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Testing for unit root bilinearity in the Brazilian stock market

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Abstract

In this paper a simple test for detecting bilinearity in a stochastic unit root process is used to test for the presence of nonlinear unit roots in Brazilian equity shares. The empirical evidence for a set of 53 individual stocks, after adjusting for GARCH effects, suggests that for more than 66%, the hypothesis of unit root bilinearity is accepted. Therefore, the dynamics of Brazilian share prices is in conformity with this type of nonlinearity. These nonlinearities in spot prices may emerge due to the sophistication of the derivatives market.

Keywords: Bilinear unit root; GARCH; Equity prices; Emerging markets; Market efficiency

1. Introduction

The past decade has witnessed a large volume of research into the nonlinear dynamic behavior of asset prices (see [1–6] and the references therein). This fact has raised many questions regarding market efficiency and has motivated research on models that may explain nonlinearities in the stock market.

Various nonlinear models have been proposed for stock prices in the financial literature. Artificial neural networks (ANN) have been used with relative success in the literature. Kanas and Yannopoulos [4] study the performance of linear and nonlinear forecasts for US indices and find that out-of-sample forecasts of nonlinear models (provided from ANN) are significantly more accurate than linear forecasts.

Bilinear and threshold autoregressive processes (TAR) are popular nonlinear models (for a detailed discussion, see [7]). As Rothman [8] points out, bilinear models can capture a wide range of nonlinear behavior, whereas TAR and self-exciting TAR (SETAR) models are specially suited to account for asymmetric limit cycle behavior.[1] Therefore, TAR models are used to model nonlinear characteristics commonly observed in practice, such as asymmetry in the declining and rising patterns of a process. Enders and Granger [9] and Enders and Siklos [10] have developed a momentum-threshold autoregressive model (MTAR), which is suitable to test for periodically collapsing bubbles.[2]

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[1]Bilinear models can capture a wide range of nonlinear behavior but they cannot produce such limit cycles.

[2]See also Shively [5] that finds evidence of nonlinear regime-reverting processes for six major stock market indices (France, Germany, UK, Japan, US and Canada).

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Bilinear models are a powerful and parsimonous nonlinear time series representation. Brocket [11] has shown that, under suitable conditions, bilinear models can approximate arbitrarily closely any Volterra series, which suggests that they are a natural extension of the class of ARMA models.[3] Peel and Davidson [13] suggest that bilinear models can capture better abrupt changes in time series than MTAR models and propose a nonlinear error correction model motivated by the bilinear form.[4]

Charemza et al. [15] have recently introduced a (bilinear) stochastic unit root test that is used to examine the presence of nonlinearity and rational bubbles in world stock markets, where the authors find evidence of speculative bubbles in many world stock markets. The authors find evidence, using data from the first of September 1995 to the 18th of September 1999, suggesting that we could not reject the null of speculative bubbles (nonlinearity) for many equity markets.

In the econophysics literature many models and a variety of methods have been developed to explain and fit bubbles, crashes and nonlinearities in financial markets, as the phenomenon is pervasive in many markets around the world [16–21,1–3].

There are interesting physical models that have been used to replicate stock market fluctuations such as spin market models [22–24], percolation market models [25–27]. These models have been proved to be quite successful in replicating statistical properties of price fluctuations.

Empirical evidence is in line with nonlinearities in the dynamics of asset prices. For example, Antoniou and Vorlow's [1] study of six major stock markets (UK, US, Japan, Hong Kong, France and Italy) and find evidence of high dimensional deterministic dynamics, unstable periodic orbits and chaos. Antoniou and Vorlow [2] study FTSE 100 stock return time series and find evidence of strong nonlinear and possibly deterministic signs in the data generating processes of these stock return sequences. Cajueiro and Tabak [3] test for rational bubbles and nonlinearity in banking indices for 39 different countries and find strong evidence of nonlinearity in these indices.[5]

Some interesting methods have been developed in the statistical physics literature to test for nonlinearities such as Detrended Fluctuation Analysis (see [28,29]) and diffusion entropy analysis [30,31].

