International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2015, 5(2), 377-389.

Earnings Response Coefficient as a Measure of Market Expectations: Evidence from Tunis Stock Exchange

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ABSTRACT

This research is a feedback to the call from Richardson et al. (2010) for more structure in researchers' forecasting frameworks. The purpose is to study the ability of three technical earnings forecasting methods (smoothing, random walk and cross-section) to reflect Tunisian stock market expectations as measured by the Earnings Response Coefficient. The results of estimating a modified version of Easton and Harris (1991) model that incorporates earnings surprise and its level as return predictors, confirm theoretical predictions on the positive earnings-returns relationship. However, only non-expected earnings are statistically significant. This result indicates a predominance of earnings surprise. Coefficient amplitudes show the subsidiary role of earnings level compared to their surprise in earnings-return regressions. This finding points out the relatively permanent nature of Tunisian firms earnings within Ali and Zarowin (1992)'s context, despite certain exceptions especially with cross-sectional forecasts. Recourse to a quality score based on extreme rankings of examined methods, allowed us to highlight a dominance of smoothing forecasts, followed by those of random walk and finally by the cross-sectional ones. These results corroborate those of Bradshaw et al. (2012) and Gerakos and Gramacy (2013) on the primacy of time series forecasts of earnings and those of Chen and Ho (2014) on the higher explanatory power of earnings changes compared to that of their levels.

Keywords: Earnings Forecasts, Earnings Quality, Earnings Response Coefficients, Fundamental Analysis, Market Expectations
JEL Classifications: G12, M41

1. INTRODUCTION

According to fundamental analysis, the value of an asset can be determined by the present value of the revenues it can earn in the future. In this valuation context, forecasted earnings are often used as a proxy for future revenues; which implicitly suppose that these forecasts are a fair proxy of market expectations regarding the future revenues that can be produced by the valued asset. Several earnings forecasting methods are proposed in the literature. It is usually distinguished between analysts and mechanical forecasts. The latter are in turn subdivided into time series and cross-sectional forecasts. Although they are the mostly used by the evaluators, analysts' forecasts were subject to much criticism due to many evidenced biases characterizing them, such as sur-optimism, selection bias, etc. Considering these criticisms and the absence of analysts' forecasts in the Tunisian context, this study shed lights on the ability of three mechanical earnings forecasting methods to represent Tunisian stock market expectations, as measured by the Earnings Response Coefficient (ERC).

The remainder of the paper is organized as follows: Section 2 reviews related literature and develops research hypothesis. Section 3 presents the research design adopted to test our hypotheses. Section 4 reports our empirical results whereas Section 5 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The ERC captures the return sensitivity to the earnings surprises. These surprises are measured by the unexpected earnings defined as the difference between realized and forecasted earnings. In other words, ERC represents the market reaction, in terms of price change, corresponding to a unit of unexpected earnings. Its appearance dates back to the seminal work of Ball and Brown (1968) and Beaver (1968). It has been used as a proxy for earnings informativeness (Collins and Kothari, 1989; Easton and Zmijewski, 1989; Kormendi and Lipe, 1987). Furthermore, the ERC provides an overview on the quality of the expected earnings, measured by their ability to reflect market expectations. Indeed, Beaver (1968) and Ball and Brown (1968) showed that the information conveyed by earnings is in relation with a variety of market attributes such as return, volume and volatility change surrounding the earnings announcement date. The fact that the variation of these attributes is the result of an adjustment by the investors of their expectations following the information provided by earnings discloser permits to conclude that this information is correlated with that used by investors in their value assessment. Accordingly, the ERC can be used as an indicator of earnings validity as a proxy for market expectations with regard to future security revenues. The multitude of earnings forecasting methods transforms the study of this variable ability to reflect market expectations to a forecasting methods quality study.

Several works have used earnings forecasts statistical properties (bias and accuracy) as criteria for assessing the quality of expected earnings. However, other studies such as Brown (1993); O'Brien (1988), have established that the more accurate or less biased expected earnings do not necessarily constitute a good representation of future earnings market expectations. For this purpose, the ERC may represent a direct method for assessing the degree of concordance between expected earnings and market expectations. According to Brown et al. (1987a), a strong response of the stock price to the unexpected earnings indicates that the underlying expected earnings have an important role in the market expectations' determination regarding future profitability[1].

From an empirical view point, the ERC is studied according to two different approaches: the event studies which depict the reaction of the stock price to the earnings announcement, and the association studies that investigate the relationship between stock price and earnings over a relatively long period (Easton et al., 1992). The advantage of event studies lies in their ability to identify over time the net effect of earnings announcement on the stock price or on its variation (return), which avoids confusion with other effects that may occur during the study period. However, the choice of the optimal observation window of the earnings announcement event[2] is often mentioned as an explanation for the weakness of this method's empirical results[3]. This problem does not arise in association studies as the study period is so long that it may exceed 1 year; even if this leads to an increase in the risk of confusion with other effects.

A synthesis of empirical works dealing with the ERC according to association studies reveals the existence of three types of models:

$$P_t = \alpha_1 + \beta_1 eps_t + \varepsilon_{1t} \tag{1}$$

$$P_t/P_{t-1} = \alpha_2 + \beta_2 eps_t/P_{t-1} + \varepsilon_{2t} \tag{2}$$

$$\Delta P_t/P_{t-1} = \alpha_3 + \beta_3 \Delta eps_t/P_{t-1} + \varepsilon_{3t} \tag{3}$$

Where:
P_t: Stock price at date t;
eps_t: Earnings per share date t;
ΔP_t: Stock Price variation between date t-1 and t;
Δeps_t: Earnings per share variation between date t-1 and t;
ε_{it}: Residual term.

Model (2) permits Basu (1977) to highlight a positive relationship between return and earnings. Easton and Harris (1991) showed that the use of the benefit level combined with its variation between two successive periods, in the same model, is better than the use of the two variables in separate models[4]. Moreover, the results of Ali and Zarowin (1992) show that the improvement made by earnings level introduction in ERC model estimation depends on the nature of these earnings[5]. Indeed, this introduction is even more interesting when the benefits are transitory. But if earnings are purely permanent, their level brings no improvement to the estimation model.

A long stream of academic research has used either analysts or time series earnings forecasts to proxy for the market's earnings expectations. Allee (2011), for example, examines the equity risk premium using time-series earnings forecasts as an alternative to analysts' earnings forecasts to proxy for the market's earnings expectations. This allows him to estimate the equity risk premium for a broad cross-section of firms and to determine whether excluding firms without an analyst following affects the estimated equity risk premium.

Many studies examined whether analysts' forecasts are superior to time-series forecasts. Results of these studies were somewhat controversial. But, this literature culminate with a conclusion in Brown et al. (1987a) that analysts' forecasts are superior to time-series forecasts because of analysts information and timing advantages. Kothari (2001) indicates that the time-series properties of earnings literature are fast becoming extinct because of "the easy availability of a better substitute" which is "available at a low cost in machine-readable for a large fraction of publicly traded firms." Hence, he concludes that "in recent years it is common

1 Brown (1993) and O'Brien (1988) showed that the ERC is the straightest method to verify if expected earnings reflect market expectations.

