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Unexpected Earnings, Stock Returns, and Risk in the Brazilian Capital Market*, **

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ABSTRACT

This article analyzes the role of risk in the earnings response coefficient (ERC) in the Brazilian capital market. Since 'risk' may be measured in various ways and it can vary systematically according to the conditions under analysis, empirical studies have reported conflicting evidence with regard to the role of risk in the ERC. The empirical study is based on annual data from a sample of 212 companies listed on the Brazilian Securities, Commodities, and Futures Exchange (BM&FBOVESPA), within the period from 1995 to 2013. The analysis takes into account longitudinal data and various measurements of unexpected earnings, risk, and several control variables. The results suggest that the earnings-return relationship is negatively affected by total risk and nonlinear effects of unexpected earnings and it is positively affected by earnings persistence. The analysis failed to indicate any significant association between the ERC and systematic risk and it failed to provide evidence that the full adoption of the International Financial Reporting Standards (IFRS), in 2010, affected the way how the market reacts to surprises in the disclosure of accounting earnings. In order to analyze the earnings-return relationship, classifying companies by the total risk ranking showed better results in terms of distinguishing high and low-risk companies. This article contributes to the accounting literature in emerging markets by reporting that controlling the earnings-return relationship through total risk, nonlinear effects, and earnings persistence may optimize financial analysis and the companies' assessment process.

Keywords: emerging markets, earnings response coefficient, accounting earnings, risk.

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1 INTRODUCTION

Several studies have analyzed the earnings-return dynamics according to various methodologies, periods, and economic conditions. The analyses of long-term earnings--return dynamics are often based on the significance and magnitude of the earnings response coefficient (ERC). Specifically, a large number of studies show that the ERC is a good proxy with regard to decision usefulness by assessing market perception of value-relevance of various accounting measurements and recognition criteria (Dechow, Ge, & Schrand, 2010).

Although there is an extensive body of research focused on the return-earnings relation, Basu (2005) and Chambers, Freeman and Koch (2005) argue that empirical evidence on the ERC sensitivity to systematic risk is controversial. While Ariff, Fah and Ni (2013) and Collins and Kothari (1989) report negative coefficients between the ERC and systematic risk, Ball, Kothari and Watts (1993) and Cready, Hurtt and Seida (2000) report a significantly positive relationship. On the other hand, Easton and Zmijewski (1989), Ghosh, Gu and Jain (2005), and Warfield, Wild and Wild (1995) do not find a consistent and significant relation between the ERC and systematic risk.

Based on international conflicting evidence and taking into account the fact that risk is likely to vary on a systematic basis within the settings examined, this article aims to shed light on this issue by analyzing the role played by risk in price responses to earnings in Brazil. This study claims that some specific characteristics of the Brazilian market – such as (i) high concentration of the stock index in a few large firms, (ii) low stock liquidity level for most firms, and (iii) high volatility due to speculative capital movements – make the market model beta a biased proxy for risk in studies addressing earnings-return.

Our approach is also motivated by the findings reported by Amorim, Lima and Murcia (2012, p. 199), who point out that accounting and market betas have a "insignificant or even nonexistent relationship," as well as those by Simon, Zani, Morais and Costa (2014) and Costa Jr., Menezes and Lemgruber (1993), who report market beta anomaly and beta misspecification in the Brazilian market. Specifically for earnings-return purposes, a simple measurement of rank-order idiosyncratic (or unsystematic) risk is more consistent with the assumption of a negative relationship in valuation models. Additionally, the role played by idiosyncratic risk is also puzzling: while Mendonça, Klotzle, Pinto and Montezano (2012, p. 256) report that idiosyncratic risk is an "excellent explanatory factor for returns," Galdi and Securato (2007) do not find evidence of a significant relationship between idiosyncratic risk and portfolio returns for the Brazilian capital market.

This empirical study is based on annual data from a sample having 212 firms listed on the Brazilian Securities, Commodities, and Futures Exchange (BM&FBOVESPA) from 1995 to 2013. The main results suggest that, for studies addressing earnings-return, rank-order total risk is a better proxy for market risk than the market model beta (systematic risk). This evidence has relevant implications for the empirical literature in Brazil, since the use of market model beta as a measurement of risk can yield biased results, especially when accounting data information is considered. Specifically, the results are consistent with Bernard and Thomas (1990), who argue that scaling dependent variables (between zero and one) produce better comparisons of abnormal returns across various variables.

The results also report that the ERC is positively related with earnings persistence and negatively related with the nonlinear effect of unexpected earnings. Although both associations are of paramount importance to the market--based accounting literature in Brazil, only a few studies address differences in cross-sectional earnings persistence and none approach nonlinear effects. Additionally, this paper reports a significant increase in the ERC after the adoption of the International Financial Reporting Standards (IFRS), in 2010, although a causal relationship is yet to be demonstrated. Overall, this paper shows that controlling the earnings-return relationship through (i) rank-order total risk, (ii) nonlinear effects of unexpected earnings, and (iii) earnings persistence may optimize the analysis of nature and magnitude of earnings in financial analysis and the valuation process.

This paper is structured as follows: section 2 introduces the literature and theoretical basis; section 3 introduces the research design and variables; section 4 describes data and draws a preliminary analysis; section 5 shows and discusses the empirical results; and section 6 summarizes findings and presents the final remarks.

2 EARNINGS RESPONSE COEFFICIENT AND RISK

The relationship between earnings and stock returns, usually measured by the ERC, is relevant to devise more powerful valuation models and more effective hiring tests, as well as political cost hypotheses (Kothari, 2001). Typically, studies on the ERC demonstrate that stock prices are a function of all information variables that predict dividends, namely, transitory components, firm's discount rates, economic growth expectations, and risk (systematic risk and firm-specific risk). Studies relating the ERC to economic variables usually consider a standard discounted cash flow valuation model to derive the theoretical ERC (Kothari, 2001).

Considering that (i) dividend expectation is a function of a firm's reported earnings (X) at a period $t - 1$ (Feltham & Ohlson, 1995) and that (ii) there is a coefficient (λ_{it+k}) which relates dividend expectation to reported earnings, Collins and Kothari (1989) show that the unexpected return (UR) associated with unexpected earnings (UX) may be expressed as:

$$UR_{it} = \left[\lambda_{it} \sum_{k=1}^{\infty} \lambda_{it+k} \prod_{\tau=1}^{k} \left\{ \frac{1}{[1+E(R_{it+\tau})]} \right\} \right] UX_{it} / P_{it-1} \text{ , where} \quad (1)$$

$E(R_{it+\tau})$ = expectation rate of return on the security from the end of $t+\tau-1$ ao final de $t+\tau$.

P_{it-1} = the stock price at the beginning of the period.

λ_{it}= the coefficient relating the review on stock prices due to new information in reported earnings.

Specifically, the unexpected earnings variable is defined as $UX_{it} = X_{it} - E(X_{it}|I_{t-1})$, where I_{t-1} represents the set of information available in t-1. Thus, the equation relates unexpected earnings to unexpected returns, and the coefficient is the ERC (the bracketed term).