This literature suggests that the study of nonlinearities is important. Modeling and understanding the dynamics of stock returns is crucial for many real world applications such as portfolio and risk management.

In this paper, we employ bilinear unit root tests in order to test for the presence of his type of nonlinearity in Brazilian equity share prices. The main goal is to analyze 53 stocks, which comprise the main index, for the period from January 1998 to September 2003.[6]

Very little research has been undertaken studying individual equity shares for emerging markets, and particularly for Brazil, which is a major stock market in Latin America. According to the Emerging Markets Database is the stock market with the largest market capitalization in Latin America, accounting for almost 40% of market capitalization.

This research is particularly important for a number of reasons. In the first place, nonlinearities in the stock market may threaten financial stability. Second, these nonlinearities may imply that bubbles may arise in the stock markets and studying the development of bubbles is crucial for the economy due to the negative impacts of bubble bursts. Finally, discovery of nonlinearities suggests that stock markets may not be weakly form efficient, and calls for the development of forecasting models that exploit such nonlinearities. This last feature is important in the development of models that forecast moments of the distribution of the underlying asset, especially for risk and portfolio management.

The remainder of the paper is structured as follows. The next section presents the bilinear unit root test. Section 3 presents the data and descriptive statistics. In Section 4 the empirical results are discussed. Section 5 concludes the paper.

[3]See Schetzen [12].

[4]See also Psaradakis et al. [14], which suggest that models that allow for random coefficient variation are likely to provide a better representation of the dynamics of a series with a bubble component.

[5]This evidence is robust to adjustments in the returns series for GARCH effects. Therefore, the nonlinearities found are not due to time-varying heterocedasticity.

[6]In 1998 a large telecommunications company was privatized, which accounted for approximately 50% of the Brazilian general index. This company was divided into other smaller companies that began to operate in the Brazilian domestic market.

2. Unit root bilinearity

In this paper we study an important class of nonlinear models, which are the bilinear models. The bilinear model takes the general form

$$\phi(B)(p_t - \mu) = \theta(B)\varepsilon_t + \sum_{i=1}^{m}\sum_{j=1}^{n}\gamma_{ij}p_{t-i}\varepsilon_{t-j}, \tag{1}$$

where B is the backshift operator, p_t stands for the asset price in logarithms, and ε_t is an error process assumed to be independent and identically normally distributed (iid) with zero mean and variance σ^2.

The second term on the right-hand side of Eq. (1) accounts for the nonlinear character of the model. If all the γ_{ij} are zero, then Eq. (1) reduces to the traditional ARMA process.

Charemza et al. [15] propose a bilinear unit root test, which can be written as

$$p_t = (a + b\varepsilon_{t-1})p_{t-1} + \varepsilon_t, \tag{2}$$

where $a = 1$, and the parameter b can be interpreted as the adjustment coefficient.[7]

They consider the problem of testing the null hypothesis of $b = 0$ and show that the t-statistic for the regression

$$\Delta p_t = bp_{t-1}\Delta p_{t-1} + \varepsilon_t, \tag{3}$$

has an asymptotic standard normal distribution. The authors employ the statistic

$$t_{\hat{b}} = \frac{\sum_{t=2}^{T} p_{t-1}\Delta p_{t-1}\Delta p_t}{\hat{\sigma}_e\sqrt{\sum_{t=2}^{T} p_{t-1}^2\Delta p_{t-1}^2}}. \tag{4}$$

Eq. (4) is the Student-t test (t-ratio) based on ordinary least squares estimation of b. Basically, the authors suggest a two-step approach. In the first step they test for unit root among asset prices. If asset prices possess unit roots then we can proceed and test for the bilinearity term.[8]

3. Data

One of the main problems when dealing with equity shares for emerging markets is the low liquidity that these markets have. Therefore, it is necessary to control for low liquidity. We have done that by focusing on individual stocks that comprise the main index in the Brazilian stock market, which is the Sao Paulo Stock Exchange Index (IBOVESPA). These stocks are the most liquid in the domestic market and are selected to be part of the index based on their liquidity performance.

