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The accuracy of financial analysts' earnings forecasts and the Tunisian market reliance with time

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Abstract: Unlike previous studies which have examined the role of financial analysts in developed economies, the aim of this paper is to investigate whether following the Tunisian stock market opening, both the analyst forecast accuracy and the market's reliance on analyst forecasts, increase with time. This study is based on the hypothesis that accuracy is expected to increase over time as analysts exert more effort and gain valuable forecasting experience, and also that the reliance on analyst forecasts should increase with time as the market opens and investors become more sophisticated. The methodology employs bi-annual panel data for Tunisian stock market from 2010 to 2015. Our results are consistent with the expectations. First, results generally confirm that both the accuracy and the higher quality of analyst earnings forecasts are increasing with time. Second, we find evidence that earnings expectations are not mainly based on analyst forecast in the first sub-period (2010–2012). However, these findings are reversed in the second sub-period (2013–2015) and for the whole period (2010–2015) as analyst forecast better explain returns and exhibit greater relative information content.

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PUBLIC INTEREST STATEMENT

Research in accounting and finance has not thoroughly examined the role of financial analysts in an emerging market setting. This study investigates whether, following Tunisian market opening, analyst forecast accuracy and the market's reliance on analyst forecasts increase with time. Accuracy is expected to increase over time as analysts exert more effort and gain valuable forecasting experience. The findings indicate that time is positively related to analyst forecast accuracy after controlling for a number of other firm and market characteristics. Furthermore, this study records that time should also be related to the market's propensity to use analyst forecasts to form earnings expectations. As Tunisian market opens and investors become more sophisticated, the reliance on analyst forecasts should also increase. Indeed, such a contribution shows the relative superiority of analysts' forecasts of disaggregated earnings over random walk earnings forecasts. This result can be useful for analyzing the relation between financial analysts and other important market characteristics in emerging economies similar to Tunisia.

Subjects: Finance; Investment & Securities; Accounting

Keywords: Tunisian stock market; informativeness; financial analysts; earnings forecasts

JEL classifications: G02; G11; G14; G17; G21

1. Introduction

Research in accounting and finance has deeply analyzed the role of financial analysts in the operating of US and developed capital markets, but this issue has not been sufficiently examined on emerging stock markets. Analyst earnings forecasts have been documented numerous times in the literature (Fried & Givoly, 1982; Hopwood & McKeown, 1990; O'brien, 1988), and show that they are more accurate than time series forecasts which push the market to rely on them than to time series model predictions.

Analyst forecasts have been related with the market and companies attributes. For example, Abarbanell, Lanen, and Verrecchia (1995), Healy, Hutton, and Palepu (1999), Hope (2003), Lang and Lundholm (1996) find that the analyst following accuracy and dispersion have been positively (negatively) associated with the quality of the firm's information environment. In this way, the studies of Lys and Soo (1995) have also noticed a positive relation between accuracy and analyst following. Lang, Lins, and Miller (2003) find that analyst coverage and accuracy have been positively associated with firm value. Botosan (1997), Frost, Gordon, and Hayes (2006), Hail and Leuz (2006), Leuz and Verrecchia (2000) propose evidence about better information environment which is resulting from lower cost of capital and greater liquidity to help improving the efficiency of the market. All of those results suggest that analysts play an important role in capital markets.

An increasing number of studies examine market characteristics in emerging markets, like return structures and their relation with risk (Bilson, Brailsford, & Hooper, 2002; Serra, 2000), volatility (Huang & Yang, 2000), and the degree of integration in developed markets (Bekaert & Harvey, 2002; Errunza & Miller, 2000). Another well-documented incentive for this research deals with the benefits and costs of market liberalizations. In this approach, Hooper (2001), Ito (2004) and Krugman (1999) show the positive impact of market opening to market's volatility and their bond to increase risk which causes financial crises. In addition, other studies suggest that market opening positively affect the markets as they decrease the cost of capital (Bekaert & Harvey, 2000; Henry, 2000), and increase stock returns and market efficiency but without increasing volatility (Kim & Singal, 2000). Due to the recent financial crisis, the interest for foreign investment in emerging markets grows significantly and the underlying structures that could affect investor decisions in a similar market become very important to learn.

This paper is aimed at providing additional insights into the role of financial analysts in Tunisian emerging stock market. In an emerging environment where there are less information and transparency, analyst should demonstrate his ability and output quality by providing accurate forecasts which are greatly important to both local and foreign investors in decision-making. What suggests a higher analyst research quality is the market's greater reliance on analyst earnings forecasts (Walther, 1997). We thus seek to better understand the change in analyst forecast accuracy and the Tunisian stock market reliance on analyst forecasts over time. For that purpose, based on Karamanou (2012) showing that following stock market opening, both the accuracy and the market reliance on analyst forecasts increase with time as investors become increasingly more sophisticated, we develop two panel models administered to a sample of Tunisian individual financial analysts. This study is important to both local and foreign investors considering they are looking for international diversification of their portfolios.

