Time-series Properties of Earnings and Their Relationship with Stock Prices in Brazil^{*}

Rene Coppe Pimentel^a Iran Sigueira Lima^b

Abstract: The aim of this paper is to analyze the firm-specific time-series properties of quarterly accounting earnings from 1995 to 2009. Based on the earning time-series process it is possible to develop robust forecasting models and to test the ability to approximate real capital market behaviour using accounting data. By analysing 71 listed Brazilian companies, we found evidence that the time series of quarterly accounting earnings in Brazil follow an autoregressive model (AR) and can be estimated (modelled) by using a seasonal component. Additionally, we found a significant relationship between earnings and stock prices, although the direction of the causality is not generally defined, which suggests that the earnings-return relationship must be analyzed at the firm-specific level.

Keywords: Emerging markets, Time series, Accounting earnings, Capital market, Valuation

JEL Classification: M41, G30

1. Introduction

Neoclassical consumption theory posits that investors are forward-looking and base their decisions not on current income (earnings) but rather on the expected discounted value of lifetime resources, known as permanent income. In its simplest form, the permanent income hypothesis (PIH) states that the choices made by investors are determined not by current income but by their longer-term income expectations.

Measured earnings contain a permanent (anticipated and planned) element and a transitory (windfall gain/unexpected) element, each of which affects the time series of earnings. Hence, the key conclusion of the permanent income hypothesis is that transitory changes in income do not affect long-run investment decisions.

Several studies have analyzed earnings time series and their relationship with stock prices (and returns). Beaver and Morse (1978), for instance, found empirical evidence that only current earnings are affected by transitory components such as results derived from sales of fixed assets. On the other hand, future earnings are affected only by permanent components. Thus, Beaver (1968) justified the weak explanatory power of earnings on returns for the market identification of transitory earnings.

Based on the above arguments, the main motivations for studies on the timeseries properties of earnings are to develop models that can robustly forecast future values of earnings time series and to test the ability to approximate the capital

^a PhD., The Foundation Institute of Accounting, Actuarial and Financial Research - FIPECAFI, Sao Paulo, Brazil, <u>rene.pimentel@fipecafi.org</u> (Corresponding Author)

^b PhD., University of Sao Paulo, Sao Paulo Brazil, iranlima@uol.com.br

^{*} We are grateful to Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES, 3980/08-1) for financial support and to Fundação Instituto de Pesquisas Contábeis, Atuariais e Financeiras (FIPECAFI).

market's expectation model when examining the market's reaction to accounting data. Additionally, Foster (1977) argued that time-series research is important for several areas of accounting and finance, such as the 'smoothing literature': managers might know the stochastic process generating the reported accounting series when making smoothing decisions.

Kothari (2001, p. 124) states that the time-series properties of earnings play a role in parsimoniously describing the revisions in earnings forecasts based on current earnings, but a rigorous theory for time-series properties does not exist. More recent studies, for instance Dichev and Tang (2009) and Frankel and Litov (2009), by including volatility analyzes of earnings, have documented an increase in the predictive power of past earnings volatility for the persistence of current earnings. Frankel and Litov (2009) found evidence that the relation between past earnings volatility and earnings persistence is robust to additional controls and to a correction for sampling bias, but that earnings volatility does not significantly predict stock returns.

In Brazil, Lopes (2002, p.58) stated that empirical evidence of the properties of accounting information and its relationship with capital market data in Latin America is almost nonexistent in the accounting literature. He also stated that the Brazilian literature has contributed poorly to empirical market-based accounting research.

Thus, to extend the studies of Foster (1977), Kormendi and Lipe (1987), Brown (1993); Galdi and Lopes (2008) and Martinez, Cupertino, Junior and Coelho (2008), this study empirically analyzes, in an exploratory way, the stochastic properties of accounting earnings by studying the time-series process of accounting earnings and their long-term relationship with stock returns for listed Brazilian companies from 1995 to 2009. The questions that motivate this study are: "What are the time-series properties of accounting earnings in Brazil?" and "Is there a long-term relationship between accounting earnings and stock prices or returns?"

The rest of this paper is structured as follows: Section 2 develops the theoretical basis for studies on earnings time-series properties and presents previous empirical findings; Section 3 presents the data and the research design; Section 4 shows the statistical test results and their analysis; and Section 5 concludes and suggests future empirical studies.

2. Time-series Properties of Accounting Earnings

Kothari (2001) identified at least four reasons for studying the time-series properties of earnings. First, almost all valuation models either directly or indirectly use earnings forecasts. (i.e. discounted cash flow valuation models often use forecast earnings, with some adjustments, as proxies for future cash flows and the analytically equivalent residual-income valuation models discount forecast earnings net of "normal" earnings, see Edwards & Bell, 1961; Ohlson, 1995; Feltham & Ohlson, 1995). Second, capital market research correlating financial statement information with security returns frequently uses a model of expected earnings to isolate the surprise component of earnings from the anticipated component. The degree of return-earnings association depends on the accuracy of the unexpected earnings proxy used by the researcher, which naturally creates a demand for the time-series properties of earnings. Third, the efficient markets hypothesis is increasingly being questioned (specially by behavioral finance models of inefficient markets). Accounting-based capital market research has produced evidence that is apparently inconsistent with market efficiency. A common feature of this research is to show that security returns are predictable and that their predictability is associated with the timeseries properties of earnings. Fourth, positive accounting theory research

hypothesises efficient or opportunistic earnings management and/or seeks to explain managers' accounting procedure choices. In this research there is often a need for 'normal' earnings that are calculated using a time-series model of earnings.

Given the different characteristics of the earnings process, the empirical literature divides the time-series properties of earnings analysis into annual and quarterly studies.

Kothari (2001, p. 148) states that the interest in the time-series properties of quarterly earnings arises for at least four reasons: (1) quarterly earnings are seasonal in many industries because of the seasonal nature of their main business activity; (2) quarterly earnings are more timely, so the use of a quarterly earnings forecasts as proxies for the market's expectation is likely to be more accurate than using a stale annual earnings forecast; (3) GAAP requires the quarterly reporting period to be an integral part of the annual reporting period, so firms are required to estimate annual operating expenses and allocate these costs to quarterly periods (more importantly, quarterly earnings are potentially a more powerful setting to test the positive accounting theory and capital market research hypotheses); and (4) there are four times more quarterly earnings observations than annual earnings ones, meaning there are less stringent data availability requirements using quarterly instead of annual earnings to achieve the same degree of forecasting precision.

Evidence in Kinney, Burgstahler and Martin (2002) shows that the odds of the same sign of stock returns and earnings surprise are no greater than 60-40%, even when using composite earnings forecasts. The lack of a strong association should not be interpreted mechanically as an indication of noise in the earnings expectation proxy. The modest association is likely to be an indication of prices responding to information about future income that are unrelated to the current earnings information. That is, the forward-looking nature of prices with respect to earnings becomes an important consideration. In addition, the increased presence of transitory items in earnings in recent years further weakens the relation between current earnings surprises and revisions in expectations about future periods' earnings, as captured in the announcement period price change.

According to Kothari (2001, p. 149), well-developed Box-Jenkins autoregressive integrated moving average (ARIMA) models of quarterly earnings exist (for instance, see Foster, 1977; Griffin, 1977; Brown and Rozeff, 1979). Research comparing models shows that the Brown and Rozeff (1979) model is slightly superior in forecast accuracy, at least over short horizons (see Brown, Griffin, Hagerman & Zmijewski, 1987a). However, this advantage does not necessarily show up as a stronger association with short-window returns around quarterly earnings announcements (see Brown Griffin, Hagerman & Zmijewski, 1987b). Simpler models like that of Foster (1977) do just as well as more complicated models. The main advantage of the Foster (1977) model is that it can be estimated without the Box-Jenkins ARIMA software.

Foster (1977) indicated some issues regarding quarterly accounting reports. The first concerns seasonal operations, which according to him require a variety of adjustment techniques to reduce the effect of seasonality. Thus, time-series analysis should provide important information for evaluating these techniques for seasonally adjusting quarterly earnings. This statement is based on the assumption that it is necessary to know something about the unadjusted series before deciding on the set of techniques to produce the seasonally adjusted series. Another interim issue he examined was whether the aggregate market, when interpreting an interim report, adjusts for seasonality in the earnings series. The argument that industry officials have advanced against extensive interim disclosure rules is that investors would be "confused" or "misled" by the interim results of seasonal firms.

Brown and Kennelly (1972) used four-period lagged models to find seasonality in accounting earnings based on:

Model 1: $E(Q_t) = Q_{t-4}$ Model 2: $E(Q_t) = Q_{t-4} + \delta$

where Q_t = earnings in quarter *t* of a given year and δ is a drift (disturbance) term. The drift term is the average change in that quarter that occurred over the available history. Models 1 and 2 assume a seasonal pattern in quarterly earnings. A set of models which ignore any such seasonality are used in studies of the information content of annual earnings. Two such non-seasonal models are:

Model 3: $E(Q_t) = Q_{t-1}$ Model 4: $E(Q_t) = Q_{t-1} + \delta$

Whether any seasonality exists in quarterly accounting data is obviously an empirical question. Models 3 and 4 provide some insight into the consequences of suppressing any seasonality in quarterly data.

The above models (one through four) can generate a misspecification problem, thus, Foster (1977) proposed a model under the strong assumption that an AR(1) process describes the time-series behaviour of the fourth difference in a quarterly datum of all firms. Therefore, the model becomes:

Model 5:
$$E(Q_t) = Q_{t-4} + \phi_1(Q_{t-1} - Q_{t-5}) + \delta$$

Foster (1977) also proposed an alternative approach to Model 5 by using the Box and Jenkins (1970) methodology for identifying the process generated in each firm's data. The Box-Jenkins' model consists of a four-step approach. The first step is model identification. This involves, among other things, a comparison of the sample autocorrelations and partial autocorrelations with theoretical patterns of particular autoregressive-moving average models. The second step is the model estimation of partial autocorrelations with theoretical patterns of particular average models. The third step is diagnostic checking, which tests for serial noncorrelation of residuals. Based on these steps, Foster (1977) identified, for each firm, the appropriate Box-Jenkins model for the accounting earnings.