Liquidity is proxied by two dimensions: large volume of transactions and a low number of missing observations (characteristic of infrequent trading). Therefore, every 4 months the stock exchange chooses the stocks that will comprise the index, selecting the most liquid.

The stocks in our sample are all stocks that belong to the index as of September 2003. Most stocks were also part of the index for the entire sample, January 1998 to September 2003.

The main goal of the paper is to test for bilinearity for all individual stocks in our sample. Hence, we would like to perform a powerful test. However, bilinearity might be confused with GARCH effects. All of the return series in the sample have a time-varying conditional variance. We have performed previous tests and evidence suggests that a GARCH(1,1) model is sufficient to purge heteroscedasticity in these return series.[9] We employed the GARCH toolbox from Matlab 6.5 to run the GARCH processes and have imposed the stationarity condition on the coefficients for the conditional variance. However, these conditions were naturally satisfied and we have not found nonstationary GARCH processes such as IGARCH.[10]

[7]This is a nonstationary process since $1 + b^2\sigma^2 \geqslant 1$ (see [15,32]).

[8]See Charemza et al. [15] for more details on testing for unit root bilinearity.

[9]Q Ljung-Box tests for autocorrelation of the squared residuals suggest that the GARCH(1,1) provides a good fit to the data.

[10]We adjust returns for the GARCH process as it is a benchmark model for conditional variance of stock returns and it fits well with the data.

Table 1
Descriptive statistics for adjusted returns

Country	Mean	st. dev	skewness	*p*-value[a]	kurtosis	*p*-value[a]
ACES4	0	0.04	−0.22	0	4.38	0
AMBV4	0	0.03	−0.3	0	3.75	0
ARCZ6	0	0.03	0.3	0	3.86	0
ITAU4	0	0.03	−0.19	0	0.82	0
BBDC4	0	0.03	−0.19	0	1.38	0
BRAP4	0	0.03	−0.44	0	3.87	0
BBAS3	0	0.03	−0.07	0.31	1.05	0
BRTP4	0	0.03	0.19	0.01	0.98	0
BRTP3	0	0.04	0.13	0.07	1.56	0
BRTO4	0	0.03	0.01	0.85	1.05	0
BRKM5	0	0.03	0.07	0.32	1.91	0
CLSC6	0	0.03	−0.02	0.77	1.67	0
CMIG3	0	0.04	−0.22	0	1.03	0
CMIG4	0	0.03	−0.2	0	0.82	0
TRPL4	0	0.05	−0.41	0	1.81	0
CGAS5	0	0.04	0.15	0.05	0.66	0
CPLE6	0	0.04	−0.5	0	5	0
CRTP5	0	0.04	−0.21	0	1.06	0
ELET3	0	0.04	−0.7	0	8.21	0
ELET6	0	0.04	−0.07	0.26	0.61	0
ELPL4	0	0.04	0.02	0.75	1.82	0
EMBR3	0	0.04	−0.18	0.01	1.1	0
EMBR4	0	0.04	0.03	0.7	1.64	0
EBTP3	0	0.04	−0.75	0	9.61	0
EBTP4	0	0.05	0.43	0	3.74	0
GGBR4	0	0.05	−0.3	0	1.93	0
PTIP4	0	0.03	0.04	0.53	0.95	0
ITSA4	0	0.04	−0.2	0	1.13	0
KLBN4	0	0.03	−0.14	0.03	1.04	0
LIGH3	0	0.04	0.26	0	1.48	0
PLIM4	0	0.04	−0.69	0	5.07	0
PETR3	−0.01	0.07	−2.84	0	39.21	0
PETR4	0	0.03	−0.15	0.02	1.22	0
SBSP3	0	0.03	−0.22	0	1.03	0
CSNA3	0	0.04	−0.6	0	2.97	0
CSTB4	0	0.04	−3.5	0	49.98	0
CRUZ3	0	0.03	−0.07	0.27	0.97	0
TCOC4	0	0.03	−0.35	0	4.57	0
TCSL3	0	0.04	0.32	0	4.74	0
TCSL4	0	0.05	−0.69	0	5.01	0
TLCP4	0	0.04	−0.41	0	1.8	0
TNEP4	0	0.05	0.12	0.1	1.38	0
TNLP4	0	0.05	−1.54	0	19.71	0
TNLP3	0	0.04	−0.07	0.29	0.5	0
TMAR5	0	0.04	−0.32	0	1.14	0
TMCP4	0	0.05	−5.8	0	112.78	0
TSPP4	0	0.04	−0.03	0.71	0.72	0
TLPP4	0	0.04	−0.37	0	2.48	0
TBLE3	0	0.03	−0.27	0	3.11	0
USIM5	0	0.04	0.04	0.56	1.68	0
VCPA4	0	0.04	−0.17	0.02	1.24	0
VALE3	0	0.03	−0.08	0.34	0.71	0
VALE5	0	0.03	−0.24	0	2.71	0