Results at first glance, suggest that in the period following market liberalization, analyst forecast accuracy increases over time, after controlling for a number of other firm characteristics, which can affect analyst accuracy. On the other hand, even though results prove that the Tunisian stock market doesn't rely mostly on analyst forecast to form earnings expectations in the first sub-period (2010–2012). Trends change toward the second sub-period (2013–2015) and for the full study's period (2010–2015), as analyst forecast errors become increasingly more important. This evidence supports the existence of a market learning mechanisms correction which enhance the importance of analyst accuracy and increase the market's reliance on analyst forecasts.

This paper is organized as follow. Section 2 presents a review of the literature and the assumptions of our work. Section 3 provides a description of the empirical validation. In this regard, two panel models are developed for Tunisian context based on bi-annual data. We discuss the empirical results and their interpretation in Section 4. Finally, we conclude and discuss the key features for future research in Section 5.

2. Literature review

2.1. The characteristics of analysts' accuracy and forecast timing

Many studies have analyzed the characteristics of analysts' performance. To rank analysts, Stickel (1992) uses as proxy for analyst performance, the number of revision, the degree of accuracy and the impact on the stock market of the individual forecasts. Mikhail, Walther, and Willis (1999) state that the bonus on top of the salary of analysts is not determined by accuracy, but rather by the trading volume stimulated and the investment business generated from the brokerage. Kutsoati and Bernhardt (1999) see this issue differently. They think that the bonus structure is a driver for accuracy. The accurate analysts attract more clients to the brokers, so relatively better forecasters are wanted by the brokers and will be rewarded with more salary. Analysts have incentives to overuse their private information, so their skill can be determined quickly. They find that 62% of the last forecasts are biased away from the consensus, and overshoot the actual EPS, but when there are more analysts following a company, the bias becomes smaller. Hong and Kubik (2003) examine how analysts move to bigger brokerages if they are more accurate. They find some evidence that being accurate might lead to a better job, but also that being optimistically helps a great deal.

Brown, Richardson, and Schwager (1987) constructed a model to investigate if company characteristics lead to superior forecasts, with controlling for the timing advantage. They conclude that the size of the company and the prior dispersion in forecasts has a significant link with superior forecasts. Another interesting research has been conducted by Clement (1999), testing the cross section of analyst forecast errors to determine why analysts perform better, measured by accuracy, with controlling for firm-year effects. He finds a positive correlation for both the size and the experience of the brokerage firm, and a negative correlation between accuracy and job difficulty.

Mikhail, Walther, and Willis (1997) theorize that the explaining factor for forecast accuracy should be experience in making forecasts for the same company. They find that forecast errors of analysts decrease with frequency, which support their learning by doing (LBD) model. Although the explanation based on experience seems plausible, Jacob, Lys, and Neale (1999) find some other justifications. They are also fascinated by how experience is gained, and propose in addition to the LBD explanation of Mikhail et al. (1997), two more explanations superiority in forecasting. Their first proposed explanation is aptitude. They suggests that there are different levels of aptitude among analysts, which essentially means that some analysts just have more talent to forecast a certain company than others, and hence pick up this skill fairly quickly. The second explanation concerns environmental factors, through using brokerage firm size as a proxy for this factor.

Brown (2001) conducts a small research to determine if either Clement (1999) or Stickel (1992) best captures analysts' characteristics and predicts forecast accuracy. Stickel (1990) uses past accuracy measured by mean average forecast error, while Clement (1999) defines five analysts' characteristics that should explain forecast accuracy. These comprise general experience, company experience, the amount of companies covered and of different industries, and the brokerage firm size for which the analysts work. He also controls for the days until fiscal year end, to adjust for the better accuracy from being later with forecasts. Surprisingly, both models work equally well with some small advantages for the past accuracy model.[1] He concludes that even though analyst' characteristics capture properties which are very useful to determine whether an analyst is good or not. Checking the previous accuracy of the analysts represents the best way to identify who is the best among all.

Regarding the forecast time of analysts and their accuracy, Cooper, Day, and Lewis (2000) show some interesting insights on how analysts time their forecasts. On the one side, analysts have incentives to generate trading volume, while on the other side not being accurate can lead to job termination. Superior analysts have incentives to bring their forecasts early, because this will create more trading volume, and they are confident that they are good forecasters. Conversely, forecasters who know they are not good have an incentive to wait to bring their forecasts until they have a chance to pick up some information from the better forecasters. Typically, an early forecaster, called a lead analyst, will submit his forecasts randomly and not specifically right after others. Followers will be quick to revise or submit after the forecast of a lead-analyst. They show that when using stock price response, forecast accuracy or abnormal trading volume as measure of identifying informative forecasts, the lead-analysts make the most informative forecasts.

