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The Impact of China on Stock Returns and Volatility in the Taiwan Tourism Industry*

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Abstract

This paper investigates the stock returns and volatility size effects for firm performance in the Taiwan tourism industry, especially the impacts arising from the tourism policy reform that allowed mainland Chinese tourists to travel to Taiwan. Four conditional univariate GARCH models are used to estimate the volatility in the stock indexes for large and small firms in Taiwan. Daily data from 30 November 2001 to 27 February 2013 are used, which covers the period of Cross-Straits tension between China and Taiwan. The full sample period is divided into two subsamples, namely prior to and after the policy reform that encouraged Chinese tourists to Taiwan. The empirical findings confirm that there have been important changes in the volatility size effects for firm performance, regardless of firm size and estimation period. Furthermore, the risk premium reveals insignificant estimates in both time periods, while asymmetric effects are found to exist only for large firms after the policy reform. The empirical findings should be useful for financial managers and policy analysts as it provides insight into the magnitude of the volatility size effects for firm performance, how it can vary with firm size, the impacts arising from the industry policy reform, and how firm size is related to financial risk management strategy.

Keywords*: Tourism, firm size, stock returns, conditional volatility models, volatility size effects, asymmetry, tourism policy reform.

JEL: C22, G18, G28, G32, L83.

1. Introduction

According to the World Tourism Organization (UNWTO), international tourism has experienced continuous expansion and diversification during the past six decades to become one of the largest and fastest-growing economic sectors in the world. International tourist arrivals have shown virtually uninterrupted growth over this period, from a mere 25 million in 1950 to 277 million in 1980, 435 million in 1990, 675 million in 2000, 935 million in 2010, and a growth of 6.5% to 996 million in 2011. These growth figures are amazing, especially in light of the Global Financial Crisis that erupted in 2007-08.

With growth slated to continue by 4% to 1,035 million in 2012, international tourism has hit a major milestone, namely one billion international tourist travellers worldwide in a single year. International tourism demand has been steady over the years and also during each year, and international tourism markets have so far not been seriously affected by the economic and financial volatility caused by the Global Financial Crisis. It has been projected that growth will continue in excess of 3.8% each year, on average, for the decade 2010-2020, in line with UNWTO's long-term forecast of international tourism toward 2030.

From the supply side of tourism, as stated by UNWTO, emerging economies (+4.1%) are tipped to regain the lead in tourism growth of international tourist arrivals in 2012 over the advanced economies (+3.6%). By region, with stronger growth, Asia and the Pacific (+7%) was the best performer in 2012, especially by sub-region, with South-East Asia (+9%) topping the rankings. Excellent international tourist arrivals in this region included Japan (with 1.7 million additional tourists, for an increase of +41%), which is recovering from the 2011 Tohoku earthquake and is on track to returning to the 8 million tourist mark, as well as Taiwan (R.O.C.), which saw nearly 1 million additional tourist arrivals, which is an impressive growth of 24%, In terms of international tourism receipts, these were led in the region by Japan and Taiwan, with double digit increases of +48% and +11%, respectively.

However, from the tourism demand side, Chinese demand for tourism is predicted to quadruple in value in the next ten years (2007-2017), according to the forecasts of the World Travel & Tourism Council (WTTC). Indeed, the number of Chinese visits abroad reached 47million, which is 5 million more than that of foreign visitors to

China for the first time in 2007. At present China ranks a distant second, behind the USA, in terms of tourism demand, but by 2018 it is expected to have closed much of the current gap.

Given the appreciation of the potential spending power of Chinese tourists, the Taiwan Tourism Bureau has been actively exploring this emerging Chinese tourism market. A series of gradual policy reforms in government policy have been introduced and encouraged, such as Chinese tourists to Taiwan for travel purposes that were approved in July 2008. As stated by the Taiwan Tourism Bureau, this was not only a breakthrough for Cross-Straits tourism, but also an important milestone in the history of the development of Taiwan tourism. In particular, such tourism policy reforms allowed Taiwan to firmly claim its rightful place on the global tourism map.

Historically, the era of Cross-Straits tension between China and Taiwan inevitably drew the world's attention because of an important security dilemma in the Asia-Pacific region. For China and Taiwan, the pre-1990 relationship was a tension under significant threat, as a declaration of independence by Taiwan could have provoked military action from China in a state of suspicion and anxiety.

Since 2005, after much effort on improving the Cross-Straits economic relationship by the Taiwan Government, China has overtaken the USA to become Taiwan's second largest source of imports after Japan. Moreover, China is also Taiwan's number one destination for foreign direct investment. Closer economic links with China brings greater opportunities for the Taiwan tourism industry. As reported by UNWTO, Chinese tourists spent 30 percent more when travelling abroad in 2012 than in the previous year.

However, not only in Taiwan, but many countries have been increasing their marketing efforts to lure Chinese tourists, especially given the economic recession and the financial debt crisis that has beset international tourism demand from the leading European and North American countries. In East Asia and South-East Asia, neighboring destinations such as Hong Kong, Macao, South Korea, Japan and Singapore, which are already very popular with Chinese tourists, are redirecting their tourism policies to absorb a greater number of Chinese tourists. Therefore, significant challenges and financial management risks can be expected for the Taiwan tourism industry arising from the increasing competition in the Asian tourism market.

For many reasons, promoting international tourism makes a great deal of sense for Taiwan. The connection between international tourism and the financial market would seem to be an important consideration for any country as demand for international tourists would seem to impact significantly on all aspects of the economy and on financial markets (see, for example, Hammoudeh and McAleer (2013) and Hammoudeh et al. (2013)). However, research which has empirically documented the link between stock returns, the associated returns volatility, and firm size on the Taiwan tourism industry seems to be scant.

There remain many unanswered questions. For instance, from the perspective of financial risk management, is the stock return performance of small firms superior to that of large firms? Is there empirical evidence regarding whether small firms generate greater financial management risk than that of large firms, on average? In particular, what is the impact on financial risk management arising from significant government policy reforms, such as in tourism policy of Chinese tourists being granted permission to travel to Taiwan, on the tourism industry in Taiwan?

As argued in Chang et al. (2013), financial decisions are generally based upon the trade-off between risk and returns. Therefore, a primary aim of this paper is to explore how the stock returns volatility for firm performance varies with firm size, as well as time periods, classified according to the full sample period, as well as prior to and after the introduction of China's tourism reform policy of allowing Chinese tourists to travel to Taiwan. Four conditional volatility models will be used to estimate the volatility size effects arising from the policy reform.

The remainder of the paper is as follows. Section 2 describes the proxies for analyzing firm size, volatility size effects, and firm performance. Section 3 illustrates the data used in the empirical analysis, and the classification of tourism stock indexes by the trade markets, as well as the sample sizes by time periods corresponding to prior to and after the introduction of China's tourism policy reform. Section 4 provides an overview of the methodology and models that will be used to estimate the size effects of volatility for firm performance. Section 5 discusses the empirical results. Section 6 presents a summary and some concluding comments.

2. Evaluating Stock Return Volatility and Volatility Size Effect

In this section we describe the stock return volatility, the volatility size effect, and the

proxies to be used to measure the magnitudes of the size effect.

2.1 Stock Return Volatility

Financial decisions are generally based on the trade-off between risk and returns. Although it is frequently inconsistent with reality, a constant standard deviation is commonly used to measure volatility, which is also used to characterize the risk associated with a security in financial markets. It is well known that stock return volatility represents the variability of stock price changes over a period of time. Investors, analysts, brokers, dealers and financial market regulators are concerned with stock return volatility, not just because it is widely used as a measure of risk, but also because they are concerned about "excessive" volatility in which observed fluctuations in stock prices do not appear to be accompanied by any important news about the firm or market as a whole.

Therefore, volatility is inherently an important concept in financial markets, as well as in practice in financial risk management and asset allocation (see, among others, Lin, Liu and Wu, 1999; Hsu, Wang and Hung 2011). Furthermore, as discussed in, for example, Liu (2006), modelling the volatility of a time series may improve the efficiency of the estimates of the parameters of a model and the accuracy of the associated interval forecasts. This is particularly the case when volatility is not constant but rather varies over time.

2.2 Size Effect of Firm Performance

The size effect refers to the effect of firm size on investment returns. As stated in Banz (1981), the common stock of small firms has, on average, higher risk-adjusted returns than that of large firms. This result will hereafter be referred to as the size effect, or small-firm effect. There are several empirical papers in the literature that have found a size effect to be prominent in many countries. Some authors have indicated that the negative relation between abnormal returns and firm size is stable over time (see, among others, Banz (1981) and Kato and Schallheim (1985)).

Firm performance may be driven by firm-specific factors, such as firm size. Several papers have shown that other factors may be more important to gauge firm performance than firm-specific factors, such as demand, technological opportunity conditions, and industry effects (Hansen and Wernerfelt (1989), Mehran (1995), Hawawini et al. (2003), Cohen (2010)). Therefore, the empirical issue of performance

in stock returns and volatility, as related to the size of a firm, would seem to be in dispute. Moreover, it is worth exploring the size effect on the performance of firms in the tourism industry, as well as for Taiwan, as there are many firms of different sizes involved in the tourism industry.

