How Robust is the Connection between Exchange Rate Uncertainty and Tunisia's Exports?

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July 2014

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Abstract: This study addresses the robustness of the connection between exchange rate uncertainty and Tunisia's exports along several econometric methods, acknowledging the complexity of this relationship. To this end, we apply conventional methods (OLS by threshold, instrumental variable by threshold and ARDL Bounds testing approach) and new methods (evolutionary co-spectral analysis and wavelet decomposition). Both methods appear complementary. We find that the exchange rate uncertainty is always more detrimental to exports in the short term or when reaching certain thresholds. These outcomes clearly indicate that Tunisia was headed in the right direction and therefore the continuation of the policies already being pursued seem beneficial, while paying proper attention to short-run disturbances.

Keywords: Exchange rate uncertainty; exports; conventional methods; new methods.

JEL Codes: F14; C13; C4; C6.

1. Introduction

Since the breakdown of the Bretton Woods system of fixed exchange rates, the volatility of real exchange rate has attracted a substantial number of researchers. The questions of the relative importance of exchange rate volatility in explaining international trade performance still have no conclusive outcomes and no widely convincing answers.

Surprisingly, the huge amount of empirical literature on this field has failed to find firm evidence with respect to sign and significance. Various studies supported a negative and significant effect of exchange rate volatility on exports (Cushman 1986; Savvides 1992; Arize et al. 2000), and linked it to the imperfect exchange and trade markets and the very cost hedging. Others showed that higher exchange rate instability can act as an incentive to exporters to strength the flows of trade (Kiheung and Wooree 1996; McKenzie and Brooks 1997), especially when exporters are sufficiently risk-averse. Large strand of literature reached conclusion suggesting an ambiguous relationship between exchange rate uncertainty and exports (Chan and Wang 1985; Daly 1998 and McKenzie 1998). Coric and Pugh (2010) tackle the issue by meta-analyzing the empirical results of studies published between 1978 and 2003. They show that the connection between exchange rate volatility and trade is substantially not robust across the used models.

The majority of the previous researches use OLS method to assess the focal relationship and the standard deviation or standard GARCH model to determine volatility (Table A.1., Appendices). The OLS regression aims at finding the factors that can explain the international trade including exchange rate uncertainty across several countries. This type of assessment was criticized by Haile and Pugh (2011) for its perceived lack of robustness. An important problem with these researches is that usually authors do not establish an effective model able to detect a conclusive link between the two variables. Most of the used models, particularly OLS and VECM, do not robustly influence statistical significance of the estimated connection. This highlights the relevance of a properly conducted robustness analysis by using more parsimonious methods.

In order to reach a one-sided conclusion, a new look at the relationship is needed. Hence, we examine how different methods might affect exchange rate uncertainty-exports nexus with special reference to Tunisian case. The use of different econometric techniques may have different implications and provide conceptual background for the adequate econometric methods at economic level in relation particularly to the focal issue. To this end, we apply classical methods such as static and threshold models, dynamic methods like ARDL Bounds testing approach as well as other more original techniques such as evolutionary co-spectral analysis and wavelet decomposition.

The remainder of the article is laid out as follows. In Section 2, we briefly review previous empirical research into the relationship between exchange rate uncertainty on international trade. Section 3 describes the followed strategy estimation and discusses the results of our robustness analyses. Section 4 discusses the main findings and offers some economic implications. Section 5 concludes.

2. Brief literature survey

Since 1973 (the onset of fluctuating exchange ragime), there have been extensive empirical studies into exchange rate uncertainty's effect on international trade. While the literature gives no such accurate guidance on this link, mixed findings have been up to now found.

The majority of works put in evidence that exchange rate volatility inevitably depresses the exports by increasing the riskiness of trading activities and indirectly through its effect on the optimal allocation of resources (Savvides 1992; Arize 1996; Peridy 2003). Few studies suggested that higher exchange rate instability can enhance international trade depending to the degree of risk-aversion (Assery and Peel 1991; Kiheung and Wooree 1996). Others argue that exchange rate uncertainty affects ambiguously exports depending on aggregate exposure to currency risk (Viaene and de Vries 1992; Daly 1998).

Although investigation of this relationship has been widely addressed linearly, there are very limited studies that assess the impact of exchange rate instability on exports in a nonlinear dynamic framework (Baum et al. 2004; Zhang et al. 2006; Arize et al. 2008; Chit and Judge 2011; Hsu and Chiang 2011). While several models have been proposed to study this link, there is not a generally effective method. Table A.1 (Appendices) provides a detailed review. Clearly, studies that neglect nonlinearity are scarce and controversial.

In addition, we notice that all the studies that consider nonlinearities emphasize this link in developed countries, while analyses across developing countries are virtually absent or very limited. For instance, Bouoiyour and Selmi (2014 a) gauge empirically the exchange rate volatility-exports relationship in a nonlinear fashion for the case of Egypt. Their study relies on an optimal GARCH model chosen by information criteria among decomposed series on a scale-by-scale basis or wavelets. They show that the interaction between exchange rate uncertainty and exports depends sharply on time scales variation (i.e. nonlinear nexus) and slightly on the leverage effect (i.e. asymmetrical relationship). They also argue that the correlation between key variables is greater at low frequency than at high frequency.

Furthermore, when reviewing the existing researches, it is striking to observe the absence of works that take into account the possible excess of co-movements between exchange rate uncertainty and exports due to the possible excessive speculation that characterize commodity prices main sources of real exchange rate volatility. Accordingly, Bouoiyour and Selmi (2014 b) applied a new approach based on a time varying dynamic coherence function, called, evolutionary co-spectral analysis in order to analyze the dynamic interactions between changes in exchange rate and exports to GDP ratio in Russia. They find that coherence pattern differs over time.

Our contribution to this debate is to resolve these inconsistencies and to point a robust connection between exchange rate uncertainty and exports by examining whether there are substantial changes in the sign and the magnitude of this relationship when moving from conventional to new methods.

3. Estimation strategy

While econometric modeling often focuses on the average, in many cases it seems more pertinent to investigate the short, medium and long-run interaction dynamics between variables. It should also be noted that the conditional average can be, in some cases, difficult to be modeled due to the extreme values. In this case, the medium is very sensitive to outliers. For example, the estimation may be highly complicated if the studied time series present thresholds. Standard methods can be partially appropriate (model with two regimes). But this is not always the case. Thus, it is sometimes useful to decompose the variables under consideration into low time frequencies and high frequency bands, using wavelets.

Given that the link between exchange rate instability and international trade may differ depending to time horizons (Baum et al. 2004; Bouoiyour and Selmi 2014 a), it is crucial to analyze whether the interaction dynamic between the two key variables emerge in a precise time frame. As mentioned above, this paper tries to evaluate the robustness of the connection between the exchange rate uncertainty and Tunisian exports. To do so, we report on a series of models, ranging from OLS estimation, instrumental variable estimation, Hansen method, evolutionary co-spectral analysis and wavelet decomposition.

Before this, we should select an appropriate proxy of exchange rate uncertainty. Empirically, no single measure of volatility has dominated the literature. Hence, we choose two measures to represent exchange rate volatility, a moving average deviation and an optimal GARCH model selected among several GARCH extensions (Table A.2., Appendices). The best GARCH model has been selected using standard criteria such as the Akaike information criterion (AIC), the Bayesian (BIC) and Hannan-Quinn information criteria (HQ). Some loss functions are also been applied including root mean square error (RMSE), mean absolute error (MAE) and bias proportion (BP). These criteria are sufficient to judge the quality of estimation, because they allow to determine the optimal model in terms of historical evaluation (AIC, BIC, HQ) and in terms of forecasting performance (RMSE, BP). From Table-1, we show that the T-GARCH (Threshold GARCH) is the optimal model.

3.1.Classical methods

3.1.2. Static models

a. OLS estimation

The ordinary least squares (OLS) or linear least squares is a method for estimating the unknown parameters in a linear regression model. The OLS estimator is consistent when several hypotheses are respected such as exogeneity, serial correlation, multicollinearity and homoscedasticity, among others. To assess the relationship between exports performance and real exchange rate volatility, we start by OLS method, widely criticized in empirical economics due to the neglect of the problem of endogeneity (Dell'Arricia, 1999). The equation is expressed as follows:

$$Ln(XPR_t) = \omega + \beta Ln(VOLR_{t-1}) + \delta Ln(X_t) + \varepsilon_t \tag{1}$$

Where $Ln(XPR_t)$ presents the logarithm of real exports, $Ln(VOLR_{t-1})$ is the logarithm of real exchange rate volatility (we use here two volatility proxies: *VOLR1* determined from moving average deviation and *VOLR2* measured by T-GARCH chosen by information criteria and loss functions as optimal GARCH extension). $Ln(X_t)$ presents the logarithm of control variables, which may have a pulling role in exports. These variables are respectively the real effective exchange rate (*REER*)[1], national *GDP* and the *GDP* of main trade partners[2] and dummy variables presenting respectively the structural adjustment program implemented in 1987 (*SAP*) and the current economic crisis (*Crisis*) that takes value 0 before the second quarter 2008 and 1 otherwise; ε_t is the error term, supposed to be iid. All these variables are taken at time t unless the volatility is taken at time t-1[3].

The data are collected from Econstats™ and International Monetary Fund (IMF), covering the period spanning between 1975 :Q1 and 2009 :Q4. The time horizon depends on data availability. Figure-1 depicts the great evolution of exports and excessive fluctuations of real effective exchange rate in Tunisian case.

Before estimating the real exchange volatility-exports nexus, we begin by a preliminary analysis reported in Table-2. The results reveal that the coefficient of kurtosis appears inferior to 3 for all considered variables (except *VOLR1* and *VOLR2*), implying that the distribution is less flattened than the Gaussian distribution. The Skewness coefficient is positive for *REER* and its volatility, while it seems negative for *XPR, GDP* and *GDP**. This indicates that the asymmetrical distribution is plausible for the first ones and implausible for the second ones. The Jarque- Bera test revealed a high value for *VOLR1*, leading to reject the assumption of normality only for this variable.

The OLS results are reported in Table-3. We show that for the equations with both volatility measures, an appreciation of real effective exchange rate leads to a decrease in exports. We also find that the Tunisian *GDP* explain the competitiveness of exports almost

[1] The real effective exchange rate is used at certain date, i.e. a postive (negative) sign of *REER* corresponds to an appreciation (depreciation) of *REER* that increases (decreases) exports.

[2] For the *GDP* of importing countries, we used the weighted average of the main partners of Tunisia, where the European zone corresponds to the share of exports to the euro area, the weight for the American zone represents the share of exports to the American countries...For example, in 2009, the share of Europe in total export was more than 50% (29% for France, 18% for Italy, 11% for Germany, among others), the share of America counties was very limited, which amounts 4.8%. For more details about Tunisian trade partners, we can refer to CIA Factbook (https://www.cia.gov/library/publications/the-world-factbook/geos/tn.html) or to Observatory of Economic Complexity (http://atlas.media.mit.edu/profile/country/tun/).

[3] The volatility is used at date t-1 because exporters need a delay to adjust their prices.

equal to the *GDP** of their importing countries, which means that the domestic production succeeds to satisfy the foreign addressed demand. The impact of the structural adjustment program appears positive and significant in all considered cases, while the current economic crisis seems associated negatively to Tunisian exports.