[a]In columns 5 and 7 the *p*-values for zero skewness and kurtosis are presented, respectively.

In order to account for heteroscedasticity we employ a correction factor for all assets adjusting for a GARCH(1,1) process and dividing returns by this correction factor ($CF_t = \sqrt{h_t}/mean(\sqrt{h_t})$), where h is the conditional variance. After adjusting returns, we rebuild individual equity prices in a recursive way.

The data series were taken from Economatica and are individual stock prices for 53 stocks. Our time period spans the period from January 1998 to September 2003. The data were collected daily. We study the behavior of logarithmic returns calculated as $\ln(p_t/p_{t-1})$.

Table 1 presents descriptive statistics for the data used in this study. We reject the null of zero skewness for the distribution of adjusted returns for approximately 70% of the full sample of stock returns.

The average skewness for all adjusted return series is negative (−0.41), while skewness range from −5.8 to 0.43. On the other hand, we reject the null of no excess kurtosis for all return time series. The average kurtosis is 6.31 and ranges from 0.5 to 112.78. Therefore, all individual stock returns exhibit fat tails, which is a stylized fact in financial returns time series. The normality assumption can be rejected from these figures.

4. Empirical results

We follow Charemza et al. [15] and test for nonstationarity of the time series (prices in logarithms). In order to run the bilinear tests we have used the BLINI package in GAUSS 5.0 language.[11]

Table 2 presents the results for joint Dickey–Fuller (DF) and KPSS tests.[12] We use a simultaneous application of a test where the null hypothesis is a unit root (with stationarity as alternative) and where the null hypothesis is that of stationarity (with a unit root alternative).[13]

As we can see from Table 2 for 50 out of 53 stock prices the unit root hypothesis is not rejected. However, for these 3 stocks where the unit root is rejected the stationarity hypothesis is also rejected. These results are robust to the use of a Leybourne type DF unit root test and the stationarity test (KPSS).[14]

This is the first step on testing for bilinearity since it is a necessary condition for bilinear unit root tests that the price series contain a unit root. As we have seen, we can proceed and test for unit root bilinearity. Table 3 presents the results for unit root bilinearity.

The main results are presented in Table 3. For 35 out of 53 stock returns, the null hypothesis that the bilinear term is insignificant is rejected, that is, 66.04% of these stock returns.

The evidence presented here is in line with other research that has found nonlinearities and bubble formation in a variety of stock market indices [36–40].

We have found evidence of nonlinearities for a large set of stocks in the Brazilian stock market. However, not all stocks have this characteristic, which suggests that studying individual stock returns may be worthwhile to investigate the origins of such nonlinearities.

It is important to notice that differences in liquidity may explain, at least partially, our results. For example, there are two stocks traded for Company Vale do Rio Doce (Vale3 and Vale5).[15] They represent the same company and therefore they should share similar properties. However, these stocks have a different liquidity level, with Vale5 having a trading volume 4.8 times larger than Vale3. Therefore, we should expect that Vale5 shares would be more efficient than Vale3, which is precisely what we obtain from Table 3 as we reject the null hypothesis of no bilinearity for Vale3 but not for Vale5.