2.3 Proxies for Firm Size and Firm Performance

This paper uses two proxies, namely stock index returns as a proxy for firm performance, and trade market value of total assets (TA) as a proxy for firm size (see Section 3 below for further details) in order to explore the volatility size effects for firm performance. Empirically, stock returns are the most appropriate proxy of firm performance for all-equity firms (Mehran 1995) because a firms' stock price reflects the value of its future earnings, both from existing assets and their expected growth (Tufano (1996), Gay and Nam (1998)). Several previous papers have indicated that a firm's total assets (TA) can be taken as a reasonably accurate proxy for firm size.

3. Data

In this section we present the data that will be used in the empirical analysis, and the classifications of tourism stock indexes by the trade market, as a proxy of firm size. The daily closing prices of tourism stock indexes are used from 30 November 2001 to 27 February 2013 for 2,793 time series observations over roughly 12 years. The sources of data are the Taiwan Stock Exchange (TWSE) and Gre-Tai Securities Markets (GTSM).

Several previously published papers have indicated that the firm's total assets (TA) can be taken as a proxy for firm size (this will be explained further in Section 2.3). For measuring the volatility size effect for firm performance, this paper classifies the tourism stock indexes into two categories, namely Large and Small, according to the trade market (a proxy for firm size), which varies according to the requirements of paid-in capital when a public issuer applies for listing.

For these reasons, the tourism-related firms listed on the Taiwan Stock Exchange (TWSE) are defined as large firms (that is, Large), whereas the tourism-related firms listed on the Gre-Tai Securities Market are regarded as small firms (that is, Small). The requirement of a firm's paid-in capital for listing on the Taiwan Stock Exchange is at least NT$600 million, which is greater than for the Gre-Tai Securities Market,

where a firm's paid-in capital is at least NT$50 million, at the time a public issuer applies for listing.

4. Univariate Conditional Volatility Models for Firm Performance

The standard assumption of a constant variance of random shocks in high frequency economic and financial markets time series data is generally unsustainable empirically. The existence of conditional heteroscedasticity of the random shocks can invalidate standard statistical tests of significance, which assumes that the model is correctly specified.

The family of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models treats the presence of heteroscedasticity as a conditional variance to be modelled. Engle (1982) and Bollerslev (1986) developed a class of models which addresses such concerns, and allows for modelling of both the levels (the conditional first moment) and variances (the conditional second moment) of a time series process. An autoregressive conditional heteroscedasticity (ARCH) model, as proposed by Engle (1982), considers the conditional variance of the current error term to be a function of the conditional variances of previous values and the 'news' effects of previous shocks to stock returns.

In terms of a univariate model, based on the framework of ARCH, the original specification has been extended in several directions. The main extensions have been the Symmetric ARCH model of Engle (1982), the GARCH model of Bollerslev (1986), the GARCH-M model of Engle et al. (1987), the asymmetric or threshold GARCH model, otherwise known as the GJR or TARCH model, of Glosten, Jagannathan and Runkle (1993) (see also McAleer, Chan and Marinova (2007) and Chang, Khamkaew and McAleer (2012)), exponential GARCH (or EGARCH) model of Nelson (1991), and symmetric and asymmetric multivariate extensions of these models in Ling and McAleer (2003) and McAleer, Hoti and Chan (2009), respectively.

Four GARCH models will be estimated in this paper, namely the GARCH, GJR (or TARCH), EGARCH, and GARCH-M models. The following discussion briefly presents the model specifications of the conditional mean and the conditional variance.

4.1 Conditional Mean Specification

The univariate GARCH model can be used to estimate and forecast risk as a conditional variance process. As mentioned above, the ARCH and GARCH models treat conditional heteroskedasticity as a variance to be modeled rather than as a problem to be corrected. The following conditional expected returns at time *t*, which is given as an AR(1) process, accommodates a returns process as depending on its own past returns lagged one period:

$$R_t = \varphi_0 + \varphi_1 R_{t-1} + \varepsilon_t$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t) \tag{1}$$

where R_t is an $n \times 1$ vector of daily stock price returns at time *t* for each series (in this case, n = 1 for stock index returns). The $n \times 1$ vector of random errors, ε_t, represents the shocks for each series at time *t*, with corresponding $n \times 1$ conditional variance of the residuals of a regression, h_t. The market information available at time *t*-1 is represented by the information set, I_{t-1}. The $n \times 1$ vector, φ_0, represents the long-term drift coefficients.

The estimate of the coefficient vector, φ_1, where $|\varphi_1| \leq 1$, provides a measure of the effect of the impacts on the mean returns of one series arising from its own past returns. The AR(1) model in equation (1) can easily be extended to univariate or multivariate ARMA(*p,q*) processes, as well as to non-stationary time series processes (for further details, see Ling and McAleer (2003) and McAleer et al. (2009)).

4.2 Conditional Variance Specification

The GARCH model developed by Bollerslev (1986) allows the conditional variance to depend upon its own lags as well as lagged shocks to stock price returns. Therefore, the conditional variance equation in the simplest case, GARCH(1,1), is given as follows:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

where h_t is the conditional variance, namely a one-period ahead estimate (or forecast) of the conditional variance based on past information. It is possible to use this model to interpret the current fitted variance as a weighted function of a

long-term average value (ω), shocks to stock returns in the previous period, and the fitted conditional variance from the model during the previous period. It should be noted that this interpretation holds if the parameter estimates, $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, satisfy appropriate sufficient conditions to ensure that the conditional variance is positive.

In equation (2), the ARCH effect (or α) captures the short-run persistence of shocks, while the GARCH (or β) effect captures the contribution of shocks to long-run persistence (namely, $\alpha + \beta$). The stationary AR(1)-GARCH(1,1) model can easily be modified to incorporate a non-stationary ARMA(p,q) conditional mean and a stationary GARCH(r,s) conditional variance (see Ling and McAleer (2003) and McAleer et al. (2009) for further details).

Moreover, in equations (1) and (2), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE), when the returns shocks do not follow a normal distribution. Ling and Li (1997) demonstrated that the local QMLE is asymptotically normal if the fourth moment of ε_t is finite, while Ling and McAleer (2003) proved that the global QMLE is asymptotically normal if the sixth moment of ε_t is finite. The well known necessary and sufficient condition for the existence of the second moment of ε_t for GARCH(1,1) is $\alpha + \beta \leq 1$.

4.3 GJR (or TGARCH) Specification of the Conditional Variance

The GJR model is an extension of the GARCH model with an additional term added to account for possible asymmetries, which the ARCH and GARCH models ignore. As the sign of the returns can affect the magnitude of the volatility, there is a variety of asymmetric GARCH models to capture asymmetric effects, such as the GJR (or TARCH) model of Glosten, Jaganathan and Runkle (1993), EGARCH model of Nelson (1991) (for further details, see Section 4.4 below), and an extension of the VARMA-GARCH model of Ling and McAleer (2003), which nests the univariate symmetric GARCH model for the conditional variance process, which is given by the VARMA-AGARCH model of McAleer et al. (2009), which nests the univariate asymmetric GJR model.

The conditional variance of the GJR model is given by:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1}^2 D_{t-1} \qquad (3)$$

$$\text{with } D_{t-1} = 1, \quad \text{if } \varepsilon_{t-1} < 0,$$
$$= 0, \quad \text{otherwise}$$

where $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$, $\beta \geq 0$ are sufficient conditions for $h_t > 0$. The possible asymmetric effect in data can be captured by the positive parameter in the context of the GJR model. For financial data, it is typically expected that $\gamma > 0$ as negative shocks increase risk by increasing the debt to equity ratio. This means that negative shocks will lead to a higher subsequent-period conditional variance than positive shocks of the same magnitude. The contribution of shocks with an asymmetric effect to both the short-run and long-run persistence are $\alpha + \frac{\gamma}{2}$ and $\alpha + \beta + \frac{\gamma}{2}$, respectively.

4.4 EGARCH Specification of the Conditional Variance

As mentioned previously, one of the primary restrictions of GARCH models is that they enforce a symmetric response of volatility to positive and negative shocks of equal magnitude. However, the EGARCH model provides an alternative view of the 'volatility-feedback' hypothesis on the conditional variance specification, as compared with GARCH and GJR models. First, the conditional variance (h_t) will be positive because the logarithm of conditional volatility, $\ln(h_t)$, is modelled, even if any or all of the parameters are negative. Thus, there is no need to artificially impose non-negativity constraints on the model parameters. In particular, asymmetric effects and leverage are permitted under the EGARCH formulation.

There are various ways to express the conditional variance for the EGARCH model, but the most common specification is given as follows:

$$\ln(h_t) = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta \ln(h_{t-1}) \tag{4}$$

where the parameters α and γ in the EGARCH model represent the magnitude and sign effects of the standardized residuals, respectively.

Furthermore, as noted in McAleer et al. (2007), there are some important differences between EGARCH, on the one hand, and GARCH and GJR, on the other, as follows:

(i) EGARCH is a model of the logarithm of the conditional variance, which implies that no restrictions on the parameters are required to ensure $h_t > 0$; (ii) moment conditions are required for the GARCH and GJR models as they are dependent on lagged unconditional shocks, whereas EGARCH does not require moment conditions to be established as it depends on lagged conditional shocks (or standardized residuals); (iii) $|\beta| < 1$ is likely to be a sufficient condition for consistency of the QMLE for EGARCH(1,1); (iv) as the standardized residuals appear in equation (4), $|\beta| < 1$ would seem to be a sufficient condition for the existence of moments; and (v) in addition to being a sufficient condition for consistency, $|\beta| < 1$ is also likely to be sufficient for asymptotic normality of the QMLE of the EGARCH(1,1) model (see Chang et al. (2011)).