2.2. Hypotheses development

Market opening corresponds to the most important turning point in time for all market participants when the flow of foreign funds is allowed thanks to regulations introduced by the authorities. We assume that after market opens the demand for better quality information increases, so that the quality of analyst research will be affected in better ways. Other benefits to emerging markets come from market openings have been documented numerous times in the related literature. For example, Henry (2000) finds that the equity price index on aggregate, exhibits abnormal returns of 3.3% during the eight month window leading up to the implementation of liberalization, consistent with a reduction in the cost of equity capital. Similar results are found by Bekaert and Harvey (2000) who show a decrease in their estimate of the cost of capital after stock market liberalizations, while Kim and Singal (2000) document that stock markets become more efficient following market liberalizations. More importantly, we try to prove that market liberalizations introduce more strong incentives for analysts to improve the quality of their research.

The analyst research quality is measured in many different ways, but the main contribution of this paper is the analysis of analyst forecast accuracy and the market reliance on them, using data of analyst earnings forecasts. In particular, we argue that financial analysts tend to learn more during the period following a market opening to improve their forecasts to which investors can rely. Drawing on related literature, forecast accuracy is identified as beneficial to capital markets (Gebhardt, Lee, & Swaminathan, 2001; Lang et al., 2003; Lang & Lundholm, 1996; Mikhail et al., 1997). According to these studies, individual analysts improve automatically their performance due to market opening which allows the flow of foreign capital and leads to give a powerful incentive for financial analysts to improve the quality of their research. Kim and Singal (2000) refer to two main characteristics, improving both the disclosure and the transparency of information.

Given the many benefits of market liberalizations, we aim to prove in this paper that following the Tunisian market opening, analyst forecast accuracy increases with time as analysts make a lot of effort considering the increase demand for higher quality research by local and foreign investors. Financial analysts gradually gain valuable forecasting experience leading to enhance the accuracy of their forecasts as they become more accustomed to the characteristics of the Tunisian market. This leads to our first hypothesis.

> H1: Following market opening in the Tunisian stock market, the accuracy of analyst earnings forecasts increases with time.

As long as investors rely on analyst forecasts, greater analyst accuracy would be very beneficial to the market. Many studies show that the US market tends to rely more on analyst forecasts than forecasts employing time series models (Brown, Richardson, et al., 1987; Fried & Givoly, 1982; Hopwood & McKeown, 1990; Kross, Ro, & Schroeder, 1990). Both the timing and the informational advantage of analysts have been addressed.

We suppose in this research that Tunisian stock market expectations are surrounded by uncertainty because investors are not enough informed about underlying market structures. We expect that this uncertainty of expected earnings decreases over time following market opening, while the reliance on analyst earnings forecasts increases, because investors will become more informed via better information and rely more on analyst forecasts. Early US evidence is consistent with the market relying on random walk earnings predictions (Bernard & Thomas,1990; Rendleman, Jones, & Latané, 1987). Aggarwal, Klapper, and Wysocki (2005) assume that investor sophistication should also increase with market liberalization because the most part of foreign capital in world markets comes from US institutional investors. Walther (1997) notes in a context of US market place that the degree of reliance on analyst forecasts is increasing in the degree of investor sophistication. Henry (2000) also adds that stock market liberalization is like a gradual process which usually involves additional liberalizations subsequent to the first one suggesting that the economic benefits stemming from market openness also gradually increase in the emerging markets. Consistent with this existent research supporting the greater reliance of investor sophistication on analyst forecasts, we think that after stock market opening, the reliance on analyst earnings forecasts will also increase over time, hence our second hypothesis.

> H2: Following market opening in the Tunisian stock market, the reliance on analyst earnings forecasts increases with time, because investor's uncertainty on expected earnings decreases.

3. Empirical design

3.1. Data source

Our sample consists of 57 listed firms in the Tunisian stock exchange (BVMT), over the 12 semesters' period from 2010 to 2015. The year period starts from 1st January to fiscal year ending 31st December . We use the last semi-annual forecast made by each analyst before the half-year t earnings announcement date. The consensus forecasts were collected from brokers who are present on the stock market as MAC sa, Tunisie Valeurs, Amen Invest, Axis Capital, CGF and BNA Capital. The forecasts are published every semester following the publication of financial statements of listed firms. We use also the actual earnings per share (EPS) provided by balance sheets and activity reports files obtained from the BVMT source.

3.2. Methodology

Following the Karamanou (2012) study, we conduct our analysis based on two panel data models. In order to test our first hypothesis H1, we use firstly a measure of the absolute forecast error as follows:

$$\mathrm{ABSUE} = \frac{|\mathrm{AE}_t - \mathrm{FE}_t|}{P_{t-1}} \quad (1)$$

where ABSUE denotes the absolute value of the forecast error deflated by the price of the beginning of semester and inversely related to analyst accuracy; AE_t and FE_t, respectively, reflect actual earnings and the consensus earnings forecast for firm i and semester t; whereas P_{t-1} correspond to the beginning of the semester price. The consensus forecast is measured as the mean or median of all forecasts made in the three-month period of semester ending. Then to derive the variable of interest, which measures the forecast accuracy, we draw the following measure:

$$\mathrm{ACC}_F = -\frac{|\mathrm{AE}_t - \mathrm{FE}_t|}{P_{t-1}} \quad (2)$$

where ACC_F represents the accuracy of analyst forecasts measured as the difference between actual earnings and the analyst forecast deflated by the beginning price. Accuracy is computed as ABSUE from Equation (1) multiplied by (−1), and thus is denoted by negative numbers so that greater values of both accuracy measures reflect lower forecast error and therefore greater accuracy. The basic accuracy function can be written as follows to test whether the accuracy of analyst forecasts has changed over time:

$$ACC_F = F(\mathrm{TM, DISP, LOSS, MNFE, MKTR}) \quad (3)$$

The variables used are:

- TM stands for the time variable which takes the value of 1 if the forecast was made during the entire period (2010–2015), and the value of 2 if the forecast was made only during the period (2013–2015);
- DISP stands for the standard deviation of analyst earnings forecasts deflated by beginning price;
- LOSS is a dummy variable which equals one when the actual semester earnings EPS are negative and otherwise it equals zero;
- MNFE is the signed percentage forecast error deflated by the mean forecast.
- MKTR is the stock market turnover ratio of domestic shares (%) (Value Traded/Capitalization).

Hypothesis H1 predicts that the coefficient on the time variable will be positive. The model controls a number of other variables that prior research has found to explain forecast accuracy. Dispersion, DISP, is the standard deviation of earnings forecasts over the three month period before semester end, deflated by beginning of period price. Dispersion proxies for earnings uncertainty (Barron & Stuerke, 1998; Diether, Malloy, & Scherbina, 2002; Zhang, 2006a, 2006b) and is inversely related to investor informativeness (Abarbanell et al., 1995; Lang & Lundholm, 1996). A strong dispersion reflects a low consensus among analysts explained by strong information uncertainty. However, low dispersion may in some cases not reflect weak informational uncertainty but a high level of analyst mimetism. Diether et al. (2002) indicate that this variable reflects a divergence of opinion but is not related to risk. Indeed, the authors found that the dispersion of forecasts is positively related to the market risk β, the variability of the profit and the standard deviation of past returns but is negatively related to future returns. Imhoff and Lobo (1992) found that the earnings forecast dispersion may reflect the uncertainty of the future cash flow. They hold the view that dispersion is a reflection of the relevant part of the financial report of the company and the price of uncertainty. Barron and Stuerke (1998) found that there is a positive correlation between the earnings forecast dispersion and release of information demand, which shows that the analysts' earnings forecast dispersion is a good method measuring the company's earnings forecast uncertainty. Thus, dispersion is expected to be inversely related to forecast accuracy.

LOSS is included in the model to control the possibility that negative earnings, if unanticipated, are harder to predict. Hope (2003) finds this variable to be negatively but not significantly related to forecast accuracy. Following Hope (2003), we also include in the model earnings surprise, MNFE, which is computed as the signed percentage forecast error. In particular, not including this variable does not change reported results. The time variable remains positive and becomes more significant. MKTR measures the general movement of equities on the country's capital market and is expected to also be positively related to forecast accuracy. Market movement reflects how important the equity market is, and hence actives markets should reflect greater demand for quality analyst research.

Hypothesis H2 posits that the market's reliance on analyst forecasts will increase over time. For that, we use previous research methodology developed by Brown, Richardson, et al. (1987), Fried and Givoly (1982) and Walther (1997), which argues that the earnings expectation model that best describes market expectations is the one whose errors are more strongly associated with returns.

Furthermore, we examine market reliance on analyst forecasts by looking at what extent the association of excess returns with earnings surprise generated by expectations is based on analyst forecasts.

$$\mathrm{MAR}_{i,t} = \alpha_1 + \beta_1 \mathrm{UER}_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$\mathrm{MAR}_{i,t} = \alpha_2 + \beta_2 \mathrm{UEF}_{i,t} + \varepsilon_{i,t} \tag{5}$$

where MAR is the cumulative market adjusted return over the three months period ending; the three months after semester end to ensure that firms have announced their earnings for semester t; $\mathrm{UER}_{i,t}$ and $\mathrm{UEF}_{i,t}$ are expressed with the following equations:

$$\mathrm{UER} = \frac{\mathrm{AE}_t - \mathrm{AE}_{t-1}}{P_{t-1}} \tag{6}$$

$$\mathrm{UEF} = \frac{\mathrm{AE}_t - \mathrm{FE}_t}{P_{t-1}} \tag{7}$$

where AE denotes the actual earnings of company i in semester t; FE represents the median of all forecasts made in the three-month period ending at semester end; and P is the company's price measured at the end of semester (t − 1).

Related research distinguishes between incremental and relative information content and shows that the two potentially address different research questions (Biddle, Seow, & Siegel, 1995). First, incremental information content tests examine whether one measure provides information content beyond that of another. Second, relative information content tests examine whether one measure has greater information content than the other. According to these researchers, relative comparisons are considered as mutually exclusive choices among alternatives.