In Brazil, Galdi and Lopes (2008) studied the quarterly long-term causality between accounting earnings and stock prices in Latin America countries. They investigated the relevance of accounting information for capital markets in Argentina, Brazil, Chile, Peru and Mexico by using cointegration tests and found empirical evidence suggesting that the variables are cointegrated (they have a long-term relationship) and some evidences indicating that accounting earnings in Argentina are typically stationary and have a higher degree of causality relation with stock prices than other Latin American countries' accounting earnings.

3. Data and Research Design

The analysis is based on all listed Brazilian firms' quarterly and annual accounting and market information from the first quarter of 1995 through the first quarter of 2009 (this period includes the Real Plan in 1994, which brought relative monetary stability after years of high inflation). Hence, the study also involves the full available period since the Instructions 202/1993 and 274/1998 from the Brazilian Securities Commission (CVM) determined the obligation of disclosing quarterly information for listed companies. Although this represents a short period compared to international studies, this is the complete official time-series available.

This period provides 57 quarterly earnings observations as well as price information (or 14 years of quarterly earnings and price information). However, since data were not available for all companies throughout this period (with the lengths varying from 22 to 57 quarterly time-series observations), we only included 71 companies in the sample for quarterly analysis. Table 1 shows a brief description of the companies, their economic sectors and size.

The last column of Table 1 shows a sample-relative classification of the companies' size according to total assets.

For each company presented in Table 1, the time-series of accounting earnings (earnings per share) and stock price were collected from the Economática database. Quarterly accounting earnings consist of accounting earnings accumulated in one specific quarter (e.g., first quarter's earnings are obtained during January, February and March). Historical earnings per share (EPS) for each company are adjusted for subsequent changes in equity structures (e.g., stock splits, mergers and acquisitions, etc.), and this adjusted figure then becomes the default EPS. We ignored the effect of accounting method changes because they were relatively infrequent in the period.

Stock price (P) is the official closing price in local currency adjusted to declared dividends, in nominal terms (not adjusted for inflation). The stock prices are adjusted for subsequent stock splits and stock dividends, and this adjusted figure then becomes the default price. The stock return (RET) was calculated on a quarterly basis by continuous capitalization as follows:

$$RET = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t is the price adjusted to dividends at the end of period t.

The quarterly returns are accumulated into quarters considering the period of March-May; June-August; September-November and December-February, for the first, second, third and fourth quarters, respectively. Hence, any return reaction associated with the announcement of earnings for quarter *t* can be captured.

Code	Company's name	Economic Sector	Size (by market capitalization)	Size (by total assets)	Classification by total assets
ALLL11	All - America Latina Logistica S.A.	Transport	6.576.122	11.471.285	MEDIUM
AMBV4	Companhia de Bebidas Das Americas-Ambev	Food and Beverage	61.414.391	41.670.570	LARGE
ARCZ6	Aracruz Celulose Sa	Pulp and Paper	7.364.437	11.579.944	MEDIUM
BBAS3	Banco do Brasil S.A.	Finance and Assurance	43.305.820	591.925.233	LARGE
BBDC4	Banco Bradesco S.A.	Finance and Assurance	65.154.338	482.140.944	LARGE
BRAP4	Bradespar S.A.	Other	7.579.546	6.663.581	MEDIUM
BRKM5	Braskem S.A.	Chemical	2.382.045	22.409.372	LARGE
BRSR6	Banco do Estado do Rio Grande do Sul S/A	Finance and Assurance	2.953.086	26.501.518	LARGE
BRTO4	Brasil Telecom S.A.	Telecomunication	18.659.355	17.709.094	MEDIUM
BRTP3	Brasil Telecom Participacoes S.A.	Telecomunication	11.986.102	19.506.681	LARGE
CCRO3	Companhia de Concessoes Rodoviarias	Transport	8.404.673	6.677.860	MEDIUM
CESP6	Cesp - Companhia Energetica de Sao Paulo	Energy	4.104.929	17.018.719	MEDIUM
CGAS5	Companhia de Gas de Sao Paulo - Comgas	Petrol	3.311.661	3.891.502	SMALL
CLSC6	Centrais Eletricas de Santa Catarina S.A.	Energy	1.466.804	4.450.261	SMALL
CMIG4	Cia Energ Minas Gerais - Cemig	Energy	15.264.095	25.126.887	LARGE
CNFB4	Confab Industrial Sa	Steelworks	1.430.776	2.077.382	SMALL
CPFE3	CPFL Energia S.A.	Energy	15.117.195	16.483.490	MEDIUM
CPLE6	Cia. Paranaense de Energia - Copel	Energy	6.087.486	13.188.444	MEDIUM
CRUZ3	Souza Cruz S.A.	Other	13.373.938	3.471.983	SMALL
CSMG3	Cia. de Saneamento de Minas Gerais	Other	2.229.824	6.531.736	MEDIUM
CSNA3	Companhia Siderurgica Nacional	Steelworks	26.098.248	31.735.764	LARGE
CYRE3	Cyrela Brazil Realty Sa Emprs e Parts	Civil building	3.265.794	7.766.726	MEDIUM
DASA3	Diagnosticos da America S.A.	Other	1.423.594	1.844.030	SMALL
DURA4	Duratex Sa	Other	1.776.711	3.239.646	SMALL
ELET3	Centrais Elet Brasileiras Sa	Energy	29.160.413	137.281.991	LARGE
ELPL6	Eletropaulo Metropolitana El.S.Paulo S.A.	Energy	4.976.986	12.327.025	MEDIUM
EMBR3	Embraer - Emp Brasileira Aeronautica Sa.	Vehicles and parts	5.622.877	20.502.468	LARGE
ETER3	Eternit S. A.	Mining	418.690	417.127	SMALL
FFTL4	Fertilizantes Fosfatados S.AFosfertil	Chemical	5.740.738	3.502.645	SMALL
GETI4	AES Tiete S.A.	Energy	6.382.268	2.489.395	SMALL
GFSA3	Gafisa S/A	Civil building	1.514.069	5.725.838	SMALL
GGBR4	Gerdau S.A.	Steelworks	17.012.558	56.104.181	LARGE
GOAU4	Metalurgica Gerdau S.A.	Steelworks	6.400.661	57.070.075	LARGE
GOLL4	Gol Linhas	Transport	1.334.835	6.629.555	MEDIUM
IDNT3	Ideiasnet S/A	Other	191.824	392.826	SMALL
ITSA4	Itausa - Investimentos Itau S.A.	Other	33.962.367	625.646.394	LARGE
ITUB4	Banco Itau Holding Financeira S.A.	Finance and Assurance	96.576.644	618.943.348	LARGE
KEPL3	Kepler Weber Sa	Steelworks	182.168	382.344	SMALL
KLBN4	Klabin S.A.	Pulp and Paper	3.089.973	8.140.421	MEDIUM
LAME4	Lojas Americanas S.A.	Comerce	4.510.032	6.011.012	SMALL
LIGT3	Light S.A.	Energy	4.523.251	9.530.895	MEDIUM
LREN3	Lojas Renner Sa	Comerce	1.732.957	1.382.198	SMALL
NATU3	Natura Cosmeticos S/A	Comerce	9.724.551	2.182.045	SMALL
NETC4	Net Servicos de Comunicacao S.A.	Other	5.861.255	6.003.998	SMALL
PCAR5	Companhia Brasileira de Distribuicao	Comerce	7.288.513	13.370.249	MEDIUM
PETR4	Petroleo Brasileiro	Petrol	285.150.830	304.426.305	LARGE
PLAS3	Plascar Participacoes Industriais S.A.	Vehicles and parts	153.116	635.031	SMALL
POMO4	Marcopolo Sa	Vehicles and parts	739.819	2.234.676	SMALL
PRGA3	Perdigao S.A.	Food and Beverage	5.937.669	10.892.799	MEDIUM
PSSA3	Porto Seguro S.A.	Finance and Assurance	2.731.547	8.112.729	MEDIUM
RAPT4	Randon S/A Implementos e Participacoes	Vehicles and parts	829.809	2.219.766	SMALL
RSID3	Rossi Residencial S/A	Civil building	705.494	2.976.516	SMALL
SBSP3	Cia Saneamento Basico Estado Sao Paulo	Other	5.878.169	20.762.026	LARGE
SDIA4	Sadia S.A.	Food and Beverage	2.521.792	11.377.790	MEDIUM
SUZB5	Suzano Papel e Celulose S.A.	Pulp and Paper	3.218.418	12.874.096	MEDIUM
TAMM4	Tam S.A.	Transport	1.976.091	13.001.190	MEDIUM
TBLE3	Tractebel Energia S.A.	Energy	11.227.166	8.459.349	MEDIUM
TCSL4	Tim Participacoes S.A.	Telecomunication	9.176.697	14.260.713	MEDIUM
TELB4	Telecom Brasileiras Sa	Telecomunication	393.745	428.645	SMALL
TLPP4	Telecomunicacoes de Sao Paulo S/A-Telesp	Telecomunication	22.708.935	19.822.300	LARGE
TMAR5	Telemar Norte Leste S/A	Telecomunication	13.078.108	56.301.593	LARGE
TMCP4	Telemig Celular Participacoes S.A.	Telecomunication	1.549.811	2.629.521	SMALL
TNLP4	Tele Norte Leste Participações S/A	Telecomunication	13.125.868	56.855.714	LARGE
TRPL4	Cteep-Cia Transm Energia Eletr. Paulista	Energy	7.454.317	5.820.284	SMALL
UGPA4	Ultrapar Participacoes S.A.	Chemical	7.449.528	10.080.489	MEDIUM
UNIP6	Unipar- Uniao de Inds. Petroquimicas S/A	Chemical	603.583	11.835.488	MEDIUM
USIM5	Usinas Siderurgicas de Minas Gerais S.A.	Steelworks	13.807.087	26.939.066	LARGE
VALE5	Cia Vale do Rio Doce	Mining	152.961.526	187.954.278	LARGE
VCPA4	Votorantim Celulose e Papel Sa	Pulp and Paper	2.174.699	29.398.254	LARGE
VIVO4	Vivo Participacoes S/A	Telecomunication	11.245.033	22.434.252	LARGE
	Weg Sa	Industrial Machines	7.213.880	5.589.565	SMALL

Table 1. Sample Descriptions

Note: Size is presented in thousands of local currency (Brazilian Reais).