Furthermore, the effect of exchange rate volatility determined by moving average deviation is positive and insignificant for all cases. Using the optimal GARCH model, the results change substantially when considering *SAP* and *Crisis* (Regression 8, Table-3). The sign of correlation between *VOLR2* and exports becomes negative and significant. The explanatory variables included in this regression explain 63% of the variation of exports.

Due to the possible reverse causation, OLS estimation is restrictive. We believe therefore that the application of instrumental variable estimation may be more appropriate.

b. Instrumental variable estimation

Instrumental variable methods allow consistent estimation when the explanatory variables are correlated with the error terms of a regression. Such correlation may occur when the dependent variable causes at least one reverse causation. In this situation, OLS generally produces biased and inconsistent estimates. The instrumental variables model asserts that the instruments affect the dependent variable only indirectly, through their correlations with the included endogenous variables. If an instrument exerts both direct and indirect effects on the dependent variable, the instrument is ineffective and it should be excluded. Nevertheless, if the considered instrumental variable affects significantly exchange rate volatility and has any influence on exports, consistent results may be obtained. For our case of study, to account for possible reverse causality between exchange rate uncertainty and exports, an instrument that affects exports only through its effect on real exchange rate volatility should be included. Following Clark et al. (2004), the standard deviation of the relative money supply can be considered as an instrumental variable. We chose this series because although relative money supply is highly correlated with real exchange rate uncertainty, it has no effect on international trade.

When we compare our findings reported in Table-4 with those reported in Table 5, we note that IV variable estimation differ considerably from those of OLS estimation in terms of significance. Adding the standard deviation of the relative money supply, we show the effect of exchange rate uncertainty on exports stills positive, but becomes significant (compared to OLS results) for the two measures of volatility under consideration. Using different diagnostic tests, we show that the volatility of relative money supply may be considered as a valid instrument for real effective exchange rate uncertainty. We initially conduct the Sargan–Hansen J-statistic test to verify the validity of our instrument[4]. By carrying out this test, the joint null hypothesis is not rejected for almost all cases (except regression 3). Then, we perform a test suggested by Stock and Yogo (2005) to identify if there exist a problem of weak instruments. According to Chit et al. (2010), if the instruments appear weak, the IV estimators would be biased. To verify this evidence, we apply Cragg–Donald F-statistic test[5]. For all the considered cases (all the equations, Table-4), we show that the standard deviation of money supply serves as effective instrument for our case of study. The results appear more robust since the sign of exchange rate volatility's effect on exports remain positive and significant for all cases (with and without *SAP*, with and without *Crisis*, with or without both *SAP* and *Crisis*).

However, exports may change over time or between regimes due to several reasons such as external shocks including ups and downs oil price fluctuations and political instability. Given these factors, we should estimate the relationship between exchange rate uncertainty and exports performance under a nonlinear fashion to show whether there are changes in magnitude and sign of the focal relationship. To this end, Hansen method has been widely used empirically to capture accurately the thresholds at which the connection between key variables under consideration changes.

3.1.2. Threshold models

While such analyses clearly illustrate the implications of excessive exchange rate volatility, they do not tell us a lot about the possible nonlinear relationship between the exchange rate uncertainty and exports performance. The linear modeling of an economic relationship imposes the same parameters over time. However, a change in the underlying nexus between the key series from one state to another can be expressed as a change in the structural parameters of the followed model (Equation (1)). There is a substantial literature

[4] The joint null hypothesis of the test is that the concerned instrument is valid when it is uncorrelated with the error term and when the instrument is correctly excluded from the regressions.
[5] If this F-statistic value is greater than the critical value provided by Stock and Yogo (2005), the null hypothesis of weak instruments can be rejected.

dealing with threshold models. Hansen (1999), for example, developed a statistical theory for threshold estimation in the regression context. This method may allow us to see whether there exists a level of exchange rate volatility at which the performance of Tunisian exports differs. By incorporating thresholds in the equation (1), the Hansen (1999)'s regression can be expressed as follows:

$$Ln(XPR_t) = \omega' + \beta' Ln(VOLR_{t-1}) + \lambda^- Ln(VOLR_{t-1}).I(VOLR < \tau) + \lambda^+ Ln(VOLR_{t-1}).I(VOLR \geq \tau) + \delta' Ln(X_t) + \xi_t \quad (2)$$

Where I takes the value 1 if *VOLR* is below a given threshold and 0 otherwise; the rest of variables is definded as above. ξ_t is supposed to be i.i.d.

To determine if there are thresholds at which the link between exchange rate uncertainty and exports changes, we follow three main steps: First, the equation (2) is estimated for different values of real exchange rate volatility. Second, we select the value that minimises the sum of squared residuals. Thirdly, we carry out a likelihood ratio statistic, which scale the variance of residuals to detect the estimated threshold. This method allows us to identify properly the real exchange rate uncertainty at which exports becomes more threatened. Our methodology avoids the arbitrariness of choosing thresholds.

Table 5 reports different levels of thresholds obtained from Hansen method. These levels obviously vary depending on the variables included in the estimation and the method used for volatility measurement.

We initially apply this method for OLS estimation. We show that the thresholds change intensely depending to the inclusion of structural adjustment program and the current economic crisis (Table-6). The OLS findings by thresholds reveal that the link between real exchange rate volatility and real exports is sharply nonlinear. The effects of the rest of explanatory variables (*REER, GDP and GDP**) do not change and are therefore independent of the detected thresholds. The effect of *VOLR* on exports appears significantly positive and stronger as high as 50.37% and negative as low 38.87% when considering moving average deviation as measure of volatility (Regression (4), Table-6). This means that the volatility of *REER* has a significantly nonlinear impact on exports, specifically when including *SAP* and *Crisis* simultaneously in the estimated equation. Inversely when using optimal GARCH as measure of volatility, we find that this effect is negative and significant as high as 73.05% and positive as low as 61.21% (Regression (7), Table-6). This means that the nonlinearity in the connection between the two key variables is conditional on the current economic crisis effect.

Similarly, when applying Hansen method for the instrumental variable estimation, we clearly note that the thresholds change considerably depending to the inclusion of structural adjustment program and the current economic crisis in the estimated equations (Table-7). Table-8 reports the results of instrumental variable estimation by thresholds. The effect of *VOLR* on exports depends strongly on the detected thresholds. It appears highly negative and significant as high as 35.68% and significantly positive as low 26.77% when using moving average deviation as volatility measure (Regression (4), Table-8). We have similar results in terms of sign when using optimal GARCH model as volatility proxy, inversely to OLS estimates. Indeed, we find that this effect is negative and significant as high as 50.73% and positive as low as 38.87% (Regression (7), Table-8). The joint null hypothesis by thresholds (the Sargan–Hansen J-statistic test) is not rejected for all cases under consideration. Additionally, the null hypothesis of weak instruments or Cragg–Donald F-statistic test can be rejected for all regressions, since the associated F-statistic values are greater than the critical values by thresholds provided by Stock and Yogo (2005).

The different methods used above show a great instability of the relationship between exchange rate volatility and Tunisian exports. Indeed, the volatility has no impact when the OLS estimation is applied, while it has a positive and significant impact when the instrumental variable specification is used. The connection between both series appears sharply nonlinear when carrying out Hansen method. The OLS and the instrumental variable by threshold results seem consistent and intuitive. The real exchange rate volatility is detrimental to exports when exceeding a certain threshold. The last outcome calls for an application of dynamic model to see if this relationship remains stable (in particular in terms of sign) when moving from short-run to long-run analysis.

3.1.3. Dynamic models

The ARDL approach proposed by Pesaran and Shin (1999) allows us to see whether there are long-run relationships beteween a group of time-series, some of which may be stationary, while others are not. The ARDL method has various advantages compared to other cointegration methods: Firstly, the time series are assumed to be endogenous. Secondly, it obviates the need to classify the time series into I(0) or I(1) as Johansen cointegration. Thirdly, it allows us to assess simultanuously the short-run and the long-run coefficients associated to the variables under consideration.

This paper applies this method to assess the short-run and the long-run connection between real exports and real exchange rate volatility by incorporating other explanatory variables including the domestic GDP and the GDP of the main trade partners and two dummies corresponding respectively to the structural adjustment program and the current economic crisis. To do so, we apply bounds test procedure by modelling the long-run equation (1) as a general vector autoregressive model of order p (the maximum lag-order selected from various critera including Akaike criterion (AIC), Schwartcz criterion (SC), among others).

$$Ln(XPR_t) = \kappa + \beta t + \sum_{i=1}^{p} \phi_i Ln(XPR)_{t-i} + \sum_{j=0}^{q} \eta_j Ln(X)_{t-j} + \upsilon_t \quad (3)$$

Where κ denotes a vector of intercepts, β represents a vector of trend coefficients, XPR : the real exports; XPR : denotes the explanatory variables which are respectively the real effective exchange rate (*REER*), real exchange rate volatility (*VOLR*) national *GDP* and the *GDP* of the main trade partners or *GDP**; and υ_t the term error. Ultimately, the following VECM is derived:

$$\Delta Ln(XPR_t) = \kappa + \beta t + \Pi_i Ln(XPR)_{t-1} \sum_{i=1}^{p} \Gamma_{ii} \Delta Ln(XPR)_{t-i} + \sum_{j=0}^{q} \Gamma_{jt} \Delta Ln(X)_{t-j} + \Pi_j Ln(X)_{t-j} + \upsilon'_t \quad (4)$$

Where $\Pi_i = I + \sum_{i=1}^{p} \psi_i$, $\Pi_j = I + \sum_{j=0}^{q} \psi_j$ and $\Gamma_i = -\sum_{i=1}^{p} \psi_i$, $\Gamma_j = -\sum_{j=0}^{q} \psi_j$, which contain respectively the long-run multipliers and the short-run dynamic coefficients of the VECM.

To check if there is a cointegration, we should refer to the critical bounds previously tabulated by Pesaran et al. (2001)[6].To show whether the considered ARDL approach to cointegration is stable, we can apply various diagnostic tests such as the adjustment R-

[6] There is a cointegration among variables if the calculated F-statistic is more than upper critical bound. If the lower bound is superior to the computed F-statistic, we accept the null hypothesis of no cointegration, while if the F-statistic seems between lower and upper critical bounds the cointegration is inconclusive

squared, the standard error regression, the Breush-Godfrey-serial correlation and Ramsey Reset test.

Before proceeding the ARDL estimation, we start by determining the degree of integration of variables. Hence, we carry out Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. We worthy notice, from Table-9, that the variables are integrated either at level or first difference (I(0) and I(1)). This implies that the ARDL approach can be employed to test the cointegration hypothesis among concerned variables.

When using moving average deviation as measure of exchange rate uncertainty, the F-statistics appear between lower and upper bounds at level 1% for all the regressions (Table-10), except regression (2) with value superior to the upper bound. This means that the cointegration is inconclusive for regressions (1), (3) and (4), while it exists when including the structural adjustment program. When using optimal GARCH model as volatility measure, we show that the F-statistics values exceed the upper bound at the 1% significance level for the model for all regressions except the estimated equation (7) with insignificant F-statistic (p-value=0.1206), implying that there is evidence of a long-run relationship among variables at this level of significance or greater.

In the short run, the real effective exchange rate affects negatively and significantly the exports (Table-11). *GDP* and *GDP** increase the exports either with or without *SAP* and *Crisis*. The effects of structural adjustment program and the current crisis are also statistically significant for all regressions. Seemingly, the impact of real exchange rate uncertainty on exports is positive and significant in all cases either using the moving average deviation or optimal GARCH model as measures of volatility. In the long-run, the majority of these coefficients appear statistically insignificant. The value of *ECT* is negative and statistically significant in all cases, but it differs depending to the proxy used to determine volatility.

