How Volatile is ENSO?

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EI 2009-18

August 2009

* Corresponding Author. The second author acknowledges the financial support of the Australian Research Council and the National Science Council, Taiwan.

Abstract

The El Niños Southern Oscillations (ENSO) is a periodical phenomenon of climatic interannual variability which could be measured through either the Southern Oscillation Index (SOI) or the Sea Surface Temperature (SST) Index. The main purpose of this paper is to analyze these two indexes in order to capture ENSO volatility. The empirical results show that both the ARMA(1,1)-GARCH(1,1) and ARMA(3,2)-GJR(1,1) models are suitable for modelling ENSO volatility. Moreover, 1998 is a turning point for the volatility of SOI, and the ENSO volatility has became stronger since 1998 which indicates that the ENSO strength has increased.

Key words: ENSO, SOI, SOT, Volatility, GARCH, GJR, EGARCH.

JEL Classifications: Q25, Q29, C22

1. Introduction

The El Niños Southern Oscillations (ENSO) is a periodical phenomenon of climatic interannual variability which has been found to be associated with regional variations in climate throughout the world. ENSO includes three phases, El Niños, La Niña, and Neutral, which could be defined through either the Southern Oscillation Index (SOI) or the Sea Surface Temperature (SST) Index. These ENSO phases have been found to have significantly impacts on global/local agriculture, water, and fishery sectors during alternative ENSO phases, strength, and frequency. For instance, the relationship between ENSO and precipitation, stream flow, floods and droughts has been investigated and analyzed (McBride and Nicholls, 1983; Ropelewski and Halpert, 1989; Dracup and Kahya, 1994; Moss et al., 1994; Piechota and Dracup, 1996) in recent years, reflecting the importance of this issue.

There is an extensive literature devoted to estimating e the economic impacts of ENSO on agricultural or water sectors, such as Handler (1983), Adams et al. (1995), Adams et al. (1999), Solow et al. (1998), Chen et al. (2001), Chen, McCarl and Hill (2002), Dilley (1997), Naylor et al. (2001), Rosenzweig et al. (2000), and Brunner (2002). These studies not only provide the importance of ENSO information to the agricultural economy, but are also linked to fluctuations in ENSO and the macro-economy (Debelle and Stevens, 1995; Brian et. al., 2008). During the last decade, some attention has been transferred to issues of food safety and public health. Some notable examples, including Davis (2001), have been devoted to the relationship between ENSO events and famine, while Kovats et al. (2003) investigated the variation in cholera risk in Bangladesh, and malaria epidemics in South Asia and South America. Other investigations suggest that hurricane losses are much greater during a La Niña year in the U.S.A. (Pielke and Landsea, 1999), while Chen et al. (2005) used ENSO frequency data to investigate Edwards Aquifer water and agricultural management on the phases of ENSO.

The above suggests that the damage of ENSO events could be mitigated if ENSO information could be forecasted accurately. This implies that ENSO information, including the strength and frequency of ENSO phases, need to be obtained. However, ENSO strength and frequency have shifted (Timmermann et al., 1999), and greenhouse gas emission may be one such cause. In other words, ENSO volatility varies overtime. The main purpose of this paper is to investigate ENSO volatility using generalized autoregressive conditional heteroskedasticity (GARCH) time series model. The empirical findings will provide further information of ENSO volatility.

The remainder of the paper is organized as follows. Section 2 presents the empirical models, while Section 3 discusses the data and descriptive statistics. Section 4 analyzes the empirical results, and concluding remarks are addressed in the final section.

2. Models

Modeling ENSO phases using ARMA or ARCH models has been considered by Chu and Katz (1985), Trenberth and Hoar (1996), and Ahn and Kim (2005). Chu and Katz (1985) found that monthly SOI can be adequately modeled by AR(3) processes, while Trenberth and Hoar (1996) found that ARMA(3,1) can be fitted for SST by using maximum likelihood and Akaike's Information Criterion (AIC). Ahn and Kim (2005) found that an ARCH model is more suitable model for SOI series. Each of these studies paid attention either to the SOI or SST index, but not both, which may misrepresent ENSO characteristics as these two indexes are used to define ENSO phases. On the other hand, although empirical research has used time series models, including ARMA, ARCH, and GARCH models to analyze the ENSO index, they did not check the model adequacy of ENSO volatility.