Regarding return measures, Collins and Kothari (1989) suggested that in earnings-returns studies, the appropriate return metric is given by abnormal return, expressed as $R_{ii} - E_{t-1}(R_{ii})$. However, they also used nominal return including dividends (R_{ii}) for three reasons: (1) $E_{t-1}(R_{ii})$ is an *ex ante* measure of expected return, but *ex ante* measures of riskless rates and risk premiums are not readily available. Most studies use an *ex post* measure of $E_{t-1}(R_{ii})$ conditional on the realized market return for period *t*, which introduces error into the return metric. (2) Regarding the temporal and cross-sectional variability in R_{ii} , the variability in $E_{t-1}(R_{ii})$ is small. Hence, the use of $R_{ii} - E_{t-1}(R_{ii})$ essentially amounts to using R_{ii} . (3). Beaver, Lambert and Morse (1980) and Beaver, Lambert, and Ryan (1987) reported that the earnings-returns relation is essentially the same whether one uses R_{ii} , inclusive or exclusive of dividends or market model prediction errors.

Foster (1977) used a similar number of time-series observations, varying from 18 to 50 observations. Regarding the sample size in Box-Jenkins analysis, he stated in the absence of structural change, the more observations one has the greater is one's ability to identify the underlying model. However, a key issue when using finite samples is the small sample properties of the estimators of B-J models. The statistical literature has not examined this issue extensively for many specific B-J models. The A.R.(1) and M.A.(I) models have been examined in most detail. Nelson [1974], for instance, examined via simulation the identification and estimation of M.A.(1) models with sample sizes of 30 and 100. His results suggest that the problem of identifying M.A'(1) models with θ_1 in the .1 to .5 range are much more severe with severe with samples of 30 than with samples of 100 observations. Nelson's result relate to nonseasonal models. There is even less evidence on the small sample properties of the estimators of seasonal Box-Jenkins models.

Brown and Kennelly (1972) also used a relatively small sample of quarterly earnings from 94 companies during the period from 1958 to 1967.

Time-series models are usually non-theoretical, implying that their construction and usage is not based on any underlying theoretical model of the behaviour of a variable. Instead, time-series models are an attempt to capture empirically relevant features of the observed data that may have arisen from a variety of different (but unspecified) structural models (Brooks, 2008 p. 206).

The following section presents the empirical research developed to verify the stationary behaviour of the variables, the autoregressive characteristics of the time-series, cointegration between earnings and price for the non-stationary variables and the Granger causality between earnings and price and their variations.

4. Statistical Testing and Analysis

4.1. Firm-specific and Box-Jenkins Identified Earnings Models

According to Collins and Kothari (1989), earnings persistence is typically measured by estimating an ARIMA time-series earnings process. If earnings follow an IMA(I,1) process, earnings expectations for all future periods will be revised by $(1-\theta)a_t$, where $a_t = X_t - E_{t-1}(X)$ and θ is the moving average process parameter.

Thus, revisions in earnings expectations are an increasing function of $(1 - \theta)$, the persistence of an IMA(I, 1) process. Because dividends are assumed to be expressed as a positive fraction of earnings, greater persistence will lead to larger revisions in dividend expectations and the earnings response coefficient will thus be larger.

To analyze the time-series behaviour of accounting earnings, Table 3 presents the individual autocorrelation of the EPS up to a lag of 12 periods. By analysing the autocorrelation, it is possible to make inferences about the dependence of a specific EPS observation and its previous values. In this context, this analysis can provide some evidence of seasonal behaviour. Seasonal differences involve four periods (quarters) per seasonal cycle. If the time series process implicit in Fosters' (1977) Model 1 ($E(Q_t) = Q_{t-4}$) or Model 3 ($E(Q_t) = Q_{t-1}$) are valid in Brazil, autocorrelations would be significant in four and one lag, respectively.

Autocorrelation is a correlation coefficient. However, instead of the correlation between two different variables, this correlation is between two values of the same variable at times X_i and X_{i+k-} , where k is an integer that defines the lag for the autocorrelation. Thus, autocorrelation is the tendency for observations made at adjacent time points to be related to one another in the past. In that sense, past values decreasingly influence future values since the strength of the correlation diminishes as the separation in time increases.

Table 2 reports the autocorrelations for individual companies. It can be seen, besides other things, that some companies have autocorrelations higher than 0.9 in the first lag (CPFE3, RAPT4 and WEGE3), suggesting that earnings cannot be formed in a random processes. In other words, the value of the current point is highly dependent on the previous point.

Additionally, for some companies (BRKM5, CSMG3, DASA3, ELET3 and TELB4), negative autocorrelations can be found in the first lags. This evidence is puzzling and demands detailed analysis. A negative autocorrelation changes the direction of the influence. It means that, if a particular value is above average, the next value (or for that matter the previous one) is more likely to be below average. If a particular value is below average, the next value is likely to be above average. In practical terms, current earnings vary negatively according to the previous earnings. This negative autocorrelation can be explained by strong seasonal components of earnings or even by randomness of earnings generation.

E:	Lags												
Firm	1	2	3	4	5	6	7	8	9	10	11	12	
ALLL11	0.226	-0.145	0.047	0.314	0.077	-0.253	0.050	0.318	0.101	-0.113	0.012	0.170	
AMBV4	0.493	0.386	0.421	0.427	0.366	0.236	0.240	0.261	0.241	0.055	0.083	0.137	
ARCZ6	0.416	0.007	0.023	0.006	-0.020	-0.029	-0.026	-0.031	-0.032	-0.037	-0.048	-0.028	
BBAS3 BBDC4	0.639 0.836	0.489 0.813	0.474 0.714	0.368 0.693	0.148 0.608	0.055 0.551	0.050 0.503	0.050 0.453	0.040 0.415	0.041 0.356	0.031 0.342	0.023 0.284	
BRAP4	0.093	-0.166	0.273	0.187	0.008	0.025	0.085	0.435	-0.025	-0.008	0.0542	-0.048	
BRKM5	-0.016	-0.040	-0.065	-0.102	0.033	-0.033	0.105	-0.035	-0.120	-0.048	-0.097	-0.020	
BRSR6	0.247	-0.024	-0.009	0.015	0.010	0.000	-0.036	-0.028	-0.031	-0.041	-0.014	-0.004	
BRTO4	0.389	0.264	0.080	-0.024	-0.004	-0.006	-0.022	-0.087	-0.187	-0.201	-0.204	-0.352	
BRTP3	0.384	0.246	0.116	-0.007	0.003	0.017	0.015	-0.012	-0.225	-0.223	-0.139	-0.399	
CCRO3 CESP6	0.105 0.138	0.089 -0.212	0.390 -0.207	-0.046 0.113	0.104 0.071	0.061 0.088	0.009	0.172 0.095	0.100 -0.110	-0.009 -0.164	0.100 -0.162	0.148 0.025	
CGAS5	0.855	0.801	0.775	0.744	0.662	0.628	0.593	0.526	0.477	0.441	0.382	0.290	
CLSC6	0.298	0.168	0.076	0.011	0.177	0.157	0.087	0.077	0.147	0.101	0.031	-0.038	
CMIG4	0.475	0.208	0.379	0.342	0.314	0.323	0.283	0.266	0.180	0.134	0.022	0.114	
CNFB4	0.657	0.410	0.292	0.283	0.147	0.065	0.048	0.085	0.079	0.124	0.165	0.238	
CPFE3 CPLE6	0.919 0.506	0.869 0.338	0.773 0.285	0.703 0.312	0.610 0.375	0.522 0.358	0.424 0.171	0.305 0.181	0.182 0.144	0.069 0.027	-0.007 0.014	-0.092 0.017	
CRUZ3	0.500	0.358	0.285	0.312	0.259	0.338	0.171	0.131	0.144	0.108	0.014	0.098	
CSMG3	-0.137	0.147	0.092	-0.105	0.018	-0.243	0.074	-0.134	-0.278	0.092	-0.040	0.099	
CSNA3	0.115	0.282	0.301	0.175	0.141	0.202	0.161	0.038	0.113	0.088	0.078	0.104	
CYRE3	0.514	0.556	0.525	0.521	0.371	0.205	0.323	0.245	0.213	0.087	0.099	0.076	
DASA3	-0.032	-0.040	-0.053	0.088	-0.168	-0.119 0.492	-0.112	0.296	-0.292	0.042	-0.047	-0.017	
DURA4 ELET3	0.835 -0.074	0.781 0.025	0.708 -0.143	0.632 0.000	0.529 -0.066	-0.029	0.433 -0.014	0.395 0.021	0.317	0.254 -0.027	0.217 -0.083	0.182 0.110	
ELPL6	0.266	0.169	-0.145	-0.032	0.101	0.133	0.054	0.067	0.052	-0.059	-0.035	-0.163	
EMBR3	0.616	0.449	0.439	0.424	0.330	0.299	0.271	0.276	0.189	0.127	0.087	0.170	
ETER3	0.441	0.339	0.239	0.247	0.077	0.125	0.042	0.037	-0.011	-0.099	-0.107	-0.135	
FFTL4	0.670	0.331	0.394	0.438	0.231	0.099	0.169	0.218	0.059	0.025	0.202	0.246	
GETI4 GFSA3	0.663 0.281	0.522 0.214	0.485 0.132	0.451 0.093	0.467 0.111	0.466 -0.069	0.452 0.068	0.262 -0.126	0.247 -0.163	0.194 -0.104	0.152 0.080	0.213 -0.166	
GGBR4	0.281	0.214	0.132	0.616	0.588	0.537	0.008	0.482	0.397	0.332	0.080	0.258	
GOAU4	0.834	0.647	0.619	0.629	0.597	0.550	0.525	0.484	0.412	0.334	0.287	0.239	
GOLL4	0.702	0.388	0.233	0.086	-0.056	-0.124	-0.155	-0.246	-0.194	-0.151	-0.197	-0.156	
IDNT3	0.201	0.284	0.061	0.165	0.085	0.066	-0.007	-0.096	-0.024	0.006	-0.021	0.008	
ITSA4 ITUB4	0.372 0.224	0.307 0.195	0.229 0.183	0.263 0.174	0.267 0.202	0.239 0.166	0.263 0.148	0.279 0.134	0.391 0.121	0.174 0.112	0.118 0.139	0.057 0.088	
KEPL3	0.224	0.193	0.185	0.174	-0.012	-0.133	-0.047	-0.087	-0.026	-0.093	0.139	-0.101	
KLBN4	0.009	0.156	-0.211	0.041	0.062	0.148	-0.054	0.041	-0.017	-0.058	0.038	0.040	
LAME4	0.059	0.079	-0.016	0.350	0.088	0.114	0.029	0.182	0.022	0.150	0.002	0.121	
LIGT3	0.577	0.342	0.279	0.263	0.231	0.168	0.208	0.291	0.143	-0.067	-0.188	-0.234	
LREN3	0.096	0.370	-0.131	0.436	0.049	0.344	0.007	0.280	-0.148 -0.156	0.178	-0.091	0.164	
NATU3 NETC4	0.257 0.665	0.277 0.568	0.112 0.513	0.398 0.393	-0.070 0.380	-0.042 0.331	-0.091 0.315	0.203 0.285	0.155	-0.018 0.188	0.000 0.152	0.056 0.135	
PCAR5	0.248	0.007	-0.053	0.190	-0.128	-0.152	-0.254	-0.076	-0.113	-0.018	-0.105	0.126	
PETR4	0.870	0.784	0.671	0.622	0.587	0.557	0.520	0.512	0.522	0.489	0.468	0.394	
PLAS3	0.494	0.434	0.441	0.375	0.287	0.149	0.158	0.114	0.004	-0.080	-0.070	0.045	
POMO4	0.615	0.336	0.300	0.449	0.458	0.398	0.294	0.333	0.265	0.207	0.185	0.256	
PRGA3 PSSA3	0.454 0.640	0.291 0.661	0.085 0.619	0.163 0.535	-0.027 0.437	0.033 0.417	0.030 0.348	0.129 0.245	-0.009 0.205	0.148 0.089	0.152 0.119	0.135 0.033	
RAPT4	0.913	0.855	0.757	0.712	0.635	0.587	0.548	0.478	0.434	0.408	0.382	0.360	
RSID3	0.453	0.261	-0.047	-0.066	-0.013	-0.014	0.098	0.003	0.012	0.063	0.151	0.128	
SBSP3	0.181	-0.019	-0.096		0.053	0.132	0.109	0.215	0.037	0.072	-0.119	0.033	
SDIA4	0.476	0.025	-0.076		-0.049	-0.014	-0.030	-0.044	0.015	0.029	-0.018	-0.075	
SUZB5 TAMM4	0.330 0.118	0.043 0.031	0.096 -0.042		0.028 0.025	0.026 0.068	0.057 -0.040	0.106 -0.092	0.084 -0.086	0.072 -0.056	0.071 -0.034	0.061 -0.055	
TBLE3	0.118	0.031	0.183	0.003	0.023	0.008	0.250	0.248	0.145	0.180	0.132	0.135	
TCSL4	0.306	0.231	0.232		0.095	-0.115	-0.168	0.051	-0.154	-0.256	-0.132	-0.137	
TELB4	-0.072	-0.010	-0.015	-0.040	-0.015	-0.007	0.037	-0.032	-0.027	-0.011	-0.074	-0.009	
TLPP4	0.656	0.567	0.510	0.606	0.436	0.366	0.378	0.428	0.270	0.245	0.205	0.355	
TMAR5	0.402	0.232	0.303	0.196	0.047	0.113	0.093	0.090	0.094	0.041	0.138	0.145	
TMCP4 TNLP4	0.169 0.407	0.191 0.410	0.222 0.230	0.222 0.332	0.187 0.083	0.196 0.013	0.073 0.097	0.077 0.100	0.093	0.203 0.110	0.091 0.126	-0.037 0.187	
TRPL4	0.407	0.410	0.230	0.332	0.083	0.165	0.097	0.100	0.038	0.110	0.120	0.132	
UGPA4	0.509	0.256	0.206	0.086	0.170	0.242	0.248	0.168	-0.035	-0.238	-0.192	-0.206	
UNIP6	0.525	0.340	0.143	-0.005	0.042	0.011	-0.002	0.022	0.011	0.039	0.005	-0.007	
USIM5	0.661	0.608	0.540		0.487	0.460	0.413	0.389	0.254	0.253	0.233	0.293	
VALE5 VCPA4	0.619 0.567	0.546	0.565 0.093	0.539 0.030	0.556 -0.005	0.469 0.011	0.390 0.018	0.382 0.031	0.312 0.022	0.232 0.008	0.214 0.035	0.195 0.074	
VCPA4 VIVO4	0.567	0.157 0.625	0.093	0.030	-0.005	0.011	-0.021	-0.054	-0.022	-0.141	-0.179	-0.198	
WEGE3	0.485	0.890	0.287		0.734	0.684	0.632	0.575	0.520	0.472	0.421	0.377	
Noto: Quarta													