When using moving average deviation, the deviation in the short-run is corrected by 13.74% towards the long-run equilibrium (without *SAP* and *Crisis*, Regression (1), Table-11) and becomes less important (13.08%) when considering *SAP* (Regression (2), Table-11) and much more important (18.27%) when accounting for the current economic crisis (Regression (3), Table-11). This indicates that *SAP* mitigates the speed of adjustment towards long run equilibrium path, while the *Crisis* increases it. The R-adjusted value shows that the Tunisia's exports are 38.16% explained by real effective exchange rate, its volatility, the *GDP* and the

*GDP**. This value increases slightly when including *SAP* (Regression (2)), it becomes 40.11%.

When using the optimal GARCH model as measure of volatility, the deviation in the short-run is corrected by about 16.50% towards the long-run equilibrium (without *SAP* and *Crisis*, Regression (1), Table-11). It appears less intense when taking into account the structural adjustment program, which amounts 14.87%. As the « naïve » model, the deviation toward the long-run equilibrium is stronger when including the Crisis, i.e. it becomes 16.90%. This confirms that *SAP* reduces the speed of adjustment. The R-adjusted value shows that the *XPR* are 40.18% explained by *REER*, *VOLR*, the *GDP* and the *GDP**. This increases slightly when including *SAP* (42.29%) and decreases when considering the *Crisis* (40.03%), (Regression (2) and (3), Table-11). The diagnostic tests also indicate that there is no evidence of serial correlation (the Breush-Godfrey serial correlation (*LM*)) and the well construction of the short-run model except some cases (the Ramsey reset test statistic (*Reset*)), which highlights the adequacy of ARDL approach and the efficience of ARDL parameters.

Nevertheless, these results seem vulnerable because ARDL bounds test is unable to detect possible structural breaks stemming in the variables. It neglects possible nonlinearities in the focal relationship. This drawback highlights the need to use more sophisticated methods that take into account the time varying dynamic in time series such as evolutionary co-spectral analysis and wavelet decomposition.

Before going further into the analysis, it is important to compare the results of different methods used to date while being careful because the logic of each methodology is different. The results obtained by the method of IV Hansen put in evidence that the exchange rate uncertainty (our variable of interest) impacts differently exports, depending on the threshold. If the threshold is low, this relationship is positive; otherwise it is negative. In the case of ARDL, volatility has a negative and significant short-run impact on exports (but at a significance level of 10%). In the long-term, this relationship is not significant (except in one case). This means that Tunisian authorities relatively successful to control currency movements. Volatility cannot always be regarded as detrimental contributor. It has harmful effects on Tunisia'exports only in the short term or when it reaches intolerable levels.

3.2. New methods

3.2.1. Evolutionary co-spectral analysis

Given that the relationship between exchange rate uncertainty and exports may vary over time (Bouoiyour and Selmi, 2014 a), it seems interesting to explore whether the co-movements between these variables emerge in a given time frame (i.e. short, medium or long-run interdependence). The procedure of the co-spectral approach considers a bivariate continuous parameter process $\{X(t), Y(t)\}$, in which each component is an oscillatory process (Priestley and Tong, 1973).

$$X(t) = \int_{-\infty}^{+\infty} A_t(w_1) e^{iwt} dZ_x(w_1) \tag{5}$$

$$Y(t) = \int_{-\infty}^{+\infty} A_{t,y}(w_2) e^{iwt} dZ_y(w_2) \tag{6}$$

$$E\left[dZ_x(w_1) dZ_x^*(w_2)\right] = E\left[dZ_y(w_1) dZ_y^*(w_2)\right]; w_1 = w_2 \tag{7}$$

$$E\left[dZ_x(w_1) dZ_y^*(w_1)\right] = d\mu_{xy}(w) \tag{8}$$

Where $(.)^*$ denotes the conjugal function of $(.)$.

Let $dH_{t,XY}(w)$ denotes a reduced definition of the cross-spectrum (Priestley, 1965).

$$dH_{t,XY}(w) = E\left[A_{t,X}(w) dZ_X(w) A_{t,Y}^*(w) dZ_Y^*(w)\right] \tag{9}$$

By virtue of the Caushy-Schwarz equality, we ultimately obtain:

$$\left|dH_{t,XY}(w)\right|^2 \leq dH_{t,XX}(w) dH_{t,YY}(w) \tag{10}$$

Next and with respect to the Lebesgue measure, we can write for each *t*:

$$dH_{t,XY}(w) = h_{t,XY}(w) dw \tag{11}$$

Where $h_{t,XY}(w)dw$ is termed as the evolutionary co-spectral function.

Still the coherence function, which is defined as the modulus of the correlation coefficient between $dZ_X(w)$ and $dZ_Y(w)$, based essentially on the estimation of the co-spectral function between two process $\{X(t)\}$ and $\{Y(t)\}$.

$$C_{t,XY}(w) = \frac{\left|h_{t,XY}(w)\right|}{\left\{h_{t,XX}(w) h_{t,YY}(w)\right\}^{1/2}} \tag{12}$$

Lastly, to apply the evolutionary co-spectral function, we retain three filters reflecting the short-term $(\pi/20)$, the medium-term $(4\pi/20)$ and the long-run interdependence $(10\pi/20)$.

Our empirical assessment resulting from the co-spectral approach as computed from Equation (12) between real exchange rate instability (moving average deviation) and Tunisian exports is presented in Figure-3. We clearly observe a time varying dynamic coherence between the pair time series under consideration. This graph indicates a divergence between the short-run, the medium-run and the long-run interdependence. The focal linkage appears strong in the short-run and less important in the medium and the long-run (right side, Figure-3). The interdependence reaches 30% in the short-run and does not exceed 20% in the medium and long terms.

Using optimal GARCH model, the time varying coherence seems stronger than when using moving average deviation. In the short-run, the interdependence between the two key variables amounts 80%, while it reaches 40% in the medium term and 20% in the long-run. This means that the instability of exchange rate plays an important role to explain exports in the short-run and then dissipates gradually.

The evolutionary co-spectral outcomes seem important but need to be checked. Thus, to see whether the relationship between real exchange rate uncertainty and exports performance differs really depending to specific time horizons, wavelet decomposition may be an appropriate technique able to assess the scale-by-scale connection between variables.

3.2.2. Wavelet method

Wavelet decomposition has been applied quite successfully to large amount data and to extract the information relevant to nonlinear interaction (Tiwari et al. 2013). The wavelet approach corresponds to oscillating functions that decay rapidly with time. It exhibits the time contribution of the different frequencies to the signal, to obtain then temporal frequency dependence and scale-by scale dynamic interaction dynamics between variables. This method allows us to extract the various time scales driving any macroeconomic variable in the time domain. This can reflect structural changes that can happen at a well-defined time scales. This approach is based on the mother wavelet denoted $\psi(t)$:

$$\psi_{u,s} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{13}$$

Where u and s are the time location and frequency ranges, respectively, and $\frac{1}{\sqrt{s}}$ indicates that the norm of $\psi_{u,s}(t)$ is equal to unity.

Unlike time domain, wavelets can identify which frequencies are present in the data at any given point in time. Ultimately, we obtain the wavelet representation of the function *Y (t)*:

$$Y(t) = \lfloor w_1(t), v_1(t), ..., w_j(t), v_j(t) \rfloor \tag{14}$$

Where $w_1(t)$ and $v_1(t)$ are respectively wavelet high frequency and wavelet low frequency.

Considering low and high scales, we can differentiate between time horizons for decision-making. With this decomposition to various time frequencies, the problem of temporal aggregation bias can be neglected. The wavelet analysis may provide a fresh look into the connection between exchange rate uncertainty and Tunisian exports by assessing it under different and precise time periods that may help policy makers to deal with external shocks. To this end, we decompose the time domain D (all returns) into six frequency bands, which are respectively $D1: 2-4Q$, $D2: 4-8Q$, $D3: 8-16Q$, $D4: 16-32Q$, $D5: 32-64Q$, $D6 > 64Q$. Figure-4 depicts the great movements of considered variables over time depending to scales variation.

The scale-by-scale findings are reported in Table-12. It is striking to note that the effect of real exchange rate volatility on exports depends to time frequency variation in terms of sign, while the rest of explanatory variables move frequently in terms of magnitude. Using moving average deviation as measure of volatility, the relationship between exchange rate uncertainty and exports appears positive and significant at time domain, insignificant at low frequencies (high time scales) and significantly negative at high ones (low time scales). When using the optimal GARCH model, the results change slightly in terms of sign (except the *VOLR*-real exports connection at D3), and substantially in terms of magnitude. Clearly, the coefficients for all the concerned variables seem stronger when applying the optimal GARCH than when considering the moving average deviation. For example, at time domain, an increase by 10% in *VOLR* leads to an increase by 0.06 in exports when using the first volatility measure compared to 0.09% when using the second one.

The results from wavelet decomposition confirm those of time varying coherence or co-spectral analysis. Indeed, the connection between exchange rate instability and Tunisia' exports changes intensely in terms of sign and magnitude when moving from low to high time scales. Additionally, this effect appears negative and more significant at low time scales than at high ones. In sum, the wavelet analysis gives more intuitive findings with more consequential conclusions that may have important economic implications.

4. Discussion and economic implications

Empirical studies on the connection between exchange rate uncertainty and exports performance covering developing countries and a wide range of techniques have showed mixed results. This research has attempted to re-evaluate the robustness of this relationship using various methods (conventional versus original), with special reference to a relatively small North African country (Tunisia). In global context, the period from 1975 to 2009 (the period of study) marked a turning point in economic, cyclical and structural policies for Tunisia. The conventional and original methods applied to regress Tunisia's exports on its main determinants reveal interesting results.

By estimating various equations (with and without inclusion of dummy variables presenting the structural adjustment program and the current economic crisis), we find that the sign of the correlation between exports and the different explanatory variables (*REER, GDP, GDP*, SAP, Crisis,* except *VOLR*) are stable.

A depreciation in real effective exchange rate leads to a decrease in exports. Obviously, depreciation lowers the foreign currency price of exports and expands the volume of exports and then export revenue in domestic currency. These results are in accordance with other findings for the region. Véganzonès-Varoudakis and Nabli (2002) and Sekkat (2012) revealed similar effects of real effective exchange rate.

The domestic economic growth as well as the GDP of main trade partners explain positively and almost equally the exports performance (Nabli et al. 2004), implying that Tunisian production effectively satisfied the foreign demand. Unsurprisingly, the World Trade Organization agreement signed in 1995 with the European Union (the main exports partner for Tunisia) has facilitated the access to developing markets. This agreement has as main goals to enhance the depth of the foreign exchange market and to limit the destabilizing effects of exogenous shocks. This enlarging of the market via exports has been accompanied with foreign technologies to improve the innovativeness of exporting firms (Rahmouni et al. 2010). Normally, the more open economic environment, the geographical diversification and the orientation towards external markets should increase the external demand (Narayanan, 2001). The creation of large markets via trade liberalization permits low-cost producers to increase their output well beyond the domestic market.

