Modelling a Latent Daily Tourism Financial Conditions Index

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Abstract

The paper uses daily data on financial stock index returns, tourism stock sub-index returns, exchange rate returns and interest rate differences from 1 June 2001 – 28 February 2014 for Taiwan to construct a novel latent daily tourism financial indicator, namely the Tourism Financial Conditions Index (TFCI). The TFCI is an adaptation and extension of the widely-used Monetary Conditions Index (MCI) and Financial Conditions Index (FCI) to tourism stock data. However, the method of calculation of the daily TFCI is different from existing methods of constructing the MCI and FCI in that the weights are estimated empirically. Alternative versions of the TFCI are constructed, depending on the appropriate model and method of estimation, namely Ordinary Least Squares (OLS) or Quasi-Maximum Likelihood Estimation (QMLE) of alternative conditional volatility models. Three univariate conditional volatility models are considered, namely GARCH, GJR and EGARCH, in an attempt to capture the inherent volatility in the daily tourism stock index returns. The empirical findings show that TFCI is estimated quite accurately using the estimated conditional mean of the tourism stock index returns, especially when conditional volatility is incorporated in the overall specification. The new daily TFCI is straightforward to use and interpret, and provides interesting insights in predicting the current economic and financial environment for tourism stock index returns, especially as it is based on straightforward calculations and interpretations of publicly available information.

1. Introduction

As discussed recently in Chang et al. (2014), the global travel, tourism and hospitality industry is one of the world's leading economic and financial industries, and has experienced continued growth over an extended period. According to the World Tourism Organization (UNWTO), international tourist arrivals worldwide have more than doubled since 1990, rising from 435 million to 1.087 billion in 2013, and the numbers are forecast to reach a total of 1.809 billion tourist arrivals by 2030.

The recent annual findings from the World Travel and Tourism Council (WTTC) and Oxford Economics show that Travel and Tourism's total contribution to global GDP comprised roughly 10% in terms of value and employment. In order to provide accurate forecasts of the contribution of the international tourism sector to sustained economic growth, a specific tourism-related index that is sensitive to economic and financial factors is essential. Such an index would provide useful insights and yield helpful information to public and private decision makers, such as government, business executives and investors, regarding the tourism sector, especially if it were based on straightforward calculations and interpretations of publicly available data.

Increasing attention has been paid to building various tourism indexes in both the public and private sectors. For example, (i) the tourism industry stock index represents the performance of stocks of tourism-related firms listed on the stock market; (ii) the tourism index of the World Economic Forum assesses the obstacles and drivers of Travel and Tourism development; (iii) the Travel and Tourism Competiveness Index (TTCI) is widely used (Blanke and Chiesa, 2013); and (iv) the statistical information of tourism listed on Tourism Bureau Executive Information System, which is available

on the government's website, are just a few of the numerous available and widely-accessed tourism-related indexes.

As argued in Chang et al. (2014), tourism can be sensitive to the impacts from the international economic environment, such as prices, exchange rates, interest rates, and domestic economic and financial conditions. The impacts from both exchange rates and interest rates affect the tourism and economic environments, as well as the domestic and international business investment. Therefore, a general tourism indicator that takes account of the inherent daily volatility in the economic, financial and tourism markets, would be very useful for purposes of decision making in the public and private sectors.

The primary purpose of the paper is to develop a daily Tourism Financial Conditions Index (TFCI) which is closely linked to the financial, economic and tourism environments. Consequently, four key components comprising the TFCI are the returns on both the tourism industry stock index and the stock exchange stock index, nominal exchange rate, and interest rates.

The foundation of the proposed TFCI is an application of the widely-used Financial Conditions Index (FCI), which is itself derived from the well-known Monetary Conditions Index (MCI). The MCI is an index number calculated from a weighted linear combination of two variables, namely the short-run interest rate and an effective exchange rate, that are deemed relevant for monetary policy. Based on the MCI, the FCI takes account of an extra factor, namely real asset prices, such as house prices and stock prices, to assess the conditions of financial markets (for further details, see Beaton, Lalonde and Luu, 2009; Brave and Butters, 2011; Ericsson, Jansen, Kerbeshian and Nymoen, 1997; Freedman, 1994, 1996a, b; Hatzius, Hooper, Mishkin, Schoenholtz and

Watson, 2010; Lin, 1999; and Matheson, 2012). As will be discussed below, the weights are based on a number of factors, but are not directly model based..

The primary purpose of the paper is to construct a novel model-based daily TFCI. The method of calculating the weights is different from existing methods of constructing the MCI and FCI in that the weights are estimated empirically based on a model of the latent TFCI variable. Alternative versions of the TFCI are constructed, depending on the appropriate model and method of estimation, namely Ordinary Least Squares (OLS) or Quasi-Maximum Likelihood Estimation (QMLE) of alternative conditional volatility models. Three well-known and widely-used univariate conditional volatility models are considered, namely GARCH, GJR and EGARCH, in an attempt to capture the inherent volatility in the daily tourism stock index returns. The empirical findings show that TFCI is estimated quite accurately using the estimated conditional mean of the tourism stock index returns, especially when conditional volatility is incorporated in the overall specification.

The approach developed in the paper can be extended to a number of areas, especially in financial econometrics and empirical finance, using a range of financial econometric and statistical tools developed recently in, for example, Chang, Allen and McAleer (2013), Chang et al. (2013), Hammoudeh and McAleer (2013), and McAleer et al. (2013a, 2013b).

The remainder of the paper is structured as follows. Section 2 discusses the definitions of MCI and FCI. Section 3 extends the existing concepts of MCI and FCI to a model-based specification of a daily TFCI. Three well-known univariate conditional volatility models, as well as their statistical properties, are discussed in Section 4 as alternative

specifications of the daily TFCI error process. The data used in the analysis, and descriptive and summary statistics, are presented in Section 5. A detailed analysis of the empirical findings is presented in Section 6. Section 7 concludes the paper by summarizing the key empirical results and findings.

2. Definitions and Construction of MCI and FCI

In this section we describe the foundations of the daily Tourism Financial Conditions Index (TFCI), which is an adaptation and extension of the widely-used Financial Conditions Index (FCI). The FCI, in turn, is derived from the well-known Monetary Conditions Index (MCI).

2.1 MCI

Freedman (1994, 1996a, 1996b) discussed the units of measurement of the MCI in terms of real interest rate changes. The MCI is defined deterministically as:

$$MCI_t = \theta_1(e_t - e_0) + \theta_2(r_t - r_0). \tag{1}$$

The subscripts t and 0 denote the current and base periods, respectively, and θ_1 and θ_2 are the weights attached to real effective exchange rates (e) (in logarithms) and real interest rates (r), respectively. The presentation of MCI in equation (1) is linear, though this is not essential. The weights on the components of the MCI (that is, θ_1 and θ_2) are the results of empirical studies that estimate the effect on real aggregate demand over six to eight quarters of changes in real exchange rates and real interest rates.

Typically, in analyzing the alternative constructed values of MCI, there is no allowance made for the fact that the weights in equation (1) are estimated from other studies, and hence contain sampling variation.

Based on equation (1), the MCI may be interpreted as the percentage point change in monetary conditions arising from the combined change in real exchange rates and real interest rates from the base period. As the MCI is measured relative to a given base period, subtracting the MCI at two points in time gives a measure of the degree of tightening or easing between these two points. Lack (2003) discusses the experience of various countries that have used the MCI as an operating target, such as Canada and New Zealand.