In order to examine hypothesis H2, both information content tests are relevant and thus, we run the following tests. First, we examine which of the two earnings surprise proxies best explains returns by examining their relative information content. In this case, the models are by construction non-nested, so, the coefficients of determination R^2 are not representing an appropriate means of comparison. We mention two non-nested model statistics available to test relative information content, the *J*-test proposed by Davidson and MacKinnon (1981), and the Vuong test relative to Vuong (1989). Both tests may have some disadvantages. For example, the Vuong test requires iid errors, while the *J* test often times is unable to indicate which is best among the two competing models. In the literature, both tests have been used in similar settings. For instance, Dechow (1994) applied the Vuong test, while Walther (1997) applied the *J*-test. This paper extends existing methodology by implementing the *J* test because it is the simplest.

The *J*-test is based on a *t*-test of the coefficient λ, which is introduced in a new regression that nests the two competing hypotheses as follows. We start with our two non-nested models.

$$\text{Model 1}: \quad \mathrm{MAR}_{i,t} = \alpha_1 + \beta_1 \mathrm{UER}_{i,t} + \varepsilon_{i,t}$$

$$\text{Model 2}: \quad \mathrm{MAR}_{i,t} = \alpha_2 + \beta_2 \mathrm{UEF}_{i,t} + \varepsilon_{i,t}$$

If Model 2 is true, then the fitted values from the Model 1, when added to the first equation, should be insignificant.

The procedure begins by estimating the Model 1 which allows to obtain fitted values $\mathrm{bUER}_{i,t}$. Then, we add $\mathrm{bUER}_{i,t}$ to the list of regressors in Model 2 such as $\mathrm{MAR}_{i,t} = \alpha_1 + \beta_2\mathrm{UEF}_{i,t} + \lambda \mathrm{bUER}_{i,t} + \varepsilon_{i,t}$. After that we do a *t*-test on λ. A significant *t*-value would be evidence against Model 2 and in favor of Model 1. We repeat the procedure for the models the other way round and finally we rank the models on the basis of this test.

Based on Biddle et al. (1995) who show the possibility that where one variable is clearly more associated with returns, the other variable can still provide incremental explanatory power. In order to test whether UEF or UER have incremental information content over one another, we use the model as follows:

$$\mathrm{CMAR}_{i,t} = \alpha_3 + \beta_3\mathrm{UER}_{i,t} + \beta_3'\mathrm{UEF}_{i,t} + \varepsilon_{i,t} \tag{8}$$

where CMAR is the three months market adjusted returns ending, three months after semester end. We examine both information content analyzes for the entire period under review. However, in order to follow the predictions of hypothesis H2 and to test whether the information content of UEF increases over time, we need to drop the assumption that the relations are constant over time by splitting the sample period into two equal semester periods. The overall period includes six years from 2010 to 2015 (12 semesters), while the sub-periods are spanned into three years equivalent to six semesters from 2010 to 2012 for the first, and from 2013 to 2015 for the second.

4. Results

4.1. Descriptive statistics and simples correlations

Table 1 presents descriptive statistics of the variables used in our analysis on a total sample of 636 observations. Model 1 provides information on the variables used to test hypothesis H1, while model 2 provides information on the variables used to test hypothesis H2. The information is analyzed for the two equal semester sub-periods (2010S1–2012S2) and (2013S1–2015S2), and also for the entire period (2010S1–2015S2), respectively.

The mean and median values of ACC_F are negative in Model 1, as expected given that the absolute value of the forecast errors was multiplied by (−1), so that greater values reflect greater accuracy. The model also shows that there are some important changes in sample characteristics from the first sub-period to the second, proving the existence of significant differences in sample composition

Table 1. Descriptive statistics

Model 1: hypothesis H1 variables									
Variable	2010S1–2012S2 (*N* = 330)			2013S1–2015S2 (*N* = 306)			2010S1–2015S2 (*N* = 636)		
	Mean	Median	Std. dev	Mean	Median	Std. dev	Mean	Median	Std. dev
ACC_F	−0.0322	−0.0159	0.0934	−0.0300*	−0.0124*	0.0682	−0.0314	−0.0141	0.0822
DISP	0.0547	0.0258	0.0908	0.0467*	0.0187*	0.0895	0.0506	0.0230	0.0900
LOSS	0.1090	0.0000	0.3122	0.1176*	0.0000*	0.3227	0.1132	0.0000	0.3171
MNFE	89.748	4.6909	1,426.02	83.777*	12.593	1,248.46	6.2594	9.8995	1345.284
MKTR	0.1086	0.0967	0.0093	0.0740*	0.0688*	0.0167	0.0912	0.0875	0.0219
Model 2: hypothesis H2 variables									
Variable	2010S1–2012S2 (*N* = 324)			2013S1–2015S2 (*N* = 336)			2010S1–2015S2 (*N* = 660)		
	Mean	Median	Std. dev	Mean	Median	Std. dev	Mean	Median	Std. dev
MAR	−0.0035	−0.0045	0.0020	−0.0032*	−0.0039*	0.0038	−0.0091	−0.0017	0.0031
UER	−0.00096	−0.0012	0.0679	−0.0034*	0.00046	0.0932	−0.00107	0.00011	0.0814
UEF	0.00072	0.0016	0.0978	−0.0028*	−0.0023	0.0805	−0.0013	−0.00076	0.0903

