Automation and Efficiency in Two Emerging Equity Markets[1]

By

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Abstract

Automation was introduced to the Stock Exchanges of Jamaica and Trinidad & Tobago on January 5, 2000 and March 18, 2005 respectively. The essential features of the automated platforms are critically evaluated. Then, using both parametric and non parametric approaches (the latter based on rescaled range analysis), the degree of informational efficiency before and after the automation on these two Exchanges is measured. The results are mixed but, in general, the exchanges are found to be inefficient both before and after automation although, in most cases, automation leads to improvement in efficiency.

JEL CLASSIFICATION NUMBERS: C14, G14, G15.

KEYWORDS: Automation, Stock Market Efficiency, correlation analysis, rescaled range analysis.

1. Introduction

After many years of trading on the 'open outcry', floor-trading system, the two most developed stock exchanges of the Caribbean, the Jamaica Stock Exchange (JSE) and the Trinidad & Tobago Stock Exchange (TTSE), began trading on an electronic platform in January 5, 2000 and March 18, 2005, respectively. This automation of the exchanges was premised on the belief that there would be improvements in efficiency, both operational and informational[2]. The question is: did this happen? A large amount of research has been done on the impact of automation, or electronic trading, on both operational and informational efficiency but none so far has focused on the stock exchanges of the emerging economies of the Caribbean. This paper is an attempt to fill that gap.

In most published papers, a change in operational efficiency following automation is measured by the change in the bid-ask spread, one of the key indicators of liquidity (Blennerhassett and Bowman 1998, Frino et al. 1998, Theissen 2002, Pinder 2003, Aitken et al. 2004, Bortoli et al. 2004, Huang (2004), Cheng and Tse 2005). Intuitively, and in theory, automated trading should be more efficient and less costly than open outcry. This should typically translate into narrower bid-ask spreads or relatively more liquid trading. In the case of the TTSE and the JSE, we were unable to perform any analysis of bid-ask spreads primarily because of the lack of available data. Currently the TTSE and JSE do not have a complete database of end of day prices of traded stocks for any significant period available to the public. Instead only daily prices are available on the website so that databases must be compiled manually. In the case of the JSE, information may be accessed for as far back as 1969 but only from daily trading reports, which are scanned versions of the original documents. The quality is extremely poor and the margin for error is large for one attempting to compile a database. Finally, intraday trading data is not available even in the period post automation despite the existence of infrastructure which enables this data to be easily tracked and collected.

The possible improvement in informational efficiency, following automation, has been addressed and investigators have generally limited their concern to Fama (1970)'s weak-

[2] Operational efficiency is measured by a market's ability to operate at lower costs either through improved liquidity, more rapid execution or lower trading costs. Informational efficiency is measured by a market's ability to evaluate information and determine the fair value of a security, in the sense of Fama (1970).

form efficiency, as is done in this paper. Many have measured changes in informational efficiency by the reaction of security prices and trading volume to new information in the market[3] following the lead Clark (1973), Epps and Epps (1976), Harris (1987), Copeland (1976), Smirlock and Starks (1984) and Campbell et al. (1993). Ciner (2002) uses this approach to compare changes in efficiency following automation on the Toronto Stock Exchange. In this paper we were unable to study price-volume relationships due to the unavailability of data.

Informational efficiency may be discerned using price data alone. Two sets of tests are used in this paper to do so: one 'parametric' and the other 'non parametric'. The first involves a Box-Jenkins type analysis to identify and estimate appropriate ARMA models, with or without GARCH residuals: if a model other than the classic random walk is identified and successfully estimated, it would mean that the process is 'forecastable' and therefore indicative of weak-form inefficiency. The second set of tests is based on the Rescaled-Range (R/S) analysis, which allows us to determine the degree of randomness inherent within a time series without a priori assumption about the distribution of the system being examined. The influential paper of Lo (1991) provides a useful derivation of the "range over standard deviation" or R/S statistic and discusses its application to the analysis of financial time series. Freund and Pagano (2000) apply R/S analysis to test the degree of informational efficiency before and after automation on the New York and Toronto Stock Exchanges mainly because of its ability to determine the level of randomness inherent within a time series without a priori assumption about the distribution of the system being examined.

The rest of the paper proceeds as follows: in the following section, a critical review of the automated systems in the JSE and the TTSE is given, followed by a discussion of the nature of the data and the methodology to be used in evaluating the impact of automation on informational efficiency. The opportunity is taken at this stage to provide some basic descriptive statistics about returns the two exchanges. This is followed by an analysis of the results obtained and, finally, some conclusions and recommendations.

