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How Does Electronic Trading Affect Efficiency of Stock Market and Conditional Volatility? Evidence from Toronto Stock Exchange

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Abstract
The present paper investigates informational efficiency and changes in conditional volatility of the TSX before and after the implementation of an automated trading system on April 23, 1997. Using a battery of unit root, stationarity, as well as linear tests, we find that the introduction of electronic trading led to an increase in linearity dependence in TSX daily returns. In addition, when we examined the nonlinearity dependences using powerful econometric tests, we find that electronic trading has increased nonlinear dependencies in return series, which is the main cause of rejecting the Random Walk Hypothesis (RWH). Our results suggest that the automated trading system has negatively affected informational efficiency of the TSX. We also find evidence of long memory following automation which suggests that the introduction of electronic trading has increased the level of persistence of information and trading shocks.

Keywords
Automated Trading, Random Walk, Nonlinear Dynamics, Conditional Volatility

JEL classification
G14, G15

1. Introduction

Operating in increasingly competitive global environments, stock markets have undergone several major changes in their market-microstructures aimed at enhancing trade transparency and efficiency. This race for higher market quality was fuelled by the spectacular advances in information technology over the last few decades. One of the major features of this worldwide stock-market restructuring is the replacement of floor trading systems by electronic trading systems. The implementation of electronic trading by major stock market exchanges has generated great debate among both practitioners and academicians on the advantages and disadvantages of adopting such systems. Opponents of electronic trading argue that it leads to lower market liquidity and increases transaction cost (see, for instance, Grossman and Miller, 1986; Miller, 1991). Advocates of electronic trading systems argue that it leads to lower bid-ask spread and higher volume transactions than floor trading systems (Blennerhasset and Brown, 1998; Frino, McInish and Toner, 1998, among others).

The present paper aims to investigate informational efficiency and changes in conditional volatility of the Toronto Stock Exchange (TSX) before and after the implementation of an automated trading system. Created on October 25, 1861, the TSX has gradually shifted its trading system from floor to automated trading system. In 1977 the TSX introduced the world's first computer-assisted trading system (CATS) to quote less liquid equities, but continued to use a floor trading system until April 23, 1997 when it became the second-largest fully automated stock exchange in North America, after the NYSE.

Several factors argue for such study. First, to the best of our knowledge, this study is the first to examine simultaneously the information efficiency and conditional volatility of the TSX before and after April 23, 1997. Previous studies focuses on the information efficiency of the TSX without taking into consideration the effect of the implementation of an automated trading system. For example, Alexeev and Tapon (2011) test the weak form efficiency using all security traded on Toronto Stock Exchange from 1980 to 2010. Although, they do not focus on the sample period prior and post implementation of the electronic trading system, they fail to reject the null hypothesis of weak form efficiency on the TSX. Second, most of the analyses are based on U.S. data, and Canadian studies are almost nonexistent (Domowitz, 1990, 1993; Beelders and Massey, 2002; Fung et al., 2005; Alexeev and Tapon, 2011). Finally, we examine trends in the daily returns series based on serial correlation and nonlinear dynamics before and after automation.

The importance of examining nonlinear dynamics in financial time series is better appreciated through its implications for the field of finance at the theoretical and empirical levels. Indeed, Evidence of nonlinear dependence has very important implications for academicians and for practitioners. For academicians, the existence of nonlinearity in financial series casts serious doubt on the adequacy of statistical models of asset pricing that implicitly take a linear form, as well as empirical tests of the weak-form market efficiency, tests of causality, tests of stationarity and tests of co-integration. For practitioners, evidence of nonlinear dependency directly affects the widely debated issue of predictability of financial time series, which has been examined mainly through a linear approach. Moreover, nonlinear models have important implications for portfolio management techniques, hedging and pricing of derivatives (such as volatility index), and allow for superior out-of-sample forecasts of financial series.

The remainder of the paper is organized as follows: Section 2 outlines our research methodology; Section 3 describes our data set; Section 4 discusses the empirical findings and section 5 concludes the paper.

2. Theory and Research Methodology

2.1. Random Walk Hypothesis

Fama (1970) argues that efficient stock market prices fully reflect all available and relevant information, meaning an absence of excess-profit opportunities. Share price changes are therefore independent and fluctuate only in response to the random flow of news. Trading strategies based on past and current information are useless in generating excess-profit

opportunities.[1] This implies a random walk market, where a random walk model best describes stock prices. According to Campbell, Lo and MacKinlay (1990), there are three different versions of the random walk model: Random Walk I, Random Walk II, and Random Walk III. The Random Walk I or *strict white noise process* requires sequences of price changes to be independent and identically distributed. If we assume sequences of price changes to be independent and drop the identically distributed assumption, we get the version of Random Walk II. Finally, the Random Walk III or *white noise process* is obtained by relaxing the independent and the identically distributed assumption.[2]
Harvey (1993) argues that non-linear models may have the *white noise* property although they are dependent and identically distributed. Given the growing theoretical and empirical studies showing that share price changes are inherently non-linear, evidence of uncorrelated share price changes are not sufficient conditions for a market to be efficient. Therefore, we examine the assumption of *i.i.d* share price changes, which is the most restrictive version of the random walk hypothesis, but most appropriate to test the efficient market hypothesis. Let P_t be the level of the TSX index at time *t*, and define $P_t \equiv Ln(P_t)$ as a stochastic process given by the recursive relation:[3]

$$p_t = \mu + p_{t-1} + \omega_t \quad (1)$$

The continuously compounded return for the period t-1 to t is expressed as

$$r_t \equiv \Delta p_t = \mu + \omega_t \quad (2)$$

where μ is the expected price change or drift and ω_t are represents the residuals.
Equation (1) describes the random walk model with a drift. Under the random walk hypothesis, the drift should be insignificantly different from zero, the distribution of returns should be stationary over time $(r_t \sim I(0))$, and the residuals should be *i.i.d* random variables or, in other words, a strict *white noise*. We estimate Equation (2) with ordinary least squares and test the statistical significance of the drift μ.