The effect of structural adjustment program seems positive. This finding is highly expected because *SAP* is based on the assumption that the stabilization and liberalization (internal and external) have the virtue to improve the functioning of competitive markets and to enhance trade performance (Dropsy and Grand, 2008). But this must be done according to the rhythm of each country. Uncontrolled liberalization can also have negative consequences. It seems that Tunisia has managed to do so gradually[7]. The effect of recent economic crisis seems associated negatively to Tunisian exports, mainly due to the substantial decrease in foreign demand especially from Europe main partner of Tunisia. This last result is in line with Mouley (2013), suggesting that the current crisis has produced negative spillover effects, highlighting therefore the incapability of Tunisia to seriously and effectively address the possible harmful impacts on the whole economy.

The conventional methods (OLS by threshold, instrumental variable by threshold and ARDL Bounds testing approach) show that the exchange rate uncertainty is ultimately more detrimental to trade performance only in the short-run or when reaching certain thresholds. New methods (evolutionary co-spectral analysis and wavelet decomposition) confirm these findings. Standard and “sophisticated” methods are therefore sharply complementary. Nevertheless, wavelet analysis appears to be more accurate and most convenient. Unsurprisingly, the decomposition of series into various scales allow us to appropriately assess the time varying dynamic between exchange rate uncertainty and exports that may occur at any point of time. These results reveal that Tunisia was headed in the right direction and thus the continuation of the policies already being pursued seem beneficial for it, while paying proper attention to short-run disturbances.

This reflects that the gradually transition towards inflation targeting, the drastic price stabilization efforts and the adoption of crawling peg or managed float have succeeded, at least partially, to react effectively to the emergence of China and the end of the Multi-Fiber Agreement in 2005. Furthermore, increasingly integrating with the global economy makes Tunisia better equipped to cope with external shocks. The deep of market integration has helped policy makers to act appropriately to the sizeable volatility of commodity price main source of exchange rate uncertainty and makes then Tunisia (David et al. 2011).

Despite these good signals, policy makers and regulators need to carefully consider the costs of possible speculative attacks and the co-movements between primary commodity and

[7] We do not address the problem of the Arab Spring. It is beyond the scope of this paper.

exchange rate markets. The fact that Tunisia incorporates imperfect factor markets functioning (Greenway et al. 1998) and the lack of efficient market instruments to deal with shocks, are likely to impede adjustment and dilute the benefits of trade reforms. Furthermore, the narrowness of exchange market and the specialization in low-cost products may expand the vulnerability to negative shocks (Hausmann et al. (2007), Arezki et al. (2011) and Bouoiyour and Selmi (2014 c). To be effective, specific actions should be undertaken to mitigate the effects of external shocks main drivers of the excessive real exchange rate volatility (Bouoiyour and Selmi 2014 a). This may be reached by fostering diversification and proactive exchange rate measures, by adopting new policies aimed at ensuring business groupings and integration into international production, by giving appropriate priority to firm innovativeness. The achievement of these reforms seriously needs more effective institutions and well-regulated financial system.

5. Conclusion

This study attempts to re-examine the effect of exchange rate uncertainty on exports along several econometric methods, acknowledging the complexity of this relationship. To this end, we carry out conventional methods (OLS and instrumental variable estimation by thresholds and ARDL Bounds testing approach) and new methods (evolutionary co-spectral analysis and wavelet decomposition).

We can summarize our main results as follows:

(i) Using OLS method, we show that there is a positive and insignificant impact of exchange rate uncertainty on exports for all cases, except one where the effect is negative but stills insignificant.

i) The use of instrumental variable estimation shows a positive and significant link between exchange rate volatility and exports.

ii) The OLS and instrumental variable estimates by thresholds (based on Hansen method) indicate that the focal relationship is negative or positive depending to the thresholds.

iii) The use of ARDL approach to cointegration shows a significant short-run relationship between exchange rate volatility and exports, while it seems insignificant in the long-run.

iv) From evolutionary co-spectral analysis, we find that the exchange rate uncertainty's effect on exports is stronger in the short-run than in the long-run.

v) Wavelet analysis indicates that the studied link is negative and significant at time domain and at high frequencies (low time scales).

vi) The use of optimal GARCH model exhibits more sizeable volatility than the moving average deviation, but this have a marginal effect on the sign of the considered relationship.

vii) The sign of explanatory variables'coefficients remain stable across estimations, implying the robustness of our results.

These findings appear complementary. They all show the utmost importance to account for nonlinearity when assessing the connection between exchange rate uncertainty and exports. With special reference to Tunisian case, the exchange rate uncertainty cannot always be regarded as detrimental contributor, since it has only a significant effect in the short term or when it reaches intolerable levels. In the long-run, this effect dissipates or becomes insignificant. This highlights the beneficial impact of the pursued price stabilization efforts. But to be effective and to act appropriately to short-run disturbances, these efforts should seriously be consolidated through drastic actions aimed at improving the institutional quality and developing the financial system.

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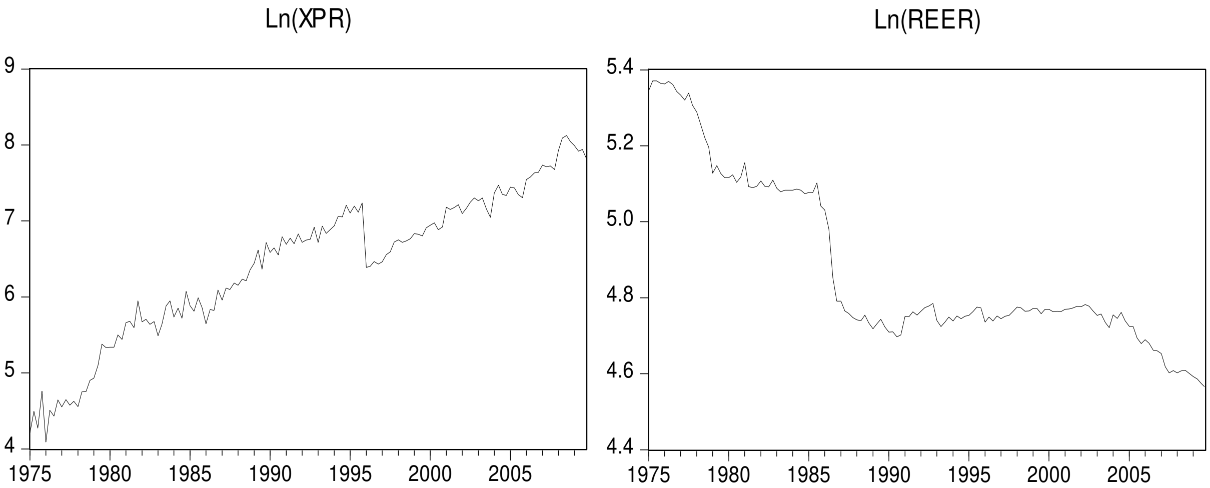
Table 1. The effectiveness of GARCH extensions (the optimal GARCH model)

	Information criteria			Loss functions		
	AIC	BIC	HQ	RMSE	MAE	BP
GARCH	-3.6374	-3.2591	-3.4982	0.2651	0.2189	0.00181
GARCH-M	-2.8937	-2.6694	-2.8016	0.2913	0.2405	0.00187
C-GARCH	-2.1049	-2.0087	-2.0695	0.3385	0.3019	0.00253
I-GARCH	-3.8096	-3.4119	-3.6724	0.2218	0.1898	0.00091
A-GARCH	-3.3697	-3.2837	-3.3619	0.2946	0.2824	0.00134
T-GARCH	-5.0982	-4.6355	-4.8931	0.1917	0.1904	0.00076
E-GARCH	-3.6134	-3.2439	-3.4528	0.2873	0.2617	0.00195
P-GARCH	-4.5619	-4.3821	-4.4942	0.2234	0.2160	0.00107

Notes: AIC : Akaike information criterion ; BIC : Bayesian information criterion ; HQ : Hannan-Quinn criterion ; RMSE : Root Mean Square Error ; MAE : Mean Absolute Error ; BP : Bias proportion; For details about GARCH extensions under consideration (GARCH, GARCH-M, C-GARCH,…, P-GARCH), see Table A.2. (Appendices).

Figure 1. Evolution of exports and real effective exchange rate



Source: Econstats™ and International Monetary Fund.

Table 2. Descriptive statistics

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Ln(XPR)	5.077935	5.098035	0.544605	-0.099074	1.621023	2.830392
Ln(REER)	5.206114	5.147494	0.114801	0.351566	1.353652	4.673751
Ln(VOLR1)	0.012043	0.009914	0.011256	1.584277	5.675473	25.08026
Ln(VOLR2)	-7.892319	-7.91784	0.679328	0.860433	3.770401	5.184229
Ln(GDP)	5.155886	5.165072	0.028590	-0.570514	2.404481	2.415855
Ln (GDP)*	4.062880	4.087320	0.071799	-0.519778	2.063275	2.855605

Notes: *VOLR 1*: the volatility's proxy is the moving average deviation of real exchange rate; *VOLR 2*: the volatility's proxy is the optimal GARCH model chosen among different GARCH extensions (see Table A.2, Appendices); Source: Econstats™ and International Monetary Fund.

Table 3. OLS estimation

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C	9.0112**	9.8763***	10.24***	10.68***	10.12***	10.1886**	10.41***	10.719***
	(2.6435)	(3.4975)	(4.0325)	(3.8745)	(3.2179)	(2.9413)	(4.2256)	(3.9169)
Ln(*REER*)	-1.4218*	-1.9773***	-1.703**	-2.64***	-1.669**	-1.8854***	-1.82***	-2.6347***
	(-1.8765)	(-8.0662)	(-5.9168)	(-10.065)	(-8.0131)	(-7.8107)	(-7.6888)	(-10.2114)
Ln(*VOLR*)	-0.0561	0.7654	0.5978	0.8896	-0.0168	0.6518	0.6311	-0.0270*
	(-0.8791)	(0.8321)	(0.4562)	(0.5891)	(-0.8243)	(0.8941)	(0.7028)	(-1.699)
Ln(*GDP*)	0.7792**	0.8731*	0.693***	0.6835*	0.810***	0.7699**	-0.782**	0.8852*
	(2.4153)	(1.9422)	(3.2056)	(1.6875)	(3.1579)	(2.1013)	(2.4156)	(1.6943)
Ln(*GDP**)	0.5698**	0.6649***	0.7234**	0.659***	0.6481**	0.7699**	0.698***	0.6821***
	(2.3665)	(4.7013)	(2.3159)	(5.4101)	(2.2913)	(2.1013)	(3.5120)	(5.0308)
SAP	-	0.2234*	-	0.1902**	-	0.6284**	-	0.1824*
		(1.8055)		(2.0834)		(3.5942)		(1.9963)
Crisis	-	-	-0.416**	-0.47***	-	-	-0.36***	-0.458***
			(-3.8921)	(-4.6811)			(-4.1372)	(-4.6369)
R^2	0.41	0.49	0.51	0.58	0.43	0.55	0.55	0.63

Notes: ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Statistics are robust to heteroscedasticity.