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[3] In this paper we were also unable to study price-volume relationships due to the unavailability of data.

2. The Nature of Automation at the JSE and the TTSE

The JSE began trading in 1968 and the TTSE in 1981. Both moved away from the traditional open outcry system to automated trading on January 4, 2000 and March 18, 2005, respectively, and both adopted similar automated trading platforms generically known as an Electronic Crossing Networks (ECN)[4]. There are several variations of ECNs in the market and the Caribbean exchanges have adopted the most popular form whereby bids and offers are published and automatically matched[5]. Table 1 below summarizes the essential differences between the new automated systems and the floor-trading (open outcry systems) that they replaced:

Table 1: Comparison between Floor-Trading and Automated Systems in JSE and TTSE

Floor Trading (Open Outcry System)	Automated Trading (Order driven electronic trading system)
Trading took place sequentially (typically in alphabetical order), that is in one security at a time.	Trading can take place simultaneously in multiple securities at the same time.
Only one trader or one representative of a brokerage house could have sat on the floor and traded at any one session.	Multiple traders from the same brokerage firm may trade at any one time.
It may be easier to pick up trading signals from a more informed trader since traders can read and interpret body language and other non-verbal signals.	While all buy and sell orders can be viewed by all traders via the centrally located electronic book, informed traders can disguise a particular strategy or knowledge of a market event by entering a series of smaller orders instead of large orders. This is why "crossing"[6] is easier under electronic trading.
It is easier to manipulate prices since traders can communicate between themselves and decide on bid and offer prices.	There is less room for informal communications except via email and instant messaging so prices are swayed by the dynamics of demand and supply.
The trading and settlement procedures are very manual and are therefore slower.	Trading and Settlement procedures are centralized through use of the Central Securities Depository and are faster and therefore more efficient.

The automated trading systems of the JSE and the TTSE are order-driven and prices are determined by the electronic publication and subsequent matching of orders to buy or sell shares. The role of the broker in such a system is to act as an intermediary to facilitate the matching of these buy and sell orders and then to execute the transactions. Under this

[4] An ECN is an electronic system that attempts to facilitate trading directly between a broker and a trader by eliminating the need for a middle man. The three main advantages of an ECN are that (1) it displays orders in real time; (2) it facilitates quicker filling of orders and (3) it reduces overall transaction costs.

[5] Other variations include systems which allow selected access to only those brokers who have large block orders to fill as well as systems in which orders may or may not be executed immediately: here, orders may not be automatically matched and filled as in the case of the TTSE and the JSE and, instead, brokers may exercise some level of discretion when executing orders.

[6] "Crossing" is the act of putting up a buy order and then buying back the same shares for another client from the same brokerage house.

kind of automated system, buy and sell orders are matched automatically in the system. The closing price is therefore the last price at which a transaction is executed. The Broker usually charges a fee or commission for this facility. This is similar to what transpires on the London Stock Exchange and at the Eastern Caribbean Stock Exchange (ECSE), which are order-driven markets as well. The New York Stock Exchange (NYSE), in contrast, operates as a quote or price-driven system in which transaction prices are determined in part by the market maker who publishes bid and offer prices for the various listed securities.

To execute buy and sell orders on the JSE and the TTSE, a client must first lodge his/her certificates in the Central Securities Depository[7] whose many functions include the safekeeping, deposit and withdrawal of securities certificates of its members. It also facilitates the change of ownership of securities electronically between parties, without the need for the movement of physical documents. Corporate actions such as dividend splits and rights may also be processed electronically with additional shares being credited to an account rather than issuing additional physical certificates. At the TTSE, all certificates are lodged and customers receive a monthly statement from the securities depository. The Jamaican equity market, on the other hand, operates with a combination of both physical certificates and dematerialized certificates. Physical certificates, however, are being slowly phased out.

Once a certificate is lodged, an order must then be placed with a broker of choice. This is because, in the current system, customers cannot individually execute transactions for themselves on the stock exchange. The Broker may require the investor to set up an account with his brokerage firm.

Orders are executed on both exchanges on behalf of the Broker by their representative called a 'Trader'. This removing of a third party appears to be one of the key advantages of automation and is the standard for several major exchanges including the LSE. The NYSE and NASDAQ, which began operations using a market maker or specialist, have retained the use of these third parties despite moving to an automated trading platform.

