value of a company's stock?
- How insolvency announcements affect the value of a company's stock?
- How financial reorganization announcements affect the value of a company's stock?
- How announcements of irregularities in the accounting documents affect the value of a company's stock?

IT competence (18 items)

What is your level of knowledge of (from low to high, 7-point Likert scale)?

- Database technologies (hierarchical, relational, object-oriented)?
- Client-server technologies (e.g., CORBA and .NET)?
- Technologies related to the electronic exchanges of data (ex: EDI and XML)?
- Web technologies (e.g., Web Services and SSL)?
- Business to consumer e-commerce solutions (B2C)?
- Business to business e-commerce solutions (B2B)?
- Enterprise Resource Planning (ERP) solutions?
- Customer Relationship Management (CRM) solutions?
- Data warehouse (OLAP, datamining) solutions?
- Best practices in the development of an information system?
- Best practices in the outsourcing of an information system?
- Best practices in the project management in IT?
- Best practices in the software prototyping?
- Best practices in the configuration of an ERP?
- Potential business opportunities related to IT?
- The identification of IT solutions related to business problems?
- The evaluation of organization impacts associated with the implementation of IT?
- The selection of IT solutions aligned with the strategic objectives of a company?

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