2.2 FCI

Owing to the recent high volatility in stock and property prices, the influence of asset prices on monetary policy has drawn greater attention of policy makers. Significant efforts have been made recently to extend additional asset variables, such as stocks and housing prices into the MCI as a new indicator, namely the Financial Conditions Index (FCI) (see Goodhart and Hofmann (2001) for the G7 countries, Mayes and Virén (2001) for 11 European countries, and Lack (2003) for Canada and New Zealand).

The FCI is defined deterministically as:

$$FCI_t = \theta_1(e_t - e_0) + \theta_2(r_t - r_0) + \theta_3(a_t - a_0). \tag{2}$$

The subscripts t and 0 denote the current and base periods, respectively, and θ_1, θ_2, and θ_3 are the weights attached to real effective exchange rates (e) (in logarithms), real interest rates (r), and real assets (a) (in logarithms), respectively. Furthermore, the relative weights on the components of the FCI, namely θ_1, θ_2, and θ_3, are the outcomes of empirical estimation. The presentation of FCI in equation (2) is linear, though this is not essential. As in the case of MCI, when analyzing the alternative constructed values of FCI, there is no allowance made for the fact that the weights in equation (2) are estimated from other studies, and hence contain sampling variation.

Just as in the case of MCI, the FCI reveals the offsetting influences among real effective exchange rates, real interest rates, and real asset prices. If the interest rate or exchange rate increases, in an opposite direction to foreign capital flows and investment, there is likely to be a negative impact on the prices of domestic real assets.

3.   A Model-based Daily TFCI

The Tourism Conditions Index (TCI) of Chang et al. (2014) is similar in spirit to the MCI and FCI in that the weights are first obtained from a separate empirical model, and are then used to construct a data series using the definition of TCI (see below). This is in marked contrast to the approach taken in this paper, whereby model-based estimates of TCI are calculated directly from empirical data. Such a contrast is explained in greater detail in this section.

As mentioned above, the new daily Tourism Financial Conditions Index (TFCI) proposed in this paper focuses on economic activities related to the tourism industry. The three components of the proposed daily TFCI, each of which can be constructed

from data that are downloaded from Datastream, are as follows:

(1) returns on nominal exchange rates, quoted as the foreign currency per unit of
    US $ to New Taiwan Dollars (ERR) (which is an alternative to the real effective
    exchange rate, which is not available at a daily data frequency);

(2) differences in interest rates, namely the daily Taiwan Interbank 1-week Swap
    Rate (DIR);

(3) returns on the Taiwan Stock Exchange Capitalization Weighted Stock Index
    (RTAIEX).

Unlike the construction of the MCI, FCI and TCI, where the weights are based on a
wide range of considerations rather than using direct model-based estimates, the TFCI
is based on estimation of a regression model. The model-based weights for the returns
on nominal exchange rates, the differences in the interest rate, and the returns on the
Taiwan stock index, will be estimated by OLS or QMLE, depending on the model
specifications that are considered.

As the models to be estimated below are linear in the variables, with the appropriate
weights to be estimated empirically, the percentage change in a variable is used to
denote simple returns rather than logarithmic differences (or log returns). The latter
would be more appropriate for calculating continuously compounded returns.

Accordingly, TFCI is defined as:

$$TFCI_t = c + \theta_1 ERR_t + \theta_2 DIR_t + \theta_3 RTAIEX_t + u_t \,, \; u_t \sim D(0, \sigma_u^2) \qquad (3)$$

where c denotes the constant term, and u denotes the shocks to TFCI, which need not be independently or identically distributed, especially for daily data. The parameters θ_1, θ_2 and θ_3 are the weights attached to exchange rates, interest rates and the stock index, respectively. Unlike the standard approach to estimating MCI and FCI, in this paper the weights will be estimated empirically and explicit allowance can be made for the sampling variation in the parameter estimates.

As TFCI is latent, it is necessary to relate TFCI to observable data. The latent variable is defined as being the conditional mean of an observable variable, namely the returns on a Tourism Stock Index, RTS, which reflects the tourism industry stock index that is listed on the Taiwan Stock Exchange (specifically, the Taiwan Stock Exchange Over the Counter Tourism Subindex), as follows:

$$RTS_t = TFCI_t + v_t \quad , \quad v_t \sim D(0, \sigma_v^2) \tag{4}$$

where RTS is observed, TFCI is latent, and the measurement error in RTS is denoted by v, which need not be independently or identically distributed, especially for daily data.

Given the zero mean assumption for v, the means of RTS and TFCI will identical, as will their estimates. Using equations (3) and (4), the empirical model for estimating the weights for TFCI is given as:

$$RTS_t = c + \theta_1 ERR_t + \theta_2 DIR_t + \theta_3 RTAIEX_t + u_t + v_t \, , \tag{5}$$

$$\varepsilon_t = u_t + v_t \sim D(0, \sigma_\varepsilon^2)$$

where $\varepsilon_t = u_t + v_t$ need not be independently or identically distributed, especially for daily data.

The parameters in equation (5) can be estimated by OLS or maximum likelihood, depending on the specification of the conditional volatility of ε_t, to yield consistent estimates of RTS. In view of the definition in equation (4), the consistent estimates of RTS will also be consistent estimates of the latent daily TFCI. Equation (4) may also be used to show that the asymptotic properties of both the OLS and maximum likelihood estimates of RTS and TFCI are equivalent (see, for example, McAleer (2005)).

This paper proposes four consistent estimates of TFCI that vary according to the method of estimation of the coefficients in equation (3):

(1) Ordinary Least Squares (OLS);

(2) Quasi-Maximum Likelihood Estimation (QMLE) of three univariate conditional volatility models, namely GARCH, GJR and EGARCH.

Given the evident volatility in the daily RTS data, it will be interesting to see if the corresponding volatility in the nominal exchange rate returns, the differences in interest rates, and the stock index returns, will be able to capture such volatility in estimating RTS, and hence also the volatility in TFCI.

4. Description of Univariate Conditional Volatility Models

As daily data will be used to construct a model-based daily TFCI based on daily exchange rates, interest rates, stock exchange returns and tourism sub-index stock returns, it is inevitable that there will be significant volatility in the data series (see Figure 1). There are numerous univariate and multivariate models of conditional, stochastic and realized volatility models that might be used to model volatility. As daily data will be considered to construct a single index for the tourism sub-index of the Taiwan stock exchange, the most straightforward, computationally convenient and well-known approach is to use univariate conditional volatility models.

There are several well-known models of univariate conditional volatility, with and without asymmetry and/or leverage. As shown in Figure 1, the daily stock index returns, exchange rate returns, interest rate differences and Taiwan stock index returns show periods of high volatility, followed by others of relatively low volatility. One implication of this persistent volatility behaviour is the presence of (conditionally) heteroskedastic residuals, which should be modelled empirically.

As discussed in, for example, McAleer (2005) and Chang and McAleer (2009), for a wide range of daily data series, time-varying conditional variances can be explained empirically through the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982). When the time-varying conditional variance has both autoregressive and moving average components, this leads to the generalized ARCH, or GARCH, model of Bollerslev (1986). The possibly asymmetric effects of positive and negative shocks of equal magnitude can be considered in the GJR model of Glosten et al. (1992) and EGARCH model of Nelson (1991). In the latter model, leverage effects, whereby negative shocks increase volatility and positive shocks decrease volatility, can also be

considered.