Consistent with the Capital Asset Pricing Model (CAPM), $E(R_{it+\tau})$ increases according to systematic risk. Consequently, high (systematic) risks must be related to low ERCs, suggesting a negative relation between these parameters. The rationale behind the negative relation is that the riskier is the firm's future expected returns, the lower its value to a risk-averse investor is. This high risk effect will affect stock prices (and stock returns) through the discount rate in the valuation model. Hence, "since investors look to current earnings as an indicator of future firm performance and stock returns, the riskier these future returns are, the lower invertor's reaction to a given amount of unexpected earnings will be" (Scott, 2012, p. 163). Thus, systematic risk has a 'negative denominator' effect on the earnings-return association.

However, Chambers et al. (2005) advert that this negative relation is based on the strong assumption of stable CAPM beta. Specifically, the derivation assumes that systematic risk does not (or should not) change from time t-1 through time t. Thus, differently from the idea introduced above, Chambers et al. (2005) argue (and report evidence) that if current earnings are informative with regard to future dividends, earnings innovations are likely to cause a greater review in expected future dividends for a high-risk firm than for a low-risk firm. Specifically, in the model proposed by the authors, the impact of an announcement of earnings is determined by reviews in investors' prior beliefs about the expected final dividend. This effect of dividend uncertainty creates a theoretical ground for a positive relationship caused by reviews in dividends, which the authors name as a 'positive numerator' effect. This theoretical conflict is also restated by Basu (2005).

Although discount rate is a controversial point in the literature on valuation, another point is consensually accepted: discount rate must reflect the risk involved in the asset to be evaluated. In this regard, one of the main subjects of study in finance is measuring risk and measuring error and it is reasonable to believe that judgments and assumptions concerning risk measurement are the main reasons for the conflicting and controversial empirical evidence shown by previous literature.

Specifically, while Ariff et al. (2013) and Collins and Kothari (1989) report negative coefficients between ERCs and systematic risk, Cready et al. (2001) report a significantly positive relationship. On the other hand, Easton and Zmijewski (1989), Ghosh et al. (2005), and Warfield et al. (1995) do not find a consistent and significant relationship between ERCs and systematic risk. These theoretical and empirical conflicts motivate this paper.

Typically, empirical literature considers, for simplicity purposes, the appropriate discounting rate (and the beta) to be constant over time. Thus, market model is applied to capture cross-sectional variation in expected returns as a function of systematic risk this way:

$$R_{it} = \alpha_i + \beta_i R_{mt} + e_{it} \text{ , where} \quad (2)$$

R_{it}= continuous compounded rate of return on the common stock of security j for period t,

R_{mt}= continuous compounded rate of return on the stock market index for period t,

β_i= slope coefficient (and estimated of systematic risk) for firm j, and

e_{it}= normally distributed disturbance term.

The CAPM and market model methodologies are based on the premises that market players assimilate new information efficiently, in addition to having homogenous expectations. However, these premises are not strongly supported in the Brazilian market (Simon et al., 2014; Costa Jr. et al., 1993). At least three variables significantly affect the stock market as a whole: market concentration, high interest rates, and high market volatility.

First, the Brazilian stock index (Ibovespa) is highly concentrated in a few large firms, which are responsible for most of the market liquidity. Thus, most (small and medium-sized) companies do not have enough stock liquidity. Machado and Medeiros (2012) report that the (il)liquidity of the Brazilian market generates two distinctive problems: a significant liquidity premium and an inability of the CAPM and the three-factor model proposed by Fama and French (1993) to explain stock returns and liquidity effect. A complementary idea of market concentration is related to firm control. The Brazilian stock market has a significant separation of voting and cash flow rights due to dual-class shares, concentrated ownership, and control. An important consequence of this institutional environment is that controlling stockholders concentrate discretionary decisions, thus leading to smaller free-float and lower trading activity (Silva & Subrahmanyam, 2007).

Second, the high levels of Brazilian interest rates, which are among the highest real interest rates in the world, have anomaly yielded a (significant) negative high equity premium (Gonçalves Junior, Rochman, Eid Junior, & Chalela, 2011) and they have been affecting portfolio allocation decisions in the case of investing in low-risk and high-yield interest-bearing assets. Additionally, high interest rates can affect market players' perception of time-orientation (Krusell, Kuruşçu, & Smith, 2002).

Finally, as other emerging markets, the Brazilian market is characterized having a high stock volatility, due to speculative capital movements and risk aversion periods (Aggarwal, Inclan, & Leal, 1999). Specifically, the emerging stock market performance is highly dependent on the structure of global risk factors and macroeconomic aggregate fluctuations (Mensi, Hammoudeh, Reboredo, & Nguyen, 2014).

Also, these three points may make the market model beta a biased proxy for risk in studies on earnings-return. From an accounting viewpoint, these factors can significantly affect the extent to which market players react to news with regard to accounting information. Moreover, Amorim et al. (2012) report a mismatch between accounting and market model beta, which is intriguing in the sense that both should represent a measurement of firm-specific risk and distinguish high and low risk firms. Nevertheless, they show a low forward-looking explanatory power from accounting data to market betas. Although this is consistent with semi-strong market efficiency, this relation was shown only "for a restricted number of companies in the sample" (Amorim et al., 2012, p. 209).

The market environment described above can potentially diminish the perceived relevance of earnings by market agents. Despite the potential low relevance of earnings, the literature on the Brazilian market has demonstrated that stock returns are significantly related to information in earnings. Specifically, there are significant relationships in the short-run (Sarlo Neto, Galdi, & Dalmácio, 2009; Paulo, Sarlo Neto & Santos, 2012) and over the long-run (Galdi & Lopes, 2008; Pimentel & Lima, 2010a, 2010b; Santos, Mol, Anjos, & Santiago, 2013). In this regard, this paper sheds some light on the earnings-return association by assuming that risk, nonlinear effects of unexpected earnings, earnings persistence, and IFRS adoption can have implications on the cross-sectional relevance of the ERC.

3 RESEARCH DESIGN AND VARIABLES

The theory based on valuation models suggests that the ERC is negatively correlated with systematic risk (generating a denominator factor). However, Chambers et al. (2005) suggest a 'numerator factor' based on the fact that reviews in expected payoffs are an increasing function of total risk.

As discussed above, this approach seems to be adequate for the Brazilian market, because the main local general stock market index (Ibovespa) reflects variation only in the most traded stocks on the BM&FBOVESPA, thus it is concentrated in a few companies. Hence, the frequently used systematic risk, measured by Sharpe-Lintner CAPM beta or Sharpe's market model beta, is likely to lead to a measurement error when applied to companies that are not in the stock index – the underdiversification hypothesis discussed by Levy (1978). Therefore, this paper applies empirical tests that consider both a measurement of total risk (including idiosyncratic risk, represented by the total variance of a given firm's stock) and a measurement of systematic risk (measured by Sharpe's market model beta).

