Hourly index return autocorrelation and conditional volatility in an EAR–GJR-GARCH model with generalized error distribution

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Accepted 21 August 2007
Available online 6 November 2007

Abstract

We study the autocorrelation and conditional volatility of the hourly Dow Jones Industrial Index return data from October 1974 to September 2002 using an exponential asymmetric AR–GARCH specification with a generalized error distribution. Our findings document a positive autocorrelation in hourly return data in the early years of the sampling period, but the autocorrelation turns negative after 1986 and the negative shock causes more impact on the conditional volatility. This latter period evidence stands in contrast to prior findings employing lower frequency and/or earlier year data. In addition, our results present some evidence of a negative relation between autocorrelation and conditional volatility before 1986 (albeit weaker than prior findings), but this negative relationship disappears after 1986.

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JEL classification: G12; G14
Keywords: Autocorrelation; Conditional volatility; Hourly returns; EAR–GARCH

1. Introduction

The objective of this study is to examine the time-series dynamics of the autocorrelation and conditional variance of hourly returns of the Dow Jones Industrial Index. Although studies investigating the autocorrelation in stock returns use daily, weekly, or monthly data, few have employed higher frequency data.1 In fact, we are the first to study the dynamic relation between autocorrelation and conditional volatility in hourly returns within the framework of a modified exponential AR–GARCH model. This model allows for asymmetric impacts on conditional volatility as well as non-normality distribution, thus subsuming other model specifications. The use of hourly returns enhances the

We would like to thank the conference participants at the 2002 FMA, an anonymous referee and Franz Palm (the editor) for helpful comments.

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1 Jain and Joh (1988) use hourly returns to study the relation between stock returns and trading volume. Gerety and Mulherin (1994) also use hourly data to study the intraday transitory volatility.

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doi:10.1016/j.jempfin.2007.08.002
understanding of stock return dynamics because lower frequency data fail to reflect information that occurs in the short horizon when information adjustment speed is rather rapid.

Using daily/weekly data, French and Roll (1986), Lo and MacKinlay (1988, 1990), Conrad et al. (1991), and Lehmann (1990) find significant and negative autocorrelation in the returns of individual securities, although Sias and Starks (1997) find positive autocorrelation for stocks with heavy institutional holdings. However, when daily index is employed, Cutler et al. (1991), and Lo and MacKinlay (1988) report a significant and positive serial correlation. Theories and hypotheses attempting to explain autocorrelation in short-horizon stock returns include microstructure-based market friction (non-synchronous trading and transaction cost), time-varying expected returns, and feedback trading. Both non-synchronous trading and time-varying risk premia hypotheses, however, are expected to generate only time invariant autocorrelation.


Seemingly unrelated to trading volume, LeBaron (1992) and Sentana and Wadhwani (1992) investigate the relation between serial correlation and conditional volatility in stock returns. LeBaron (1992) implements GARCH and exponential AR (EAR) models on daily and weekly index data and finds a negative relation between serial correlation and conditional volatility. Koutmos (1997b) applies the EAR-TGARCH model to six Asian emerging stock markets and finds that the lower serial correlation is associated with high stock return volatility. Sentana and Wadhwani (1992) and Watanabe (2002) also document that higher volatility is associated with a negative serial correlation and lower volatility is in tandem with positive serial correlation.

The contribution of this study to the literature is fourfold. First, this paper uses hourly index returns, the highest frequency data used to date for this research topic. Second, we analyze autocorrelation in hourly index returns and its relation with conditional variance. Unlike earlier studies (e.g., Jain and Joh, 1988; Berry and Howe, 1994) that investigate unconditional volatility in hourly stock returns, we focus on the conditional volatility measure. The use of conditional variance is more consistent with the notion that stock returns are conditionally heteroscedastic (Bollerslev, 1986, Lamoureux and Lastrapes, 1990).

Third, the exponential asymmetric GARCH model used in this study accommodates the asymmetric effect of economic shocks on volatility, in which both the magnitude and the direction of shocks impact future volatility differently. For this purpose, we implement a model specification that combines the non-linear EAR–GARCH model in LeBaron (1992) and the asymmetric GARCH in Glosten et al. (1993), or GJR-GARCH model.