The conditional volatility literature has been discussed extensively in recent years for a wide range of high frequency data sets, especially daily data. The discussion in the remainder of this section follows the work of Chang and McAleer (2012) closely. Rewriting the composite error in equation (5) as $\varepsilon_t = u_t + v_t$, the GARCH(1,1) model for the shocks to RTS for $t = 1,...,n$, are given as:

$$
\begin{aligned}
\varepsilon_t &= \eta_t \sqrt{h_t}, \quad \eta_t \sim iid(0,1) \\
h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1},
\end{aligned}
\tag{6}
$$

where $\omega > 0, \alpha \geq 0, \beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. In equation (6), the ARCH (or α) effect indicates the short run persistence of shocks, while the GARCH (or β) effect indicates the contribution of shocks to long run persistence (namely, $\alpha + \beta$).

For equations such as (5) and (6), the parameters are typically estimated by the maximum likelihood method to obtain Quasi-Maximum Likelihood Estimators (QMLE) in the absence of normality of η_t, the conditional shocks (or standardized residuals). The conditional log-likelihood function is given as follows:

$$
\sum_{t=1}^{n} l_t = -\frac{1}{2} \sum_{t=1}^{n} \left(\log h_t + \frac{\varepsilon_t^2}{h_t} \right).
$$

The QMLE is efficient only if η_t is normal, in which case the QMLE is the MLE. If

η_t is not normally distributed, adaptive estimation can yield efficient estimators, although this can be computationally intensive. Ling and McAleer (2003b) investigated the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH errors. The extension to multivariate processes is very complicated.

As the GARCH process in equation (6) is a function of the unconditional shocks, it is necessary to examine the moments conditions of ε_t. Ling and McAleer (2003a) showed that the QMLE for GARCH(p,q) is consistent if the second moment of ε_t is finite. Using results from Ling and Li (1997) and Ling and McAleer (2002a, 2002b), the necessary and sufficient condition for the existence of the second moment of ε_t for GARCH(1,1) is $\alpha + \beta < 1$ and, under normality, the necessary and sufficient condition for the existence of the fourth moment is $(\alpha + \beta)^2 + 2\alpha^2 < 1$.

Among others, McAleer et al. (2007) discussed that it was established by Elie and Jeantheau (1995) and Jeantheau (1998) that the log-moment condition was sufficient for consistency of the QMLE of a univariate GARCH process (see Lee and Hansen (1994) for an analysis of the GARCH(1,1) process), while Boussama (2000) showed that the log-moment condition was sufficient for asymptotic normality. Based on these theoretical developments, a sufficient condition for the QMLE of GARCH(1,1) to be consistent and asymptotically normal is given by the log-moment condition, namely

$$E(\log(\alpha\eta_t^2 + \beta)) < 0 . \tag{7}$$

However, this condition is not easy to check in practice, even for the GARCH(1,1) model, as it involves the expectation of a function of a random variable and unknown parameters. Although the sufficient moment conditions for consistency and asymptotic normality of the QMLE for the univariate GARCH(1,1) model are stronger than their log-moment counterparts, with $\alpha + \beta < 1$ ensuring that the log-moment condition is satisfied, the second moment condition is more straightforward to check. In practice, the log-moment condition in equation (7) would be estimated by the sample mean, with

the parameters α and β, and the standardized residual, η_t, being replaced by their QMLE counterparts.

The effects of positive shocks on the conditional variance, h_t, are assumed to be the same as the negative shocks in the symmetric GARCH model. In order to accommodate asymmetric behaviour, Glosten, Jagannathan and Runkle (1992) proposed the GJR model, for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \qquad (8)$$

where $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0, \beta \geq 0$ are sufficient conditions for $h_t > 0,$ and $I(\eta_t)$ is an indicator variable defined by:

$$I(\eta_t) = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \varepsilon_t \geq 0 \end{cases}$$

as η_t has the same sign as ε_t. The indicator variable differentiates between positive and negative shocks of equal magnitude, so that asymmetric effects in the data are captured by the coefficient γ.

It is generally expected that $\gamma \geq 0$ because negative shocks increase risk by increasing the debt to equity ratio. The asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \dfrac{\gamma}{2}$, and to long run

persistence, $\alpha + \beta + \dfrac{\gamma}{2}$. It is not possible for leverage to be present in the GJR model, whereby negative shocks increase volatility and positive shocks of equal magnitude decrease volatility.

The regularity condition for the existence of the second moment for GJR(1,1) under symmetry of η_t was shown by Ling and McAleer (2002a) to be:

$$\alpha + \beta + \frac{1}{2}\gamma < 1, \tag{9}$$

while McAleer et al. (2007) showed that the weaker log-moment condition for GJR(1,1) was given by:

$$E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0. \tag{10}$$

Nelson (1991) developed an alternative model to capture asymmetric behaviour in the conditional variance, namely the Exponential GARCH (or EGARCH(1,1)) model, which is given as:

$$\log h_t = \omega + \alpha \mid \eta_{t-1} \mid + \gamma \eta_{t-1} + \beta \log h_{t-1}, \quad \mid \beta \mid < 1 \tag{11}$$

where the parameters α, β and γ have different interpretations from those in the GARCH(1,1) and GJR(1,1) models. If $\gamma = 0$, there is no asymmetry, while $\gamma < 0$, and $\gamma < \alpha < -\gamma$ are the conditions for leverage to exist, whereby negative shocks increase volatility and positive shocks of equal magnitude decrease volatility.

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As noted in McAleer et al. (2007), for example, there are some important differences between EGARCH and the previous two models, GARCH and GJR, 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) Shephard (1996) observed that $|\beta| < 1$ is likely to be a sufficient condition for consistency of QMLE for EGARCH(1,1); (iv) as the standardized residuals appear in equation (7), $|\beta| < 1$ 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 EGARCH(1,1).

EGARCH also captures asymmetries differently from GJR. The parameters α and γ in EGARCH(1,1) represent the magnitude (or size) and sign effects of the standardized residuals, respectively, on the conditional variance, whereas α and $\alpha + \gamma$ represent the effects of positive and negative shocks of equal magnitude, respectively, on the conditional variance in GJR(1,1).

5. Data

In this section we present the data used for the empirical analysis. Daily data on the tourism stock index, exchange rate, interest rate, and the stock exchange index are downloaded from Datastream for the period 1 June 2001 - 28 February 2014. As

discussed in Section 3 above, the observable variables that will be used to estimate the latent daily TFCI are as follows:

(1) returns on the Taiwan Stock Exchange Over the Counter Tourism Subindex, which reflects the tourism industry stock index (RTS);

(2) returns on nominal exchange rates (ERR);

(3) differences in interest rates (DIR);

(4) returns on the Taiwan Stock Exchange Index (RTAIEX).

The sources of the daily data are the Taiwan Stock Exchange (TWSE), Taiwan First Bank and Taipei Foreign Exchange Market Development Foundation for the tourism industry stock index, one-year deposit rate, and the nominal effective exchange rate, respectively. The daily returns on nominal exchange rates, quoted as the foreign currency per unit of US $ to New Taiwan Dollars Rate, is used instead of real effective exchange rates, as in Chang et al. (2014), as real effective exchange rates are observed only at the monthly data frequency.

These data will be used to estimate equation (5) by OLS, without taking account of the inherent conditional volatility in the data, and the three pairs of equations, namely (5)-(6), (5)-(8) and (5)-(11), by QMLE, to obtain four alternative consistent estimates of TFCI. The alternative estimates of daily RTS in equation (5), which are equivalent to alternative estimates of daily TFCI, are defined as TFCI(OLS), TFCI(GARCH), TFCI(GJR) and TFCI(EGARCH) according to the method of estimation and the specification of the conditional volatility.