3.1 The Basic Empirical Model

The first step in this study was estimating the basic longitudinal regression model (panel data analysis) proposed by Chambers et al. (2005), which relates the ERC and the two measurements of risk:

$$UR_{it} = a + b_1 UX_{it} + b_2 TRK_{it} * UX_{it} + b_3 SRK_{it} * UX_{it} + error_{it} \quad \text{, where} \qquad (3)$$

UR_{it} = unexpected returns for firm i cumulated over year t,

UX_{it} = unexpected earnings for firm i in the year t,

TRK_{it} = standardized ranking of total risk (based on firm-specific monthly returns' variance),

SRK_{it} = standardized ranking of systematic risk (based on market model beta), and

$error_{it}$ = error term independent and identically distributed with $N(0, \sigma^2_e)$.

3.1.1. Measurement of unexpected earnings.

Consistent with the valuation model presented in Eq. 1, measuring unexpected earnings (UX) is the widely accepted and well-documented earnings change scaled by beginning-of-period market value of equity (Collins & Kothari, 1989). Specifically, *UX* is calculated by the nominal variation of earnings per share (*EPS*) in year t (fiscal year) scaled by the price in the beginning of the period, P_{t-1}. Thus, $UX_{it} = (EPS_{it} - EPS_{i,t-1})/P_{i,t-1}$, where the implicit assumption is that earnings follow a random walk process that assumes the current period's annual earnings is the best unbiased expectation of the next period's earnings (Ariff et al., 2013). The random walk process is a time series process where the current value of a variable is explained by (it consists of) the lagged value (past value) plus an error term. In other words, the estimation of earnings in a given year is the last year's earnings plus an error term (Kormendi & Lipe, 1987). Additional measurements of unexpected earnings are described in the next sections.

3.1.2. Measurement of abnormal return.

The measurement of accumulated abnormal return (*UR*) is the ex-post measurement of $E_{t-1}(R_{it})$, which is conditional upon the realized market return for period *t*. Month's return is the natural logarithm of the division between end-of-month and beginning-of-month price [$R_{it} = \ln (P_t / P_{t-1})$], where P_t is the price adjusted to dividends at period *t*. The adjusted return of a particular firm might represent the return derived exclusively from the firm's operations and its specific risks. Thus, the unexpected returns for each specific firm are calculated by the difference between monthly observed return and expected return by regressing firm-specific return on market returns (similar to the market model). Thus, $UR_{it} = R_{it} - (\lambda_{li} + \lambda_2 R_{mt})$, where λ_1 and λ_2 are the coefficients of OLS regression between monthly return (R_{it}) and the market return (R_{mt}) over 48 months (minimum of 24 months is required). Consistent with previous studies, annual returns are cumulated from April of year *t* to March of *t + 1* to capture any return reaction associated with the announcement of earnings for year *t*.

3.1.3. Measurement of idiosyncratic and systematic risks.

The two measurements of risk used in this paper, standardized total risk (*TRK*) and standardized systematic risk (*SRK*) are based on the methodology proposed by Chambers et al. (2005), where *TRK* is the variance of monthly returns over the previous 48 months (a minimum of 24 months of returns is required). Thus, considering that *VRanq* denotes the rank position of total risk (i.e. variance of returns over 48 months) associated with a sample observation in year *t*, and that *N* denotes the number of observations in that year, the standardized rank of total risk is given by $TRK_{it}(VRanq_{it}-1)/(N-1)$. Therefore, in a particular year, *TRK* is equal to zero for the firm with the smallest total risk and it is equal to one for the firm with the highest total risk. If everything else is equal, b_2, in Eq. 3, is the difference between the ERC of observations with the highest and lowest total risks in a particular year (Chambers et al., 2005).

The second measurement of risk is *SRK*, which is measured by Sharpe's market model beta estimated from monthly returns over the previous 48 months (a minimum of 24 months is required). In order to capture cross-sectional variation in the expected annual rates of returns as a function of systematic risk, stock betas were estimated from monthly returns as $R_{it} = \alpha_i + \beta_i R_{mt} + e_{it}$, where R_{it} is the monthly continuous compounded rate of return on the common stock of security *i*, R_{mt} is the monthly continuously compound rate of return on the Ibovespa, representing the market return, α_i is intercept coefficient, β_i is the slope coefficient, and e_{it} is the normally distributed disturbance term.

Considering that *BRanq* denotes the rank of beta (systematic risk) associated with a sample observation in year *t*, and *N* denotes the number of observations in that year, the standardized rank of systematic risk is determined by: $SRK_{it} = (BRanq_{it}-1)/(N-1)$. In a particular year, SRK_{it} is equal to zero for the firm with the smallest total risk and it is equal to one for the firm with the highest total risk. If everything else is equal, b_3, in Eq. 3, is the difference between the ERC of observations with the highest and lowest systematic risk in a particular quarter (Chambers et al., 2005).

3.2 The Extended Empirical Model

Since this paper mainly focuses on cross-sectional determinants of the ERC (mainly on risk), it includes additional controlling variables to the basic model proposed. Specifically those related to risk and to relevant characteristics of the Brazilian environment.

First, this paper uses a control for the nonlinear relationship between unexpected earnings and return. Freeman and Tse (1992) report that extreme values of transitory unexpected earnings are less persistent and they do not affect stock prices in the same magnitude. This is an important variable in the Brazilian market, because within stressed periods, such as those of the 2002 and 2008 international crises, variation in exchange rates causes huge losses (high magnitudes) to firms exposed to international currencies. However, those variations are expected to be transitory, thus they affect the ERC in a lower magnitude. Therefore, in line with Chambers et al. (2005), a control variable of nonlinear effects, *NLEF*, is included, which is defined as: $NLEF_{it} = (|UX|Ranq_{it}-1)/(N-1)$, where $|UE|Ranq_{it}$ is the rank of the absolute value of *UX* of firm *i* at year *t*, and *N* is the number of observations at a given year. *NLEF* is expected to have a negative and significant effect on the ERC in the Brazilian market. Hence, a higher absolute *UX* value decreases the magnitude of the ERC.

Second, empirical literature reported that size is a determinant of earnings quality (Dechow et al., 2010). In this paper, size (*SIZE*) consists in the standardized total assets, where $SIZE_{it} = (TAssets_{it}-1)/(N-1)$; $TAssets_{it}$ is the natural logarithm of total assets of a firm *i* in year *t*; and *N* represents the number of observations in that year. Although size may be correlated with other economic variables, such as risk (negative relation), stock liquidity (negative relation), and information environment (positive relation), a positive effect of size on the ERC is expected.

Third, market reaction to earnings innovation is strongly related to earnings persistence (Kormendi & Lipe, 1987). In order to control cross-sectional effects of earnings persistence (*PER*), this paper regards the standardized rank of firm-specific first-order autoregressive coefficient, AR(1), as a measurement of earnings persistence proxy. Thus, $PER_i = ([AR(1)]-1)/(N-1)$.