2 Windows event are usually short; that is few days surrounding earnings announcement date.

3 These studies are characterized by low coefficients of determination exceeding rarely 10%. Several other explanations for this weakness have been advanced varying from the market inefficiency and the sluggishness of the financial information incorporation in the stock price (Kothari 2001) to the earnings forecasting model misspecification, through the earnings imperfection as a fair representation of market expectations. Espahpodi (2001) invoques three problems related to this question: OLS assumptions violation (especially that of the earnings-return relationship linearity: Freeman and Tse (1992), Das and Lev (1994), Beneish and Harvey (1998)), omitted variables and the choice of earnings-return model variables.

4 The model takes the following form: $AR_{it} = b_{0t} + b_{1t}(eps_{it} - eps_{it-1})/p_{it-1} + b_{2t}(eps_{it}/p_{it-1}) + \varepsilon_{it}$. It was derived on the basis of the two following assumptions:
A1) Abnormal returns are a linear function of unexpected earnings as measured by earnings change between two successive periods: $AR_{it} = a_{0t} + a_{1t}(UE_{it}/p_{it-1}) + \varepsilon_{it}$ where $UE_{it} = eps - eps_{it-1}$
A2) Annual earnings follow an IMA (1,1): $eps_{it} = eps_{it-1} + UE_{it} - \delta UE_{it-1}$; δ is the process parameter.

5 Improvement is measured by the regression determination coefficient as well as by the ERC amplitude.

practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts."

On the other side, recent research like Bradshaw et al. (2012); Gerakos and Gramacy (2013) re-examines time-series and analysts' forecasting performance and reports a time-series forecasts dominance compared to analysts' forecasts in predicting quarterly earnings for longer periods. Bradshaw et al. (2012) for example compare analysts' earnings per share forecasts performances to those of random walk time-series ones. Their results indicate that simple random walk earnings per share forecasts are more accurate than analysts'' forecasts over longer horizons, for smaller or younger firms, and when analysts forecast negative or large changes in earnings per share. According to O'Brien (1988), Schipper (1991), Walther (1997), tests of market reactions to unexpected earnings, where both analysts' and time-series earnings forecasts are used as expected earnings, provide mixed results dealing with analysts' forecasts predominance as proxy for the market's earnings expectations.

Other recent works like Hou et al. (2012); Lee et al. (2011) generate earnings forecasts using a cross-sectional model and performed comparison between this forecasting method and analysts' one. Cross-sectional forecasts permit to have larger sample of firms including those not covered by analysts. Hou et al. (2012)'s results document that their cross-sectional earnings forecasts outperform analysts' one. Li and Mohanram (2014) extend Hou et al. (2012) procedure by considering two other cross-sectional earnings forecast models (Residual Income and Earnings Persistence models). They document that the earnings forecasts generated from their models outperform those from Hou et al. (2012) model with respect to forecast accuracy, forecast bias, and ERC.

Harris and Wang (2013) implement the Ashton and Wang (2013)[6] earnings model to generate forecasts of one to 3-year ahead earnings for individual U.S. firms. They compare the performance of the forecasts from the Ashton and Wang (2013) model with those based on the Hou et al. (2012) earnings model and with IBES consensus analysts' earnings forecasts. They show that all three forecasts have similar accuracy, but in contrast with IBES consensus forecasts, which display very significant upward bias, the Ashton and Wang (2013) and Hou et al. (2012) models generate forecasts of future earnings that are unbiased. The Ashton and Wang (2013) and Hou et al. (2012) model-based forecasts also contain significantly more information about future earnings. Of the two model-based forecasts, the Ashton and Wang (2013) model displays the greatest accuracy, lowest bias, and highest informational content with respect to future earnings. Encompassing tests of the three forecast series reveal that the optimal combination of forecasts would give weights to the Ashton and Wang (2013) forecasts, Hou et al. (2012) forecasts and IBES consensus forecasts of about 59.3%, 8.5% and 32.2%, respectively.

Considering that analysts' earnings are the most used forecasts not only in academic research area but also among practitioners, prior research dealing with earnings forecasts' quality are focused mainly on comparisons between analysts forecasts and alternative methods. Specifically, there is few works performing performance's comparisons within mechanical forecasting methods independently from (without reference to) analyst forecasts. In this study we examine the ability of three mechanical earnings forecasting methods to represent Tunisian Stock Market' expectations of earnings. The first two methods belong to the time series approach (smoothing and random walk). Whereas, the third one represents the cross-sectional approach (Rolling Dynamic Panel Data procedure). Despite the major interest granted to cross-sectional approach, notably in recent works (Hou et al. [2012]; Lee et al. [2011]; Li and Mohanram [2014]), we hypothesize that time series earnings forecasts outperform those of cross-sectional ones in terms of market's expectations of future earnings as measured by the ERC. This position is motivated by the fact that regardless of cross-sectional models' severity, it is difficult to obtain reliable individual forecasts on the basis of estimation parameters (forecasting model's coefficients) common to all individuals in the sample. This means that we neglect companies' individual specificities and assume that they have, all, the same characteristics. This might be valid at the industry level, but never at the individual level. Considering that we examine two time series forecasting methods against just one cross-sectional, our main research hypothesis will be more operational if it is announced as follows:

H1: Smoothing earnings forecasts outperform (higher ERC) cross-sectional earnings forecasts in terms of market's expectations of future earnings.

H2: Random walk earnings forecasts outperform (higher ERC) cross-sectional earnings forecasts in terms of market's expectations of future earnings.

3. METHODOLOGY AND RESEARCH DESIGN

To test our research hypotheses, we adopt an association study. This choice is motivated by two purposes: one is general whereas the other is specific to the context of our study. Indeed, the primary motivation comes from the empirical problems related to the choice of the optimal event date and the observation window[7]. The second motivation is due to the non-availability of earnings announcement precise dates for Tunisian firms[8]. Furthermore, the publication of the interim financial statements further complicates the choice of the optimal event window.

6 Ashton and Wang (2013) have developed a model of earnings based on theoretical foundations. The AW model relies on three basic assumptions: (i) capital markets are free of arbitrage opportunities, (ii) the clean surplus accounting identity holds, and (iii) dividends fully displace current prices. Using these assumptions, Ashton and Wang (2013) show that one-period-ahead earnings can be written as a function of five variables: current earnings, current and lagged book values of equity, and current and lagged market prices of equity.

7 Several event dates have been considered varying from the year-end-closing works' achievement date up to the financial statements discloser date, through the date of the Ordinary General Meeting (OGM) relating to financial statement approval. It is the same for the event window length ranging from few days to some weeks.

8 Article 21, of the Tunisian Accounting Law 96-112 , December 30, 1996.

3.1. The Model

We start from the Easton and Harris (1991)'s model, while generalizing it to cover forecasting horizons beyond 1 year[9]. Specifically, we consider the surprises of 1-3 years ahead forecasted earnings. Abnormal return (AR_{it}) is intended with respect to the market return. That is, the difference between the stock return of interest and the Tunisian stock-market index return, during the same period. In line with Easton and Harris (1991), we also run the same model with the return (R_{it}) as dependent variable. Having used this same model, Ali and Zarowin (1992) indicated that their results remain unaffected if abnormal return is replaced by return level. Thus, the ERC are estimated for the three forecasting horizons (t + 1, t + 2, and t + 3), by regressing 1-3 years ahead realized abnormal returns, on the corresponding unexpected earnings considered on the same horizon, combined with their level. Both explicative variables are deflated by the beginning of period stock price. Hence, the panel regression model takes the following form:

$$AR_{it+\tau} = \propto_{0it} + \propto_{1it} (UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2it} (eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it} \quad (4)$$

$$R_{it+\tau} = \propto_{0it} + \propto_{1it} (UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2it} (eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it}$$

$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$ i's abnormal stock return during the period $t+\tau$;

$R_{it+\tau} = \dfrac{(p_{it+\tau} - p_{it+\tau-1}) + d_{it+\tau}}{p_{it+\tau-1}}$: i's stock return during the period $t+\tau$;

$MR_{t+\tau} = \dfrac{(M_{t+\tau} - M_{t+\tau-1})}{M_{t+\tau-1}}$: Stock market return during the period $t+\tau$ (M: the stock market Index);

$eps_{it+\tau}$: Stock i's earnings per share during period $t+\tau$;

$p_{it+\tau-1}$: Beginning-of-period $t+\tau$ share price;

$UE_{it+\tau} = eps_{it+\tau} - E_t(eps_{it+\tau})$: Un-expected earnings during period $t+\tau$; $E_t(.)$ is the expectation operator.