[Table 1 goes here]

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[Figure 1 goes here]

The plots in Figure 1 are instructive. The returns on the tourism stock index and Taiwan stock exchange index, RTS and TRAIX, respectively, exhibit standard stock market returns, with considerable volatility clustering, namely sustained periods of high volatility interspersed with periods of low volatility (and vice-versa). The exchange rate returns, ERR, exhibit relatively low volatility, except for a few periods of relatively high volatility. The differences in interest rates, DIR, have considerable volatility at the beginning of the sample period, after which they display similar characteristics to the plot of the exchange rate returns.

The descriptive statistics of the variables that are used to estimate alternative versions of equation (5) are given in Table 2. There are 3,324 observations in total. The means of the four variables are close to zero, while the medians are all exactly zero. All four distributions are found to be significantly different from the normal distribution, as shown by the Jarque-Bera Lagrange multiplier test of normality. This is not surprising for daily tourism stock returns, exchange rate returns, interest rate differences, or stock index returns. The departures from symmetry are relatively small, but the kurtosis suggests a significant departure from what would be expected under normality.

[Table 2 goes here]

The alternative estimates of TFCI, as defined in Table 1, will be compared and contrasted in the next section to determine consistent estimates of TFCI for purposes of sensible public and private policy considerations that focus on economic activities related to the tourism industry.

6. Empirical Results

This section discusses the estimates of the daily TFCI based on the regression model in equation (5) that relates RTS to ERR, DIR, and RTAIX. Estimation of the model in equation (5) by OLS and QMLE are undertaken using the EViews and RATS econometric software packages.

The descriptive statistics of the estimated daily TFCI from equation (5) are given in Table 3, where the alternative estimates are given as TFCI(OLS), TFCI(GARCH), TFCI(GJR) and TFCI(EGARCH) according to the method of estimation and the specification of the conditional volatility. The four sets of daily time series estimates of TFCI are given in Figure 2.

The means and medians of the four sets of estimates are very close to zero, with OLS providing the largest differences from zero. The range, or difference between the largest and smallest daily TFCI estimates, are also largest for the OLS estimates. All four distributions are found to be significantly different from the normal distribution, as shown by the Jarque-Bera Lagrange multiplier test of normality. The departures from symmetry are relatively small, but the kurtosis suggests a significant departure from what would be expected under normality.

[Table 3 goes here]

[Figure 2 goes here]

The four sets of estimates are given in Table 4. In all four cases, the exchange rate

returns have a negative impact on the estimated daily TFCI, while the interest rate differences and the returns on the stock exchange index have positive effects. The robust Newey-West HAC standard errors are reported for the OLS estimates, and asymptotic standard errors are given for QMLE. Apart from the insignificant effect of exchange rate returns estimated by OLS, all other parameters estimates are statistically significant. The Jarque-Bera Lagrange multiplier statistics for normality indicate that the residuals from none of the four series is normally distributed.

The OLS estimates generally have similar estimates for the coefficients of ERR and DIR, but the coefficient of RTAIEX is considerably higher at 0.654 than for the GARCH, GJR and EGARCH counterparts.

[Table 4 goes here]

Considering the GARCH estimates, the ARCH, or short-run persistence, effect of shocks on volatility is 0.059, while the contribution of the GARCH effect to long-run persistence of shocks is 0.935. The log-moment condition is necessarily satisfied as the second moment condition is satisfied. The sum of the two effects is 0.994, which suggests that the unconditional variance is finite, so that standard asymptotic inference is valid.

The GJR estimates are similar to their GARCH counterparts. The ARCH effect of shocks on volatility is 0.066, while the contribution of the GARCH effect to long-run persistence of shocks is 0.94. The asymmetry effect is -0.027 and significant. The log-moment condition is necessarily satisfied as the second moment condition is satisfied. The sum of the ARCH and GARCH effects, plus one-half of the asymmetry effect, is

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0.992, which also suggests that the unconditional variance is finite, so that standard asymptotic inference is valid.

Finally, the EGARCH estimates suggest that there is asymmetry through the significance of the asymmetric effect, although there is no leverage. The size, or EARCH effect, is not statistically significant. The lagged logarithmic volatility effect has a coefficient that is close to unity at 0.99.

Prior to examining the alternative daily TFCI estimates, which are shown graphically in Figures 4 and 5, it is useful to compare the daily RTS and RTAIEX plots in Figure 3. It is clear that the variation in RTS is greater than in RTAIEX. This empirical observation that RTAIEX compresses the variation in RTS, is consistent with the estimated effect of RTAIEX on RTS, which is significant and lies in the range (0.56, 0.65) (see Table 4).

[Figure 3 goes here]

The impact of RTAIEX on RTS in estimating daily TFCI is reflected in Figures 4 and 5, in which the four sets of TFCI estimates are compared and contrasted with RTAIEX and RTS, respectively. The estimated daily TFCI and RTAIEX have very similar patterns as well as magnitudes in Figure 4. This shows the importance of the returns on the stock exchange index is vital in determining the daily TFCI, regardless of the method of estimation or conditional volatility specification that might be used.

On the other hand, the differences in the magnitudes of RTS and the TFCI estimates, which are also alternative estimates of RTS from equation (5), indicate the importance

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of the model-based estimates of TFCI. The use of RTS as an indicator of the general activity of the tourism sector in the stock exchange would provide an exaggerated explanation of tourism financial conditions, which has far less volatility, as captured in the alternative estimates of TFCI in Figure 5.

[Figures 4-5 go here]

7. Conclusion

The paper used daily data on financial stock index returns, tourism stock sub-index returns, exchange rate returns and interest rate differences from 1 June 2001 - 28 February 2014 for Taiwan to construct a novel latent daily tourism financial indicator, namely the Tourism Financial Conditions Index (TFCI). The TFCI is an adaptation and extension of the widely-used Monetary Conditions Index (MCI) and Financial Conditions Index (FCI) to the tourism industry stock data that is listed on the Taiwan Stock Exchange (specifically, the Taiwan Stock Exchange Over the Counter Tourism Subindex). However, the method of calculation of the daily TFCI is different from existing methods of constructing the MCI and FCI in that the weights are model based and are estimated empirically.

Alternative versions of the TFCI were constructed, depending on the model and method of estimation, namely Ordinary Least Squares (OLS) or Quasi-Maximum Likelihood Estimation (QMLE) of alternative conditional volatility models. Three univariate conditional volatility models were considered, namely GARCH, GJR and EGARCH, in an attempt to capture the inherent volatility in the daily tourism stock index returns. The empirical findings showed that TFCI can be estimated quite accurately using the

estimated conditional mean of the tourism stock index returns, especially when conditional volatility is incorporated in the overall specification.

The new daily TFCI is straightforward to use and interpret, and provides interesting insights in predicting the current economic and financial environment for tourism stock index returns. Overall, the empirical findings should be helpful for public and private decision makers, such as government, business executives and investors, as the TFCI provides useful insights that can be based on straightforward calculations and interpretations of publicly available information.