Finally, the entire period (1995-2013) includes a significant shift in accounting standards, after the mandatory adoption of full IFRS, in 2010. Thus, a dummy variable, *IFRS*, was included in the empirical model, in order to control the shift in accounting practices by assuming 1 for IFRS years (2010 to 2013) and 0 otherwise. Hence, the extended model is:

$$UR_{it} = a + b_1 UX_{it} + b_2 TRK_{it} * UX_{it} + b_3 SRK_{it} * UX_{it} + b_4 NLEF_{it} * UX_{it} + b_5 SIZE_{it} * UX_{it} + b_6 PER_i * UX_{it} + b_7 IFRS_t * UX_{it} + error_{it} \text{, where} \quad (4)$$

UR_{it} = unexpected returns for firm *i* cumulated over year *t*,

UE_{it} = unexpected earnings for firm *i* in year *t*,

TRK_{it} = standardized rank of total risk (based on firm-specific monthly returns' variance),

SRK_{it} = standardized rank of systematic risk (based on market model beta),

$NLEF_{it}$ = standardized rank of absolute value of earnings innovation, for firm *i* in the year *t*,

$SIZE_{it}$ = standardized rank of total assets, for firm *i* in the year *t*,

PER_i = earnings persistence firm *i* (based on AR(1) parameter of annual earnings),

$IFRS_t$ = dummy variable assuming 1 for IFRS years (2010 to 2012) and 0 otherwise,

$error_{it}$ = error term identically and independently distributed with $N(0, \sigma^2_e)$.

During the years 2008 and 2009, there were also changes in accounting standards. This paper also regards dummy as equal to 1 for these years, but as this paper discusses in the section on empirical results, accounting differences seem to be offset by the nonlinear effect (or, at least, more relevant and persistent than accounting changes).

3.3 Additional Measurements of Unexpected Earnings

Empirical literature shows that measurement error of unexpected earnings, UX_{it}, can bring bias to the earnings-return relationship and produce conflicting results. Thus, in order to mitigate this problem and provide more robust results, this paper takes into account three different proxies of unexpected earnings. The second measurement of unexpected earnings follows Ball et al. (1993), by adjusting scaled earnings change (*UX*) to market return:

$$UX_t = \gamma_{0t} + \gamma_{0t}\,(R_M - R_{RF}) + \eta_{it} \text{, and} \quad (5a)$$

$$UX_t^{ORT} = \gamma_{0t} + \eta_{it} \quad (5b)$$

where R_M is Ibovespa (Brazilian' stock market index) accumulated annual return and R_{RF} is the Brazilian interbank deposit rate (CDI), regarded as the measurement of credit-default risk free rate in the Brazilian market. According to Ball et al. (1993, p. 626), this measurement "avoids any correlation between the market return and the assignment of stocks to portfolio that could induce a spurious association between changes in risk and changes in earnings."

The third measurement of unexpected return is based on Kormendi and Lipe (1987), who estimate unexpected return for a firm *i* in a year *t* as the residual of a firm-specific autoregressive earnings model:

$$\Delta X_t = k_2 + \sum_{\tau=1}^{N} \theta_i \Delta X_{t-\tau} + UX_t^{AR} \quad (6)$$

where UX_t^{AR} = is the residual of an autoregressive model, representing unexpected earnings by the portion of earnings which cannot be explained by the equation with past earnings (X_t). Thus, this measurement considers the autoregressive time series process of earnings (i.e. the persistence parameter, θ_i) in earnings estimation, and as a consequence, the residual is the unexpected part of earnings. Given the reduced length of data, UX^{AR} is estimated by an AR(1) model, where τ $=1$ in Eq. 9.

Thus, the following extended empirical equations are also estimated:

$$UR_{it} = a + b_1UX_{it}^{ORT} + b_2TR_{it} * UX_{it}^{ORT} + b_3SR_{it} * UX_{it}^{ORT} + b_4NLEF_{it} * UX_{it}^{ORT} + b_5SIZE_{it} * UX_{it}^{ORT} + b_6PER_i * UX_{it}^{ORT} + b_7IFRS_t * UX_{it}^{ORT} + error_{it}^{OR} \quad (7)$$

$$UR_{it} = a + b_1UX_{it}^{AR} + b_2TR_{it} * UX_{it}^{AR} + b_3SR_{it} * UX_{it}^{AR} + b_4NLEF_{it} * UX_{it}^{AR} + b_5SIZE_{it} * UX_{it}^{AR} + b_6PER_i * UX_{it}^{AR} + b_7IFRS_t * UX_{it}^{AR} + error_{it}^{AR} \quad (8)$$

where UX^{ORT} and UX_t^{AR} are both measurements of unexpected earnings, they are orthogonalized and autoregressive unexpected earnings, respectively. The remaining variables are the same as previously defined.

4 SAMPLE DESCRIPTION AND PRELIMINARY ANALYSIS

The analysis is based on all firms listed on the BM&FBOVESPA from 1995 to 2013. The length of this series and the number of firms were dictated by data availability. Data were collected from the Economatica database and they comprise the whole period of relative monetary stability – which began in 1995, after the implementation of the Brazilian 'Real Plan,' on February 27, 1994. For reducing survivor bias effects, all firms with a minimum of six consecutive annual observations were included in the analysis. Additionally, in order to provide a minimum stock liquidity level, all firms which showed a stock liquidity index equal to zero or lower then 0.001 within the last ten years considered in data collection were excluded from the analysis. The stock liquidity index provided by Economatica takes into account the proportion between (i) the number of days when a given stock was traded, (ii) the number of trading activities in a single day, and (iii) the amount traded for a given stock and the figures from the total market. Since the unexpected earnings are estimated based on earnings variation, a minimum of six consecutive annual observations leads to a minimum of five consecutive earnings innovations. Thus, the length of the time series of variables for each firm varies from 5 to 18 yearly observations. Based on data availability, 212 firms were included in the sample.

Considering the periods and firms without data, the analysis was based on 2,335 firm-year observations. The sample included firms from various economic sectors and the market capitalization of these companies accounted for more than 80% of the total market capitalization of the BM&FBOVESPA.

Stock prices and stock market index were identified on a monthly basis and they were adjusted for subsequent stock splits and stock dividends, thus leading this adjusted figure to become the default price. Prices were based on the month's last trading day and missing values of price, up to three consecutive months, were estimated by using the general market index. Historical *EPS* for each company was also adjusted to subsequent changes in equity structures (e.g. stock splits, mergers, and acquisitions, etc.), enabling this adjusted figure to become the default *EPS*. The effect of accounting methods changes was controlled by the variable IFRS, which assumes 1 for periods which complied with the IFRS (from 2010 to 2013).

According to its design, the cross-sectional explanatory variables of the ERC are proportionally rank-ordered. Thus, significant Spearman's (lower diagonal) and Kendall's (upper diagonal) rank-order correlations are displayed in Table 1.