4.5 GARCH-M Specification of the Conditional Mean and Variance

As discussed in Brooks (2008), most of the models used in empirical finance presume that investors should be rewarded for taking additional risks to try to obtain a higher return. In order to make the concept of 'risk premium' measurable, Engle, Lilien and Robins (1987) proposed an ARCH-M specification, where the conditional variance of asset returns enters into the conditional mean equation. This specification means that the GARCH-M model allows the return of a security to be determined, among other factors, by its risk component.

The GARCH-M model is given as follows:

$$R_t = \varphi_0 + \delta h_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, h_t)$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

The main thrust of the GARCH-M model is given by the parameter δ in the conditional mean equation. If the sign of δ is positive, then increased risk, given as an increase in the conditional variance, leads to a rise in mean returns. Thus, the parameter δ can be interpreted as a risk premium. In some empirical applications, the conditional variance term, as expressed in the square root form, $\sqrt{h_t}$, appears directly in the conditional mean equation rather than in the conditional variance term, h_t. Therefore, for a risk premium interpretation, we would expect $\delta > 0$.

5. Empirical Results

This section will examine the volatility size effects for firm performance in the tourism industry of Taiwan, using four univariate conditional volatility models, namely GARCH, TGARCH (GJR), EGARCH and GARCH-M, in modelling the conditional variance process according to the full sample period, and two sub-samples prior to and after the tourism policy reform. The empirical findings for each model will be discussed below.

First, tourism stock index returns are given as the first difference in log prices, defined as $R_t = 100(\ln P_t - \ln P_{t-1})$, where P_t and P_{t-1} are the daily closing prices at time periods t and t-1, respectively. Table 1 shows the operational definitions of the log return series used in the paper.

Furthermore, as described in Section 1, China's tourism reform policy was such that Chinese tourists were permitted to travel to Taiwan from 13 June 2008 to 18 July 2008. This paper will examine if the risk associated with tourism stock index returns varies according to firm size. Moreover, we will explore how the volatility size effects for firm performance in the Taiwan tourism market may have been affected by the tourism reform policy over different time periods.

It is intended to examine the volatility size effects for different time periods, that is, for the whole sample, as well as prior to and after the tourism reform policy came into effect, for each of two tourism stock index series, namely Large and Small Firms. This paper takes a specific day (1 July, 2008) as the breakpoint, which coincides with the introduction of China's tourism reform policy that allowed Chinese tourists to travel to Taiwan. Therefore, the full sample is divided into two segments, namely Sub-sample A and Sub-sample B, corresponding to the time periods prior to and after the introduction of the tourism policy reform.

This paper applies two stock index returns series, namely Large Firms and Small Firms, to examine the returns and volatility size effects for firm performance during different periods corresponding to three sample sizes, namely the Full sample from 30 November 2001 to 27 February 2013, Sub-sample A from 30 November 2001 to 30 June 2008, and Sub-sample B form 1 July 2008 to 27 February 2013.

There is a statistically significant break (or structural change) at the specified breakpoint between the two periods of Sub-samples A and B, which is shown by the Chow breakpoint test (see more in Section 5.1 below). The notation is as follows: (i)

Sample F Large for Full sample and Large Firms, (ii) Sample F Small for Full sample and Small Firms, (iii) Sample A Large for Sub-sample A and Large Firms, (iv) Sample A Small for Sub-sample A and Small Firms, (v) Sample B Large for Sub-sample B and Large Firms, and (vi) Sample B Small for Sub-sample B and Large Firms.

[Tables 1-2 here]

5.1 Chow Breakpoint Test

Table 2 illustrates the results of the Chow breakpoint tests of the null hypothesis of no breaks at the specified breakpoint between two regimes, namely Sub-sample A and Sub-sample B. All three tests, including the F statistic, Likelihood Ratio test, and Wald statistic, reject the null hypothesis of no structural change at the 1% and 10% levels of significance for the Large and Small series, respectively. This implies that the specific event does indeed have different impacts for the different sub-samples, so it will be interesting to explore this issue further below.

[Table 3 here]

5.2 Descriptive Statistics of Returns

This paper examines the time series data graphically. Figures 1.1 to 3.3 plot the trends, logarithms, and log differences (that is, the growth rate or continuously compounded returns) of six data series. Moreover, Table 4 presents the basic descriptive statistics for the two returns series (Large and Small) according to three sample periods. In terms of the Full sample and Sub-sample A, both average returns of Large and Small Firms are positive and low, whereas both average returns of Large and Small Firms in Sub-sample B are negative and very low.

[Figures 1.1- 3.3 here]
[Table 4 here]

In general, all six series mentioned above display significant leptokurtic behaviour, as evidenced by large kurtosis in comparison to the Gaussian distribution. In addition, four of the six series show mild positive skewness, with only Small Firms in Sub-sample B being negatively skewed. The negative skewness statistic implies the series has a shorter right tail than left tail. The Jarque-Bera Lagrange multiplier test statistics indicate that none of these return series is normally distributed, which is not

at all surprising for daily financial returns data.

5.3 Unit Root Test of Returns

A unit root test examines whether a time series variable is non-stationary. Two well-known tests, the GLS-detrended Dickey-Fuller test and the Phillips-Perron (PP) test, are calculated to test for unit root processes in stock price returns. The results of the unit root tests are shown in Table 5, and indicate that all returns series are stationary, which is not particularly surprising. The unit root tests for each individual returns series reject the null hypothesis of a unit root at the 5% level of significance.

However, the same outcome does not hold for two price series, namely the daily closing prices and log daily closing prices. For these two price and log price variables, the unit root tests do not reject the null hypothesis of a unit root at the 5% level of significance, which implies that the series are non-stationary. Again, this is not a particularly surprising empirical finding.

[Tables 5.1-5.3 here]

5.4 A Return Spillovers by Firm Size

As mentioned in Sections 4.2 to 4.5 above, the ARCH/GARCH and GARCH-M models enforce a symmetric response of volatility to positive and negative shocks of equal magnitude. However, the asymmetric GJR and threshold EGARCH models provide an alternative perspective to account for the 'volatility-feedback' hypothesis, namely the presence of asymmetric effects.

In order to capture returns spillovers, the first step is to consider returns spillovers from the own past returns. Additional information is provided in Tables 6.1-6.3, and is given by the parameter φ_1. For the Large Firms, the empirical results indicate that returns spillovers from own past returns are predictable for all three models for each time period. However, for the Small Firms, this holds only in Sub-sample A, implying that the size effects of the returns spillovers from own past returns existed between the two stock index returns series.

It is worth noting the consistent results in that the returns spillovers from the own previous returns for Small Firms are stronger than those of the Large Firms, regardless of the estimated models and time periods. Moreover, both Large and Small

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Firms do not appear to have risk premium spillovers from the own conditional volatility (or variance) of asset returns, as the estimates of the GARCH-M model are insignificant at the 5% level, as shown by estimates of the parameter δ .

5.5 A Volatility Spillovers by Firm Size

In order to describe the volatility spillovers from the own past impacts, the empirical results are shown in Table 6.1-6.3. The ARCH effect, α , referred to the short-run persistence of shocks to returns, reveal significant estimates for both the Large and Small Firms.

It is worth noting that the magnitude of the ARCH effects for Large Firms is relatively stronger than that of Small Firms for both the Full sample and Sub-sample A. However, it holds in reverse for Sub-sample B, where the ARCH effects for Large Firms is relatively weaker than that of Small Firms, with the exception of the EGARCH model, as shown in Table 6.3.

Furthermore, the GARCH (or β) effect indicates the contribution of shocks to long-run persistence (namely, $\alpha + \beta$). As shown in Tables 6.1-6.3, where the value given by $\alpha + \beta$, is very close to unity, this suggests that a shock at time t persists for many future periods because shocks to the conditional variance take a long time to dissipate.

Regarding the long-run persistence of shocks with spillover effects from previous impacts, the empirical results show that the estimates for Small Firms is relatively stronger, but with a minor difference, from those of Large Firms for most of the GARCH models. These results suggest that there were not strong size effects of the long-run persistence of shocks for different time periods.

As noted in Sections 4.3-4.4, the significant and positive coefficient, γ , namely the asymmetric effect, indicates that a negative shock leads to higher volatility in the future than does a positive shock of the same magnitude. Tables 6.1-6.3 indicate that, as shown by the estimate of γ , only positive estimates for Large Firms in Sub-sample B confirm the presence of asymmetry. This suggests that the asymmetric effect varies according to firm size and time period, and only after the tourism policy reform in the case of Large Firms.

Alternatively, the significant coefficient, γ , in the EGARCH model represents the

sign effects of the standardized residuals. The empirical findings show the sign effect of the standardized residuals, γ, is significantly negative and the absolute value of γ is lower than for the corresponding estimates α, such that the estimates of the absolute value -0.00742 < 0.07768 in the Full sample and in Sub-sample B. These results suggest that the asymmetric effect is present. However, according to these estimates, there is no leverage effect, whereby negative shocks increase volatility but positive shocks of a similar magnitude decrease volatility.