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Figure 1

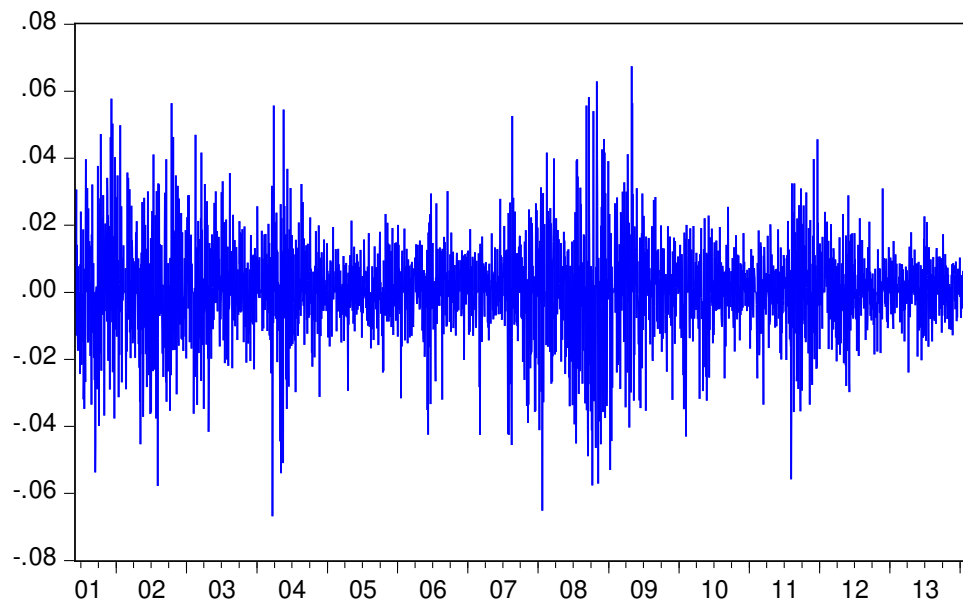**Daily Time Series Plots for 01/06/2001 – 28/02/2014**

(a) Returns on Tourism Stock Index (RTS)
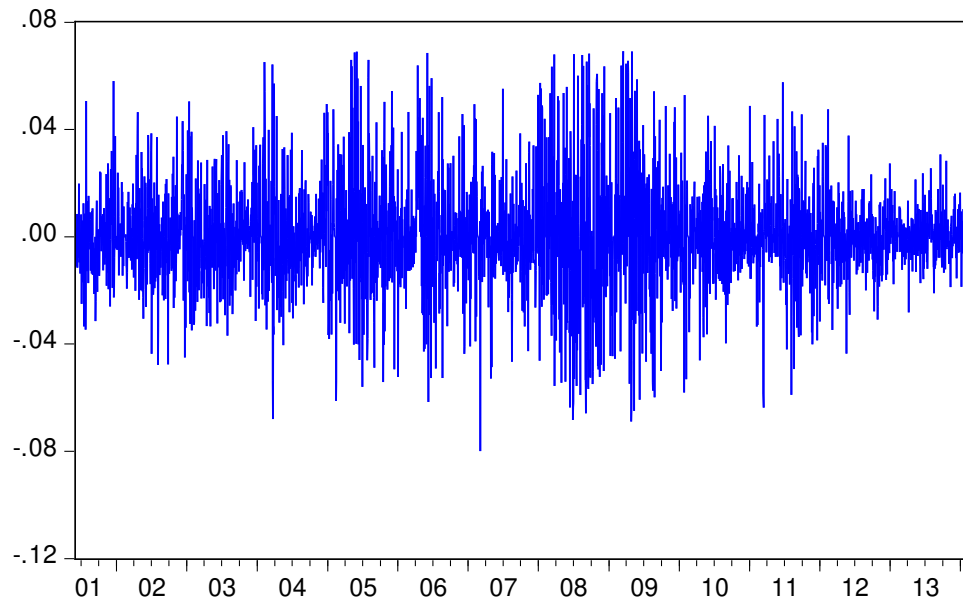
(b) Exchange Rate Returns (ERR)
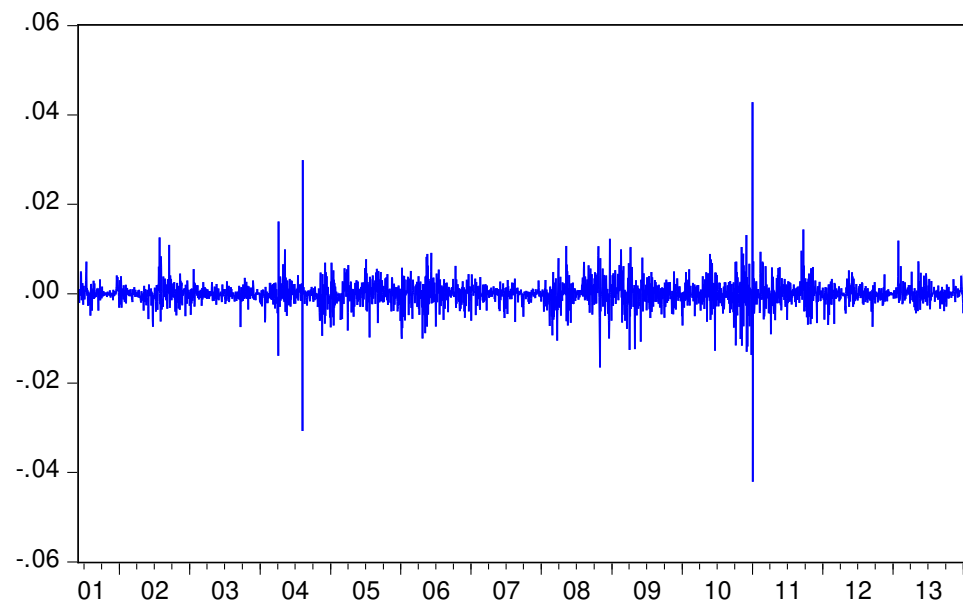
(c) Returns on Taiwan Stock Exchange Index (RTAIEX)
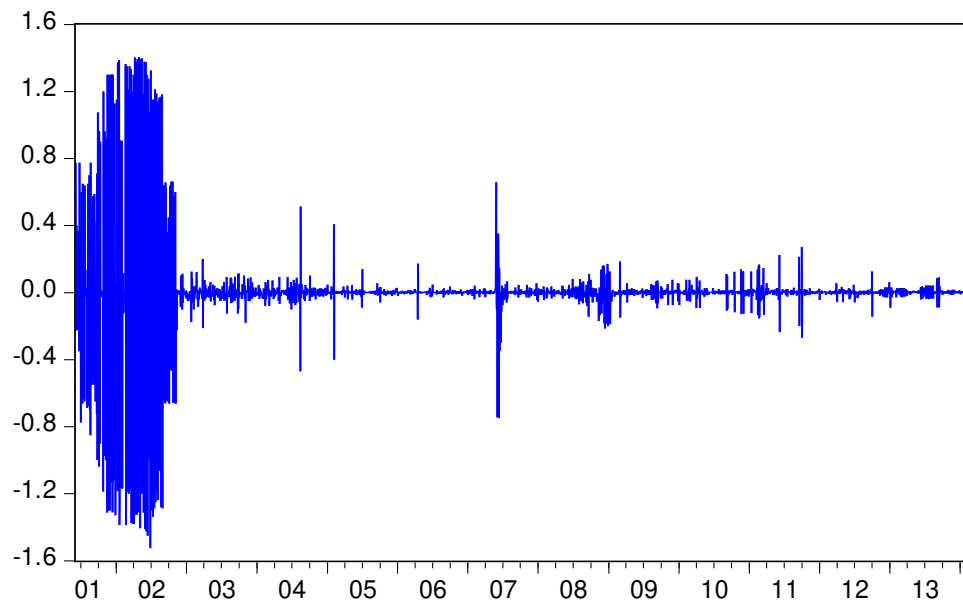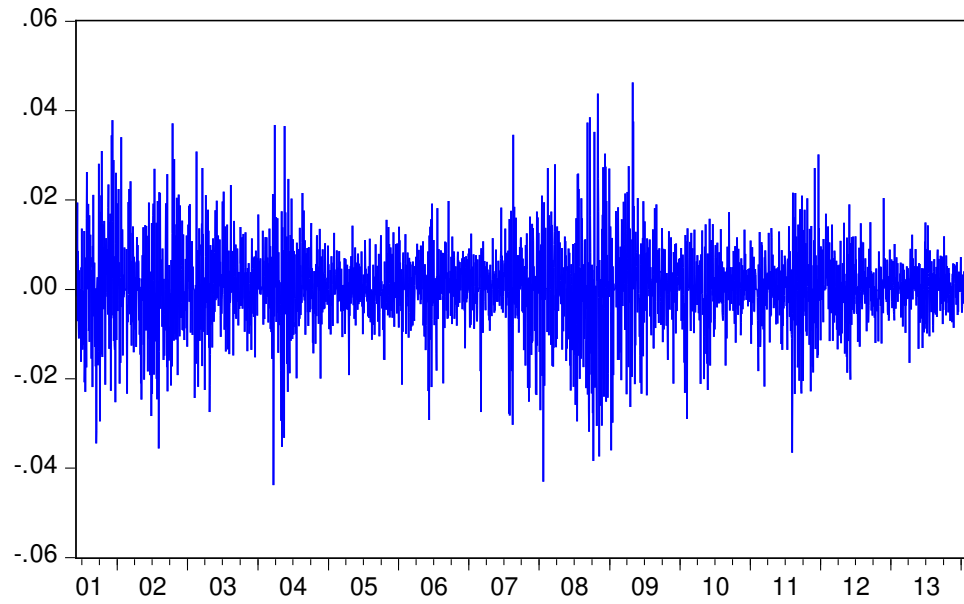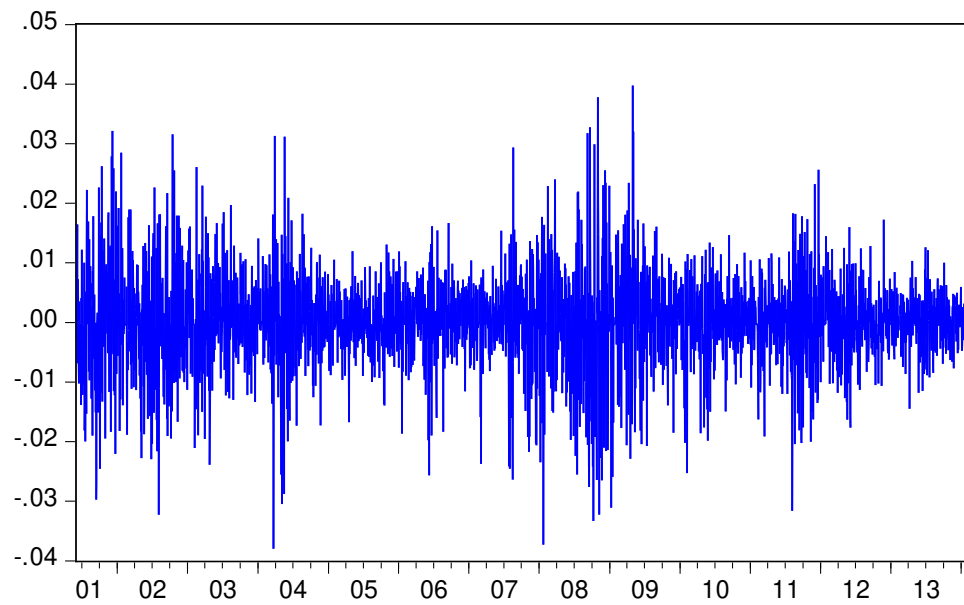