Note: Asterisks (*) next to the numbers show that the mean or median of the variable in question for the indicated period is significantly different from the respective value reported in the other sub-period at the 0.10 level or better.

across the two periods. In order to provide some evidence on univariate changes in accuracy over the study's period, we compare the accuracy variables. Both mean and median forecast accuracy values increased significantly in the second sub-period compared to the first. Thus, it is clear from the results of the univariate tests what the effect of time on analyst accuracy. These differences should be controlled for by other variables in order to make more evidence and reliable inferences. Indeed, this increase in accuracy measures in the second sub-period is also accompanied by a decrease in forecast dispersion (lower forecast dispersion) and a further decrease in earnings surprise (lower signed percentage forecast error).

If we take a look at Model 2 of the same table, we can see some interesting facts. For all the three variables used to test hypothesis H2, there are significant changes in values across the two periods. Even though, they are always negative. Market adjusted returns exhibit a gradual increase in their mean and median value over time. We notice through the *t*-test for the equality of means that UER is statistically more negative in the second sub-period than the first. Another interesting fact is that as time passes, the mean value of UEF is positive in the first sub-period and negative in the second sub-period.

Relevant US research finds that on average financial analysts issue optimistic forecasts indicated by negative values of UEF in response to a number of different incentives that they face. Following Cowen, Groysberg, and Healy (2006), Das, Levine, and Sivaramakrishnan (1998), Dugar and Nathan (1995), and Lim (2001), analyst optimism in the US refer to the result of a number of incentives analysts face. For example, we mention the investment banking incentive, the access to management incentive and the trading incentive. In our study case, analyst optimism is apparent in the last period but not in the first one. Maybe, this is explained mostly by the fact that if analyst research becomes more important to capital market participants, his incentives for optimistic research also become stronger.

To avoid problems of autocorrelation between our variables, a survey of correlation matrix has been done. Table 2 presents the Pearson correlations for dependent and independent variables employed in our two models. Results of Model 1 show correlations between the variables used to test the hypothesis H1 for the entire period (2010S1–2015S2). As expected, we find that the accuracy measure is positively related to the time variable TM (*p*-value equals to 0.0353). Moreover, the table reveals some other interesting correlations, as well.

Table 2. Pearson correlations

Model 1: hypothesis H1 variables

Variable	ACC_F	TM	DISP	LOSS	MNFE
ACC_F *p*-value	1.0000	0.0448** (0.0353)	−0.4961*** (0.000)	−0.2503*** (0.000)	−0.0938** (0.0515)
TM *p*-value		1.0000	−0.0125* (0.0794)	0.01009 (0.8346)	−0.0807* (0.0943)
DISP *p*-value			1.0000	0.2574*** (0.000)	0.0349 (0.4693)
LOSS *p*-value				1.0000	0.2345*** (0.000)
MNFE *p*-value					1.0000

Model 2: hypothesis H2 variables

Variable	2010S1–2012S2 (*N* = 324)		2013S1–2015S2 (*N* = 336)		2010S1–2015S2 (*N* = 660)	
	UER	UEF	UER	UEF	UER	UEF
MAR *p*-value	0.0630 (0.2581)	0.00077* (0.0989)	−0.0106 (0.8519)	0.0084* (0.0823)	0.0279 (0.7011)	0.0025** (0.0502)
UER *p*-value		0.1018* (0.0670)		0.4538*** (0.000)		0.2988 (1.2295)

*Statistical significance at the 1% levels of confidence.

**Statistical significance at the 5% levels of confidence.

***Statistical significance at the 10% levels of confidence.

First, forecast accuracy is negatively related to analyst forecast dispersion DISP (p-value = 0.000), which proxies for overall earnings uncertainty. Second, the correlations between the independent variables and the time variable TM support the previous findings regarding differences in sample composition across the two sub-periods. For example, analyst dispersion DISP is negatively correlated with time TM (p-value = 0.0794), suggesting that analyst forecast dispersion decreases with time. We observe also that earnings surprise (forecast errors) is negatively correlated with time TM (p-value = 0.0943), implying that analyst forecast errors are lower (decreases) with time. The results in this analysis are consistent with Chang, Khanna, and Palepu (2000) and prior research.