Thus, our model is a generalization of that of Easton and Harris (1991), in the sense that unexpected earnings (earnings surprise) are not limited to the earnings change between two successive periods[10]. From now on, this variable would indicate the difference between realized and forecasted earnings, whatever adopted prediction method and forecast horizon. We consider a maximum of 3 years prediction horizon. This is the optimal forecasting horizon with regard to the availability of inputs needed for the forecasting process, on one hand; and the lack of accuracy for longer forecasting horizons, on the other hand. The ERC we consider is the sum of coefficients of the earnings level and its surprise: $\propto_{1t} + \propto_{2t}$.

9 Easton and Harris (1991) consider a one year ahead forecasting horizon within a random walk process.

10 This situation corresponds to the special case where earnings are represented by a random walk process.

3.2. Variables Measurement

Three variables are needed to estimate model (4): the level of earnings per share ($eps_{it+\tau}$), unexpected earnings (earnings surprise, $UE_{it+\tau}$) and the return ($R_{it+\tau}$) or the abnormal return ($AR_{it+\tau}$), according to the case. Return is that of the earnings announcement year according to their forecasting horizon. Whereas firms in our sample close their accounting cycles at the end of December and usually disclose their financial statements no later than 3 months following the closing date, the abnormal return period extends from the beginning of April of the earnings announcement year until the end of March of the following year. This is to have a stock price that reflects the maximum earnings' information content conveyed by the most recent disclosure. It is in fact, a cumulative annual return. Abnormal return is obtained by removing market return from the so calculated return. Earning is net income before extraordinary items. Unexpected earnings are determined by the difference between realized and forecasted earnings. The beginning-of-period stock price being the first working day's opening price of April of the earnings announcement year, while the end-of-period stock price is the last working day's closing price of March of the following year.

3.3. Data

Our sample is composed of 32 Tunisian companies listed at Tunisian Stock Exchange. The period of study covers 15 years (1997-2011) for the 1 year ahead forecasting horizon, 14 years (1997-2010) for the 2 years ahead forecasting horizon and 13 years (1997-2009) for the 3 years ahead forecasting horizon. This is the case for smoothing and random walk forecasted earnings. Indeed, the calculation of bias requires 1-3 years ahead current realized earnings (the whole study period covers 16 years spanning from 1997 to 2012). However, for the cross-sectional forecasted earnings, the study period covers only 11 years (2001-2011) for 1 year ahead forecasting horizon, 10 years (2001-2010) for the 2 years ahead forecasting horizon and 9 years (2001-2009) for the 3 years ahead forecasting horizon. This study period decrease is due to the requirement of a minimum of 4 years historical panel data for the cross-sectional forecasting model estimation. All of the predictions being out of the sample, we conduct a first whole period comparison between the first two methods' ERC (smoothing and random walk). The introduction of the cross-sectional method restricts the comparison to a shorter period: the comparison period.

3.4. Individual and Time Effect Specification

Expression (4) is estimated on a panel data[11]. In this type of regression, it is essential before any estimation, to specify the individual effect in the model: an effect that remains constant over time, but which varies from one individual to another. Sometimes, it is also necessary to introduce a time effect in the model to reflect the temporal variations due for example to economic cycle's changes; an effect that does not vary across individuals[12]. If they

11 Ali and Zarowin (1992) estimate a similar cross-sectional model with as earning surprise its variation between two successive periods. The authors have made their interpretations on the basis of time series average values through the years of study, considering the significance of averaged values according to Fama and Mac Beth (1973) methodology.

12 A model with both, individual and time, effects takes the form: $y_{it} = \alpha + \beta X_{it} + u_i + \delta_t + \varepsilon_{it}$

are significant, individual or time effects are either fixed or random. A specification test must then be performed. The most used one is that of Hausman (1978).

The Hausman test is a specification test for determining whether the two estimates (fixed and random) coefficients are statistically different. The idea behind this test is that, under the null hypothesis of independency between errors terms and explanatory variables, the two estimators are unbiased; that is the estimated coefficients should differ little. Statistic (H) proposed by Hausman (1978) follows a (k-1) degrees of freedom Chi-squared (χ^2) distribution; k being the number of coefficients to estimate. If we cannot reject the null (i.e. if the "p-value" is greater than the convenient confidence level) random effects are more appropriate if there is no correlation between the error terms and the explanatory variables. However, the specification of fixed or random effect assumes the existence of a significant individual effect and hence the need for a preliminary test. Unless the individual effect is significant, no individual specification in the model is required.

3.5. Size Effect Adjustment due to Stock Split

For cross-sectional data, size differences arise when large (small) firm's variables take too high (low) values. If the magnitude of these differences is not related to the research question, they lead to biased estimators. The bias comes from heteroskedasticity related problems. Lo and Lys (2000) have shown that size differences are so significant that they lead to opposite signs coefficients of residual income valuation models. Barth and Kallapur (1996) have shown that these differences are always problematic even if the variables are deflated or expressed in per share data. Thus, the best solution to avoid size effect is the use of homogeneous firm size sample. Otherwise, according to Christie (1987), to resolve the possible problem of heteroskedasticity associated with size differences, all accounting variables shall be considered in per share and deflated by the beginning-of-period price.

Dealing with time series, heteroskedasticity may be the result of an abnormal variability through time between the different values of the considered variable. This is the case in particular with stock splits leading to a significant increase in the number of shares outstanding[13]. This considerable change results in an abnormal variation in the time series per share values, such as income, equity book value, or dividend. In this study, the profit used in estimating model (4) is earnings per share. Using per share data in the presence of stock split imposes data adjustment to correct the resulting heteroskedasticity. In our case, the adjustment consists of dividing the total earnings before extraordinary items by the number of shares outstanding as adjusted for stock split operations. In other words, adjustment to stock split consists of a retroactive taking into account of any stock nominal value division coming up during the study period. Thus, the number of share outstanding of a company having realized a stock split in a given year is treated as if this operation has occurred since its creation. Such adjustment allows mastering the resulting problem of heteroskedasticity "stock split" operations.

13 Stock split consists of dividing the stock nominal value; either in the context of a capital reduction by nominal value decrease, or for liquidity related reasons.

3.6. Preliminary and Post Estimation Tests

As ERC estimation model is estimated on panel data, some prior tests are required to decide on the estimation method and to verify regression regularity conditions. Two preliminary tests are conducted. The first deals with the presence of individual effect, while the second relates to the detection of a potential heteroskedasticity problem characterizing the model variables. To quantify the severity of multicollinearity, we perform a post estimation test: the Variance Inflation Factor (VIF).