[7] A financial institution providing custodial and securities settlement services to one or several markets. Certificates deposited in the central depository are dematerialized, which is typical of most international markets.

This market maker or specialist, through use of a personal inventory of stocks and by publishing bid and offer quotes as necessary, manages the liquidity of particular stocks to ensure the orderly conduct of the market.

Once the Broker has received orders, he enters them into an electronic order log which is a centrally located order book that allows all registered traders to see all buy and sell orders which have been entered. This effectively eliminates the need for face to face trading and marks the end of the open-outcry system.

The sequence of the order log is of particular importance since orders must be dealt with both on a price and time priority basis. Price priority is determined in descending order of prices for bids and ascending order of price for offers. It should be noted, however, that price priority takes precedence over time priority. That is to say, for two buy orders, the order with the higher price takes precedence even if it was received after a buy order at a lower price. Orders are time-stamped when they are electronically entered which provides an objective way for determining time priority.

When trading begins on the exchange, the Market Official from the Stock Exchange must open the session to allow brokers and traders access. Traders may trade remotely from their offices. Orders are exposed to other brokers via the limit order book display. Time priority between competing brokers is determined by the sequence by which the brokers enter their respective orders into the trading system. The System then proceeds to try and match orders with orders from other brokers. Brokers may also match orders with themselves that is, they may act as the party on both sides of the transaction, a process known as “crossing”.

The final stage in this process is called the “Settlement Cycle”; it is the time taken for the buyer to pay for the stocks purchased and the seller has to deliver the stocks sold. At the TTSE and the JSE, the current cycle is T+3[8]. More developed markets, including the United States and the United Kingdom, are at a T+1 settlement cycle. Trading may be done online in all U.S. and European futures and options contracts via the Internet. Orders are electronically routed directly to the filling broker in the trading pit without any

[8] “Trade day” plus 3 business days, i.e. buying and selling clients should expect to make and receive payments within 3 business days.

interruption of any kind. Transmission time for execution of an order is minimal. The TTSE and the JSE are nowhere near being able to offer these kinds of services. For instance, only licensed traders are able to log on to the electronic system. Also, the platform still operates on a secure server and no infrastructure is yet in place to allow public access over the Internet.

3. Data and Methodology

For both the TTSE and the JSE, we examine the daily common stock returns of 11 of the most liquid stocks as well as the corresponding composite indices. For the TTSE, the pre-automation period is taken as the 275 trading days from March 12th, 2003 to March 16th, 2005 while the post- automation period ranges from 18th, March 2005 to March 14th, 2007, again 275 trading days. For the JSE, the pre-automation period is the 175 trading days from January 9th, 1998 to January 4th, 2000 while the post- automation period ranges from January 5th, 2000 to October 23rd, 2001 (175 trading days). The 11 securities are chosen because their high trading volumes and relatively larger market capitalizations ensure that these stocks are routinely among the most actively traded stocks.

Weak-form efficiency implies that stock prices follow a random walk process such as

$$\ln p_t = \alpha + \beta t + \ln p_{t-1} + u_t \qquad (1)$$

where p_t is the stock price at time t, α and $\beta$are constant (drift and trend) terms and $\{u_t\}$ is an identically and independently distributed (IID) Gaussian process. A Box-Jenkins type 'correlation' analysis may be used to determine the existence or not of ARIMA type models for the stock market prices, other than the random walk. This requires, in the first instance, tests for the existence of one unit root in model (1) and the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are used to do this. If the presence of exactly one unit root is established, the autocorrelation function of $\Delta \ln p_t$ (the rate of return based on the index) is examined to determine whether the process (1) may be modeled as IID; (2) as a GARCH (q,p) process or (3) it may conform to a stationary ARMA model, with or without GARCH(q,p) disturbances. In cases (2) and (3), the process is predictable and consequently indicative of weak-form inefficiency. Procedures similar to the one being proposed here have been used by Kawakatsu and

Morey (1999), Groenewold et al. (2003), Chang et al. (2004), Boguk and Brorsen (2003), Dragotă and Mitrică (2004) and others.

A fundamental weakness of the Box-Jenkins approach is the underlying normality (Gaussian) assumption which is not at all a usual attribute of stock prices. Table 2 below displays some interesting descriptive statistics derived from the various returns used in this study. These are the mean return, the standard deviation, the coefficient of variation (CV), skewness, kurtosis and the Jarque-Bera statistic (used to test the normality of the series).