Results of Model 2 show correlations between variables used to test the hypothesis H2 during the two sub-periods as well as the entire period. In the first sub-period, returns are not significantly correlated with UER (p-value = 0.2581), but exhibit a weak and positive correlation (p-value = 0.0989) with unexpected earnings based on analyst forecasts UEF. However, in the second sub-period, returns are only positively and significantly correlated with unexpected earnings based on analyst forecasts (UEF) (p-value = 0.0823). As found before, when we look to the full period under review, we see that market adjusted returns MAR are significant and positively correlated with unexpected earnings based on analyst forecasts (UEF) (p-value = 0.0502), while the association with unexpected earnings based on (UER) is also positive but not statistically significant (p-value = 0.7011). Accordingly, the evidence confirmed the hypothesis H2 that the market reliance on analyst forecasts increases with time.

4.2. Empirical results

Table 3 presents the estimation results of panel data for hypothesis H1 testing the effect of time on forecast accuracy. The regression covers the full period of analysis (2010S1–2015S2) and the two sub-periods (2010S1–2012S2, 2013S1–2015S2). This basic model is estimated using fixed effects. Hausman test shows that the model follows a fixed effect made by a χ^2 value very significant at the 90 and 95% levels. In addition, the Durbin–Watson test indicates that serial correlation does not pose a problem for our model.

According to the hypothesis H1 following market liberalization in the Tunisian market, analyst forecast accuracy should increase with time. As predicted, the coefficient of the time variable TM remains positive and highly significant across all three periods. These findings prove that time is an important factor in determining analyst forecast accuracy in recently liberalized markets such as for the Tunisian emerging country. This evidence corroborates and complements the prior research

Table 3. The effect of time on analyst accuracy in the Tunisian stock market

Hypothesis H1 results			
Model (1): $ACC_F = F$ (TM, DISP, LOSS, MNFE, MKTR)			
Variables	2010S1–2012S2	2013S1–2015S2	2010S1–2015S2
Intercept p-value	−0.0403*** (0.0000)	−0.0541** (0.0387)	−0.0245*** (0.0001)
TM p-value	0.0176*** (0.0000)	0.0208** (0.0201)	0.0056*** (0.0015)
DISP p-value	−0.5120*** (0.0000)	−0.1059*** (0.0016)	−0.4570***(0.0000)
LOSS p-value	−0.0052*** (0.0023)	−0.0419*** (0.0000)	−0.0111*** (0.0005)
MNFE p-value	−0.0000228 (0.9145)	−0.0000215 (0.9996)	−0.0000226 (0.6979)
MKTR p-value	0.1575*** (0.0063)	0.2040*** (0.0039)	0.1168* (0.0748)
N	330	306	636
R^2 (%)	58.55	62.48	73.05
F-value p-value	13.314*** (0.0000)	17.359*** (0.0000)	39.516*** (0.0000)
χ^2 p-value	23.578*** (0.0003)	43.145*** (0.0000)	19.704*** (0.0014)

*Statistical significance at the 1% levels of confidence.

**Statistical significance at the 5% levels of confidence.

***Statistical significance at the 10% levels of confidence.

results of Hope (2003) and Chang et al. (2000), who examine the determinants of analyst forecast accuracy in an international setting.

Some other interesting relations arise from empirical results. First, the coefficient of dispersion DISP is always negatively and significantly related with accuracy. Dispersion has been suggested to be used as a proxy for earnings uncertainty and the results of this paper are in line with this interpretation.

Second, the LOSS dummy variable is always negative and significant in association with accuracy showing that it is more difficult to forecast firm earnings when they are negative. Globally, the model exhibits high coefficients of determination R^2 (around 60%) and have significant explanatory power evidenced by the strong significance of the model's *F*-statistics.

Mikhail et al. (1997) confirm these results by finding a statistically significant decline in the absolute value of analyst quarterly forecast errors with time as firm-specific experience increases, controlling for both the functional form of the learning-by-doing phenomenon and factors previously shown to be associated with analyst forecasting performance. This evidence suggests that accuracy increases with the amount of information available about the firm collected over time.

Table 4 reports results of the regression for hypothesis H2. According to this second hypothesis, the Tunisian market reliance on analyst forecasts following market liberalization increases with time. The panel 1 includes the relative information content results where we use the *J*-test to evaluate and compare which of the two different measures of market expectations explain best returns.

Table 4. The effect of time with the Tunisian stock market reliance on analyst forecasts