Table 2. Earnings Time-series Properties: Autocorrelations by Firm

Note: Quarterly time-series autocorrelation in earnings per share (EPS) variable for each company in the sample.

Table 3 summarizes the findings presented in Table 2 by presenting the pooled autocorrelations in mean terms. Additionally, Table 3 reports polled autocorrelation according to the relative firm size classification presented in Table 1.

Firm	Lags												
FILI	1	2	3	4	5	6	7	8	9	10	11	12	
Cross-sectional sample Autocorrelation (ALL FIRMS)													
MEAN	0.426	0.322	0.255	0.269	0.202	0.170	0.151	0.160	0.082	0.071	0.058	0.066	
MAXIMUM	0.927	0.890	0.847	0.795	0.734	0.684	0.632	0.575	0.522	0.489	0.468	0.394	
MINIMUM	-0.137	-0.212	-0.211	-0.105	-0.168	-0.253	-0.254	-0.246	-0.292	-0.256	-0.204	-0.399	
STD. DEVIATION	0.269	0.265	0.268	0.242	0.225	0.223	0.201	0.185	0.190	0.164	0.153	0.164	
				L	ARGE CO	MPANIE	S						
MEAN	0.470	0.369	0.320	0.320	0.256	0.229	0.219	0.207	0.151	0.118	0.099	0.115	
MAXIMUM	0.870	0.813	0.714	0.693	0.608	0.557	0.525	0.512	0.522	0.489	0.468	0.394	
MINIMUM	-0.074	-0.040	-0.143	-0.102	-0.066	-0.033	-0.036	-0.054	-0.225	-0.223	-0.179	-0.399	
STD. DEVIATION	0.267	0.257	0.254	0.243	0.231	0.211	0.191	0.192	0.200	0.169	0.165	0.174	
				MI	DIUM CC	MPANIE	2S						
MEAN	0.364	0.209	0.160	0.169	0.123	0.079	0.063	0.091	0.007	-0.025	-0.023	-0.020	
MAXIMUM	0.919	0.869	0.773	0.703	0.610	0.522	0.424	0.318	0.213	0.180	0.152	0.170	
MINIMUM	-0.137	-0.212	-0.211	-0.105	-0.128	-0.253	-0.254	-0.246	-0.278	-0.256	-0.204	-0.352	
STD. DEVIATION	0.241	0.257	0.246	0.217	0.180	0.197	0.169	0.154	0.135	0.117	0.112	0.136	
				SN	AALL CO	MPANIE	s						
MEAN	0.448	0.390	0.289	0.320	0.230	0.205	0.174	0.185	0.091	0.123	0.099	0.106	
MAXIMUM	0.927	0.890	0.847	0.795	0.734	0.684	0.632	0.575	0.520	0.472	0.421	0.377	
MINIMUM	-0.072	-0.040	-0.131	-0.066	-0.168	-0.133	-0.112	-0.126	-0.292	-0.104	-0.107	-0.166	
STD. DEVIATION	0.295	0.252	0.285	0.242	0.245	0.238	0.216	0.193	0.206	0.163	0.150	0.150	

Table 3. Earnings Time-series Properties: Autocorrelations Cross-sectional Sample

Note: Quarterly time-series autocorrelation in earnings per share (EPS) variable. All Firms includes the 71 cross-sectional companies. Large, Medium and Small companies are classified according to total assets in December 2008.

As expected, Table 3 shows that the levels of quarterly earnings are highly correlated over time ($r_1 = 0.426$ for the general mean). Evidence of high autocorrelations suggests non-stationary behaviour, while low autocorrelations suggest a stationary condition in level. An important point to mention is that with the application of Foster's model, strong evidence of seasonality in quarterly earnings in fourth and eighth lags for the cross-sectional sample ($r_4 = 0,269$ and $r_8 = 0,160$) was found. This seasonality suggests that Foster's models 3 and 4 may be misspecified for many firms.

Table 3 also reports some insights regarding earnings persistence and seasonality when controlled by size. The first point is that medium companies have significant lower autocorrelation then large and small companies. However, the mean difference is not significant when small and large companies are compared. The second point is that large firms seem to present lower seasonal changes then medium and small companies (see mean correlation changes from third and fourth lags). On the other hand, relatively small companies present higher seasonal changes in earnings, since the fourth and eighth lags' autocorrelation values increase significantly more than those of medium and large firms.

Figures 1 and 2 show the mean autocorrelation and the mean partial autocorrelation, respectively, for each of the 12 period lags.

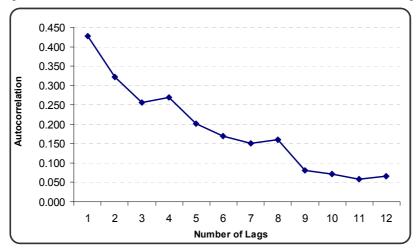


Figure 1. Cross-sectional Sample Autocorrelation for 1 to 12 Lags

Figure 1 clearly shows the two high points in lags four and eight. The seasonal behaviour tendency of accounting earnings in Brazil is evident. Furthermore, in the 12th lag there is a small increase in autocorrelation. It is important to clarify that this is a cross-sectional sample, and undoubtedly seasonality is higher for some companies than others.

Figure 2. Cross-sectional Sample Partial Autocorrelation for 1 to 12 Lags

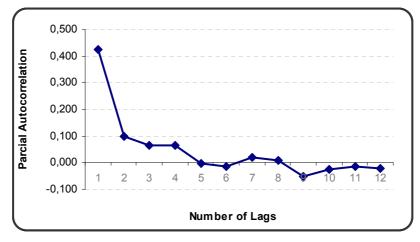


Figure 2 shows that the first lag presents a high partial autocorrelation value that decreases abruptly in the second lag, which suggests once again the usage of an autoregressive model (AR). It can also be seen that the fourth lag presents a small increase in comparison to the third lag. In the ninth lag another sudden decrease occurs, after which the behaviour is stable.

