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Modelling Returns and Trading Volume in the Chilean Stock Market. Are Nonlinearities Important?[*]

Rodrigo F. Aranda[†]   Patricio Jaramillo[‡]

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Abstract

Using a sample of daily data for the Santiago Stock Exchange, we investigate the empirical relationship between stock returns and trading volume. To capture any possible nonlinear patter in the relationship we estimate a Smooth Transition Autoregressive (STAR) model, and test this model against the linear alternative. We find significative nonlinear patterns in both variables and some evidence of bidireccional causality.

Keywords: Returns, Trading Volume, Random Walk, Granger Causality, Nonlinearities, Smooth Transition Models.

JEL Clasiffication: C1, C22, G10, G14.

1 Introduction

The Efficient Market Hypothesis (Fama, 1979; 1991) states that stock prices (p_t) change only on the arrival of new information or news about fundamentals (the future course of either dividends or discount rates); this means that stock prices adjust almost instantaneously to new levels corresponding to new net present value of cash flows, and forecast errors - defined as $\varepsilon_{t+1} = p_{t+1} - E_t p_{t+1}$ - should therefore be zero on average; they should also be uncorrelated with any information set $\ _t$ that was available at the time the forecast was made. When applied to stock returns, the EMH implies that one cannot earn abnormal

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profits by buying and selling stocks: actual returns will sometimes be above and sometimes below expected returns, but on average unexpected returns are zero. Furthemore, as prices already contain all relevant information in the market, other variables such as trading volume cannot be used to forecast prices either.

Empirical evidence on the EMH has been contradictory. Some evidence show that price increases are positively correlated with trading volume, though the relationship between trading volumen and price falls is more ambiguous. Typically, the price-volume relationship depends on the rate of information flow and dissemination to the market, the extent to which market prices convey information, the size of the market and the existence of short-selling constraints. Price changes Δp_t can be interpreted as the market evaluation of new information, while the corresponding volume V_t is an indicator of investors disagreement about the meaning of this information. Karpoff (1987) points out that several empirical tests about the price-volume relatonship are based on the wrong assumption about the functional relationship between these variables, as well as this relationship being monotonic. Tests of linear dependence between volume and returns are thus mis-specified, and we would expect them to yield poor results.

The relationship between stock markets returns and volume is important for at least four reasons (Karpoff, 1987; Saatcioglu and Starks, 1998) . First, it provides insight into the structure of financial markets in the sense that empirical relations between both variables can help to discriminate between competing hypothesis about market structure. Second, the relationship is important for event studies that use combination of price and volume data from which to draw inferences on the event under analysis; the construction of the tests and the validity of the inferences depend on the joint distribution of returns and volume. Third, it is critical in assessing the distribution of returns themselves; one of the most noticeable features of the unconditional distribution of asset returns is their leptokurtic property: they have fat tails and high peakedness compared to a normal distribution, and two competing hypothesis explainig this are the stable paretian hypothesis (rates of return are best characterized by a member of a class of distributions with infinite variance) and the mixture of distribution hypothesis (the distribution of rates of returns appears to kurtotic because the data are sampled from a mixture of distributions that have different conditional variances[1]. Finally, the fourth reason is that a better understanding of the statistical structure of volume and return can help explain technical analysis: if markets are efficient in the sense that current price compounds all information then technical analysis is pointless; but if the process by which prices adjust to information is not instantaneous, then market statistics may capture information that is not yet incorpored into the current market price; in

[1]Price-volume tests generally support the mixture of distributions hipothesis, which have several implications; for example, it appears that price data are generated by a conditional stochastic process with a changing variance parameter that can be proxied by volume.

particular, volume may be informative about the process of security returns.

Beyond these reationales, how can we explain any possible relation between returns and volume? Several reasons are found in the literature (Hiemstra and Jones, 1994). For example, the sequential arrival of information model developed by Copeland (1976) and Jennings, Stark and Felligham (1981) postulates that new information that reaches the market is not disseminated to all participants simultaneously, but to one investor at a time; final information equilibrium is reached only after a sequence of transitional equilibria. Hence, due to the sequential information flow, lagged trading volume may have predictive power for current absolute stock returns and lagged absolute stock returns could have predictive power for current trading volume. A second explanation for causal relationship between returns and trading volume is based on the mixture of distributions models. This model states that if trading is used to measure the disagreement as traders revise their reservation prices based on the arrival of new information, the greater the disagreement; that is, the larger the level of trading volume, the large the absolute price changes. Thus there is a positive causal relation running from trading volume to absolute stock return. This, of course, implies that knowledge of the behavior of volume can marginally improve conditional price change forecasts based on past price change forecast alone. Finally, noise trader models is a fourth explanation for a causal relation; these type of model can reconcile the difference between the short- and long-run autocorrelation properties of aggregate stock returns. Aggregate stock returns are positively autocorrelated in the short run, but negatively autocorrelated in the long run. Since noise traders do not trade on the basis of economic fundamentals, they impart a transitory mispricing component to stock prices in the short run. The temporary component dissapears in the long run, producing mean reversion in stock returns. A positive causal relation from stock returns to volume is consistent with the positive feedback trading strategies of noise traders, for which the decision to trade is conditioned on past stock price movements.

Attending the importance of the topic, the purpose of this paper is to reexamine the evidence on the stock return and volume relationship in an emerging economy. By using a sample from the stock index return and volume for the Santiago Stock Exchange (the chilean stock market), the contribution to the literature on emerging stock markets are threefold. First, we use daily information for the variables of interests, instead of monthly data as in the previous literature concerning emerging markets. Second, we look for any nonlinear pattern in the relationship by formulating and estimating a Smooth Transition Autoregressive (STAR) model, and test this model against the linear alternative. Third, we use linear and nonlinear Granger causality tests to clear up any positive correlation between stock index return and volume. To our knowledge this is the first time that these three characteristics are combined in a work for the chilean stock market.

The structure of the paper is as follows. The next section briefly summarizes some of the literature concerning the relation between stock price and volume. Section 3 describes our data and the econometric methodology we use in this study. Section 4 reports and discuss our main results. Finally, section 5 gives some conclusiones and limitations.

2 Previous Literature

Two stylized facts have emerged from empirical research on stock prices and volume. First, the correlation between trading volume and the absolute value of the price change or volatility is positive (that is, $corr(V_t, |\Delta p_t|) > 0$); that is, a large increase in volume is usually accompanied by either a large rise or a large fall in prices. Second, the correlation between volume and returns is also positive (that is, $corr(V_t, \Delta p_t) > 0)$[2].

While earlier research on the topics mainly focuses on the contemporaneous relationship between returns and volume, as surveyed in Karpoff (1987), more recent studies examine causal dynamics. For example, Smirlok and Starks (1988), Gallant, Rossi and Tauchen (1992) and Hiemstra and Jones (1994) point out significan linear and nonlinear dynamics between trading volume and returns and conclude that more can be learned by studying prices jointly with volume. On the other hand, Blume, Easley and O'Hara (1994) examines the information content of volume in a theoretical context. These authors show that lagged volume could be useful to predic price movements when prices are noisy and market participants cannot obtain the full information signal from price alone; their model is consisten with the widespread use of technical analysis in financial markets.

Empirical evidence also shown that the return and trading volume time-series properties are best described using nonlinear models. For example, the returns data oftend reveals the volatility clustering phenomenon associated with GARCH of large (small) shocks of either sign tending to follow large (small) shocks. The evidence of nonlinearity in returns and trading volume is not limited to the case in which these series are individually described. Hiemstra and Jones (1994) report unidirectional linear Granger causality from returns to volume in contrast to bidirectional nonlinear causality between these variables; they also filter stock returns with Exponential GARCH (EGARCH) to control for volatility persistence, and still find nonlinear causality running from volume to stock returns. Silvapulle and Choi (1992) get similar results focusing on the emergin Korena stock market. Campbell,

[2]If we assume that we have at least two types of investors in the market (informed and uninformed), then the volume that results when a prevoiously uninformed trader interpret the news pessimistically is less than when the trader is an optimist. Since prices decreases with a pessimist (who sells) and increase with an optimisit (who buys), it is argued that trading volume is relatively high when the price increases, and low when the prices decreases.

Grossman and Wang (1993) find a negative relation between daily stock index return autocorrelations and trading volume; they assume that two types of investors exist in the market: noninformational investors who want to sell stocks for exogenous reasons, and market makers who are willing to buy stocks to accomodate the market selling pressure, but who require compensation for taking the risk in the form of a lower stock price or a higher expected stock return. For such traders stock return reversals tend to cause an abnormally large increase in volume, as prices tend to fall, increasing the trading volume as long as the reallocation of risk between heterogeneous traders is completed. Therefore, large trading volume will be associated with relatively large negative serial correlation of returns. Saatcioglu and Starks (1998) examines the stock price-volume relation in a set of Latin American markets (Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela), documenting a positive relation between volume and both the magnitude of price change and price change itself, but they do not find strong evidence on stock price changes leading volume, in contrast to the evidence reported by studies on developed markets. They conclude that the set of emerging markets with different institutions and information flows than developed markets, do not present similar stock price-volume lead-lag relation to the preponderance of studies employing data from developed countries. Finally, Sarantis (2001) finds that STAR models are useful in describing asymetric cycles in stock price growth rates in most industrial countries.

3 Data and Econometric Approach

3.1 The Data

In financial markets, the price of a stock depends not only on the asset exchanged and the timing of the trade, but also on the trade volume (number of stock shares) and on the investor's characteristics. Then quoted prices could differ from the true prices involved in transactions. We must also take into account the spread between bid and ask prices that arise from the need to cover any cost involved in financial intermediation; this spread can be very informative about the liquidity and efficiency of the stock market. However, all these problems can be overcomed if we consider a price index. In this paper we consider the closure price of stocks given by an index of selective stocks[3]. Figure 1 below shows the evolution of this index from january 2, 1989 to june 6, 2003. As we can see, there is some evidence of nonlinearity.

The behavior of returns is particularly interesting. As we said before, in an efficient market the path of prices and return per period are unpredictable. Besides, the EMH

[3]The index used is the IPSA, "Índice de Precios Selectivo de Acciones" (Index of Selective Stock Prices). This index comprises the fourty most traded stocks in the Santiago Stock Exchange, selected annualy.

hypothesis implies that the expected value of tomorrow's price, p_{t+1}, given all relevant information up to and including today, $_t$, should equal today's price, p_t, possible up to a deterministic growth component (a drift). In testing the EMH the model commonly used is $p_t = \mu + p_{t-1} + \varepsilon_t$, where $\varepsilon_t \overset{iid}{\sim} D(0, \sigma^2)$ and D is some distribution, or returns follow a random walk with drift $\Delta p_t = \mu + \varepsilon_t$. Is the random walk model a good approximation for the actual behavior of returns in the Santiago Stock Exchange?

The next figure depicts the actual behavior of stock prices for the whole sample, together with three alternative simulated path for prices from the random walk model. As we can see, the random walk model is far from being a good approximation for the actual behavior of stock prices in Chile.

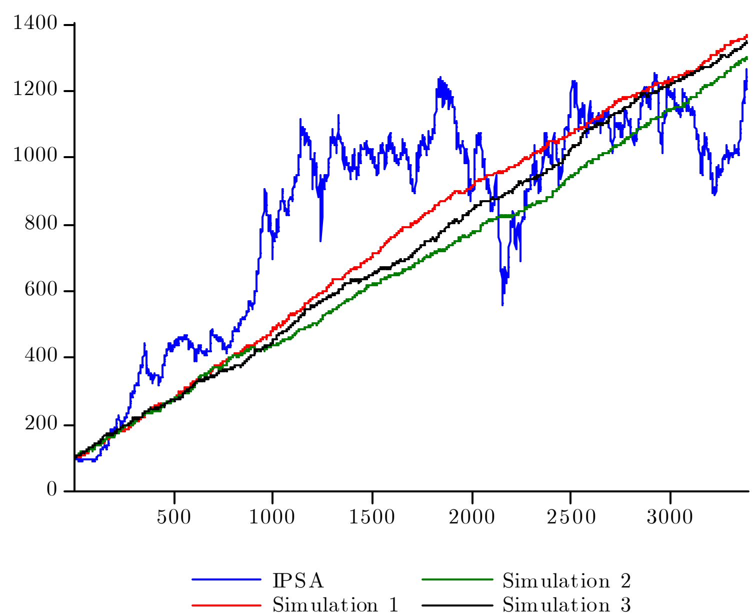

Figure 1. Stock Price Index and Random Walk Simulations.

This figure also shows that, as is common in many economic time series, a positive trend in the long-run is present, and also that some changes in the level of the series are identifiable both in the short and the medium run; that is, the data generating process for prices would be characterized by changing means implying different regimes for the stock prices. This is important because changing regimes is a source of nonlinearities in time series processess. A usefult transformation is to consider returns instead of prices, defined by $R_{t+1} = \frac{p_{t+1} - p_t}{p_t}$, which can be approximated by[4],

$$R_{t+1} = \ln(p_{t+1}) - \ln(p_t).$$

The time series for the level and the first difference of prices (returns) for the actual sample we use in the empirical analysis - from july 18, 1995 to april 15, 2003 - is depicted in figure 2. This figure also show the time series of trading volume and its first difference.

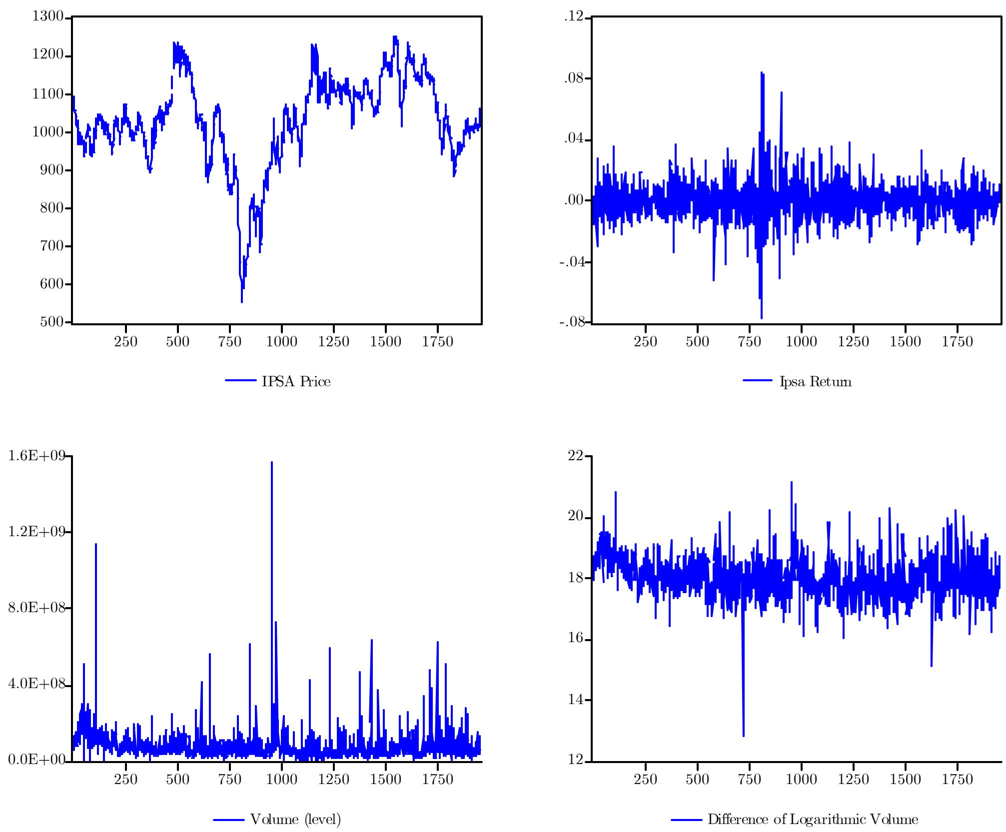

Figure 2: Returns and Volume (Levels and First Differences).

As we can see, both variables show nonlinear patterns, and heteroskedasticity is a possible source of problems in our data. The table below presents some statistics for both series.

[4]This transformation tends to subestimate the true value for returns, $\widetilde{R}_{t+1}$. In fact, it can be shown that

$$\widetilde{R}_{t+1} = \ln(1 + \frac{p_{t+1} - p_t}{p_t}) = R_{t+1} - \frac{R_{t+1}^2}{2}.$$

Descriptive Statistics		
Sample: july 18, 1995 - April 15, 2003		
Statistic	Return	Volume
Mean	0.0000147	83972149
Median	-0.000235	65945188
Maximum	0.083705	1.57E+09
Minimum	-0.076656	0.000
Std. Dev.	0.011598	79972930
Skewness	0.318205	7.251148
Kurtosis	8.626445	98.77135
Jarque-Bera	2614.381	765062.1
Prob.	0.000	0.000
Doornik-Hansen	882.353	9431.683
Prob.	0.000	0.000
Sum Sq. Dev.	0.263131	1.25E+19
Observations	1957	1957

Source: Own calculations.

Table 1. Descriptive Statistics.

As we can see, both series presents excess of skewness and kurtosis, and the Jarque-Bera and Doornik and Hansen test rejects the null of normality for both variables. To gain further insights on the statistical distributions of the series, figure 3 shows the empirical distribution compared to the standardized normal distribution.

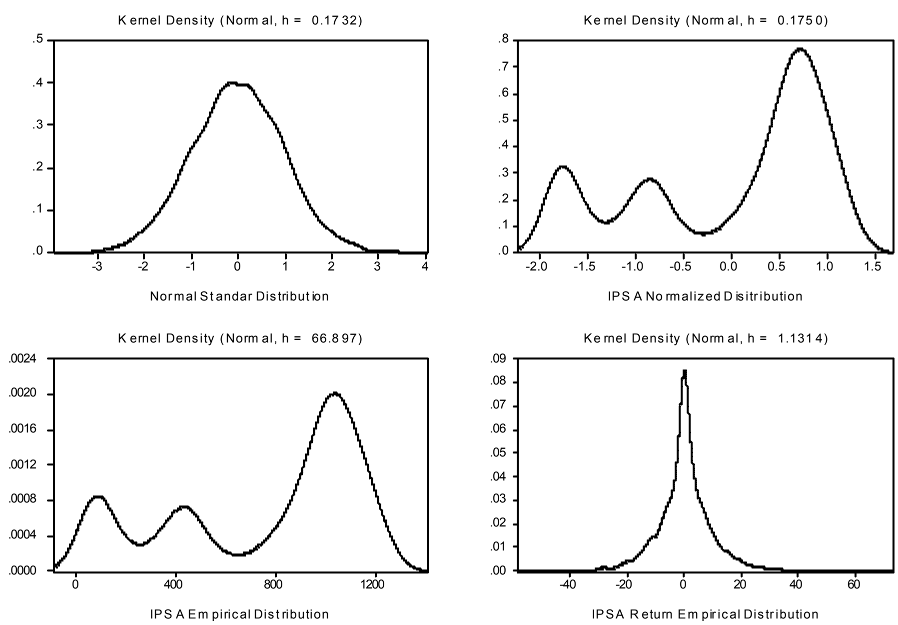

Figure 3. Kernel Densities.

The figure is very illustrative of the leptokurtic nature of returns, and the existence of at least two modes perfectly identifiable. Again, this is evidence of nonlinearities in the data.

3.2 The Smooth Transition Autoregressive (STAR) Model

Modeling nonlinearities with regime-switching models is a common practice today. Roughly speaking, two main classes of regime-switching model can be distinguished: those in which the regimes can be characterized by an observable variable, and those in which the regime cannot actually be observed but is determined by an unobservable underlying stochastic process. In the later case one can never be certain that a particular regime has occurred at a particular point in time, but only assign probabilities to the occurrence of the various regimes. A special case of switching regression models is the threshold model. This type of model may be viewed as a two-regime system, in which a linear model describes each of the regimes. Any change between these regimes is assumed to be abrupt (van Dijk, 1999).

The smooth transition autoregressive STAR model is a generalization of the two-regime system, in which the transition between the two extreme regimes is smooth. The STAR models are estimated when the linearity hypothesis is strongly rejected for at least one transition variable. This connects two linear autoregressive models by a bounded transition function and different transition functions characterize different dynamic properties of data, resulting in different specification for the STAR models (see van Dijk, 1999; van Dijk et. al., 2000, Krolzig, 2002, Potter, 1999; and Teräsvirta, 1994). The general structure of this type of model is:

$$y_t = \left[\alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i}\right] + \Phi(y_{t-d}, \delta)\left[\beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}\right] + u_t \tag{1}$$

whre u_t is an independent and identically distributed random variable with mean zero and variance σ^2 (or alternately a martingale difference sequence[5]) and d is the "delay" parameter whose value is a positive integer. In this specification, two linear AR component are connected using a nonlinear transition function (Φ) whose value is determined by y_{t-d}, a lagged (delayed) y_t, and is a continuous function that is bounded between 0 to 1 (Teräsvirta, 1994).

To empirically implement the STAR model, we must first select the autoregressive order of autoregression p, and then choose d by varying it and selecting the value of d that minimizes the $p-value$ in a linearity test. Different choices for the transition function give rise to two different types of regime-switching models with a smooth transition. We can consider two alternative STAR models: the Logistic STAR (LSTAR) model, in which the transition function is the logistic function,

[5] The normality assumption is needed if the specification test are derived as Lagrange Multiplier (LM)-type test; if they are interpreted as tests based on artificial regressions, then a martingale difference assumption is sufficient (Teräsvirta, 1994).

$$\Phi_L(y_{t-d}, \delta) = \{1 + \exp[-\gamma(y_{t-d} - c)]\}^{-1} \;\; ; \gamma > 0 \quad (2)$$

where $\delta = (y, c)'$; and the Exponential STAR (ESTAR) model, in which the transition function is modeled as an exponential function:

$$\Phi_E(y_{t-d}, \delta) = 1 - \exp\left[-\gamma(y_{t-d} - c)^2\right] \quad (3)$$

The STAR models can be considered as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function (0 or 1), where the transition from one regime to the other is smooth. Also, the STAR model can be said to allow for a continuum of regimes, each associated with a different value of transition function between 0 and 1 (Teräsvirta, 1994). In the univariate case, it is straightforward to extend the model to allow for exogenous variables as additional regressors. The transition variable can also be exogenous, or a function possibly nonlinear combinations of lagged endogenous variables. It is also the possible to include a linear time trend as a transition variable (Lin and Teräsvirta, 1994).

If a logistic STAR model of order p is chosen, high and low trading volume/stock returns may have rather different dynamics, and the change in dynamic from one regime to the other is smooth. Parameters change monotonically and the transition variable deviates from a fixed point c, the threshold between the two regimes. In an exponential STAR of order p, volume/returns may move rapidly between very small and very large values for which local dynamics are stable. The parameter γ determines the smoothness of the change in the value of the transition function, and thus the smoothness of the transition from one regime to the other. In this study we assume that the conditional variance of μ_t is constant.

Finally, even though several useful extensions of the basic STAR model, from models for vector time series, to multiple regimes, or time varying nonlinear propierties are proposed in the literature (see, for example, van Dijk et. al., 2000), but this topics to get away of the spirit of this paper.

4 Empirical Results

In this section we first address the linear or nonlinear dependence in the data. Hiemstra and Jones (1994) provide empirical evidence for argumenting that more can be learned about the stock market dynamic by studying the joint dynamics of stock prices and trading volume rather than by focusing only on the univariate dynamics of stocks prices.

As we said in the previous section, the time series for stock returns and trading volume show some nonlinearities and possibly heteroskedasticity. Also there is visual evidence for nonstationarity. For testing for stationarity in both variables we apply a batery of unit roots tests, including the standard Augmented Dickey-Fuller (ADF) tests, the Phillips-Perron tests, the Dickey-Fuller tests with GLS Detrending (DFGLS), the Kwiatowski, Phillips, Schmidt, and Shin (KPSS) test, and the Elliot, Rothemberg and Stock Point Optimal (ERS) test[6]. The reason for using this set of tests is that there is evidence of problems both in the size and power of standard unit root tests (i.e, ADF), and also with the null of nonstationarity rather than stationarity as a null (Maddala and Kim, 1998). The results are reported in table 2 below.

Unit Roots Tests

Null Hypothesis		ADF unit root	Phillips-Perron unit root	ADF-GLS unit root	ERS unit root	KPSS stationary
Return	Level	-34.776	-34.751	-4.414	0.103	0.040
	First Difference	-20.566	-626.338	-1.740	111.687	0.051
Volume	Level	-14.597	-36.511	-5.580	0.255	0.443
	First Difference	-23.895	-1279.575	-66.022	16.881	0.103
Critical Values						
1%		-3.963	-3.963	-3.480	3.960	0.216
5%		-3.412	-3.412	-2.890	5.620	0.146
10%		-3.128	-3.128	-2.570	6.890	0.119

Table 2. Unit Root Tests.

As we can see from the table, returns are stationary at conventional significance levels. The evidence for trading volume is mixed; however, we assume that they are nonstatinary.

On the other hand, looking at the first difference of returns and volume in figure 2, larger variances than in the surrounding periods suggest that the data may not be generated by the same data-generating process during the whole sample period. However, what is in appariance a structural break may also be due to nonlinearity, which can be modeled with a constant parameter model.

As the sample includes 1985 observations, it is reasonable to assume that we would observe regime shifts in the data. To motivate the possibility of modeling different regimes, lets consider the figure 4, showing the residuals from a linear model, in which we have regressed the logarithm of returns (trading volume) on a constant and a trend. It is observed that returns and trading volume tend to stay either above or below a trend, and the changes around the trend have been quite abrupt. However, if we expect that the change in model parameters have been smooth, this can be modeled by a nonlinear STAR model.

[6] All these tests ara availabe in Eview 4.1. See QMS (2000).

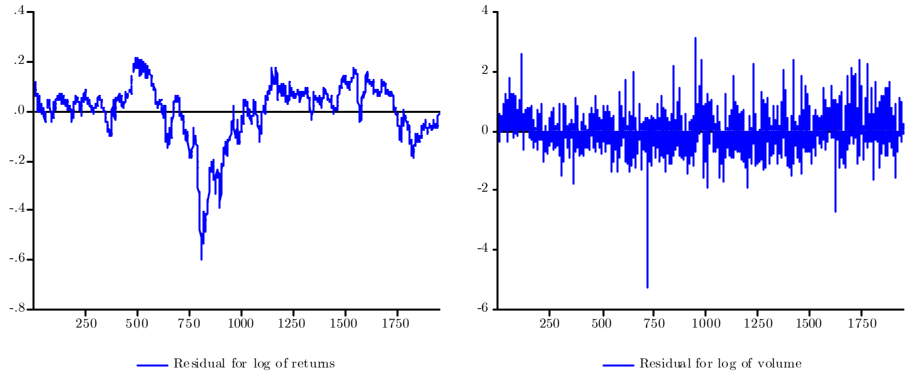

Figure 4. Residuals from a Linear Regression Model (constant and trend).

To gain further insights on nonlinearities, we test for linear Granger causality (see table 2), where Δy_t is the logarithmic difference of returns and trading volume, Δy_t^2 is the squared logarithmic difference of returns and volume, and $|\Delta y_t|$ is the volatility (absolute value) of logarithmic difference of returns and volume.

Direction of causality	Δy_t	Δy_t^2	$\|\Delta y_t\|$
Return to Volume	11.0089	4.47772	7.94404
Volume to Return	1.42341	1.24742	2.11907

Table 3. Granger causality[7]

We find significant causality running from volume to absolute returns as distinct from bidirectional causality between stock returns and trading volume. Again the results suggests that nonlinear modeling may be useful in describing the behavior.

The problem of choosing the right lag in the case of nonlinear models is not trivial. A common approach is to start by specifying an $AR(p)$ model and assume that the order p is appropriate in both regimes of the nonlinear model. Hence, we fit an $AR(p)$ model to both variables (returns and trading volume). Unfortunately, the final model selection for the whole sample period was ambiguous as large lags proved to be significant in the $AR(p)$ models fitted, perhaps because of unmodeled seasonality in the data. However, as many authors suggest that nonlinear models are best fitted to seasonally unadjusted data so that nonlinearities are not accidentally removed, we leave the data unadjusted. Table 4 shows the best $AR(p)$ specfications.

[7]Critical value for Granger causality test at the 5% significance level equals 1.750

Dependent Variable: Return
Method: Least Squares
Sample(adjusted): 2 1931
Included observations: 1930 after adjusting endpo

Variable	Coefficie	Std. Error	t-Statistic	Prob.
RET(-1)	0.229	0.0220	10.406	0.000
RET(5)	0.053	0.0221	2.383	0.017
RET(7)	-0.046	0.0221	-2.089	0.037
RET(10)	0.048	0.0221	2.160	0.031
RET(17)	-0.053	0.0227	-2.333	0.020
RET(18)	0.041	0.0227	1.823	0.068
RET(24)	-0.053	0.0222	-2.372	0.018
RET(26)	-0.072	0.0222	-3.256	0.001
R-squared	0.074	Mean dependent		-3.49E-06
Adjusted R-squared	0.070	S.D. dependent va		0.011659
S.E. of regression	0.011	Akaike info criteric		-6.134244
Sum squared resid	0.243	Schwarz criterion		-6.111175
Log likelihood	5927.545	Durbin-Watson st		1.979936

Dependent Variable: Difference of logarithmic trading volume
Method: Least Squares
Sample(adjusted): 15 1956
Included observations: 1942 after adjusting endpoints

Variable	Coefficie	Std. Error	t-Statistic	Prob.
DF(-1)	-0.614	0.0226	-27.162	0.000
DF(-2)	-0.479	0.0263	-18.216	0.000
DF(-3)	-0.418	0.0281	-14.876	0.000
DF(-4)	-0.355	0.0292	-12.184	0.000
DF(-5)	-0.250	0.0297	-8.403	0.000
DF(-6)	-0.238	0.0292	-8.156	0.000
DF(-7)	-0.204	0.0281	-7.270	0.000
DF(-8)	-0.160	0.0263	-6.068	0.000
DF(-9)	-0.100	0.0226	-4.431	0.000
R-squared	0.288	Mean dependent		-0.002
Adjusted R-squared	0.285	S.D. dependent va		0.657
S.E. of regression	0.556	Akaike info criteric		1.668
Sum squared resid	598.553	Schwarz criterion		1.693
Log likelihood	-1614.401	Durbin-Watson st		2.010

Table 4. The Best Linear Model Specifications.

The model diagnosis from linear autoregression for returns and trading volume are reported in table 5.

Residuals in the Linear AR(p) Model for Returns

Mean	4.93E-06	Std. Dev.	0.011
Median	-0.0002	Skewness	0.320
Maximum	0.0767	Kurtosis	7.795
Minimum	-0.0725	Jarque-Bera	1882
Probability	0.0000	Sum Sq. Dev.	0.243
Sum	0.0095	Observations	1930

Residuals in the Lineal AR(p) model for the First difference of Logarithmic Trading Vol

Mean	-0.006583	Std. Dev.	0.555
Median	-0.017527	Skewness	-0.106
Maximum	3.189205	Kurtosis	9.548
Minimum	-5.442659	Jarque-Bera	3482
Probability	0.000	Sum Sq. Dev.	598
Sum	-12.81645	Observations	1947

Test for ARCH Effects

Variable	F-statistic	Obs*R-squared
Return	48.635	92.736
Volume*	15.677	30.903

*Difference of logarithmic trading

Table 5. Model Diagnosis and ARCH Effects.

The results indicate that the null hypothesis that residuals are white noise, and that there is no skewness and extra kurtosis in the residuals, are rejected at the 1% level. Substantial excess of kurtosis as well as moderate negative (positive) skewness in residuals suggest the presence of mainly negative (positive) outliers in the trading volume series. As the no-ARCH hypothesis is also rejected at the 1% level, this leads us to assume a nonconstant conditional variance in the error processess; but this may also be a signal of a nonlinear conditional mean (Teräsvirta, 1994; van Dijk, 1999).

The next step is, then, to estimate a STAR model for both series. The results are reported in table 6 and 7. In selecting the models, we follow a sequential approach based on the transition variable considered and different specifications for the transition function (conditional to the transition variable) and the variables included in the linear and nonlinear parts of the STAR model.

Returns: LSTAR Model 1

Variable	Linear Part	Nonlinear Part
Constante	0.0000139 (0.0555)	253 (4.48)
R1	0.235 (10.8)	
R5	0.0637 (2.93)	
R7	(0.0506) (-2.33)	
R17	(0.0462) (-2.08)	1.94e+004 (11.8)
R18	0.0682 (3.03)	(5.74e+003) (-9.98)
R24	(0.0551) (-2.54)	(428) (-0.874)
R26	(0.064) (-2.96)	(6.37e+003) (-7.18)
Transition Variable	R10	
Gamma	10 (5.68)	
c	0.0516 (38)	
AIC / SBIC	-9.01	-8.97
R2 / SD.residuals	0.101	0.011

Returns: LSTAR Model 2

Variable	Linear Part	Nonlinear Part
Constante	0.0385 (2)	(0.0385) (-1.99)
R1	0.227 (10.2)	
R5	0.0613 (2.81)	
R7	(0.0673) (-2.95)	
R10	0.0535 (2.46)	
R18	1.25 (1.49)	(1.21) (-1.44)
R24	(1.39) (-2.63)	1.36 (2.56)
R26	2.47 (0.912)	(2.54) (-0.937)
Transition Variable	R17	
Gamma	26.1 (0.67)	
c	(0.0424) (-17.5)	
AIC / SBIC	-9.01	-8.97
R2 / SD.residuals	0.0964	0.011

Returns: LSTAR Model 3

Variable	Linear Part	Nonlinear Part
Constante	0.0291 (4.64)	(0.0291) (-4.63)
R1	0.246 (11.2)	
R5	0.0491 (2.24)	
R7	(0.0419) (-1.9)	
R10	0.0196 (0.879)	
R17	(0.0216) (-0.988)	
R24	3.43 (5.49)	(3.48) (-5.57)
Transition Variable	R18	
Gamma	99	
c	(0.0382) (-70.2)	
AIC / SBIC	-9	-8.96
R2 / SD.residuals	0.0892	0.0111

Returns: LSTAR Model 4

Variable	Linear Part	Nonlinear Part
Constante	0.000631 (1.51)	(0.000939) (-1.76)
R1	0.237 (10.8)	
R5	0.0588 (2.68)	
R7	(0.0626) (-2.83)	
R10	0.0513 (2.35)	0.0513 (2.35)
R17	(0.151) (-4.28)	0.187 (3.97)
R18	0.114 (3.41)	(0.116) (-2.53)
R24	(0.0456) (-1.41)	(0.0244) (-0.553)
Transition Variable	R26	
Gamma	99 (0.711)	
c	(0.00317) (-5.56)	
AIC / SBIC	-8.99	-8.95
R2 / SD.residuals	0.0812	0.0111

Returns: LSTAR Model 5

Variable	Linear Part	Nonlinear Part
Constante	(0.00378) (-0.757)	0.00382 (0.763)
R1	(0.261) (-0.907)	0.512 (1.79)
R5	0.584 (2.85)	(0.533) (-2.58)
R7	0.114 (0.709)	(0.182) (-1.13)
R10	0.218 (1.05)	(0.171) (-0.82)
R17	(0.0494) (-2.16)	
R18	0.0463 (2.02)	
R24	(0.0525) (-2.39)	
Transition Variable	R26	
Gamma	27 (0.242)	
c	(0.0317) (-14.2)	
AIC / SBIC	-8.99	-8.95
R2 / SD.residuals	0.0808	0.0111

Transition Variable	Gamma	c	SSR
R10	10	0.0516	0.23172
R17	26	-0.0424	0.23367
R18	99	-0.0382	0.23558
R26	99	-0.00317	0.23751
R26	27	-0.0317	0.23751

Table 6. Alternative STAR Models for Returns.

The statistical significance of each variable included and standard information criteria (i.e., Akaike and Schwartz) were also considered in selecting the models. However, since the information criteria do not show any significant difference between alternative models, the sum of squared residuals was decisive rule in selecting the models. On the other hand, since the parameter γ determines the smoothness of the transition between regimes, a higher value for this parameter is a clear indication for abrupt changes between regimes, and should also be an important source of information about the properties of the models.

First Difference of Volume: LSTAR Model 1

Variable	Linear Part	Nonlinear Part
Constante	(0.14) (-7.89)	0.368 (11.8)
DF1	(0.479) (-22.5)	
DF3	(0.229) (-8.96)	
DF4	(0.207) (-7.29)	
DF5	(0.131) (-4.39)	
DF6	(0.136) (-3.84)	(0.0347) (-0.725)
DF7	(0.136) (-3.87)	(0.0251) (-0.466)
DF8	(0.107) (-3.19)	0.0233 (0.439)
DF9	(0.0619) (-2.02)	(-0.00858) (-0.184)
Transition Variable	DF2	
Gamma	131 (547)	
c	(0.169) (-34.4)	
AIC / SBIC	-1.08	-1.03
R2 / SD.residuals	0.224	0.581

First Difference of Volume: LSTAR Model 2

Variable	Linear Part	Nonlinear Part
Constante	(0.244) (-6.8)	0.288 (7.22)
DF1	(0.555) (-24.8)	
DF2	(0.378) (-15.2)	
DF3	(0.266) (-11.1)	
DF5	(0.0782) (-3.16)	
DF6	(0.104) (-1.84)	(0.0101) (-0.17)
DF7	(0.152) (-2.43)	0.0479 (0.715)
DF8	(0.117) (-1.93)	0.0341 (0.513)
DF9	(0.115) (-2.13)	0.062 (1.05)
Transition Variable	DF4	
Gamma	9.66 (39.8)	
c	0.52 (261)	
AIC / SBIC	-1.12	-1.07
R2 / SD.residuals	0.255	0.569

First Difference of Volume: LSTAR Model 3

Variable	Linear Part	Nonlinear Part
Constante	(0.00398) (-0.311)	
DF1	(0.582) (-25.7)	
DF2	(0.415) (-16.2)	
DF3	(0.326) (-12.4)	
DF4	(0.234) (-9.05)	
DF5	(0.0833) (-3.59)	
DF7	(0.0549) (-2.49)	
DF8	(0.0587) (-2.46)	
DF9	(0.043) (-1.96)	1.17 (1.73)
Transition Variable	DF6	
Gamma	2.85	
c	-2.15	
AIC / SBIC	-1.14	-1.1
R2 / SD.residuals	0.265	0.565

Transition Variable	Gamma	c	SSR
DF2	131	-0.169	652.245
DF4	9.66	0.52	626.934
DF6	2.85	-2.15	617.199

Figure 7. Alternative STAR Models for the First Difference of Trading Volume.

Figures 5 and 6 depict the transition function against the transition variable and against time for the models estimated. Notice that the figures are coincident with our criteria of choosing the models with the lower sum of squared residuals. In fact, the models selected are those with the lower γ, which implies the smoothness transition between regimes. This is also very informative with respect to the timing of the changes between regimes affecting the chilean economy: in the case of returns, the transition function indicates that the change in regime occurs approximately at the same time that the asian crisis hits the chilean economy (august of 1998), and when the Russian and Brazilian economies begun to experience some troubles (the late 1990s).

Considering the above discussion, table 8 summarize the information for the best estimated models for both variables compared to the linear AR(p) specification previously estimated. Again, these models are characterized by statistically significant parameters, both in the linear and nonlinear parts, and show better statistical properties than their linear counterparts.

Returns: AR(p) and LSTAR Models

Variable	AR(p) Model	LSTAR Linear Part	LSTAR Nonlinear Part
Constante		0.0000139 (0.0555)	253 (4.48)
R1	0.229	0.235 (10.8)	
R5	0.053	0.0637 (2.93)	
R7	-0.046	(0.0506) (-2.33)	
R10	0.048		
R17	-0.053	(0.0462) (-2.08)	1.94e+004 (11.8)
R18	0.041	0.0682 (3.03)	(5.74e+003) (-9.98)
R24	-0.053	(0.0551) (-2.54)	(428) (-0.874)
R26	-0.072	(0.064) (-2.96)	(6.37e+003) (-7.18)
Transition Variable		R10	
Gamma		10 (5.68)	
c		0.0516 (38)	
AIC / SBIC	-6.134	-9.01	-8.97
R2 / SD.residuals	0.074	0.101	0.011

First Difference of Volume: AR(p) and LSTAR Models

Variable	AR(p) Model	LSTAR Linear Part	LSTAR Nonlinear Part
Constante		(0.00398) (-0.311)	
DV(-1)	-0.614	(0.582) (-25.7)	
DV(-2)	-0.479	(0.415) (-16.2)	
DV(-3)	-0.418	(0.326) (-12.4)	
DV(-4)	-0.355	(0.234) (-9.05)	
DV(-5)	-0.250	(0.0833) (-3.59)	
DV(-6)	-0.238		
DV(-7)	-0.204	(0.0549) (-2.49)	
DV(-8)	-0.160	(0.0587) (-2.46)	
DV(-9)	-0.100	(0.043) (-1.96)	1.17 (1.73)
Transition Variable		DV6	
Gamma		2.85	
c		-2.15	
AIC / SBIC	1.668	-1.14	-1.1
R2 / SD.residuals	0.288	0.265	0.565

Table 8. STAR Models Selected (t statistic in parenthesis).

The information provided by the estimation of STAR models in important for our purpose. They show that there are significant nonlinearities both in returns and trading volume. This is a key issue in testing the efficient market hypothesis. As we said in the introduction, the efficient market hypothesis states that if stock markets are efficient, then stock prices (returns) and trading volume should not be related. Previous works on efficiency in the chilean stock market, using a linear approach, conclude that the market is efficient (see for example Solarzano, 1998); however, the nonlinearity we find in the data is a clear signal for misspecification in the testing procedure using a linear approach.

Up to this point we have analized the existence of nonlinear patterns in trading volume and stock returns in the Santiago Stock Exchange, and the evidence reported support the hypothesis of nonlinearities in the data. As we said before, this is very important for the EMH testing for the chilean market. Since stock returns and trading volume are best modeled as nonlinear processess, is there evidence of any statistical causality between them? This is an open question that requires further research. However, a simple cointegration analysis is very informative in the sense that if both variables cointegrate, this is evidence on the existence of a long-run relationship between them.

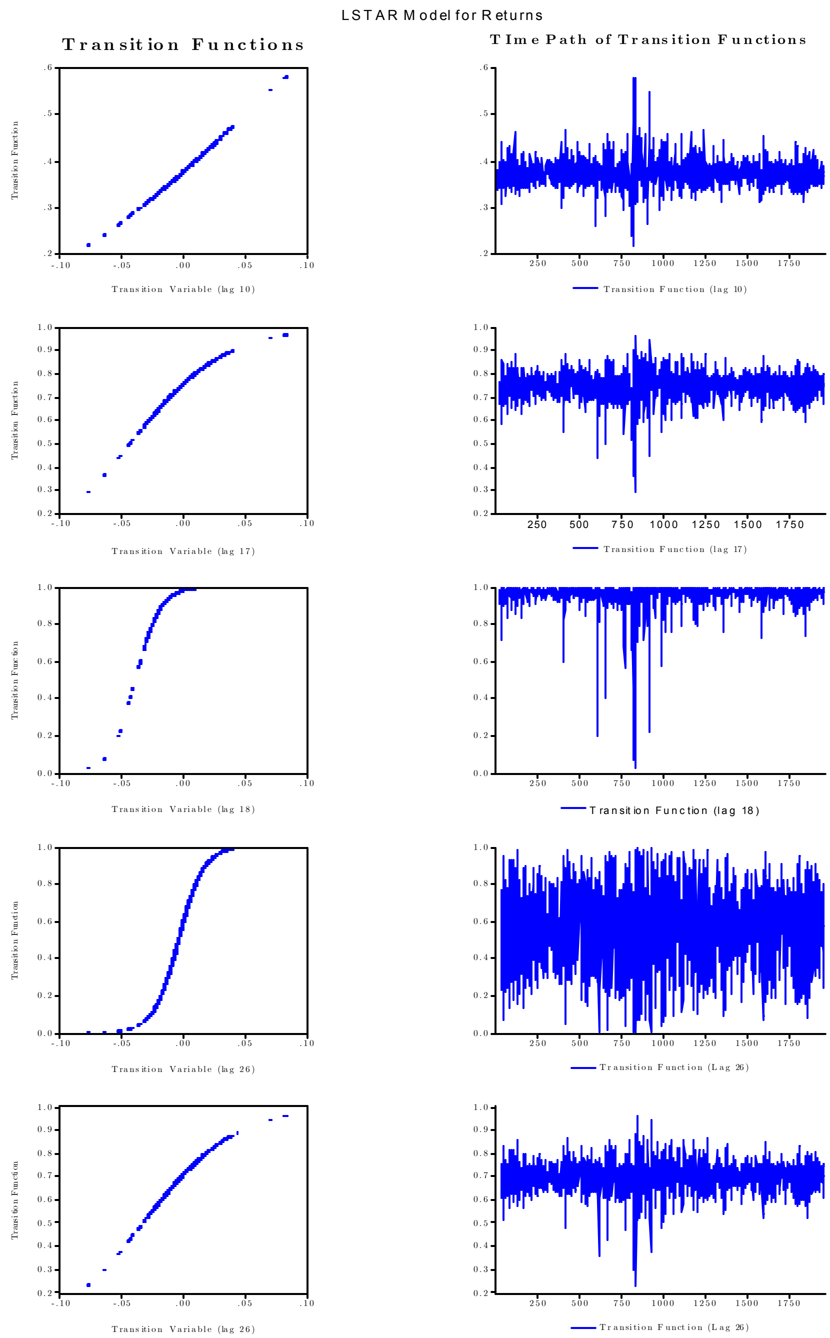

Figure 5. STAR Model: Transition Functions for Returns.

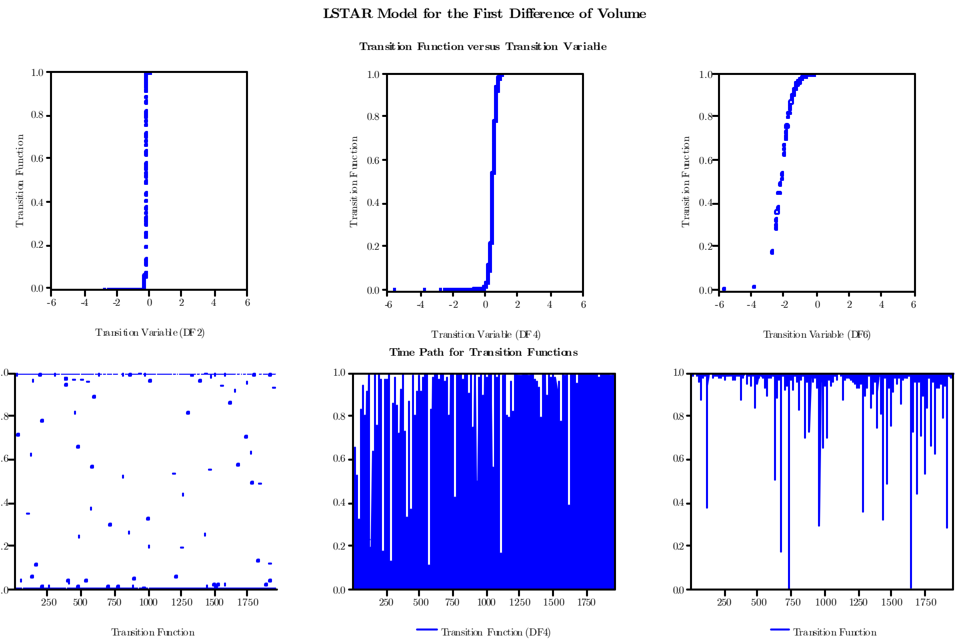

Figure 6. STAR Model: Transition Functions for Trading Volume.

A preliminary exploration of cointegration is done using the stock price index and trading volume. Prices are clearly nonstarionary. With respect to trading volume, the mixed evidence reported in table 2 and, as we said before, the problems in conventional test for unit roots, lead us to assume that it is also nonstationary.

In order to find out whether the data support the fact that periods with large price movements are also periods with larger thatn average trading volume, and viceversa (Karpoff, 1987), the next table reports the correlation matrix for both stock returns and trading volume.

	Returns	Trading Volume
Returns	1.0000	-0.025863
Trading Volume	-0.025863	1.0000

Table 9. Correlation Matrix.

As we can see, the evidence suggest a negative correlation between returns and trading volume as in Gallant et. al. (1993). Notice also that the correlation is very low, and we may conclude that there is no significant relations between our variables. However, this would be incorrect if we find a cointegrating vector between both variables, indicating a long run relationship. Moreover, depending on the cointegrating vector, this would indicative of causality running in one direction or another, or even bidirectional causality. Since returns are stationary, the cointegration analysis is performed considering the stock price index instead. The results are reported in table 10.

Series: Trading Volume and Stock Price Index				
Lags interval (in first differences): 1 to				
Unrestricted Cointegration Rank Test (Johanssen)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.088	180.173	12.530	16.310
At most 1	0.000	0.070	3.840	6.510

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Trace test indicates 1 cointegrating equation(s) at both 5% and 1% levels

Included observations: 1952 after adjusting endpoints

CE: Cointegrating Equations.

Table 10. Johansen Cointegration Test (QMS, 2000).

As the result of the Trace Statistic indicates, there is evidence of one cointegrating vector. This implies that since these two series are cointegrated, volume should cause stock prices, or vice versa; in other words, there is a possibility for causality in any direction. Notice that the results are based on a linear multivariate approach (a vector autoregression); but considering our previous discussion, nonlinearity in the variables is an issue that should be taken into account when estimating the vector autoregression and testing for a possible cointegrating vector. However, modelling this relationship is beyond the scope of this paper, and we leave it for a next one.

5 Concluding Remarks (Preliminary)

In this paper we provide preliminary evidence on the relationship between stock returns and trading volume for the Santiago Stock Exchange. Formulating and Estimating Smooth Transition Autoregressive (STAR) models for returns and trading volume, our results indicate substantial nonlinear pattern in both variables. We also find some evidence of bidireccional causality. Since de Efficient Market Hypothesis states that stock prices and trading volume should not be related in an efficient market, suggest that the Santiago Stock Exchange is not efficient according to the standar approach for testing efficiency. Considering the evidence on bidireccional causality, the next step is to model the joint distribution of stock returns and trading volume with a nonlinear multivariate model, a task we will explore in a following paper.

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