[1] Samuelson (1965) also shows that share prices, in an efficient stock market, fluctuate randomly and only in response to the arrival of new information.

[2] A white noise process is a sequence of uncorrelated random variables with constant mean and variance: for any s ≠ 0 $E(\epsilon_t \epsilon_t\text{-}s) = 0$, and for s = 0, $E(\epsilon_t) = 0$, and $E(\epsilon_t \epsilon_s) = \sigma^2_t$

[3] We use the natural logarithm of prices in order to make the process generating the times series to be independent of the actual price levels. Furthermore, p_t has favorable econometric properties in comparison to P_t (see Campbell, Lo and MacKinlay, 1997).

To examine the stationarity assumption; we employ the unit root tests advocated by Carrioni-Silvestre, Kim and Perron (2009). By allowing for multiple structural breaks, Carrioni-Silvestre et al's procedure extends the unit tests of Elliott, Rothenberg, and Stock (1996) and Ng and Perron (2001) used in other studies such as by Al Janabi, Hatemi-J and Irandoust (2010). We employ Carrioni-Silvestre et al's test with three structural breaks and provide three test statistics (MZα, MSB, MZt) to test the null of a unit root against the alternative of trend stationarity. We note however that testing for linear serial independence of price changes is neither a necessary nor a sufficient condition to accept or reject the random walk hypothesis. If the index returns (either before or after automation) turn out to be serially correlated, this should not necessarily imply that the Canadian stock market is inefficient. Spurious autocorrelation may exist due to institutional factors such as non-synchronous trading which may induce price-adjustment delays into the trading process (Lo and Mackinlay, 1990).[4] As a non-synchronous trading autocorrelation effect is relatively short-timed, we should expect autocorrelation to be persistent in daily index returns series. If price changes turn out to be statistically uncorrelated, it would not necessarily imply efficiency. Market-index returns can be linearly uncorrelated but at the same time non-linearly dependent. Hence, we will analyse the impact of automation on market efficiency by analysing stionarity, linearity and nonlinearity before and after the date of the implementation of electronic trading.

2.2. Testing for Non-linearity and Uncovering its Source

The theory and empirical evidence of non-linearity in share price changes suggest that the *i.i.d* assumption is a necessity for an appropriate examination of efficiency market hypothesis. Hence, statistical techniques capable of detecting linearity as well as non-linearity in share price changes need to be used. To test whether the share price changes are *i.i.d* we use a powerful test originally proposed by Brock, Dechert and Scheinkman (1987) (henceforth *BDS*) and designed by Brock et al (1996). The *BDS* test is a non-parametric test with the null hypothesis that the series in question are *i.i.d* against an unspecified alternative. The test is based on the concept of correlation integral, a measure of spatial correlation in n-dimensional space originally developed by Grassberger and Procaccia (1983). In general, a rejection of the null hypothesis is consistent with some type of dependence in the returns that could result from a linear stochastic process, non-stationarity, a non-linear stochastic process, or a non-linear deterministic system.[5] According to Hsieh (1991), linear dependence can be ruled out by prior fitting of Akaike Information Criterion (*AIC*)-minimizing autoregressive moving average (ARMA) model. In addition, since we are using daily data over a relatively short time period, is it safe to argue that for an economically and politically stable country such as Canada, non-stationarity is unlikely to

[4] See Campbell, Grossman and Wang (1993) for a modeling of autocorrelations in index and stock returns.

[5] The Simulation studies of Brock, Hsieh and LeBaron (1991) show that the BDS test has power against a variety of linear and non-linear processes, including for example GARCH and EGARCH processes.

be the cause of non-linearity; a hypothesis that will be tested using unit root tests.[6] Therefore, a rejection of the *i.i.d* assumption using filtered data can be the result of a non-linear stochastic process or a non-linear deterministic system. However, the *BDS* test is neither able to distinguish between stochastic and deterministic non-linearity nor can it discriminate between additive and multiplicative stochastic dependence. We are therefore concerned with a stochastic explanation of returns behaviour before and after automation, the latter issue mattering in this case. To determine the source of non-linearity in the returns series we use Hsieh's test.

As stated earlier, in order to choose an appropriate non-linear model describing the returns series, it is crucial to know the source of non-linearity in the data. Non-linearity can enter through the mean of a return generating process (additive dependence) as in the case of a threshold autoregressive model, or through the variance (multiplicative dependence), as in the case ARCH model proposed by Engle (1982). Non-linearity can be both additive and multiplicative as in the case of GARCH-M model.

2.3. Modeling Conditional Heteroscedasticity

Although the Hsieh Test provides us with the type of non-linearity underlying the data series, it does not tell us what model to choose for the returns generating process. Still, the results of the third-moment test provide the first step towards finding the best non-linear model to fit the data. If the source of non-linearity turns out to be the variance (a multiplicative dependence) then we should look into ARCH models. Engle (1982) was first to introduce these models, which are now very widely used in financial time series modeling. For example the generalized ARCH (GARCH) models, designed by Bollerslev (1986), are very successful in describing certain properties of high frequency financial time series such as excess kurtosis and volatility clustering. Assuming that the returns process is expressed as an autoregressive process of order *k*:

$$r_t = \beta_0 + \sum_{i=1}^{k} \beta_i r_{t-i} + \omega_t \quad (3)$$

Conditional on information set up to time t-1, ω_t is an *i.i.d* random variable with mean 0 and variance σ_t^2, a GARCH(p,q) model. It is noteworthy that the GARCH (p,q) model is a symmetric variance process, in that the sign of the disturbance is ignored. Several empirical studies show that a GARCH(1,1) model expressed as:

$$\sigma_t^2 = \eta + \lambda_1 \omega_t^2 + \theta_1 \sigma_{t-1}^2 \quad (4)$$

provides a parsimonious fit for share price changes series (see, for instance, Baillie and Bollerslev ,1989). Similar to the GARCH process, the FIGARCH model of Baillie et al (1996) does not allow for the "leverage effect", which is also known as a volatility asymmetry. Discovered by Black (1976), "leverage effect" means that volatility tends to rise in response to

