Automation, Stock Market Volatility and Risk-Return Relationship: Evidence from "CATS"

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Abstract

We employ *GARCH (p,q)* and *GARCH (p,q)-M* models to determine the impact of electronic trading on both volatility and risk-return relationship pre- and post-automation in the Toronto Stock Exchange. The evidence indicates that there have been significant changes in the structure of volatility and the risk-return relationship. Our results are consistent with the interpretation that there has been an increase in the quantity of information flowing into the market post-automation. This accords with the view that automation provides a more cost efficient method of acquiring market exposure and in doing so results in an increase in the number of participants involved in the market. For the full sample, the risk-return parameter is found to be positive and statistically significant. However, we find a considerable upward shift in the parameter occurring during the post-automation period for the returns of TSE 300 and TSE 35, but a downturn shift for the returns of TSE 100 and TSE 200. Our results imply that investors who placed their funds in the TSE 300 and TSE 35 became significantly more rewarded for bearing risk, while those investing in the TSE 100 and TSE 200 were penalized.

Key words: *GARCH (p,q)-M*, Canadian Equity Markets, risk-return relationship.
JEL Classifications: C3, C4, G15, C45.

Introduction

Stock exchanges around the world have automated to varying degrees and some have eliminated floor trading altogether. The Toronto Stock Exchange (TSE) has automated its operations through the use of an electronic trading system (referred to as the Computer-Assisted Trading System, or CATS). Though the TSE retained its floor until 1996, it gradually implemented electronic trading on CATS starting in the late 1970s. On April 23, 1997, the TSE stopped using the floor and all trading has been fully electronic since then. Now, all trading takes place electronically. The TSE ranks third in terms of the U.S. dollar value of total North American trading activity, after the NYSE and Nasdaq. It is fundamentally an order-driven market in which specialists bear market-making responsibilities and which has designated market makers who are responsible for maintaining orderly markets. It also maintains a central order book where limit orders are stored.

The issue of the effects of electronic trading raises the following issue: how does automation affect the volatility dynamics in financial markets. An investigation of the TSE contributes to this literature because it permits to examine the impact of electronic trading on the dynamics of volatility and market efficiency, since the TSE has moved all trading from floor to an electronic platform during the sample period of our study (i.e., 1989 to 2002). We attempt to address the following questions. First, what are the stylized facts characterizing the behavior of the TSE stock returns, and how sensitive are these characteristics to automation? Second, to what degree is the TSE efficient in pricing securities? Third, what has been the impact of conditional volatility (i.e., risk) on stock returns, and did shocks to volatility tend to persist over time pre- and post- automation? And fourth, is there evidence of significant changes in the impact of volatility on stock returns as a result of shifts in regimes affecting the trading environment?

The rationale for these questions has to do with the importance of a well-functioning stock market for the achievement of key policy objectives of higher rates of investment and economic growth. In a competitive market with little informational impediments, prices of financial assets and portfolios tend to adjust very rapidly to new information regarding prospects for investment and the business environment. In contrast, in markets where information on company performance and policies is less available and only gradually known to market participants, investors may have difficulties in selecting investment opportunities. The resulting uncertainty may induce potential investors to shorten their investment horizons, or to withdraw altogether from the market until this uncertainty is resolved. The supply of investable resources may be similarly reduced if investors perceive to be penalized for bearing risk, or if excessive volatility weakens confidence and deters risk-neutral or risk-averse investors.

The article is organized as follows. Section 2 presents a review on automation and financial markets. Section 3 discusses the empirical methodology. Section 4 deals with the empirical results and section 5 concludes.

Automation and Financial Markets

Advocates of automation suggest that execution of trades is faster and less costly under computerized trading systems. Traders have access to broader information including bid and ask prices, trades sizes and volume, at lower costs, due to the existence of a limit order book than under systems that restrict access to information about standing orders above and below the market. That would attract more investors and improve volume and liquidity and generate better price discovery. However, critics of automation argue that electronic trading could lead to less efficient prices since judgmental aspects of trade execution are lost with automation, which could be particularly important in times of fast market movements. Further, it can be argued that price efficiency remains unchanged after automation. According to this viewpoint, liquidity and efficiency on a stock market depend on rules on handling and execution of trades. If these rules do not change, then liquidity and efficiency are not expected to change.

Several papers, such as Freund (1989, 1993), Freund and Pagano (2000) and Naidu and Rozeff (1994), discuss the mechanics of automated trading systems and the benefits and disadvantages of implementing such systems and the effects of automation on price efficiency[1]. Freund (1989, 1993) discusses the role of electronic trading and its impact on the US exchanges members, the brokerage community, and international financial markets. Freund and Pagano (2000) examine price efficiency before and after automation on the NYSE and the TSE. Although they find that automation is associated with an improvement in market efficiency on the TSE relative to the NYSE, they do not detect any changes in the nonrandom patterns in returns before and after automation, which leads them to conclude that automation has not changed price efficiency on the TSE. Freund and Pagano (2000) point out that their results should be interpreted with caution since they rely on a relatively short sample. Their data cover the period between 1986 and 1997 and they specify between 1992 and 1997 as the post automation period. Since the floor trading co-existed with electronic trading on the TSE until April 23, 1997, they examine a brief period under full electronic trading. In contrast, our paper uses data until the end of 2002, which should enable a more complete analysis of the impact of electronic trading.

Naidu and Rozeff (1994) examine the effects of automation on liquidity, volume and volatility at the Singapore Stock Exchange post-automation. They advance that when automation speeds up the dissemination of prices, then volatility is likely to increase, especially when information is hitting the market. They find reduced autocorrelations of returns, leading them to conclude that market efficiency improves after automation. In other related studies, Taylor *et al*. (2000) and Anderson and Vahid (2001) investigate the impact of electronic trading on price efficiency on the London and Australian stock exchanges, using smooth transition error-correction models. Their studies focus on arbitrage between spot and futures markets of stock indices and report a significant decrease in transaction costs faced by arbitragers and conclude that the markets have become more efficient under electronic trading. Related to TSE, Bacidore (1997) and Porter and Weaver (1997) explore the trading rule changes and their impact on the TSE's market microstructure. They study the effect of rule changes on the minimum tick size, and find that measures of market quality related to market-making activities are unaffected by the rule changes.

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[1] Others include Domowitz (1990, 1993), Massimb and Phelps (1994).

Empirical methodology

We investigate the impact of automation on volatility by considering volatility before and after automation using an approach that is capable of detecting whether volatility has changed or not. We employ the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model[1]. The standard *GARCH (p,q)* model introduced by Bollerslev (1986) suggests that the conditional variance of returns is a linear function of lagged conditional variance terms and past squared error terms. The standard *GARCH(m,s)* model can be expressed as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{j=1}^{s} \beta_j h_{t-j} \ , \tag{1}$$

where $\{\varepsilon_t\}$ is a sequence of i.i.d. random variables with mean 0 and variance 1.0. $\alpha_0, \alpha_l \geq 0, \beta_j \geq 0$ and $\sum_{k=1}^{\max(m,s)} \alpha_i + \beta_j) < 1$. The strength of the *GARCH (m,s)* model can be seen by focusing on the simplest GARCH (1,1) model with:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \ , \tag{2}$$

where h_t represents the conditional variance term in period *t*, α_1 represents the news coefficient and β_1 represents a persistence coefficient with $0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$. Following the automation, an increase in α_1 would suggest that news is impounded into prices more rapidly, and a decrease in β_1 would suggest that old news has a less persistent effect on prices changes. Conversely, a reduction in α_1 would suggest that news is being impounded into prices more slowly, and an increase in β_1 would suggest greater persistence. Hence, the GARCH framework enables changes in both the level and structure of volatility to be detected. Further, Bollerslev, Chou and Kroner (1992) show that the persistence of shocks to volatility depends on the sum of the $\alpha+\beta$ parameters. Values of the sum lower than unity imply a tendency for the volatility response to decay over time, at a slower rate the closer the sum is to unity. In contrast, values of the sum equal to (or greater than) unity imply indefinite (or increasing) volatility persistence to shocks over time.

In the context of GARCH model, the return of a security may depend on its volatility. To model such a phenomenon, one may consider the *GARCH-M* model, where "M" stands for GARCH in mean. The *GARCH-M* model allows for mean returns to be specified as a linear function of time-varying conditional second moments. As a result, the framework uses the conditional variability of returns as a measure of time-varying risk, and captures the interdependence between expected returns and changing volatility of asset holdings postulated by portfolio theory. A simple *GARCH (1,1)-M* model can be written as:

$$r_t = \delta h_t + \varepsilon_t \ , \tag{3}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} , \tag{4}$$

where δ is a constant. δ links market returns to stocks' volatility, measured by the standard deviation of the conditional distribution of returns. In some papers, for instance like Choudhry (1996), the parameter δ is interpreted as the risk premium associated with time-varying volatility effects on stock returns. In our case, this interpretation is not fully warranted, since we model market returns rather than excess returns. Based on a portfolio theory, a positive and statistically significant parameter δ indicates that the return is positively related to its past volatility. That indicates that investors trading stocks were rewarded with higher returns for bearing risk during the sample period. The reward varies with h_t, in turn reflecting periods of relatively low or high volatility, however, Glosten, Jakannathan and Runkle (1993) discuss special circumstances that would

[1] See Bollerslev, Chou and Kroner (1992) for a survey of empirical applications of GARCH type models in finance.

make it possible to have a negative correlation between current returns and current measures of risk. As an example, investors may not demand a risk premium if the former are better able to bear risk at times of particular volatility.

Data and Empirical Results

We examine four Canadian equity indices. These are the TSE 300, TSE 35, TSE 100 and TSE 200. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. The price data were obtained from DataStream. Each of the price indices was transformed via first differencing to create a series, which approximates the continuously compounded percentage return. The TSE 300 Composite Index introduced in 1977 is a market value-weighted index and based on a very broad set of companies. It contains the 300 largest securities (in terms of value) traded on the TSE regardless of industry group, but excluding *control blocks* composed of more than 20 percent of outstanding shares.

The Toronto Stock Exchange also computes two other indices, the TSE 35 and the TSE 100; as well it presents several stock indices based on narrow industry groupings, such as the Oil and Gas Index. The TSE 35, introduced in 1987, was aimed especially at the trading of derivative products, such as index options and futures. The 35 firms whose stocks are represented in the index are some of the largest and most actively traded Canadian firms. It is a modified market value-weighted index, with a ceiling of 10 percent placed on any one stock so that it does not dominate the index. All major industry groupings in the TSE 300 are also represented in the TSE 35, with the exception of Real Estate.

The TSE 100 and TSE 200, another value-weighted indices, were introduced in 1993. Like the TSE 35, the TSE 100 is composed of stocks drawn from the largest firms in the TSE 300 group. It includes the 100 largest and most liquid TSE stocks such as consumer, industrial, interest sensitive, and resource sectors and represents an intermediate benchmark, geared toward those investors who feel that the TSE 300 contains too many relatively illiquid stocks, while the TSE 35 has too few stocks to be really representative. There are also some derivative products on the TSE 100. The stocks left over in the TSE 300 after the removal of the TSE 100 firms from what is known as the TSE 200 index. The TSE 200 is used as a proxy for returns on small-cap stocks. Both TSE 100 and TSE 200 are designed primarily for institutional investors as an instrument for passive management.

In 1999, a new value-weighted index of 60 stocks, the S&P/TSE 60 index was introduced jointly by the TSE and Standard & Poor's Corporation. The S&P/TSE 60 index is designed to mimic the performance of the TSE 300 and will eventually replace the TSE 35 and the TSE 100 as the basis for derivative products including index funds and index-linked GICs. The inclusion of 60 stocks in the index was made because the 35 stocks were too few to provide enough diversity for index funds, were not liquid enough, and did not closely track the performance of the TSE 300. While 100 stocks were too many to ensure adequate liquidity and large for institutions to use for complex hedging strategies, and had too many marginal stocks, the goal was to create an index of blue-chip companies in 11 industries, providing investors with broad but manageable index.

The stock indices are not adjusted for dividends following studies of French *et al.* (1987) and Poon and Taylor (1992) who found that inclusion of dividends affected estimation results only marginally. The summary statistics are presented in Table 1. We observe that the TSE 300 and TSE 35 show an increase in the mean returns after automation, while TSE 100 and TSE 200 show a decrease in the mean returns. All the indices exhibit an increase in volatility represented by the standard deviation. We observe that all the indices show a higher kurtosis after automation and that returns are highly autocorrelated at lag 1 but these values get lower when we compare pre- and post-automation periods. The exception is TSE 200 that maintains a high autocorrelation at lag 1 after automation. The high first-order autocorrelation reflects the effects of non-synchronous or thin trading, whereas highly correlated squared returns can be seen as an indication of volatility clustering. The *Q(12)* test statistic, which is a joint test for the hypothesis that the first twelve autocorrelation coefficients are equal to zero, indicates that this hypothesis has to be rejected at the 1% significance level for all return series and squared return series. A number of empirical studies have found similar results on market returns distributional characteristics. For example, Campbell, Lo and Mackinlay (1997) concluded that daily US stock indices show negatively skewed and positive excess kurtosis.

Table 1

Summary statistics of daily returns

	TSE 300		TSE 35		TSE 100		TSE 200	
	Pre-	Post	Pre-	Post	Pre-	Post	Pre-	Post
Mean	0.027	0.048	0.022	0.062	0.042	0.0039	0.037	0.014
S.D.	0.0035	0.011	0.0063	0.011	0.0062	0.0128	0.0047	0.0086
Skewness	-0.513	-0.858	0.090	-0.614	-0.618	-0.539	-0.575	-0.877
Kurtosis	5.784	9.340	7.609	7.227	5.869	7.350	6.757	7.195
J.B.	700.23	2135.9	1691.5	959.48	377.98	1213.73	597.73	1249.53
ρ_1	0.232	0.118	0.159	0.043	0.182	0.051	0.264	0.217
ρ_2	0.075	-0.019	0.021	-0.008	0.007	-0.027	0.083	0.065
ρ_3	0.072	-0.019	0.040	-0.030	-0.013	0.009	0.127	0.051
Q(12)	130.36	120.36	62.13	20.29	43.90	16.32	102.35	100.48

Notes: J.B. is the Jarque-Bera normality test statistic with 2 degrees of freedom; ρ_k is the sample autocorrelation coefficient at lag k and $Q(k)$ is the Box-Ljung portmanteau statistic based on k-squared autocorrelations. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. Pre- and Post automation period is April 23, 1997.

GARCH (p,q) models are estimated for both sub-periods. The GARCH (1,1) model was found to be an appropriate representation of the conditional variance in line with many previous studies, and the results for this model are reported in Tables 2 and 3. In Table 2 all the GARCH parameters are statistically significant at the 5% level and the evidence indicates that there have been significant changes in the structure of volatility following the automation. For TSE 300 returns, there has been a substantial increase in the α_0 coefficient post-automation, and together with the changes in β_1 this indicates that there has been a large increase in unconditional variance. The unconditional variance (i.e., $\alpha_0/(1-\alpha_1-\beta_1)$) has increased from 1.718E5 to 2.003E4 following the onset of automatic trading. This is consistent with the interpretation that there has been an increase in the quantity of information flowing into the market and accords with the view that automation provides a more cost efficient method of acquiring market exposure compared to traditional trading of stocks, and in doing so results in an increase in the number of participants involved in the market.

Table 2

Standard *GARCH (1,1)* model applied to TSE 300 and TSE35

Pre Automation		Post Automation		Whole Sample	
Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
	TSE 300				
α_0	4.35E-06 (0.646)	α_0	5.81E-06 (5.83)*	α_0	1.00E-06 (6.85)*
α_1	0.149 (2.72)*	α_1	0.149 (6.079)*	α_1	0.0945 (16.88)*
β_1	0.599 (4.68)*	β_1	0.822 (34.26)*	β_1	0.891 (117.39)*
σ_η	1.718E5	σ_η	2.003E4	σ_η	6.896E5
LogL	8154.72	LogL	2863.98	LogL	11091.92

Table 2 (continuous)

	TSE 35				
α_0	1.34E-05 (3.38)*	α_0	5.55E-06 (3.39)*	α_0	8.66E-07 (6.04)*
α_1	0.149 (3.26)*	α_1	0.0612 (3.20)*	α_1	0.063 (12.41)*
β_1	0.599 (12.94)*	β_1	0.903 (34.09)*	β_1	0.925 (153.02)*
σ_η	3.137E-05	σ_η	1.55E-04	σ_η	7.126E-05
LogL	7870.80	LogL	2796.44	LogL	10670.35

Notes: The *t*-values are reported in parentheses. * indicates significance at 5% level. $\sigma_\eta=(\alpha_0)/(1-\alpha_1-\beta_1)$ is the unconditional variance. LogL is the Log Likelihood. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. Pre- and Post automation period is April 23, 1997.

Table 3

Standard *GARCH (1,1)* model applied to TSE 100 and TSE 200

Pre Automation		Post Automation		Whole Sample	
Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
	TSE 100				
α_0	1.29E-06 (4.27)*	α_0	2.27E-07 (3.05)*	α_0	6.84E-07 (4.97)*
α_1	0.1078 (10.21)*	α_1	0.056 (7.36)*	α_1	0.0789 (13.33)*
β_1	0.881 (73.99)*	β_1	0.934 (124.05)*	β_1	0.920 (189.97)*
σ_η	1.151E-04	σ_η	2.27E-05	σ_η	6.218E-04
LogL	5456.14	LogL	2322.93	LogL	7767.77
	TSE 200				
α_0	3.85E-06 (7.33)*	α_0	3.03E-07 (3.55)*	α_0	1.83E-06 (7.50)*
α_1	0.257 (14.41)*	α_1	0.138 (6.68)*	α_1	0.160 (17.27)*
β_1	0.676 (28.25)*	β_1	0.829 (39.66)*	β_1	0.8175 (81.84)*
σ_η	5.746E-05	σ_η	9.181E-06	σ_η	8.133E-05
LogL	5891.31	LogL	2710.29	LogL	8589.96

Notes: The *t*-values are reported in parentheses. * indicates significance at 5% level. $\sigma_\eta=(\alpha_0)/(1-\alpha_1-\beta_1)$ is the unconditional variance. LogL is the Log Likelihood. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. Pre- and Post automation period is April 23, 1997.

Table 4

Standard *GARCH (1,1)-M* model applied to TSE 300 and TSE 35

Pre Automation		Post Automation		Whole Sample	
Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
	TSE 300				
δ	0.041 (1.21)	δ	0.119 (4.08)*	δ	0.071 (3.86)*
α_0	4.17E-06 (0.53)	α_0	1.91E-06 (3.48)*	α_0	1.10E-06 (7.13)*
α_1	0.149 (2.56)*	α_1	0.183 (11.73)*	α_1	0.100 (17.48)*
β_1	0.599 (4.09)*	β_1	0.816 (56.81)*	β_1	0.884 (111.40)*
σ_η	1.65E-05	σ_η	1.91E-04	σ_η	6.875E-05
LogL	7480.73	LogL	3526.44	LogL	11100.16
	TSE 35				
δ	0.0398 (1.76)*	δ	0.106 (3.65)*	δ	0.061 (3.45)*
α_0	1.01E-06 (3.82)*	α_0	2.38E-06 (3.67)*	α_0	6.54E-07 (5.34)*
α_1	0.020 (4.39)*	α_1	0.112 (7.11)*	α_1	0.052 (11.46)*
β_1	0.953 (94.30)*	β_1	0.880 (56.04)*	β_1	0.938 (170.21)*
σ_η	3.74E-05	σ_η	2.975E-04	σ_η	6.54E-05
LogL	7265.21	LogL	3412.63	LogL	10667.23

Notes: The *t*-values are reported in parentheses. * indicates significance at 5% level. $\sigma_\eta=(\alpha_0)/(1-\alpha_1-\beta_1)$ is the unconditional variance. LogL is the Log Likelihood. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. Pre- and Post automation period is April 23, 1997.

Table 5

Standard *GARCH (1,1)-M* model applied to TSE 100 and TSE 200

Pre Automation		Post Automation		Whole Sample	
Parameter	Coefficient	Parameter	Coefficient	Parameter	Coefficient
	TSE 100				
δ	0.083 (1.78)	δ	0.025 (0.92)	δ	0.063 (2.99)*
α_0	1.30E-05 (0.95)	α_0	4.19E-06 (7.46)*	α_0	7.72E-07 (4.88)*
α_1	0.149 (1.70)	α_1	0.076 (8.25)*	α_1	0.090 (13.94)*
β_1	0.599 (3.29)*	β_1	0.900 (99.40)*	β_1	0.909 (175.41)*
σ_η	5.158E-05	σ_η	1.746E-04	σ_η	7.72E-04
LogL	3616.03	LogL	4157.80	LogL	7769.74

Table 5 (continuous)

	TSE 200				
δ	0.103 (2.15)*	δ	0.076 (2.72)*	δ	0.104 (4.96)*
α_0	6.83E-06 (1.53)*	α_0	5.33E-06 (6.54)*	α_0	1.96E-06 (7.57)*
α_1	0.149 (2.18)*	α_1	0.180 (10.49)*	α_1	0.174 (17.68)*
β_1	0.599 (5.57)*	β_1	0.763 (41.87)*	β_1	0.803 (75.12)*
σ_η	2.71E-05	σ_η	9.35E-05	σ_η	8.25E-05
LogL	5891.31	LogL	4719.25	LogL	8602.06

Notes: The *t*-values are reported in parentheses. * indicates significance at 5% level. $\sigma_\eta=(\alpha_0)/(1-\alpha_1-\beta_1)$ is the unconditional variance. LogL is the Log Likelihood. TSE 300 and TSE 35 cover the period of 01/02 /1989 to 11/14/2002 and those of TSE 100 and TSE 200 cover the period of 01/10/1993 to 11/14/2002. Pre- and Post automation period is April 23, 1997.

Comparing parameters across the two-sub periods, we observe that in the post-automation period there has been a significant increase in the persistent coefficient β_1 while the news coefficient α_1, still statistically significant, did not change. These results indicate that automation did not lead to a change in how news being impounded into prices, but resulted in a greater persistence. This is not surprising given the nature of the TSE; the market is highly liquid and it is reasonable to expect that well-informed investors will dominate.

Considering Pre- and Post-automation, the measures of volatility persistence given by the sum of the $\alpha+\beta$ coefficients are less than unity pre-automation, implying that the effect of shocks to volatility tends to decay within a few time lags. In the case of the TSE 35 returns, instead the sum of the $\alpha+\beta$ parameters in this case is very high and close to one, indicating a tendency for the volatility to shocks to display a longer memory. However, when considering post-automation, all index returns display a similar pattern where the sum of the $\alpha+\beta$ are mostly close to one, indicating again a longer duration for shocks to decay.

Risk-return relationship

The relation between expected stock returns and conditional volatility has received great attention in the literature. Although a positive relationship between expected returns and volatility is consistent with the CAPM and intuitively appealing, as rational risk-averse investors require higher expected returns during more volatile periods, empirical research has been unable to establish a convincing positive relationship between expected risk premium and conditional volatility using *GARCH-M* models. For US stock markets, French *et al*. (1987) and Campbell and Hentschel (1992) observe a positive relation, whereas Glosten *et al*. (1992) who develop a much richer asymmetric *GARCH-M* model present evidence of a negative relation, as Nelson (1991) does with his EGARCH model and Poon and Taylor (1992) who study the UK stock market report a weak positive relationship.

For Canadian equity markets, the hypothesis that volatility is a significant determinant of stock pricing is confirmed for all TSE stock returns. Irrespective of the index, the estimated parameter δ capturing the influence of volatility on stock returns is positive and statistically significant (at the 5% level in all cases) for the whole sample period. The range of estimates is of similar order of magnitude for TSE 300, TSE 35, and TSE 100, with a stronger impact of conditional variability on TSE 100 stock returns (i.e., δ=0.104 and significant). These results are consistent with the basic postulate of portfolio theory, and indicate that on average investors trading stocks were compensated with higher returns for bearing risk. As discussed by Engle, Lilien and Robins (1987), and Bollerslev, Chou and Kroner (1992), the sign and magnitude of the risk-return parameter depend on the investors' utility function and risk preference, and the supply of assets under consideration. Empirical applications to date, found mixed results regarding the sign and statistical significance of the risk-return parameter. Elyasiani and Mansur's (1998) estimates on U.S. data were negative and statistically significant, while Porterba and Summers' (1986) estimates on excess returns for daily S&P index, weekly NYSE returns and UK stock indices were positive and significant.

This relationship is affected by the changes in the trading environment (i.e., automation) of the TSE. Tables 4 and 5 strongly reject the time invariance of the risk-return parameter. The δ parameters are significant and positive post-automation except for TSE 100. For TSE 300 and TSE 35, the δ parameters are confirmed to be positive and significant, with higher values relative to pre-automation period, but they decrease for TSE 100 and TSE 200, even they become insignificant for TSE 100. Although conclusions can only be tentative on the basis of the aggregate indices used in this paper, the implication is that the risk-return parameter shifted upward to estimate values that are positive and significant for TSE 300 and TSE 35, but shifted downward to estimate values that are positive and insignificant for those of TSE 100 and TSE 200. This suggests that the market upturn was associated with a move in the risk-return relationship such that investors trading stocks on TSE 300 and TSE 35 became rewarded for bearing higher risk, but those trading TSE 100 and TSE 200 became penalized for bearing higher risk.

Conclusion

We examine the impact of automation on the volatility dynamics and risk-return relationship in the Toronto Stock Exchange. The results from TSE 300 indicate that automation has significantly altered the structure of market volatility. Specifically, we find that following the onset of automation, new information is assimilated into prices and leading to an increase in the persistence of volatility. Further, our analysis supports the existence of a significant link between conditional volatility and stock returns. The full sample estimates indicate that the risk-return parameter is positive and statistically significant. However, a considerable upward shift in the risk-return parameter appears during the post-automation period for TSE 300 and TSE 35, but a downturn shift for TSE 100 and TSE 200. These results indicate that, on average, automation had a significant impact on the volatility and hence on the pricing of securities on the Toronto Stock Exchange.

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