In order to answer these two questions, the generalized autoregressive conditional heteroskedasticity (GARCH) model will be applied to the SOI and SST indexes. The Bai and Perron's (1998, 2003) approach will be adopted in order to capture the structural break point of the ENSO series, which could identify alternative time periods for ENSO volatility.

2.1 Conditional Mean and Conditional Volatility Models

Based on the pioneering work of Engle (1982) in capturing time-varying volatility, the autoregressive conditional heteroskedasticity (ARCH) model, and subsequent developments forming the generalized ARCH (GARCH) model of Bollerslev (1986), has been used to capture volatility. The GARCH model is most wildly used for symmetric shocks, but when asymmetric shocks exist, the GJR model of Glosten et al. (1992), or the EGARCH model of Nelson (1991), are also popular models. Some further theoretical developments have been suggested by Wong and Li (1997), and Ling and McAleer (2002a, 2002b, 2003a, 2003b) and McAleer (2005).

The following model is based on McAleer et al. (2007) and Divino and McAleer (2009). To date, the method has been extended in detecting the volatility in patent growth (Chan, Marinova and McAleer, 2005a) and in analyzing the volatility of USA ecological patents (Marinova and McAleer, 2003; Chan, Marinova and McAleer, 2005b). Moreover, the method has further been used in modelling the volatility of environment risk (Hoti, McAleer and Pauwels, 2005) and the volatility of atmospheric carbon dioxide concentrations (McAleer and Chan, 2006). So far as climate change is considered, there does not seem to have been any empirical analysis of such volatility. In this paper, we consider the stationary AR(1)-GARCH(1,1) or

ARMA(p,q)-GARCH(1,1) models for the SOI and SST series data, namely y_t:

$$y_t = \phi_1 + \phi_2 y_{t-1} + \varepsilon_t, \qquad \text{for } t = 1,\dots,n, \qquad (1)$$

$$y_t = ARMA(p,q) + \varepsilon_t$$

where ε_t is unconditional shocks (or movements in the indices of SOI or SST) are given by:

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

and $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t \geq 0$. Ling and McAleer (2003b) indicated equation (2) in AR(1) process could be modified to incorporate a non-stationary ARMA(p,q) conditional mean and a stationary GARCH(r,s) conditional variance. In (2), the α (or ARCH) effect indicates the short run persistence of shocks, while the β (or GARCH) effect indicates the contribution of shocks to long run persistence (namely, $\alpha + \beta$).

The parameters in equations (1) and (2) are typically estimated by the maximum likelihood method. Ling and McAleer (2003b) investigate the properties of adaptive estimators for univariate non-stationary ARMA models with GARCH(r,s) errors. The conditional log-likelihood function is given as follows:

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

As the GARCH process in equation (2) is a function of the unconditional shocks, the moments of ε_t need to be investigated. Ling and Li (1997) showed that the ARCH(p,q) model is strictly stationary and ergodic if the second moment is finite, that is, $(\alpha + \beta)^2 + 2\alpha^2 < 1$. Ling and McAleer (2003a) showed that the Quasi MLE (QMLE) for GARCH(p,q) is consistent if the second moment is finite. Ling and Li (1997) demonstrated that the local QMLE is asymptotically normal if the fourth moment is finite, that is, $E(\varepsilon_t^4 < \infty)$, while Ling and McAleer (2003a) proved that the global QMLE is asymptotically normal if the sixth moment is finite, that is, $E(\varepsilon_t^6 < \infty)$. Using results from Ling and Li (1997) and Ling and McAleer (2002a, 2002b) (see also Bollerslev (1986) and Nelson (1990), 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 $(\alpha + \beta)^2 + 2\alpha^2 < 1$.