[6] Non-stationarity is assumed to be mainly the result of structural change, such as policy changes, technological and financial innovation.

lower than expected returns and to fall in response to higher than expected returns. Several researchers have found empirical evidence of such asymmetry in stock returns behaviour (Nelson, 1992; Glosten, Jagannathan and Runke, 1993). Hence, we also use the FIEGARCH of Bollersev and Mikkelsen (1996).[7] The superiority of FIEGARCH model, in comparison to GARCH, comes from its flexibility. In fact, other than modeling volatility clustering and excess kurtosis, FIEGARCH process is capable of describing high volatility persistence, long memory in the conditional variance, as well as leverage effect, which are common features that stock market indices are likely to exhibit.

Now let us go back to the implications of Hsieh's test. If the result from the third-moment test shows that the non-linearity dependence is additive then a GARCH-in-mean (GARCH-M) model of Engle et al. (1987), would better describe returns series. The particularity of GARCH-M model is that it accounts for risk premium effect by introducing a volatility term into the return equation:

$$r_t = \beta_0 + \sum_{i=1}^{k} \beta_i r_{t-i} + \delta\sigma_t^2 + \omega_t \quad (5)$$

That is, GARCH-M measures the relationship between risk and returns. An insignificant δ implies that risk does not affect the returns process. Once we select the model that best fits the data, we test for any ARCH effects using the Lagrange Multiplier test (LM) proposed by Engel (1982).[8] If the null hypothesis that the disturbance lacks ARCH effect is accepted, then we employ the BDS test to the standardized residuals of the model to see whether all the non-linearity is accounted for.[9]

3. Data and Descriptive Statistics

Empirical research in non-linear dynamics needs large sample sets. Working with ultra-high frequency data or choosing a long time interval or both, can solve this. However, as noted by Hiesh (1991), ultra-high frequency data captures some artificial dependencies, which are caused by market microstructure and are detected easily by the *BDS* test. On the other hand, long time interval data series can be non-stationary. To handle this problem, we use the daily closing price of the Toronto Stock Exchange Index, TSX, from April 23, 1994 to April 23, 2000. That is 3 years before the automation date (i.e. April 23, 1997) and 3 years after, with a total of 1,512

[7] Bollerslev and Mikkelsen (1996) argue that FIEGARCH is stationary when the integration parameter is between 0 and 1.

[8] It is important to mention that to the extent that any non-normality is attributable mainly to excess kurtosis, we expect deviation from normality of returns to diminish when ARCH effects are accounted for.

[9] Brock (1987) proves that BDS test provides the same results whether employed to residuals or raw data in linear models.

observations. The data is obtained from the CFMRC database. Market index prices are transformed to daily returns $r_t = 100 \cdot \ln(P_t / P_{t-1})$, where P_t and P_{t-1} are prices at date *t* and *t-1* respectively.

Fig. 1

Table 1 below provides descriptive statistics of index returns for the whole sample, before and after automation. Figs 2 and 3 present the graphs of the log daily market index, the ACF and partial ACF as well as the *QQ* plot for each sub-sample.[10] The distribution of daily returns is negatively skewed before and after automation. The null hypothesis of skewness coefficient conforming to the normal distribution value of zero is rejected at 1% level. In addition, the null hypothesis of kurtosis coefficient conforming to the normal distribution value of three is rejected at 5% level. The daily returns are thus not normally distributed before and after automation, a conclusion confirmed by the *QQ* plots. We can also see that large price changes tend to follow large changes, and small changes tend to follow small changes. The volatility clustering seems to be more apparent after automation. Further analysis is needed to investigate this pattern in daily returns and volatility clustering following automation.

4. Empirical Results

4.1. Testing for Normality, Stationarity and Linear Dependence

Table 2 below reports the OLS estimate of the constant (or drift) by estimating Equation (2), along with a *JB* test statistic. The results suggest that the mean of the return series before automation is significantly different from zero, which is inconsistent with the random walk hypothesis. After automation, however, the intercept is insignificantly different from zero. Note that *JB* test statistic for both series supports the same conclusion as with the descriptive statistic in Table 1, indicating a departure from normality in return series.

As mentioned earlier, under the random walk hypothesis, the distribution of returns should be stationary over time. Furthermore, since structural changes can cause a rejection of the *i.i.d* process, it is important to explore the possible non-stationarity before and after automation to see whether we have chosen the right sample interval. To examine the stationarity assumption, we employ Carrioni-Silvestre, Kim and Perron (2009) unit root tests with three structural breaks. Table 3 presents the outcomes of unit root tests where we provide three test statistics (MZα, MSB, MZt) to test the null of a unit root against the alternative of trend stationarity. Our unit root test results suggest that the series before and after automation are stationary, at 1% level of significance.

Although these results are consistent with the random walk hypothesis, we cannot decide on the latter until we explore the dependence structure of the returns series.[11] To examine the linear

[10] The *QQ*-plot is a scatter plot of the standardized empirical of data series against the quantiles of a standard normal random variable.

[11] The reason is simple; unit root tests are not tests for predictability. They are designed just to investigate whether a series is difference-stationary or trend stationary.

dependence of the returns series, we use the modified *Q*-statistic of Ljung and Box (1978). The results of *Q*-statistic up to lag 40 (not tabulated here) suggest the existence of significant serial autocorrelation at several lags. As mentioned earlier, evidence of a temporal linear relationship can be spurious; therefore, independence assumption should not be ruled out without an extensive examination of the underlying linear as well as non-linear dependencies.