As the stationarity conditions, namely ($\alpha + \beta < 1$), for the GARCH, GJR, and GARCH-M models, and $|\beta| < 1$ for the EGARCH model, are confirmed for each returns series examined in Table 6.1, all the returns series satisfy the second moment and log-moment conditions. These are sufficient conditions for the Quasi-Maximum Likelihood Estimator (QMLE) to be consistent and asymptotically normal (for further details, see McAleer, Chan and Marinova (2007)). Therefore, it is valid to conduct standard statistical inference using these estimates.

6. Conclusion

This paper investigated the volatility size effects of stock indexes for large and small firms in Taiwan during the period 30 November 2001 to 27 February 2013. In addition to the full sample period, we divided the sample period into two subsamples, namely prior to and after the introduction of China's policy reform that allowed Chinese tourists to travel to Taiwan. Four GARCH models were used to estimate volatility.

The primary objective was to identify whether the volatility size effects for firm performance, as measured by the returns to stock prices for large and small firms in Taiwan, varied according to firm size and time period, namely before and after the policy reform. Moreover, we investigated how the volatility size effects have been affected by the policy reform in China's tourism policy.

The empirical findings confirmed that there have been important changes in the volatility size effects for firm performance prior to and after the tourism policy reform, regardless of firm size and estimation period. In addition, the returns-spillovers from past returns were found to be stronger before rather than after the policy reform. Moreover, the volatility spillovers for all volatility models and firm sizes suggested that the volatility size effects arose from the impacts of the tourism policy reform that

allowed Chinese tourists to travel to Taiwan.

Overall, the long-run persistence of shocks indicated the ambiguous situation of volatility size effects of the returns to stock prices for large and small firms in Taiwan for the two sample periods. Furthermore, the risk premium revealed insignificant estimates in both time periods, while asymmetric effects were found to exist only for large firms after the policy reform.

The empirical findings should be useful for financial managers and policy analysts as it provides insight into the magnitude of the volatility size effects for firm performance, as measured by the returns to stock prices for large and small firms, how the size effects can vary with firm size, the impacts arising from China's tourism policy reform, and how firm size is related to financial risk management strategy.