Fourth, since stock returns often exhibit large skewness and kurtosis, we employ an EAR–GARCH model with a generalized error distribution (GED), under which the fat tail property of stock returns is considered, and the normal distribution becomes a special case of the GED (Nelson, 1991).

Our results indicate the existence of stock return autocorrelation and conditional volatility in hourly data. Consistent with prior findings, stock return autocorrelation is positive and significant during the sampling period before 1986. In a sharp contrast to the earlier studies, the autocorrelation turns negative and/or insignificant during the latter part of the sample. In addition, before 1986, a negative relation between autocorrelation and conditional volatility exists, as found in prior studies using lower frequency data. However, this relation is absent after 1986. Conditional volatility, on the other hand, is significantly impacted by negative economic shocks in the latter years, but not in the early years of the sample.

The rest of the paper is organized as follows. Section 2 presents the EAR(1)–GJR–GARCH(1,1) model with generalized error distribution (GED) and the data source. In Section 3 we show the results of the autocorrelation estimates, the relation between conditional volatility and autocorrelation, and the asymmetric impacts of economic shocks on volatility. Section 4 concludes.

2. Methodology and data

We employ the modified Exponential AR(1) Asymmetric GARCH(1,1) model (hereafter, EAR(1)–GJR–GARCH (1,1)) for our empirical study. This unique specification combines aspects of the EAR–GARCH model of LeBaron

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2 In the case of using transaction data, bid-ask bounce is shown to induce first lag negative autocorrelation (Roll, 1984).
(1992) and the GJR–GARCH(1,1) model developed by Glosten et al. (1993), hence a general model with prior models as special cases. Our model incorporates the following stock return characteristics: (1) stock returns are autocorrelated and conditionally heteroscedastic (French et al., 1987, Nelson, 1991); (2) stock returns exhibit large kurtosis; (3) intraday stock returns are impacted by conditional volatility (LeBaron, 1992, Sentana and Wadhwani, 1992); and (4) past economic shocks have asymmetric effects on conditional volatility. The EAR(1)–GJR–GARCH(1,1) model with these four stock return characteristics can be summarized by the following two equations:

\[ R_t = a + a_1 \text{Dovernight} + a_2 \text{Dweekend} + \left( \phi_0 + \phi_1 e^{-\left( \frac{h_t^{1/2}}{C_0} \right)} \right) R_{t-1} + \varepsilon_t \]

\[ h_t = \begin{cases} 0 + (\alpha_1 + \delta_1)\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_2 \text{Dovernight} + \delta_3 \text{Dweekend} & \text{if } \varepsilon_{t-1} < 0 \\
0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_2 \text{Dovernight} + \delta_3 \text{Dweekend} & \text{otherwise} \end{cases} \]

where \( \varepsilon_t = h_0^{1/2} \varepsilon_t \) and \( \varepsilon \sim iid \) (GED).

Under this specification, the observed return series \( (R_t) \) contain a constant; an overnight dummy (Dovernight) that takes a value of 1 if the observation is the overnight non-trading period return, zero otherwise; a weekend dummy (Dweekend) that measures the weekend non-trading effect (or, Monday effect); and a time-varying conditional volatility dependent autoregressive term, \( \phi_0 R_{t-1} \), where \( \phi_t = \phi_0 + \phi_1 e^{-\left( \frac{h_t^{1/2}}{C_0} \right)} \) (see Eq. (1)). The time-varying component of the autocorrelation, determined by the exponential function of the conditional variance, \( h_t \), is measured by \( \phi_1 e^{-\left( \frac{h_t^{1/2}}{C_0} \right)} \), whereas \( \sigma^2 \) is the unconditional variance of stock returns. Hence Eq. (1) tests if 1st order autocorrelation is related to conditional volatility, and the coefficient \( \phi_0 \) measures the 1st order autocorrelation in the absence of the impact of conditional volatility, i.e., \( \phi_t = \phi_0 \) when \( \phi_1 = 0 \). In this case, the EAR(1)–GJR–GARCH(1,1) model reduces to AR(1)–GJR–GARCH(1,1). Hence a significant and positive \( \phi_1 \) indicates that time-varying autocorrelation decreases as conditional variance rises. Therefore, the EAR(1)–GJR–GARCH(1,1) model is a more general model, whereas AR(1)–GJR–GARCH(1,1) is a special case.