Table 4. Instrumental variable estimation

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C	7.6643**	10.08***	10.25***	8.79***	7.98***	9.765***	10.13***	10.174***
	(6.0412)	(3.8921)	(4.1366)	(4.930)	(4.3725)	(3.6089)	(5.0261)	(6.2697)
Ln(*REER*)	-1.876**	-2.1269***	-2.4127*	-2.30***	-2.07***	-2.1336**	-2.256**	-2.592***
	(-2.8915)	(-8.7955)	(61.986)	(-12.737)	(-4.6638)	(-3.8779)	(-2.3621)	(-17.418)
Ln(*VOLR*)	0.2315*	0.1234*	0.2516**	0.3763**	0.0904*	0.0094**	0.0315**	0.0295*
	(1.6274)	(1.9863)	(2.5011)	(2.3034)	(1.6681)	(2.1582)	(2.0736)	(1.7448)
Ln(*GDP*)	0.6985*	0.7452*	0.6392**	0.7873**	0.6378*	0.7014*	0.6638**	0.7125**
	(1.7033)	(1.6920)	(2.4017)	(2.3558)	(1.6209)	(1.8653)	(1.9947)	(2.1549)
Ln(*GDP**)	0.6597*	0.6188**	0.4987**	0.576***	0.5964**	0.4991*	0.536***	0.6728***
	(1.6598)	(2.0453)	(2.0995)	(9.2538)	(2.1559)	(1.6782)	(6.7422)	(10.5235)
SAP	-	0.1866***	-	0.269***	-	0.1810***	-	0.2456***
		(3.4211)		(4.9473)		(3.0975)		(5.5175)
Crisis	-	-	-0.372**	-0.49***	-	-	-0.283**	-0.7168***
			(-2.6829)	(-7.9735)			(-2.9784)	(-12.422)
Cragg Donald test	28.762	40.229	39.924	49.162	31.157	46.018	41.683	52.049
J-statistic test	0.029	0.037	0.051	0.042	0.040	0.044	0.037	0.041
	[.1875]	[.4619]	[.0568]	[.2581]	[.1276]	[.1582]	[.1249]	[.1083]

Notes: ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Estimates are efficient for arbitrary heteroscedasticity and autocorrelation. Statistics are robust to heteroscedasticity and autocorrelation. Cragg–Donald F-statistic tests for weak identification. Critical values are for Cragg-Donald F statistic and i.i.d. errors. Ten per cent and 15 per cent critical value of Stock–Yogo weak idetification test are 17.02 and 13.85, respectively; [.]: p-value.

Table 5. OLS estimation: The thresholds from Hansen method

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
τ_{max}	49.80	45.78	52.19	50.73	68.54	66.09	73.05	72.11
	[.0002]	[.0000]	[.0016]	[.0042]	[.0026]	[.0012]	[.0009]	[.0017]
τ_{min}	36.74	32.98	40.12	38.87	59.05	55.92	61.21	59.46
	[.0000]	[.0007]	[.0003]	[.0002]	[.0004]	[.0002]	[.0000]	[.0001]

Notes: τ_{max} : Maximum LR-Fstatistic; τ_{min} : Minimum LR-Fstatistic; [.]: p-values.

Table 6. OLS estimation of a threshold model (Hansen method)

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	τ_{max} = 49.8	τ_{max} = 45.7	τ_{max} = 52.19	τ_{max} = 50.73	τ_{max} = 68.54	τ_{max} = 66.09	τ_{max} = 73.05	τ_{max} = 72.1
C	9.371***	10.1***	13.125***	17.32***	16.32***	11.076***	11.352***	12.10***
	(21.560)	(13.119)	(9.0827)	(12.006)	(8.7205)	(6.9185)	(9.1826)	(9.8466)
$Ln(REE$	-2.77***	-2.345**	-2.7691**	-2.61***	-3.22***	-2.8963**	-3.1048***	-3.371**
	(-11.949)	(-2.4977)	(-2.8073)	(-3.0179)	(-7.9588)	(-2.1994)	(-6.5210)	(-2.9514)
$Ln(VOLR)$	0.0293*	-0.0324*	0.0572**	0.0638*	-0.014**	-0.0143*	-0.0181**	-0.0165*
	(1.9383)	(-1.8253)	(2.0143)	(1.9240)	(-2.1409)	(-1.5992)	(-2.4567)	(-1.6487)
$Ln(GDP)$	0.8241*	0.6799**	0.7150*	0.6999**	0.4962**	0.6623**	0.6974**	0.6721*
	(1.8937)	(2.5211)	(1.6317)	(2.4156)	(2.9913)	(2.0169)	(2.1063)	(1.9325)
$Ln(GDP^*)$	0.16***	0.32***	0.3517**	0.3286**	0.108***	0.1974***	0.2340**	0.199***
	(9.1067)	(6.7138)	(2.3294)	(2.9075)	(7.5735)	(4.1550)	(2.0151)	(3.7104)
SAP	-	0.2355*	-	0.1928*	-	0.2914**	-	0.2015**
		(1.8974)		(1.6739)		(2.2589)		(2.2268)
$Crisis$	-	-	-0.1610*	-0.138**	-	-	-0.1457*	-0.1185*
			(-1.5988)	(-2.0791)			(-1.6643)	(-1.6093)
	0.63	0.69	0.64	0.69	0.76	0.73	0.79	0.72
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	τ_{min} = 36.74	τ_{min} = 32.98	τ_{min} = 40.12	τ_{min} = 38.87	τ_{min} = 59.05	τ_{min} = 55.92	τ_{min} = 61.21	τ_{min} = 59.46
C	13.29***	10.87***	12.041***	11.53***	11.85***	12.135***	12.4469**	13.00***
	(6.9951)	(5.1964)	(8.1072)	(6.1286)	(5.0610)	(7.4206)	(2.8815)	(5.7692)
$Ln(REER)$	-2.75***	-2.71***	-2.9083***	-2.78***	-3.17***	-2.0976***	-3.1865***	-2.66***
	(-12.525)	(-9.7522)	(-12.009)	(-10.356)	(-9.2008)	(-6.5432)	(-11.0327)	(-9.2476)
$Ln(VOLR)$	-0.0271*	0.0132**	-0.0156***	-0.019**	0.0106*	0.0207**	0.0165***	0.0189**
	(-1.6305)	(2.1768)	(-3.4810)	(-2.5328)	(1.8534)	(2.5211)	(3.0177)	(2.1934)
$Ln(GDP)$	0.5685*	0.6241**	0.5381**	0.601***	0.609***	0.7213***	0.5976*	0.681***
	(1.8421)	(2.3975)	(2.1573)	(3.4278)	(10.162)	(5.6100)	(1.8369)	(6.1432)
$Ln(GDP^*)$	0.1571*	0.192***	0.1504**	0.176***	0.138***	0.1821**	0.0917*	0.152***
	(1.6495)	(4.1658)	(2.1831)	(5.9671)	(7.4592)	(2.9055)	(1.6285)	(4.3760)
SAP	-	0.202***	-	0.1875**	-	0.2354***	-	0.1985**
		(6.1583)		(2.2594)		(4.7562)		(2.5276)
$Crisis$	-	-	-0.1322	-0.1189*	-	-	-0.1524*	-0.1504*
			(-0.5876)	(-1.7264)			(-1.8033)	(-1.6621)
R^2	0.68	0.76	0.68	0.71	0.81	0.85	0.79	0.81

Notes: ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Statistics are robust to heteroscedasticity.

Table 7. Instrumental variable estimation: The thresholds from Hansen method

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
τ_{max}	32.26 [.1002]	44.12 [.1922]	26.79 [.0810]	35.68 [.0219]	39.72 [.1063]	32.48 [.0615]	40.15 [.0219]	37.56 [.0112]
τ_{min}	24.89 [.1698]	30.84 [.1501]	20.12 [.0786]	26.77 [.0332]	33.14 [.1029]	24.65 [.0557]	33.81 [.0104]	28.35 [.0096]

Notes: τ_{max} : Maximum LR-Fstatistic; τ_{min} : Minimum LR-Fstatistic; [.]: p-values.

Table 8. Instrumental variable estimation of a Threshold model (Hansen method)

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3) τ_{max} = 26.79	(4) τ_{max} = 35.68	(5)	(6) τ_{max} = 32.48	(7) τ_{max} = 40.15	(8) τ_{max} = 37.56
C	-	-	6.1542* (1.9073)	7.2983** (2.5672)	-	5.1322*** (4.0017)	6.4489** (2.8613)	5.692*** (3.4682)
Ln(REER)	-	-	-1.761** (-2.8394)	-1.985** (-2.1976)	-	-2.3386* (-1.9754)	-1.867** (-2.5143)	-2.09*** (-3.2576)
Ln(VOLR)	-	-	-0.03*** (-3.5616)	-0.0376 (-0.9120)	-	-0.0276** (-2.5181)	-0.04*** (-3.2756)	-0.036** (-2.2391)
Ln(GDP)	-	-	0.5543** (2.0814)	0.628*** (4.2561)	-	0.6071*** (5.1833)	0.6482** (2.9315)	0.602*** (4.1667)
Ln(GDP)*	-	-	0.1286* (1.6954)	0.1973** (2.5042)	-	0.1794* (1.8250)	0.1877** (2.2546)	0.1839** (2.3780)
SAP	-	-	-	0.1789** (2.1136)	-	0.1810* (1.9245)	-	0.1796** (2.2685)
Crisis	-	-	-0.1572* (-1.8355)	-0.140** (-2.0016)	-	-	-0.148** (-2.5312)	-0.1405* (-1.9216)
Cragg Donald test	-	-	44.153	56.231	-	38.799	50.462	49.175
J-statistic	-	-	0.021 [.1234]	0.026 [.2017]	-	0.038[.1459]	0.029[.1516]	0.35 [.2238]
	(1)	(2)	(3) τ_{min} = 20.12	(4) τ_{min} = 26.77	(5)	(6) τ_{min} = 24.65	(7) τ_{min} = 33.81	(8) τ_{min} = 28.35
C	-	-	5.4370*** (10.6124)	5.698*** (8.1927)	-	6.1291*** (9.5764)	5.3263** (8.1950)	6.29*** (12.041)
Ln(REER)	-	-	-1.8972 (-1.3865)	-2.1153* (-1.6372)	-	-2.0765** (-2.1798)	-2.10*** (-3.0059)	-2.101** (-2.4065)
Ln(VOLR)	-	-	0.0237** (2.4053)	0.0258* (1.6697)	-	0.0282** (2.1678)	0.030*** (3.4107)	0.028*** (3.6792)
Ln(GDP)	-	-	0.5490** (2.6431)	0.6318* (1.9025)	-	0.7034** (2.1559)	0.6560** (2.3218)	0.691*** (3.2100)
Ln(GDP)*	-	-	0.1322 (1.2158)	0.1738* (1.8169)	-	0.1805** (2.0774)	0.1592 (1.4473)	0.1732* (1.6892)
SAP	-	-	-	0.1455* (1.8962)	-	0.1612** (2.1653)	-	0.160*** (3.1127)
Crisis	-	-	-0.1463** (-2.1019)	-0.1479* (-1.6890)	-	-	-0.1517* (-1.8122)	-0.148** (-2.0549)
Cragg test	-	-	41.211	48.259	-	48.547	44.018	49.336
J-statistic	-	-	0.032 [.1246]	0.036 [.1205]	-	0.049[.1093]	0.042[.1000]	0.047[.1032]

Notes: ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Estimates are efficient for arbitrary heteroscedasticity and autocorrelation. Statistics are robust to heteroscedasticity and autocorrelation. Cragg–Donald F-statistic tests for weak identification. Critical values are for Cragg test and i.i.d. errors. Ten per cent and 15 per cent critical value of Stock–Yogo weak idetification test are 18.29 and 15.16, respectively, for the maximum LR-statistic and 16.27 and 14.81 for the minimum LR-statistic; [.]: p-value; The equations where the thresholds are insignificant were not estimated (Regressions (1), (2) and (5)).