The empirical results imply a certain degree of market inefficiency. If markets are efficient we should expect to rule out nonlinear dynamics. However, it is not clear how this nonlinear could be exploited in trading strategies, which is an interesting topic that could be exploited in future research. These results should be expected as the Brazilian stock market is an emerging market and it is still developing. On the other hand, we

[11] See Charemza and Makarova [33].

[12] We employ the Leybourne [34] DF type test for testing for unit roots.

[13] Charemza and Syczewska [35] have shown that conventional critical values for these tests should be replaced by symmetrical critical power values. If both tests agree with the unit root hypothesis, that is the DF does not reject the null and the KPSS does, at the 5% significance level, then one might claim that the joint probability of the acceptance of the hypothesis that the price series possesing a unit root is at least equal to 95%. Their critical power values are employed in the present paper.

[14] Cajueiro et al. [21] show that Brazilian stock returns may have long-range dependence. Therefore, in this case the stationary/non-stationary hypotheses would be strong. It could be the case that these time series are fractionally integrated.

[15] The difference between these stocks is that they represent ordinary and preferred stocks, respectively.

Table 2
Joint confirmation of the unit root tests for adjusted returns

Company	Leybourne Dfmax significance	max. aug.	B/F	KPSS significance	AC length
ACES4	0	37	Backward	***	0
AMBV4	0	35	Forward	***	0
ARCZ6	***	24	Forward	***	0
ITAU4	0	32	Forward	***	0
BBDC4	***	29	Backward	***	0
BRAP4	0	42	Backward	***	0
BBAS3	0	11	Forward	***	0
BRTP4	0	15	Forward	***	0
BRTP3	0	39	Forward	***	0
BRTO4	0	18	Forward	***	0
BRKM5	0	34	Forward	***	0
CLSC6	0	39	Backward	***	0
CMIG3	0	42	Backward	***	0
CMIG4	0	37	Backward	***	0
TRPL4	0	37	Backward	***	0
CGAS5	0	42	Forward	***	0
CPLE6	0	32	Backward	***	0
CRTP5	0	4	Backward	***	0
ELET3	0	35	Forward	***	0
ELET6	0	37	Backward	***	0
ELPL4	0	37	Backward	***	0
EMBR3	0	42	Backward	***	0
EMBR4	0	14	Backward	***	0
EBTP3	0	41	Backward	***	0
EBTP4	0	42	Forward	***	0
GGBR4	0	39	Backward	***	0
PTIP4	0	37	Backward	***	0
ITSA4	0	20	Backward	***	0
KLBN4	0	37	Backward	***	0
LIGH3	0	31	Backward	***	0
PLIM4	0	14	Forward	***	0
PETR3	0	25	Forward	***	0
PETR4	0	42	Backward	***	0
SBSP3	0	37	Backward	***	0
CSNA3	0	33	Backward	***	0
CSTB4	0	39	Backward	***	0
CRUZ3	0	37	Backward	***	0
TCOC4	0	31	Backward	***	0
TCSL3	0	27	Backward	***	0
TCSL4	0	0	Forward	***	0
TLCP4	0	34	Forward	***	0
TNEP4	0	42	Forward	***	0
TNLP4	0	36	Forward	***	0
TNLP3	0	20	Forward	***	0
TMAR5	0	18	Forward	***	0
TMCP4	0	39	Backward	***	0
TSPP4	0	26	Forward	***	0
TLPP4	0	32	Forward	***	0
TBLE3	0	37	Backward	***	0
USIM5	***	37	Backward	***	0
VCPA4	0	40	Backward	***	0
VALE3	0	33	Forward	***	0
VALE5	0	11	Backward	***	0

The "0" indicates that we cannot reject the null hypothesis, while the "***" indicates rejection at the 1% significance level. The third and fourth columns present the maximum augmentation and whether the DF test was performed using forward or backward regressions, respectively.