To test for the *i.i.d* assumption before and after automation we employ the *BDS* test. Table 4 and 5 below reports the *BDS* statistic for embedding dimension 2 to 8 and for epsilon values starting from 0.5 to 2 times the standard deviation of the returns series before and after automation, respectively. The results for both sub-samples strongly reject the null hypothesis of independently and identically distributed index price changes at 1% significance. However, we note a higher level of nonlinearity following the implementation of electronic trading. Now that we reject the Random Walk I, we focus on uncovering the structure of dependency in the returns series. Since the *BDS* test has a good power against linear as well as non-linear systems, we use a filter to remove the serial dependence in the return series and the resulting residuals series are re–tested for possible non-linear hidden structures. We use an autoregressive AR(k) model to take out all the linearity in each series. The identification of the AR(k) is based on the lowest *AIC*. Fig. 3 below shows a plot of Akaike's criterion for each sub-sample. Both start indexing at 1, but the first element of the *AIC* component is for order 0. Note that the minimum *AIC* is at 1 for sub-sample before automation, suggesting an autoregressive model of order 1 to fit the returns series. However, the AIC criterion suggests introducing 15 lags to capture the serial correlation after automation (Fig. 4).
To confirm the presence of non-linear dependence, we applied the *BDS* test to the residuals of the whitened series. Although lower than those of Tables 4 and 5, the *BDS* statistics displayed in Table 6 and 7 strongly reject the *i.i.d* assumption, which gives a clear indication of the existence of non-linear dependencies in returns series of both period. The squared residuals measures the second moments of the series and therefore, significant autocorrelations are evidence of time varying conditional heteroskedasticity in the residuals of the AR(1) and AR(15). It is noteworthy however, that evidence of non-linear dependence is stronger in the period after automation. Since we can rule out the non-stationarity and linearity as causes of the rejection of the *i.i.d* assumption, we can say that the inherent non-linearity in both sub-samples is either stochastic or deterministic. The results from Lyapunov exponents tests and Kolmogorov-Sinai entropy tests tests (not tabulated here), strongly reject the hypothesis that chaos is the cause of non-linearity in each sub-period, which suggest that the rejection of the *i.i.d* assumption is due to non-linear dependency.

4.2. Uncovering the Source of Nonlinearity and Modeling it
Although the results from the *BDS* test strongly support the existence of inherent non-linearity, it does not tell us whether it enters through the mean or variance of the returns series. To uncover the source of non-linear behaviour, we calculate the third-order moment test statistics of Hsieh (1991). All the values of the approximately normally distributed Hsieh test statistic (not tabulated here) are significant, implying a rejection of the null hypothesis of multiplicative dependence in both sub-samples. Therefore, a GACRH-M model is most likely to succeed in describing the return generating process than a GACRH model for both sub-samples.

Given the results of Hsieh's test, for each sub-sample, we have examined several GARCH-M (p,q) models.[12] Using the *AIC* and *BIC* as tools for model selection, it turns out that a AR(1)-GARCH-M (1,1) is the best model to fit the data before automation and a AR(15)-GARCH-M (1,1) for returns series after automation. Table 8 reports the estimation results of both GARCH-M(1,1) processes under the assumption that the innovations follow a student distribution. The coefficients of the conditional variance equation, λ_1 and θ_1, are significant at 1% level implying a strong support for the ARCH and GARCH effects in both periods. However the ARCH and GARCH effect seems to be more persistent for the period after automation, which is consistent with our prior analysis.

It is noteworthy that coefficient of arch-in-mean measures the inter-temporal relationship between expected return and conditional volatility in a series. The results from Table 8 suggest that, before automation, the conditional volatility is weakly priced in the Canadian stock market. An increase in the conditional variance is associated with a small, if any, decrease in the conditional mean; implying that risk neutral investors may have dominated trading in the TSX before automation. This is somewhat consistent with most of the studies that examined the inter-temporal relationship between expected returns and conditional volatility. For example, Theodossiou and Lee (1995) found no relationship between returns and volatility in ten industrialized countries. Chan, Karolyi and Stulz (1992) showed that the conditional expected excess return on S&P 500 is not related to its conditional volatility.

After automation, however, the coefficient of the conditional volatility in mean equation is negative and significant (p-value = 0.004), which suggests a negative relationship between risk and returns. This is consistent with Nelson (1992) and Glosten, Jagannathan, and Runkle (1993) stating that unanticipated stock market returns are negatively related to unanticipated movement in conditional volatility.

Note however, that for both models the sum of the parameters estimated by the variance equation is close to one. A sum of λ_1 and θ_1 near one is an indication of a covariance stationary model with a high degree of persistence; and long memory in the conditional variance. The sum $\lambda_1 + \theta_1$ is also an estimation of the rate at which the response function decays on a daily basis. Since the rate is high, the response function to shocks is likely to die slowly. During the period before automation, a month after an initial shock, 15% (or 0.938^{30}) of the impact remains in effect. Six months later, the initial shock vanishes ($0.938^{180} = 0\%$). However, after automation, a month after an initial shock 75% (or 0.991^{30}) of the impact remains in effect. After six months, 18% of the initial stock remains persistent.

4.3. Diagnostic tests

The results of the diagnostic tests show that the two models are correctly specified. The modified *Q*-statistics for the standardized residuals and standardized squared residuals are both insignificant, suggesting the chosen GARCH-M process are successful at modeling the serial

[12] It is should be noted, however, that our analysis is not limited to GARCH type models. In fact, we have tested numerous varieties of volatility models including bilinearity models. Our results are consistent with the results of Hansen and Lunde (2005) who compare 330 ARCH-type models in terms of their ability to describe the conditional variance, and find that a GARCH (1,1) outperforms all tested models.

correlation structure in the conditional mean and conditional variance. Given the evidence of long memory in the period after automation we have estimated the series with a FIGARCH type models and also FIEGARCH type models to examine the leverage effect. The results presented in Table 8 show that our original GARCH-M model is better than a FIGARCH (1,1) in modeling volatility following automation.