Table 1 *Pooled Spearman's and Kendall's rank order correlation*

	UR	UX	UX^{OR}	UX^{AR}	TRK	SRK	NLEF	SIZE	PER	IFRS
UR		0.206[a]	0.165[a]	0.165[a]	-0.090[a]	-0.069[a]	-0.005	0.012	0.077[a]	-0.039[a]
UX	0.288[a]		0.646[a]	0.606[a]	0.007	0.009	0.099[a]	-0.004	0.035[b]	-0.069[a]
UX^{OR}	0.233[a]	0.761[a]		0.476[a]	-0.008	0.001	0.066[a]	-0.009	0.019	-0.081[a]
UX^{AR}	0.233[a]	0.715[a]	0.590[a]		0.009	0.010	0.075[a]	0.005	-0.017	-0.039[a]
TRK	-0.131[a]	0.010	-0.012	0.011		0.291[a]	0.231[a]	-0.257[a]	-0.173[a]	0.002

Table 1 *Continuation*

SRK	-0.104[a]	0.014	0.002	0.014	0.402[a]		-0.007	0.142[a]	0.037[b]	0.002
NLEF	-0.011[a]	0.114[a]	0.085[a]	0.091[a]	0.341[a]	-0.011		-0.183[a]	-0.226[a]	0.009
SIZE	0.022[b]	-0.007	-0.014	0.009	-0.377[a]	0.211[a]	-0.270[a]		0.078[a]	-0.048[a]
PER	0.112[a]	0.052[b]	0.028	-0.025	-0.260[a]	0.053[a]	-0.331[a]	0.114[a]		-0.044[a]
IFRS	-0.069[a]	-0.124[a]	-0.144[a]	-0.069[a]	0.003	0.004	0.016	-0.085[a]	-0.079[a]	

Spearman's (lower diagonal) and Kendall's (upper diagonal) rank-order nonparametric correlations with balanced sample (list-wise missing value deletion) with 1,999 observations included. Where *UR* is 12-month cumulated abnormal return; *UX*, UX^{OR} and UX^{AR} are measurements of unexpected earnings; *TRK* is standardized total risk; *SRK* is standardized systematic risk in a market model approach; *NLEF* is standardized magnitude of unexpected earnings (*UX*); *SIZE* is measured by the standardized total assets; *PER* is standardized by rank of earnings persistence based on AR(1) parameter of reported earnings; and *IFRS* is a dummy control variable for IFRS adoption, assuming 1 for the period from 2010 to 2013. [a] and [b] indicate correlations statistically significant at 1% and 5%, respectively.

As expected, Table 1 shows not only positive significant correlations between proxies for unexpected earnings and unexpected (abnormal) returns, but also a negative significant correlation between unexpected returns and both risk measurements (TRK and SRK). The three proxies for unexpected earnings are highly correlated (more than 0.7), except for the correlation between UXOR and UXAR, 0.590 (Spearman). However, intriguing evidence is find with regard to size and total risk (TRK) and systematic risk (SRK): while large firms tend to have lower total risk (i.e. higher stock volatility), they have higher systematic risk (beta). This is a first indication that rank-order total risk is a better discriminant of risk, since large firms are assumed to have lower risks (negative relation). Thus, given the strong concentration in only a few large firms, systematic risk may be biased towards the volatility of these firms. Concomitantly, smaller firms might not be strongly correlated to stock index, resulting in a smaller Sharpe's market model beta (consistent with Costa Jr. et al., 1993). Moreover, large firms have, on average, lower extreme unexpected earnings (NLEF), making their earnings less volatile than small-sized firms. This is also reflected in the two measurements of risk, something which is consistent with Amorim et al. (2012), since accounting (earnings) information has a weak relation with the market model beta.

Finally, firms with higher earnings persistence tend to have lower risk. This negative correlation is consistent with previous studies, which claimed that more persistent earnings produce better inputs to equity valuation models, hence a more persistent earnings value has higher predictability and quality than a less persistent earnings value (Dechow et al., 2010). The negative and significant correlation between PER and NLEF follows the expectation that firms with higher magnitudes of unexpected earnings have lower earnings persistence (Ali & Zarowin, 1992; Freeman & Tse, 1992).

5 EMPIRICAL RESULTS

5.1 Estimation of the Basic Empirical Model

Chambers et al. (2005) argue that total risk, *TRK*, and systematic risk, *SRK*, have complementary information for earnings-returns association by introducing a numerator and a denominator factor. However, this paper claims that, taking the Brazilian environment into account, rank-order total risk is a better proxy for cross-sectional variation in the ERC than systematic risk measured by the market model beta.

The econometric approach for estimating the basic model is grounded in a random-effects model. Specifically, the model accounts for heterogeneity between individuals ($\sigma_u^2 > 0$) and it allows estimating the effects of variables that are individually time-invariant (Baltagi, 2005). The random effect assumes that error variances are randomly distributed across group and/or time and that individual effects are not correlated with regressors. In order to check for potential correlations between the error component u_i and regressors, Hausman's test was performed. By using $\chi^2 = 2.46$ (sig. = 0.4828), it was not possible to reject the null hypothesis that estimators under fixed and random effect are identical. Hausman's test was also performed taking into account that covariance matrices are based on the same estimated disturbance variance through an effective estimator and the conclusion was the same ($\chi^2 = 2.60$, sig. = 0.4575). Thus, differences in coefficients are not systematic, suggesting that random effects estimates can be consistent and effective (Baltagi, 2005). A second step was confirming if the random effects model is preferable to pooled data. To test for the poolability hypothesis against the random effect, Breusch-Pagan's test (Lagrangian multiplier test for random effects) was performed, where $\chi^2 = 3.83$ (sig. 0.0252). At a 5% level, it is possible to reject the null hypothesis that specific variance components are equal to zero ($H_0 : \sigma_u^2 = 0$). Thus, there is evidence of significant differences across individuals and the random effects model can deal with heterogeneity better than the pooled OLS. Estimations consider the diagonal heteroscedasticity corrections proposed by White (1980).

Table 2 displays the results of the basic model, where Panel A includes all firms and periods under analysis and Panels B and C divide the estimation into two groups, according to high *TRK* and high *SRK* firms, respectively. Estimating the entire sample in Panel A shows that the ERC (coefficient b_1 in Eq. 3) is positive and significant at a 5% level. Only the coefficient in *TRK* is negative and significant at standard levels, while *SRK* is not statistically significant as a determinant of the ERC.

Panel B divides estimates into two different equations through the estimation into two groups (portfolios) of high *TRK* and low *TRK*. It is clearly showed that the portfolio with lower *TRK* firms (lower idiosyncratic risk) have higher ERC (0.228 for low *TRK* against 0.044 for high *TRK*), confirming the expectation that firms with low risk have higher ERC. The test of difference in coefficients estimates confirm the statistical significance of the difference ($\chi2 = 5.52$; p value = 0.019). Additionally, estimation with low risk firms shows higher explanatory power than the high-risk portfolio.

On the other hand, Panel C shows that, when portfolio segregation is based on *SRK*, the ERC of lower risk firms is lower than the high-risk portfolio (0.055 for low *SRK* against 0.118 for high *SRK*). Yet, the ERC for higher risk firms loses its statistical significance. The difference between coefficients estimates was not statistically significant ($\chi^2 = 0.51$; p value = 0.475).

Overall, the results in Table 2 show that *TRK* seems to be more effective to distinguish high and low risk firms than *SRK* in studies on earnings-returns association and that the ERC is positive and statistically significant, it decreases according to risk (total risk).