3.6.1. Individual effect relevance

The first step consists of checking if our data really contain significant individual effects. If they exist, these effects are represented in the regression model by an intercept specific to each individual, u_i. Therefore, we seek to test the null hypothesis H_0: $u_i = 0$ in the regression model $y_{it} = \gamma + X_{it}\beta + u_i + e_{it}, e_{it} \sim iid$. The null hypothesis indicates that the model contains only one intercept common to all individuals. That is, no individual effect is significant. The result is a Fisher statistic (F) with (n-1, nt-n-k-1) degrees of freedom. If the null hypothesis is rejected, then the model must include individual effects.

3.6.2. Heteroskedasticity

Breusch-Pagan test is designed to test the existence of a possible heteroskedasticity problem characterizing the model variables. It allows detecting linear forms of heteroskedasticity[14]. Hence the null hypothesis (H_0) indicates that the variance is constant. Its acceptance indicates the absence of heteroskedasticity. The Breusch-Pagan statistic is distributed as a (k-1) degrees of freedom Chi-squared law, k being the number of explanatory variables. Rejecting hypothesis H_0 at the convenient confidence level, provides information on the existence of a significant heteroskedasticity that should be corrected via the White (1980) procedure[15]. In fact, this correction consists of adjusting standard deviations and therefore the Student statistic, while keeping unchanged the main regression coefficients.

3.6.3. Multicolinearity

If two or more predictor variables in a multiple regression model are highly correlated, coefficient estimates may change erratically in response to small changes in the model or the data. The square root of the VIF indicates how much larger the standard error is, compared with what it would be if that variable were uncorrelated with the other independent variables in the equation. Various recommendations for acceptable levels of VIF have been published

14 While the Breusch-Pagan test can detect linear forms of heteroskedasticity, the White test allows taking into account non-linearities using all explanatory variables' squares and cross products. In fact, it is the same procedure by introducing just all xj, xj^2, and $xj\,xi$, and testing that associated parameters are jointly significant (F-test or LM-test). White (1980)'s works was used to determine a variance estimate of within-estimator in the presence of heteroskedasticity and autocorrelation.

15 Generally, the form of heteroskedasticity is unknown and the variance/covariance matrix is therefore not accessible. White matrix correction provides a consistent estimate of parameter estimates covariance matrix. This estimator can be used to implement usual post-estimation tests. Some studies suggest adjusting White matrix by report n/(n – k – 1). When $n \rightarrow \infty$ the two approaches are equivalent while the two-step approach is only asymptotically valid.

in the literature. The common used maximum VIF level is a value of 10. However, a recommended maximum VIF value of 5 and even 4 has been recommended.

4. EMPIRICAL RESULTS

Three earnings forecasting methods are examined in this study. We estimate the ERC for each of them. A higher ERC suggests that the market reacts more strongly to the model's forecasted earnings meaning that these forecasts reflect better market expectations. Hence, the best method would be the one having the highest ERC. We adopt panel data regressions to estimate the ERC. The use of panel data is driven by the small size of our sample as well as by the shortness of the study period. Indeed this estimation procedure increases the number of observations which allows improving the estimator precision, reducing the risk of multi-colinearity, and especially expanding the investigation field. After presenting the descriptive statistics of the three types of earnings forecasts, we expose the results of preliminary tests. Finally, we conduct a comparative study on the ability of the three forecasting methods to represent market expectations as measured by ERC.

4.1. Descriptive Analysis of Expected Earnings Time Series

Table 1 displays descriptive statistics of smoothing (panel A), random walk (panel B) and cross-sectional (panel C) earnings forecasts, as calculated over 1-3 years prediction horizons. Smoothing and random walk forecasts cover the period 1997-2011 for the 1 year ahead forecasting horizon (t + 1), 1997-2010 for the 2 years ahead horizon (t + 2), and 1997-2009 for the 3 years ahead horizon (t + 3). However, the requirement of a minimum of 5 years historical data for the rolling panel reduces the cross-sectional forecasting study period. Indeed, 1 year ahead forecasts according to this method cover only the period 2001-2011. Those of 2 years ahead span the period 2001-2010, while those of 3 years ahead are calculated through the period 2001-2009.

Table 1 shows that on average, forecasts of the three methods have the same magnitude. For the three types of forecasts, average forecasted earnings increase with the forecasting horizon length. This result indicates that the business grows from 1 year to another. But on the other side, forecasts' volatility increases with forecasting horizon length. This could be explained by the high level of uncertainty characterizing long term forecasts. Comparison of the standard deviations indicates that cross-sectional earnings forecasts are the most volatile.

4.2. Preliminary Tests

We present the results of preliminary tests for heteroskedasticity and those relating to the presence of individual effects. These tests determine the final shape of the econometric model that will be used for ERC estimation and the appropriate adjustments of estimated coefficients significance indicators. Although the individual effect test is used to gain knowledge of the appropriateness of such effect introduction in the model, heteroskedasticity's test helps to refine the model coefficients significance via the standard deviations adjustment.

4.2.1. Individual effect test

The test results regarding the presence of individual effects on the ERC sample estimation are displayed in Table 2. Panels A, B and C relate, respectively, to smoothing, random walk and cross-sectional earnings forecasts. The test is conducted with respect to return and abnormal return as dependent variable.

Fisher statistics values and related probabilities contained in Table 2 indicate the non-significance, at the conventional level of 5%, of the individual effect, for all forecasting horizons. The result remains unchanged when return is replaced by abnormal return as dependent variable. Hence, the ERC on both the total and the comparison period will be estimated according to a model with one intercept commune to all firms in the sample ($\propto_{0t}$).

4.2.2. Heteroskedasticity test

The Breusch-Pagan test results concerning smoothing (panel A), random walk (panel B), and cross-sectional (panel C) ERC sample estimation are contained in Table 3. The test is performed by reference to return and abnormal return as dependent variable.

The values of Chi-squared statistics and the related probabilities contained in Table 3 indicate the rejection of the null hypothesis of the variance constancy. This result indicates the existence of a significant heteroskedasticity on three forecast horizons, both for the return and the abnormal return as dependent variable. This heteroskedasticity will be corrected via the White (1980) approach. Thus, standard deviations we use for the Student's *t* calculation are corrected via the White matrix.

Table 1: Earnings forecasts descriptive statistics

Forecasting horizon	Nber Obs.	Mean	Median	Stan. Dev.	Minimum	Maximum
Panel A: Smoothing earnings forecasts						
t+1	480	1.537239	0.8916987	2.832142	–13.27383	17.38176
t+2	448	1.573962	0.8811117	3.325707	–20.58037	20.32631
t+3	416	1.642995	0.9927681	3.79235	–27.88691	19.11997
Panel B: Random walk earnings forecasts						
t+1	477	1.648554	0.887	2.874854	–16.85613	14.61965
t+2	445	1.672239	0.887	2.888159	–16.85613	14.61965
t+3	413	1.638087	0.8371733	2.9049	–16.85613	14.61965
Panel C: Cross-sectional earnings forecasts						
t+1	352	1.368651	0.8305707	3.273317	–15.70537	13.85265
t+2	320	1.533232	0.7601421	3.65942	–6.216972	35.02779
t+3	288	1.737885	0.6506438	4.300348	–10.66526	28.58376