Hypothesis H2 results			
Variables	2010S1–2012S2	2013S1–2015S2	2010S1–2015S2
Panel 1: relative information content results			
Model (2): $\text{MAR}_{i,t} = \alpha_1 + \beta_1 \text{UER}_{i,t} + \varepsilon_{i,t}, \text{MAR}_{i,t} = \alpha_2 + \beta_2 \text{UEF}_{i,t} + \varepsilon_{i,t}$			
Intercept *p*-value	−0.0028*** (0.000)	−0.00088** (0.042)	−0.00016** (0.000)
	−0.0030*** (0.000)	−0.00098 (0.123)	−0.00018 (0.000)
UER *p*-value	0.0019*** (0.004)	−0.00015 (0.734)	0.00093 (0.198)
UEF *p*-value	0.00058 (0.309)	0.0006*** (0.002)	0.00062** (0.021)
N	324	336	660
F-value *p*-value	2.375** (0.012)	0.115 (0.734)	2.111 (0.146)
	0.209 (0.647)	1.010** (0.031)	1.708** (0.019)
R^2 (%)	7.190	0.377	2.902
	0.637	4.952	3.340
J test	UER is best	UEF is best	UEF is best
Panel 2: incremental information content results			
Model (2): $\text{CMAR}_{i,t} = \alpha_3 + \beta_3 \text{UER}_{i,t} + \beta_3' \text{UEF}_{i,t} + \varepsilon_{i,t}$			
Intercept *p*-value	−0.0027*** (0.000)	−0.00072 (0.214)	−0.00054** (0.001)
UER *p*-value	0.0018*** (0.006)	0.000185 (0.6782)	0.0010 (0.649)
UEF *p*-value	0.00022 (0.680)	0.00071** (0.044)	0.00217** (0.035)
N	324	336	660
F-value *p*-value	1.230 (0.293)	0.629** (0.053)	0.862** (0.042)
R^2 (%)	7.467	4.110	5.260

*Statistical significance at the 1% levels of confidence.

**Statistical significance at the 5% levels of confidence.

***Statistical significance at the 10% levels of confidence.

Concerning the first sub-period (2010S1–2012S2), the coefficients of the unexpected earnings measures are all positive, but only the coefficient of UER is significantly related with returns. The UER coefficient is equals to 0.0019 and it is statistically significant at the 99% level of confidence. Thus, both the result and the *J*-test show that these earnings expectations proxy explains returns better for this period. For the second sub-period (2013S1–2015S2), results are different. The UER coefficient becomes negative and it is insignificant (the *p*-value decreases from 0.004 to 0.734), while the coefficient of UEF is positive and significant at the 99% level of confidence. For the three periods, findings indicate that earnings expectations based on analyst forecasts best explain returns. These results suggest that the relationship between analyst forecasts and returns is very strong, and thus we conclude that the evidence in panel 1 is relevant and consistent with our hypothesis H2.

Panel B presents the incremental information content results which confirm the results of relative information content. In the first sub-period (2010S1–2012S2), the UER and UEF coefficients are positive but only the UER coefficient is significant. It is worthy to note that the Tunisian market does not rely on analyst forecast in forming expectations because the second model seems to dominate analyst forecasts as a proxy for market earnings expectations. Interestingly, the observations change for the second sub-period (2013S1–2015S2). Even though the coefficient on UER is positive, but only the unexpected earnings variable which is based on analyst forecasts (UEF) is positively and significantly related to returns (p-value = 0.044). This finding suggests again the superiority of analyst forecasts as a proxy for market expectations.

Finally, UEF is associated with returns but UER is not statistically significant for the full period. Based on the *J*-test, the results also interpret the UEF as a variable that best explains returns. These findings corroborate and support hypothesis H2. However, we have to mention that the first and second sub-period results should be interpreted with caution given the relative close number of observations.

Research literature direct comparing the forecast accuracy confirms our findings and concludes that analysts are generally more accurate than other models in predicting earnings (e.g. Brown, Griffin, Hagerman, & Zmijewski, 1987). Therefore, using average accuracy as the decision criterion, a rational investor should always place more weight on the analyst forecast than on another model forecast in forming expected earnings. Walther (1997) corroborates also this by proving that earnings-announcement-related returns are more closely associated with analyst forecasts for firms for which sophisticated investor. Market participants place more weight on the analyst forecast for firms with high institutional ownership, firms with high analyst following, and large firms as proxies for investor sophistication.

5. Conclusion

In this paper, we provide additional insights on the role of financial analysts on Tunisian emerging stock market. Following the recent market opening which is assumed to affect the level of investor sophistication, we focus on how earnings forecast quality changes over time. In particular, we investigate the role of financial analysts in Tunisian market directly by looking at forecast quality measured by analyst accuracy and indirectly by examining the market reliance on these forecasts.

The evidence found in this paper suggests that analyst forecast accuracy increases over time, supporting the hypothesis that analysts exert more effort on the quality of their forecasts, through gaining more experience and/or by responding to quality demands to more sophisticated investors. Moreover, the empirical results show that the Tunisian stock market increasingly relies on analyst earnings forecasts. Specifically, even though in the first period of analysis (2010–2012), the Tunisian stock market isn't relied on analyst forecasts earnings to form its expectations, however, it is mostly relies on them in the later period of analysis (2013–2015). Indeed, the relative information content test indicated that analyst forecasts explain best returns in the later period. The tests of incremental information content confirm these results.

This study contributes to the behavioral finance literature as the role of financial analysts in emerging market settings has not been thoroughly examined. This research can be extended by focusing on the interplay between financial analysts and important market characteristics.

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Note

1. For example, the best decile of past forecast accuracy performs 31.9% better than the average. The best decile of the analyst characteristics performs 31.6% better than the average.

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