4.2. Test for Stationary Behaviour

A stationary series can be defined as one with a constant mean, constant covariance and constant autocovariance for each given lag. Given the nature of quarterly earnings and their tendency to grow or undergo cyclic behaviour, they are not expected to follow a stationary process. According to Brooks (2008), there are several reasons why the concept of non-stationarity is important and why it is essential

that variables that are non-stationary be treated differently from those that are stationary. Among these reasons are: (i) whether or not a series is stationary can strongly influence its behaviour and properties; and (ii) the use of non-stationary data can lead to spurious regressions and if the variables employed in a regression model are not stationary, so it can be proved that the standard assumptions of asymptotic analysis will not be valid.

To test for stationary conditions, we used the augmented Dickey-Fuller (ADF) unit root test, applied to the accounting earnings and stock prices. The augmented Dickey-Fuller (ADF) test consists of identifying any unit root. This can be done by estimating the following regression:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^p \alpha_i \Delta y_{t-i} + u_t$$
⁽²⁾

where u_t is a pure white noise error term, p is the number of lags of the dependent variable and where $\Delta y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc. The number of lagged difference terms to include is often determined empirically. The idea is to include enough terms so that the error term is serially uncorrelated. The ADF test for the null hypothesis of non-stationarity in level verifies whether $\psi = 0$ and if the ADF test follows the same asymptotic distribution as the DF statistic, then the same critical values can be used. Although several ways of choosing the number of lags (p) have been proposed, they are all somewhat arbitrary. Brooks (2008, p.329) suggested a rule to define the numbers of lags (p) according to the frequency of the data. For instance, "if the data are monthly, use 12 lags, if the data are quarterly, use 4 lags, and so on."

To define whether or not to include intercepts and trends in the unit root test equations, a graphical analysis can be conducted. Figure 3 shows four graphs reporting the time-series behaviour of EPS values of some companies from different economic sectors. It can be seen that in all the companies analyzed, there is increasing trend behaviour in quarterly EPS. This evidence suggests the use of a trend in the unit root test regressions.

We also performed this graphical analysis for the remaining variables and, as expected, only the variables EPS and price can be assumed to have an increasing trend. Given that SEPS and returns are "first differencing" of EPS and price, these variables do not seem to have any trend. Considering this, we used the trend and intercept to verify all the companies' EPS and price series and tested the remaining variables by using only the intercept in the unit root equations. Additionally, we also ran tests by simulating regressions with and without trend, obtaining similar results.

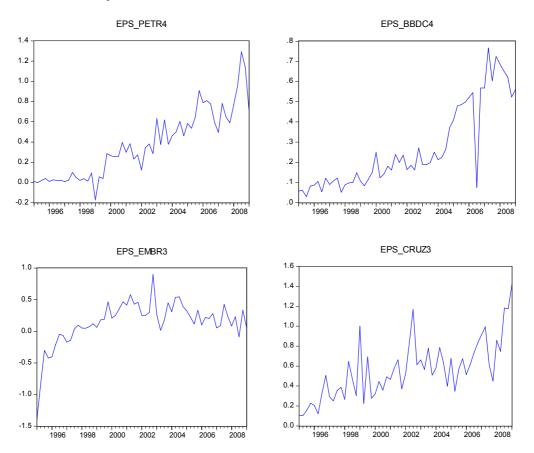




Table 4 shows the augmented Dickey-Fuller unit root test results for the quarterly variables of each firm. The quarterly firm-observations contain a maximum of 56 observations and a minimal of 11 observations.

As expected, the results of the unit root test presented in Table 4 show that, in general, EPSVAR and RET do not have a unit root in level, since the null hypothesis of a unit root was rejected at the 5% level. Hence, it is possible to assume that, except for two cases, these variables are I(0), meaning they are stationary in level.

On the other hand, it is not possible to reject the null hypothesis of a unit root for the variables EPS and P. In these cases, the variables have a unit root in level, which suggests that the variables are I(1) or, non-stationary in level. However, these variables present firm-observations that are considered stationary. This means that for some companies the variables are stationary and must be treated as statistically different.

				-	EPS (EPS		-			-		
Series		per Share (Prob. 0	EPS) bs			by AR)		Price (P) Prob.	Obs		turn (RE1 Prob.) Dbs
ALLL11	-4,857	0,000	40	-7,588	0,000	37	-1,238	0,628	15	-2,816	0,217	13
AMBV4	-3,174	0,027	56	-8,981	0,000	54	-0,113	0,943	55	-6,379	0,000	55
ARCZ6	-1,531	0,511	54	-13,255	0,000	54	-1,270	0,637	55	-4,741	0,002	55
BBAS3	-5,508	0,000	54	-11,081	0,000	54	-0,803	0,810	55	-8,736	0,000	55
BBDC4	-0,988	0,752	55	-12,695	0,000	55	-3,623	0,009	46	-6,809	0,000	55
BRAP4	-2,848	0,066	26	-6,870	0,000	26	-1,176	0,671	29	-5,395	0,001	33
BRKM5	-7,467	0,000	56	-8,619	0,000	54	-1,911	0,325	52	-5,040	0,001	55
BRSR6	-2,831	0,061	50	-4,909	0,000	49	-1,900	0,330	55	-8,826	0,000	55
BRTO4	-4,716	0,000	56	-10,502	0,000	55	-1,384	0,584	55	-6,727	0,000	55
BRTP3	-4,131	0,002	44	-9,223	0,000	43	0,913	0,995	40	-6,258	0,000	40
CCRO3	-5,085	0,000	33	-9,208	0,000	31	-0,941	0,759	27	-4,607	0,005	27
CESP6	-6,392	0,000	56	-8,416	0,000	53	-2,479	0,126	53	-7,266	0,000	55
CGAS5	0,337 -5,391	0,978 0,000	49 56	-7,235 -11,243	0,000	49 55	-0,216 -0,741	0,929 0,828	45 55	-6,022	0,000	45 55
CLSC6 CMIG4	-4,389	0,000	56	-10,081	0,000 0,000	55 54	0,970	0,828	53	-7,031 -8,263	0,000 0,000	55 55
CNFB4	-3,229	0,023	56	-8,733	0,000	55	-0,783	0,816	55	-6,931	0,000	55
CPFE3	-1,403	0,568	31	-2,998	0,000	31	-1,425	0,545	17	-4,342	0,016	17
CPLE6	-4,103	0,002	56	-6,517	0,000	52	-1,334	0,608	55	-7,295	0,000	55
CRUZ3	-1,550	0,501	55	-12,938	0,000	55	0,535	0,987	54	-7,112	0,000	55
CSMG3	-5,443	0,000	24	-6,597	0,000	22	-1,393	0,546	11	-4,449	0,029	10
CSNA3	-0,387	0,904	54	-9,910	0,000	54	3,225	1,000	45	-8,111	0,000	55
CYRE3	0,919	0,995	43	-4,345	0,001	43	-3,377	0,017	45	-6,348	0,000	48
DASA3	-3,966	0,007	20	-6,070	0,000	19	-1,696	0,415	16	-5,322	0,004	15
DURA4	-1,508	0,522	55	-10,620	0,000	55	-1,988	0,291	54	-7,471	0,000	55
ELET3	-7,906	0,000	56	-13,382	0,000	55	-2,320	0,169	55	-8,763	0,000	55
ELPL6	-4,912	0,000	44	-10,634	0,000	43	-1,205	0,664	43	-4,962	0,001	43
EMBR3	-5,506	0,000	56	-6,965	0,000	53	-1,447 4,534	0,553	55	-8,648	0,000	55
ETER3	-4,430 -1,187	0,001 0,674	56 54	-11,675	0,000	55 54	4,534	1,000 1,000	48 48	-6,805 -6,965	0,000	55 55
FFTL4 GETI4	-0,630	0,874	34	-11,298 -5,175	0,000 0,000	54 34	0,923	0,995	36	-8,905	0,000 0,000	37
GFSA3	-4,633	0,001	41	-9,394	0,000	40	-0,257	0,903	11	-4,709	0,000	11
GGBR4	-1,487	0,533	54	-9,270	0,000	54	-0,668	0,845	51	-6,760	0,000	55
GOAU4	-1,534	0,509	54	-8,397	0,000	54	-1,659	0,446	51	-6,017	0,000	55
GOLL4	-2,791	0,078	19	-2,942	0,060	18	-0,834	0,785	18	-5,758	0,001	18
IDNT3	-4,856	0,000	35	-10,580	0,000	34	-3,660	0,010	34	-5,155	0,001	34
ITSA4	1,857	1,000	48	-1,909	0,325	46	0,148	0,967	55	-7,533	0,000	55
ITUB4	1,131	0,997	55	-14,967	0,000	55	-0,005	0,954	55	-8,336	0,000	55
KEPL3	-4,501	0,001	56	-12,468	0,000	55	-1,468	0,532	24	-4,941	0,003	24
KLBN4	-7,282	0,000	56	-14,087	0,000	55	-0,937	0,769	55	-5,715	0,000	55
LAME4	-6,922	0,000	56	-9,342	0,000	53	-1,630	0,461	54	-5,843	0,000	55
LIGT3	-3,792	0,005	56	-9,125	0,000	55	-1,278	0,634	55	-6,366	0,000	55
LREN3 NATU3	-1,883 -0,323	0,338 0,902	53 17	-8,700 -7,202	0,000 0,000	53 17	-3,425 -2,118	0,016 0,241	39 18	-5,371 -4,562	0,000 0,010	44 18
NETC4	-3,067	0,902	51	-7,202	0,000	49	-2,118	0,241	31	-4,502	0,010	45
PCAR5	-5,667	0,000	56	-8,060	0,000	53	-2,229	0,199	52	-8,108	0,000	52
PETR4	-1,118	0,703	55	-9,890	0,000	55	0,792	0,993	45	-7,084	0,000	55
PLAS3	-4,294	0,001	56	-8,416	0,000	54	-9,491	0,000	51	-7,100	0,000	52
POMO4	-3,672	0,007	56	-8,376	0,000	53	5,571	1,000	45	-3,854	0,022	50
PRGA3	-2,302	0,175	56	-7,693	0,000	55	-0,316	0,915	55	-6,933	0,000	55
PSSA3	-1,698	0,425	44	-7,644	0,000	43	-1,396	0,558	16	-3,724	0,051	16
RAPT4	-1,510	0,521	56	-8,978	0,000	55	0,783	0,993	46	-6,269	0,000	55
RSID3	-4,193	0,002	48	-9,264	0,000	47	-1,950	0,307	41	-5,756	0,000	42
SBSP3	-5,880	0,000	52	-8,069	0,000	49	-1,259	0,641	48	-6,328	0,000	48
SDIA4	-8,447	0,000	55	-6,252	0,000	47	-1,254	0,645	55	-5,742	0,000	55
SUZB5	-5,204 -5,748	0,000 0,000	56 44	-8,523 -10,324	0,000	54 43	-2,949 -1,147	0,047 0,683	52 29	-5,328 -3,658	0,000	55
TAMM4 TBLE3	-5,748 -4,204	0,000	44	-10,324 -7,986	0,000 0,000	43 41	0,285	0,663	42	-3,658 -8,224	0,043 0,000	28 42
TCSL4	-4,520	0,002	44	-7,980	0,000	41	-2,270	0,186	41	-5,922	0,000	42
TELB4	-13,891	0,000	42	-8,746	0,000	40	-3,656	0,009	41	-6,640	0,000	40
TLPP4	-1,674	0,438	53	-8,835	0,000	53	-0,324	0,914	55	-8,262	0,000	54
TMAR5	-4,816	0,000	56	-8,743	0,000	54	-1,542	0,505	55	-7,342	0,000	55
TMCP4	-5,463	0,000	44	-5,908	0,000	40	-3,121	0,033	41	-6,103	0,000	41
TNLP4	-4,155	0,002	44	-11,080	0,000	43	-2,660	0,090	41	-7,860	0,000	41
TRPL4	-1,939	0,312	39	-8,243	0,000	38	3,225	1,000	32	-6,018	0,000	37
UGPA4	-3,856	0,005	40	-7,522	0,000	39	-0,658	0,845	36	-5,582	0,000	36
UNIP6	-3,370	0,016	56	-10,048	0,000	55	-1,315	0,617	55	-6,059	0,000	55
USIM5	-3,166	0,027	56	-10,394	0,000	55	0,093	0,962	45	-7,003	0,000	55
VALE5	2,174	1,000	52	-7,936	0,000	52	6,114	1,000	48	-6,372	0,000	55
	-1,870	0,344	54	-9,341	0,000	54 42	-1,772	0,390	54	-4,459	0,004	55 41
VIVO4 WEGE3	-1,995 -0 425	0,288	43 52	-14,165	0,000	43 52	-1,998	0,286	39 45	-6,478 -6 894	0,000	41 55
WEGE3	-0,425	0,897	52	-3,533	0,011	52	5,493	1,000	40	-6,894	0,000	55