We also calculate the Lagrange-multiplier (*LM*) for ARCH effect proposed by Engle (1982); results are shown in Table 8. The null hypothesis, that the residuals lack ARCH effect, is not rejected, which shows that the GARCH-M models has counted for all the volatility clustering in the data.[13] *JB* and Sharp tests for normality fail to reject the null hypothesis that the standardized residuals are normally distributed. To examine whether the GARCH-M model has succeeded in capturing all the nonlinear structure in the data, we employ the *BDS* test to its standardized residuals. A rejection of the *i.i.d* hypothesises will imply that the conditional heteroskedasticity is not responsible for all the nonlinearity in index returns, and there is some other hidden structure in the data. To have a preliminary view of the GARCH-M modeling capability, we look at the autocorrelation coefficient for both the standardized residuals and squared standardized residuals. Our results show that the AR(1)-GARCH-M and AR(15)-GARCH-M models capture all the linear as well non-linear dependencies in the index returns series. Tables 9 and 10 displays the *BDS* statistics on the standardized residuals from the GARCH-M processes. In line with the observations from Table 8, the *BDS* test fails to reject the null hypothesis that the standardized residuals are *i.i.d* random variables at 5% and 1% degree of significance for the sub-sample. This confirms that the AR(1)-GARCH-M and AR(15)-GARCH-M models indeed capture all the non-linearity in the both series, and that the conditional heteroscedasticity is the cause of the non-linearity structure uncovered in the returns series.

5. Summary and Conclusion

One of the major features of the worldwide stock-market restructuring is the replacement of floor trading systems by electronic trading systems. The implementation of electronic trading by major stock market exchanges has generated great debate among both practitioners and academicians on the advantages and disadvantages of adopting such systems. Opponents of electronic trading argue that it leads to lower market liquidity and increases transaction cost while advocates of electronic trading systems argue that it leads to lower bid-ask spread and higher volume transactions than floor trading systems.

The present paper investigates this issue using the case of Toronto Stock Exchange (TSX) where an automated trading system was implemented on April 23, 1997. Using a battery of unit root, stationarity, as well as linear tests, we find that though the Random Walk Hypothesis (RWH) is rejected before and after the automation, the latter led to an increase in linearity dependence of the TSX daily returns. In addition, when we examine the nonlinearity dependencies using powerful econometric tests, we find that the introduction of electronic trading has increased nonlinear dependencies in returns series, which tend to be the main cause of rejecting the RWH. This pattern seems to be the cause of a high level of conditional volatility that may be due to an

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[13] Under the null hypotheses the test statistic $LM = T \cdot R^2 \overset{A}{\sim} \chi^2(p)$, where T is the sample size and R^2 is computed using the estimated residuals.

increase in trading volume since automation facilitated trading and increased liquidity. We also find evidence of long memory following automation, which suggests that the introduction of electronic trading systems have increased the level of persistence of information and trading shocks.