Table 2 – Descriptive Statistics

JSE Securities	Mean	Standard Deviation	CV	Skewness	Kurtosis	Jarque-Bera
CAR Pre	-0.003207	0.069305	-0.04627372	-7.607379	92.52086	59779.69
Post	0.003262	0.038830	0.084007211	1.761982	9.358812	383.1830
CCC Pre	0.000500	0.075927	0.006585273	1.939154	15.13213	1176.166
Post	-0.001527	0.058991	-0.0258853	0.167555	6.827994	107.0523
CRTS Pre	-0.011005	0.140141	-0.07852805	-9.231838	101.8101	73256.54
Post	-0.002539	0.090847	-0.02794809	-1.978284	27.19681	4358.265
CWJA Pre	-0.004102	0.043499	-0.09430102	0.881234	8.058957	208.0702
Post	0.001282	0.066532	0.019268923	2.845437	20.49634	2454.182
DG Pre	-0.001173	0.094308	-0.01243797	-9.898379	122.3483	106110.5
Post	0.000388	0.056964	0.006811319	-6.252580	68.19478	31948.86
GK Pre	0.000706	0.019905	0.035468475	1.552787	20.76188	2357.186
Post	0.000371	0.041844	0.008866265	-0.527770	13.43006	796.7778
GLNR Pre	0.000886	0.048708	0.01819003	-3.737878	32.52392	6724.728
Post	0.002192	0.068036	0.032218237	-0.321474	8.296612	206.3892
JBG Pre	-0.003524	0.049092	-0.07178359	-0.515530	7.718574	169.1282
Post	0.006195	0.072195	0.085809267	0.771167	5.761075	72.51689
LOJ Pre	-0.003984	0.027722	-0.14371257	-0.889223	9.611940	339.8844
Post	0.007507	0.104610	0.071761782	6.647766	58.65910	23741.62
NCBJ Pre	-0.002153	0.046792	-0.04601214	-0.460528	7.912852	181.1373
Post	0.005089	0.057280	0.088844274	0.583236	6.316064	89.58778
RJR Pre	-0.001653	0.045515	-0.0363177	1.025326	13.45387	822.7929
Post	0.004119	0.074298	0.055438908	1.059179	7.578244	184.4963
TTSE Securities	**Mean**	**Standard Deviation**	**CV**	**Skewness**	**Kurtosis**	**Jarque-Bera**
AMCL Pre	0.003689	0.006655	0.55432	3.716214	20.34299	3693.710
Post	-0.000491	0.008458	-0.05805	-7.860904	93.60068	87727.68
GHL Pre	0.002451	0.011110	0.220612	7.315067	59.93315	35850.03
Post	-0.002763	0.027474	-0.10057	0.045539	16.00523	1754.871
JMMB Pre	0.002131	0.019650	0.108448	2.117422	17.17244	2269.968
Post	-0.000991	0.027239	-0.03638	0.188148	8.304035	293.3487
NEL Pre	0.002938	0.011725	0.250576	4.470221	32.25393	9708.136
Post	-0.001815	0.022531	-0.08056	-1.808953	10.33976	694.7237
NFM Pre	-0.000465	0.011432	-0.04068	-3.468854	34.16549	10576.48
Post	-0.001959	0.034534	-0.05673	0.052721	6.347475	116.3734
NML Pre	0.003410	0.006115	0.557645	2.647188	12.02854	1136.528
Post	-0.001283	0.008493	-0.15107	-0.523712	20.49162	3185.683
RBL Pre	0.003689	0.006394	0.576947	4.158742	27.17744	6782.438
Post	-0.001061	0.006488	-0.16353	-4.632007	39.75031	14902.73
RBTT Pre	0.002222	0.010016	0.221845	4.936339	32.83237	10244.69
Post	-0.001786	0.014903	-0.11984	1.828582	18.32061	2573.996
SBTT Pre	0.002134	0.009528	0.223971	7.920442	70.85581	50374.20
Post	-0.000342	0.010921	-0.03132	-0.149465	21.86351	3692.685
TCL Pre	0.002826	0.010549	0.267893	0.853166	8.741253	372.1881
Post	-0.002525	0.022306	-0.1132	-1.090345	12.01928	893.3177
WCO Pre	0.000553	0.002416	0.228891	-0.781745	28.86459	6965.998
Post	0.000250	0.009222	0.027109	1.406943	29.67203	7462.894