Table 4. Augmented Dickey-Fuller Unit Root Test for the Quarterly Variables

4.3. Test for Cointegration: Accounting Earnings and Stock Prices

In most cases if two variables are I(1) (non-stationary), they are linearly combined. Therefore, the combination will also be I(1). If variables with differing orders of integration are combined, the combination will have an order of integration that is equal to the largest variable.

According to Engle and Granger (1987), if we let w_t be a $k \ge 1$ vector of variables, then the components of w_t are integrated of order (*d*,*b*) if:

(1) All components of w_t are I(d), and

(2) There is at least one vector of coefficients α such that $\alpha' w_t \sim I(d-b)$

According to Brooks (2008 p. 336), "in practice, many financial variables contain one unit root, and are thus I(1) [...]. In this context, a set of variables is defined as cointegrated if their linear combination is stationary." Many time series are nonstationary but 'move together' over time - that is, there is some influence on the series, which implies that the two series are bound by some relationship in the long run.

A cointegrating relationship may also be seen as a long-term or equilibrium phenomenon, since it is possible that cointegrating variables may deviate from their relationship in short run, but their association would return in the long run.

We applied the Johansen (1991; 1995) technique for testing and estimating cointegrating systems. There are two test statistics, the trace λ_{trace} and the maximum eigenvalue λ_{max} , for cointegration under the Johansen approach, which are formulated as

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{s} \ln(1 - \hat{\lambda}_i)$$
(3)

and

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$$
(4)

where *r* is the number of cointegration vectors under the null hypothesis, $\hat{\lambda}_i$ is the estimated value for the *t*th ordered eigenvalue from the Π matrix and *T* is the number of observations in the series. Intuitively, the larger $\hat{\lambda}_i$ is, the more negative will be $\ln(1-\hat{\lambda}_i)$ and hence the larger will be the test statistic. Each eigenvalue will be associated with a different cointegrating vector, which will be eingenvectors. A significantly non-zero eigenvalue indicates a significant cointegration vector (Brooks, 2008, p.351)

The trace test (λ_{trace}) is a joint test where the hypotheses tested are defined as follows:

Ho – The number of cointegrating vectors is less than or equal to *r*.

 H_1 – There are more than *r* cointegrating vectors.

The maximum eigenvalue test routine (λ_{max}) entails conducting separate tests on each eigenvalue, in which the hypotheses are defined as follows:

Ho – The number of cointegrating vectors is equal to *r*.

 H_1 – The number of cointegrating vectors is more than *r*+1.

We applied the cointegration test to all the companies for which both variables (earnings per share and stock prices) were non-stationary, in order to identify the long memory relationship between accounting earnings and stock prices in the Brazilian market. Table 5 shows the cointegration results for the companies.

COINTEGRATION TEST (*)												
		Trace Statistic (1)		Maximun Eigenvalue (1)				Trace Sta	tistic (1)	Maximun Eigenvalue (1)		
Company		r = 0	r < 1	r = 0	r<1	Company		r = 0	r<1	r = 0	r < 1	
ARCZ6	Statistic	61,278	1,427	59,850	1,427	ITUB4 (3)	Statistic	13,974	2,473	11,501	2,473	
	Prob.	0,000	0,232	0,000	0,232		Prob.	0,026	0,137	0,045	0,137	
BRAP4	Statistic	28,656	1,787	26,869	1,787	LREN3	Statistic	11,513	1,212	10,301	1,212	
	Prob.	0,000	0,181	0,000	0,181		Prob. (4)	0,182	0,271	0,193	0,271	
BRSR6	Statistic	22,076	1,701	20,376	1,701	NATU3 (2)	Statistic	20,227	3,354	16,873	3,354	
	Prob.	0,004	0,192	0,005	0,192		Prob.	0,028	0,067	0,055	0,067	
CGAS5 (2)	Statistic	28,187	5,106	23,081	5,106	PETR4 (2)	Statistic	23,565	3,873	19,692	3,873	
	Prob.	0,002	0,024	0,006	0,024		Prob.	0,009	0,049	0,021	0,049	
CPFE3	Statistic	15,594	5,531	10,063	5,531	PRGA3	Statistic	20,886	2,132	18,755	2,132	
	Prob.	0,048	0,019	0,208	0,019		Prob.	0,007	0,144	0,009	0,144	
CRUZ3	Statistic	16,172	2,317	13,855	2,317	PSSA3	Statistic	26,093	3,923	22,170	3,923	
	Prob.	0,040	0,128	0,058	0,128		Prob.	0,001	0,048	0,002	0,048	
CSNA3	Statistic	40,157	0,401	39,756	0,401	RAPT4	Statistic	11,121	1,321	9,800	1,321	
	Prob.	0,000	0,527	0,000	0,527		Prob. (4)	0,204	0,250	0,225	0,250	
DURA4	Statistic	21,876	2,336	19,539	2,336	TLPP4	Statistic	19,344	0,054	19,289	0,054	
	Prob.	0,005	0,126	0,007	0,126		Prob.	0,013	0,816	0,007	0,816	
FFTL4	Statistic	32,424	0,585	31,839	0,585	TRPL4	Statistic	21,747	1,837	19,910	1,837	
	Prob.	0,000	0,444	0,000	0,444		Prob.	0,005	0,175	0,006	0,175	
GETI4	Statistic	29,073	1,044	28,029	1,044	VALE5	Statistic	38,203	1,119	37,085	1,119	
	Prob.	0,000	0,307	0,000	0,307		Prob.	0,000	0,290	0,000	0,290	
GGBR4 (2)	Statistic	21,134	2,544	18,590	2,544	VCPA4	Statistic	48,048	3,341	44,706	3,341	
	Prob.	0,020	0,111	0,031	0,111		Prob.	0,000	0,068	0,000	0,068	
GOAU4 (2)	Statistic	18,522	2,151	16,372	2,151	VIVO4 (2)	Statistic	23,657	6,216	17,442	6,216	
	Prob.	0,048	0,143	0,065	0,143		Prob.	0,008	0,013	0,045	0,013	
GOLL4	Statistic	16,617	2,033	14,585	2,033	WEGE3 (2)	Statistic	30,013	5,453	24,560	5,453	
	Prob.	0,034	0,154	0,045	0,154		Prob.	0,001	0,020	0,004	0,020	
ITSA4	Statistic	17,357	0,882	16,475	0,882							
	Prob.	0,026	0,348	0,022	0,348							

Table 5. Cointegration Test for the Non-stationary Company Variables (Earnings Per Share and Stock Prices)

* Johansen Cointegration Test

(1) Considering Linear Deterministic Trend Assumption except when mentioned. Critical values: 15,495 and 14,265 for trace and maximum eigenvalue statistics respectively.

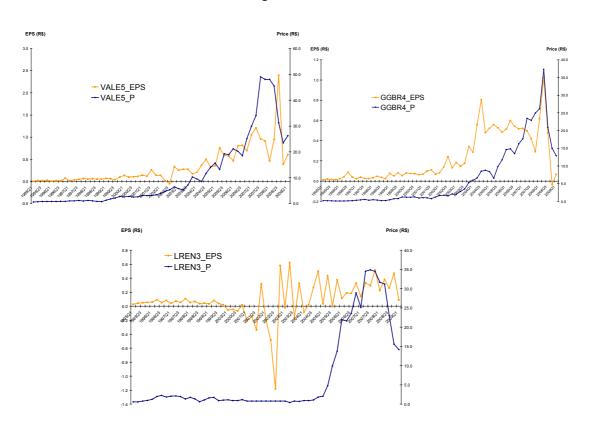
(2) Considering Quadratic Deterministic Trend Assumption. Critical values: 18,398 and 17,148 for trace and maximum eigenvalue statistics respectivel.y

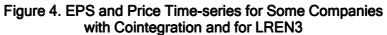
(3) Assumption of no deterministic trend.