In millions of dinars. ERC: Earnings response coefficient

Table 2: Individual effect test H_0: ui=0

Period	Return	ERC t+1	ERC t+2	ERC t+3
Panel A: Smoothing earnings forecasts				
Total	Abnormal	F (31, 436)=0.71 Prob>F=0.8788	F (31, 410)=0.78 Prob>F=0.8026	F (31, 382)=1.01 Prob>F=0.4587
	Level	F (31, 436)=0.55 Prob>F=0.9784	F (31, 410)=0.60 Prob>F=0.9578	F (31, 382)=0.72 Prob>F=0.8698
Comparison	Abnormal	F (31, 318)=0.90 Prob>F=0.6190	F (31, 286)=0.94 Prob>F=0.5547	F (31, 254)=1.49 Prob>F=0.0533
	Level	F (31, 318)=0.67 Prob>F=0.9079	F (31, 286)=0.75 Prob>F=0.8311	F (31, 254)=1.08 Prob>F=0.3535
Panel B: Random walk earnings forecasts				
Total	Abnormal	F (31, 436)=0.88 Prob>F=0.6495	F (31, 410)=0.70 Prob>F=0.8910	F (31, 382)=0.88 Prob>F=0.6491
	Level	F (31, 436)=0.70 Prob>F=0.8864	F (31, 410)=0.5 Prob>F=0.9899	F (31, 382)=0.62 Prob>F=0.9491
Comparison	Abnormal	F (31, 318)=1.08 Prob>F=0.3603	F (31, 286)=0.89 Prob>F=0.6366	F (31, 254)=1.26 Prob>F=0.1680
	Level	F (31, 318)=0.83 Prob>F=0.7245	F (31, 286)=0.68 Prob>F=0.9029	F (31, 254)=0.94 Prob>F=0.5635
Panel C: Cross-sectional earnings forecasts				
Comparison	Abnormal	F (31, 318)=1.18 Prob>F = 0.2406	F (31, 286)=1.28 Prob>F = 0.1540	F (31, 254)=1.44 Prob>F = 0.0677
	Level	F (31, 318)=0.95 Prob>F = 0.5507	F (31, 286)=0.97 Prob>F = 0.5160	F (31, 254)=1.08 Prob>F = 0.3661

ERC: Earnings response coefficient

Table 3: Heteroskedasticity test H_0: Constant variance

Period	Return	ERC t+1	ERC t+2	ERC t+3
Panel A: Smoothing earnings forecasts				
Total	Abnormal	Chi-2 (1)=162.68 Prob>Chi-2=0.000	Chi-2 (1)=60.13 Prob>Chi-2=0.000	Chi-1 (1)=65.92 Prob>Chi-2=0.000
	Level	Chi-2 (1)=100.09 Prob>Chi-2=0.000	Chi-deux (1)=31.09 Prob>Chi-2=0.000	Chi-2 (1)=24.59 Prob>Chi-2=0.000
Comparison	Abnormal	Chi-2 (1)=148.61 Prob>Chi-2=0.000	Chi-2 (1)=64.16 Prob>Chi-2=0.000	Chi-2 (1)=40.38 Prob>Chi-2=0.000
	Level	Chi-2 (1)=80.66 Prob>Chi-2=0.000	Chi-2 (1)=32.82 Prob>Chi-2=0.000	Chi-2 (1)=14.98 Prob>Chi-2=0.0001
Panel B: Random walk earnings forecasts				
Total	Abnormal	Chi-2 (1)=3.89 Prob>Chi-2=0.0486	Chi-2 (1)=32.93 Prob>Chi-2=0.0000	Chi-2 (1)=86.81 Prob>Chi-2=0.0000
	Level	Chi-2 (1)=3.36 Prob>Chi-2=0.0668	Chi-2 (1)=16.90 Prob>Chi-2=0.0000	Chi-2 (1)=46.66 Prob>Chi-2=0.0000
Comparison	Abnormal	Chi-2 (1)=8.02 Prob>Chi-2=0.0046	Chi-2 (1)=55.86 Prob>Chi-2=0.0000	Chi-2 (1)=35.01 Prob>Chi-2=0.0000
	Level	Chi-2 (1)=4.01 Prob>Chi-2=0.0453	Chi-2 (1)=29.65 Prob>Chi-2=0.0000	Chi-2 (1)=16.77 Prob>Chi-2=0.00
Panel C: Cross-sectional earnings forecasts				
Comparison	Abnormal	Chi-2 (1)=1.17 Prob>Chi-2=0.2800	Chi-2 (1)=103.81 Prob>Chi-2=0.0000	Chi-2 (1)=2.14 Prob>Chi-2=0.1440
	Level	Chi-2 (1)=0.23 Prob>Chi-2=0.6319	Chi-2 (1)=60.62 Prob>Chi-2=0.0000	Chi-2 (1)=2.30 Prob>Chi-2=0.1295

ERC: Earnings response coefficient

4.3. ERC

After presenting the ERC estimates for each of the three forecasting methods, we conduct a comparative study to determine the one that best reflects market expectations concerning future revenues which may be generated by the valuated asset.

4.3.1. Smoothing earnings forecasts

Table 4 displays ERC (level and surprise) for return and abnormal return as dependent variable. Panels A and B deal with total period although panels C and D relate to comparison period. Earnings forecasts are those of smoothing.

$$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$$

Though apparently weak, the adjusted R^2 are conform to common standards specific to this field of research where this indicator rarely exceeds 10%. Easton and Harris (1991) report a regression coefficient of 7.5%, Easton et al. (1992) report an average coefficient of 6%. The coefficient of Easton et al. (2000) is about 9%, although that's of Hayn (1995) is about 9.3%, Li and Mohanram (2014)'s coefficients vary between 1.6% and 5.3%. Fisher statistics values and related probabilities indicate that, despite this weakness of determination coefficient, the estimation model remains globally significant, both for the total period as well as for the comparison one. Moreover, the results remain qualitatively unchanged when abnormal return is replaced by return as dependent variable in the ERC estimation model.

In accordance with the theoretical predictions on the positive relationship between earnings and returns as evidenced by Basu (1977); Beaver, et al. (1979); and by Beaver, et al. (1980), all the coefficients contained in Table 4 are positive. This result is an empirical support to the "prices lead earnings' relation" indicating that information in realized earnings actually leads prices (Ball and Brown [1968], Beaver, et al. [1980], Beaver, et al. [1987], Collins, et al. [1987], Basu [1977], and Ryan and Zarowin [2003]), even if the estimation procedure is reversed[16]. However, only non-expected earnings (earnings surprise) are statistically significant, for the total period as well as for the comparison one. This result is in contradiction with Easton and Harris (1991) who find that earnings level is better than earnings change.

