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National University of Ireland, Galway

Essays on Nonlinearity in Exchange Rates

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

by

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Declaration

This thesis is my own work and I have not obtained a degree in National University of Ireland, Galway, or elsewhere, on the basis of this work.

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Chapter 1 Introduction

This thesis comprises four essays that explore three important issues relating to exchange rates: (1) the relationship between real exchange rates and economic fundamentals, (2) the predictability of exchange rate volatility, and (3) the effects on trade of exchange rate volatility. This thesis focuses on nonlinear aspects of these issues.

The first two essays investigate the nonlinear relationship between real exchange rates and economic fundamentals. The question of how well economic fundamentals can explain the behaviour of real exchange rates is important for both academic researchers and policymakers. However, to date no consensus on this issue has been reached. In the empirical literature, the weak link between exchange rates and fundamentals is known as the so-called "disconnection puzzle", which is still one of the important puzzles in the field of international finance.

Some studies on the determination of nominal exchange rates find a nonlinear relationship between nominal exchange rates and economic fundamentals. In contrast, the literature on the determination of real exchange rates focuses only on linear relationships and ignores the possible nonlinear relationship. The first two essays attempt to fill this gap in the literature.

The first essay explores the potential nonlinear cointegrating relationship between economic fundamentals and the real exchange rates of both the Chinese yuan and the Korean won using quarterly data over the period 1980-2009. The ARDL bounds testing approach and nonlinear cointegration tests are employed to test for linear and nonlinear relationships. The results show that for both China and Korea, there exists a nonlinear relationship between real exchange rates and economic fundamentals such as productivity, terms of trade, and net foreign assets. The elasticity of the real exchange rate with respect to fundamentals changes substantially in both magnitude and direction over time, in sharp contrast with the assumption of a linear relationship. This essay has been published in the *Journal of International Money and Finance*.

The second essay provides further evidence of the nonlinear relationship between real exchange rates and fundamentals by examining the real exchange rates of the euro and 10 former currencies of EMU member countries. Many existing studies of real exchange rates in the euro area only cover the early years in the short history of the euro. This essay broadens the sample to examine the relationship between real exchange rates and fundamentals by also considering the former currencies of the EMU countries.

This essay tests for linear and nonlinear cointegrating relationships. In addition, the nonlinear Granger causality test is employed to test for a possible dynamic nonlinear causal relationship between real exchange rates and fundamentals. The analysis confirms the finding in the first essay that there is a nonlinear relationship between real exchange rates and fundamentals. We find evidence of nonlinear cointegration between the real exchange rates and fundamentals for Austria and Germany. We also find evidence of nonlinear causality from fundamentals to real exchange rates in all of the cases under consideration. In addition, there is a linear cointegrating relationship between the real exchange rates and fundamentals for Finland, Belgium, Spain and the euro. Also, we find evidence of a structural break in the long-run relationship between the real exchange rates and fundamentals for the Netherlands and Portugal. For both these countries, linear cointegration is evident over the period before the introduction of euro.

Put together, the results in the first two essays paint a complex picture of the relationship between real exchange rates and fundamentals, but generally point to the importance of allowing for nonlinearity in modelling the relationship. In the long term, there is evidence that real exchange rates are nonlinearly cointegrated with fundamentals. In the short term, there exists nonlinear Granger causality from some economic fundamentals to real exchange rates.

The third essay explores the dynamics of volatility of the euro nominal exchange rate. Volatility plays a prominent role in financial markets because it is a measure of risk or uncertainty -- a key concern in investment analysis, derivative securities pricing and risk management. Both researchers and practitioners have made great efforts to improve the accuracy of forecasts of volatility. However, it is still very difficult to forecast asset price volatility accurately, especially for exchange rates.

Euro exchange rates seemed to have been more volatile during the global economic crisis and debt crisis in the euro zone than before. It is therefore natural to conjecture that euro volatility may exhibit different dynamics during economic crises compared with more normal times. Examining this conjecture is one of the goals of this essay. In the existing literature the regime-switching GARCH (RS-GARCH) model has been shown to be superior in forecasting volatility of asset prices compared with single-regime GARCH models, and the stochastic volatility (SV) model has also been shown to have some advantages over other volatility models. However, the RS-GARCH model has not been compared with the SV model in forecasting exchange rate volatility. In addition, little attention has been paid to the effect of using exogenous variables on forecasting power. Hence this study attempts to complement the literature by modelling and forecasting volatility of euro exchange rates using ten volatility models.

In this essay, the volatility of four daily euro exchange rate series are estimated and forecasted over the period from 4 January 1999 to 15 March 2011 using ten volatility models. For reason of comparison and based on graphical observation of the volatility series, the whole sample period is divided into a normal period (before 1 January 2008) and a volatile period (after 1 January 2008). The ten models include short-memory and long-memory GARCH models, single-regime and regime-switching GARCH models, deterministic and stochastic volatility models, and linear and nonlinear volatility models. The out-of-sample forecasting performance of these models is compared using different criteria over the two periods. By comparing short-memory models with long-memory models, we investigate whether considering the long-memory properties of volatility processes can improve the forecast accuracy. By comparing single-regime models with regime-switching models, we examine whether exchange rate volatility displays regime-switching properties. Furthermore, by comparing the GARCH models with and without a dummy variable indicating the volatile period, we examine whether using an exogenous variable can enhance the forecasting performance of the models during the volatile period.

Besides confirming some established findings in the existing literature, this essay also provides some important new findings. First, the relative good performance of the RS-GARCH model implies that euro exchange rate volatility displays regime-switching characteristics. Accounting for the regime-switching behavior of volatility can improve the forecasting accuracy. Second, the FIGARCH model with a dummy variable performs the best among all the models over the volatile period after 2008. It not only forecasts better than FIGARCH but also performs better than RS-GARCH and SV. Third, GARCH models with a dummy variable for the volatile period generally perform better than those without a dummy over the volatile period, indicating that including a dummy variable into the models contributes substantially to the forecasting performance of the models. This result also confirms that the volatility of euro exchange rates displays different dynamics during the volatile period than during the normal period.

The fourth essay also examines exchange rate volatility and explores how volatility affects exports. Economic theory predicts that it is possible for exchange rate volatility to exert positive or negative effects on exports, and empirical studies also show mixed results. The question of whether exchange rate volatility stimulates or depresses exports remains open. During the current economic recession in Europe, exports from EMU member countries to other countries exhibit bigger fluctuations than before. This may be in part due to higher volatility of the euro exchange rates. Therefore it is interesting to examine whether euro exchange rate volatility has substantial effects on the exports of EMU member countries. In addition, the conventional concept of linear cointegration assumes implicitly that economic variables adjust towards their long-run equilibrium linearly at a constant adjustment speed over time. However, in reality adjustment often occurs only when the costs of deviations from equilibrium are larger than the costs of adjustment, and the adjustment speed may change over time depending on whether deviations from equilibrium exceed certain critical value. Therefore it is important to take into consideration the possible existence of nonlinear adjustment. However, potential nonlinear relationships between exchange rate volatility and exports have not attracted much attention. This essay attempts to fill this gap by investigating the potential nonlinear effects of exchange rate volatility on exports of ten EMU member countries.

Two cases are examined using a monthly dataset over the period 1975-2010: exports from ten EMU member countries to the US and exports from these EMU countries to the UK. Cointegration techniques are employed to test for the potential long-run relationships among the variables of interest. Analyses of both cases suggest that for most of the ten EMU countries, real exports are cointegrated with GDP of their trading partner, the real exchange rate and the volatility of exchange rates. Rising income of trading partners boosts exports, while real appreciation of the exchange rate and greater exchange rate volatility depresses exports.

We also find that the adjustment process of exports towards equilibrium is country-specific. While the exports of some countries adjust towards equilibrium following a linear error correction process, for some other countries (namely, Finland, Ireland and Austria) the adjustment process follows an asymmetric nonlinear process, that is, the adjustment speed of exports changes across regimes and decreases in exports trigger a stronger reaction than increases in exports. In addition, comparisons of the two cases indicate that the exports from Finland and Ireland to the UK are less sensitive to economic shocks than their exports to the US.

In summary, this thesis examines nonlinearity in exchange rate-related issues. The first two essays investigate both the short-term and long-term nonlinear relationship between real exchange rates and fundamentals and find evidence of nonlinear relationships. The third essay models and forecasts the volatility of euro exchange rates and finds evidence of regime-switching nonlinearity of volatility. The final essay examines the effects on trade of exchange rate volatility and finds evidence of threshold nonlinearity in the adjustment process of exports. These four essays correspond to Chapters 2-5 in this thesis. After this brief introduction, Chapters 2-5 proceed to investigate the three issues in detail, and Chapter 6 concludes the thesis.

Chapter 2 Nonlinear Relationship between Real Exchange Rates and Economic Fundamentals: Evidence from China and Korea[1]

2.1 Introduction

The issue of how well economic fundamentals can explain changes in exchange rates has been long investigated in the literature. There are two strands of literature in this regard. One strand focuses on analysis of nominal exchange rates and the other focuses attention on real exchange rates. As is well known, theories on the determination of nominal exchange rates are not well supported by empirical studies, since little empirical evidence has been found in favour of a strong link between nominal exchange rates and economic fundamentals. When it comes to the determination of real exchange rates, no theoretical or empirical consensus has been achieved, though great efforts have been taken to explore the relationship between real exchange rates and fundamentals.

Some studies on the determination of nominal exchange rates find a nonlinear relationship between nominal exchange rates and economic fundamentals (see Chinn, 1991; Meese & Rose, 1991; Ma & Kanas, 2000). In contrast, the literature on the determination of real exchange rates has focused only on linear relationships. This chapter attempts to fill this gap by investigating the possible nonlinear cointegrating relationship between the real exchange rates of the Chinese yuan (CNY) and the Korean won (KRW) and economic fundamentals. China and South Korea are two emerging economies in east Asia and have undergone major economic reforms in the sample period 1980-2009. However, the exchange rate regime adopted by these two countries is different from each other: China adopts a managed floating exchange rate regime, CNY is not yet a freely traded currency in foreign exchange markets. In contrast, South Korea adopts a floating

[1] This essay has been published in the Journal of International Money and Finance.

exchange rate regime, and KRW is a freely traded currency. By examining CNY and KRW, we attempt to seek evidence of nonlinearity in the real exchange rate-fundamentals relationship. In the meantime, we can also compare the behaviour of these two currencies.