(4) Cointegration vectors were not find at 0,05 or 0,10 significance level.

Similar to the findings of Galdi and Lopes (2008), Table 5 shows that almost every company presents at least one cointegration vector. The exceptions are LREN3 and RAPT4. This finding suggests there is a significant long-term relationship between quarterly earnings and stock prices in Brazil. It is possible to hypothesize that the absence of cointegration in the two companies can be explained by the high volatility in the accounting earnings, as seems to be the case of LREN3, and by the lack of market liquidity, especially in the case of RAPT4.

Figure 4 sheds some light on the evidence obtained in Table 5. The three charts present, as an illustration, the intertemporal behaviour of EPS and P for VALE5 and GGBR4, which present cointegration vectors, and for LREN3, which does not evidence a long-term relationship.





The illustration regarding LREN3 shows the high volatility in its accounting earnings. Since the company is a commercial firm, it seems to have non-constant EPS in the period. This evidence is corroborated by the extremely low autocorrelation presented in Table 2.

4.4. Test for Causality

According to Gujarati (2004), "although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. In other words, the existence of a relationship between variables does not prove causality or the direction of influence." This means that a correlation does not necessarily imply causation in any meaningful sense of the word.

Granger's (1969) approach to the question of whether *x* causes *y* is to see how much of the current *y* can be explained by past values of *y* and then to see whether adding lagged values can improve the explanation. *Y* is said to be Granger-caused by *x* if *x* helps in the prediction of *y*, or equivalently if the coefficients of the lagged *x*'s are

statistically significant. Two-way causation is frequently the case, such that x Granger causes y and y Granger causes x.

It should be noted that the statement "x Granger causes y" does not imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common sense of the term. The basic approach (for stationary variables) for the Granger causality test is based on running bivariate regressions of the following form:

$$y_{t} = \alpha_{0} + \alpha_{1}y_{t-1} + \dots + \alpha_{l}y_{t-l} + \beta_{1}x_{t-1} + \dots + \beta_{l}x_{t-l} + \varepsilon_{t}$$
(5)

$$x_{t} = \alpha_{0} + \alpha_{1}x_{t-1} + \dots + \alpha_{l}x_{t-l} + \beta_{1}y_{t-1} + \dots + y_{l}x_{t-l} + u_{t}$$
(6)

for all possible pairs of (x, y) in the group. The reported F-statistics are the Wald statistics for the joint hypothesis $\beta_1 = \beta_1 = ... = \beta_l = 0$, for each equation. The null hypothesis is that *x* does not Granger-cause *y* in the first regression and that *y* does not Granger-cause *x* in the second regression.

According to Gujarati (2004 p. 698), since the Granger causality test tests for the lagged relations between two variables, the variables must be assumed to be stationary. However, in the case of non-stationarity conditions but cointegration between the variables, the tests can also be used with a correction term, and in the case of non-stationarity and absence of cointegration, the test can be applied using the first difference of the variables. In this study, the first difference of EPS is the variation between *t* and *t*-1, already defined as EPSVAR, and the first difference of stock price can be expressed as the stock return.

Base on this consideration, we tested the causality between accounting earnings and stock returns using two different but complementary functional forms. The first analysis was of the Granger causation between price and earnings per share for the group of variables considered non-stationary but cointegrated. The second analysis was of the Granger causation for the variation of EPS and the stock returns for all companies, since stationary conditions were verified in both.

4.4.1. Accounting Earnings and Stock Price Causality

The Granger causality test applied in this analysis considers two lags. However, we also applied three and four lags randomly for some companies. The results were consistent for two, three and four lags. Table 6 shows the results of the Granger causality test, with correction term, between EPS and stock prices for those companies with cointegrated series, as presented in Table 5.

Of the 25 companies analyzed, nine presented bicausality (ARCZ6, CRUZ3, GETI4, ITSA4, ITUB4, TLPP4, TRPL4, VALE5 and VCPA4); seven presented causality in the market price to EPS direction; one presented causality in the EPS to market price direction (WEGE3) and seven did not show any causality in the variables with two lags (BRSR6, CPFE3, GGBR4, GOAU4, NATU3, PRGA3, and PSSA3). Based on these findings, there is no conclusive empirical evidence regarding the causality between the variables for all Brazilian companies.

However, the number of companies with Granger causality in the direction of price to earnings is greater than the number of companies with earnings-to-price relations. This suggests that the stock prices anticipate EPS values with two lags (or

two quarters). This is in accordance with the concept of accounting timeliness presented in Beaver, Lambert and Morse (1980). Additionally, Galdi and Lopes (2008) justified the non-robust conclusion regarding the lack of significant earnings-price relationship in Latin America by the different nature of the relation between priceearnings and return-earnings.

Pairwise Gra	nger C	ausality T	ests		Pairwise Granger Causality Tests					
Causality Direction	Obs	F- Statistic	Prob. (2)	TEST RESULT	Causality Direction	Obs	F- Statistic	Prob. (2)	TEST RESULT	
$\textbf{ARCZ6_LPA} \rightarrow \textbf{ARCZ6_P}$	54	5,745	0,006	Causa Granger***	$\textbf{ITSA4_LPA} \rightarrow \textbf{ITSA4_P}$	54	5,302	0,008	Causa Granger***	
$\textbf{ARCZ6}_\textbf{P} \rightarrow \textbf{ARCZ6}_\textbf{LPA}$		2,535	0,090	Causa Granger*	$\textbf{ITSA4_P} \rightarrow \textbf{ITSA4_LPA}$		7,321	0,002	Causa Granger***	
$BRAP4_LPA \to BRAP4_P$	32	0,329	0,722	No	$\text{ITUB4_LPA} \rightarrow \text{ITUB4_P}$	54	2,519	0,091	Causa Granger*	
$\textbf{BRAP4_P} \rightarrow \textbf{BRAP4_LPA}$		5,112	0,013	Causa Granger**	$\textbf{ITUB4_P} \rightarrow \textbf{ITUB4_LPA}$		2,700	0,077	Causa Granger*	
$BRSR6_LPA \to BRSR6_P$	52	0,115	0,892	No Causality	$NATU3_LPA \to NATU3_P$	17	0,324	0,729	No Causality	
$BRSR6_P \to BRSR6_LPA$		0,537	0,588	No Causality	$NATU3_P \to NATU3_LPA$		0,182	0,836	No Causality	
$CGAS5_LPA \to CGAS5_P$	44	1,951	0,156	No Causality	$PETR4_LPA \to PETR4_P$	54	1,211	0,307	No Causality	
$\textbf{CGAS5_P} \rightarrow \textbf{CGAS5_LPA}$		3,187	0,052	Causa Granger*	$\textbf{PETR4_P} \rightarrow \textbf{PETR4_LPA}$		5,091	0,010	Causa Granger***	
$CPFE3_LPA \to CPFE3_P$	16	1,942	0,190	No	$PRGA3_LPA \to PRGA3_P$	54	1,292	0,284	No Causality	
$CPFE3_P \to CPFE3_LPA$		0,297	0,749	No Causality	$PRGA3_P \to PRGA3_LPA$		1,182	0,315	No Causality	
$\textbf{CRUZ3_LPA} \rightarrow \textbf{CRUZ3_P}$	54	3,868	0,028	Causa Granger**	$PSSA3_LPA \to PSSA3_P$	15	1,665	0,238	No Causality	
$\textbf{CRUZ3_P} \rightarrow \textbf{CRUZ3_LPA}$		3,393	0,042	Causa Granger**	$PSSA3_P \to PSSA3_LPA$		0,195	0,826	No Causality	
$CSNA3_LPA \to CSNA3_P$	54	0,715	0,494	No Causality	$\textbf{TLPP4_LPA} \rightarrow \textbf{TLPP4_P}$	54	4,249	0,020	Causa Granger**	
$\textbf{CSNA3}_\textbf{P} \rightarrow \textbf{CSNA3}_\textbf{LPA}$		27,525	0,000	Causa Granger***	$\textbf{TLPP4_P} \rightarrow \textbf{TLPP4_LPA}$		5,593	0,007	Causa Granger***	
$DURA4_LPA \to DURA4_P$	54	0,537	0,588	No Causality	$\textbf{TRPL4_LPA} \rightarrow \textbf{TRPL4_P}$	36	2,895	0,070	Causa Granger*	
DURA4_P \rightarrow DURA4_LPA		7,545	0,001	Causa Granger***	$\textbf{TRPL4_P} \rightarrow \textbf{TRPL4_LPA}$		7,321	0,003	Causa Granger***	
$FFTL4_LPA \to FFTL4_P$	54	1,749	0,185	No Causality	$\textbf{VALE5_LPA} \rightarrow \textbf{VALE5_P}$	54	13,152	0,000	Causa Granger***	
$\textbf{FFTL4_P} \rightarrow \textbf{FFTL4_LPA}$		19,025	0,000	Causa Granger***	$\textbf{VALE5_P} \rightarrow \textbf{VALE5_LPA}$		21,689	0,000	Causa Granger***	
$\textbf{GETI4_LPA} \rightarrow \textbf{GETI4_P}$	36	3,037	0,062	Causa Granger*	$\textbf{VCPA4_LPA} \rightarrow \textbf{VCPA4_P}$	54	3,450	0,040	Causa Granger**	
$\textbf{GETI4_P} \rightarrow \textbf{GETI4_LPA}$		5,242	0,011	Causa Granger**	$\textbf{VCPA4_P} \rightarrow \textbf{VCPA4_LPA}$		8,789	0,001	Causa Granger***	
$GGBR4_LPA \rightarrow GGBR4_P$	54	0,333	0,719	No Causality	$VIVO4_LPA \to VIVO4_P$	40	0,818	0,449	No Causality	
$GGBR4_P \to GGBR4_LPA$		0,623	0,541	No Causality	$\textbf{VIVO4_P} \rightarrow \textbf{VIVO4_LPA}$		4,087	0,025	Causa Granger**	
$GOAU4_LPA \to GOAU4_P$	54	1,471	0,240	No Causality	$\textbf{WEGE3_LPA} \rightarrow \textbf{WEGE3_P}$	54	3,641	0,034	Causa Granger**	
$GOAU4_P \to GOAU4_LPA$		0,046	0,955	No Causality	$WEGE3_P \to WEGE3_LPA$		0,933	0,400	No Causality	
$GOLL4_LPA \rightarrow GOLL4_P$	17	1,477	0,267	No Causality						
$\textbf{GOLL4_P} \rightarrow \textbf{GOLL4_LPA}$		3,727	0,055	Causa Granger*						

Table 6. Pairwise Granger Causality Test for EPS and Stock Price (1)

(1) Results presented for two lags. Similar results were found for three and four lags.