Table 9. Results of ADF and PP tests

Variables	ADF test		PP test	
	Level	First difference	Level	First difference
$Ln(XPR)$	-3.6894**(1)	-	-2.6790***(4)	-
$Ln(REER)$	-4.6938***(1)	-	-4.2317 (3) **	-
$Ln(VOLR1)$	-0.7510 (1)	-4.8325**(0)	-0.6217 (2)	-4.1649**(6)
$Ln(VOLR2)$	-4.1067 (2) **	-	-3.5954 (8) ***	-
$Ln(GDP)$	-4.3859 (3) **	-	-4.2611 (6) **	-
$Ln(GDP*)$	-0.1367 (0)	-5.2189 (1) ***	-1.0072 (1)	-5.3411(4) ***

Notes: ***, **, * imply significance at the 1%, 5%, 10% level, respectively ; The numbers within parentheses for the ADF and PP statistics represents the lag length of the dependent variable used to obtain white noise residuals ; The lag lengths for the ADF and PP tests were selected using Akaike Information Criterion (AIC).

Table 10. ARDL Bounds testing analysis

	Estimated model	Optimal lag length	F-statistic	Prob.
	Volatility with moving average deviation			
(1)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*)*	1, 1,0, 1,3	7.2189**	.0057
(2)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, SAP)*	1, 1, 0, 1, 3, 1	9.0456***	.0003
(3)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, Crisis)*	1, 1, 0, 1, 3, 0	6.9412*	.0228
(4)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, SAP, Crisis)*	1, 1, 0, 1, 3, 1, 0	7.5801*	.0316
Significance level/ Critical values: T=19		Lower bounds I(0)	Upper bounds I(1)	
1%		6.8513	7.6954	
5%		4.7952	5.4480	
10%		4.1527	4.7235	
	Volatility with optimal GARCH model			
(5)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*)*	1, 1,2, 1,3	8.5124*	.0239
(6)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, SAP)*	1, 1, 2, 1, 3, 1	9.0613**	.0074
(7)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, Crisis)*	1, 1, 0, 1, 3, 0	7.4025	.1206
(8)	F_{XPR} *(XPR/REER, VOLR, GDP, GDP*, SAP, Crisis)*	1, 1, 0, 1, 3, 1, 0	9.1864*	.0100
Significance level/ Critical values: T=21		Lower bounds I(0)	Upper bounds I(1)	
1%		7.2394	7.9852	
5%		5.1825	5.8617	
10%		4.3561	5.0394	

Notes: ***, **, * imply significance at the 1%, 5%, 10% levels ; Critical values were obtained from Pesaran etal. (2001).

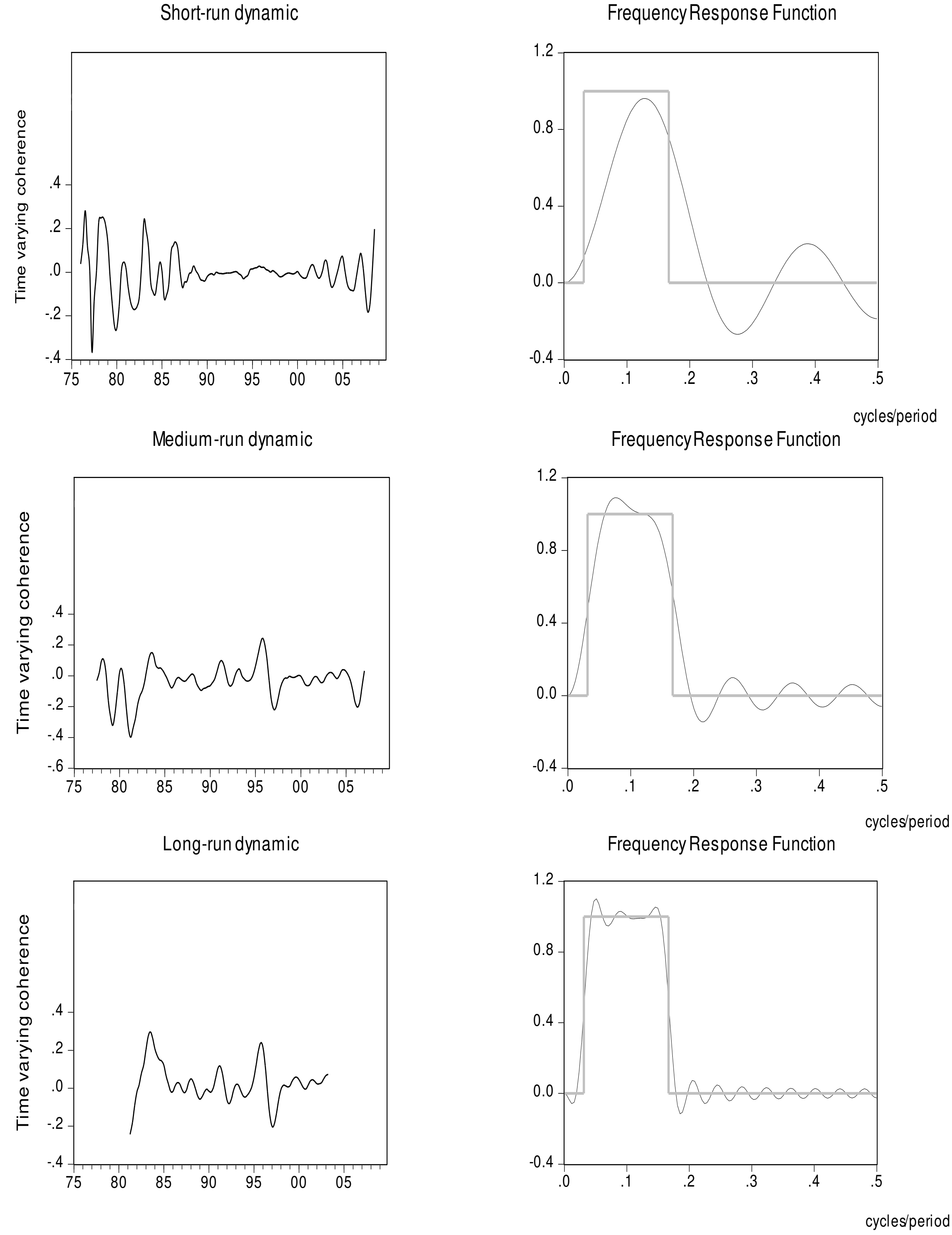
Table 11. ARDL to cointegration (short-run and long-run analyses)

	Volatility with moving average deviation				Volatility with optimal GARCH model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Short-run				
C	1.89**	2.047**	1.995*	1.876**	2.25***	2.419**	2.261***	2.3847**
	(2.451)	(2.3186)	(1.7206)	(1.6534)	(3.1072)	(2.6371)	(3.4049)	(2.7152)
$\Delta Ln(REER)_t$	-1.562*	-1.304	-1.612*	-1.58**	-1.796*	-1.5913*	-1.620**	-1.5982**
	(-1.840)	(-1.459)	(-1.723)	(-2.147)	(-1.883)	(-1.6244)	(-2.3915)	(-2.1763)
$\Delta Ln(VOLR)_t$	0.0281*	0.019*	0.035*	0.0269*	0.0348*	0.0296*	0.0366**	0.0359**
	(1.935)	(1.6054)	(1.8341)	(1.7128)	(1.6513)	(1.6754)	(2.5058)	(2.5711)
$\Delta Ln(GDP)_t$	0.4672**	0.4809**	0.4633*	0.4678**	0.590**	0.6201**	0.5018	0.6034*
	(2.1049)	(2.3521)	(1.6247)	(2.2035)	(2.6168)	(2.2853)	(1.5529)	(1.7381)
$\Delta Ln(GDP^*)_t$	0.3816*	0.3697**	0.3358**	0.3600*	0.4255*	0.3967**	0.3418*	0.3966*
	(1.8920)	(2.0658)	(2.8912)	(1.7982)	(1.6023)	(2.1354)	(1.6975)	(1.8854)
$Ln(ECT)_t$	-0.1374*	-0.1308*	-0.1827*	-0.1619*	-0.165*	-0.1487*	-0.169**	-0.1628**
	(-1.6952)	(-1.5992)	(-1.9134)	(-1.8872)	(-1.839)	(-1.6231)	(-2.3406)	(-2.5155)
				Long-run				
$Ln(REER)_t$	-0.8321	0.9354	1.1720	-1.5691	-1.4687	-1.1956	-1.4421	-1.8890*
	(-1.2742)	(1.0183)	(0.8516)	(-1.0120)	(-1.135)	(-1.1028)	(-1.0259)	(-1.6172)
$Ln(VOLR)_t$	-0.0415	-0.0501	0.0387	-0.0632	0.0692	0.0318*	0.0596	0.0367
	(-0.9023)	(-1.4238)	(1.0592)	(-1.0294)	(0.8415)	(1.7654)	(1.0418)	(1.5210)
$Ln(GDP)_t$	0.3376*	0.1928	0.4218*	0.3512	0.4256	0.3890	0.4476	0.5109
	(1.6209)	(0.6745)	(1.6077)	(1.2216)	(1.0128)	(1.0015)	(1.1589)	(1.0018)
$Ln(GDP^*)_t$	0.0668	0.1392	-0.2350	0.2159	0.4039	0.3827	0.2908	0.3127
	(0.7325)	(1.000)	(-0.9421)	(0.6382)	(1.0185)	(0.6795)	(1.1143)	(0.8651)
SAP	-	0.1128**	-	0.1139*	-	0.1347***	-	0.1298***
		(2.3195)		(1.6740)		(3.8052)		(3.1904)
$Crisis$	-	-	-0.1197*	-0.0875	-	-	-0.0862	-0.1263*
			(-1.6281)	(-1.3467)			(-1.2755)	(-1.8510)
				Diagnostic tests				
ARS	0.3816	0.4011	0.3502	0.4023	0.4018	0.4229	0.4003	0.4216
SER	0.0274	0.0312	0.0259	0.0285	0.0266	0.0341	0.0261	0.0338
LM	1.0351	1.1537	1.0061	1.0492	1.1256	1.1911	1.2207	1.1492
	[.1290]	[.2419]	[.1793]	[.1000]	[.2311]	[.0876]	[.0102]	[.1054]
$Reset$	0.2536	0.2581	0.1987	0.2387*	0.2911*	0.2582	0.2075	0.2310*
	[.1028]	[.1649]	[.1165]	[.0615]	[.0284]	[.1046]	[.1632]	[.0527]

Notes : ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Statistics are robust to heteroscedasticity; Diagnostic tests results are based on F-statistic ; [.] : p-values ; ARS denotes the adjustment R-squared. SER means the standard error regression ; LM means the Breush-Godfrey serial correlation ; Reset denotes Ramsey Reset test.