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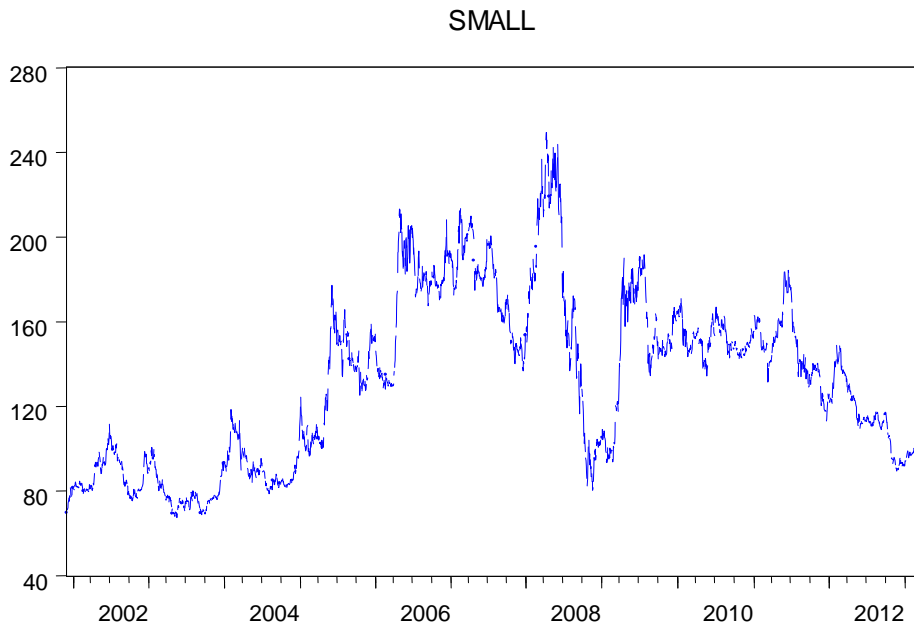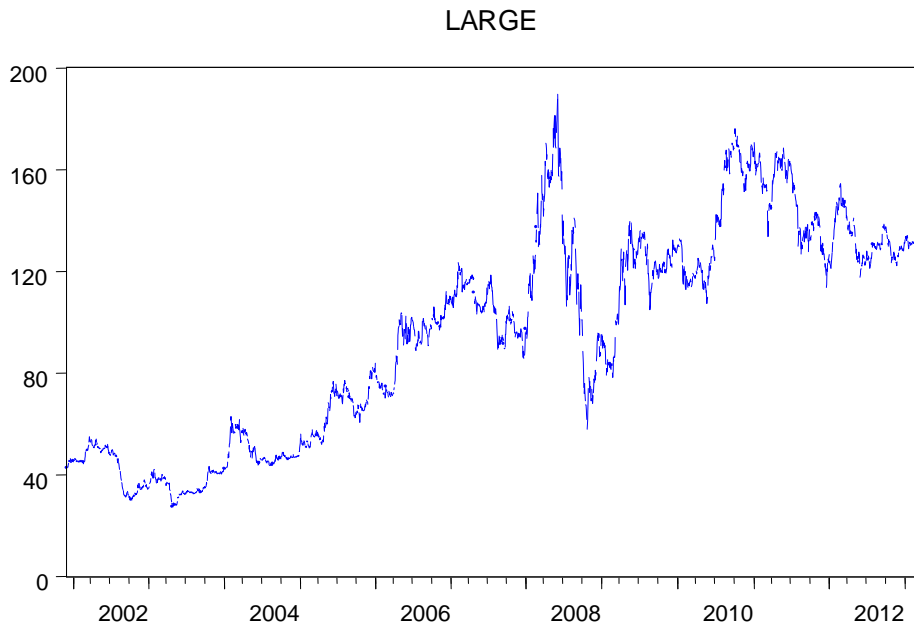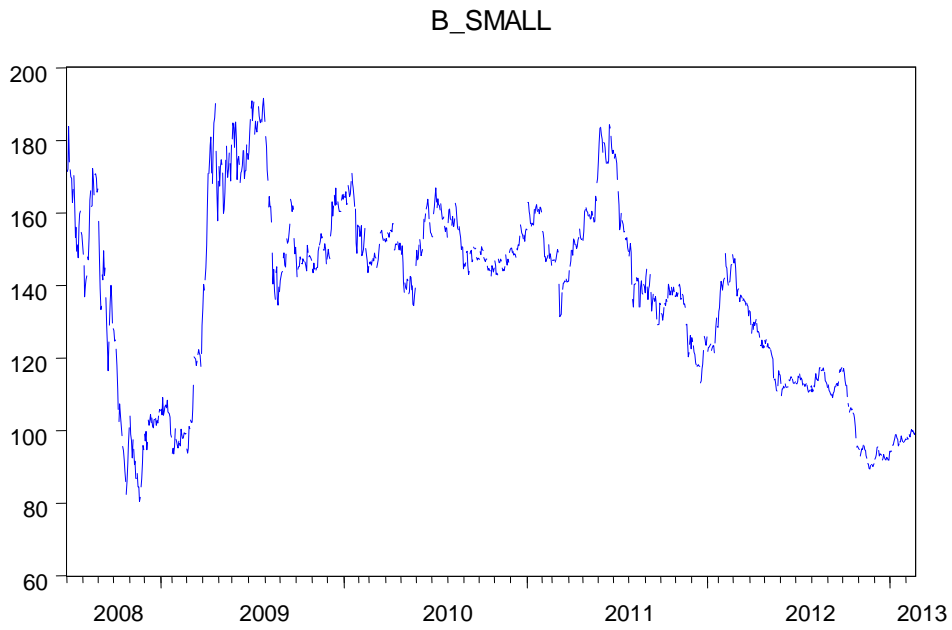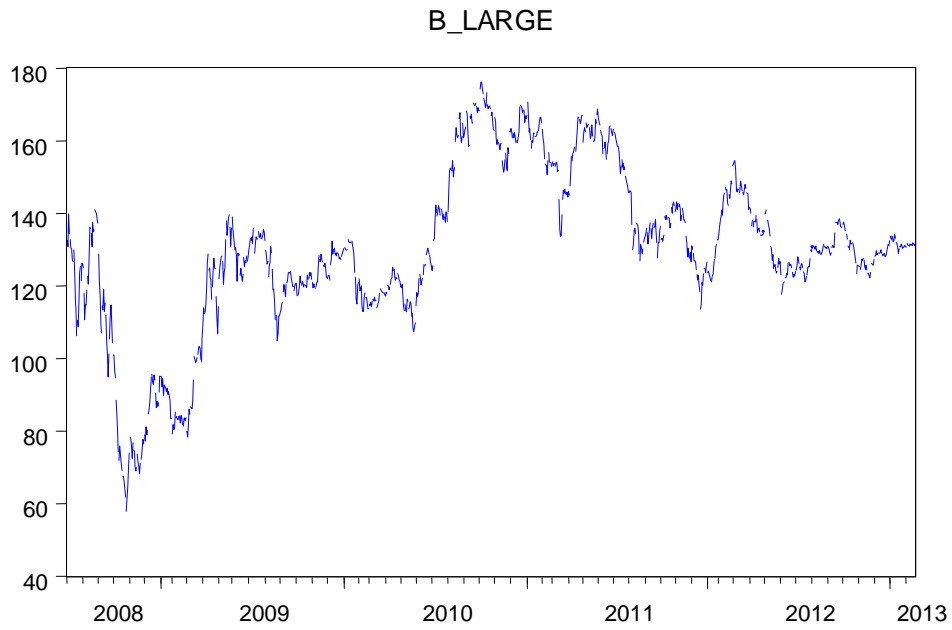
Figure 1.1
Time Series Plots of Daily Closing Prices
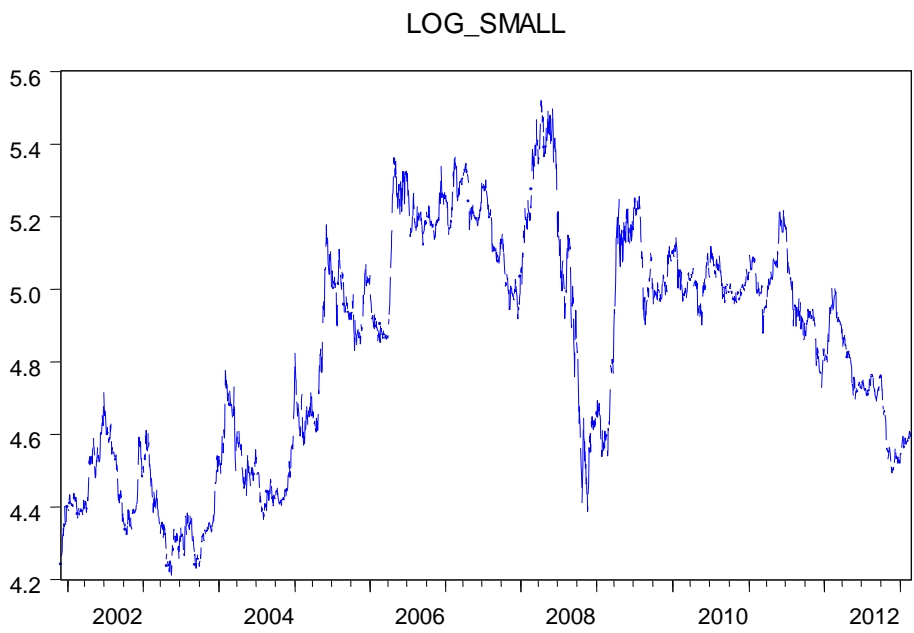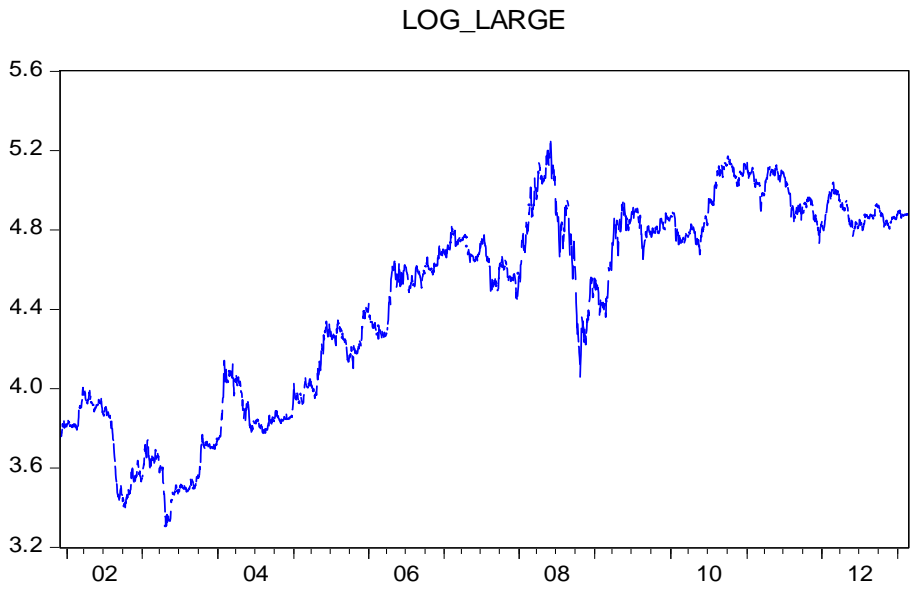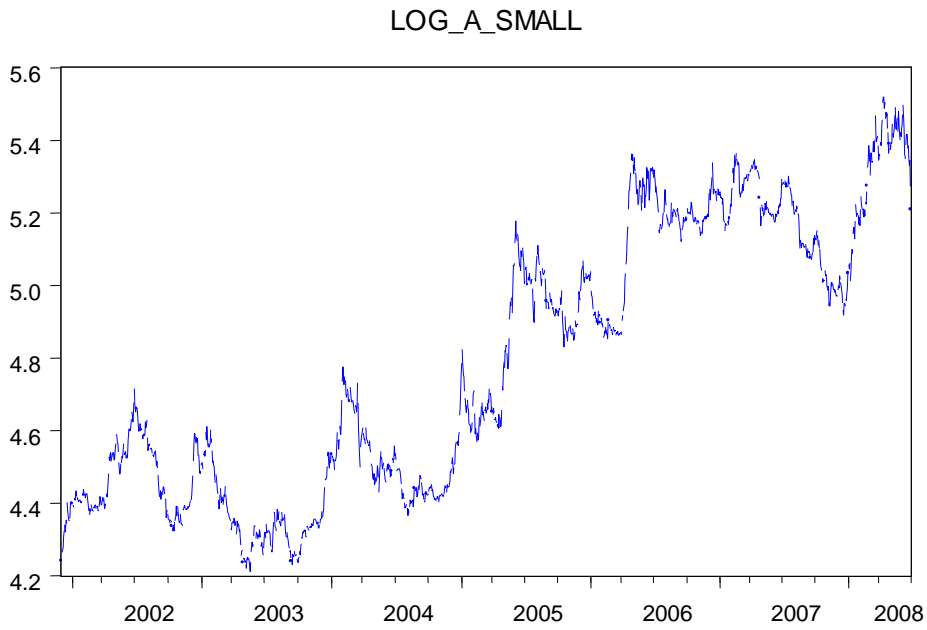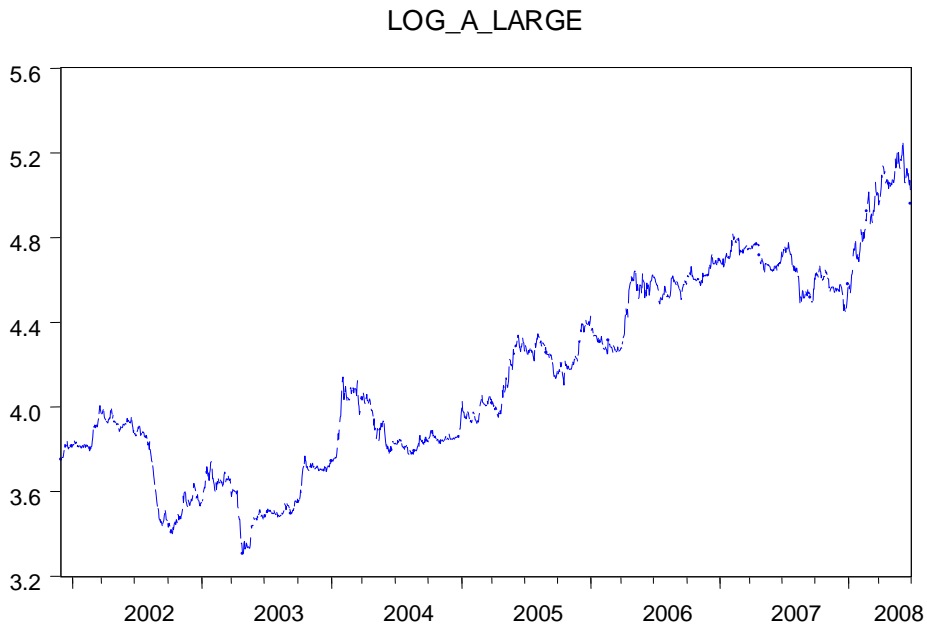**(2001/11/30-2011/10/31)**