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Fig. 1 Before Automation

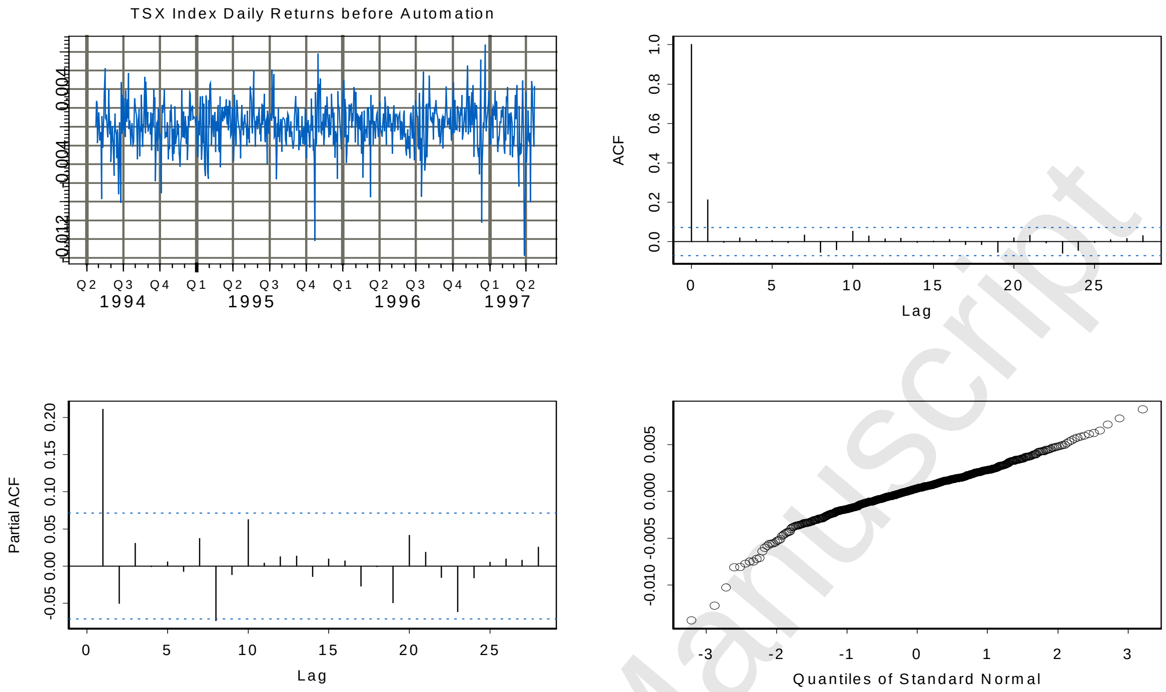

Fig. 2 After Automation

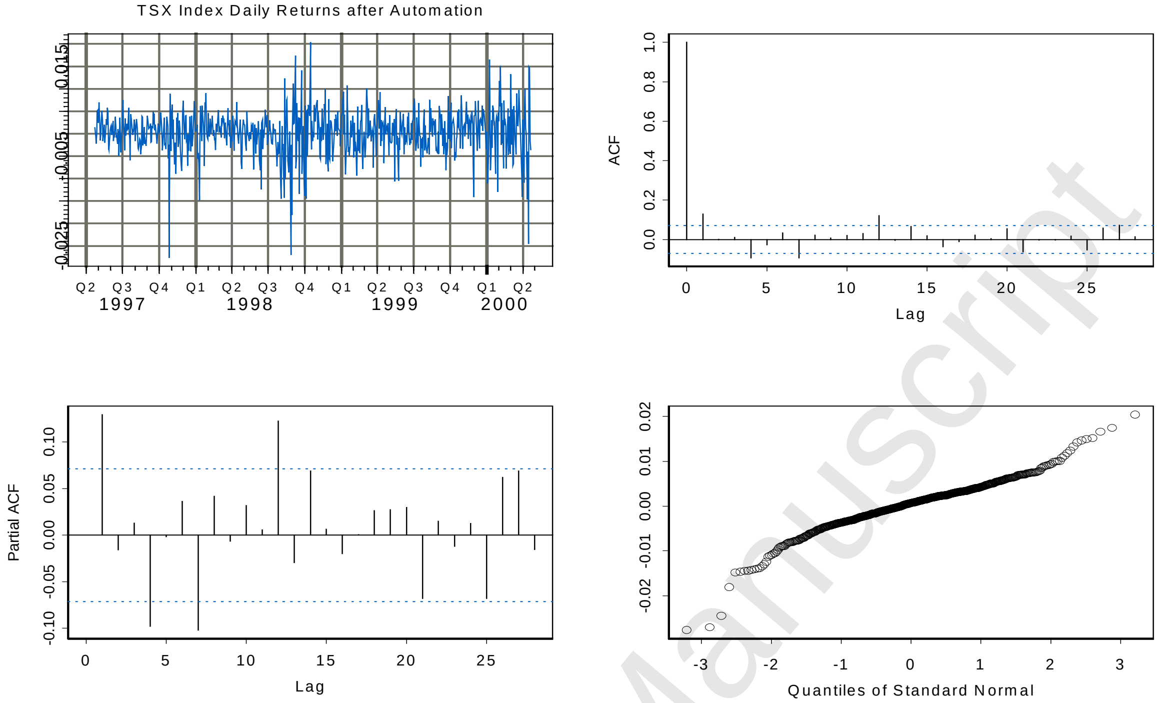

Fig. 3 Optimal Number of Lags Based on AIC: Before and After Automation

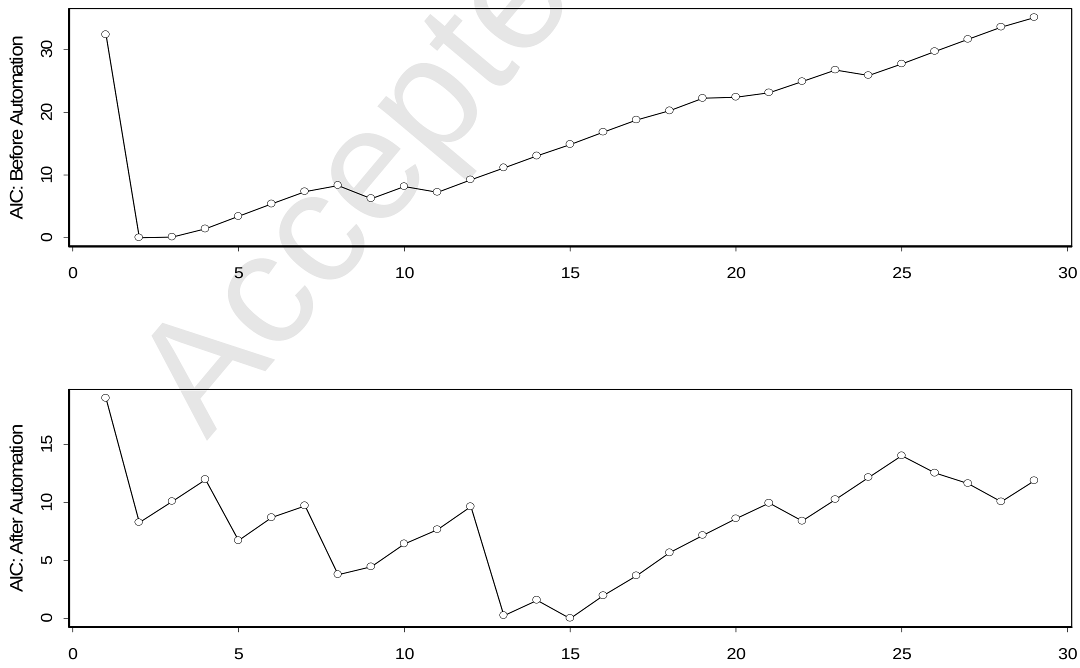

Fig. 4 ACF of Residuals and Squared Residuals from AR(1) and AR(15)