For the univariate GARCH(p,q) model, Bougerol and Picard (1992) derived the necessary and sufficient condition, namely the log-moment condition or the negativity of a Lyapunov exponent, for strict stationarity and ergodicity (see also Nelson (1990)). Using the log-moment condition, Elie and Jeantheau (1995) and Jeantheau (1998) established it was sufficient for consistency of the QMLE of GARCH(p,q) (see Lee and Hansen (1994) for the proof in the case of GARCH(1,1)), and Boussama (2000) showed that it 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

$$E(\log(\alpha\eta_t^2 + \beta)) < 0. \quad (3)$$

However, this condition is not straightforward 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. The extension of the log-moment condition to multivariate GARCH(p,q) models has not yet been shown to exist, although Jeantheau (1998) showed that the ultivariate log-moment condition could be verified under the additional assumption that the determinant of the unconditional variance of ε_t in (1) is finite. Jeantheau (1998) assumed a multivariate log-moment condition to prove consistency of the QMLE of the multivariate GARCH(p,q) model. An extension of Boussama's (2000) log-moment condition to prove the asymptotic normality of the

QMLE of the multivariate GARCH(p,q) process is not yet available.

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 behavior, Glosten et al. (1992) proposed the GJR model, for which GJR(1,1) is defined as follows:

$$h_t = \omega + (\alpha + \gamma I(\eta_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{4}$$

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, so that asymmetric effects in the data are captured by the coefficient γ, with $\gamma \geq 0$. The asymmetric effect, γ, measures the contribution of shocks to both short run persistence, $\alpha + \gamma/2$, and to long run persistence, $\alpha + \beta + \gamma/2$.

Ling and McAleer (2002b) derived the unique strictly stationary and ergodic solution of a family of GARCH processes, which includes GJR(1,1) as a special case, a simple sufficient condition for the existence of the solution, and the necessary and sufficient condition for the existence of the moments. For the special case of GJR(1,1), Ling and McAleer (2002b) showed that the regularity condition for the existence of the second moment under symmetry of η_t is

$$\alpha + \beta + \frac{1}{2} < 1, \tag{5}$$

and the condition for the existence of the fourth moment under normality of η_t is

$$\beta^2 + 2\alpha\beta + 3\alpha + \beta\gamma + 3\alpha\beta + \frac{3}{2}\gamma^2 < 1, \tag{6}$$

while McAleer et al. (2007) showed that the weaker log-moment condition for

GJR(1,1) was given by

$$E(\ln[(\alpha + \gamma I(\eta_t))\eta_t^2 + \beta]) < 0, \tag{7}$$

which involves the expectation of a function of a random variable and unknown parameters.

An alternative model to capture asymmetric behavior in the conditional variance is the Exponential GARCH (EGARCH(1,1)) model of Nelson (1991), namely:

$$\log h_t = \omega + \alpha|\eta_{t-1}| + \gamma\eta_{t-1} + \beta \log h_{t-1}, \quad |\beta| < 1 \tag{8}$$

where the parameters α, β and γ have different interpretations from those in the GARCH(1,1) and GJR(1,1) models.

As noted in McAleer et al. (2007), there are some important differences between EGARCH and the previous two models, 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) Nelson (1991) showed that $|\beta| < 1$ ensures stationarity and ergodicity for EGARCH(1,1); (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 conditional (or standardized) shocks 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 EGARCH(1,1).

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

2.2 Modelling Structural Breaks

The strength, duration, and frequency of ENSO phases have increased during the last two decades (Trenberth and Hoar, 1996; Hall et al., 2001) which suggests that there may have been structural breaks in ENSO. Much research related to structural breakpoints have been undertaken by Quandt (1958), Chow (1960) Andrews (1993), and Hansen (2001), of which need a priori break points before implementation. However, the approach by Bai and Perron (1998, 2003) (hereafter BP) does not need the a priori assumption.