Table 2 *Basic model testing the effect of risk on the earnings-return association (Eq. 3)*

PANEL A – BASIC MODEL: ALL FIRMS					
Coeff.	Const.	UX	UX*TRK	UX*SRK	Wald $\chi^2 = 11.76^a$
Z stat	0.036^a	0.057^b	-0.066^a	0.034	$R^2 = 0.012$
	[3.2]	[2.4]	[-2.6]	[1.4]	Clusters = 212
PANEL B – BASIC MODEL: FIRMS SEGREGATION BASED ON TRK					
Firms with highest TRK (50% highest idiosyncratic risk)					
Coeff.	Const.	UX	UX*TRK	UX*SRK	Wald $\chi^2 = 19.85^a$
[Z stat]	-0.011	0.044^a	-0.050^a	0.031	$R^2 = 0.009$
	[-0.6]	[3.1]	[-2.8]	[1.4]	Clusters = 212
Firms with lowest TRK (50% lowest idiosyncratic risk)					
Coeff.	Const.	UX	UX*TRK	UX*SRK	Wald $\chi^2 = 24.55^a$
[Z stat]	0.074^a	0.228^a	-0.535^a	0.112	$R^2 = 0.044$
	[6.2]	[2.7]	[-2.9]	[0.9]	Clusters = 212
PANEL C – BASIC MODEL: FIRMS SEGREGATION BASED ON SRK					
Firms with highest SRK (50% highest systematic risk)					
Coeff.	Const.	UX	UX*TRK	UX*SRK	Wald $\chi^2 = 10.01^b$
[Z stat]	-0.014	0.118	-0.250^b	0.193^c	$R^2 = 0.028$
	[-0.8]	[1.1]	[-1.9]	[1.8]	Clusters = 212
Firms with lowest SRK (50% lowest systematic risk)					
Coeff.	Const.	UX	UX*TRK	UX*SRK	Wald $\chi^2 = 6.70^c$
[Z stat]	0.085^a	0.055^b	-0.053^b	-0.029	$R^2 = 0.011$
	[6.5]	[2.5]	[-2.3]	[-0.9]	Clusters = 212

Note: Const. is the constant term; *UR* is 12-month cumulated abnormal return; *UX* is the measure of unexpected earnings, earnings changes scaled by price; *TRK* is standardized total risk; *SRK* is standardized systematic risk in a market model approach. [a], [b], and [c] indicate correlations statistically significant at 1%, 5%, and 10%, respectively.

Two natural extensions of the basic model are (1) to add (and control) nonlinear relations of unexpected earnings and abnormal return and (2) to control the estimation by the period with the Brazilian Generally Accepted Accounting Principles (BR GAAP) and the IFRS. Since the ERC may be a time and cross-sectional variant and these variations may be directly related to macroeconomic and financial environments, within some periods (stressed periods, such as 2002 and 2008), firms tend to incur in high magnitude of unexpected transitory earnings. Those high magnitudes of unexpected earnings may lead to a nonlinear effect of earnings and stock returns (Freeman & Tse, 1992). Thus, *NLEF* was included to control nonlinear effects on the basic model (Panel A – Table 3) and, additionally, it interacted with the IFRS variable (Panel B – Table 3).

Panel A in Table 3 shows that the nonlinear effect is significant in the Brazilian market by yielding a highly negative coefficient, a finding consistent with Freeman and Tse (1992) and Chambers et al. (2005). This suggests that market players do not react in the same manner to different magnitudes of unexpected earnings. Particularly, players tend to react less to high unexpected earnings, something which is consistent with the idea of a transitory component of earnings (Ali & Zarowin, 1992). However, as far as we know, no market-based accounting study conducted in Brazil accounts for that. That seems to be a key control for studies on earnings quality in environments where extreme earnings are often related to specific periods. Additionally, Panel C in Table 3 shows that the interaction between *NLEF* and *IFRS* is statistically significant, suggesting that there is a high association between the period pre-IFRS with higher magnitudes of unexpected earnings.

Table 3 *Basic model: estimation with control for nonlinear effects and the IFRS*

PANEL A – CONTROL FOR NONLINEAR EFFECTS OF EXTREME EARNINGS								
	Const.	UX	UX*TRK	UX*SRK	UX*NLEF			Obs./Clust.= 2079/212
Coeff. / Z stat	0.026^{b}	1.032^{a}	-0.044^{a}	-0.032	-0.990^{a}			Wald $\chi^2 = 94.0^{a}$
	[2.4]	[6.9]	[-3.9]	[-1.5]	[-6.5]			$R^2 = 0.047$
PANEL B – CONTROL FOR IFRS FULL ADOPTION (2010-2013)								
	Const.	UX	UX*TRK	UX*SRK		UX*IFRS		Obs./Clust.= 2079/212
Coeff. / [Z stat]	0.035^{a}	0.056^{b}	-0.065^{b}	0.035		-0.012		Wald $\chi^2 = 13.7^{a}$
	[3.2]	[2.3]	[-2.5]	[1.5]		[-0.5]		$R^2 = 0.012$
PANEL C – INTERACTION OF NONLINEAR EFFECTS AND THE IFRS								
	Const.	UX	UX*TRK	UX*SRK	UX*NLEF	UX*IFRS	UX*NLEF *IFRS	Obs./Clust.= 2079/212
Coeff. / [Z stat]	0.025^{b}	0.970^{a}	-0.043^{a}	-0.031	-0.929^{a}	3.872^{a}	-3.897^{a}	Wald $\chi^2 = 13.7^{a}$
	[2.4]	[6.6]	[-3.9]	[-1.5]	[-6.2]	[4.1]	[-4.1]	$R^2 = 0.047$

Note: Const. is the constant term; *UR* is 12-month cumulated abnormal return; *UX* is the measurement of unexpected earnings, earnings changes scaled by price; *TRK* is standardized total risk; *SRK* is standardized systematic risk in a market model approach; *NLEF* is standardized magnitude of unexpected earnings (*UX*); and *IFRS* is a dummy control variable for IFRS adoption, assuming 1 for the period from 2010 to 2013. [a], [b], and [c] indicate correlations statistically significant at 1%, 5%, and 10%, respectively.

When the IFRS interacts only with unexpected earnings (Panel B in Table 3), there is no statistical significance for the IFRS, suggesting that IFRS adoption, by itself, does not explain variations in the ERC. When interacting together (*NLEF* and *IFRS*) in the model (Panel C in Table 3), there is a correction in the IFRS explanation in almost the same magnitude (3.872 against -3.897), suggesting there is a high overlap of information between *IFRS* and *NLEF*, since the pre-IFRS period has higher extreme values of unexpected earnings than the post-IFRS period. Thus, additional interaction between *UX*, *NLEF*, and *IFRS* suggests that a portion of the ERC may be explained by high volatility and nonlinear effects of the series. This is a relevant result because it suggests additional caution when interpreting empirical results relating accounting and market variables before and after the IFRS were adopted in Brazil, as the differences might not be related to accounting practices themselves, but to a macroeconomic environment effect on earnings. Therefore, a control for volatility must include not only market variables, but the volatility (and variance) in earnings due to macroeconomic factors (see Clubb & Wu, 2014; Shu, Broadstock, & Xu, 2013).