We specify an empirical model for the determination of real exchange rates based on the work by Montiel (1999). Specifically, the economic fundamentals chosen include productivity growth, terms of trade, net foreign assets, economic openness, and government expenditure. We use the ARDL bounds testing approach proposed by Pesaran and Shin (1999) and Pesaran et al. (2001) to test for a linear cointegrating relationship between the real exchange rates and fundamentals. We use the nonlinear cointegration test developed by Granger and Hallman (1991) to explore the nonlinear relationship between the variables of interest. As will be seen later on, the choice of the ARDL bounds testing approach is due to its advantages over the traditional cointegration techniques. The nonlinear cointegration test is based on the Alternating Conditional Expectation (ACE) algorithm developed by Breiman and Friedman (1985), which conducts a nonparametric and nonlinear transformation of a variable to make it suitable for linear regression analysis. As shown by Wang and Murphy (2004), the advantage of ACE is its ability to correctly reveal a nonlinear relationship if it does exist between variables in question and to improve the model fit considerably compared with the conventional linear model.

The empirical results show that for China and Korea the relationship between the real exchange rates and economic fundamentals is indeed highly nonlinear.

The remainder of this chapter is organized as follows. Section 2.2 briefly reviews the relevant literature. Section 2.3 explains the empirical framework and the variables used in the empirical analysis. Then section 2.4 introduces the methodologies used in this chapter. And then section 2.5 presents the empirical results and discusses their implications. Finally, section 2.6 concludes.

2.2 Literature Review

To investigate the behavior of real exchange rates, many approaches have been developed and many empirical specifications have been used in a large empirical literature. All the approaches relate real exchange rates to fundamentals via an important concept of equilibrium exchange rates. Williamson (1983) put forward the initial concept of Fundamental Equilibrium Exchange Rate (FEER) based on the notion of macroeconomic internal and external balance.[2] Another approach that is closely related to FEER is the Natural Real Exchange Rate (NATREX) approach, which is mainly due to Stein (1994,1999).[3] Edwards (1989) provides an extensive analysis of the determination of the real exchange rate in developing countries and develops a so-called Equilibrium Real Exchange Rate (ERER) approach in the literature. He constructs a dynamic model relating real exchange rate behavior to fundamentals such as terms of trade, government consumption, level of import tariffs, technological progress, capital inflows and so on. Clark and MacDonald (1998) introduce the Behavioural Equilibrium Exchange Rate (BEER) approach as a new framework for empirical analysis.[4] They construct a basic model relating real exchange rates to fundamentals such as terms of trade, interest rates, government debt, productivity, and net foreign assets. Due to its flexibility, the BEER approach has been widely applied to analysis of real exchange rates.

Montiel (1999) develops a model that synthesizes the previous models of the equilibrium real exchange rate. According to Montiel (1999), the variables that may act as long-run determinants of real exchange rates come from four groups. The first group consists of domestic supply-side factors, particularly the Balassa–Samuelson effect arising from faster productivity growth in the tradable relative to non-tradable goods sector. Second, the structure of fiscal policy, such as permanent changes in the composition of government spending between tradable and non-tradable goods, is relevant. Third, changes in the international economic environment, including changes in an economy's external terms of trade, the flow of external transfers, foreign inflation, and the level of the world real interest rates, are important. Fourth, liberalization of commercial policy, for example, a

[2] The FEER approach has been further developed by Williamson (1994), Wren-lewis, et al. (1991), Wren-lewis (1992), Bayoumi et al. (1994), Isard and Faruqee (1998) and Driver et al. (1999).

[3] The NATREX approach has also been discussed by Stein and Allen (1995), Stein and Saurenheimer (1995) and Stein and Paladino (1998).

[4] The BEER approach has been further discussed by Macdonald (2000), Macdonald and Swagel (2000) and Clark and Macdonald (2004).

reduction in export subsidies, may affect the long-run real exchange rates.

There is a large literature on application of these approaches. We restrict our attention to a few studies closely relating to our empirical analysis. Zhang (2001) carries out a cointegration analysis on the CNY real exchange rates using the BEER based on annual data over the period 1955-1999. The results show that fundamentals such as economic openness, gross fixed capital formation, government consumption, and the growth rate of exports have significant effects on the CNY real exchange rates. Coudert and Couharde (2007) investigate the CNY real exchange rates using both the Purchasing Power Parity (PPP) and the FEER approach. They find no evidence of significant Balassa-Samuelson effects in the dynamics of the CNY real exchange rates. Wang, et al. (2007) estimate a BEER model and show that terms of trade, the relative price of the tradable goods to nontradable goods (proxy for Balassa-Samuelson effect), foreign exchange reserve, and the change of money supply are significant determinants of the CNY real exchange rates.

A common feature of the existing literature is that it assumes a linear cointegrating relationship between real exchange rates and economic fundamentals, completely ignoring potential nonlinearity in the dynamics of real exchange rates. This chapter attempts to complement the literature by investigating the nonlinearity in the real exchange rate-fundamentals relationship.

2.3 Empirical Specification and Variables

2.3.1 Empirical specification

Various model specifications with different explanatory variables have been used to examine real exchange rates. The empirical specification used in this chapter is based on the insights of Montiel (1999). The behavior of the real effective exchange rates of CNY and KRW is assumed to be determined by a set of economic fundamentals in the following way:

$$REER = f(PROD, TOT, GEXP, OPEN, NFA) + \varepsilon \qquad (2.3.1)$$

where *REER* denotes real effective exchange rates, the right-hand-side variables are the proxies for productivity growth, terms of trade, government expenditure, economic openness, and net foreign assets, respectively, and ε is an error term.[5]

2.3.2 Variables construction

Before we explain how the variables in Equation (2.3.1) are constructed, it should be pointed out that, just as the exchange rate measures the relative value of one currency vis-à-vis another, the fundamental determinants are also expressed as relative values of the domestic variables vis-à-vis the foreign counterparts. Therefore only the difference between the domestic and foreign variables matters for the movements of the exchange rate.[6] Moreover, since we want to have an overall assessment of the relationship between the real exchange rate and its fundamental determinants, we will study the multilateral effective exchange rate instead of a single bilateral exchange rate.[7] Therefore, analogous to the calculation of effective exchange rates, all economic fundamentals are expressed in effective terms, namely, as the ratio of the domestic variable relative to its foreign counterpart, while the foreign counterpart is a trade weighted average of the corresponding values of home country's main trading partners. The weights are equal to trading partners' shares in foreign trade of the home country. Specifically, for each country we first identify its top ten trading partners according to their gross bilateral trade volumes (exports plus imports).[8] We calculate the weight for partner i of home country H in year t as $W_{iHt} = FT_{iHt} / TFT_{Ht}$, where i=1,2,3,…,10, H=C, K denoting China and Korea, respectively. FT_{iHt} is partner i's trade volume with home country H and

5 The real interest rate is not included as a variable because of problems with data availability.

6 Note that the monetary approach to the exchange rate explicitly argues that only the home-foreign differences in such fundamentals as the money supply and real income are true determinants of the exchange rate. It is also a common practice to construct variables in this way in the literature on determination of real exchange rate.

7 An alternative approach would be to use a panel of several bilateral exchange rates for empirical analysis, which requires a good understanding of the statistical properties of the estimates of a nonlinear panel cointegration model.

8 The top ten trading partners of Mainland China vary over time. They include Australia, Brazil, Canada, France, Germany, Hong Kong, Italy, Japan, Jordan, Korea, Malaysia, Netherland, Romania, Russia, Singapore, the United Kingdom, and the United States. The top ten trading partners of Korea are: Australia, Canada, China, Chile, France, Germany, Hong Kong, Indonesia, Japan, Malaysia, Russia, Singapore, Saudi Arabia, Kuwait, the United Kingdom, and the United States.

TFT_{Ht} is home country's total foreign trade with its top ten trading partners. For the four quarters in the same year, the weights are assumed unchanged. By construction the weights sum up to unity.

(1) Real effective exchange rate (*REER*)

We define the exchange rate in terms of foreign currency per unit of domestic currency, so that an increase in its value means an appreciation of the home currency. The real effective exchange rate of home country H is calculated as:

$$REER_{Ht} = P_{Ht}R_{Ht} / \prod_{i=1}^{10} (P_{it}R_{it})^{W_{iHt}} \tag{2.3.2}$$

where $REER_{Ht}$ is the real effective exchange rate of home country in period t, P is the consumer price index (CPI), R is the nominal exchange rate in terms of the US dollars, and subscripts H and i denote home country and its partner i, respectively.[9]

(2) Difference in productivity (*PROD*)

The effect of differences in productivity on the real exchange rate is expected to follow the well-known Balassa-Samuelson theory (Balassa, 1964; Samuelson, 1964), which predicts that an increase in productivity in the tradable goods sector relative to the non-tradable goods sector leads to a real appreciation. This is typically driven by a rise of the non-tradable goods price relative to the tradable goods price. A commonly used measure of the Balassa-Samuelson effect is the relative price of non-tradable to tradable goods, which is often proxied by the ratio of the CPI (consumer price index) to the PPI (producer price index) or by per capita GDP. Following Kim and Korhonen (2005), we use per capita GDP (*PCGDP*) as a proxy for the difference in productivity, which is calculated using the following formula:

$$PROD_{Ht} = PCGDP_{Ht} / \prod_{i=1}^{10} (PCGDP_{it})^{W_{iHt}} \tag{2.3.3}$$

[9] Quarterly data for CPI levels for China are not directly available. We calculate these data using the quarterly data on percent change in CPI from the IMF's IFS dataset and annual CPI data from China Economic Statistical Yearbooks, and its base year has been adjusted to the same base year of the data from IMF (base year=2000).