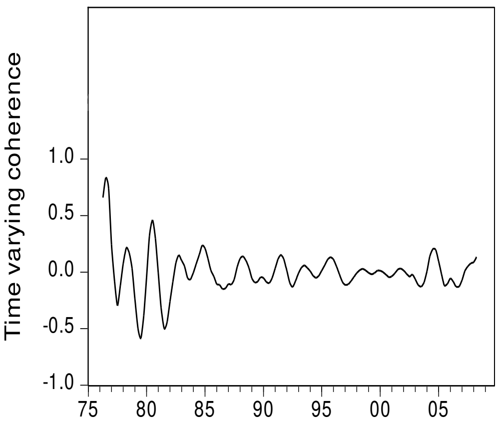
Figure 3. Time varying dynamic between real exchange rate volatility and exports

Volatility with moving average deviation

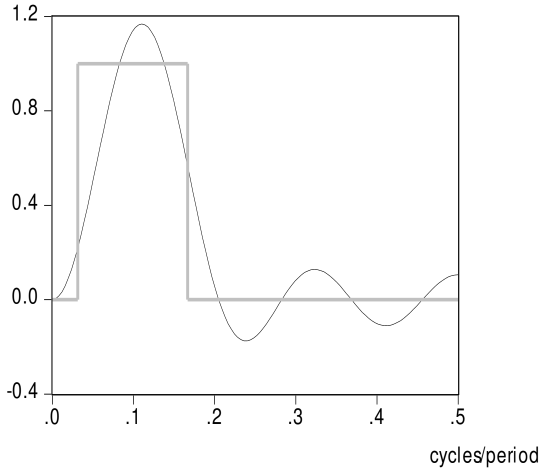


Volatility with optimal GARCH model

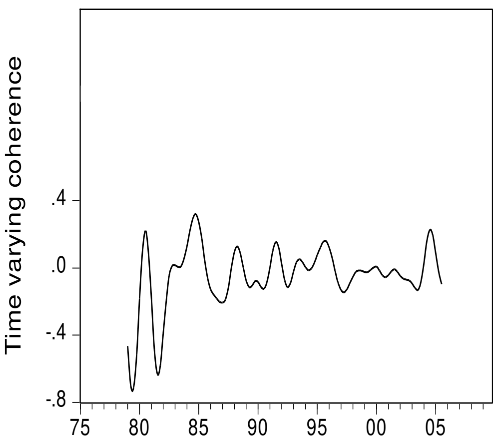
Short-run dynamic



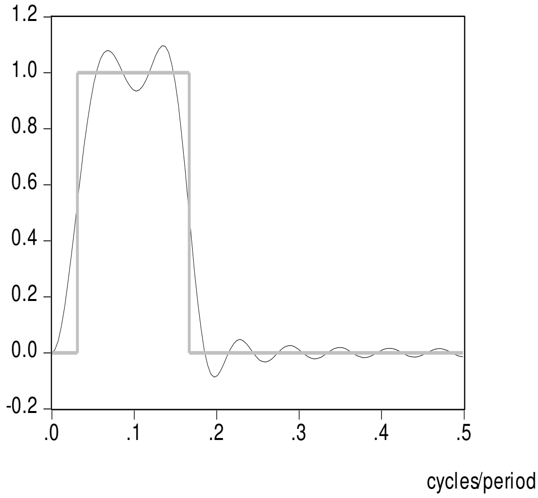
Frequency Response Function



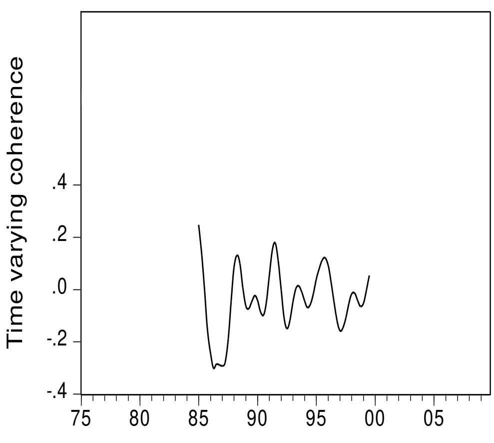
Medium-run dynamic



Frequency Response Function



Long-run dynamic



Frequency Response Function

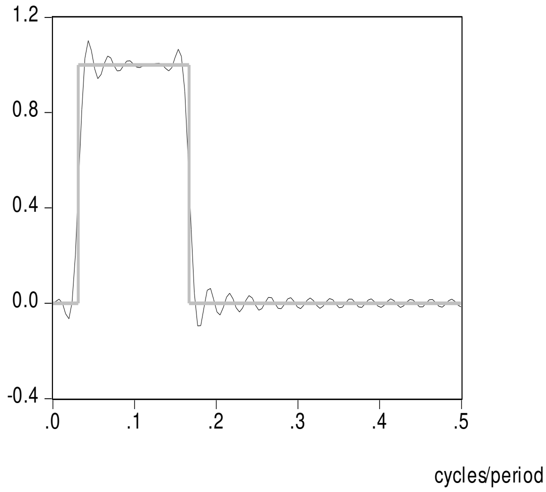
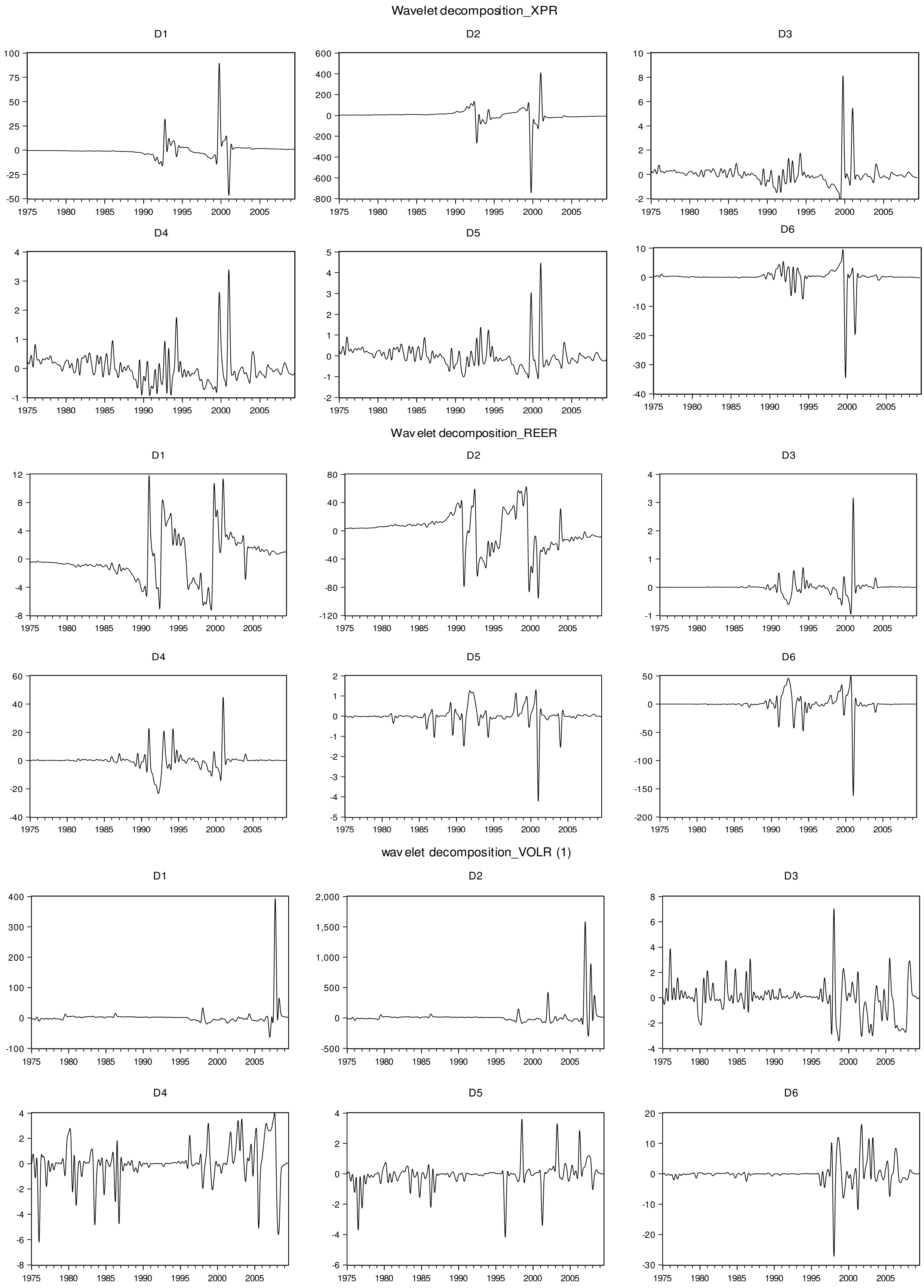
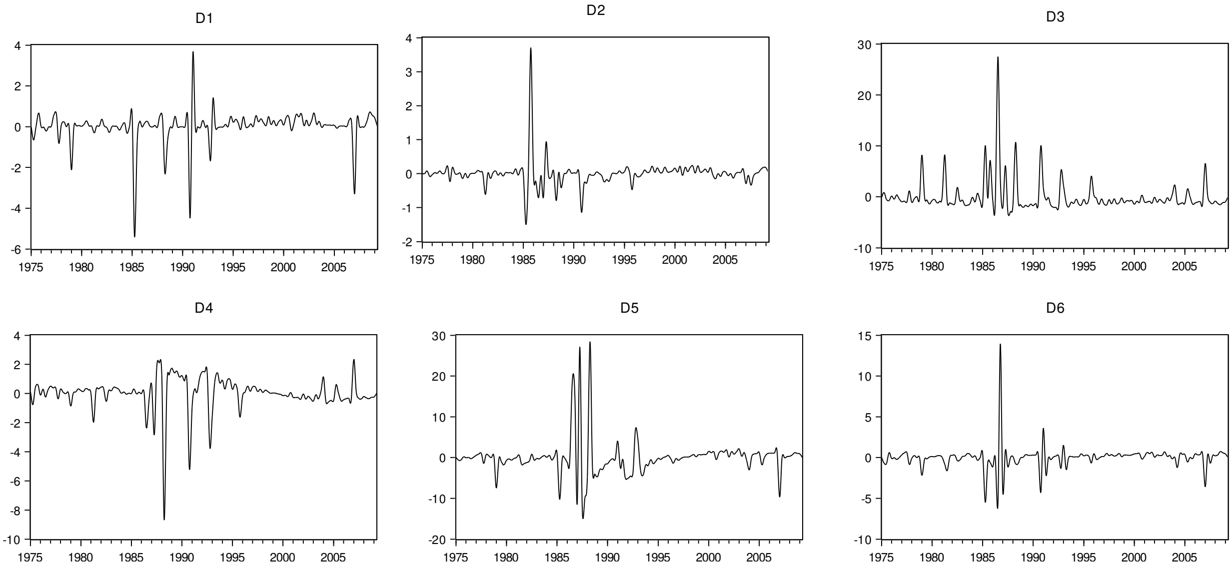


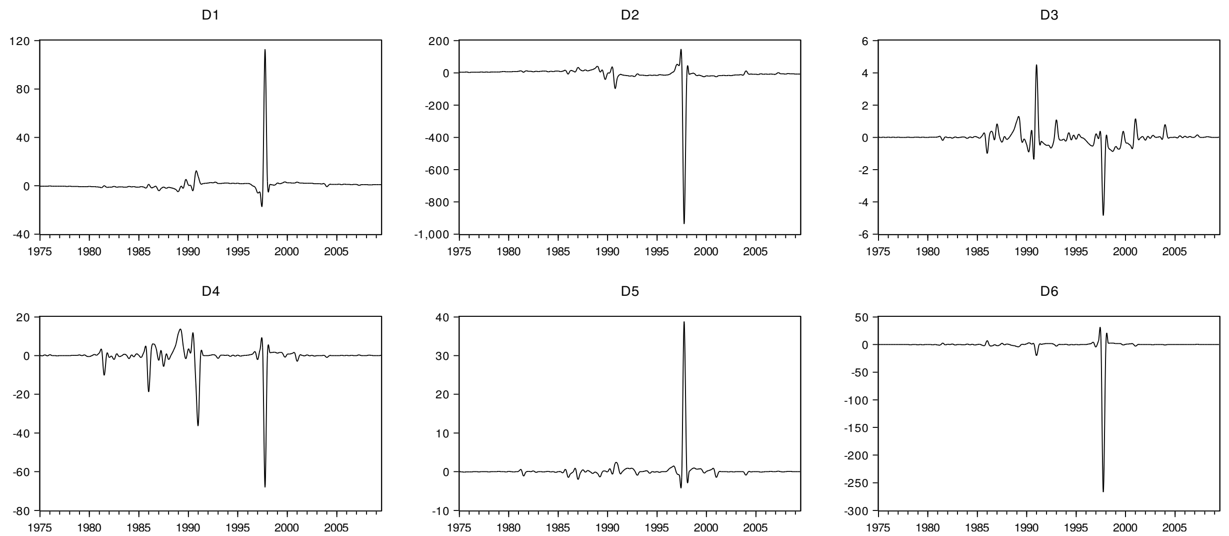
Figure 4. Frequency-to-frequency series' variation