A_LARGE

A_SMALL
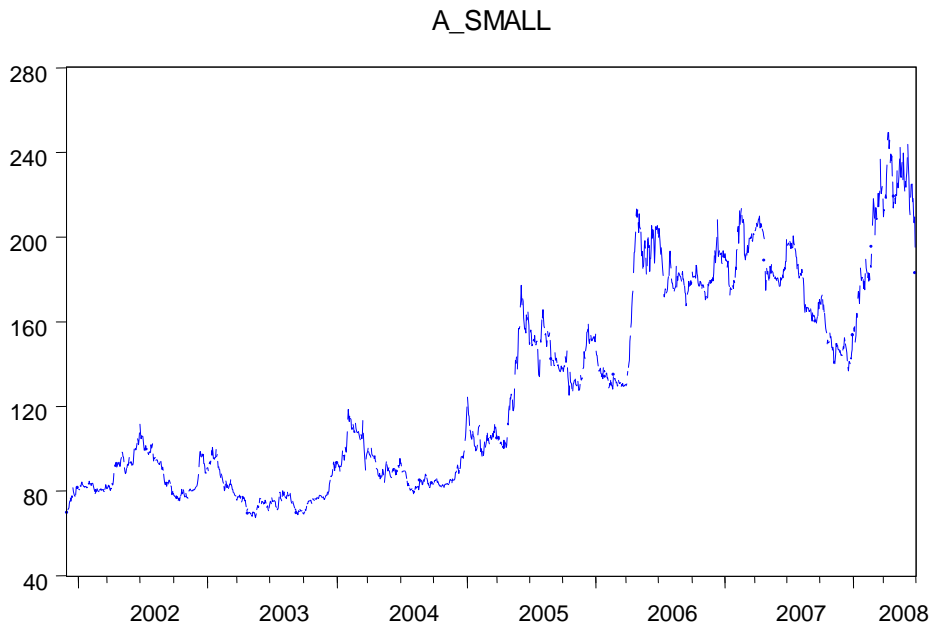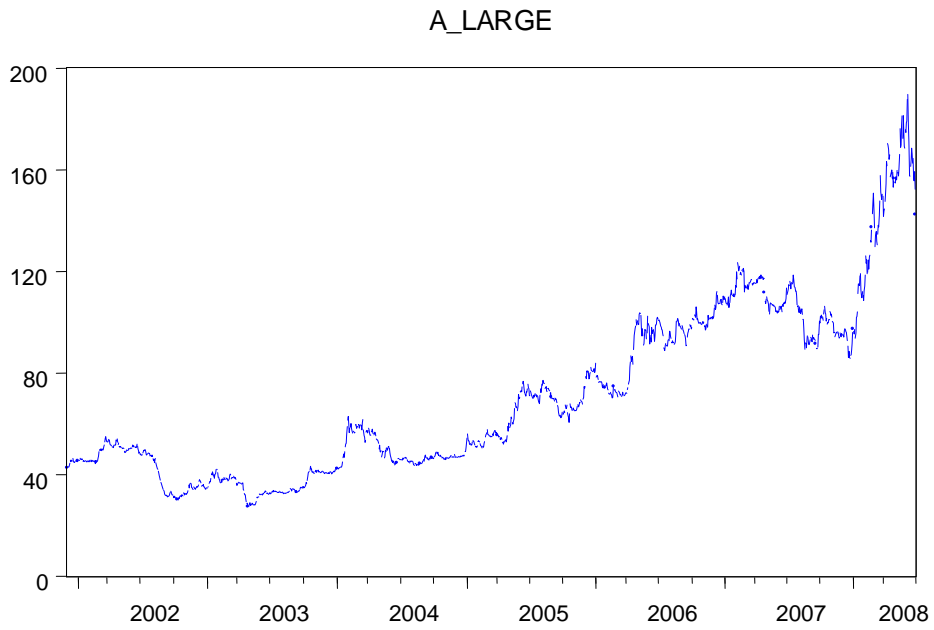
Figure 1.2
Time Series Plots of Daily Closing Prices
Subsample A
(2001/11/30-2008/06/30)

Figure 1.3
Time Series Plots of Daily Closing Prices
Subsample B
(2008/07/01-2013/02/27)

23

LOG_LARGE

LOG_SMALL

Figure 2.1
Time Series Plots for Log Daily Closing Prices
(2001/11/30-2011/10/31)

24

Figure 2.2
Time Series Plots for Log Daily Closing Prices
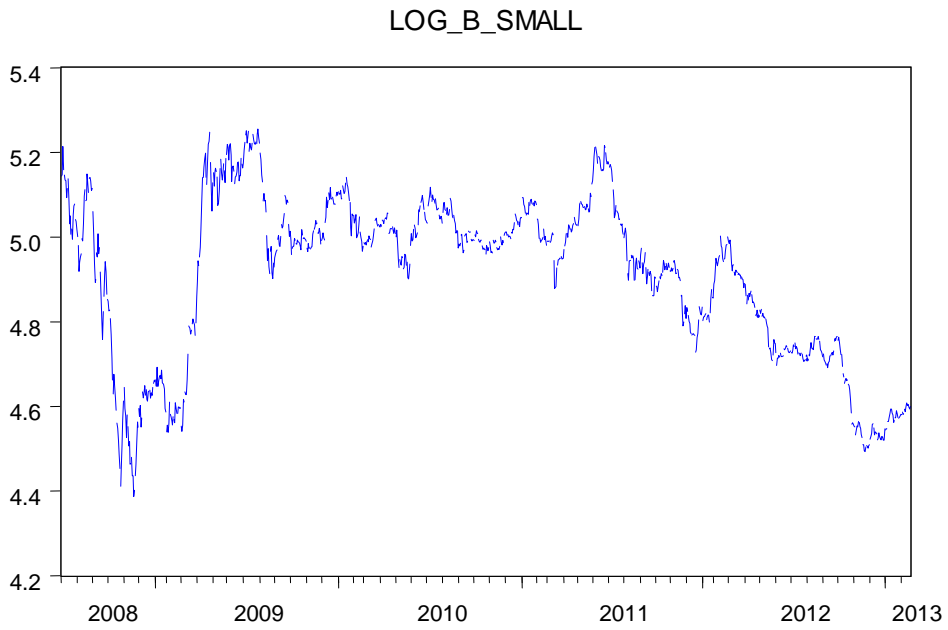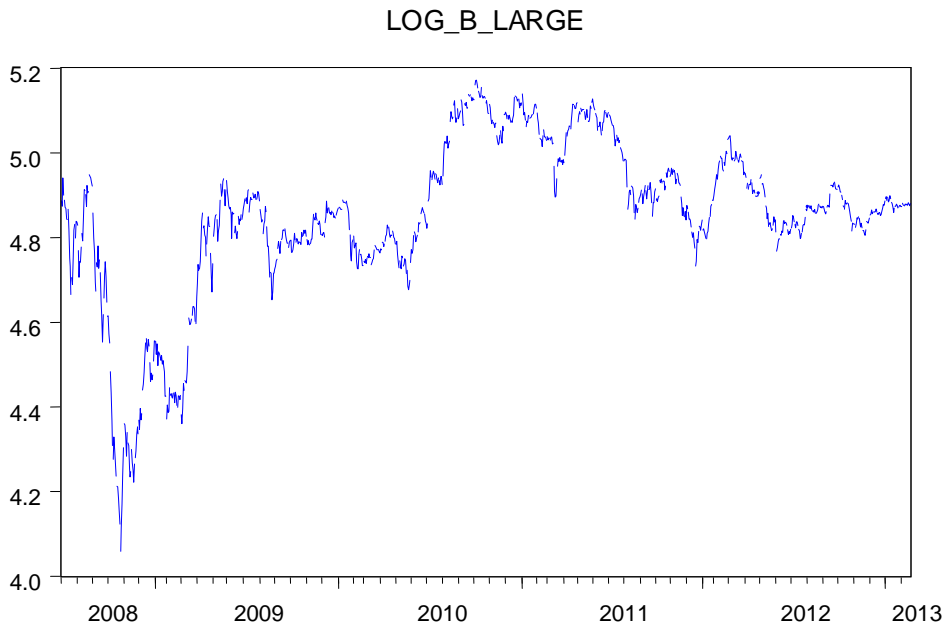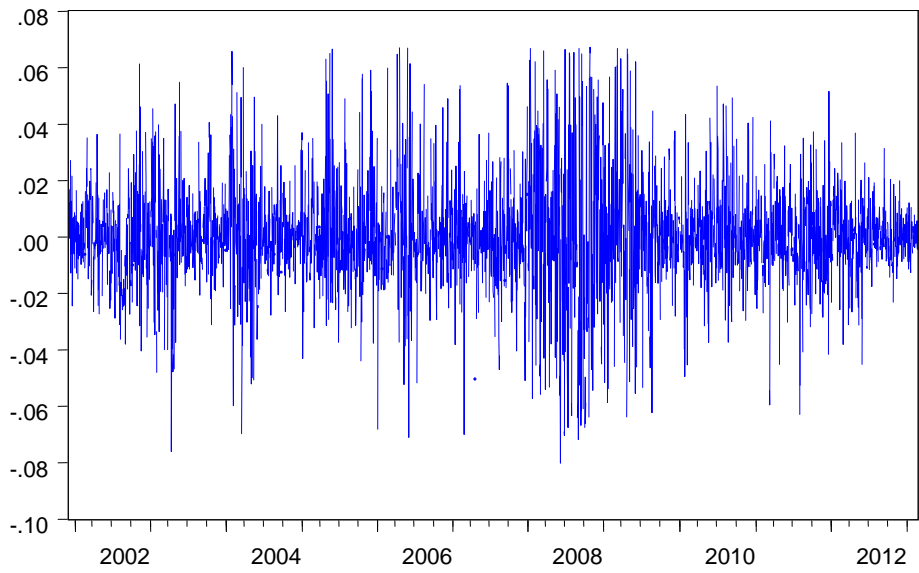**Subsample A**
(2001/11/30-2008/06/30)

25

Figure 2.3
Time Series Plots for Log Daily Closing Prices
Subsample B
(2008/07/01-2013/02/27)