(3) Terms of trade (*TOT*)[10]

Terms of trade is defined as the relative price of a country's exports compared to its imports, and is calculated as the ratio of the export unit value to the import unit value. While it is often used to represent changes in the international economic environment, its effect on the real exchange rate is ambiguous due to two conflicting effects. One is the income effect, which predicts that when the terms of trade improves, income from exports will increase, demand for non-tradable goods will rise, and hence the price of non-tradable goods will go up, leading to a real exchange rate appreciation. The other is the substitution effect, which predicts that an improvement in terms of trade means imports become cheaper, and at least part of domestic demand for non-tradable goods will be substituted by that for imports, so the price of non-tradable goods will be driven down. This would result in a real depreciation. Which effect dominates is an empirical question.

The formula for calculating *TOT* is as follows:

$$TOT_{Ht} = (XV_{Ht} / MV_{Ht}) / \prod_{i=1}^{10} (XV_{it} / MV_{it})^{W_{iHt}} \tag{2.3.4}$$

where *XV* and *MV* denote export unit value and import unit value, respectively.

(4) Government expenditure (*GEXP*)[11]

The relationship between government spending and real exchange rates have long been investigated theoretically and empirically (Frenkel and Mussa, 1988; Froot and Rogoff, 1995; Obstfeld and Rogoff, 1996; Fischer, 2004; and Kim and Korhonen, 2005). Government expenditure also has a substitution effect and income effect on the real exchange rate. On the one hand, government spending is mainly composed of nontradables, so if the crowding out effect of government spending is low, rising government expenditure will lead to an increase in demand for nontradables and hence drive nontradables price up. Therefore a rise in government expenditure can lead to real exchange rate appreciation via a substitution effect. On the other

[10] In China, Malaysia and Russia, no export and import unit value data are available, so we use instead the ratio of exports to imports as a proxy to reflect this effect.

[11] Quarterly data on government expenditure for China are not available over the period 1994-1998. To get a complete quarterly time series, we use quadratic interpolation method to convert the annual data into quarterly data.

hand, an increase in government expenditure has to be financed by higher taxes, which results in a decline of disposable income and a fall in demand for nontradables. This results in real exchange rate depreciation via the income effect. Furthermore, the duration of the high government expenditure policy also affects the real exchange rate. Elevated government expenditure would not be expected to have a very strong impact on the real exchange rate in the short run. However, lasting high government spending will most likely undermine confidence in a currency, since it could be followed by highly distortionary taxes with negative effects on economic growth and the real exchange rate. Thus high government spending with a long duration may cause depreciation of the real exchange rate.

This variable is calculated as the relative ratio of government expenditure to nominal GDP using the following formula:

$$GEXP_{Ht} = (GEX_{Ht} / GDP_{Ht}) / \prod_{i=1}^{10} (GEX_{it} / GDP_{it})^{W_{iHt}} \tag{2.3.5}$$

where *GEX* refers to government expenditure in absolute terms.

(5) Openness of economy (*OPEN*)

The variable *OPEN* measures the degree of openness of an economy. It is calculated as the ratio of total trade (imports plus exports) to GDP.

Theoretically, the impact of openness on the real exchange rate is uncertain and hence is unpredictable a priori. Openness may change as a result of a decrease in tariffs, increase in quotas, or reduction in export taxes. A decrease in tariffs or increase in quotas can decrease the domestic price of tradables and thus result in both income and substitution effects. The substitution effect, whether it is intertemporal or intra-temporal, will stimulate demand for importables, resulting in a deterioration in the trade balance, which in turn leads to depreciation of the real exchange rate. However, the income effect of openness on nontradable goods is ambiguous depending on the home country’s propensity to consume tradables or nontradables. If increased income is spent more on nontradables, then the real exchange rate is expected to appreciate. Connolly and Devereux (1995) argue that the substitution effect of openness usually dominates the income effect in such cases. Thus an increase in openness in this way may lead to depreciation of real exchange rate via a deterioration in the trade balance. If openness is increased through reduced export taxes, as argued by Connolly and Devereux (1995), income and substitution effects tend to work in the same direction. In this case there is no ambiguity that the trade balance will improve and hence lead to a real exchange rate appreciation.

The variable, *OPEN,* is constructed as follows:

$$OPEN_{Ht} = (TFT_{Ht} / GDP_{Ht}) / \prod_{i=1}^{10} (TFT_{it} / GDP_{it})^{W_{iHt}} \qquad (2.3.6)$$

where TFT_{Ht} and TFT_{it} denotes home country H and its trading partner i's total foreign trade.

(6) Net foreign assets (*NFA*)

Net foreign assets equal a country's total foreign assets less its total foreign liabilities. From a portfolio-balance perspective, a deficit in the current account causes an increase in the net foreign debt of a country, which has to be financed by international capital inflows. However, foreign investors demand a higher yield to start the necessary adjustment of their portfolios. At given interest rates, this can only be accomplished through a depreciation of the currency of the debtor country. In addition, the balance of payments channel assumes that foreign debts accumulated through current account deficits must be serviced with interest payments, which can be financed by a trade surplus. This in turn requires a depreciation of the currency, so that international competitiveness of the country can be strengthened and more net exports can be achieved. Therefore, a strong net foreign assets position will lead to real appreciation, while a weak position is expected to be associated with real depreciation.

In order to take into account the size of an economy, we divide the stock of net foreign assets by GDP. We calculate *NFA* using the following formula:

$$NFA_{Ht} = (TFA_{Ht} - TFL_{Ht}) / GDP_{Ht} - \sum_{i=1}^{10} w_{iHt} (TFA_{it} - TFL_{it}) / GDP_{it} \qquad (2.3.7)$$

where *TFA* and *TFL* denote total foreign assets and total foreign liability respectively.

The dataset used in this study consists of quarterly data from China and Korea over the period 1980Q1-2009Q4. Except for the cases specified in the associated footnotes, the data used to calculate the above variables are directly retrieved from the IMF's databases: Direction of Trade Statistics

(DOTS) and International Financial Statistics (IFS). Data have been seasonally adjusted where necessary. Variables expressed in italics and denoted by lowercase letters are logarithms of the original variables, for example,*reer*=ln(*REER*).

As can be seen from Figure 2.1 and Figure 2.2, the real exchange rate of CNY showed a depreciation trend during the period from 1980 to 1994. But after 1994, it displayed a gradual appreciation trend. In contrast, the real exchange rate of KRW remained stable over the sample period except that there was a big depreciation in 1997 due to the Asian financial crisis. For China, the variable *prod* exhibited an upward trend after 1994. And *prod* of Korea was on an upward trend except for a period of oscillation before late 1980s and a slump in Asian financial crisis in 1997 and global economic crisis in 2008 as well. For China, the *open* curve shows that China's economy relied more on foreign trade in the second half of the sample period than in the first half of the sample period. In comparison, Korea's economy showed higher overall level of openness. The other three variables (*NFA*, *gexp* and *tot*) fluctuated frequently and they seemed to be more volatile for China than for Korea. And no obvious rising or declining trends can be seen for these variables.

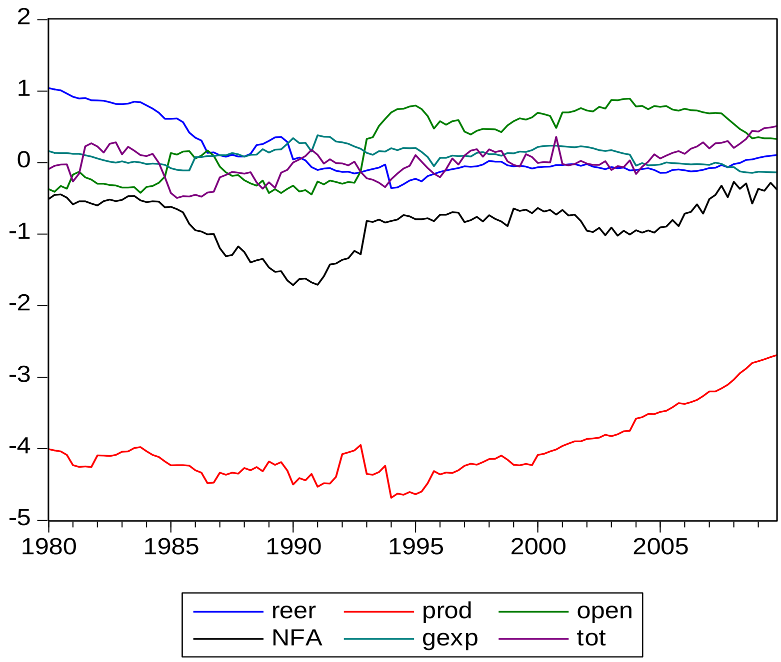


Figure 2.1 Variables of China

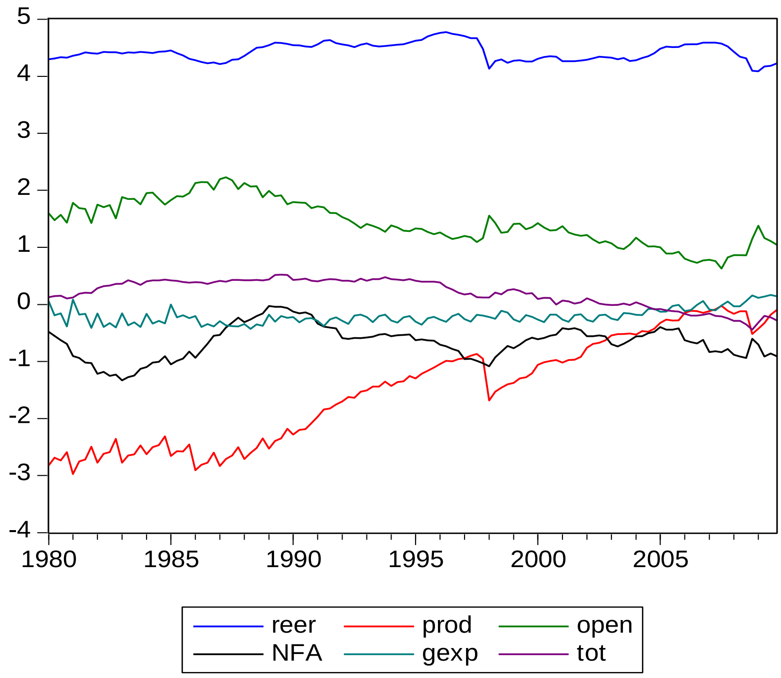


Figure 2.2 Variables of Korea

2.4 Methodologies

As mentioned before, to explore the possible linear and nonlinear cointegrating relationship between the real exchange rates and fundamentals, techniques such as the ACE algorithm, the ARDL bounds testing approach and the nonlinear cointegration test are employed in this chapter. This section introduces the basic ideas of these methods and the motivation for using them.

2.4.1 The ACE Algorithm

The ACE algorithm, developed by Breiman and Friedman (1985), is a method for estimating optimal transformations for multiple regressions that maximizes the coefficient of multiple correlations, R^2. Because the optimal transformations produced by the ACE algorithm are usually nonlinear, we can uncover the nonlinearity present in the data generating process by using this algorithm.

Generally speaking, a linear regression model for a response variable, y, and k independent variables, x_1, x_2, …, x_k, takes the following form:[12]

$$y_t = \sum_{i=1}^{k} \beta_i x_{it} + \varepsilon_t \tag{2.4.1}$$

where β_i $(i = 1, 2, \ldots, k)$ are the regression coefficients to be estimated, and ε_t is an error term. An ACE regression model based on Equation (2.4.1) can be written as:

$$f(y_t) = \sum_{i=1}^{k} g_i(x_{it}) + e_t \tag{2.4.2}$$

where f is a function of the dependent variable y, and g_i is a function of the independent variables x_i $(i = 1, 2, \ldots, k)$.

The ACE algorithm starts out by defining arbitrary measurable mean zero transformations, $f(y_t)$ and $g_i(x_{it})$ $(i = 1, 2, \ldots, k)$. In order to obtain the optimal transformations, we need to maximize the R^2 from a regression as specified in Equation (2.4.2). Under the normalization constraint of $E\left[f(y_t)\right]^2 = 1$, this is equivalent to minimizing the expected mean squared error of the regression, which is given by

$$e_t^2(f, g_1, g_2, \cdots, g_k) = E[f(y_t) - \sum_{i=1}^{k} g_i(x_{it})]^2 \tag{2.4.3}$$

The minimization of e^2 with respect to $g_i(x_i)$ $(i = 1, 2, \ldots, k)$ and $f(y)$ is carried out through a series of single-function minimizations, resulting in the following equations:

$$g_i(x_{it}) = E\{[f(y_t) - \sum_{j \neq i}^{k} g_j(x_{jt})] \big| x_{it}\} \tag{2.4.4}$$

[12] The independent variables may include a constant term.

$$f(y_t) = \frac{E[\sum_{i=1}^{k} g_i(x_{it}) \mid y_t]}{\left\| E[\sum_{i=1}^{k} g_i(x_{it}) \mid y_t] \right\|} \tag{2.4.5}$$

with $\|\bullet\| \equiv [E(\bullet)^2]^{1/2}$.

The algorithm involves two basic operations: conditional expectation and iterative minimization; hence the name Alternating Conditional Expectations. In Equation (2.4.4), the transformations of all variables except one are treated as fixed, and the transformation for the variable in question is estimated with a nonparametric "data smoothing" technique. The algorithm then proceeds to the next variable. After the estimation of $g_i(x_{it})\ (i = 1, 2, \ldots, k)$, $f(y_t)$ is estimated conditioning on these estimates according to Equation (2.4.5). By alternating between Equation (2.4.4) and Equation (2.4.5), we iterate until Equation (2.4.3) is minimized. The transformations $g_i^*(x_i)\ (i = 1, 2, \ldots, k)$ and $f^*(y)$ that achieve the minimization are the optimal transformations.

In the optimally transformed space, the variables are related as follows

$$f^*(y_t) = \sum_{i=1}^{k} g_i^*(x_{it}) + e_t^* \tag{2.4.6}$$

where e_t^* is the error not captured by the use of the ACE transformations and is assumed to have a normal distribution with zero mean.[13]

To sum up, the ACE algorithm conducts a nonparametric and nonlinear transformation of a set of variables to make it suitable for linear regression analysis. Some studies (see Ma & Kanas, 2000; Wang and Murphy 2004, etc.) show that the ACE algorithm is able to correctly reveal a nonlinear relationship if it does exist between variables in question and to improve the model fit considerably compared with the conventional linear model. This is

[13] Tibshirani (1988) proposes another algorithm called additivity and variance stabilization (AVAS), which is a modification of ACE and is similar to the ACE algorithm. Since Tibshirani (1988) shows that ACE and AVAS generate similar transformations in most cases, only ACE is applied in this chapter.

why we use it to explore nonlinear cointegration between variables under consideration.

2.4.2 Linear and nonlinear cointegration

Generally, cointegration models can be roughly divided into two categories: one category consists of linear cointegration models and the other one consists of nonlinear cointegration models.

(1) Linear cointegration

The general definition of linear cointegration proposed by Engle and Granger (1987) is as follows. If some variables are integrated of the same order d (I(*d*)), and at least one linear combination of these variables is integrated of order (*d*-*b*), then these variables are cointegrated of order (*d*, *b*). In practice, most financial variables are I(1), so in the case where *d*=*b*=1, a set of variables is said to be cointegrated if a linear combination of them is stationary.

More specifically, suppose Y_t and $X_t = (x_{1t}, x_{2t}, \cdots, x_{kt})'$ are cointegrated with $(1, \alpha')$ as the cointegrating vector, where $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_k)'$. The cointegrating relationship can be written as $Y_t + \alpha' X_t = \varepsilon_t$, where ε_t is the deviation from equilibrium, which is also called the equilibrium error in the literature.

(2) Nonlinear cointegration

According to Granger and Hallman (1991) and Granger (1991), the original variables y_t and x_{it} $(i = 1, 2, \ldots, k)$ are said to be nonlinearly cointegrated if there are nonlinear functions $f(\cdot)$ and $g_i(\cdot)$ $(i = 1, 2, \ldots, k)$ such that $f(y_t)$ and $g_i(x_{it})$ $(i = 1, 2, \ldots, k)$ are integrated of order 1 (*I*(1)) and that a linear combination of $f(y_t)$ and $g_i(x_{it})$ $(i = 1, 2, \ldots, k)$ is stationary (*I*(0)). Thus, linear cointegration among the ACE-transformed variables can be characterized as nonlinear cointegration among the original variables.

Generally, there are three possibilities for long-term relationships between variables: first, variables may be linearly cointegrated with each other; second, variables may be nonlinearly cointegrated with each other; and third, variables may be not cointegrated at all. Therefore to avoid misleading conclusion, one should take all of these possibilities into account when investigating long-term relationships between variables.

2.4.3 ARDL bounds testing approach

The bounds testing approach is based on the following autoregressive distributed lag model of orders ($p,q_1,q_2,\ldots, q_k$) (ARDL($p,q_1,q_2,\ldots, q_k$)):

$$\phi(L,p)y_t = \sum_{i=1}^{k} \beta_i(L,q_i)x_{it} + \delta' w_t + u_t \tag{2.4.7}$$

where $\phi(L,p) = 1 - \sum_{n=1}^{p} \phi_n L^n$, $\beta_i(L,q_i) = 1 - \sum_{j=1}^{q_i} \beta_{ij} L^j$, for i=1,2,…,k. L is a lag operator such that $Ly_t=y_{t-1}$, w_t is a vector of deterministic variables such as the intercept term, time trends, or other exogenous variables with fixed lags, δ_t is the coefficient vector associated with w_t, and u_t is an error term.

The ARDL approach does not require a precise pretest for the integration order of the time series under consideration, as long as no time series is integrated of order two or above. This approach is based on standard F and t statistics used to test the significance of the lagged levels of the variables in a univariate equilibrium correction mechanism. Pesaran et al. (2001) tabulate critical value bounds for the two border cases: the lower bound for the case that all time series are I(0) and the upper bound for the case that all of them are I(1). If the test statistic exceeds the upper bound, it indicates that there exists a long-run relationship among the variables. If it falls inside the critical bounds, the test is inconclusive and if it falls below the lower bound, then there is no cointegration.

It is noteworthy that a possible consequence of the ACE algorithm is that it may cause a time series that is originally *I*(1) to become *I*(0) after transformation. Therefore, even if these original series are all I(1), there may be a mixture of I(1) and I(0) series after transformation. In this context, the ARDL bounds testing approach proposed by Pesaran and Shin (1999) and Pesaran et al. (2001) has an advantage over cointegration techniques such as the Engle-Granger (1987) method and the Johansen (1995) approach, which generally require that all the series are integrated of the same order 1.

Furthermore, the ARDL bounds testing approach is more powerful for small samples than the latter methods. Therefore, we use the ARDL bounds testing approach to investigate the linear long-run relationship among the variables of interest.

2.5 Empirical Results and Discussion

2.5.1 Empirical results

The empirical investigation is conducted using a two-step testing procedure. First, we test for linear cointegration between the variables included in Equation (2.3.1). If no evidence of linear cointegration is found, we take the second step to test for nonlinear cointegration. If this test does not show any evidence of nonlinear cointegration, we conclude that exchange rates and the fundamentals are not cointegrated, either linearly or nonlinearly. The testing procedure proposed by Granger and Hallman (1991) and Granger (1991) is adopted at the second step. According to this testing procedure, the ACE algorithm is first used to transform the nonlinear relationship into a linear form, and then we test for potential cointegrating relationship among the transformed variables.

Before carrying out cointegration tests, we perform the Augmented Dickey-Fuller (ADF) unit root test to examine the stochastic characteristic of the original variables. The results of the ADF test for these time series are presented in Table 2.1 and Table 2.2. We find that all original series are non-stationary at 5% significance level, and the first-differenced series are all stationary, so no series is integrated of order 2 or greater.[14]

We then employ the ARDL bounds testing approach to examine if there is a cointegrating relationship among the variables in question. It turns out that no linear cointegrating relationship is found among the series, so we proceed to test for nonlinear cointegration. To this end, we first transform the variables using the ACE algorithm. The transformed variables are indicated by a superscript *A*. We then apply the ADF unit root test to the ACE-transformed variables and report the results in Table 2.1 and Table 2.2. The tests show that most transformed series remain non-stationary except that Chinese tot^A, Korean $prod^A$ and NFA^A become stationary. So we have to

[14] The unit root test results of the first-differenced series are omitted here to save space, they are available upon request.

deal with a mixture of I(1) and I(0) series; this is a context where the ARDL bounds testing approach is best applicable.

Because the ACE transformation is nonparametric and has no simple functional representation, the relationship between the original and the transformed variables is difficult to comprehend. In order to better understand the effect of the ACE transformation on the variables, we present scatter plots of the transformed versus the original variables in Figure 2.3 and Figure 2.4. If the plot demonstrates a straight line, it means that the transformed variable has a linear relationship with the original variable, so there is no need for transformation. We can see clearly from Figure 2.3 and Figure 2.4 that, as none of the plots show a straight line, the relationship between the transformed and original variables are all nonlinear. It is noteworthy, however, that among all the plots the scatter plots of *reer* versus $reer^A$ are closest to straight lines, indicating that the relationship between these two variables are nearly linear.

Table 2.1 ADF unit root tests of the raw and transformed series (China)

variables	intercept	trend	ADF test statistic	Critical value (5%)
reer	yes	no	-2.796(0.068)*	-2.886
$reer^A$	yes	no	-2.229(0.197)	-2.886
neer	yes	no	-1.733(0.412)	-2.886
prod	yes	yes	-0.958(0.945)	-3.448
$prod^A$	yes	yes	-2.389(0.384)	-3.448
tot	yes	no	-2.159(0.226)	-2.886
tot^A	no	no	-3.549(0.001)***	-1.944
open	yes	no	-1.178(0.217)	-1.944
$open^A$	no	no	-1.692(0.086)*	-1.944
gexp	no	no	-1.337(0.167)	-1.944
$gexp^A$	yes	no	-2.031(0.273)	-2.886
NFA	yes	no	-2.250(0.190)	-2.886
NFA^A	no	no	-1.471(0.132)	-1.944

Notes: 1. The transformed variables are indicated by a superscript A; 2.The choice of intercept and trend is based both on AIC and graphical inspection of the series; 3. MacKinnon (1996) one-sided p-values are in parentheses; 4. Null Hypothesis: series has a unit root; 5. Lag length is chosen automatically based on AIC; 6. *, **, *** denotes the 10%, 5%, 1% significance level respectively.

Table 2.2 ADF unit root tests of the raw and transformed series (Korea)

variables	intercept	trend	ADF test statistic	Critical value (5%)
reer	no	no	-0.184(0.618)	-1.944
$reer^A$	yes	no	-2.586(0.099)*	-2.886
neer	yes	yes	-3.251(0.080)*	-3.449
prod	yes	yes	-2.935(0.156)	-3.449
$prod^A$	no	no	-4.308(0.000)***	-1.944
tot	no	no	-2.472(0.342)	-3.448
tot^A	yes	yes	-2.710(0.235)	-3.448
open	yes	yes	-2.634(0.266)	-3.449
$open^A$	yes	no	-1.462(0.549)	-2.887
gexp	yes	yes	-0.944(0.306)	-1.944
$gexp^A$	no	no	0.642(0.854)	-1.944
NFA	no	no	-0.194(0.615)	-1.944
NFA^A	no	no	-3.556(0.000)***	-1.944

Notes: 1. The transformed variables are indicated by a superscript A; 2.The choice of intercept and trend is based both on AIC and graphical inspection of the series; 3. MacKinnon (1996) one-sided p-values are in parentheses; 4. Null Hypothesis: series has a unit root; 5. Lag length is chosen automatically based on AIC; 6. *, **, *** denotes the 10%, 5%, 1% significance level respectively.

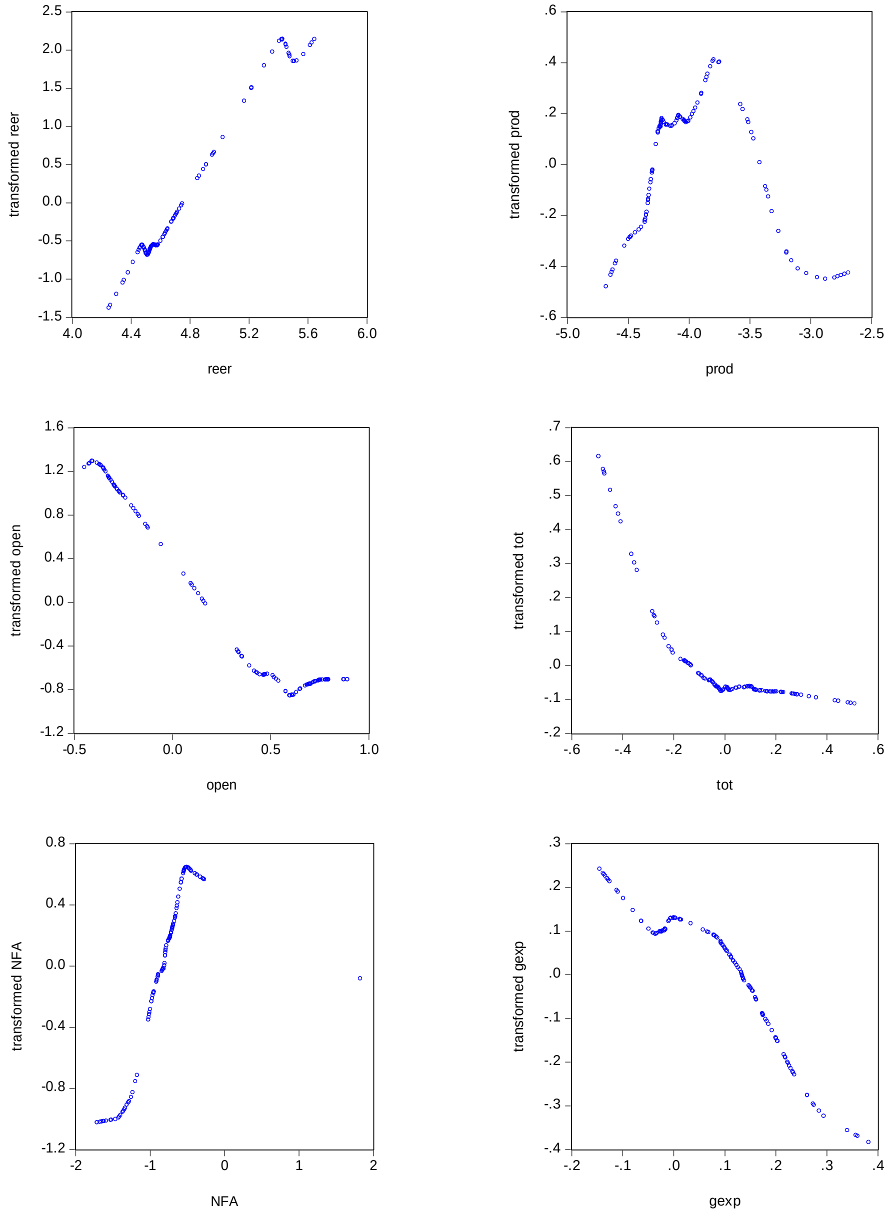


Figure 2.3 Scatter plots of the transformed versus raw variables (China)

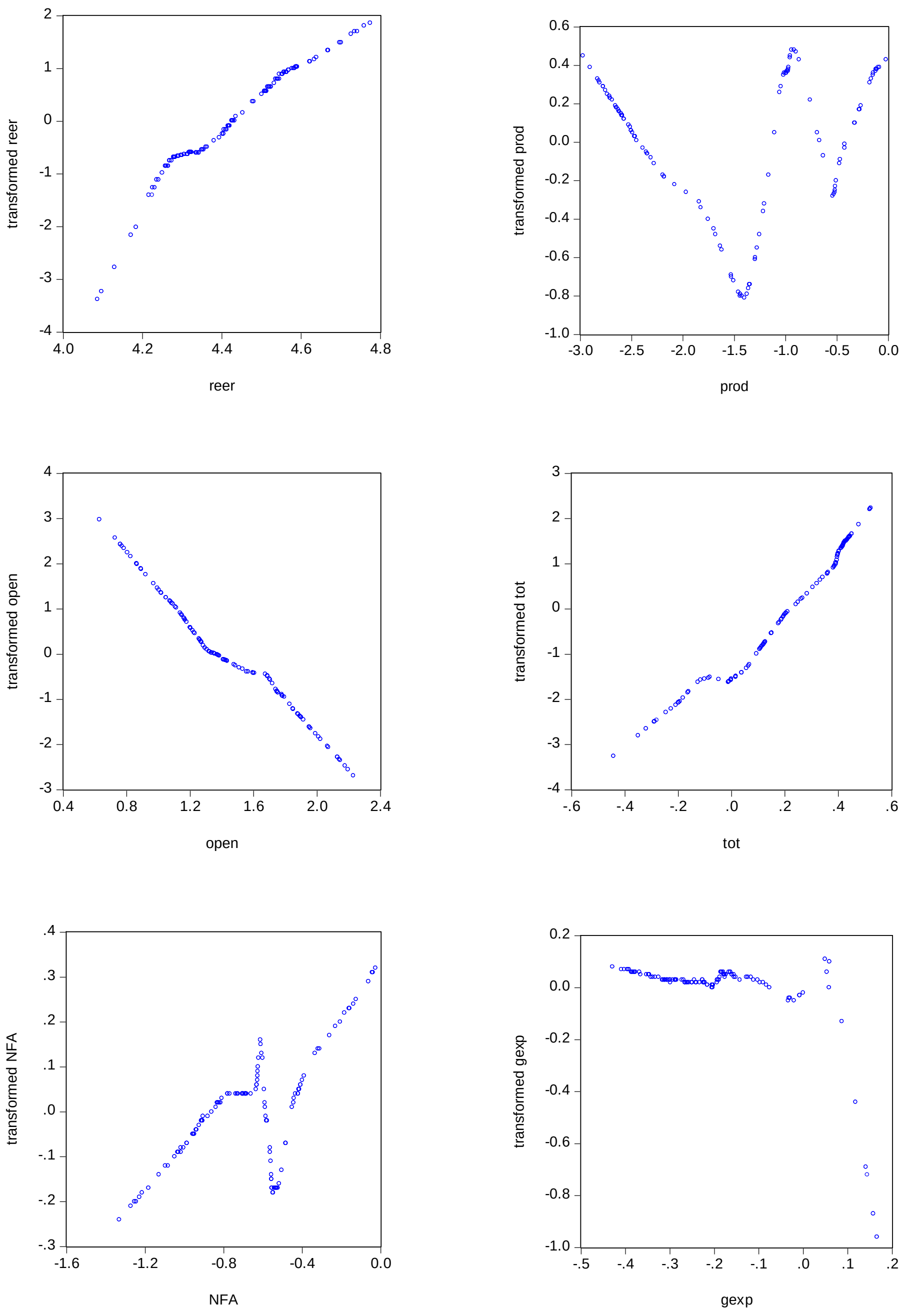


Figure 2.4 Scatter plots of the transformed versus raw variables (Korea)

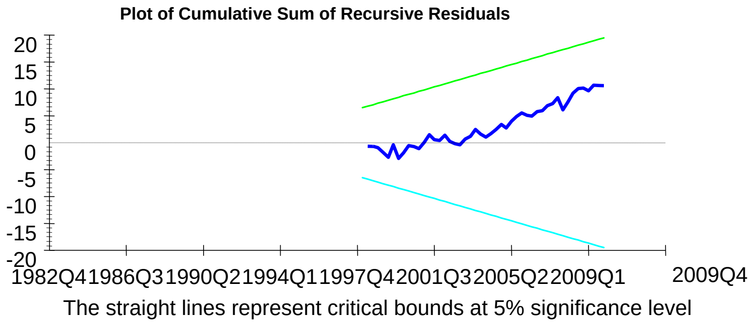


Figure 2.5 Plot of Cumulative Sum of Recursive Residuals (China)

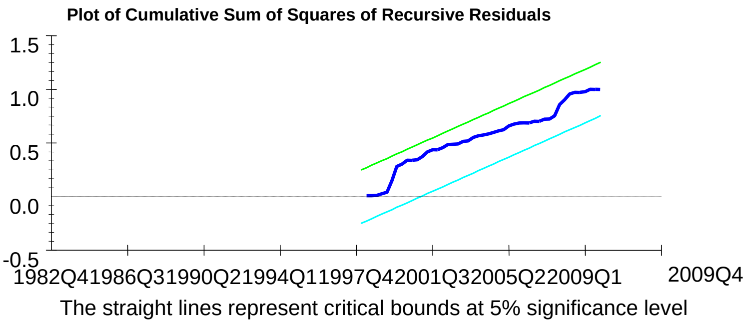


Figure 2.6 Plot of Cumulative Sum of Squares of Recursive Residuals (China)

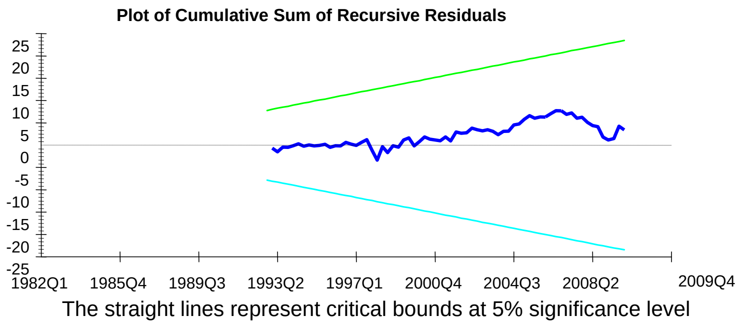


Figure 2.7 Plot of Cumulative Sum of Recursive Residuals (Korea)

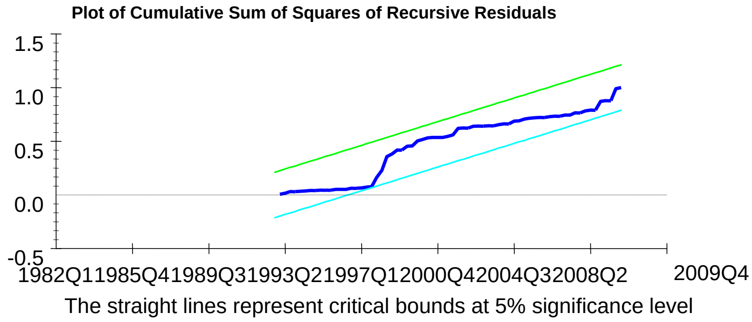


Figure 2.8 Plot of Cumulative Sum of Squares of Recursive Residuals (Korea)

For China and Korea, we do find cointegrating relationship among the transformed series in question, meaning that there does exist nonlinear relationships among the corresponding raw series. Due to the close relationship between real and nominal effective exchange rates (*neer*), it is expected that the nominal effective exchange rate may also be cointegrated with the fundamentals. If this is the case, then we may get more insight in the dynamic relationship between *neer* and *reer*. With this in mind, we also estimate the similar model taking *neer* as the dependent variable[15]. In addition, in order to get a clearer view of the nonlinear relationship, we calculate the elasticity of the real exchange rate with respect to the fundamentals in the next subsection. Noticing that the relationship between *reer* and $reer^A$ are nearly linear, we conjecture that the raw *reer* will also be cointegrated with the transformed fundamentals. If this conjecture is confirmed, then we can simplify the elasticity analysis substantially by analyzing the reduced model $reer = \sum_{i=1}^{5} g_i(x)$ instead of the originally complicated model $f(reer) = \sum_{i=1}^{5} g_i(x)$, where f and g_i denote nonlinear functions and x denotes fundamentals. This is why we also test for the potential cointegrating relationship between *reer* and the transformed fundamentals. The estimation results are summarized in Table 2.3.

[15] *neer* is calculated as the trade weighted average of the nominal bilateral exchange rate and is in logarithms.

Table 2.3 Summary of ARDL test results

	Cointegrating eqaution	Estimated model	F Statistic	CUSUM test	$x^2_{SC}(4)$	$x^2_{FF}(1)$	$x^2_{N}(2)$	$x^2_{H}(1)$
China	(2.5.1)	ARDL(2,1,1,1,1,0)	4.013**	stable	3.209 [0.523]	2.259 [0.133]	3.802 [0.082]*	0.131 [0.718]
China	(2.5.2)	ARDL(9,10,8,9,9,8)	6.344***	stable	3.733 [0.112]	.5598 [0.454]	0.372 [0.830]	0.790 [0.374]
China	(2.5.3)	ARDL(2,2,2,0,0,1)	4.384**	stable	8.899 [0.064]*	0.760 [0.383]	3.244 [0.090]*	0.266 [0.606]
Korea	(2.5.4)	ARDL(2,6,0,1,2,4)	6.078***	stable	1.508 [0.825]	2.906 [0.088]*	3.457 [0.075]*	0.376 [0.540]
Korea	(2.5.5)	ARDL(4,6,0,0,1,2)	5.329***	stable	2.889 [0.577]	1.958 [0.162]	2.196 [0.333]	0.010 [0.919]
Korea	(2.5.6)	ARDL(4,2,0,0,0,1)	5.348***	stable	2.244 [0.691]	0.742 [0.389]	2.783 [0.120]	0.382 [0.536]

Notes: 1. All ARDL models are selected based on Akaike Information Criterion; 2. The critical bounds for F Statistics are (2.26,3.35), (2.62,3.79) and (3.41,4.68) at 10% , 5% and 1%, respectively; 3. The stability of parameter is tested using CUSUM and CUSUMSQ tests based on residual series of the ARDL models, CUSUM and CUSUMSQ all stay between the two critical bounds at 5% significance level; 4. Diagnostic test results are presented in the last four columns, $x^2_{SC}(4)$, $x^2_{FF}(1)$, $x^2_{N}(2)$ and $x^2_{H}(1)$ denote chi-squared statistics to test for no residual serial correlation, no functional form mis-specification, normal errors and homoscedasticity respectively with p-values given in []; 5. *, **, *** denotes the 10%, 5%, 1% significance level respectively.

To ensure the robustness of the empirical results, we also performed four diagnostic tests to test for no residual serial correlation, no functional form mis-specification, normal errors and homoscedasticity, respectively. The results are presented in the last four columns of Table 2.3, where we can see that all the regressions fits reasonably well and pass the diagnostic tests.

We present the cointegrating equations for the two countries as follows.

China

For China, we find one cointegrating equation between $reer^A$ and the transformed fundamentals at the 5% significance level, which is given as follows:

$$\underset{}{reer_t^A} = \underset{(0.151)^{***}}{0.952\,prod_t^A} + \underset{(0.048)^{***}}{0.969\,open_t^A} + \underset{(0.359)^{***}}{1.335\,gexp_t^A} + \underset{(0.095)^{***}}{1.006\,NFA_t^A} + \underset{(0.308)^{*}}{0.556\,tot_t^A} \tag{2.5.1}$$

where the values in parentheses are the standard errors of the coefficients, the symbols *, ** and *** denote the 10%, 5% and 1% significance levels respectively, and these notations extend to equations 13-15 too.

As can be seen from Figure 2.3, *reer* and $reer^A$ are mostly positively correlated with each other. When we use the raw real effective exchange rate as the dependent variable instead of its transformed counterpart, we obtain the following cointegrating equation:

$$reer_t = \underset{(0.115)^{**}}{0.269\,prod_t^A} + \underset{(0.085)^{***}}{0.238\,open_t^A} - \underset{(0.295)}{0.144\,gexp_t^A} + \underset{(0.065)^{***}}{0.374\,NFA_t^A} + \underset{(0.800)^{*}}{1.418\,tot_t^A} + \underset{(0.020)^{***}}{4.721} \tag{2.5.2}$$

Similarly, if we take the nominal effective exchange rate as the dependent variable instead of its real counterpart, the following cointegrating equation is identified:

$$neer_t = \underset{(0.073)^{***}}{0.407\,prod_t^A} + \underset{(0.022)^{***}}{0.513\,open_t^A} + \underset{(0.153)^{*}}{0.280\,gexp_t^A} + \underset{(0.044)^{***}}{0.387\,NFA_t^A} + \underset{(0.147)^{***}}{0.573\,tot_t^A} + \underset{(0.018)^{***}}{3.970} \tag{2.5.3}$$

We can see from equation (2.5.1) that all of the ACE-transformed variables are statistically significant and have positive impacts on the transformed real exchange rate. Similarly, in equation (2.5.2) the coefficients of the transformed variables are also positive and differences are mainly confined to their magnitudes. In contrast, in equation (2.5.2) the transformed *gexp* becomes insignificant, indicating that equation (2.5.2) does not capture the whole relationship between *reer* and fundamentals presented in equation (2.5.1). Therefore it is suggestive that equation (2.5.2) can only serve as a rough benchmark for further analysis.

In equation (2.5.2), the coefficient on tot^A is much larger than the other coefficients, indicating that terms of trade may contribute to the real effective exchange rate more than the other fundamentals. This is also the case in equation (2.5.3), which may be mainly because both *reer* and *neer* are trade weighted average exchange rates. By comparing equation (2.5.2) and (2.5.3), we can see that all of the transformed variables except tot^A in equation (2.5.3) have larger coefficients than those in equation (2.5.2), indicating that the CNY nominal exchange rate usually shows stronger responses to fundamental shocks and is generally more volatile than the real exchange rate. By construction, *reer* and *neer* are both trade weighted average exchange rates, but *reer* removes the price differential between countries from *neer*, so *reer* can better measure the comparative economic activities between countries than *neer*. This explains why the coefficient on tot^A in equation (2.5.2) is larger than that in equation (2.5.3). As we can see below, the same reasoning applies to the case of Korea too.

As mentioned before, Figure 2.3 and Figure 2.4 show that the relationships between the transformed and original variables are all nonlinear. Put mathematically, $reer^A$=f($reer$) and x^A=g(x), where x denotes the fundamental variable, and f and g are nonlinear functions. The problem is that the ACE algorithm does not show the exact functional forms of f and g, so equation (2.5.1) does not tell us directly the direction of the impact of fundamentals on real exchange rates. This problem will be further discussed in subsection 2.5.3.

Before going into details, we can get a preview of the impact of fundamentals on the real exchange rate by observing the scatter plots of the raw explanatory variables against the transformed ones. Equation (2.5.2) tells us that except for $gexp^A$ the transformed variables have a positive effect on the real exchange rate. Thus a scatter plot of the raw explanatory variable against the transformed one, as depicted in Figure 2.3, can roughly reveal the qualitative impact of the original explanatory variable on the raw *reer*. Specifically, a negative (positive) slope of the scatter plot implies a negative (positive) effect of the corresponding raw explanatory variable on the real exchange rate. Figure 2.3 suggests that *prod* has a positive effect on *reer* in a certain lower-value range and has negative effect over a higher-value range. In contrast, at lower values *open* has a negative effect on *reer*, while at higher values its effect becomes positive. Most of the time *NFA* exerts a positive effect on *reer*, but *tot* tends to have negative effects on *reer*. As for *gexp*, we have to turn to equation (2.5.1) for information regarding its impact, since *gexp* is insignificant in equation (2.5.2). Equation (2.5.1) shows that $gexp^A$ is positively related to $reer^A$, which in turn is positively correlated with *reer*. Figure 2.3 tells us that *gexp* and $gexp^A$ are negatively correlated, thus *gexp* tends to affect *reer* negatively.

In Figure 2.4 the scatter plot of $prod^A$ versus *prod* is more irregular than that in figure 2.3, and it is also the case for NFA, indicating that for Korea the impact of these two variables on *reer* changes more often than that in the case of China. Similar to the case of China, Figure 2.4 shows that for Korea *gexp* also tends to affect *reer* negatively. We can also see from Figure 2.4 that for Korea *open* mostly exerts a negative effect on *reer,* but *tot* mostly exerts a positive effect on *reer*. What mentioned above is a rough qualitative analysis based on visual observation of the scatter plots, subsection 2.5.3 will carry out an elasticity analysis to investigate the quantitative impact of the original explanatory variable on real exchange rates.

Korea

In the case of Korea, the following cointegrating equation is identified among the six ACE-transformed variables:

$$\underset{}{reer_t^A} = \underset{(0.164)^{***}}{0.993\,prod_t^A} + \underset{(0.065)^{***}}{1.050\,open_t^A} + \underset{(0.389)}{0.081\,gexp_t^A} + \underset{(0.324)^{***}}{1.079\,NFA_t^A} + \underset{(0.062)^{***}}{1.071\,tot_t^A} - \underset{(0.036)}{0.002} \quad (2.5.4)$$

If we take the raw real effective exchange rate as dependent variable instead of its transformed counterpart, we obtain the following cointegrating equation:

$$reer_t = \underset{(0.035)^{***}}{0.138\,prod_t^A} + \underset{(0.013)^{***}}{0.169\,open_t^A} - \underset{(0.061)}{0.056\,gexp_t^A} + \underset{(0.060)^{***}}{0.202\,NFA_t^A} + \underset{(0.013)^{***}}{0.173\,tot_t^A} + \underset{(0.007)^{***}}{4.427} \quad (2.5.5)$$

If we take the nominal effective exchange rate as the dependent variable instead of its real counterpart, we obtain the following cointegrating equation:

$$neer_t = \underset{(0.044)^{***}}{0.137\,prod_t^A} + \underset{(0.019)^{***}}{0.105\,open_t^A} + \underset{(0.087)}{0.056\,gexp_t^A} + \underset{(0.100)^{**}}{0.224\,NFA_t^A} + \underset{(0.019)^{***}}{0.170\,tot_t^A} + \underset{(0.012)^{***}}{4.563} \quad (2.5.6)$$

In the above three specifications $gexp^A$ is insignificant, but the other transformed variables have significant positive effects on the raw and transformed exchange rate series.

Like the case of China, the terms of trade may play a relatively important role in affecting the real effective exchange rate compared with the other fundamentals because the coefficient on tot^A in each of the three equations is larger than that on other fundamentals, except NFA^A. Furthermore, we find that equation (2.5.6) tracks (2.5.5) closely in terms of the coefficients on the transformed variables. Specifically, while the coefficient on NFA^A in equation (2.5.5) is slightly smaller than that of equation (2.5.6), the coefficients on $prod^A$, $open^A$ and tot^A in equation (2.5.5) are slightly larger than their counterparts in equation (2.5.6). This reflects the fact that the nominal and real exchange rates of KRW respond similarly to fundamental shocks.

Equation (2.5.5) shows that the transformed variables except $gexp^A$ have positive effects on the real exchange rate. As can be seen from Figure 2.4, the slope of the scatter plot of *open* versus $open^A$ is largely negative, implying that *open* tends to exert a negative impact on *reer*. In contrast, the scatter plot of *tot* versus tot^A displays a largely positive slope, indicating that *tot* usually exerts a positive impact on *reer*. But the scatter plots of *prod* and *NFA* versus their transformed counterpart are highly irregular, therefore the effect of these variables on *reer* is complicated in the sense that the direction of the impact may change frequently over time (see subsection 2.5.3).

In sum, the transformations that linearize the relationship between the real exchange rate and the explanatory variables exhibit a non-monotonic nature. This finding is very similar to that of a study on nominal exchange rates by Meese and Rose (1991). It is noteworthy that caution should be taken when interpreting the graphs since the horizontal axis is scaled by the variable’s value rather than by time. As a matter of fact, the changes in signs are not temporally correlated across variables.

2.5.2 Exchange rate policy and stability of cointegrating relationships

The exchange rate system in both China and Korea had undergone some major adjustments in the period 1980-2009. In the period 1980-1993 China's exchange rate policy aimed to encourage exports and limit imports. China adopted a dual exchange rate regime, and CNY was pegged to a basket of currencies. The CNY exchange rate had been on a depreciation trend during this period, moving from around 1.8 CNY per USD in 1981 to 8.3 CNY per USD in 1994. The unification of the dual exchange rate system on 1 Jan 1994 led to a large depreciation of CNY. In the period 1994-2004, China adopted a conventional pegged exchange rate regime, and CNY was pegged to the US dollar. The CNY exchange rate had remained stable in this period. China revalued the official bilateral exchange rate of CNY/USD by 2.1% on 21 July 2005. The previous pegged exchange rate regime was replaced by a managed floating exchange rate regime, under which the CNY exchange rate is mainly determined base on market supply and demand with reference to a basket of currencies. China has been committed to more flexible exchange rate regime since then. The CNY exchange rate has been on a gradual appreciation path and has appreciated substantially against major international currencies.

Korea abandoned the KRW's fixed link to the US Dollar and established a controlled floating Effective Rate in February 1980. A multiple currency basket peg system was introduced to Korea in March 1980. The Effective Rate was linked to the SDR and a basket of the currencies of South Korea's major trading partners. And other policy factors were also considered in determining the value of KRW. Beginning from 1989, the exchange rate of KRW was allowed to fluctuate within a range against the basic rate. The Effective Rate was replaced by a Market Average Rate (MAR) in March 1990. A managed floating exchange rate regime was adopted and the exchange rate was determined by the market forces in the interbank market, the Seoul Foreign Exchange Market. Under the MAR system, the intraday fluctuation of the KRW/USD spot rate was restricted within a narrow band. The fluctuation range of the exchange rate in the interbank market was widened from 0.4% to 2.25% during 1990-1995. Korea adopted a floating exchange rate regime at the end of 1997. The exchange rate of the KRW was determined on the basis of market supply and demand and was allowed to float freely.

It is possible that the reforms took place in the sample period might have led to structural break in the long-run real exchange rate-fundamentals relationship. To examine these possibilities, we first check the stability of the cointegrating vectors using the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests based on the residuals of the estimated equations (2.5.1)-(2.5.6). The test results are also reported in Table 2.3. No evidence of instability is found for any case. Figures 2.5-2.8 illustrate the test results corresponding to Equation (2.5.2) and Equation (2.5.5).[16] We can see that all the plots of CUSUM and CUSUMSQ stay between the two straight lines that represent critical bounds at a 5% significance level, indicating the stability of the coefficients in the long run relationships. Therefore for both China and Korea the long-run relationship between the real exchange rate and fundamentals is stable over the sample period, though the exchange rate systems in both countries had undergone substantial changes as results of exchange rate regime reform.