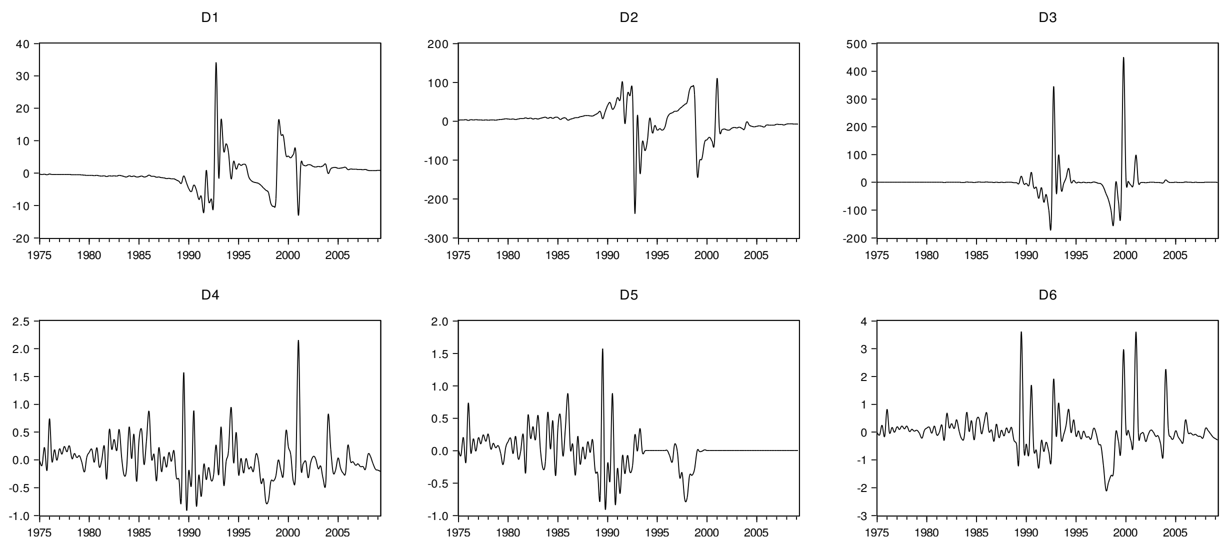
Wav elet decomposition_VOLR (2)



Wav elet decomposition_GDP



Wav elet decomposition_GDP*



Notes: *VOLR* (1): the volatility's proxy is the moving average deviation of real exchange rate; *VOLR* (2): the volatility's proxy is the optimal GARCH model chosen among 13 GARCH extensions.

Table 12. Scale-by-scale OLS estimation

	Volatility with moving average deviation						
	D	$D1:2-4Q$	$D2:4-8Q$	$D3:8-16Q$	$D4:16-32Q$	$D5:32-64Q$	$D6\succ 64Q$
C	2.680* (1.594)	2.560* (1.832)	2.9227* (1.8105)	3.0318*** (6.5923)	2.8582* (1.5924)	2.9800* (1.7053)	3.712** (2.096)
$Ln(REER)$	-1.5*** (-12.7)	-1.44*** (-12.401)	-1.68*** (-13.646)	-1.6447*** (-12.5103)	-1.6708*** (-13.0159)	-1.6754*** (-8.6497)	-1.6*** (-11.50)
$Ln(VOLR)$	0.006** (2.057)	0.0018 (0.1496)	0.0061 (0.6247)	-0.0015 (-0.7422)	-0.0024* (-1.6630)	-0.0492 (-1.0821)	-0.003* (-1.674)
$Ln(GDP)$	0.6442* (1.7660)	0.623*** (3.9855)	0.6921* (1.6123)	0.6822*** (7.1709)	0.8891*** (3.7685)	0.9011*** (4.0158)	0.87*** (3.262)
$Ln(GDP^*)$	0.31*** (6.7332)	0.249*** (4.9220)	0.230*** (3.6505)	0.3924*** (4.6314)	0.5278*** (3.1791)	0.5024*** (4.5671)	0.44*** (5.021)
R^2	0.41	0.40	0.41	0.46	0.45	0.47	0.47
	Volatility with optimal GARCH model						
C	3.0632* (1.9053)	4.2082** (2.4175)	2.0841* (1.8748)	3.3182** (2.0548)	2.8245*** (7.4426)	3.0228* (1.7499)	3.5100* (1.691)
$Ln(REER)$	-1.5*** (-13.95)	-1.61*** (-15.210)	-1.47*** (-12.246)	-1.6773*** (-15.3291)	-1.6093*** (-18.5098)	-1.5255*** (-13.7108)	-1.7*** (-12.52)
$Ln(VOLR)$	0.0096* (1.6339)	0.0025 (0.4619)	0.0062 (0.5303)	0.0113 (0.6905)	-0.0182* (-1.7394)	-0.0195* (-1.9114)	-0.02* (-1.679)
$Ln(GDP)$	0.781** (2.2150)	0.7793** (2.8308)	0.791*** (4.4573)	0.9354* (1.6312)	0.8695* (1.7248)	0.7381** (2.1958)	0.932** (2.512)
$Ln(GDP^*)$	0.59*** (4.8635)	0.5426** (2.1874)	0.3826** (2.5483)	0.4616** (2.7053)	0.4843** (2.9523)	0.4192*** (4.2330)	0.50*** (4.221)
R^2	0.32	0.29	0.41	0.38	0.52	0.52	0.67

Notes: ***, ** and * in the table denote statistical significant coefficients at 1 per cent, 5 per cent and 10 per cent level, respectively. Statistics are robust to heteroscedasticity.

Appendices

Table A.1. Literature survey on the exchange rate's impact on exports

Studies	Countries	Econometric methods	Findings
Aktar and Hilton (1984)	Germany USA	Standard deviation and OLS	Negative effect of nominal exchange rate uncertainty on nominal exports.
Chan and Wong (1985)	Hong Kong	Standard deviation and OLS	Negative and significant effect (in nominal terms).
Klein (1990)	USA	GARCH and OLS	Insignificant impact of exchange rate instability on exports.
Arize (1996)	Panel of eight European countries	Standard deviation and GMM	Ambiguous nexus (in real terms).
Fountas and Bredin (1998)	Ireland	Moving standard deviation of the growth rate of exchange rate and VECM	In the short-run, real exchange rate volatility affects negatively Irish exports.
McKenzie and Brooks (1997)	Germany	Standard deviation and OLS	Positive and significant nominal exchange rate risk 's effect on exports.
McKenzie (1998)	Australia	ARCH model and OLS	Positive relationship between the two variables (in nominal terms).
Daly (1998)	Japan	Standard deviation and OLS	Ambiguous effect of exchange rate variability on real exports.
Vergil (2002)	Turkey	Standard deviation and OLS	Negative effect of exchange rate volatility on exports.
Nabli et al. (2004)	Panel of MENA countries	Standard GARCH model and OLS	Negative nexus between exchange rate uncertainty and exports (in real terms).
Baum et al. (2004)	Panel of 13 developed countries	Construction of Poisson lag terms within a standard nonlinear estimation	They find a nonlinear interaction dynamic between exchange rate variability and trade.
Zhang et al. (2006)	G 7 countries	A grid-searching method	The results put in evidence that trade volume tends to increase when exchange rate uncertainty surpasses a certain threshold point.
Chit and Judge (2011)	Five East Asian countries (country-by-country variation)	GMM-iv estimation	They find that there is a nonlinear effect of exchange rate volatility on exports, which is conditional on the level of financial sector development. The less financially developed an economy, the more its exports are adversely affected by exchange rate instability.
Hsu and Chiang (2011)	USA	The threshold regression model of Hansen	They show that the threshold effects exist. Exchange rate volatility reduces the exports from the US to relative high-income partners but increases exports from the US to relative low-income ones.
Bouoiyour and Selmi (2014 a)	Egypt	Wavelet decomposition and scale-by-scale optimal GARCH model.	They show that the exchange rate uncertainty's impact on Egyptian exports depends on frequencies' transformations.

Source: Authors'compilation.

Table A.2. GARCH extensions used in this study

	linear	nonlinear	symmetrical	Asymmetrical
1. GARCH (Bollerslev, 1986) $\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2$	x		x	
2. GARCH-M (GARCH in mean, Bollerslev et al. 1993) $r_t = \mu_t + \varepsilon_t + \lambda \sigma_t^2$	x		x	
3. C-GARCH (Component GARCH, Ding et al. 1993) $(\sigma_t^2 - \sigma^2) = \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(\sigma_{t-1}^2 - \sigma^2)$	x		x	
4. I-GARCH (Integrated GARCH, Bollerslev et al. 1993) $\sigma_t^2 = \omega + \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \alpha_i (\varepsilon_{t-i}^2 - \varepsilon_{t-1}^2) + \sum_{i=1}^{p} \beta_j (\sigma_{t-j}^2 - \varepsilon_{t-1}^2$	x		x	
5. A-GARCH (Asymmetric GARCH, Bollerslev et al., 1993) $\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i (\lvert\varepsilon_{t-i}\rvert + \gamma_i \varepsilon_{t-i})^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2$	x			x
6. T-GARCH (Threshold GARCH, Zakoian, 1994) $\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \lvert\varepsilon_{t-i}\rvert + \gamma_i \lvert\varepsilon_{t\_i}^{+}\rvert) + \sum_{i=1}^{p} \beta_j \sigma_{t-j}$		x		x
7. E-GARCH (Exponential GARCH, Nelson, 1991) $\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} (\alpha_i z_{t-i} + \gamma_i (\lvert z_{t-i}\rvert - \sqrt{2/\pi})) + \sum_{i=1}^{p} \beta_j \log(\sigma_{t-j}^2)$				x
8. P-GARCH (Power GARCH, Higgins and Bera, 1992) $\sigma_t^{\varphi} = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\varphi} + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^{\varphi}$	x		x	
9. A-PGARCH (Asymmetric power GARCH, Ding et al., 1993) $\sigma_t^{\varphi} = \omega + \sum_{i=1}^{q} \alpha_i (\lvert\varepsilon_{t-i}\rvert + \gamma_i \varepsilon_{t-i})^{\varphi} + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^{\varphi}$				x

Notes: ${\sigma_t}^2$: conditional variance, α_0 : reaction of shock, α_1 : ARCH term, β_1 : GARCH term, ε : error term; I_t: denotes the information set available at time t; z_t : the standardized value of error term where $z_t = \varepsilon_{t-1}/\sigma_{t-1}$; μ : innovation, γ : leverage effect; φ : power parameter.