Figure 3.1
Time Series Plots for Daily Returns
(2001/11/30-2011/10/31)

Figure 3.2
Time Series Plots for Daily Returns
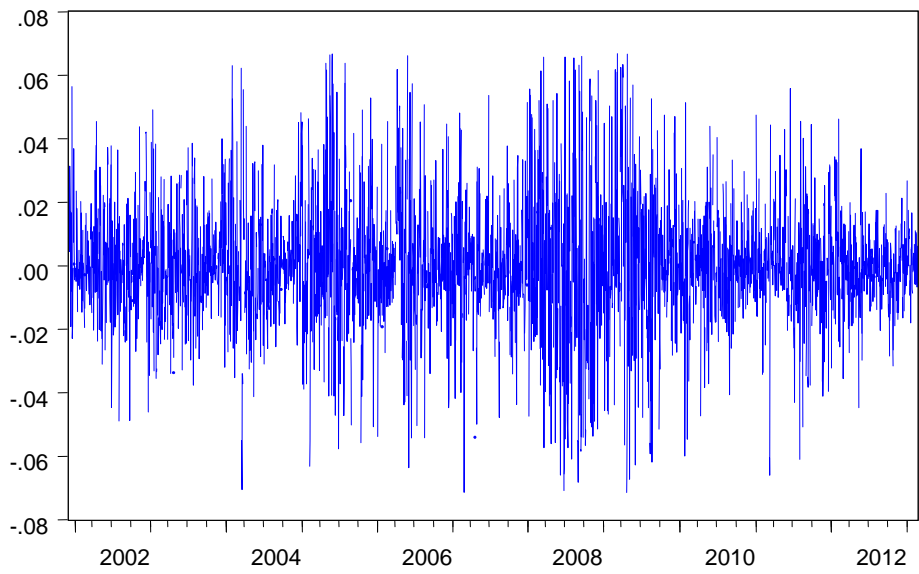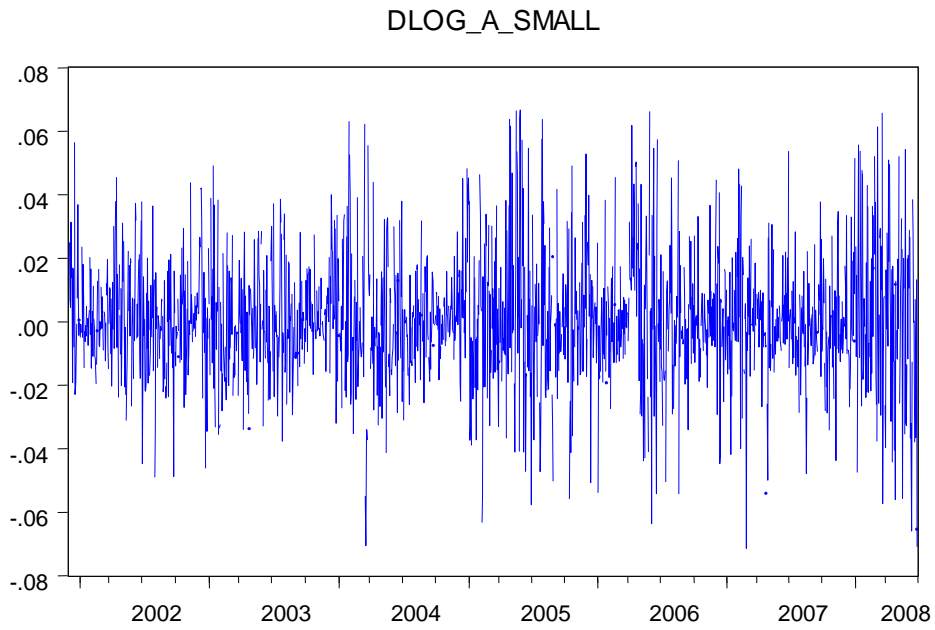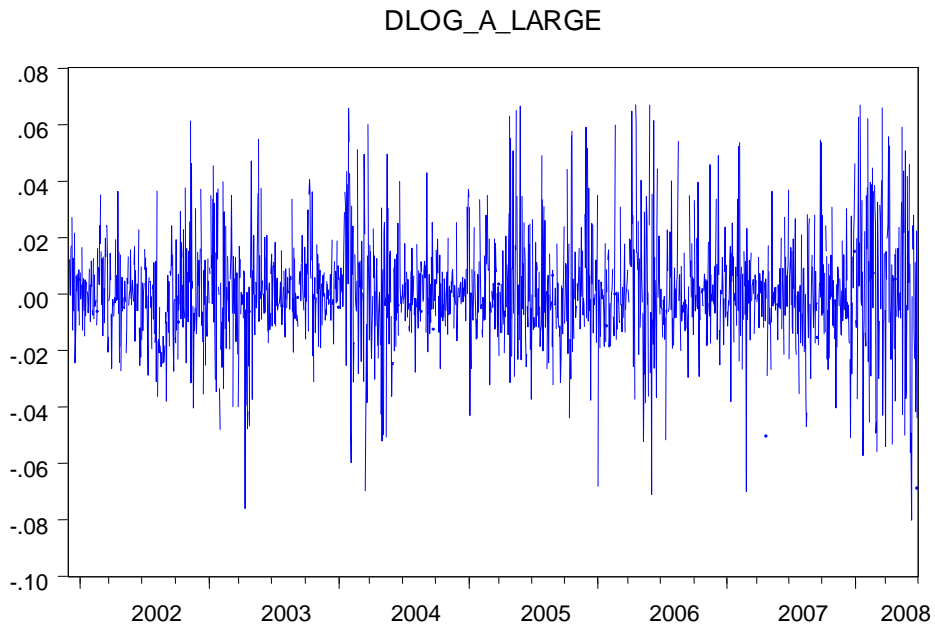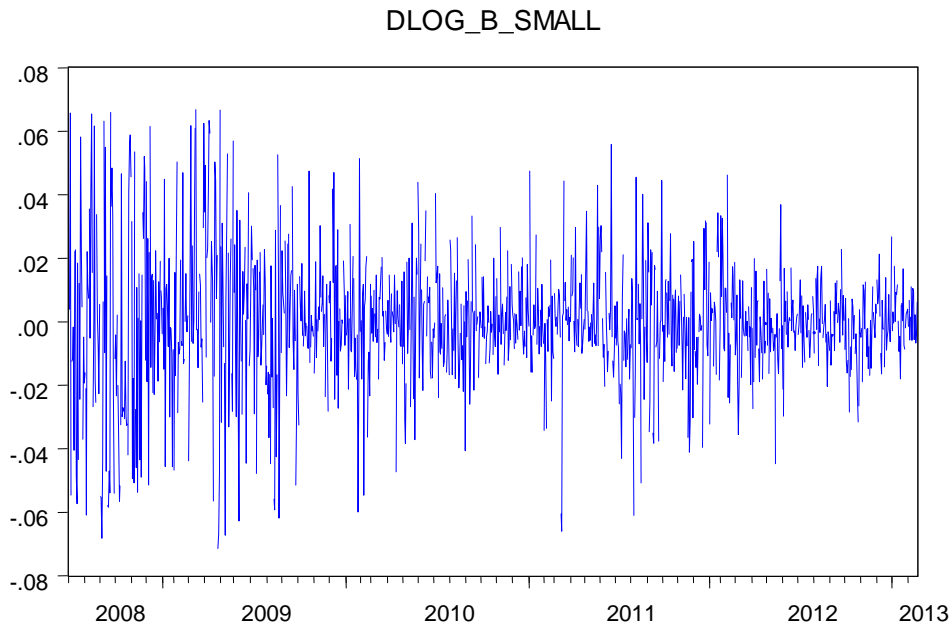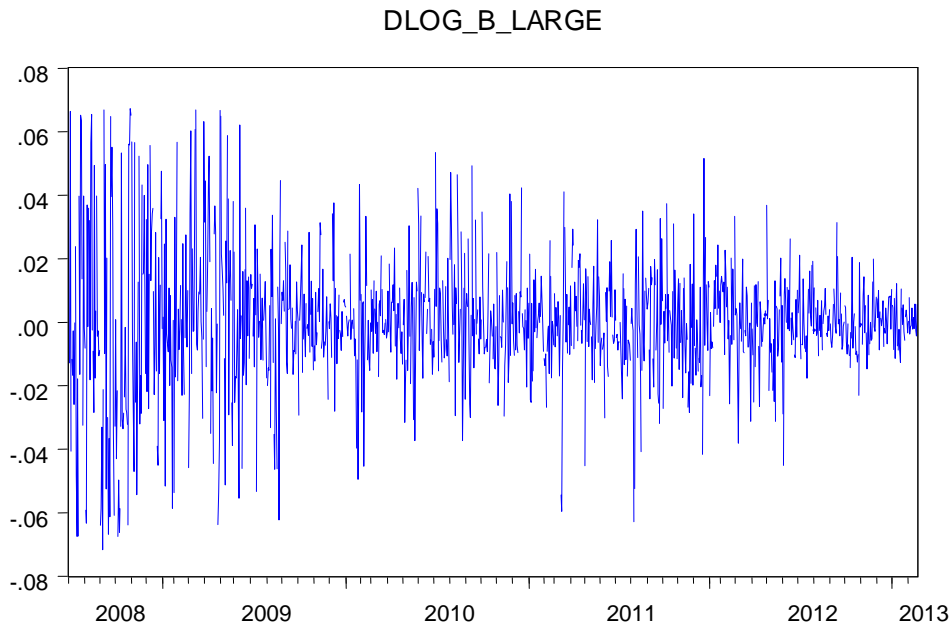**Subsample A**
(2001/11/30-2008/06/30)