In addition to the coefficients' significance difference, the amplitude of these coefficients over the two study periods also confirms the complementary role of the earnings level compared to its surprise as measured by non-expected value. This result reveals the relatively permanent nature of our earnings. Indeed,

16 In "prices lead earnings' relation" realized earnings are regressed on returns.

Table 4: Smoothing earnings response coefficients

Abnormal return: $AR_{it+\tau} = \propto_{0t} + \propto_{1t} (UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2t} (eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it}$
Return: $R_{it+\tau} = \propto_{0t} + \propto_{1t} (UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2t} (eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it}$

	ERC t+1		ERC t+2		ERC t+3	
	UE	Eps	UE	Eps	UE	Eps
Panel A: Abnormal return (total period)						
Coefficient	0.4583561***	0.0057317	0.2502984***	0.0097214	0.4016184***	0.0065944
T-stat (Prob)	6.11 (0.000)	0.93 (0.354)	4.27 (0.000)	1.50 (0.135)	7.31 (0.000)	1.13 (0.258)
Adjusted R²	9%		5.4%		13.3%	
Global siginificant: F-stat	F (2, 468)=23.81		F (2, 441)=13.56		F (2, 413)=32.80	
	Prob>F=0.0000		Prob>F=0.0000		Prob>F=0.0000	
VIF	1.13		1.11		1.10	
Panel B: Return (total period)						
Coefficient	0.5540887***	0.0051505	0.2837095**	0.0108593	0.4257519***	0.007932
T-stat (Prob)	3.11 (0.002)	0.68 (0.500)	2.53 (0.012)	1.54 (0.125)	4.18 (0.000)	1.14 (0.255)
Adjusted R²	9.75%		5.3%%		11.1%	
Global siginificant: F-stat	F (2, 468)=9.51		F (2, 441)=7.68		F (2, 413)=17.80	
	Prob>F=0.0001		Prob>F=0.0005		Prob>F=0.0000	
VIF	1.13		1.11		1.10	
Panel C: Abnormal return (comparison period)						
Coefficient	0.4413315***	0.003231	0.250511***	0.006896	0.3712273***	0.007567
T-stat (Prob)	5.92 (0.000)	0.48 (0.633)	4.24 (0.000)	0.95 (0.344)	6.07 (0.000)	1.07 (0.286)
Adjusted R²	10.3%		6.5%		13.3%	
Global siginificant: F-stat	F (2, 349)=21.17		F (2, 317)=12.04		F (2, 285)=22.98	
	Prob>F=0.0000		Prob>F=0.0000		Prob>F=0.0000	
VIF	1.14		1.12		1.10	
Panel D: Return (comparison period)						
Coefficient	0.5266431***	0.0034671	0.2627988***	0.0083369	0.3726104***	0.0102553
T-stat (Prob)	6.15 (0.000)	0.45 (0.656)	3.96 (0.000)	1.02 (0.308)	5.29 (0.000)	1.26 (0.209)
Adjusted R²	11%		6%		11%	
Global siginificant: F-stat	F (2, 349)=22.69		F (2, 317)=10.85		F (2, 285)=18.45	
	Prob>F=0.0000		Prob>F=0.0000		Prob>F=0.0000	
VIF	1.14		1.12		1.10	

$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$, is the abnormal return's stock i during the period $t+\tau$; $R_{it+\tau} = \frac{(p_{it+\tau} - p_{it+\tau-1}) + d_{it+\tau}}{p_{it+\tau-1}}$, is the return's stock i during the period $t+\tau$; $MR_{t+\tau} = \frac{(M_{t+\tau} - M_{t+\tau-1})}{M_{t+\tau-1}}$, corresponds to the stock market return during the period $t+\tau$ (M: the stock market Index); $eps_{it+\tau}$ represent earnings per share of stock i during the period $t+\tau$; is the Beginning-of-period $t+\tau$ stock i price; and $UE_{it+\tau} = eps_{it+\tau} - E_t(eps_{it+\tau})$ defines un-expected earnings during period $t+\tau$; $E_t(.)$ being the expectation operator. ***indicate a significance level of 1%. **indicate a significance level of 5%. *indicate a significance level of 10%. ERC: Earnings response coefficient

Ali and Zarowin (1992) have shown that if earnings are purely permanent, then their level has no improvement when it is added to earnings surprise in the ERC estimation model. Moreover, VIF values indicate no significant multicoliniarity.

4.3.2. Random walk earnings forecasts

Table 5 displays ERCs (level and surprise) with respect to return and abnormal return as dependent variable for the total period as well as that of comparison; Earnings forecasts being those of random walk.

$$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$$

The positive sign characterizing the entire model coefficients for different forecasting horizons and over the two study periods, is consistent with theoretical predictions on the positive earnings-returns relationship. However, most of statistically significant coefficients are those of non-expected earnings. Indeed, only two coefficients of the earnings level are statistically significant. VIF test values indicate no significant multicoliniarity. This result confirms, once again, the primacy of earnings surprise compared to their level, in terms of the ERC study. Meanwhile, it points out the permanent character of our sample earnings within the meaning of Ali and Zarowin (1992).These findings are in accordance with Chen and Ho (2014) who find that the relative explanatory power of earnings changes is higher than that of earnings levels and that the earnings change variable can substitute for the earnings level variable in explaining stock returns[17].

Despite the relative weakness of adjusted R_2, the model remains globally significant, both for the total and the comparison period, as shown by the values taken by Fisher statistics and related probabilities. The results remain the same when the regression is conducted on the basis of return instead of abnormal return as the dependent variable in the ERC estimation model.

17 Chen and Ho (2014) findings were established on the basis of a US sample firms examined through the period 1998-2011 and compared to a Chinese sample firms.

Table 5: Random walk earnings response coefficients

Abnormal Return: $AR_{it+\tau} = \propto_{0t} + \propto_{1t}(UE_{it+\tau}/p_{it+\tau-1}) + \propto_{2t}(eps_{it+\tau}/p_{it+\tau-1}) + \varepsilon_{it}$ **Return:** $R_{it+\tau} = \propto_{0t} + \propto_{1t}(UE_{it+\tau}/p_{it+\tau-1}) + \propto_{2t}(eps_{it+\tau}/p_{it+\tau-1}) + \varepsilon_{it}$	**ERC t+1**		**ERC t+2**		**ERC t+3**	
	UE	**eps**	**UE**	**eps**	**UE**	**eps**
Panel A: Abnormal return (total period)						
Coefficient	0.2444817**	0.0141951**	0.4068609***	0.0087356	0.3342423***	0.0089631
T-stat (Prob)	2.35 (0.019)	2.26 (0.025)	4.89 (0.000)	1.36 (0.176)	4.92 (0.000)	1.47 (0.143)
Adjusted R²	3%		6.5%		7.5%	
Global significant: F-stat	F (2, 468)=7.60 Prob>F=0.0006		F (2, 441)=16.48 Prob>F=0.0000		F (2, 413)=17.08 Prob>F=0.0000	
VIF	1.10		1.10		1.14	
Panel B: Return (total period)						
Coefficient	0.2851527**	0.0156239**	0.521324***	0.0083087	0.3932832***	0.009231
T-stat (Prob)	2.41 (0.016)	2.19 (0.029)	5.55 (0.000)	1.14 (0.254)	4.95 (0.000)	1.29 (0.197)
Adjusted R²	3%		8%		7.3%	
Global significant: F-stat	F (2, 468)=7.60 Prob>F=0.0006		F (2, 441)=19.91 Prob>F=0.0000		F (2. 413)=17.39 Prob>F=0.0000	
VIF	1.10		1.10		1.14	
Panel C: Abnormal return (comparison period)						
Coefficient	0.2295387**	0.0121523*	0.444403***	0.0048232	0.2683851***	0.011196
T-stat (Prob)	2.19 (0.029)	1.74 (0.083)	5.23 (0.000)	0.67 (0.502)	3.49 (0.001)	1.49 (0.137)
Adjusted R²	3%		9%		6.1%	
Global significant: F-stat	F (2, 349)=5.75 Prob>F=0.0035		F (2, 317)=16.82 Prob>F=0.0000		F (2, 285)=10.30 Prob>F=0.0000	
VIF	1.12		1.12		1.14	
Panel D: Return (comparison period)						
Coefficient	0.2513267**	0.0145986*	0.5306116***	0.004403	0.3014002***	0.0127988
T-stat (Prob)	2.08 (0.038)	1.81 (0.071)	5.62 (0.000)	0.55 (0.581)	3.45 (0.001)	1.50 (0.134)
Adjusted R²	2.6%		10.1%		6%	
Global significant: F-stat	F (2, 349)=5.61 Prob>F=0.0040		F (2, 317)=18.91 Prob>F=0.0000		F (2, 285)=10.16 Prob>F=0.0001	
VIF	1.12		1.12		1.14	