Since the results reported in Table 3 suggest time differences in the ERC, this paper also tested significant annual time-effects by including dummy variables for time. Basically, with the inclusion of dummy variables, 12 years (out of 18 years) were statistically significant at a 5% level, with an additional increase in R^2 to about 14%. Moreover, the test for time effect strongly rejected ($\chi^2 = 166.35$ with sig. = 0.000) the null hypothesis that coefficients for all years are jointly equal to zero, suggesting that the ERC is not fixed in time. Thus, controlling time variations can mitigate possible sources of spuriousness, due to common trends in the variables observed. Moreover, this does suggest that further studies might be interested in identifying the relevant time-determinants of the ERC under an inconstant environment such as that of emerging markets.

5.2. Estimation of the Extended Empirical Model

This paper extends the previous analysis by including various proxies of unexpected earnings based on the orthogonalized earnings innovation (UX^{OR}) proposed by Ball et al. (1993) and autoregressive measurement (UX^{AR}), based on Kormendi and Lipe (1987). The extended models do not confirm the random effect assumption that individual effects are uncorrelated with the regressors, as Hausman's test results reject the null hypothesis that the estimators under fixed and random effect are identical, indicating that random effects estimates might be inconsistent (see the bottom of Table 4 for test results). Additionally, Chow's (F-)test for poolability rejected the joint null hypothesis of equal coefficients at standard significance levels. Although the fixed effects model controls time-invariant differences between individuals (such as industry), Baltagi (2005, p. 68) argues that if disturbances are heteroscedastic and/or serially correlated, fixed effect OLS estimations are not efficient and "the standard formulae for the asymptotic variance in these estimators are no longer valid." Wooldridge tests for cross-sectional dependence and Wald's test for group-wise heteroscedasticity report both problems (see the bottom of Table 4). Notice that only the first equation (*UX*) does not show autocorrelation at a 10% significance level. Thus, following Bressan, Braga, Bressan and Resende-Filho (2012) and Baltagi (2005), the three models were reestimated by using feasible generalized least squares (FGLS). This study also estimated the fixed-effect OLS estimation, because if heteroscedasticity is incorrectly specified, the FGLS estimator may be less effective than the OLS estimator. However, results in fixed effects are qualitatively similar and they are available under request to the authors. Table 4 displays results of the extended empirical model, considering the three proxies of unexpected earnings, *UX*, UX^{OR} and UX^{AR}, as pointed out above.

Table 4 *Estimation for the cross-sectional determinants of the ERC (Eq. 4, 7, and 8)*

	(Eq. 4)		(Eq. 7)		(Eq. 8)
Const.	-0.210 [a]	Const.	-0.223 [a]	Const.	-0.116 [c]
	[-3.2]		[-3.3]		[-1.7]
UX	0.786 [a]	UX^{OR}	0.076 [a]	UX^{AR}	0.036 [a]
	[6.5]		[3.4]		[2.9]
UX*TRK	-0.060 [a]	UX^{OR}*TRK	-0.055 [a]	UX^{AR}*TRK	-0.014 [b]
	[-2.9]		[-3.4]		[-2.2]
UX*SRK	-0.020	UX^{OR}*SRK	0.026 [b]	UX^{AR}*SRK	0.015
	[-1.1]		[2.1]		[1.2]
UX*NLEF	-0.751 [a]	UX^{OR}*NLEF	-0.046 [b]	UX^{AR}*NLEF	-0.007
	[-6.2]		[-2.1]		[-0.9]
UX*SIZE	0.021	UX^{OR}*SIZE	0.018	UX^{AR}*SIZE	-0.042[a]
	[1.3]		[1.5]		[-3.3]
UX*PER	0.047 [b]	UX^{OR}*PER	0.040 [a]		
	[1.9]		[3.6]		
UX*IFRS	4.012 [a]	UX^{OR}*IFRS	-0.077	UX^{AR}*IFRS	-0.005
	[5.1]		[-0.9]		[-0.9]
UX*IFRS*NLEF	-4.043 [a]	UX^{OR}*IFRS*NLEF	0.062	UX^{AR}*IFRS*NLEF	0.027
	[-5.1]		[0.7]		[1.5]
Wald (25) χ^2	369.71[a]	Wald (25) χ^2	288.72 [a]	Wald (25) χ^2	229.70 [a]
Obs.	2079	Obs.	2079	Obs.	1999
N. groups	212	N. groups	212	N. groups	212
Log likelihood	-1190.7	Log likelihood	-1225.6	Log likelihood	-1179.5
Hausman χ^2	66.37 [a]	Hausman χ^2	55.37 [a]	Hausman χ^2	53.22 [a]
Chow F-test	1.25 [a]	Chow F-test	1.27 [a]	Chow F-test	1.17 [a]
Autoc. Wooldr (χ^2)	2.609	Autoc. Wooldr (χ^2)	5.622 [b]	Autoc. Wooldr (χ^2)	4.819 [b]
Heter. Wald (χ^2)	35372.9 [a]	Heter. Wald (χ^2)	80870.3 [a]	Heter. Wald (χ^2)	36888.2 [a]

FGLS estimation. Const. is the constant term; *UR* is 12-month cumulated abnormal return; *UX*, UX^{OR}, and UX^{AR} are measurements of unexpected earnings; *TRK* is standardized total risk; SRK is standardized systematic risk in market model approach; *NLEF* is standardized magnitude of unexpected earnings (*UX*); *SIZE* is measured by standardized total assets; *PER* is standardized rank of earnings persistence based on AR(1) parameter of reported earnings; and *IFRS* is a dummy control variable for IFRS adoption, assuming 1 for the period of 2010. [a], [b], and [c] indicate statistical significance at 1%, 5%, and 10%, respectively.

Results in Table 4 indicate that the ERC is statistically significant in the three estimations at a 1% level. Overall, the results confirm that the ERC is a decreasing function of *TRK* and extreme *NLEF* and an increasing function of *PER*. No systematic relationship was reported in the market model beta (systematic risk – *SRK*), size, and IFRS adoption, as results in the three regressions yield conflicting evidence with regard to the proxy for unexpected earnings used.

The significant and negative coefficient of total risk is partially consistent with previous expectations. On the one hand, although valuation models rely on systematic risk rather than idiosyncratic risk, a negative significant coefficient is consistent with the discounted valuation approach (Collins & Kothari, 1989). In this regard, Basu (2005) suggests the existence of a positive relationship between idiosyncratic risk and cost of capital, arguing that a few theories try to explain this relationship based on underdiversication, bias in risk estimation, and investor's clientele. On the other hand, the negative signal is inconsistent with the hypothesis of a 'numerator' effect proposed by Chambers et al. (2005); i.e. in the Brazilian market, reviews in expected payoffs (earnings/dividends) are not an increasing function of total risk. A possible explanation is that speculative capital movements in Brazil (or some market inefficiency level) play a more important role than firm-specific fundaments (from an idiosyncratic viewpoint). This is consistent with Barry and Brown (1984), who argue that traditional risk measurements do not consider the firm-specific information content. Thus, Barry and Brown (1984, p. 284) state that: "if risk is measured empirically without regard to the amount of information available, then there may appear to be 'abnormal' returns for low information securities."

Associated with the discussion above and in a way consistent with empirical evidence reported by Easton and Zmijewski (1989), Ghosh et al. (2005), and Warfield et al. (1995), Table 4 also shows that the role played by systematic risk (*SRK*) is not significant to explain ERCs. There are at least three potential explanations for this phenomenon in Brazil: (i) measuring error in systematic risk (beta), (ii) non-controlled leverage, and (iii) which kind of risk ERCs actually reflect. First, since the stock index reflects a reduced number of the (larger) most traded liquid stocks, this characteristic might suggest underdiversification of the market portfolio (Levy, 1978). Second, this non-negative coefficient (contrary to the literature on valuation) is due to non-controlled changes in leverage and in investment risks (Ball et al., 1993). Finally, the ERC may not reflect systematic risk, but idiosyncratic risk, captured by the total risk (Basu, 2005).

The results are relatively consistent across the three different proxies of unexpected earnings, except for the positive significant relationship between *SRK* and ERC in the UX^{OR} regression. Since UX^{OR} is an adjusted-to-the-market variable, it can reduce bias towards market variations that are noticed due to firm-specific response to earnings.

Despite strong previous evidence reported in the international literature, size is not regarded as a significant determinant of the ERC. Initially, this evidence might be intriguing, but control for size might be outperformed by *TRK* as a cross-sectional control of the ERC. Recalling Table 1, the highest correlation between explanatory variables was between size and total risk (negative and significant Spearman's value = -0.377). Additionally, size may be a proxy for various constructs rather than risk. For instance, it may be a useful proxy for information environment, since large firms must have higher analysts' coverage. Consequently, firm size can play different roles on capital market activities.

So, corroborating the previous literature, earnings persistence (PER) is found to be an increasing function of earnings-return relationship. This evidence is strongly consistent with previous empirical literature (Collins & Kothari, 1989; Kothari, 2001). Notice that the equation using UX^{AR} already considers an autoregressive estimation of the earnings time series process and it incorporates the persistence parameter of earnings in unexpected (autoregressive) earnings estimation.

Finally, IFRS adoption, in 2010, seems to not affect ERCs with any statistical significance. Although the period post-IFRS may be too short to draw a strong conclusion, the market effect does seem to play an important role. Thus, as discussed in a previous section, variations on ERCs before and after IFRS adoption may be more related to 'change' in the stock market and earnings patterns than to the changes in accounting practice. This is also supported by the estimation considering UX^{OR}, since the IFRS variable loses its statistical significance when adjusted for market variations. This conclusion may also be supported by empirical evidence provided by Santos and Calixto (2010) and Santos (2012), which does not support significant changes in earnings quality after IFRS adoption.

5.3 Additional Tests for Consistency and Limitations of the Study

As many market-based accounting studies, the conclusions of this paper are subject to measurement error in the variables and bias with regard to the sample selection. In order to minimize the effects of measurement error, this study used the three different measurements of unexpected earnings (this is the most 'unobserved' variable in the study). Although this research follows the most relevant literature in this subject, there are still possibilities of measurement error in the remaining variables. An additional cause of measurement and sample selection bias is the lack of stock liquidity. As stated before, the Brazilian market has many stocks with low market liquidity. Therefore, this paper tried to reduce such bias by requiring a minimum stock liquidity. However, the results may still be affected by the lack of sufficient trading activities that capture market efficiency in incorporating new information on earnings. Thus, this paper also analyses the role of stock liquidity (*SLIQ*).

Typically, stock liquidity leads to price effectiveness and, if prices are efficient, further earnings must be reflected in current prices (Fang, 2012). The lack of liquidity for some companies in our sample can affect this association, leading to biased results. However, no significant relationship was found between *SLIQ* and the ERC when risk measurements were combined. Moreover, when stock liquidity is included in the empirical models, as shown in sections 5.1 and 5.2, stock liquidity and ERCs lose their statistical significance (results are available under request).

Specifically, stock liquidity is strongly correlated with other explanatory variables, especially firm size (positive, 0.668) and total risk (negative, 0.331). These correlations are consistent with those reported by Spiegel and Wang (2005), in the U.S. market, and Mendonça et al. (2012), in the Brazilian market. Thus, despite the theoretical lure of stock liquidity, a first possible explanation is supported by Spiegel and Wang (2005, p. 1) who find that "the impact of idiosyncratic risk is much stronger and often eliminates liquidity's explanatory power." A second explanation is provided by Fang (2012), who reports that stock prices convey information about further earnings only when stock liquidity is above a certain threshold. Therefore, considering the extreme concentration of liquidity in few firms, it may be argued that, as only large firms tend to have more stock liquidity and to be included in the stock index, only very few firms reach this 'liquidity threshold.'

6 FINAL REMARKS

Based on this conflicting evidence with regard to the role played by risk in the ERC, this paper aimed to shed some light on this issue by analyzing the role played by risk in price reactions to earnings in Brazil, a market which is characterized by having high stock concentration, high interest rates, and high market volatility. The study was based on a sample of 212 firms listed on the BM&FBOVESPA through annual time series data and various measurements of risk and unexpected earnings were used.

The results indicate a significant and negative coefficient of total risk (*TRK*), which is partially consistent with the previous expectation presented in the discounted valuation model, whereas it is inconsistent with the 'numerator' hypothesis proposed by Chambers et al. (2005). In terms of systematic risk, the results suggest that CAPM beta leads to error in the measurement of risk, which is consistent with underdiversification of local stock market indexes and also recent empirical evidence (Amorim et al., 2012; Simon et al., 2014). Thus, the results reported herein suggest that, for earnings-return studies, the rank-order total risk may be a better measurement to discriminate firm-specific risk than the market model beta. Nevertheless, the role played by idiosyncratic risk in firm valuation and cost of capital is a phenomenon without full consensus in the literature (Mendonça et al., 2012; Galdi & Securato, 2007; Spiegel & Wang, 2005; Fang, 2012).

Results also show that nonlinear effect is significant in the Brazilian market. This means that market agents do not react in the same manner to different magnitudes of unexpected earnings. That seems to be a key control for earnings quality studies in environments where extreme earnings are often related to specific periods. However, as far as we know, no market-based accounting study conducted in Brazil addresses that.

Additionally, this paper reports that earnings persistence is a positive cross-sectional determinant of ERCs and that neither size or stock liquidity are significant determinants of ERCs when combined with other variables. It may be argued that these variables are strongly correlated with idiosyncratic risk and that the impact of idiosyncratic risk is much stronger and often eliminate size and liquidity's explanatory power (Spiegel & Wang, 2005).

Finally, the results failed to demonstrate that full IFRS adoption, in 2010, significantly affected market's reaction to earnings surprise. So far, the results suggest that any change in ERCs may be due to lower magnitudes of unexpected earnings after IFRS adoption. Data from further years within the period post-IFRS may be required in order to enable a robust conclusion.

Overall, this study indicates that controlling the earnings-return relationship through (i) rank-order total risk, (ii) nonlinear effects of unexpected earnings, and (iii) earnings persistence may optimize an approach to the nature and magnitude of earnings in financial analysis and the valuation process.

Further research may address the reasons why market model beta fails to explain cross-sectional variance in ERCs and/or explore time determinants of ERCs in Brazil or other emerging markets.

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