(d) Differences in Interest Rates (DIR)

Figure 2
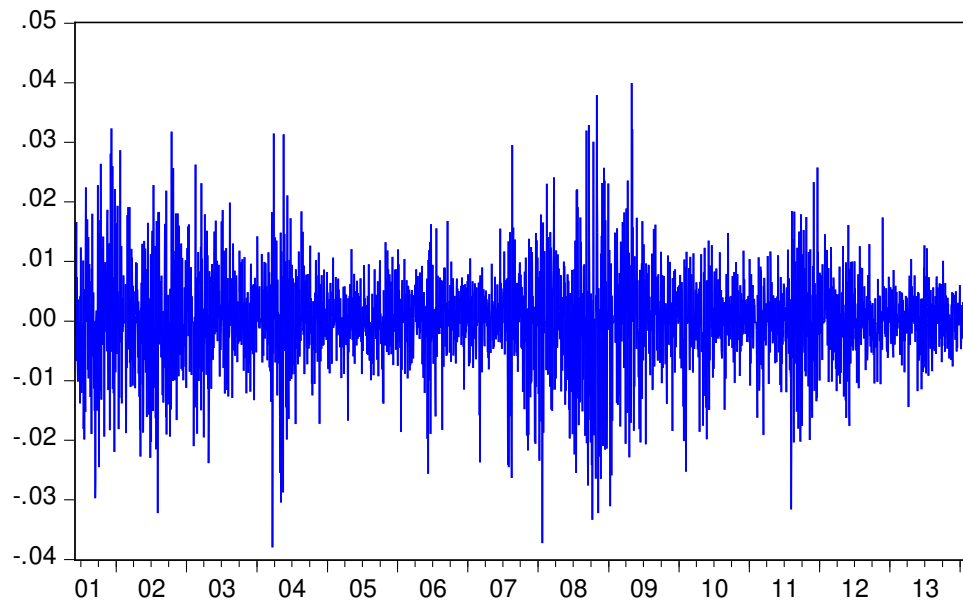**Daily Time Series Estimates of TFCI for 01/06/2001 – 28/02/2014**

(a) OLS

(b) GARCH(1,1)
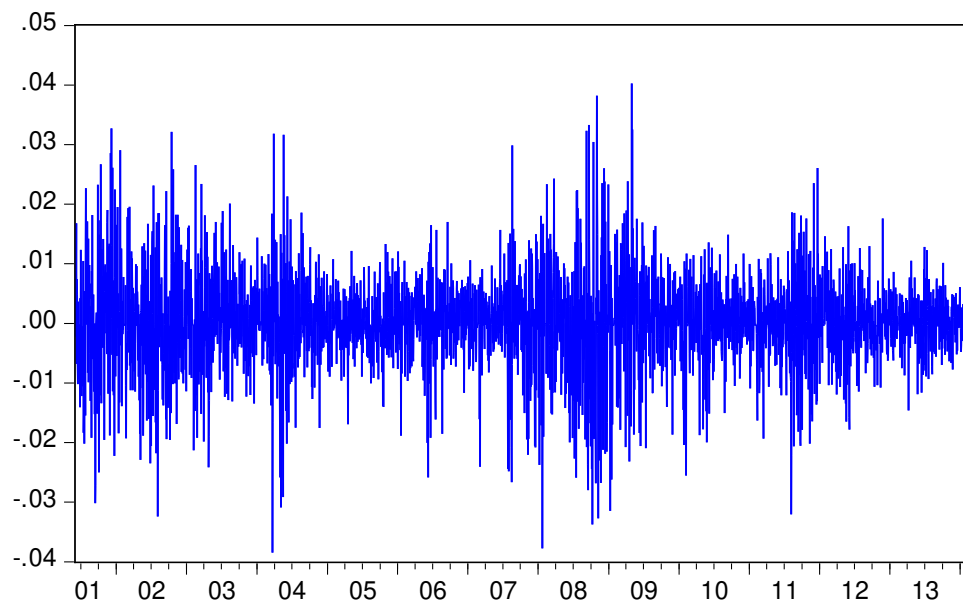
(c) GJR(1,1)