$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$, is the abnormal return's stock i during the period $t+\tau$; $R_{it+\tau} = \frac{(p_{it+\tau} - p_{it+\tau-1}) + d_{it+\tau}}{p_{it+\tau-1}}$, is the return's stock i during the period t+τ; $MR_{t+\tau} = \frac{(M_{t+\tau} - M_{t+\tau-1})}{M_{t+\tau-1}}$, corresponds to the stock market return during the period $t+\tau$ (M: the stock market Index); $eps_{it+\tau}$ represent earnings per share of stock i during the period $t+\tau$, $p_{it+\tau-1}$ is the Beginning-of-period $t+\tau$ stock i price; and $UE_{it+\tau} = eps_{it+\tau} - E_t(eps_{it+\tau})$ defines Un-expected earnings during period $t+\tau$, $E_t(.)$ being the expectation operator. ***indicate a significance level of 1%. **indicate a significance level of 5%. *indicate a significance level of 10%. ERC: Earnings response coefficient

Comparison of adjusted determination coefficients displayed in Tables 4 and 5 shows that the smoothing forecasted earnings explain return better (higher adjusted R^2) than random walk ones. Thus, smoothing forecasted earnings seem to reflect Tunisian market expectations better than do random walk ones. This result puts into question the claims of Gerakos and Gramacy (2013) according to which Random Walk and AR (1) are hard to beat.

4.3.3. Cross-sectional earnings forecasts

For cross-sectional earnings forecasts, the ERC can be determined only for the comparison period. The results of regressing abnormal returns and returns on earnings surprises and level of earnings are summarized in Table 6.

$$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$$

On the 2 and 3 years ahead forecasting horizons, only non-expected earnings are statistically significant. However, on the nearest horizon of 1 year ahead, it is rather the level of earnings which becomes statically significant, at the conventional confidence level of 5%. This result indicates that on the 1 year ahead forecasting horizon, Tunisian firms' earnings seem transitory, while they become permanent when the forecasting horizon is extended to 2 and 3 years ahead. This is for cross-sectional earnings forecasts. The coefficients of determination are admittedly weak. But the model remains globally significant on different forecasting horizons for the ERC determination, as shown by the values taken by Fisher statistics and related probabilities. These results remain valid when the abnormal return is replaced by the return as the dependent variable in the ERC estimation model. The values taken by the VIF test are below the thresholds of tolerance indicating no significant multicoliniarity.

Comparison of adjusted determination coefficients displayed in Tables 4-6 shows that cross-sectional forecasted earnings admit the worst explanatory power of return. This result is in accordance with the conclusions of Gerakos and Gramacy (2013) and those of Li and Mohanram (2014) indicating that the Hou et al. (2012) model[18] underperforms a naïve random walk model.

4.3.4. An aggregate ERC based-comparative study

ERCs are obtained according to a model that incorporates earnings surprise and its level as return predictors. Considering that in this case, the response coefficient is determined by the sum of the earnings surprise coefficient and that of its level ($\propto_{1t} + \propto_{2t}$), the comparison between different forecasting methods should be based on this aggregate coefficient ($\propto_t$) as indicated in Table 7.

According to theoretical predictions, ERC should decrease as the forecasting horizon increases. That is the longer the forecasting horizon, the weaker the relationship between earnings and returns. This result comes from the inverse relationship between forecasts reliability and their horizon length. However, a horizontal reading of Table 7 shows a non-regular evolution over different forecasting horizons, for smoothing and random walk earnings forecasts. Indeed, on the total period, the evolution of the ERC in respect of the forecasting horizon length takes a U shape (decreasing then increasing) for smoothing earnings forecasts. Whereas it takes a

18 Hou et al. (2012) model is a cross-sectional earnings forecasting model.

Table 6: Cross-sectional earnings response coefficients

Abnormal Return: $AR_{it+\tau} = \propto_{0t} + \propto_{1t}(UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2t}(eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it}$

Return: $R_{it+\tau} = \propto_{0t} + \propto_{1t}(UE_{it+\tau} / p_{it+\tau-1}) + \propto_{2t}(eps_{it+\tau} / p_{it+\tau-1}) + \varepsilon_{it}$

	ERC t+1		ERC t+2		ERC t+3	
	UE	eps	UE	eps	UE	eps
Panel A: Abnormal return (comparison period)						
Coefficient	0.0987878	0.0155423**	0.3498976***	0.0086819	0.3832499***	0.0102792
T-stat (Prob)	0.91 (0.362)	2.27 (0.024)	4.68 (0.000)	1.23 (0.220)	3.30 (0.001)	1.34 (0.182)
Adjusted R²	1.5%		7.5%		5.7%	
Global significant: F-stat	F (2, 349)=3.72		F (2, 317)=14		F (2, 285)=9.64	
	Prob>F=0.0251		Prob>F=0.0000		Prob>F=0.0001	
VIF	1.06		1.07		1.19	
Panel B: Return (comparison period)						
Coefficient	–0.002258	0.0200398**	0.2424325***	0.0131601	0.3254583**	0.0145429
T-stat (Prob)	–0.02 (0.984)	2.54 (0.012)	2.83 (0.005)	1.63 (0.104)	2.42 (0.015)	1.65 (0.099)
Adjusted R²	1.4%		3.6%		4.1%	
Global significant: F-stat	F (2, 349)=3.40		F (2, 317)=6.94		F (2, 285)=7.12	
	Prob>F=0.0345		Prob>F=0.0011		Prob>F=0.0010	
VIF	1.06		1.07		1.19	

$AR_{it+\tau} = R_{it+\tau} - MR_{t+\tau}$, is the abnormal return's stock i during the period $t+\tau$; $R_{it+\tau} = \frac{(p_{it+\tau} - p_{it+\tau-1}) + d_{it+\tau}}{p_{it+\tau-1}}$, is the return's stock i during the period $t+\tau$; $MR_{t+\tau} = \frac{(M_{t+\tau} - M_{t+\tau-1})}{M_{t+\tau-1}}$, corresponds to the stock market return during the period t+τ (M: the stock market Index); $eps_{it+\tau}$ represent earnings per share of stock i during the period $t+\tau$; $p_{it+\tau-1}$ is the Beginning-of-period t+τ stock i price; and $UE_{it+\tau} = eps_{it+\tau} - E_t(eps_{it+\tau})$ defines Un-expected earnings during period $t+\tau$; $E_t(.)$ being the expectation operator. ***indicate a significance level of 1%. **indicate a significance level of 5%. *indicate a significance level of 10%. ERC: Earnings response coefficient

Table 7: Aggregate earnings response coefficients

Forecasting method	(Aggregate ERC)		
	t+1	t+2	t+3
Panel A: Abnormal return (total period)			
Smoothing	0.4640878	0.2600198	0.4082128
Random walk	0.2586768	0.4155965	0.3432054
Panel B: Return (total period)			
Smoothing	0.5592392	0.2945688	0.4336839
Random walk	0.3007666	0.5296327	0.4025142
Panel C: Abnormal return (comparison period)			
Smoothing	0.4445625	0.257407	0.3787943
Random walk	0.241691	0.4492262	0.2795811
Cross-section	0.1143301	0.3585795	0.3935291
Panel D: Return (comparison period)			
Smoothing	0.5301102	0.2711357	0.3828657
Random walk	0.2659253	0.5350146	0.314199
Cross-section	0.0177818	0.2555926	0.3400012

ERC: Earnings response coefficient

reversed U shape (increasing then decreasing) for random walk earnings forecasts. On the comparison period, the results show the same evolution structure for time series earnings forecasts (smoothing and random walk), with an increasing trend evolution for cross-sectional earnings forecasts. These results remain unbothered, if considered returns are measured either by their level or by their abnormal value.