DLOG_B_LARGE

DLOG_B_SMALL

Figure 3.3
Time Series Plots for Daily Returns
Subsample B
(2008/07/01-2013/02/27)

Table 1

Definitions of Variables of Stock Indexes

Notation	Variables		Definition
R_1	Stock Indexes	Large Firms	Returns of tourism indexes listed on the Taiwan Stock Exchange (TWSE) for large firms
R_2		Small Firms	Returns of tourism indexes listed on Taiwan Gre-Tai Securities Markets (GTSM) for small firms

Table 2

Chow Breakpoint Test

Stock Return	Test	t-Statistic	P-value
Large Firms	F-statistic	8.860***	0.0029
	Likelihood ratio	8.852***	0.0029
	Wald Statistic	8.860***	0.0029
Small Firms	F-statistic	2.723*	0.0990
	Likelihood ratio	2.723*	0.0989
	Wald Statistic	2.723*	0.0989

Note:

(1) Null hypothesis: No breaks at specified breakpoint across the two regimes, namely Sub-Sample A (2001/11/30 – 2008/06/30) and Sub-Sample B (2008/07/01 – 013/02/27).,

(2)*** denotes the null hypothesis is rejected at the 1% level.

(3) *   denotes the null hypothesis is rejected at the 10% level.

Table 3
Descriptive Statistics
(2001/11/30 – 2013/02/27)

Notation	Full Sample (2001/11/30 – 2013/02/27)		Sub-Sample A (2001/11/30 – 2008/06/30)		Sub-Sample B (2008/07/01 – 013/02/27)	
Returns	**Large Firms**	**Small Firms**	**Large Firms**	**Small Firms**	**Large Firms**	**Small Firms**
Mean	0.00041	0.00013	0.00074	0.00060	-1.5E-05	-0.00048
Median	-0.00049	-0.00078	-0.00041	-0.00077	-0.00052	-0.00087
Maximum	0.06730	0.06676	0.06700	0.06669	0.06730	0.06676
Minimum	-0.08020	-0.07146	-0.08020	-0.07139	-0.07171	-0.07146
Std. Dev.	0.02010	0.02063	0.01940	0.02030	0.02090	0.02095
Skewness	0.09679	0.08457	0.17572	0.18147	0.04556	-0.01289
Kurtosis	4.95556	4.33072	4.92567	4.08573	4.91837	4.60998
Jarque-Bera	449.405	209.409	260.237	89.0069	179.504	126.179
P-value	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	1.13149	0.35935	1.20811	0.96768	-0.01789	-0.56049
Sum Sq. Dev.	1.12803	1.18804	0.61295	0.67114	0.50977	0.51224
Observations	2793		1630		1163	

Table 4

Unit Root Tests

(2001/11/30 – 2013/02/27)

Sample Size	Stock Indexes		ADF (GLS)	PP (Phillips-Perron)
Full Sample	Large Firms	Daily Closing Prices	-0.469075	-1.559358
		Log Daily Closing Prices	-0.080134	-1.405231
		Daily Returns	**-5.475867**	**-47.31039**
	Small Firms	Daily Closing Prices	-1.159756	-2.470365
		Log Daily Closing Prices	-0.845077	-2.397466
		Daily Returns	**-2.954372**	**-47.19056**
Sub-sample A	Large Firms	Daily Closing Prices	0.725423	-0.247743
		Log Daily Closing Prices	0.858037	-0.318582
		Daily Returns	**-4.002927**	**-38.02121**
	Small Firms	Daily Closing Prices	-0.159895	-1.450627
		Log Daily Closing Prices	0.073113	-1.419732
		Daily Returns	**-1.935731**	**-32.91321**
Sub-sample B	Large Firms	Daily Closing Prices	-2.187020	-2.088783
		Log Daily Closing Prices	-2.200165	-2.120806
		Daily Returns	-4.886771	**-28.83408**
	Small Firms	Daily Closing Prices	-0.887882	-2.081643
		Log Daily Closing Prices	-0.787128	-1.857554
		Daily Returns	**-28.52462**	**-29.36070**

Note: Entries in bold are significant at the 5% level.

Table 5.1

**Volatility Size Effects for Firm Performance between Large and Small Firms
– Full Sample
(2001/11/30-2013/02/27)**

Model	GARCH		GJR (TGARCH)		EGARCH		GARCH-M	
$R_{1,t}$ / $R_{2,t}$	Large	Small	Large	Small	Large	Small	Large	Small
Coefficient	**Mean Equation**		**Mean Equation**		**Mean Equation**		**Mean Equation**	
φ_0	0.00047	4.96E-05	0.00043	0.00021	0.00040	0.00017	-0.00010	-0.00482
φ_1	**0.06993**	**0.08887**	**0.06963**	**0.09265**	**0.06061**	**0.08837**	-	-
δ	-	-	-	-	-	-	-6.72E-05	-0.00059
Coefficient	**Variance Equation**		**Variance Equation**		**Variance Equation**		**Variance Equation**	
ω	**7.94E-06**	**6.50E-06**	**8.10E-06**	**4.79E-06**	**-0.43956**	**-0.30138**	**8.53E-06**	**7.89E-06**
α	**0.09094**	**0.07424**	**0.08824**	**0.07768**	**0.22355**	**0.15853**	**0.09540**	**0.08180**
γ	-	-	0.00846	-0.02870	-0.00742	0.02439	-	-
β	**0.88934**	**0.91019**	**0.88764**	**0.92179**	**0.96617**	**0.97724**	**0.88377**	**0.89948**

Diagnostics

Second moment 0.98029 0.98443 0.97588 0.99947

Log-moment -0.117234 -0.02258 -0.11915 -0.00471

Note: Entries in bold are significant at the 5% level. $R_{1,t-1}$ / $R_{2,t-1}$

.

Table 5.2

Volatility Size Effects for Firm Performance between Large and Small Firms

- Subsample A

(2001/11/30-2008/06/30)

Model	GARCH		GJR (TGARCH)		EGARCH		GARCH-M	
$R_{1,t}$ / $R_{2,t}$	Large	Small	Large	Small	Large	Small	Large	Small
Coefficient	Mean Equation		Mean Equation		Mean Equation		Mean Equation	
φ_0	0.00045	0.00027	0.00065	0.00062	0.00059	0.00048	-0.00678	-0.00950
φ_1	0.03460	**0.06009**	0.03763	**0.06886**	0.02741	**0.05984**	-	-
δ	-	-	-	-	-	-	-0.00087	-0.00120
Coefficient	Variance Equation		Variance Equation		Variance Equation		Variance Equation	
ω	**2.26E-05**	**1.66E-05**	**2.30E-05**	**1.08E-05**	**-0.79267**	**-0.56316**	**2.18E-05**	**1.69E-05**
α	**0.145313**	**0.11689**	**0.177328**	**0.120495**	**0.288660**	**0.214729**	**0.14561**	**0.120952**
γ	-	-	**-0.07274**	**-0.07313**	**0.051316**	**0.060183**	-	-
β	**0.800533**	**0.846523**	**0.801160**	**0.870013**	**0.928041**	**0.949589**	**0.802711**	**0.842432**

Diagnostics

Second moment	0.74384	0.9634	0.97849	0.9905
Log-moment	-0.08407	-0.05287	-0.05907	-0.00437

Note: Entries in bold are significant at the 5% level.

Table 5.3

Volatility Size Effects for Firm Performance between Large and Small Firms
- Subsample B
(2008/07/01-2013/02/27)

Model	GARCH		GJR (TGARCH)		EGARCH		GARCH-M	
$R_{1,t}$ / $R_{2,t}$	Large	Small	Large	Small	Large	Small	Large	Small
Coefficient	Mean Equation		Mean Equation		Mean Equation		Mean Equation	
φ_0	0.00010	-0.00049	-0.00011	-0.00049	-0.00018	-0.00035	0.00382	0.00158
φ_1	**0.12626**	**0.12741**	**0.12544**	**0.12733**	**0.11591**	**0.12247**	-	-
δ	-	-	-	-	-	-	-0.00042	0.00024
Coefficient	Variance Equation		Variance Equation		Variance Equation		Variance Equation	
ω	-1.1E-07	**1.1E-06**	**4.4E-07**	**1.1E-06**	**-0.18098**	**-0.16831**	-1.9E-07	**1.3E-06**
α	**0.02706**	**0.02888**	**0.01796**	**0.02877**	**0.12379**	**0.10415**	**0.02979**	**0.03308**
γ	-	-	**0.04650**	0.00077	**-0.06608**	-0.00988	-	-
β	**0.97114**	**0.96544**	**0.95688**	**0.96512**	**0.98972**	**0.98914**	**0.96915**	**0.96112**

Diagnostics

Second moment	0.99707	0.99398	0.97588	0.99374
Log-moment	-0.00415	-0.00747	-0.03456	-0.00766

Note: Entries in bold are significant at the 5% level.