(2) Null Hypothesis: first variable does not Granger Cause the second. *** Granger Causality significant at 0,01 level. ** Granger Causality significant at 0,05 level. *Granger Causality significant at 0,10 level.

Other information that can be extracted from the test is that in most cases the companies with Granger causation relations are those with the greatest market capitalization. This suggests that the bigger the company is in terms of market capitalization, the higher the ability to anticipate variations in accounting earnings (it is implicit that the bigger the company is, the greater the coverage by analysts is). However, the present study is not properly designed to provide a robust conclusion on that specific question. Future studies can explore the determinants of the earnings-return causality in Brazil.

4.4.2. Accounting Earnings Variation and Stock Returns Causality

The following analysis attempts to complement the empirical findings of Galdi and Lopes (2008), by analysing if a variation in accounting earnings significantly Granger-causes changes in stock returns or vice-versa, as we hypothesised.

Based on the 70 firms analyzed (the company ITSA4 was not analyzed since the EPS variation was not stationary), 5 companies showed bicausality between the variables (CNFB4, ELET3, GOAU4, IDNT3, TBLE3); 22 companies presented Granger causality in the return to EPS variation direction; 20 companies presented Granger causality in the EPS variation to return direction; and 23 companies did not present Granger causality in any direction.

The results of the Granger causality test show that it is not possible to generalize the results. The 23 companies that do not present Granger causality and the number of companies with different Granger causality direction is puzzling and can suggest that returns are defined by other variables rather than accounting information. Unlike from prices and EPS Granger causality, it is not possible to infer that variations in EPS are anticipated by abnormal returns (abnormal returns here means unexpected returns given an accounting earnings variation).

According to Collins and Kothari (1989), while their analysis suggests that the earnings-returns association is enhanced by including returns from an earlier time frame, the results do not identify exactly how far back one should go (in terms of lags). On this challenge, the authors add that "this is difficult to specify a priori and will vary as a function of the timing of valuation relevant economic events, the nature of a firm's information environment, and how quickly economic events are captured in the accounting earnings numbers."

Additionally, Ball and Shivakumar (2008) claim that "even though earnings announcements undoubtedly contain an element of 'surprise,' there are valid reasons not to expect them to provide substantial new information to the share market," such as: (1) earnings announcements are low-frequency, occurring quarterly; (2) earnings announcements are not discretionary - many disclosures are selected as a function of their informativeness; and (3) accounting income is based primarily on backward-looking information, such as past product sales and past production costs. According to the authors, these reasons lead to the expectation that earnings announcements are unlikely to be a major source of timely new information.

The question of accounting earnings and stock returns is also documented by Frankel and Litov (2009). They found empirical evidence that the relation between past earnings volatility and earnings time persistence is robust, but earnings volatility does not predict stock returns with statistical significance.

Hence, in terms of Granger causality, the evidence in the accounting literature does not allow a robust conclusion about causality between the variables, since no general behaviour is identified. Additional tests should be developed to test conditional Grager causality in relation to some firm-specific characteristics and also to understand the determinants of earnings-return causality.

5. Conclusions

The rich empirical and theoretical literature relating earnings to enterprise value suggests that accounting earnings play an important role in the valuation process. However, Ball and Shivakumar (2008) claim that earnings announcements are unlikely to be a major source of timely new information. Additionally, analysts, investors and managers face many challenges in aggregating accounting information and all the economic information available in a feasible valuation model.

To shed light on the interaction between earnings and stock returns, in this paper we (1) examined the time-series properties of quarterly accounting earnings series of 71 Brazilian companies during the 1995-2009 period; (2) examined the predictive ability of the same series; and (3) examined the ability to approximate the markets' expectation of quarterly earnings when examining the securities market reaction to accounting data in a long-term sense.

The empirical evidence presented here suggests that accounting numbers, namely earnings per share (EPS), earnings per share variation (EPSVAR) and stock prices, showed stationary and seasonal behaviour for most firms. A strong autocorrelation was found in the first lag, with exponential decline until the twelfth lag. The partial autocorrelation abruptly decreased from the first to the second lag, and underwent non-significant partial autocorrelation after that. Analysing the evidence together suggests that accounting earnings in Brazil follow an autoregressive model AR(1). Additionally, our findings suggest that most companies have a significant seasonal component of earnings, meaning that the model of Foster (1977) might perform better in the Brazilian market.

Companies with non-stochastic variables presented long term-relationship as shown in the cointegration test, and in terms of Granger causality, most of the companies presented causality between earnings variation and returns. However, the evidence was not general for the sample. It is not possible robustly to infer about causality between the variables, since a general behaviour was not identified. The present findings corroborate the empirical evidence of Galdi and Lopes (2008) in the Latin America market by aggregating several observations about the Brazilian market.

The pragmatic conclusion is that time-series of quarterly accounting earnings in Brazil can be modelled (estimated) by using a seasonal component and a significant relationship between earnings and stock prices does exist. However, the direction of the causality is not generally defined, suggesting that earnings-return analysis must be developed on a firm-specific basis.

Future studies can focus on finding the firm-specific determinants of Granger causality and analyze the same relationship under conditional tests. In other words, future research can try to explain why some companies' returns are more (or less) related to accounting earnings than others. These fields of study are in accordance to Frankel and Litov (2009): the economic forces that would cause persistence to be a fundamental earnings property are still not discussed in the literature. We also agree with the view that identifying factors that predict earnings persistence is useful for valuation.

References

- Ball, R. & Shivakumar, L. (2008). How much new information is there in earnings? Journal of Accounting Research, 46(5), 975-1016.
- Beaver, W. (1968). The information content of earnings announcements. Journal of Accounting Research, 6, 67-92.
- Beaver, W. & Morse, D. (1978). What Determines Price-Earnings Ratios? Financial Analysts Journal, 34, 65-76.
- Beaver, W., Lambert, R. & Morse, D. (1980). The information content of security prices. Journal of Accounting and Economics, 2, 3-28.
- Beaver, W., Lambert, R. & Ryan, S. (1987) The information content of security prices: a second look. Journal of Accounting and Economics, 9, 139-157.
- Box, G. & Jenkins, G. (1970). Time Series Analysis: Forecasting and Control. Holden-Day.
- Brooks, C. (2008). Introductory Econometrics for Finance. 2. ed. Cambridge: Cambridge University Press.
- Brown, L. (1993). Earnings forecasting research: its implications for capital markets research. International Journal of Forecasting, 9, 295-320.
- Brown, L., Griffin, P., Hagerman, R. & Zmijewski, M. E. (1987a). Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. Journal of Accounting and Economics, 9, 61-87.
- Brown, L., Griffin, P., Hagerman, R. & Zmijewski, M. E. (1987b). An evaluation of alternative proxies for the market's expectation of earnings. Journal of Accounting and Economics, 9, 159-193.
- Brown, L. & Rozeff, M. (1979). Univariate time series models of quarterly accounting earnings per share: a proposed model. Journal of Accounting Research, 17, 179-189.
- Brown, P. & Kennelly, J. (1972). The information content of quarterly earnings: An extension and some further evidence. Journal of Business, 45, 403-415.
- Collins, D. W. & Kothari, S. P. (1989). An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. Journal of Accounting and Economics, 11, 143-181.
- Dichev, I. & Tang, V. (2009). Earnings volatility and earnings predictability. Journal of Accounting and Economics, Journal of Accounting and Economics, 47, 160-181.
- Edwards, E. O. & Bell, P. W.(1961). The Theory and Measurement of Business Income. Berkeley: University of California Press.
- Engle, R. F. & Granger, C. W. (1987). Cointegration and error correction: representation, estimation and testing. Econometrica, 55, (2) 251-276.
- Feltham, G. & Ohlson, J. (1995). Valuation and clean surplus accounting for operating and financial activities. Contemporary Accounting Research, 11, 689-731.
- Foster, G. (1977). Quarterly accounting data: time-series properties and predictiveability results. Accounting Review, 52, 1-21.
- Frankel, R. & Litov, L. (2009). Earnings persistence. Journal of Accounting and Economics, 47, 182-190.

- Galdi, F. C. & Lopes, A B. (2008). Relação de longo prazo e causalidade entre o lucro contábil e o preço das ações: evidências do mercado latino-americano. Revista de Administração da USP, 43(2), 186-201.
- Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross spectral methods. Econometrica, 37(3), 424-438.
- Griffin, P. (1977). The time-series behavior of quarterly earnings: preliminary evidence. Journal of Accounting Research, 15, 71-83.
- Gujarati, D. N. (2004). Basic Econometrics. Boston: McGraw-Hill.
- Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. Econometrica, 59(6), 1551-1580.
- Johansen, S. (1995). Likelihood-based inference in cointegrated vector autoregressive models. Oxford: Oxford University Press.
- Kinney, W., Burgstahler, D. & Martin, R. (2002). Earnings surprise "materiality" as measured by stock returns. Journal of Accounting Research, 40(5), 1297-1329.
- Kormendi, R. & Lipe, R. (1987). Earnings innovations, earnings persistence and stock returns. The Journal of Business, 60(3), 323-345.
- Kothari, S. P. (2001). Capital markets research in accounting. Journal of Accounting and Economics, 31, 105-231.
- Lopes, A. B. (2002). The value relevance of Brazilian accounting numbers: an empirical investigation. Working Paper. SP: EAESP-Fundação Getúlio Vargas.
- Martinez, A. L., Cupertino, C. M., Junior, N. C. F. & Coelho, R. A. (2008). Propriedades das séries temporais de lucros trimestrais das empresas brasileiras. RCO - Revista de Contabilidade e Organizações, 2(2), 19 - 35.
- Nelson, C. R. (1974). The first-order moving average process: Identification, estimation and prediction. Journal of Econometrics, 2, 121-141.
- Ohlson, J. (1995). Earnings, book values, and dividends in equity valuation. Contemporary Accounting Research, 11, 661-687.

Bu Sayfa Boş Bırakılmıştır This Page Intentionally Left Blank