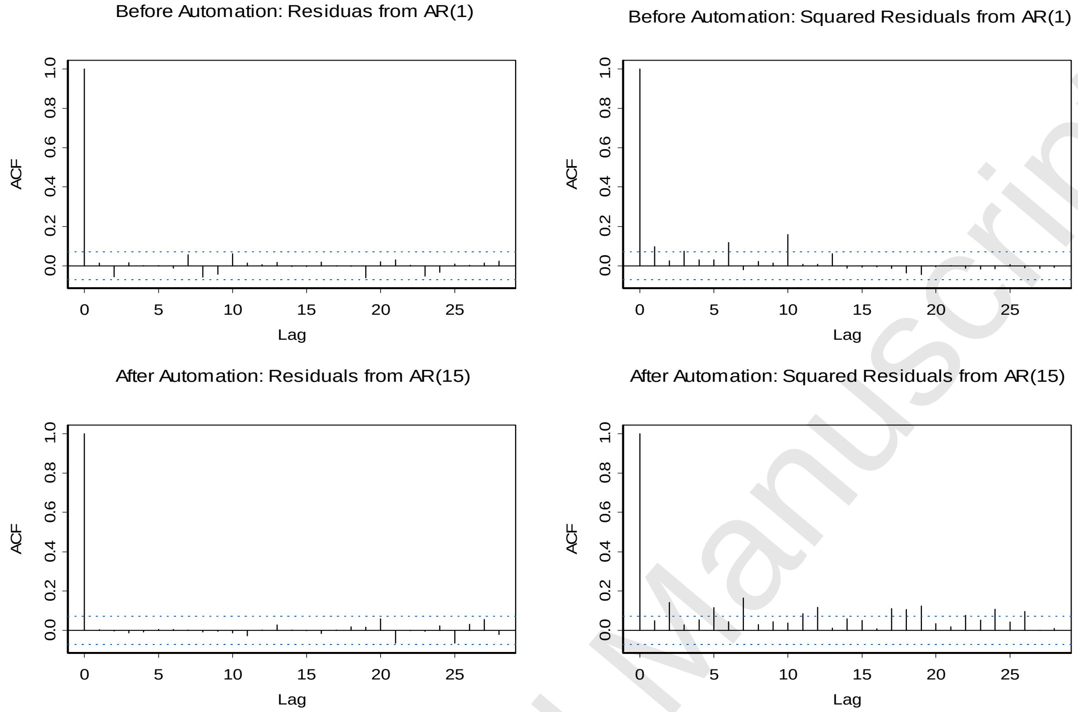

Table 1 Descriptive statistics

	Whole Series	Before Automation	After Automation
Mean	0.0002	0.0002	0.0002
Standard Error	0.0001	0.0001	0.0002
Median	0.0004	0.0003	0.0007
Standard Deviation	0.0039	0.0024	0.0049
Kurtosis	6.8447	3.1959	4.2863
Skewness	-0.8029	-0.6737	-0.7227
n	1512	756	756

Table 2 Results of the Regression of Random Walk Model with Drift

	Estimated constant	P-value	JB
Before	0.0186*	0.0349	374.46**
After	0.0244	0.1722	634.53**

Note: *, ** Significance at the 5% and 1% level. JB is the Jarque-Bera test for normality

Table 3 M unit root test with multiple structural breaks of Carrion-i-Silvestre et al. (2009)

	MZα	MSB	MZt
Before	-42.12 **	-0.11 **	-4.54 **
After	-39.12 **	-0.13 **	-4.44**

Note: *, ** Significance at the 5% and 1% level respectively.

Table 4 BDS test statistic: Before automation

m	ϵ/σ		ϵ/σ		ϵ/σ		ϵ/σ	
2	0.5	4.664 **	1	5.087 **	1.5	4.964 **	2	4.352 **
3	0.5	5.367 **	1	5.731 **	1.5	5.420 **	2	4.717 **
4	0.5	5.517 **	1	5.981 **	1.5	5.773 **	2	5.074 **
5	0.5	5.686 **	1	6.345 **	1.5	5.991 **	2	5.234 **
6	0.5	6.314 **	1	6.725 **	1.5	6.421 **	2	5.541 **
7	0.5	6.616 **	1	6.973 **	1.5	6.670 **	2	5.843 **
8	0.5	7.545 **	1	7.059 **	1.5	6.763 **	2	5.998 **

Note. m is embedding dimension, ε *is the bound,* *,** Significance at the 5% and 1% level respectively.

Table 5 BDS test statistic: After automation

m	ϵ/σ		ϵ/σ		ϵ/σ		ϵ/σ	
2	0.5	7.363 **	1	6.852 **	1.5	6.366 **	2	5.519 **
3	0.5	8.480 **	1	7.712 **	1.5	7.281 **	2	6.825 **
4	0.5	10.200 **	1	8.848 **	1.5	8.227 **	2	7.805 **
5	0.5	11.699 **	1	10.289 **	1.5	9.353 **	2	8.633 **
6	0.5	13.634 **	1	11.506 **	1.5	10.159 **	2	9.286 **
7	0.5	16.027 **	1	12.482 **	1.5	10.785 **	2	9.746 **
8	0.5	18.487 **	1	13.836 **	1.5	11.508 **	2	10.271 **

Note. m is embedding dimension, ε *is the bound,* *,** Significance at the 5% and 1% level, respectively.

Table 6 BDS test statistic for residuals of AR(1): Before automation

M	ϵ/σ		ϵ/σ		ϵ/σ		ϵ/σ	
2	0.5	3.293 **	1	3.550 **	1.5	3.499 **	2	3.124 **
3	0.5	3.313 **	1	3.756 **	1.5	3.428 **	2	2.989 **
4	0.5	3.267 **	1	4.216 **	1.5	3.807 **	2	3.353 **
5	0.5	3.484 **	1	4.615 **	1.5	4.068 **	2	3.597 **
6	0.5	2.964 **	1	5.071 **	1.5	4.557 **	2	3.988 **
7	0.5	2.366 *	1	5.387 **	1.5	4.911 **	2	4.355 **
8	0.5	1.536	1	5.601 **	1.5	5.070 **	2	4.596 **

Note. m is embedding dimension, ε is the bound, *,** Significance at the 5% and 1% level respectively.