(d) EGARCH(1,1)

Figure 3
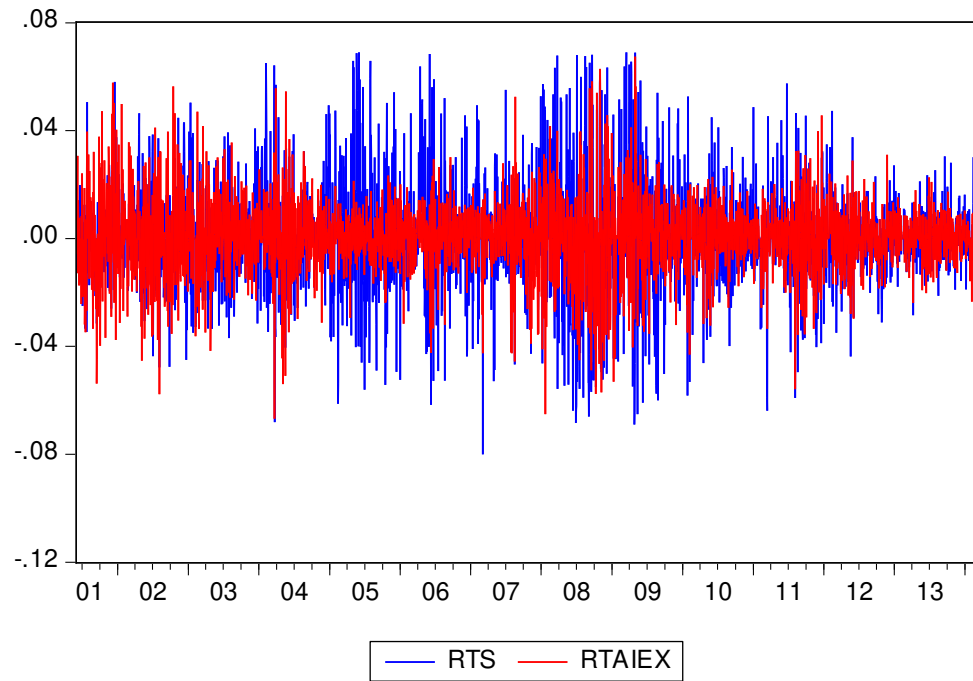**Daily Time Series of RTS and RTAIEX for 01/06/2001 – 28/02/2014**

Figure 4

Daily Time Series of RTAIEX and TFCI Estimates for 01/06/2001 – 28/02/2014
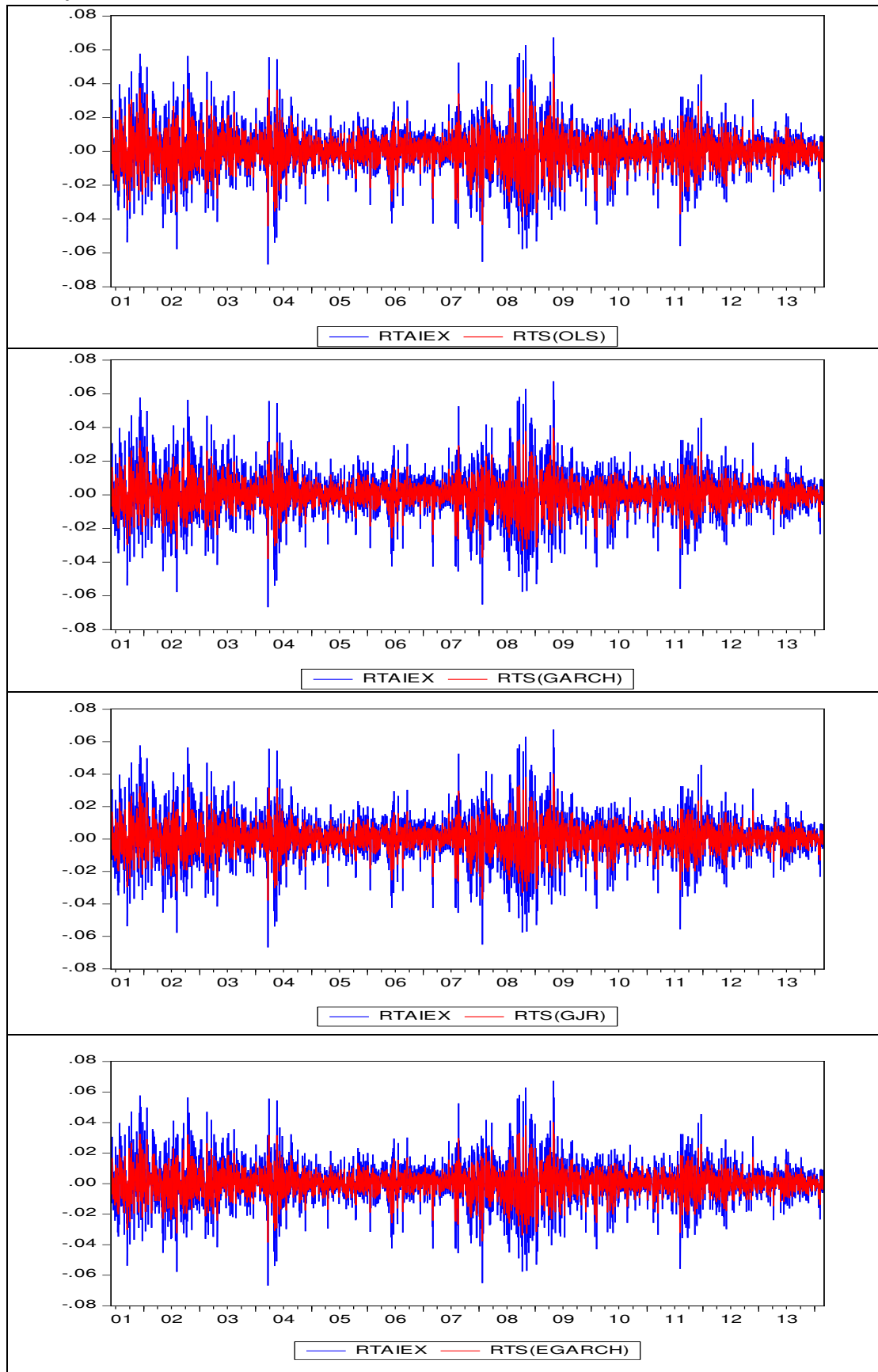
Figure 5
Daily Time Series of RTS and TFCI Estimates for 01/06/2001 – 28/02/2014
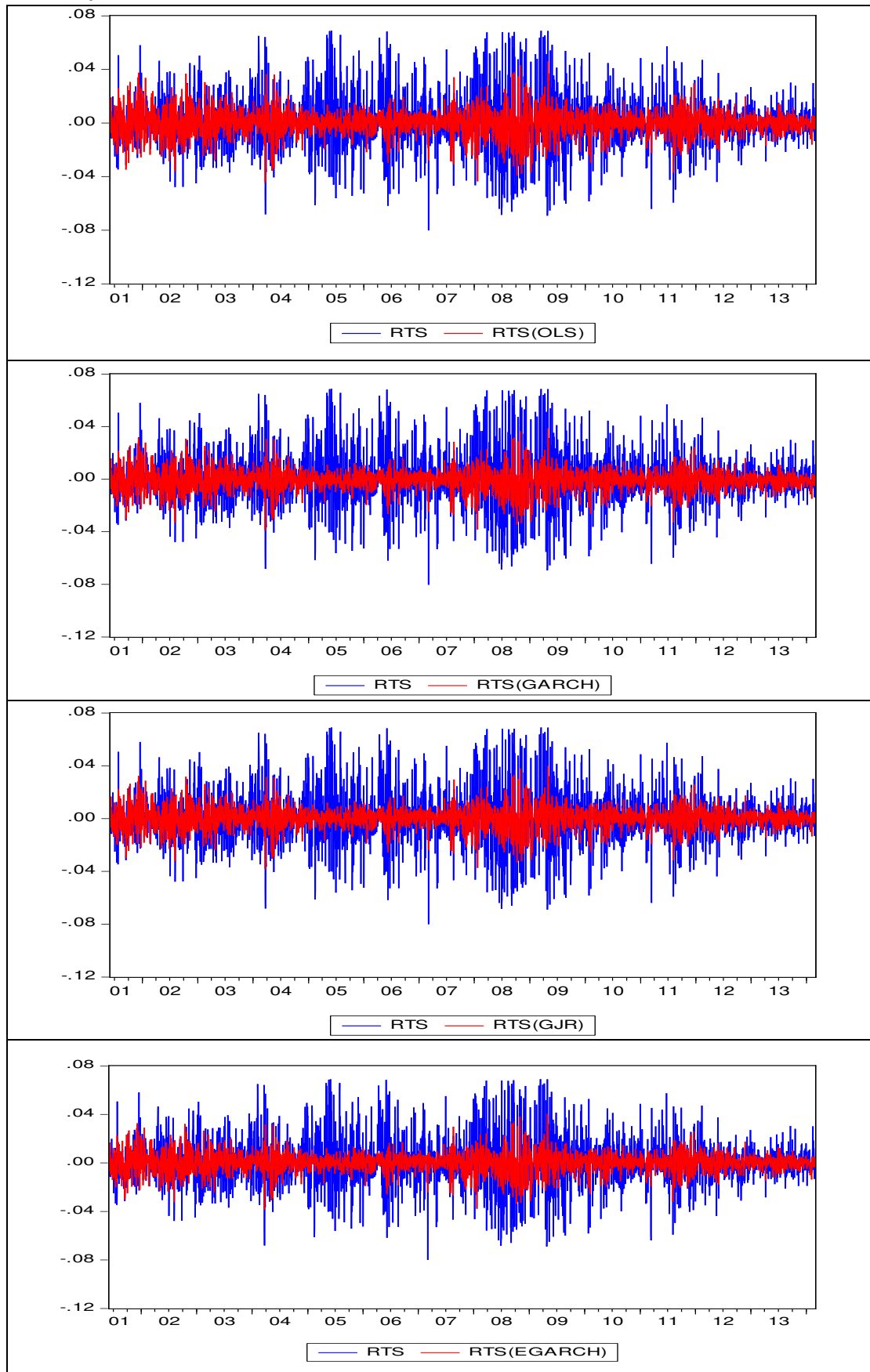
Table 1

