Chapter 2
Theory and Literature Review

2.1 Modeling the exchange rate process

This paper will study the property of the asymptotic theory for a vector ARMA-GARCH model. In this section will present a simplified version of the model that Barkoulas, et al. (2002) propose to investigate the effects of exchange rates on the level and variability of export volumes. The model assumes that each period exporter decide upon the quantities to export depending on the exchange rate level expected to prevail over the next period. The exchange rate denoted by $\tilde{e}_t$, follows the random process given by

$$\tilde{e}_t = \bar{e} + \varepsilon_t \tag{1}$$

The determined component $\bar{e}$ is the publicly known mean of the exchange rate process. The stochastic component of the fundamentals follows

$$\varepsilon_t = \rho\,\varepsilon_{t-1} + \nu_t \text{ where } \nu_t \sim N(0, \sigma^2_\nu)$$

Here, ν_t captures the information advantage policy makers have relative to the public over changes affecting the fundamentals. Assuming that economic agents observe a noisy signal

$S_t = \nu_t + \psi_t$ and that they know the fundamentals driving the exchange rate process ($\bar{e}$ and ρ) and can observe ε_{t-1} at the beginning of each period, they may form the one-step-ahead forecast of the exchange rate that will prevail. The noise, ψ_t is assumed to be normally distributed with mean zero and variance σ^2_ψ

($\psi_t \sim N(0, \sigma^2_\psi)$) and is independent of the ν_t. Hence, the one period ahead forecast of the exchange rate, conditional on the signal St takes the form:

$$E(\tilde{e}_t | S_t) = \bar{e} + \rho\, \varepsilon_{t-1} + \lambda\, S_t, \text{ where } \lambda = \frac{\sigma_v^2}{\sigma_\psi^2 + \sigma_v^2}$$

To find the impact of the exchange rate on real exports, this paper assumes an expected utility function, which is increasing in expected profits and decreasing in the variance of profits, conditional on the signal:

$$E(\tilde{U} | S_t) = E(\tilde{\pi} | S_t) - \tfrac{1}{2}\, \Upsilon \text{ Vary } (\tilde{\pi} | S_t) \quad (2)$$

Where the profit function is given as $\tilde{\pi} = (\tilde{e} - d)\, X - \tfrac{1}{2}\ X^2$ Here d > 0 and X and denote the volume of exports and the coefficient of risk aversion for exporters, respectively. Maximization of equation (2) with respect to X yields the optimal level of exports:

$$X = \frac{\bar{e} + \rho\varepsilon_{t-1} + \lambda S_t - d}{1 + \gamma\lambda\sigma_\psi^2} \quad (3)$$

Where $\bar{e} + \rho\ \varepsilon_{t-1} + \lambda S_t$ > d is assumed to be satisfied for an economically meaningful (positive) optimal level of exports.

Barkoulas, et al. (2002) investigate the impact of exchange rate volatility on trade flows because trade flow volatility directly relates to smoothing the business cycle, which is an important argument in the macro welfare function using equation (3), it can be obtained the variance of exports, for the stochastic nature of this variable is wholly derived from the signal S_t, conditional on other parameters and information known to the agent at time t-1. Hence, the variance of exports can be shown to be:

$$\text{Var}(X) = \frac{\lambda\sigma_v^2}{(1 + \gamma\sigma_\psi^2\lambda)^2} \quad (4)$$

2.2 Impact of exchange rate uncertainty

Taking the derivatives of equations (3) and (4) with respect to σ_v^2 and obtain simpler variants of the two relationships. The first relationship is the impact of uncertainty on trade flows:

$$\frac{\partial X}{\partial \sigma_v^2} = \frac{\sigma_\psi^2}{(\sigma_\psi^2 + \sigma_v^2)^2} \frac{(1+\gamma\lambda\sigma_\psi^2)S_t + \gamma\sigma_\psi^2(d - (\bar{e} + \rho\varepsilon_{t-1} + \lambda S_t))}{(1+\gamma\lambda\sigma_\psi^2)^2} \tag{5}$$

This result implies that the effect of the variance of the stochastic elements in the fundamentals driving the exchange rate process on trade flows is ambiguous because the sign of the relationship depends on the behavior of the signal St. Next look at the impact of volatility of the fundamentals in the exchange rate process on the volatility of export:

$$\frac{\partial Var(X)}{\partial \sigma_v^2} = \lambda \frac{(2-\lambda) + \gamma\lambda^2 \ \sigma_\psi^2}{(1+\gamma\lambda\sigma_\psi^2)^3} > 0 \tag{6}$$

Here there is an unambiguous relationship trade flow volatility is positively related to the variance of the fundamental forces driving the exchange rate process. The data and mechanism that generate measures of exchange rate and trade volatility as well as the model that will implement to test for the linkages between exchange rate volatility and the variance of trade flows. The variances of exports and the trade balance are positively related to the variance of the fundamental forces driving the exchange rate process.

2.3 Unit Root Test Model

Consider a simple AR(1) process

$$y_t = \rho y_{t-1} + \chi_t{}' \delta + \varepsilon_t \tag{7}$$

Where χ_t are optional exogenous which may consist of constant, or a constant and trend ρ, δ and are parameters to be estimated, and the ε_t are assumed to be white noise. If $|\rho| \geq 1, y$ is a non-stationary series and the variance of increases with time and approaches infinity. If, $|\rho| < 1$, y is a trend-stationary series. Thus, the hypothesis of trend-stationary can be evaluated by testing whether the absolute value of ρ is strictly less than one.

The null hypothesis $H_0: \rho = 1$ against the one-sided alternative. In some cases, the null is tested against a point alternative $H_1: \rho < 1$.In some cases, the null is tested against a point alternative. In contrast, the KPSS Lagrange Multiplier test evaluates the null of $H_0: \rho < 1$ against the alternative $H_1: \rho = 1$.

2.3.1 The Augmented Dickey-Fuller (ADF) Test

The standard DF test is carried out by estimating Equation (7) after y_{t-1} subtracting from both sides of the equation:

$$\Delta y_t = \alpha y_{t-1} + \chi_t{}'\delta + \varepsilon_t \tag{8}$$

where $\alpha = \rho - 1$. The null and alternative hypotheses can be written as,

$$\begin{aligned} &H_0 : \alpha = 0 \\ &H_1 : \alpha < 0 \end{aligned} \tag{9}$$

and evaluated using the conventional t-ratio for α :

$$t_\alpha = \hat{\alpha}/(se(\hat{\alpha})) \tag{10}$$

where $\hat{\alpha}$ is the estimate of α, and $se(\hat{\alpha})$ is the coefficient standard error. Dickey and Fuller show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes.

The simple Dickey-Fuller unit root test described above is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of white noise disturbances is ε_t violated. The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the y series follows an AR(ρ) process and adding ρ lagged difference terms of the dependent variable to the right hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + \chi_t ' \delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + ... + \beta_p \Delta y_{t-p} + v_t \tag{11}$$

This augmented specification is then used to test (9) using the t-ratio (10). An important result obtained by Fuller is that the asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences included in the ADF regression. Moreover, the assumption demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression.

In practically, first, the data must be chosen whether to include exogenous variables in the test regression. There is a choice of including a constant, a constant and a linear time trend, or neither in the test regression.

One approach would be to run the test with both a constant and a linear trend since the other two cases are just special cases of this more general specification. However, including irrelevant regressors in the regression will reduce the power of the test to reject the null of a unit root. The standard recommendation is to choose a specification that is a plausible description of the data under both the null and alternative hypotheses.

Second, this paper has to specify the number of lagged difference terms to be added to the test regression (0 yields the standard DF test; integers greater than 0 correspond to ADF tests). The usual (though not particularly useful) advice is to include a number of lags sufficient to remove serial correlation in the residuals.

2.3.2 The Phillips-Perron (PP) Test

The alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. The PP method estimates the non-augmented- DF test equation (8), and modifies the t-ratio of the α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\tilde{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^{1/2} - \frac{T(f_0 - \gamma_0)(se(\hat{\alpha}))}{2 f_0^{1/2} s} \tag{12}$$

where $\hat{\alpha}$ is the estimate, and t_α the t-ratio of α, $se(\hat{\alpha})$ is coefficient standard error, and s is the standard error of the test regression. In addition γ_0, is a consistent estimate of the error variance in (8) (calculated as $(T-k)s^2/T$, where k is the number of regressors). The remaining term, f_0 is an estimator of the residual spectrum at frequency zero.

There are two choices you will have make when performing the PP test. First, you must choose whether to include a constant, a constant and a linear time trend, or neither, in the test regression. Second, you will have to choose a method for estimating f_0.

2.3.3 The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test

The testing differs from the other unit root tests described here in that the series y_t is assumed to be trend stationary under the null. The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables χ_t:

$$y_t = \chi_t'\delta + u_t \tag{13}$$

The LM statistic is be defined as:

$$LM = \sum_t S(t)^2 / (T^2 f_0) \tag{14}$$

where f_0, is an estimator of the residual spectrum at frequency zero and where $S(t)$ is a cumulative residual function:

$$S(t) = \sum_{\gamma=1}^{t} \hat{u}_\gamma \tag{15}$$

based on the residuals $\hat{u}_t = y_t - \chi_t{}'\delta(0)$. This paper points out that the estimator of δ used in this calculation differs from the estimator for δ used by GLS distending since it is based on a regression involving the original data and not on the quasi-differenced data. To specify the KPSS test, you must specify the set of exogenous regressors χ_t and a method for estimating f_0.

2.4 ARCH/ GARCH Model

The autoregressive conditional heteroskedasticity (ARCH) model is the first model of conditional heteroskedasticity. The original idea was to find a model that could assess uncertainty changing over time. Let ε_t be a random variable that has a mean and a variance conditionally on the information set F_{t-1} (the σ-field generated by $\varepsilon_{t-n}, n \geq 1$) :The ARCH model of ε_t has the following properties.

First, E$\{\varepsilon_t | F_{t-1}\} = 0$ and, second, the conditional variance h_t =E$\{\varepsilon_t^2 | F_{t-1}\}$

is a nontrivial positive-valued parametric function of F_{t-1} the sequence $\{\varepsilon_t\}$ may be observed directly, or it may be an error or innovation sequence of an econometric model. In the latter case,

$$\varepsilon_t = y_t - \mu_t(y_t) \tag{16}$$

where y_t is an observable random variable and $\mu_t(y_t) = \text{E}\{y_t | F_{t-1}\}$, the conditional mean of y_t given F_{t-1} the application was of this type. In what follows, the focus will be on parametric forms of h_t, and $\mu_t(y_t)$ will be ignored. Engle assumed that ε_t can be decomposed as follows:

$$\varepsilon_t = z_t h_t^{1/2} \tag{17}$$

where $\{z_t\}$ is a sequence of independent, identically distributed (iid) random variables with zero mean and unit variance. This implies $\varepsilon_t | F_{t-1}$ ~D$(0, h_t)$ where D stands for the distribution (typically assumed to be a normal or a leptokurtic one). The following conditional variance defines an ARCH model of order q:

$$h_t = \alpha_0 + \sum_{n=1}^{q} \alpha_n \varepsilon_{t-n}^2 \tag{18}$$

Where $\alpha_0 > 0, \alpha_n \geq 0, n = 1,..., q-1,$ and $\alpha_q > 0$ the parameter restrictions in (18) form a necessary and sufficient condition for positively of the conditional variance. Suppose the unconditional variance $\mathrm{E}\,\varepsilon_t^2 = \alpha^2 < \infty$ the definition of ε_t through the decomposition (17) involving z_t then guarantees the white noise property of the sequence $\{\varepsilon_t\}$, since $\{z_t\}$ is a sequence of iid variables. Engle and others soon realized the potential of the ARCH model in financial applications that required forecasting volatility. The ARCH model and its generalizations are applied to modeling, among other things, exchange rates and export volumes. Forecasting volatility of these series is different from forecasting the conditional mean of a process because volatility, the object to be forecast, is not observed. The question then is how volatility should be measured. Using ε_t^2 is an obvious but not necessarily.

In applications, the ARCH model has been replaced by the so-called generalized ARCH (GARCH) model, the conditional variance is also a linear function of its own lags and has the form

$$h_t = \alpha_0 + \sum_{n=1}^{q} \alpha_n \varepsilon_{t-n}^2 + \sum_{n=1}^{p} \beta_n h_{t-n} \tag{19}$$

The conditional variance defined by (19) has the property that the unconditional autocorrelation function of ε_t^2 if it exists, can decay slowly, albeit still exponentially. For the ARCH family, the decay rate is too rapid compared to what is typically observed in financial time series, unless the maximum lag q in (18) is long. As (19) is a more parsimonious model of the conditional variance than a high-order ARCH model, most users prefer it to the simpler ARCH alternative. The overwhelmingly most popular GARCH model in applications has been the GARCH(1,1) model, that is, p = q = 1 in (19). A sufficient condition for the conditional variance to be positive with probability one is $\alpha_0 > 0, \alpha_n \geq 0, n = 1,..., q; \beta \geq 0, n = 1,..., p$ The necessary and sufficient conditions for positivity of the conditional variance in higher-order GARCH models are more complicated than the sufficient conditions just mentioned and have been given in Nelson and Cao (1992). Note that for the GARCH model to be identified if at least one $\beta_n > 0$ (the model is a genuine GARCH model) one has to require that also at least one $\alpha_n > 0$. If $\alpha_1 = ... = \alpha_q = 0$, the conditional and unconditional variances of ε_t are equal and $\beta_1,...,\beta_p$ are unidentified nuisance parameters. The GARCH(p,q) process is weakly stationary if and only if $\sum_{n=1}^{q} \alpha_n + \sum_{n=1}^{p} \beta_n < 1$

The stationary GARCH model has been slightly simplified by variance targeting. This implies replacing the intercept α_0 in (19) by (1- $\sum_{n=1}^{q} \alpha_n - \sum_{n=1}^{p} \beta_n)\sigma^2$ where $\sigma^2 = \mathrm{E}\,\varepsilon_t^2$, The estimate $\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{T} \varepsilon_t^2$ is substituted for σ^2 before estimating the other parameters. As a result, the conditional variance converges towards the long-run unconditional variance, and the model contains one parameter less than the standard GARCH(p,q) model. It may be pointed out that the GARCH model is a special case of an infinite-order (ARCH(∞)) model (17) with

$$h_t = \alpha_0 + \sum_{n=1}^{\infty} \alpha_n \varepsilon_{t-n}^2 \tag{20}$$

The ARCH(∞) representation is useful in considering properties of ARCH and GARCH models such as the existence of moments and long memory.

2.5 Models of Multivariate Volatility

The multivariate GARCH model takes the following form

$$H_t = C'C + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B \tag{21}$$

To preserve symmetry, the conditional mean of the variables are defined in terms of its own lag with a moving average innovation of order one. The vector of innovations is defined as $u_t = [\varepsilon_{2_t}, \varepsilon_{1_t}]'$. The diagonal elements of H_t are the conditional variances of logarithm of export volumes, $\sigma^2_{11_t}$ and logarithm of exchange rate, $\sigma^2_{22_t}$ respectively.

The first parameterization of $\sum_t$ is to use the conditional correlation coefficients and variances of ε_t. Specifically, is writen $\sum_t$ as

$$\sum\nolimits_t \equiv \left[\sigma_{ij,t}\right] = D_t \rho_t D_{t,} \tag{22}$$

where ρ_t is the conditional correlation matrix of ε_t, and D_t is a $k \times k$ diagonal matrix consisting of the conditional standard deviations of elements of ε_t *(i.e.,)*

$$D_t = diag\left\{\sqrt{\sigma_{11,t}},...,\sqrt{\sigma_{kk,t}}\right\}$$

Because ρ_t is symmetric with unit diagonal elements, the time evolution of ε_t is governed by that of the conditional variances $\sigma_{ii,t}$ and the elements $\rho_{ij,t}$ of ρ_t , where $j < i$ and $1 \le i \le k$ Therefore, to model the volatility of ε_t , it suffices to consider the conditional variances and correlation coefficients of ε_{it}. Define the $k(k+1)/2$ dimension vector. If ε_t is a multivariate normal random variable, then H_t is given in

$$H_t = (\sigma_{11,t}, \sigma_{22,t}, \rho'_{21,t})' \quad \text{and}$$

The conditional density function of ε_t given lag of H_t is

$$f(\varepsilon_{1_t}, \varepsilon_{2_t} \middle| H_t) = \frac{1}{2\pi\sqrt{\sigma_{11,t}\sigma_{22,t}(1-\rho^2_{21,t})}} \exp\left(-\frac{Q(\varepsilon_{1_t}, \varepsilon_{2_t}, H_t)}{2(1-\rho^2_{21,t})}\right)$$

Where

$$Q(\varepsilon_{1_t}, \varepsilon_{2_t} \middle| H_t) = \frac{\varepsilon^2_{1_t}}{\sigma_{11,t}} + \frac{\varepsilon^2_{2_t}}{\sigma_{22,t}} - \frac{2\rho_{21,t}\varepsilon_{1_t}\varepsilon_{2_t}}{\sqrt{\sigma_{11,t}\sigma_{22,t}}}$$

The log probability density function of ε_t relevant to the maximum likelihood estimation is

$l(\varepsilon_{1_t}, \varepsilon_{2_t}, H_t)$

$$= -\frac{1}{2}\left\{\ln\left[\sigma_{11,t}\sigma_{22,t}(1-\rho_{21,t}^2)\right] + \frac{1}{1-\rho_{21,t}^2}\left(\frac{\varepsilon_{1_t}^2}{\sigma_{11,t}} + \frac{\varepsilon_{2_t}^2}{\sigma_{22,t}} - \frac{2\rho_{21,t}\,\varepsilon_{1_t}\,\varepsilon_{2_t}}{\sqrt{\sigma_{1,t}\sigma_{2,t}}}\right)\right\}$$

This reparameterization is useful because it models covariance and correlations directly. In this paper, This paper propose a new MGARCH model with time-varying correlations. This allows large shocks in one variable to affect the variances of the others which follow instruction estimates a DCC-GARCH model.

$$H_{ii}\ (t) = c_{ii} + \sum_j a_{ij}\, u_j\ (t-1)^2 + \sum_j b_{ij} H_{jj}\ (t-1) \qquad (23)$$

Where $;u_j\ (t-1)^2$ is volatility from previous period measured as the lag of the squared residual from the mean equation; $H_{jj}\ (t-1)$ is last previous forecast variance. The 23[th] equation shows the multivariate GARCH model.

Given c_{ij}, a_{ij}, b_{ij} are parameters which show the relationship between volatility of export volumes and exchange rate. Where a_{ij} , b_{ij} are the coefficient of volatility relationship between export volumes and exchange rate. The hypothesis test c_{ij}, a_{ij}, b_{ij} where $i \neq j$; $i , j > 0$ (Barkoulas, T. John; Baum, C. F. and Caglayan, M., 2002)

The hypothesis given by

H_0 : $a_{ij}, b_{ij} = 0$

H_a: $a_{ij}, b_{ij} > 0$

Rejection null hypothesis means that there is correlation on conditional variance of exchange rate and export volumes.

2.6 Literature Review

Barkoulas, et al.(2002) considered about "Exchange Rate Effects on the Volume and Variability of Trade Flows". This paper investigates the effects of exchange rate uncertainty on the volume and variability of trade flows. Employing a signal extraction framework, they show that direction and magnitude of importers' and exporters' optimal trading activities depend upon the source of the uncertainty (general microstructure shocks, fundamental factors driving the exchange rate process, or a noisy signal of policy innovations), providing a rationale for the contradictory empirical evidence in the literature. They also show that exchange rate uncertainty emanating from general microstructure shocks the fundamental factors reduces the variability of trade flows, while that related to a noisy signal of policy innovations increases variability.

Pickard (2003) studied about "Exchange rate volatility and bilateral trade flows:An analysis of U.S. demand for certain steel products from Canada and Maxico" This empirical study uses stochastic coefficients econometric modeling to forecast real exchange rate volatility and examine how expected and unexpected volatility affect bilateral trade flows of certain steel products between Canada, Mexico and the United States using monthly data for the seven-year period 1996-2002. The results of the model indicate that the effects of exchange rate volatility on bilateral trade flows for this sector are relatively minor, where sustained changes in the spot exchange rate, sectoral economic growth, and the price of goods being traded all exert more significant influence on trade levels than exchange rate volatility. However, the model results also tend to indicate that as exchange rate volatility increases, the well-developed U.S.-Canadian forward currency exchange market may present economic agents with profit opportunities through risk-portfolio diversification, resulting in a positive correlation between volatility and trade. For the less-developed U.S.-Mexican forward currency market, the model results indicate that the relationship between trade and volatility, both expected and unexpected, is weak and predominantly negative.

Ling and McAleer (2003) This paper investigates the asymptotic theory for a vector autoregressive moving average–generalized autoregressive conditional heteroskedasticity (ARMA-GARCH) model. The conditions for the strict stationarity, the ergodicity, and the higher order moments of the model are established. Consistency of the quasi maximum-likelihood estimator (QMLE) is proved under only the second-order moment condition. This consistency result is new, even for the univariate autoregressive conditional heteroskedasticity (ARCH) and GARCH models. Moreover, the asymptotic normality of the QMLE for the vector ARCH model is obtained under only the second-order moment of the unconditional errors and the finite fourth-order moment of the conditional errors. Under additional moment conditions, the asymptotic normality of the QMLE is also obtained for the vector ARMA-ARCH and ARMA-GARCH models and also a consistent estimator of the asymptotic covariance.

Fang and Thompson (2004) verified with "Exchange rate risk and export revenue in Taiwan". The effect of exchange rate risk on export revenue in Taiwan between 1979 and 2001 is investigated in a bivariate GARCH-M model that simultaneously estimates time-varying risk. Depreciation is found to stimulate export revenue in domestic currency, but the quantitative impact is small and any associated increase in exchange risk has a negative impact. Implications for economic policy are discussed.

Fang, et al. (2004) They studied about "Exchange rates, exchange risk, and Asian export revenue". While depreciation may raise export revenue, associated exchange risk could offset any positive effect. The present paper investigates this net effect for eight Asian countries using a bivariate GARCH-M model that simultaneously estimates time varying risk. The fundamental result is that export markets react differently to exchange rates and associated risk. High degrees of risk apparently stimulate efforts to avoid its impact. Exchange risk has a dominating negative impact for the appreciating Japanese yen. Depreciation has no impact in Malaysia and Singapore, and exchange risk has a negative effect in Singapore. For the other five countries, depreciation stimulates export revenue but risk leads to a negative net effect in Taiwan.

Fang and Miller (2004) ascertained the topic of "Exchange rate depreciation and exports". This paper revisits the weak relationship between exchange rate depreciation and exports for Singapore, using a bivariate GARCH-M model that simultaneously estimates time-varying risk. The evidence shows that depreciation does not significantly improve exports, but that exchange rate risk significantly impedes exports. In sum, Singaporean policy makers can better promote export growth by stabilizing the exchange rate rather than generating its depreciation.

Christopher, et al. (2006) found out "Effects of Exchange Rate Volatility on the Volume and Volatility of Bilateral Exports" They present an empirical investigation of a recently suggested but untested proposition that exchange rate volatility can have an impact on both the volume and variability of trade flows, considering a broad set of countries' bilateral real trade flows over the period 1980–1998. They generate proxies for the volatility of real trade flows and real exchange rates after carefully scrutinizing these variables' time series properties. Similar to the findings of earlier theoretical and empirical research, our first set of results show that the impact of exchange rate uncertainty on trade flows is indeterminate. Our second set of results provide new and novel findings that exchange rate volatility has a consistent positive and significant effect on the volatility of bilateral trade flows.

Chalinee Sannarin (2007) studied about "The Impacts of Exchange Rate on Thai Real Export Value to the U.S" This study was an attempt to ascertain whether the exchange rate volatility, the relative export price index and the US. Gross Domestic Product (GDP) had impacts on the value of total exports, the value of industry exports and the value of non-industry exports of Thailand. This study employed the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH) to estimate the exchange rate volatility, and the Cointegration and Error Correction Model (ECM) to define the correlation between the long-run equilibrium relationship and the short-run adjustment process in these models. Furthermore, dummy variables were included in the models to consider the structural change and trend. At the time of this study, Thailand used two systems of exchange rate: the basket of currencies exchange Rate and the managed float system which covered the first quarter of 1991 to the forth quarter of 2007 including a total 64 observations. For time series data, it is important to investigate stationary property of all variables using unit roots test. The results revealed that all series were found to be stationary at the first order of integration. The Engle and Granger Cointegration test results substantially supported the long-run equilibrium relationship.