On the total period (Panels A and B of Table 7) the aggregate ERC (surprise and level) of smoothing forecasts is higher than the random walk forecasts' one. This is for 1 and 3 years ahead horizons. However, this order is reversed for the 2 years ahead horizon. This is valid for both the return and the abnormal return. On the comparison period Panels C and D of Table 7, the aggregate cross-sectional ERCs are the lowest on the 1 year ahead horizon. Beyond this scope, the results are not consistent. Indeed, on the 2 years ahead horizon, smoothing coefficient is the lowest for abnormal return dependent variable. But for return dependent variable, it is the aggregate cross-sectional ERC which is the lowest. On 3 years ahead horizon, it is rather aggregate random walk ERC which is the lowest, whether the dependent variable is return or abnormal return. Thus, assumptions (H1) and (H2) are absolutely validated only for the shortest forecasting horizon (1 year ahead). The lack of concordance over longer forecasting horizons could be explained by the fact that forecasts are losing their reliability with the extension of the forecasting horizon. This result indicates that at long term, earnings lose their ability to reflect market expectations.

Synthetic aggregate ERC values contained in Table 7, do not allow the formulation of clear-cut preferences about different forecasting methods performance. Indeed, each forecasting horizon reveals its proper ranking. To reduce discrepancies, we suggest a forecasting quality-score based on extreme rankings (best or worst) exhibited by the examined methods on each of the forecasting horizons. The quality score is determined by the difference between the number of times in which the concerned method has been the best on the three horizons and the number of times in which it has been the worst. Then, better forecasting method in terms of reflecting market expectations would be the one having the highest score.

Panel A of Table 8, summarizes extreme rankings of the three examined forecasting methods, on every horizon. This content is transformed in encrypted terms to obtain the quality score according to the ERC displayed in panel B of Table 8. According to this criterion, smoothing earnings forecasts are the best with a score of +2, followed by those of the random walk then by the cross-sectional ones. Thus, on the basis of the quality score, it is possible to argue that the assumptions H1 and H2 dealing with the dominance of time series forecasts compared to cross-sectional methods, are valid. Within time series methods, the forecasting quality-score permits to favor smoothing forecasts over those of random walk. This result puts into question the claims of Gerakos and Gramacy (2013) according to which "Random Walk and AR (1) are hard to beat". However, our results should be carefully considered, in the sense that they represent a general trend, without being verified on all forecasting horizons.

5. CONCLUSION

Earnings forecasts are crucial in estimating Implied Costs of Capital (e.g., Lee, et al. [2011], Hou, et al. [2012], Evans, et al. [2012], and Li and Mohanram [2014]), marginal tax rates (e.g., Graham [1996] and Blouin, et al. [2010]), and anomalies studies (e.g., Wu and Zhang [2011]). The purpose of this work was to study the ability of three technical earnings forecasting methods (smoothing, random walk and cross-section) to reflect Tunisian stock market expectations as measured by the ERC. The results of estimating a modified version of Easton and Harris (1991) model confirm theoretical predictions on the positive relationship between earnings and returns as evidenced by Basu (1977); Beaver, et al. (1979); and by Beaver, et al. (1980). However, only the non-expected earnings are statistically significant, on the total period as well as on the comparison one. The latter finding suggests a predominance of this variable with respect to the ERC as an indicator of market expectations. In addition to the significance differences of the model explanatory variables, the coefficient amplitudes on the two periods of study (total and comparison), also show the subsidiary role of earnings level compared to his surprise regarding return explanation. This result points out the relatively permanent nature of Tunisian firms earnings, despite certain exceptions especially with cross-sectional forecasts. At this subject, Ali and Zarowin (1992) have shown that if the benefits are purely permanent, their level does no significant improvement when it is added to their surprise in the ERC model estimation. That's why many studies like Hou et al. (2012), Li and Mohanram (2014), use only earnings surprise as explanatory variable while estimating ERC.

Our findings are in accordance with those of Chen and Ho (2014) who replicate Easton and Harris (1991)'s model on a sample of US firms trough the period 1998-2008 and proceed to a comparative study between the American and the Chinese contexts. Their

Table 8: Earnings forecasts' quality score according to ERC

Panel A: Forecasting methods extreme ranking						
	ERC t+1		ERC t+2		ERC t+3	
Extreme ranking	Best	Worst	Best	Worst	Best	Worst
Return	Smoothing	Cross-section	Random walk	Cross-section	Smoothing	Random walk
Abnormal return	Smoothing	Cross-section	Random walk	Smoothing	Cross-section	Random walk

Panel B: Earnings forecasts' quality-score			
Forecasting method	Quality score		
	Best	Worst	Score
Smoothing	3	1	+2
Random walk	2	2	0
Cross-section	1	3	–2

ERC: Earnings response coefficient

results indicate that the relative explanatory power of earnings changes is higher than that of earnings levels and that the earnings change variable can substitute for the earnings level variable in explaining stock returns.

We estimate ERC according to a model that incorporates earnings surprise and its level as return predictors. Thus the comparison between different forecasting methods was based on an aggregate ERC (surprise and level). On the total period, aggregate smoothing ERC is higher than that of random walk over 1 and 3 years ahead horizons. However, this order is reversed on the 2 years ahead prospect. This is the case for both the return and the abnormal return. Over the comparison period, the aggregate cross-sectional ERC are the lowest on the 1 year ahead horizon. Beyond this scope, results are not consistent. Indeed, on the 2 years ahead horizon, smoothing coefficient is the lowest for abnormal return dependent variable. But for return dependent variable, it is the aggregate cross-sectional ERC which is the lowest. On 3 years ahead horizon, it is rather aggregate random walk ERC which is the lowest, whether the dependent variable is return or abnormal return. The lack of concordance on longer horizons may be due to the reverse relation between forecasts reliability and forecasting horizon length. This indicates that at long term, earnings lose their ability to represent market expectations.

To reduce performance discrepancies on long forecasting horizons we propose a forecasting quality-score based on extreme rankings (best or worst) of different examined methods. This indicator allowed us to conclude that smoothing forecasts are dominant; followed by those of random walk and finally by the cross-sectional ones. Hence the validation of our two research hypotheses on the primacy of time series forecasts compared to cross-sectional ones in terms of market expectation-representation. Within time series methods, the quality score permits to favor smoothing forecasts over those of random walk. These results however, must be carefully considered. Indeed, they represent a general trend, without being verified on all forecasting horizons. It is then worthwhile to use further forecasting quality-indicator to refine these conclusions.

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