Table 3
Bilinear test results for adjusted returns

Company	obs.	bmax	Significance	max. aug.
ACES4	1401	3.114	***	37
AMBV4	1398	1.88	**	37
ARCZ6	1376	−1.403	0	27
ITAU4	1401	−2.22	0	32
BBDC4	1401	3.238	***	29
BRAP4	757	1.54	*	42
BBAS3	1391	−2.78	0	11
BRTP4	1224	2.052	**	15
BRTP3	1213	2.68	***	39
BRTO4	1400	2.543	***	27
BRKM5	1387	1.822	**	34
CLSC6	1399	−0.873	0	37
CMIG3	1392	1.507	*	42
CMIG4	1286	2.073	**	37
TRPL4	380	2.183	**	37
CGAS5	1018	0.352	0	42
CPLE6	1389	1.922	**	32
CRTP5	1400	2.253	**	30
ELET3	977	2.557	***	36
ELET6	1401	3.039	***	37
ELPL4	1401	1.828	**	37
EMBR3	1401	−1.11	0	42
EMBR4	1196	1.409	*	14
EBTP3	1295	1.924	**	41
EBTP4	1220	2.151	**	42
GGBR4	1224	−0.479	0	39
PTIP4	1399	4.842	***	37
ITSA4	1396	−1.294	0	20
KLBN4	1400	−2.441	0	37
LIGH3	1394	−0.378	0	31
PLIM4	1399	1.947	**	14
PETR3	1207	0.979	0	25
PETR4	1400	3.747	***	42
SBSP3	1400	−1.516	0	37
CSNA3	1401	−0.327	0	33
CSTB4	1394	3.595	***	39
CRUZ3	1380	2.098	**	37
TCOC4	1392	−1.458	0	31
TCSL3	1223	2.406	***	27
TCSL4	1221	0.303	0	0
TLCP4	1224	1.39	*	34
TNEP4	1224	2.915	***	42
TNLP4	1224	2.897	***	32
TNLP3	1224	3.166	***	20
TMAR5	1215	1.579	*	18
TMCP4	1399	−1.906	0	39
TSPP4	1224	2.639	***	26
TLPP4	1224	2.73	***	32
TBLE3	1223	2.102	**	37
USIM5	1301	0.312	0	42
VCPA4	1135	3.974	***	40
VALE3	926	1.911	**	33
VALE5	1360	1.044	0	28

The third column presents the bilinear coefficient while the fourth and fifth columns present the significance level (0 denotes not significant and ***, ** and * significance at the 1%, 5% and 10% level, respectively) and the maximum number of augmentations used in the bilinear unit root test, respectively.

should not expect these features in developed markets as they possess a higher information flow, high liquidity and a large base of investors.

5. Conclusions

This paper contributes to the financial literature by examining empirical evidence for a set of 53 individual stocks for individual stocks in the Brazilian stock market, for the recent period (1998–2003).

The empirical evidence presented in this paper suggests that a substantial number of Brazilian stock prices exhibit unit root bilinearity, which can be seen as evidence of nonlinearity. These results are robust to filtering returns for GARCH effects.

The empirical results suggest that nonlinearities might be important in assessing time series characteristics of prices for these series and should be taken into account when making investment decisions. Further research could focus on the microstructure characteristics of the equity market and exploring what are the correlates between microstructure variables and efficiency and speculation.

Empirical results for the Brazilian stock market suggest a departure from market efficiency. Equity prices seem to follow a nonlinear dynamics (bilinear type). Further research could exploit whether this nonlinear behavior could be exploited in forecasting models, which could be useful for building trading strategies.

Other methods such as stochastic resonance, classical phase transitions and others may be employed to study these stock prices. This would add to our understanding of the formation of nonlinearities in stock markets. An important issue that could be studied in further research is comparing the dynamics of different stock markets and assessing their degree of market efficiency using nonlinear tools. This should add some insights on what are the key elements that drive nonlinearities in stock markets.

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