In Eq. (2), the conditional variance, \( h_t \), is a function of the squared innovation at time \( t-1 (\varepsilon_{t-1}^2) \), the one-period lagged conditional variance (\( h_{t-1} \)), the overnight dummy, and the weekend dummy. Overnight as well as weekend dummies are also included in the conditional volatility equation because there is evidence that non-trading period volatility is different from trading period volatility. Since large kurtosis is common in stock returns, \( \varepsilon_t \) (and thus \( \varepsilon_t \)) are assumed to follow a generalized error distribution (GED) where the fat tail property of equity returns is considered in the model and normal distribution becomes a special case of the GED (Nelson, 1991).

The GJR asymmetric GARCH model specified in Eq. (2) is constructed to capture the potential larger impact of negative shocks on return volatility. Combined with the EAR(1) model for the return generation equation, this specification captures the asymmetric effects of return shocks on volatility, and the dynamic relation between conditional variance and autocorrelation simultaneously. The notion that economic shocks have an asymmetric effect on stock markets can be found in arguments suggesting that good news and bad news impact volatility differently (see French et al., 1987; Schwert, 1989, and Nelson, 1991). The GJR asymmetric GARCH(1,1) model implies two regimes for the coefficient of the lagged squared innovation, \( \varepsilon_{t-1}^2 \), depending on the sign of the conditional disturbance (Eq. (2)). The impact of \( \varepsilon_{t-1}^2 \) on the conditional variance is \( \alpha_1 \) when \( \varepsilon_{t-1} \) is positive. However, this influence becomes \( \alpha_1 + \delta_1 \) when negative shocks occur. Since it is commonly believed that negative shocks generate larger volatility than positive shocks, \( ceteris paribus \), the coefficient \( \delta_1 \) is expected to be positive.3

The Maximum Likelihood Estimation (MLE) method is used to estimate the parameters in the model. For the GED errors, the contribution to the log-likelihood function for observation \( t \) is expressed in general terms as:

\[ l_t = -\frac{1}{2} \log \left( \frac{\Gamma(1/\gamma)^3}{\Gamma(3/\gamma)(\gamma/2)^2} \right) - \frac{1}{2} \log \sigma^2 - \left( \frac{\Gamma(3/\gamma)(\gamma_t - X_t/\theta)^2}{\sigma^2 \Gamma(1/\gamma)} \right)^{\gamma/2} \]

3 In a standard AR(1)–GARCH(1,1) model, the coefficient \( \delta_1 \) is zero and the term \( (\alpha_1 + \delta_1) \) thus measures volatility persistence.
Table 1
The EAR(1)–GJR-GARCH(1,1) model: sample 1

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<td>(0.048)</td>
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Hourly return, $R_t$, has been rescaled by a factor of 100. Sample 1 includes hourly returns from 10/01/74 to 09/26/85 and is divided into 11 yearly subperiods, A01–A11.

\[
R_t = a + a_1\text{Dovernight} + a_2\text{Dweekend} + \left(\phi_0 + \phi_1 e^{-\left(\frac{t}{\phi_1}\right)}\right)R_{t-1} + \epsilon_t
\]

\[
h_t = \left\{ \begin{array}{ll}
  \sigma^2 + \delta_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_2 Dovernight + \delta_3 Dweekend & \text{if } \epsilon_{t-1} < 0 \\
  \sigma^2 + \delta_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_2 Dovernight + \delta_3 Dweekend & \text{otherwise}
\end{array} \right.
\]

where $\epsilon_t \sim \text{GED}(\delta, \sigma^2)$, and $\epsilon_t$ follows generalized error distribution (GED).

The non-trading hour returns are calculated as logarithm of the ratio between the price index level at the end of the first trading hour and the closing price index from previous trading day. *** and * denote that the coefficient is statistically significant at the 1%, 5% and 10% level, respectively.
### Table 2

The EAR(1)–GJR-GARCH(1,1) model: sample 2

<table>
<thead>
<tr>
<th>Sample 2</th>
<th>B01</th>
<th>B02</th>
<th>B03</th>
<th>B04</th>
<th>B05</th>
<th>B06</th>
<th>B07</th>
<th>B08</th>
<th>B09</th>
<th>B10</th>
<th>B11</th>
<th>B12</th>
<th>B13</th>
<th>B14</th>
<th>B15</th>
<th>B16</th>
<th>B17</th>
<th>C03</th>
</tr>
</thead>
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<td>110930</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Hourly return, $R_t$, has been rescaled by a factor of 100. Sample 2 includes hourly returns from 09/30/85 to 09/30/02 and is divided into 17 yearly subperiods, B01-B17. Subperiod C03 contains data from subperiod B03 excluding the period from 10/01/87 to 10/31/87.

$$R_t = a + a_1Dovernight + a_2Dweekend + \left( \phi_0 + \phi_1 e^{-\left(\frac{\epsilon_t}{2}\right)} \right) R_{t-1} + \epsilon_t$$

$$h_t = \delta_0 + \delta_1 C_{t-1} + \delta_2 h_{t-1} + \delta_3 Dovernight + \delta_4 Dweekend$$

where $\epsilon_t \sim N(0, \sigma^2)$, and $\epsilon_t$ follows generalized error distribution (GED).

The non-trading hour returns are calculated as logarithm of the ratio between the price index level at the end of the first trading hour and the closing price index from previous trading day. ***, ** and * denote that the coefficient is statistically significant at the 1%, 5% and 10% level, respectively.
where $\Gamma(\bullet)$ is the gamma function, $\sigma_t^2$ is the conditional variance, $y_t$ stands for the endogenous variable, $X_t$ is a vector of exogenous variables, $\theta$ is a coefficient vector, and $\gamma$ is a tail-thickness parameter. The GED reduces to a normal distribution if $\gamma=2$; fat-tailed if $\gamma<2$; and thin-tailed when $\gamma>2$.

We hand collect Dow Jones hourly index data from October 1, 1974 to June 30, 1993 from the Wall Street Journal, and obtain the remaining data (from July 1, 1993 to September 30, 2002) from Global Financial Data, retaining a total of 46,528 hourly returns. Among these observations, 7,032 are “non-trading returns”. We compute these “non-trading returns” based upon the prior day’s closing price and the following day’s ending price of the first trading period. Traditional measurement of close–open return is modified in this case in order to avoid any possible non-synchronous opening price because of the opening rotation procedure used in the NYSE.

Because the stock market trades earlier and begins at 9:30 a.m. after September 30, 1985, the sample is separated into two subsamples: sample 1 includes hourly returns from October 1, 1974 to September 26, 1985 and sample 2 from September 30, 1985 to September 30, 2002. Therefore, non-trading returns are computed based upon the prior day’s closing price and the following day’s price at 11:00 a.m. for sample 1; but based upon the prior day’s closing price and the following day’s price at 10:00 a.m. for sample 2. Although the dividing point is based upon the change in trading time, it is also fairly close to the 1987 market crash.

Finally, to analyze potential regime shift across time, each subsample is further broken down into yearly subperiods for stability analysis. There are eleven yearly subperiods in sample 1 (subperiods A01 to A11) and seventeen yearly subperiods in sample 2 (subperiods B01 to B17). To isolate the impact of the 1987 market crash, a special subperiod, C03, is constructed based on subperiod B03 with the period from October 1, 1987 to October 31, 1987 excluded.

3. Empirical results

Column 2 in Tables 1 and 2 presents the parameter estimates of Eqs. (1)–(3) for subsamples 1 and 2 respectively, while other columns show results for individual yearly subperiods. In the return equation (Eq. (1)), overnight dummies are significant and positive in both samples 1 and 2, and statistically significant in eleven (out of twenty-eight) years. The existing literature, however, does not provide us with much insight about the regularity/irregularity of overnight returns. The significant and negative weekend dummies, nevertheless, are consistent with prior findings of the weekend effect (Abraham and Ikenberry, 1994). The negative weekend effect, however, is more evident in sample 1 than in sample 2.

In the conditional volatility equation (Eq. (2)), overnight dummies are positive and significant for both subsamples and twenty-two out of twenty-eight yearly coefficients are statistically significant. The positive overnight dummies, however, do not imply a more volatile non-trading period returns because the overnight non-trading period is aggregated over 18 hours.

Finally, the generalized error distribution gamma tail-thickness parameter estimates (GED $\gamma$) as specified in Eq. (3) show that virtually all $\gamma$ estimates are substantially below a normal distribution value of 2. Since all $\gamma$’s are less than 2, GED errors are fat-tailed.

3.1. Time-varying stock return autocorrelation and conditional volatility

Because EAR(1)–GJR–GARCH(1,1) reduces to a special case of AR(1)–GJR–GARCH(1,1) when $\phi_1=0$, in Tables 1 and 2 we report both $\phi_0$ and $\phi_1$ when $\phi_1$ is significant and EAR(1) better fits the data; otherwise, only $\phi_0$ is reported and $\phi_0=\phi_1$, which is estimated from an AR(1) model. Several observations regarding the first-order autocorrelation are in order. First, in the second column of Table 1, the positive coefficients of both $\phi_0$ and $\phi_1$ suggest that overall stock returns are positively correlated in sample 1, and the higher the conditional variance, the lower the autocorrelation. The positive and significant autocorrelation in sample 1 is thus consistent with prior findings of a positive autocorrelation in index returns using lower frequency data. Furthermore, the positive and significant $\phi_1$ reveals a negative relation between autocorrelation and conditional volatility, which is in line with the finding in

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4 We thank the referee for suggesting this alternative measurement of non-trading returns.

5 For literature in volatility during non-trading periods, see French and Roll (1986), Lockwood and Linn (1990), Berry and Howe (1994), and Foster and Viswanathan (1993).

6 Strictly speaking, $\phi_1=\phi_0$ as one sets the time-varying autocorrelation equal to a constant.
LeBaron (1992), and the negative feedback trading results reported in Koutmos (1997a) and Watanabe (2002), all based on lower frequency data.

Second, in column 2 of Table 2, we find that $\phi_1$ is not statistically significant in the EAR(1) model, hence the EAR(1) model reduces to an AR(1) model, and the first-order autocorrelation is measured by $\phi_0 = \phi_r$. Two points are relevant for this finding: (1) with $\phi_1$ being not significant, the negative relation between conditional volatility and autocorrelation seen in sample 1 is missing in sample 2; and (2) the negative $\phi_0$, significant only at the 5% level, indicates that the positive first-order stock return autocorrelation found in sample 1 has turned into weakly negative in sample 2.

Comparing these results, therefore, we spot structural shift in the hourly stock return autocorrelation. To better understand the time-varying behavior of autocorrelations, in both tables we also report the $\phi$’s for the yearly subperiods. In sample 1, virtually all yearly subperiods exhibit positive stock return autocorrelations, which are significant in ten out of the eleven subperiods. However, only three $\phi_1$’s are significant. The significant relation between conditional volatility and autocorrelation observed in sample 1, therefore, is weaker than that reported in prior studies (e.g., LeBaron, 1992).7

In sample 2, results of yearly subperiods seem to tell a different story, i.e., most of the stock return autocorrelations are not statistically significant, and the few significant ones carry mostly a negative sign, suggesting a significant autocorrelation sign reversal in sample 2. Furthermore, only two out of seventeen subperiods signify a significant relation between conditional volatility and autocorrelation — but with opposite signs.

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7 The weaker results could be due to a number of factors, such as data frequency, model specification, and/or distributional assumptions. We reexamine the same model (i.e., Eqs. (1) and (2)) assuming $e_t$ and $\varepsilon_t$ are iid $N(0,1)$ (the same assumption in LeBaron’s model). We find a stronger relationship between conditional volatility and autocorrelation under this distributional assumption. More specifically, seven out of eleven yearly $\phi_1$’s are now statistically significant. Results found in LeBaron (1992), therefore, could be in favor of a stronger relationship between conditional volatility and autocorrelation due to the normality assumption.
All these yearly subperiods results can be better viewed in Fig. 1. Emerging from Tables 1 and 2, and Fig. 1, four findings are worth mentioning. First, positive and significant yearly $\phi$’s are evident in sample 1. Second, in sample 2 the only positive and significant yearly $\phi$ (subperiod B05) corresponds to the 1990 Gulf conflict and oil shock. Third, there are five negative and significant $\phi$’s in sample 2 (subperiods B01, B02, B05, B07 and B09) and they respectively coincide with the stock market run-ups shortly before the 1987 market crash, the 1987 market crash, the 1992 Soviet Union collapse, and the 1994 global recession. Fourth, other major economic shocks, such as the 1997–98 Asian financial crisis, the 1998–99 Russian and Brazilian currency crises, and the burst of the 2000 internet bubble followed by the worst recession in decades, however, induce no significant autocorrelations. Therefore, the pattern of autocorrelation in sample 2 is dramatically different from that in sample 1, and is not consistent with most of the prior findings of a positive index return serial correlation.