Table 7 BDS test statistic for residuals of AR(14): After automation

M	ϵ/σ		ϵ/σ		ϵ/σ		ϵ/σ	
2	0.5	4.204 **	1	4.807 **	1.5	4.583 **	2	4.140 **
3	0.5	4.672 **	1	5.281 **	1.5	5.361 **	2	5.307 **
4	0.5	5.200 **	1	5.837 **	1.5	5.968 **	2	5.937 **
5	0.5	5.990 **	1	6.866 **	1.5	6.754 **	2	6.432 **
6	0.5	6.681 **	1	7.807 **	1.5	7.448 **	2	6.993 **
7	0.5	6.220 **	1	8.485 **	1.5	7.903 **	2	7.350 **
8	0.5	7.154 **	1	9.546 **	1.5	8.563 **	2	7.834 **

Note. m is embedding dimension, ε is the bound, *,** Significance at the 5% and 1% level respectively.

Table 8 Modeling Conditional Heteroscedasticity: before and after automation

	Before Automation		After Automation			
	AR(1)-GARCH-M(1,1)		AR(15)-GARCH-M(1,1)		AR(15)-FIEGARCH(1,1)	
Coefficient	*Estimate*	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
$\beta 0$	0.001	0.007	0.001	0.000	0.000	0.024
$\beta 1$	0.203	0.000	0.186	0.000	0.185	0.000
$\beta 2$	-	-	-0.057	0.124	-0.080	0.032
$\beta 3$	-	-	-0.034	0.348	-0.028	0.277
$\beta 4$	-	-	-0.071	0.049	-0.071	0.067
$\beta 5$	-	-	0.017	0.645	0.015	0.370
$\beta 6$	-	-	0.030	0.408	0.010	0.414
$\beta 7$	-	-	-0.080	0.019	-0.075	0.039
$\beta 8$	-	-	0.050	0.153	0.047	0.147
$\beta 9$	-	-	-0.014	0.677	0.017	0.351
$\beta 10$	-	-	0.073	0.028	0.078	0.035
$\beta 11$	-	-	-0.017	0.591	-0.020	0.317
$\beta 12$	-	-	0.053	0.116	0.068	0.054
$\beta 13$	-	-	-0.005	0.880	-0.035	0.230
$\beta 14$	-	-	0.052	0.097	0.052	0.120
$\beta 15$	-	-	-0.010	0.763	-0.012	0.395
Arch-in-Mean	-106.601	0.062	-44.257	0.004	-	-
η	0.000	0.049	0.000	0.021	0.000	0.030
λ_1	0.095	0.001	0.126	0.000	0.300	0.000
θ_1	0.843	0.000	0.864	0.000	0.500	0.001
$\lambda_1 + \theta_1$	0.938	-	0.991	-	-	-
d	-	-	-	-	0.500	0.001
ρ	-	-	-	-	0.166	0.000
AIC	-7077.29	-	-6097.86	-	-6014.61	-
BIC	-7044.91	-	-6005.30	-	-5922.05	-
LM Test	17.039	0.148	12.350	0.418	14.045	0.298
JB	125.7 04	0.000	149.801	0.000	186	0.000
S-W	0.975	0.000	0.983	0.000	0.984	0.225
MQ(10)	13.329	0.207	9.350	0.499	9.198	0.513
MQ(20)	17.366	0.629	19.866	0.466	16.721	0.671
MQ(30)	25.050	0.723	40.004	0.105	33.551	0.299
MQ(40)	39.217	0.505	47.572	0.192	40.263	0.459
MQ(50)	45.043	0.672	60.852	0.140	52.518	0.377
ML(10)	14.561	0.149	9.884	0.451	14.985	0.133
ML(20)	22.693	0.304	15.484	0.748	20.924	0.402
ML(30)	25.080	0.721	19.867	0.920	24.570	0.746
ML(40)	31.013	0.845	30.269	0.868	33.498	0.756
ML(50)	37.224	0.910	32.748	0.972	36.750	0.919

Note: λ, θ, d and ρ are the ARCH, GARCH, integration and leverage parameters, respectively. S-W is the Shapiro-Wilk test for normality proposed by Shapiro and Wilk (1965). MQ(k) is the modified Q-statistic at lag k for the standardized residuals series. ML(k) is the McLeod-Li test at lag k for the squared standardized residuals series.

Table 9 BDS test Statistic for Residuals of AR(1)- GARCH-M(1,1): Before Automation

M	ε/σ		ε/σ		ε/σ		ε/σ	
2	0.5	-2.218 *	1	-1.773	1.5	-1.075	2	-0.405
3	0.5	-1.484	1	-1.370	1.5	-1.087	2	-0.278

4	0.5	-1.587	1	-1.606	1.5	-1.430	2	-0.544
5	0.5	-1.126	1	-1.186	1.5	-1.157	2	-0.342
6	0.5	-0.986	1	-1.004	1.5	-1.110	2	-0.291
7	0.5	-0.020	1	-0.921	1.5	-0.917	2	-0.088
8	0.5	0.674	1	-0.657	1.5	-0.610	2	0.174

Note. m is embedding dimension, ε is the bound, * Significant at the 5% level., ** Significant at the 1% level.

Table 10 BDS test Statistic for Residuals of AR(15)- GARCH-M(1,1): After Automation

M	ϵ/σ		ϵ/σ		ϵ/σ		ϵ/σ	
2	0.5	-0.290	1	-0.187	1.5	0.210	2	1.129
3	0.5	-0.147	1	-0.239	1.5	0.276	2	1.121
4	0.5	-0.427	1	-0.470	1.5	0.106	2	1.026
5	0.5	-0.714	1	-0.677	1.5	0.029	2	1.155
6	0.5	-0.747	1	-0.677	1.5	0.071	2	1.236
7	0.5	-0.871	1	-0.589	1.5	0.169	2	1.264
8	0.5	-0.726	1	-0.644	1.5	0.134	2	1.220

Note. m is embedding dimension, ε is the bound, * Significant at the 5% level., ** Significant at the 1% level.