The BP method provides a comprehensive treatment based on the following steps. First, consider the supF(i | 0) type tests (that is, a series of Wald tests) of non-structural break (i=0) against i=k breaks. This test requires the investigator to pre-specify a particular number of breaks for making inferences and then to use the double maximum test (UD_{max} and WD_{max}) of the null hypothesis of no structural break against an unknown number of breaks. These tests are used to determine if there is at least one structural break, while the structural break is determined endogenously. In this paper, the maximum number of breaks (i) is chosen to be 5, which is based on the Liu, Wu and Zidek (LWZ) criterion. Following the estimation approach of Bai and Perron (1998, 2003), if these tests show evidence of at least one structural break, then the number of breaks can be determined by using the supF (i+1| i) test, which performs parameter constancy tests for every subsample obtained by cutting off at the estimated breaks, and then adding a break to a sub-sample associated with a rejection. This process is repeated by increasing i sequentially until the test fails to reject the null hypothesis of no additional structural breaks.

3. Data and Descriptive Statistics

The most comment indexes to describe ENSO phases are referred to as the Southern Oscillation Index (SOI) and Sea Surface Temperature (SST) Index, which are monthly data sets. SOI is calculated from the monthly inverse variations in the air pressure difference between Tahiti (17.5˚S, 149.6˚W) in the South Pacific Ocean and Darwin (12.4˚S, 130.9˚W) in northern Australia. Positive values of the SOI are popularly known as a La Niña phase, while negative values are called El Niño. SST is the water temperature close to the surface in the Equatorial Pacific Ocean (that is, 4 for the region 5°N–5°S, 120°– 170°W). If the periods during 5-month running means of the monthly SST anomalies in the above-mentioned area $+5^0C$ or more for at least six consecutive months, calling if a Niño year (Trenberth, 1997).

Figure 1 plots the time series data set for SOI and SST. These two graphs indicate periods of high volatility followed by others of relatively low volatility, which implies that using homoskedastic residuals to model volatility behavior is inappropriate. Furthermore, we also find that volatility the most recent periods is higher than the in earlier periods, as shown in the left graph of Figure 1, which implies that ENSO volatility has been increasing.

The data sets for the SOI and SST observations are collected from the Climate Prediction Center from January 1933 to July 2007 and January 1950 to April 2007, respectively. Table 1 displays the descriptive statistics for the SOI and SST series. The SOI series has a larger variance than the SST series. The Ljung-Box Q-statistics for SOI and SST are given as Q(12)=1290.20 and Q(12)=2149.50 respectively, which correspond to p-values of the two test statistics less than 5%, thereby suggesting that SOI and SST are correlated. In order to test normality, the JB Lagrange multiplier test statistics is used. Table 1 shows that SOI and SST are not normality distributed, as the p-values of the JB statistics are less than 5%.

Before establishing the volatility model for the SOI and SSI series, unit roots tests have to be implemented to ensure the data of the SOI and SSI series are stationary. The most common unit root tests are those of Dickey and Fuller (1979, 1981), who developed tests of null hypothesis of a unit root against the alternative of stationarity. In this paper, the augmented Dickey-Fuller (ADF) unit root test is calculated for the SOI and SST series. The results of the unit root tests are reported in Table 2, which indicate that both SOI and SST are all stationary at the 1% significance level.

4. Empirical Results

4.1 AR(p) and ARMA(p,q) Processes

In order to investigate the ENSO volatility, an appropriate time series model needs to be determined that satisfies appropriate regularity conditions. The first task is to determine the processes for the mean equation. From Tables 3, the ARMA(1,1) process for the SOI series has the smallest Schwarz Bayesian Information Criterion (BIC), while ARMA(3,2) has the smallest BIC for the SST series. The p-values of the Ljung-Box Q statistics of the residuals from the fitted models indicate that there is no autocorrelation at the 5% level. The estimated ARMA(1,1) and ARMA(3,2) models are seen to be appropriate models for the SOI and SST series, respectively. Therefore, the specification of the mean and variance equations for SOI and SST are given as follows:

$$SOI = ARMA(1,1) + \varepsilon_t,$$

conditional volatility = {GARCH(1,1), GJR(1,1) or EGARCH(1,1)},

$$SST = ARMA(3,2) + \varepsilon_t,$$

conditional volatility = {GARCH(1,1), GJR(1,1) or EGARCH(1,1)}.

4.2 Alternative Volatility Models for SOI and SST

The empirical estimates for alternative volatility models for the SOI and SST series are shown in Tables 4 and 5 The estimated model for the SOI and SST series for GARCH(1,1) shows that all the estimated coefficients satisfy the sufficient regularity conditions for the conditional variance to be positive ($h_t \geq 0$). Moreover, the log-moment and second moment conditions are satisfied for SOI, so the QMLE for two series are consistent and asymptotically normal. The estimates for the GJR(1,1) model show that SOI and SST satisfy the sufficient conditions for the conditional variance and weak log-moment condition, which indicates that the QMLE of SOI and SST are consistent and asymptotically normal.

All the β estimates from the EGARCH(1,1) model for SOI and SST are less than one in absolute value, which indicates that all the moments exist and the estimates are likely to be consistent and asymptotically normal. As EGARCH(1,1) is a model of the logarithm of the conditional variance, there is no parametric restriction for conditional volatility to be positive. The size effects for the namely SOI and SST series have positive impacts on the conditional variance. These estimation results indicate that the sign effects have larger impacts than size effects on the conditional variance. Furthermore, the appropriate model for the SOI series could be chosen by the BIC criterion and the regularity conditions. The GARCH (1,1) model for the SOI and SST series is the optimal model as it has the smallest BIC value.

4.3 Structural Change

In order to exam whether structural change exists for the SOI series, the BP approach is implemented, and the estimaes are shown in Table 6. The Table shows that the values of UD_{max} and WD_{max} are greater than those at the 5% critical value, which indicates the probably existence of structural breaks. Since the values of F(1|0), F(2|0), F(3|0), F(4|0), F(5|0) are greater than the critical value at the 5% significance level, while the sequential supF(i+1|i) exhibits significance only for i=1, this suggests only one break in the SOI series, which occurs at 1998(4).

4.4 Estimating the ENSO Volatility between two Different Structural Breaks

The section investigates and compares the ENSO volatility before and after the structural breakpoint. From the estimates of structural change, the breakpoint is located at April 1998, which will be treated as a boundary to split the sample into two periods for the SOI and SST series. In other words, the first period is from January 1950 to April 1998, while the second period is from May 1998 to July 2007. We applied the ARMA(1,1)-GARCH(1,1) model to SOI and the ARMA(3,2)-GARCH(1,1) model to SST.

The empirical results of volatility for SOI and SST are presented in Table 7. The ARMA(1,1)-GARCH(1,1) estimates for SOI suggest that the short run persistence of shocks in periods 1 and 2 are 0.008 and 0.438, respectively, while the long run persistence of shocks in periods 1 and 2 are 0.359 and 0.530, respectively. The ARMA(3,2)-GARCH(1,1) estimates for SST suggest that the short run persistence of shocks in periods 1 and 2 are 0.255 and 0.046, respectively, while the long run persistence of shocks in periods 1 and 2 are 0.402 and 0.706, respectively. Both SOI and SST have larger long run persistence of shocks during the second period from May 1998. The estimates show that the ENSO volatility has increased since 1998, which implies that the ENSO strength and frequency has increased recently. This finding is consistent with the previous study by Timmermann et al. (1999).

5. Concluding Remarks

The main purpose of the empirical analysis in this paper was to determine an empirically adequate model of volatility of the Southern Oscillation by checking the regularity conditions of the estimated models, and then detecting whether structural breaks exist in the climate indexes. First, the GARCH, GJR and EGARCH models were estimated for Southern Oscillation volatility, based on the SOI and SST indexes, to answer the following questions: Under what conditions do GARCH-type processes have finite moments? Under what conditions are they stationary? These questions are important as the existence of moments permits verification of theoretical models to match stylized facts, such as fat tails and the temporal persistence observed in financial data (Carrasco and Chen, 2002). In practice, these conditions may not be satisfied. Although there have been many contributions to the ARCH/GARCH literature, it seems that until recently very little attention has been paid to appropriate model selection. Apart from diagnostic checks (see Li, Ling and McAleer, 2002), ARCH-type models generally do not satisfy these conditions.

The empirical results indicated that the second moment and log-moment conditions for the ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-GJR(1,1) models for SOI are satisfied. The ARMA(1,1)-GARCH(1,1) model has the smallest BIC, and hence is superior to ARMA(1,1)-GJR(1,1). The second moment and log-moment conditions for the ARMA(3,1)-GARCH(1,1) and ARMA(3,1)-GJR(1,1) models for SST are also satisfied. The ARMA(3,2)-GARCH(1,1) model has the smallest BIC, and hence is superior to ARMA(3,2)-GJR(1,1). Therefore, we conclude that nonlinear stochastic models are suitable for modelling the SOI and SST indexes after checking the regularity conditions.

In the second task, we tested for structural breaks in SOI and SST by using the

Bai and Perron (1998, 2003) test and then estimated the volatility of the SOI and SST indexes based on the structural breaks. The result showed that SOI had a structural break point in 1998(04). Therefore, we re-estimated the ARMA(1,1)-GARCH(1,1) model for SOI and the ARMA(3,2)-GARCH(1,1) for SST to examine the volatility by using 1998(04) as a structural point. The results indicated that the contribution of shocks to long run persistence of SOI and SST during 1998(05)-2007(07) is larger than during 1950(01)-1998(04), such that the volatility of ENSO over the decade had become stronger than in the previous period of over 50 years.

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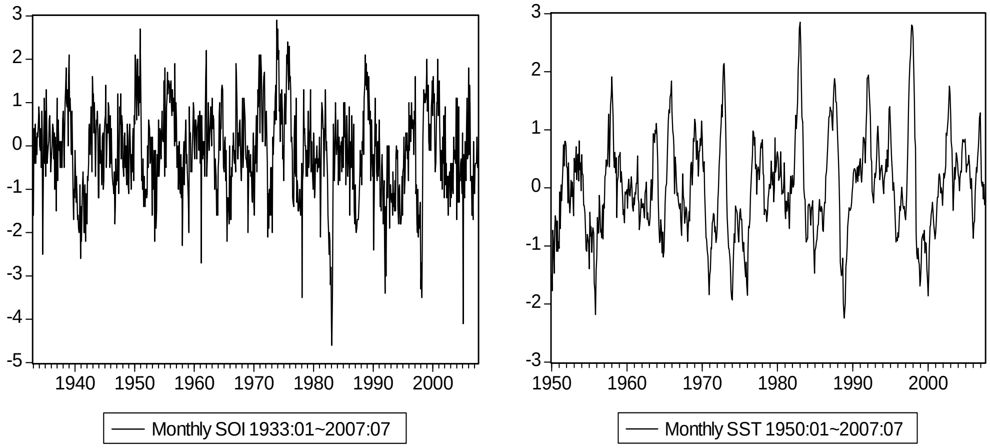

Figure 1. SOI and SST

Table 1. Descriptive Statistics for SOI and SST

Variables	Number of observations	Mean	Max	Min	Std Dev	Q(p)	JB
SOI	895	-0.147	2.900	-4.600	1.048	1290.20 (0.00)	30.09 (0.00)
SST	691	0.018	2.85	-2.250	0.859	2149.50 (0.00)	19.09 (0.00)

Note: 1. Q(p) is the Box-Pierce statistic for serial independent.

2. JB is the Jarque-Bera test for normality.

3. The values in the parenthesis are p-values.

Table 2. ADF Unit Root Test for SOI and SST

Variables	Level			First-Difference Level		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
SOI	-8.17(12)*	-8.24(9)*	-8.06(9)*	-20.60(8)*	-20.59(10)*	-20.61(7)*
SST	-7.87(10)*	-7.90(10)*	-7.86(9)*	-15.76(9)*	-15.75(9)*	-15.77(8)*

Note 1: * represents the 1% significant level.

2: Model 1: the auxiliary regression equation with only intercept.

Model 2: the auxiliary regression equation with only time trend.

Model 3: the auxiliary regression equation with non intercept and time trend.

3: BIC is the criteria for selecting the optimal lags and the values in the parenthesis are the lag period.

Table 3. ARMA(p,q) Models for SOI and SST

SOI			SST		
p	q	BIC	p	q	BIC
1	0	2.481	1	0	0.573
1	1	2.387	1	2	0.561
2	0	2.405	2	1	0.530
2	2	2.391	2	2	0.531
3	0	2.392	3	1	0.524
5	2	2.410	3	2	0.481
5	4	2.412	3	3	0.490
6	2	2.421	3	4	0.540
6	3	2.416	4	1	0.527
			4	2	0.534
			4	3	0.538

Table 4. ARMA(1,1) and GARCH, GJR and EGARCH Models for SOI

Variable(SOI)	Model		
	GARCH(1,1)	GJR(1,1)	EGARCH(1,1)
Mean Equation			
AR(1)	0.896(0.021)	0.901(0.019)	0.896(0.019)
MA(1)	-0.477(0.044)	-0.474(0.042)	-0.471(0.042)
Variance Equation			
ω	0.337 (0.145)	0.470 (0.166)	-0.532 (0.144)
α	0.103 (0.044)	0.202 (0.063)	0.245 (0.071)
β	0.361 (0.152)	0.127(0.267)	0.077(0.043)
γ		-0.139 (0.072)	0.292(0.261)
Log moment	-0.351	-0.719	
Second moment	0.464	0.127	
BIC	2.399	2.405	2.404

Note: The values in the parenthesis are the standard errors.

Table 5. ARMA(3,2) and GARCH, GJR and EGARCH models for SST

Variable(SST)	Model		
	GARCH(1,1)	GJR(1,1)	EGARCH(1,1)
Mean Equation			
AR(1)	0.823(0.045)	0.849(0.032)	0.858(0.029)
AR(2)	0.957(0.006)	0.955(0.006)	0.958(0.005)
AR(3)	-0.846(0.041)	-0.866(0.029)	-0.876(0.026)
MA(1)	0.233(0.060)	0.188(0.048)	0.179(0.044)
MA(2)	-0.762(0.059)	-0.807(0.048)	-0.816(0.044)
Variance Equation			
ω	0.003(0.045)	0.051(0.051)	-1.667(0.450)
α	0.034(0.006)	0.179(0.092)	0.400(0.095)
β	0.930(0.059)	0.224(0.110)	0.447(0.053)
γ		0.125(0.177)	-0.067(0.176)
Log moment	-0.015	-0.712	
Second moment	0.963	0.466	
BIC	0.483	0.488	0.485

Note: The values in the parenthesis are the standard errors.

Table 6. Estimation Results of SOI Series for Structural Break Test

Test	Hypothesis		Statistics	
			SOI	Critical value[a]
UD_{max}	H_0:m=0	H_1:m>0	13.14 *	8.88
WD_{max}	H_0:m=0	H_1:m>0	13.14 *	9.91
supF(i|0) Test	H_0:m=0	H_1:m=1	13.14 *	8.58
	H_0:m=0	H_1:m=2	8.04*	7.22
	H_0:m=0	H_1:m=3	7.37*	5.96
	H_0:m=0	H_1:m=4	5.58*	4.99
	H_0:m=0	H_1:m=5	4.50*	3.91
supF(i+1| i) Test	supF(2| 1)		7.34*	8.58
	supF(3| 2)		2.49	10.13
	supF(4| 3)		2.02	11.14
	supF(5| 4)		0.00	11.83
LWZ	1	0.1662*		
	2	0.1889		
	3	0.2228		
	4	0.2581		

Note: “a” is the critical value of 5% significant level.

“*” represents the 5% significant level.

LWZ(1): means the number of breaks chosen by LWZ is 1.

Table 7. Estimation Results of ENSO Volatility for Different Periods

	SOI		SST	
	Period 1	Period 2	Period 1	Period 2
Variance Equation				
ω	0.363	0.413	0.058	0.015
	(0.243)	(0.236)	(0.017)	(0.015)
α	0.008	0.438	0.255	0.046
	(0.053)	(0.210)	(0.077)	(0.012)
β	0.351	0.092	0.147	0.660
	(0.408)	(0.279)	(0.190)	(0.316)

Note: The values in the parenthesis are the standard errors.