In addition to Fig. 1, Fig. 2 plots autocorrelation in relation to conditional volatility. The autocorrelation and conditional variance are initially calculated using the first 500 hourly returns. This procedure is then repeated using a moving window of 100 observations. A series of different pairs of autocorrelation and corresponding variance are obtained and plotted. To better visualize the association between first-order autocorrelation and volatility, we also add the fitted line to Fig. 2 by fitting the coefficients estimated by the EAR(1)–GJR–GARCH (1,1) model to the different pairs of variance and autocorrelation shown in Fig. 2. As shown in Panel A, the plots depict a negative exponential relation between volatility and autocorrelation in sample 1, replicating the findings in LeBaron (1992). This negative relation, however, vanishes in Panel B for sample 2.

3.2. Asymmetric impact of shocks on conditional volatility

As illustrated by Eq. (2), our model captures the asymmetric effects of market shocks on the conditional volatility. The model suggests that there are two regimes for the coefficient of the lagged squared innovation depending on the

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8 When the model favors an EAR(1), the autocorrelation is calculated based upon the parameter estimates of $\phi_0$, $\phi_1$, and the average of conditional volatility, $h_c$.
sign of the conditional disturbance. The impact of $\varepsilon_{t-1}$ on the conditional volatility is $\alpha_1$ when $\varepsilon_{t-1}$ is positive, and $\alpha_1 + \delta_1$ when negative shock occurs. A positive (negative) $\delta_1$ is thus consistent with the notion that negative (positive) shocks generate more volatility than positive (negative) shocks.

In Table 1, a negative and weakly significant $\delta_1$ is observed, implying positive shocks have a larger impact on conditional volatility, which contradicts a priori expectation. Examining the yearly subperiods, however, we discover that only three yearly $\delta_1$’s are statistically significant. This weak evidence in sample 1 seems to be more consistent with the hypothesis of symmetric impact of economic shocks on conditional volatility.

However, for sample 2 (reported in Table 2), the opposite appears to be true. That is, $\delta_1$ is positive and significant at the 1% level for the whole sample, and fourteen (out of seventeen) yearly $\delta_1$’s carry a positive sign, indicating that negative shocks have larger impacts on the conditional variance. Furthermore, nine among these fourteen positive yearly $\delta_1$’s are statistically significant. This sign reversal seems to be related to the observed changes in the first-order autocorrelation patterns reported earlier.

In summary, results reported in Tables 1 and 2 document the existence of first-order autocorrelation and GARCH process in the hourly index return data, although the change in pattern and sign reversal in autocorrelation after 1986 are not reported in prior studies using lower frequency data. The empirical evidence also supports the existence of asymmetric conditional volatility in hourly returns. Nevertheless, the larger impact of negative economic shocks on conditional volatility prevails only in data after 1986.

4. Conclusions

In this paper, we study the stock return autocorrelation and conditional volatility based upon the hourly return data of the Dow Jones Industrial Index from October 1974 to September 2002. An EAR(1)–GJR–GARCH(1,1) model with GED distribution is employed for this purpose. Our major findings are as follows:

1) Similar to prior findings employing lower frequency data, we also find a positive first-order autocorrelation in hourly index returns before 1986.

2) In contrast to prior findings, stock return autocorrelations exhibit regime shift where negative, albeit weaker, first-order autocorrelation is detected during the latter half of the sampling period (after 1986). The lack of significant autocorrelations during the more recent years implies a more efficient equity market.

3) We find a negative relation, though not as strong as those reported in prior studies, between autocorrelation and conditional volatility in hourly returns before 1986. This relation, however, disappears during the latter half of the sampling period, suggesting an unstable relationship between conditional volatility and autocorrelation. The weaker relation between conditional volatility and autocorrelation uncovered in this study may be attributed to the inappropriate normality assumption in prior studies.

4) The notion that negative economic shocks have larger impact on volatility cannot be supported in hourly data before the 1987 market crash. However, we do find evidence that conditional volatility responds strongly to negative shocks after 1986.

References