Description of Variables

Variables	Description
RTS	Returns on Taiwan Stock Exchange Over the Counter Tourism Subindex
ERR	Daily Exchange Rate Returns, quoted as the foreign currency per unit of US $ to New Taiwan $
DIR	Difference in Daily Taiwan Interbank 1-week Swap Rate
RTAIEX	Returns on Daily Taiwan Stock Exchange Capitalization Weighted Stock Index
TFCI	Latent Daily Tourism Financial Conditions Index
Estimated TFCI	TFCI(OLS), TFCI(GARCH), TFCI(GJR), TFCI(EGARCH)

Table 2

Descriptive Statistics for Daily RTS, ERR, DIR and RTAIEX

for 01/06/2001 – 28/02/2014

Variables	RTS	ERR	DIR	RTAIEX
Mean	0.0002	0	-0.0013	0.0003
Median	0	0	0	0
Maximum	0.069	0.0429	1.405	0.0674
Minimum	-0.08	-0.0421	-1.525	-0.0668
Std. Dev.	0.0193	0.0028	0.2376	0.0135
Skewness	0.21	-0.05	-0.12	-0.13
Kurtosis	4.92	44.87	24.68	5.8
Jarque-Bera	535	242757	65121	1096
Prob-value	0	0	0	0
Sum	0.6839	-0.1052	-4.21	0.8554
Sum Sq. Dev.	1.2323	0.0263	187.561	0.61
Observations	3324	3324	3324	3324

Table 3

Descriptive Statistics for Estimated Daily TFCI by OLS and QMLE

for 01/06/2001 – 28/02/2014

Variables	TFCI (OLS)	TFCI (GARCH)	TFCI (GJR)	TFCI (EGARCH)
Mean	0.0002	-0.0001	0	0
Median	0.0001	-0.0003	-0.0002	-0.0002
Maximum	0.0463	0.0397	0.0399	0.0403
Minimum	-0.0438	-0.038	-0.038	-0.0384
Std. Dev.	0.009	0.0077	0.0078	0.0079
Skewness	-0.1407	-0.1364	-0.1365	-0.1372
Kurtosis	5.7496	5.7354	5.7361	5.7418
Jarque-Bera	1058.3	1046.9	1047.5	1051.9
Prob-value	0	0	0	0
Sum	0.6871	-0.4185	-0.034	-0.1275
Sum Sq. Dev.	0.2699	0.1993	0.2003	0.205
Observations	3325	3325	3325	3325

Table 4

Estimated Daily TFCI by OLS and QMLE for 01/06/2001 – 28/02/2014

Parameters	OLS	GARCH	GJR	EGARCH
Constant	3.75E-05	-0.0003	-0.0002	-0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
θ_1	-0.168	-0.175***	-0.173***	-0.162***
	(0.131)	(0.053)	(0.055)	(0.054)
θ_2	0.003**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
θ_3	0.654***	0.560***	0.562***	0.569***
	(0.033)	(0.017)	(0.017)	(0.017)
ω	--	1.98E-06***	1.94E-06***	-0.156***
		(3.57E-07)	(3.35E-07)	(0.015)
GARCH/GJR α	--	0.059***	0.066***	--
		(0.005)	(0.006)	
GARCH/GJR β	--	0.935***	0.94***	--
		(0.005)	(0.005)	
GJR γ	--	--	-0.027***	--
			(0.007)	
EGARCH α	--	--	--	0.096***
				(0.008)
EGARCH γ	--	--	--	0.036***
				(0.005)
EGARCH β	--	--	--	0.990***
				(0.001)
Diagnostics				
Adjusted R^2	0.22	0.213	0.214	0.214
AIC	-5.307	-5.525	-5.528	-5.53
BIC	-5.3	-5.513	-5.513	-5.515
Jarque-Bera	702.1***	523.7***	488.4***	457.6***

Notes: The dependent variable is RTS, the returns on the Taiwan Stock Exchange Over the Counter Tourism Subindex. The numbers in parentheses for OLS are robust Newey-West HAC standard errors, and are asymptotic standard errors for QMLE. The log-moment condition is necessarily satisfied as the second moment condition is satisfied in all cases. AIC and BIC denote the Akaike Information Criterion and Schwarz Bayesian Information Criterion, respectively.

***, **, and * denote the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively.