Energy prices and China's international competitiveness

Chen, Guifu and Hamori, Shigeyuki

Xiamen University, Kobe University

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Guifu Chen
Assistant Professor, Center for Macroeconomic Research, School of Economics,
Xiamen University, Xiamen, China
Email: chenguifu@xmu.edu.cn

Shigeyuki Hamori*)
Faculty of Economics, Kobe University, Kobe, Japan
Email: hamori@econ.kobe-u.ac.jp

Abstract

This paper uses the CCF approach to analyze and determine whether there is a causal relationship between the world energy price index and China's international competitiveness. The data on the volatility of energy prices can provide information in addition to that available in the price data alone. Our analysis suggests that the volatility of energy prices has significant implications concerning information linkages between the energy market and China's international competitiveness.

Keywords: energy prices, international competitiveness, CCF approach, Chinese economy
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*) Corresponding author

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Abstract

This paper uses the CCF approach to analyze and determine whether there is a causal relationship between the world energy price index and China's international competitiveness. The data on the volatility of energy prices can provide information in addition to that available in the price data alone. Our analysis suggests that the volatility of energy prices has significant implications concerning information linkages between the energy market and China's international competitiveness.

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1. Introduction

Nobody can deny the importance of the Chinese economy in the world. China plays an important role as a leader of developing countries, and thus many researchers have analyzed the Chinese economy from many perspectives. As is known, although China was a self-sufficient energy consumer until 1993, at present, it is the second largest importer of energy products in the world, behind the USA. This huge growing demand for energy is the result of China's spectacular economic growth, and mainly comes from one sector—industry (including construction). Consequently, world energy price changes will strongly impact the Chinese economy, because Chinese economic growth is highly industry-oriented and energy-intensive. Some studies have shown that energy price increases have negative effects on the Chinese economy (Lin and Mu 2008; Lescaroux and Mignon 2009).

This paper analyzes the relationship between world energy prices and the Chinese economy. In particular, we focus on how the world energy price index and China's international competitiveness affect each other. This paper uses the real effective exchange rate as the measure of international competitiveness. The effective exchange rate is an indicator that can be used to grasp China's international competitiveness in terms of its foreign exchange rates that cannot be understood by examining only individual exchange rates between the renminbi and other currencies. International competitiveness is affected not only by the exchange rate but also by domestic and foreign price movements. For example, even when the nominal effective exchange rate of the renminbi remains unchanged, the relative competitiveness of Chinese goods increases when the inflation rates of its trading partners are higher than its inflation rate. Taking this into account, the nominal effective exchange rate is adjusted to incorporate inflation rate differences. This indicator is called the real effective exchange rate and is used to represent the international competitiveness of a country.

In spite of its importance, there is no enough empirical research information on the relationship between energy prices and Chinese economy until recently. Some include Wolde-Rufael (2004), Shiu and Lam (2004), Yuan, *et al*, (2007), Lin and Mu (2008), Cong et al. (2008), and Lescaroux and Mignon (2009).

. Wolde-Rufael (2004) investigates the causal relationship between industrial energy consumption and GDP in Shanghai during 1952–1999 using a modified version of the Granger causality test proposed by Toda and Yamamoto (1995). The empirical evidence from disaggregated energy series seems to suggest that there was a unidirectional Granger causality running from coal, coke, electricity, and total energy consumption to real GDP but no Granger causality running in any direction between oil consumption and real GDP.

Shiu and Lam (2004) apply the error-correction model to examine the causal relationship between electricity consumption and real GDP in China during 1971–2000. The empirical results indicate that real GDP and electricity consumption in China are cointegrated and there is unidirectional Granger causality running from electricity consumption to real GDP but not vice versa.

Yuan, *et al*, (2007) apply the cointegration theory to examine the causal relationship between electricity consumption and real GDP in China during 1978–2004. The estimation results indicate that real GDP and electricity consumption in China are cointegrated and there is a unidirectional Granger causality running from electricity consumption to real GDP but not vice versa. They apply the Hodrick-Prescott (HP) filter to decompose the trend and fluctuation component of the GDP and electricity consumption series. Their empirical results indicate that there is cointegration between not only the trend components but also the cyclical components of the two series, which implies that, the Granger causality may be related to the business cycle. The empirical results have policy implications for the development of the electricity sector in China.

Lin and Mu (2008) show that the impacts of energy price increases have contraction effects that differ significantly across industries. This not only affects economic growth but also fosters structural industrial changes. For most industries in China, the contraction effects of coal are two to three times that of oil for the same price increase, and the conclusion holds even for the less-energy-intensive service industries. They also show that the impact differences of coal and oil are in line with the observed energy consumption structure of China: coal forms 70% and oil forms 20% of the primary energy consumption.

Cong et al. (2008) empirically analyze the relationship between oil price shocks and the Chinese stock market using multivariate vector auto-regression. They find that oil price shocks do not have statistically significant impact on the real stock returns of most Chinese stock market indices. It is also found that an increase in oil volatility may increase the speculations in the mining index and petrochemicals index, which raises their stock returns.

Lescaroux and Mignon (2009) suggest that an oil price shock leads to (1) a contemporaneous increase in consumer and producer price indexes, inducing a rise in interest rates; (2) a delayed negative impact on GDP, investment, and consumption; and (3) a postponed increase in coal and power prices.

Turning now to the previous studies, it should be noted that, to the best of our knowledge, little work has been done on the links between energy prices and international competitiveness in China. This paper attempts to shed new light on this problem. The contribution of this paper is two-fold. First, this paper focuses on the relationship between the world energy price index and China’s international competitiveness over the period from January 1994 to December 2008. We use the real effective exchange rate as a proxy for international competitiveness. Second, this paper uses the cross correlation function (CCF) approach that was recently developed by Cheung and Ng (1996). The CCF approach is an outstanding approach permitting an analysis of not only causality in mean but also causality in variance. As Ross (1989) has pointed out, changes in uncertainty include valuable information on information flow. This type of analysis, therefore, would seem to be valuable.

2. Empirical Techniques

Cheung and Ng (1996) developed a two-step procedure to test for causality in mean and variance.[1,2] The procedure is based on the residual CCF and is robust to distributional assumptions. In the first of the two steps, we estimate a set of univariate time-series models that allow for time variation in both conditional mean and conditional variance. The second step is conducted by constructing the residuals standardized by conditional mean, and the squared residuals standardized by conditional variance. The CCF of the standardized residuals is used to test the null hypothesis of no causality in mean, while the CCF of squared standardized residuals is used to test the null hypothesis of no causality in variance.

[1] Also see Hamori (2003).

[2] For the application of CCF approach, see e.g., Bhar and Hamori (2005, 2006, 2008).

Let us begin by summarizing the two-step procedure for testing causality developed by Cheung and Ng (1996). Suppose that there are two stationary time series, X_t and Y_t, and three information sets, $I_{1t} = (X_{t-j}; j \geq 0)$, $I_{2t} = (Y_{t-j}; j \geq 0)$, and $I_t = (X_{t-j}, Y_{t-j}; j \geq 0)$. Y_t is said to cause X_t in mean if

$$(1) \qquad E[X_t \mid I_{1t-1}] \neq E[X_t \mid I_t].$$

Similarly, X_t is said to cause Y_t in mean if

$$(2) \qquad E[Y_t \mid I_{2t-1}] \neq E[Y_t \mid I_t].$$

We encounter feedback in mean if Y_t causes X_t in mean or *vice versa*.

Y_t, on the other hand, causes X_t in variance if

$$(3) \qquad E[(X_t - \mu_{x,t})^2 \mid I_{1t-1}] \neq E[(X_t - \mu_{x,t})^2 \mid I_{t-1}],$$

where $\mu_{x,t}$ is the mean of X_t conditioned on I_{1t-1}. Similarly, X_t causes Y_t in variance if

$$(4) \qquad E[(Y_t - \mu_{y,t})^2 \mid I_{2t-1}] \neq E[(Y_t - \mu_{y,t})^2 \mid I_{t-1}],$$

where $\mu_{y,t}$ is the mean of Y_t conditioned on I_{2t-1}. We encounter feedback in variance if X_t causes Y_t in variance or *vice versa*. The causality in variance is interesting in itself, given that it has a direction relation to volatility spillover across different assets or markets.

The concept defined in equations (1) through (4) is too general to test empirically; hence, we need an additional structure to make the general causality concept applicable in practice.

Suppose X_t and Y_t can be written as

(5) $$X_t = \mu_{x,t} + \sqrt{h_{x,t}}\varepsilon_t,$$

(6) $$Y_t = \mu_{y,t} + \sqrt{h_{y,t}}\varsigma_t,$$

where ε_t and ς_t are two independent white noise processes with zero mean and unit variance.

For the causality in mean test, we can use the following standardized innovations:

(7) $$\varepsilon_t = \frac{X_t - \mu_{x,t}}{\sqrt{h_{x,t}}},$$

(8) $$\varsigma_t = \frac{Y_t - \mu_{y,t}}{\sqrt{h_{y,t}}}.$$

As both ε_t and ς_t are unobservable, we must use their estimates, $\hat{\varepsilon}_t$ and $\hat{\varsigma}_t$, to test the hypothesis of no causality in mean.

Next, we compute the sample cross-correlation coefficient at lag k, $\hat{r}_{\varepsilon\varsigma}(k)$, from the consistent estimates of the conditional mean and variance of X_t and Y_t. This leaves us with

(9) $$\hat{r}_{\varepsilon\varsigma}(k) = \frac{c_{\varepsilon\varsigma}(k)}{\sqrt{c_{\varepsilon\varepsilon}(0)c_{\varsigma\varsigma}(0)}},$$

where $c_{\varepsilon\varsigma}(k)$ is the k-th lag sample cross-covariance given by

(10) $$c_{\varepsilon\varsigma}(k) = \frac{1}{T}\sum(\hat{\varepsilon}_t - \bar{\hat{\varepsilon}})(\hat{\varsigma}_{t-k} - \bar{\hat{\varsigma}}), \qquad k = 0, \pm1, \pm2, \cdots,$$

where $c_{\varepsilon\varepsilon}(0)$ and $c_{\varsigma\varsigma}(0)$ are defined as the sample variances of ε_t and ς_t, respectively.

Causality in the mean of X_t and Y_t can be tested by examining $\hat{r}_{\varepsilon\varsigma}(k)$, the univariate standardized residual CCF. Under the condition of regularity, it holds that

(11) $$\sqrt{T}\hat{r}_{\varepsilon\varsigma}(k_i) \xrightarrow{L} N(0,1), \quad i = 1, 2, \cdots, m,$$

where $\xrightarrow{L}$ shows the convergence in distribution.

This test statistic can be used to test the null hypothesis of no causality in mean. To test for a causal relationship at a specified lag k, we compare $\hat{r}_{\varepsilon\varsigma}(k)$ with the standard normal distribution. If the test statistic is larger than the critical value of normal distribution, we reject the null hypothesis.

For the causality in variance test, let u_t and v_t be the squares of the standardized innovations, given by

(12) $$u_t = \frac{(X_t - \mu_{x,t})^2}{h_{x,t}} = \varepsilon_t^2,$$

(13) $$v_t = \frac{(Y_t - \mu_{y,t})^2}{h_{y,t}} = \varsigma_t^2.$$

As both u_t and v_t are unobservable, we must use their estimates, $\hat{u}_t$ and $\hat{v}_t$, to test the hypothesis of no causality in variance.

Next, we compute the sample cross-correlation coefficient at lag k, $\hat{r}_{uv}(k)$, from the consistent estimates of the conditional mean and variance of X_t and Y_t. This yields

(14) $$\hat{r}_{uv}(k) = \frac{c_{uv}(k)}{\sqrt{c_{uu}(0)c_{vv}(0)}},$$

where $c_{uv}(k)$ is the k-th lag sample cross-covariance given by

(15) $$c_{uv}(k)=\frac{1}{T}\sum(\hat{u}_t-\bar{\hat{u}})(\hat{v}_{t-k}-\bar{\hat{v}}), \qquad k=0,\pm1,\pm2,\cdots,$$

where $c_{uu}(0)$ and $c_{vv}(0)$ are defined as the sample variances of u_t and v_t, respectively.

Causality in the variance of X_t and Y_t can be tested by examining the squared standardized residual CCF, $\hat{r}_{uv}(k)$. Under the condition of regularity, it holds that

(16) $$\sqrt{T}\hat{r}_{uv}(k_i)\xrightarrow{L}N(0,1) \qquad i=1,2,\cdots,m.$$

This test statistic can be used to test the null hypothesis of no causality in variance. To test for a causal relationship at a specified lag k, we compare $\hat{r}_{uv}(k)$ with the standard normal distribution. If the test statistic is larger than the critical value of normal distribution, we reject the null hypothesis.

3. Data

The empirical research in this paper is performed using monthly data from the world energy price index and the Chinese real effective exchange rate over the period from January 1994 through December 2008. These data are obtained from the International Financial Statistics (International Monetary Fund; IMF). The world energy price index developed by IMF is known as the representative energy price index in the world, and hence, is used for empirical analysis in this paper. This paper uses the real effective exchange rate as a proxy for China's international competitiveness. This exchange rate is used to determine an individual country's currency value relative to the other major currencies in the index, as adjusted for the effects of inflation. The weights are determined by comparing the relative trade balances, in terms of one country's currency, with each other country within the index.

The statistics in Table 1 summarize the growth rate of each variable. Each rate is calculated by the log difference as follows:

(17) $$ep_t=\log(EP_t)-\log(EP_{t-1}),$$

(18) $ex_t = \log(REER_t) - \log(REER_{t-1})$,

where EP_t is the world energy price index at time t and $REER_t$ is the real effective exchange rate at time t. This table shows the mean, standard deviation (Std. Dev.), skewness, kurtosis, and Jarque-Bera test statistic with the associated p-value. The Jarque-Bera statistic is used to test whether or not the series is normally distributed. It measures how widely the skewness and kurtosis of the series differ from the normal distribution. The reported p-value is the probability that a Jarque-Bera statistic exceeds the critical value under the null hypothesis. Thus, a small p-value leads to the rejection of the null hypothesis of a normal distribution.

According to Table 1, the average growth rates are 0.00643 for the world energy price index, and 0.00246 for the real effective exchange rate, while the standard deviations are 0.07239 and 0.01535, respectively. We thus find that the world energy price index is far more volatile than the real effective exchange rate. The Jarque-Bera statistic (p-value) is 38.4010 (0.0000) for the world energy price index, and 358.6154 (0.0000) for the real effective exchange rate. Thus, the null hypothesis of normal distribution is statistically rejected at the 5% significance level. This evidence indirectly supports the ARCH effects for each variable.

4. Empirical Results

We use the two-step procedure proposed by Cheung and Ng (1996) to analyze the causal relationship between the mean and variance of the variables. First, we estimate a series of univariate time series models to allow for time variation in both conditional mean and conditional variance. The AR(k)-ARCH(p) model is used to model the dynamics of each variable. The conditional mean and conditional variance are, respectively, expressed as follows:

(17) $x_t = a_0 + \sum_{i=1}^{k} a_i x_{t-i} + u_t$, $E_t(u_t) = 0$, $E_{t-1}(u_t^2) = \sigma_t^2$,

(18) $\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$.

These models are applied to the growth rates of the world energy price index, and the real effective exchange rate. Each model is estimated by the method of maximum likelihood. Parameter estimates and their asymptotic standard errors are reported in Table 1. The Schwarz Bayesian information criterion (SBIC) and residual diagnostics are used to check the specification of the models. The following models are thus selected: the AR(1)-ARCH(1) model for the world energy price index, and the AR(1)-ARCH(1) model for the real effective exchange rate.

As shown in Table 2, the coefficient of the ARCH term (α_1) is estimated to be 0.2040 for the world energy index, and 0.1383 for the real effective exchange rate. Both may be statistically significant. Table 2 also shows the diagnostics of the empirical results of the AR-ARCH model. The Ljung-Box test statistic at lag s, $Q(s)$, is a test statistic for the null hypothesis that there is no autocorrelation up to order s for standardized residuals. $Q(s)$ is asymptotically distributed as χ^2 with degrees of freedom equal to the number of autocorrelations minus the number of parameters. As we clearly see in the table, $Q(36)$ (p-value) is 41.7130 (0.2360) for the world energy index, and 29.9440 (0.7510) for the real effective exchange rate. Thus, the null hypothesis of no autocorrelation up to order 36 for standardized residuals is accepted for all variables. Table 2 also indicates the $Q^2(s)$ statistic and its associated p-value. $Q^2(s)$ is a test statistic for the null hypothesis that there is no autocorrelation up to order s for squared standardized residuals. $Q^2(36)$ (p-value) here is 30.8200 (0.7130) for the world energy price index, and 10.7040 (1.0000) for the real effective exchange rate. Thus, the null hypothesis of no autocorrelation up to order 36 for squared standardized residuals is accepted for all variables. These results empirically support the specification of the selected AR-ARCH model.

In the second step of the Cheung-Ng procedure, we analyze the causality in mean and variance based on the empirical results obtained in the previous section. Sample cross-correlation test statistics of the standardized residuals and squared standardized residuals are reported in Tables 3. As the table shows, the test statistic has a standard normal distribution in large samples. The causality pattern is indicated by the significance of the test statistic. In other words, we obtain evidence of causality in mean (variance) if one or more of the test statistics calculated from the standardized residuals (squared standardized residuals), at all possible leads and lags, are significantly different from zero. Figures 1 and 2 show the standardized residuals and the squared standardized residuals of world energy prices and the real effective exchange rate, respectively.

The "Levels" column gives the test statistic based on the standardized residuals. This statistic is used for testing causality in mean. The "Squares" column contains the test statistic based on the squared standardized residuals and is used to test for causality in variance. Table 3 shows the results of the causality test between the world energy price index and the real effective exchange rate. Here, we see that the world energy price index unidirectionally causes the real effective exchange rate in mean. The causation pattern is of lags 2 and 4 from world energy price index to the real effective exchange rate. We also see that the world energy price index unidirectionally causes the real effective exchange rate in variance as well. The world energy price index causes the real effective exchange rate at lags 2 and 6 in variance.

5. Concluding Remarks

Because of its influence in the world economy, many people pay attention to the relationship between world energy prices and Chinese economy nowadays. However, there is no enough empirical research accumulation on this topic until recently. To the best of our knowledge, our analysis is the first one to examine the relationship between the world energy price index and China's international competitiveness. Moreover we apply the CCF approach to analyze to see whether there is a causal relationship between the world energy price index and China's international competitiveness, which has hardly been analyzed. Our empirical results show that the world energy price index causes China's international competitiveness not only in mean but also in variance.

We have analyzed the relationship of conditional variance across the energy prices and international competitiveness and its implications concerning information transmission mechanism. As clearly demonstrated by Ross (1989), volatility also provides useful data on information flows. Thus, the data on the volatility of energy markets can provide information in addition to that available in the price data alone. Our analysis suggests that the volatility of energy prices has significant implications concerning information linkages between the energy market and China's international competitiveness.

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Table 1 Summary Statistics

	ep_t	ex_t
Mean	0.00643	0.00246
Std. Dev.	0.07239	0.01535
Skewness	−0.90509	−0.47891
Kurtosis	4.36820	9.86769
Jarque-Bera	38.4010	358.6154
p-value	0.0000	0.0000

Table 2 Empirical Results of AR−ARCH Model

Mean Equation: $y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + u_t$, $E_t(u_t) = 0$, $E_{t-1}(u_t^2) = \sigma_t^2$

Variance Equation: $\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$

	ep_t		ex_t	
Mean Equation				
a_0	0.0095	(0.0055)	0.0016	(0.0013)
a_1	0.2079	(0.0962)	0.1752	(0.0909)
Variance Equation				
ω	0.0037	(0.0005)	0.0002	(0.0000)
α_1	0.2040	(0.1047)	0.1383	(0.0595)
Diagnostic				
Log Likelihood	228.1140		500.9951	
$Q(36)$	41.7130		29.9440	
p-value	0.2360		0.7510	
$Q^2(36)$	30.8200		10.7040	
p-value	0.7130		1.0000	

Note: The numbers in parentheses are the p-values.

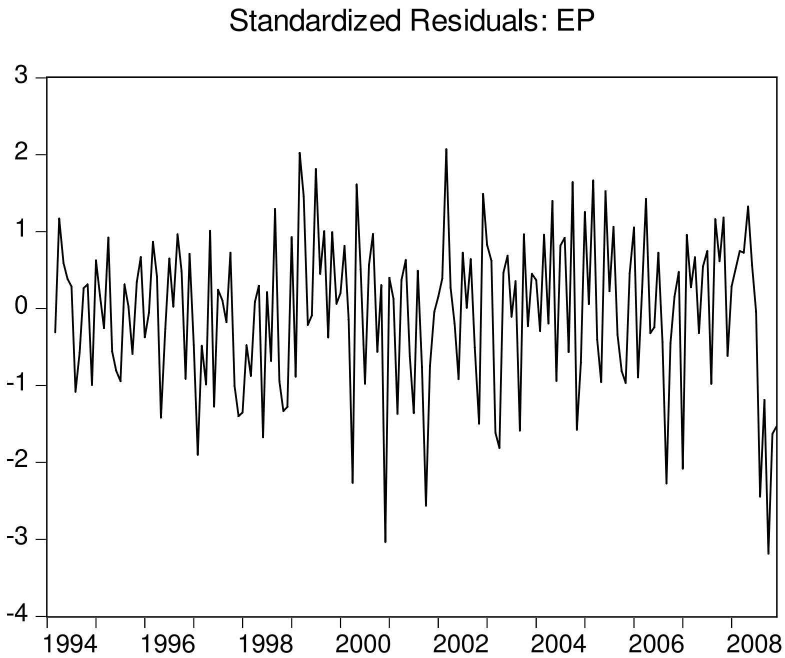
Table 3

Cross-Correlation Analysis for the Levels and Squares of the Standardized Residuals

k	Levels		Squares	
	Lag	Lead	Lag	Lead
	ex_t and $ep_t(-k)$	ex_t and $ep_t(+k)$	ex_t and $ep_t(-k)$	ex_t and $ep_t(+k)$
0	−1.8065		−0.2802	
1	−0.7378	−0.3109	0.3402	−0.5350
2	2.0586*	−0.3709	2.6336*	−0.5016
3	−0.2041	−1.1567	−0.5243	−0.8432
4	−0.1881	−0.5443	−0.3149	−0.2735
5	0.4870	0.4630	−0.7525	−0.2228
6	2.0906*	−1.6610	2.2788*	0.4403
7	0.1961	−1.7918	−0.0867	−0.0854
8	−0.3175	−0.7992	−0.0067	0.4083
9	0.5337	0.5990	−0.4616	−0.3536
10	0.9606	−1.0900	−0.4910	−0.4896
11	−1.2608	−1.3729	0.5724	−1.0313
12	0.1828	0.0067	−0.6537	−0.5617

Note:
Significance at the 5% level is shown by *. Lag refers to the periods when the real effective exchange rate lagged behind the energy price index, whereas Lead refers to the periods when the real effective exchange rate leads the energy price index. Cross-correlation test statistic under the Levels column is based on the standardized residuals and is used to test for causality in mean. Cross-correlation test statistic under the Squares column is based on the squared standardized residuals and is used to test for causality in variance.

Figure 1 Standardized Residuals



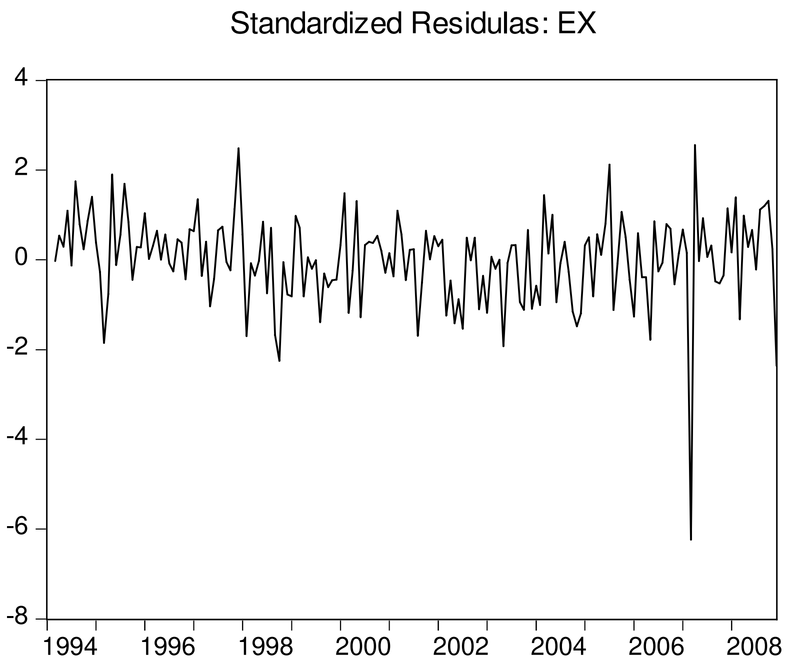


Figure 2 Squared Standardized Residuals