The stocks on the JSE seem, at first blush, to have performed better following automation: returns improved, many earning positive returns instead of negative returns,

and the associated risks (standard deviations) generally fell as well. This resulted generally in improvements in the coefficients of variation. In the case of the TTSE stocks, however, the opposite seems to have happened: the mean returns deteriorated and the riskiness of the stocks increased. In both markets, skewness and kurtosis generally fell following automation, with resultant 'improvement' in Jarque-Bera statistic, but normality is far from being attained even after automation. The absence of normality is typical of financial returns whether the market is automated or not.

The absence of normality in all cases may put in doubt the results arrived at using the Box-Jenkins type approach, especially if the random walk hypothesis is 'verified'. An alternative approach, whose validity does not depend on the Gaussian assumption, is to use Rescaled Range analysis, which may be used to measure and compare efficiency levels in the TTSE and JSE before and after automation. It is based on ordinary least squares (OLS) estimation of the following equation:

$$Log_{10}(R/S)_i = \log_{10} c_i + H_i \, Log_{10} \, n + e_i$$

R/S is the 'range over standard deviation' statistic defined in Lo (1991). $Log_{10} \, c_i$ and H_i are parameters that may be estimated for the i^{th} security, n is the length (in days) of the sub sample corresponding to the respective rescaled range value and e_i is a stochastic disturbance term. H_i is the 'Hurst component' for a particular security or index and it will be estimated and tested by comparing the estimated value to the expected Hurst component of a random walk model, or by looking at changes in the value of a component itself. According to the R/S theory, if a time series is persistent (exhibiting a trend or pattern), the Hurst component is within the range 0.5-1.0. When the Hurst component is between 0 and 0.5, the time series is anti-persistent or one which exhibits mean reverting behaviour.

4. Results and analysis

The ADF and the KPSS tests are used to establish the existence of a unit root in the $\{\ln p_t\}$ process. This is equivalent to determining whether $\phi=1$ in the following:

$$\ln p_t = \alpha + \beta t + \phi \ln p_{t-1} + u_t$$

The null hypothesis, in the case of the ADF, is that $\phi=1$ and the alternative is $\phi<1$. In the KPSS case, the roles of the null and alternative are swapped. Table 3 below shows the results of these tests on the various stock prices:

Table 3- ADF and KPSS tests for Unit Roots

JSE Securities	ADF Level	ADF 1st Diff	KPSS Level	KPSS 1st Diff
CAR Pre	-2.117862	-12.59844[a]	0.096701	0.081783
Post	-2.556114	-12.10030 [a]	0.234905 [a]	0.628792[b]
CCC Pre	-2.285242	-12.37688 [a]	0.212745 [b]	0.072590
Post	-3.941856 [b]	-11.09865 [a]	0.125860 [c]	0.128955
CRTS Pre	-2.426270	-12.93531 [a]	0.143692 [c]	0.055314 0.209571
Post	-1.865723	-11.49540 [a]	0.180211 [b]	
CWJA Pre	-1.994890	-11.40512 [a]	0.240457 [a]	0.056988
Post	-2.485285	-13.33511 [a]	0.211628 [b]	0.276902
DG Pre	-2.128795	-3.764330 [a]	0.274381 [a]	0.075321
Post	-2.424766	-12.14430 [a]	0.151652[b]	0.096062
GK Pre	-2.720136	-15.20036 [a]	0.078241	0.045026 0.108820
Post	-1.877097	-15.04649 [a]	0.266423 [a]	
GLNR Pre	-2.262754	-13.01891[a]	0.220832 [a]	0.071582
Post	-3.089819	-14.09608 [a]	0.127980 [c]	0.179522
JBG Pre	-2.654415	-14.63330 [a]	0.315696 [a]	0.106535
Post	-2.972577	-15.52889 [a]	0.150293 [b]	0.252567
LOJ Pre	-1.550794	-12.06888 [a]	0.193287 [b]	0.124854
Post	-2.110212	-6.312613 [a]	0.289597 [a]	0.111625
NCBJ Pre	-0.931484	-9.813048 [a]	0.313237 [a]	0.241385
Post	-1.830434	-13.66381 [a]	0.151400 [b]	0.258636
RJR Pre	-0.187719	-13.00607 [a]	0.288825 [a]	0.605548[b]
Post	-2.566719	-12.91366 [a]	0.185618 [b]	0.129738
TTSE Securities	**ADF Level**	**ADF 1st Diff**	**KPSS Level**	**KPSS 1st Diff**
AMCL Pre	-2.121710	-11.55759 [a]	0.121373 [b]	0.098401
Post	-1.442569	-14.60484 [a]	0.278797 [a]	0.106931
GHL Pre	-2.467618	-5.940986 [a]	0.366727 [a]	0.477553 [b]
Post	-2.710747	-8.762465 [a]	0.113353	0.071869
JMMB Pre	-1.512861	-6.902693 [a]	0.298071 [a]	0.151491
Post	-1.930411	-14.52119 [a]	0.212460 [b]	0.060746
NEL Pre	-0.835151	-6.704166 [a]	0.385125 [a]	0.314619
Post	-3.860294 [b]	-4.500515 [a]	0.070959	0.111899
NFM Pre	-2.281949	-6.099862 [a]	0.233197 [a]	0.085662
Post	-2.410080	-8.251700 [a]	0.218192 [a]	0.112055
NML Pre	-1.426571	-8.288110 [a]	0.316124 [a]	0.214645
Post	-2.538151	-14.85613 [a]	0.114476	0.179233
RBL Pre	-1.614358	-12.77429 [a]	0.309487	0.086571
Post	-1.336932	-12.55503 [a]	0.347963 [a]	0.185968
RBTT Pre	-1.285763	-10.07822 [a]	0.478462 [a]	1.103821[a]
Post	-2.943615	-8.513124 [a]	0.172520 [b]	0.190345
SBTT Pre	-2.105366	-1.751700	0.399002 [a]	0.171238
Post	-1.535418	-6.693629 [a]	0.362539 [a]	0.088820
TCL Pre	0.950546	-6.806397 [a]	0.438896 [a]	0.422968 [c]
Post	-2.412486	-8.839749 [a]	0.377551 [a]	0.187523
WCO Pre	-1.375868	-13.83231 [a]	0.285522 [a]	0.161676
Post	-2.346718	-5.016951 [a]	0.138957 [a]	0.132235

a: sig at 1%. b: sig at 5%. c: sig at 10%. Otherwise, not significant. Tests at levels include constant and trend terms. Tests in 1st diff include constant only.

The ADF tests clearly show the existence of unit root in all cases, both before and after automation, but the KPSS test is sometimes ambiguous. Examination of the correlograms shows plots consistent with non stationarity in levels and stationarity in 1st differences: it seems reasonable to conclude that all prices are I(1). Though they are non stationary, this does not prove that they are random walks. A follow-up step is a Box-Jenkins type examination of the autocorrelation functions of the returns, $\{\Delta \ln p_t\}$ to identify any discernible patterns. A returns series is considered to be white noise (WN) for sufficiently small values of the Box-Ljung Q-statistic over a sustained period (or, equivalently, for sufficiently large corresponding p-values) and if, on the basis of Engle's LM test, there is no evidence of GARCH effects. If the Q-statistics are sufficiently large, then the returns are not a white noise process (they are predictable) and an ARMA model, an ARMA model with GARCH residuals, or a purely GARCH process is sought. The results of this exercise are summarized in Table 4 below:

Table 4- Identification of Return Behaviour

JSE Securities	Process	TTSE Securities	Process
CAR Pre	WN	AMCL Pre	AR(1) with GARCH resid
Post	GARCH	Post	WN
CCC Pre	WN	GHL Pre	AR(1)
Post	GARCH	Post	ARMA(1, 1) with GARCH resid
CRTS Pre	WN	JMMB Pre	ARMA(1, 1) with GARCH resid
Post	WN	Post	GARCH
CWJA Pre	AR(1)	NEL Pre	MA(1) with GARCH resid
Post	WN	Post	MA(1) with GARCH resid
DG Pre	WN	NFM Pre	AR(1) with GARCH resid
Post	WN	Post	AR(1) with GARCH resid
GK Pre	MA(1)	NML Pre	ARMA(1, 1) with GARCH resid
Post	MA(1) with GARCH resid	Post	ARMA(1, 1) with GARCH resid
GLNR Pre	GARCH	RBL Pre	ARMA(1, 1)
Post	GARCH	Post	ARMA(1, 1) with GARCH resid
JBG Pre	WN	RBTT Pre	ARMA(1, 1) with GARCH resid
Post	AR(1)	Post	ARMA(1, 1) with GARCH resid
LOJ Pre	WN	SBTT Pre	ARMA(1, 1)
Post	WN	Post	ARMA(1, 1)
NCBJ Pre	MA(1) with GARCH resid	TCL Pre	ARMA(1, 1) with GARCH resid
Post	GARCH	Post	ARMA(1, 1) with GARCH resid
RJR Pre	WN	WCO Pre	ARMA(1, 1) with GARCH resid
Post	WN	Post	ARMA(1, 1) with GARCH resid

In the case of the JSE, in only one case (CWJA) does automation result in efficiency when the pre-automation period was inefficient. In some cases, pre-automation efficiency

was converted into a post-automation inefficiency (CAR, CCC, JBG) and in no case was pre-automation inefficiency converted to post automation efficiency. Finally, in some cases, the market appeared efficient both before and after automation.

In the case of the TTSE, in only one case (AMCL) did post automation efficiency follow pre-automation inefficiency. In all other cases, the market remained inefficient both before and after automation.

A fundamental shortcoming of the tests discussed above, which are widely used in the literature, is that they can distinguish only between 'efficiency' and 'inefficiency': the relative degree of efficiency and inefficiency is not discernible. If for instance, automation resulted in more or less inefficiency, we cannot conclude on the basis of these tests. Furthermore, the tests depend on the normality of the returns, which we have already shown to be untrue. R/S analysis overcomes these two shortcomings: it measures the degree of efficiency/inefficiency and it is robust to non normality.

The Hurst component was estimated using a RATS routine HURST.SRC, available on www.estima.com, where R/S is calculated using a procedure due to Peters (1991). The results obtained are shown in Table 5 below:

Table 5- Estimates of Hurst Components

Security JSE	Pre	Post	Security TTSE	Pre	Post
CAR	1.05039	1.01670	**AMCL**	1.07391	1.04014
CCC	1.01196	0.96305	**GHL**	1.22122	1.03467
CRTS	1.03768	1.06979	**JMMB**	1.05066	1.05657
CWJA	0.95087	0.97247	**NEL**	1.11960	1.06319
DG	1.21027	1.02200	**NFM**	0.96618	0.86601
GK	1.16845	1.03275	**NML**	1.07337	1.03300
GLNR	1.10340	1.03280	**RBL**	1.06312	1.08145
JBG	1.02942	0.92571	**RBTT**	1.08397	1.01998
LOJ	1.12588	1.57426	**SBTT**	1.13686	1.02751
NCBJ	1.00724	0.98074	**TCL**	1.10402	1.00806
RJR	1.15630	1.03019	**WCO**	0.97802	1.02991

The regressions on which the calculation of the individual Hurst components is based are all very good: the estimated coefficients are highly significant, the $\bar{R}^2$ values are all very close to 1and there is almost no evidence of serial correlation (on the basis of the p-values associated with the Breusch-Godfrey statistics). The values of the estimated Hurst index are very high in all cases, both before and after automation and in all cases are significantly different from their expected values. This indicates that, in both periods,

both the JSE and the TTSE are highly inefficient. However, there seems to be an improvement in efficiency in both the JSE and the TTSE although the value of the index actually increases in 3 of the cases in both exchanges indicating that automation may have resulted in further inefficiency.

5. Conclusions and recommendations

The evidence to date about the efficacy of automation is not conclusive, whether or not the classical parametric tests or the non parametric R/S analysis is employed. It is possible that the jury should remain out until more data are collected, especially in the case of R/S analysis, which is sensitive to the length of the series. Data collection, in fact, is a major failing of both the TTSE and the JSE and data limitations result in corresponding limitations to data analysis. A firm recommendation is that intraday data on bid-ask spreads as well as on prices and volumes should become an absolute priority of both exchanges. After all, automation and computerisation now make this an extremely straightforward task to perform. A second recommendation is that physical certificates be phased out as soon as possible on the JSE. Finally, on-line discount trading services must be the next step in the evolution of automated trading on both exchanges, which are more appropriate for individuals who require fast execution, lowest commissions and have the expertise to make their own trading decisions without the direction of a full service broker. It provides the opportunity to leverage independence to execute, receive automatic fills, monitor, and manage your account on your time. With an online order-entry system orders are transmitted via the Internet (electronically), directly to the Pit or to the Exchange floor in real time (in as little as 2.5 seconds).

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