The effects of exchange rate policy on different fundamentals are different, depending on how close the policy target is to the fundamentals and how fast the policy will take effect. Furthermore, the effects of exchange rate policy on fundamentals will vary over time if the policy changes. For instance, in one period income effect of fundamentals may dominate the substitution effect, if the policy changes, then the substitution effect may dominate the income effect in another period. The underlying force behind the nonlinear relationship is the changing dominance of the income effect and substitution effect of economic fundamentals and the interaction of exchange rate policy and other economic policies as well. Therefore the changes in policy may contribute significantly to the nonlinear relationship, though it is shown that the reforms did not cause structural breaks in the long-run real exchange rate-fundamentals relationship. This point will be further confirmed by the elasticity analysis in the next subsection.

2.5.3 Elasticity analysis

The cointegrating equations identified among the transformed variables can be rewritten in the form of (2.4.2) as:

$$f(reer_t) = \beta_1 g_1(prod_t) + \beta_2 g_2(open_t) + \beta_3 g_3(gexp_t) + \beta_4 g_4(NFA_t) + \beta_5 g_5(tot_t) + c \tag{2.5.7}$$

where β_i are coefficients and f and g_i $(i = 1, 2, 3, 4, 5)$ are nonlinear functions.

Because the ACE algorithm does not report the exact functional forms

[16] To save space, the other figures corresponding to equation (2.5.1), (2.5.3), (2.5.4) and (2.5.6) are omitted here.

of f and g_i $(i = 1, 2, 3, 4, 5)$, it is difficult to calculate precisely the quantitative effects of the raw variables on the real exchange rate. In order to investigate the quantitative impact on the real exchange rate when the raw fundamentals change their values, we attempt to calculate the elasticity of the real exchange rate with respect to the fundamentals. As mentioned in the previous subsection, the model $reer = \sum_{i=1}^{5} \beta_i g_i(x)$ tracks model $f(reer) = \sum_{i=1}^{5} \beta_i g_i(x)$ reasonably well, therefore we can simplify the elasticity analysis substantially by analyzing the simplified model $reer = \sum_{i=1}^{5} \beta_i g_i(x)$ instead of the model $f(reer) = \sum_{i=1}^{5} \beta_i g_i(x)$. For the purposes of comparison, we also analyze the model $neer = \sum_{i=1}^{5} \beta_i g_i(x)$. In the analysis to follow, we focus on equations (2.5.2), (2.5.3), (2.5.5) and (2.5.6).

Before calculating the elasticity, we first apply cubic spline interpolation methods to obtain an analytical function to approximate the unknown nonlinear functions g_i. The essential idea of this method is to fit a piecewise function to all the sample points (x_i, x_i^A) so that the curve obtained is continuous and smooth. Specifically, the values of series $\{x_i\}$ are ranked from smallest to largest so that $x_i<x_{i+1}$, i=1,2,3,…,119. Then a series of unique cubic polynomials of the form, $s_i = a_i(x-x_i)^3 + b_i(x-x_i)^2 + c_i(x-x_i) + d_i$, are fitted between two adjacent points, (x_i, x_i^A) and (x_{i+1}, x_{i+1}^A). The coefficients a_i, b_i, c_i and d_i are determined by some continuity and smoothness constraints that make the resulting curve continuous and smooth. In this manner, the nonlinear function g_i is approximated by the piecewise function consisting of 119 cubic polynomials.

To perform elasticity analysis, we choose the first 11 of 12-quantiles of each raw fundamental series as reference points. Specifically, we take the first reference point of series {*prod*}, for example, in the case of China the first 12-quantile of {*prod*} is -4.48304, it is in the interval $[x_{10}, x_{11})$=[-4.48311,-4.48297), in which the corresponding nonlinear function, g_1(prod), is approximated by the following cubic polynomial interpolated using the cubic spline interpolation method:

$$g_1(prod) \approx s_{10}(prod) = -3.9*10^7(prod+4.48311)^3 + 2828.682(prod+4.48311)^2 + 3.115(prod+4.48311) - 0.286 \quad (2.5.8)$$

After substituting s_{10} into equation (2.5.2), we have the following equation:

$$reer = 0.269s_{10}(prod) + 0.238g_2(open) - 0.144g_3(gexp) + 0.374g_4(NFA) + 1.418g_5(tot) + 4.721 \quad (2.5.9)$$

We take the first order derivative of equation (2.5.9) with respect to *prod* and calculate the elasticity of *reer* with respect to *prod* at *prod*=-4.48304, denoted by E_{prod}^{reer} =0.802.

We repeat the above process to calculate the elasticity at the other 10 reference points for all the cases in question, where all raw explanatory variables are set at their second to eleventh 12-quantiles, respectively. The results are reported in Table 2.4 and Table 2.5.

Table 2.4 Elasticity of *reer* and *neer* with respect to fundamentals at 12-quantiles (China)

12-quantiles	E_{prod}^{reer}	E_{prod}^{neer}	E_{open}^{reer}	E_{open}^{neer}	$E_{g\exp}^{reer}$	$E_{g\exp}^{neer}$	E_{NFA}^{reer}	E_{NFA}^{neer}	E_{tot}^{reer}	E_{tot}^{neer}	sum E_x^{reer}	sum E_x^{neer}
1	0.802	1.213	-0.390	-0.841	-0.284	-0.395	0.074	0.076	-3.059	-1.236	-2.858	-1.183
2	2.488	3.765	-0.594	-1.281	-0.033	-0.093	0.357	0.370	-3.668	-1.482	-1.450	1.278
3	0.676	1.022	-0.466	-1.005	0.483	0.563	-0.102	-0.106	-1.839	-0.743	-1.249	-0.269
4	-1.266	-1.916	-0.547	-1.180	0.122	-0.158	0.845	0.875	0.328	0.132	-0.763	-2.247
5	0.530	0.801	-0.642	-1.383	-1.663	-3.274	-0.330	-0.341	-0.410	-0.166	-2.515	-4.363
6	0.083	0.126	-0.482	-1.039	-0.414	-0.459	1.124	1.163	0.902	0.365	1.214	0.156
7	-0.300	-0.454	-0.020	-0.043	1.217	-1.489	0.283	0.293	0.521	0.210	-0.734	-1.483
8	0.074	0.112	-0.561	-1.209	0.283	-0.321	6.395	6.529	-0.820	-0.331	4.720	4.780
9	0.422	0.639	-0.087	-0.187	-5.952	-6.525	-1.410	-1.459	-0.071	-0.028	-7.097	-7.560
10	-0.407	-0.616	0.163	0.351	-0.664	-0.699	0.174	0.180	-0.027	-0.011	-0.761	-0.795
11	-0.383	-0.579	0.012	0.027	-0.654	-0.769	-0.310	-0.321	-0.171	-0.069	-1.505	-1.711

Note: 1.The integer n in the first column denotes the nth 12-quantile; 2. E_x^y denotes the elasticity of y with respect to x. Note that NFA is in level rather than in logarithm, so E_{NFA}^{reer} and E_{NFA}^{neer} is actually semi-elasticity; 3. Since *gexp* is insignificant in equation (2.5.2), $E_{g\exp}^{reer}$ is calculated based on equation 10 using quadratic interpolation for simplicity. 4. sum

E_x^{reer} and sum E_x^{neer} denotes the sum of the elasticity of reer and neer respectively.

Table 2.5 Elasticity of *reer* and *neer* with respect to fundamentals at 12-quantiles (Korea)

12-quantiles	E_{prod}^{reer}	E_{prod}^{neer}	E_{open}^{reer}	E_{open}^{neer}	E_{NFA}^{reer}	E_{NFA}^{neer}	E_{tot}^{reer}	E_{tot}^{neer}	sum E_x^{reer}	sum E_x^{neer}
1	-0.031	-0.031	-0.797	-0.495	0.174	0.193	1.564	1.537	0.911	1.205
2	-0.105	-0.104	0.014	0.009	-0.023	-0.026	0.682	0.670	0.576	0.541
3	-0.132	-0.131	-0.958	-0.595	-0.426	-0.473	1.042	1.024	-0.487	-0.162
4	-0.081	-0.081	-0.677	-0.421	0.000	0.000	1.052	1.034	0.270	0.557
5	-0.165	-0.164	-0.744	-0.462	0.000	0.000	1.398	1.374	0.297	0.940
6	0.074	0.074	-0.272	-0.169	1.724	1.911	1.068	1.050	2.738	2.720
7	0.477	0.473	-0.380	-0.236	-0.546	-0.605	1.566	1.539	1.059	1.229
8	0.597	0.592	-0.813	-0.505	-0.650	-0.721	5.448	5.353	4.582	4.719
9	-0.238	-0.236	0.067	0.042	0.490	0.543	-0.550	-0.540	-0.369	-0.053
10	-9.983	-9.910	-0.559	-0.347	-0.109	-0.121	1.572	1.545	-9.102	-8.811
11	0.678	0.673	-0.646	-0.401	0.070	0.077	-0.084	-0.082	-0.085	0.370

Note: 1.The integer n in the first column denotes the nth 12-quantile; 2. E_x^y denotes the elasticity of y with respect of x. Note that NFA is in level rather than in logarithm, so E_{NFA}^{reer} and E_{NFA}^{neer} is actually semi-elasticity; 3. sum E_x^{reer} and sum E_x^{neer} denotes the sum of the elasticity of *reer* and *neer* respectively.

With respect to the economic fundamentals, we can see from Table 2.4 and 2.5 that the elasticity of the real exchange rate is changing both in size and in sign over the sample range. This is in sharp contrast with conventional linear analysis, which assumes that both the magnitude and sign of elasticity are constant.

A positive elasticity of *reer* with respect to *prod* is consistent with conventional wisdom based on the Balassa-Samuelson effect (increases in *prod* lead to a real appreciation of the home currency). However, a negative elasticity is at odds with the conventional wisdom. In the existing literature, there are many studies that are not supportive of the Balassa-Samuelson effect. For instance, Chinn (1997) finds that *prod* has a negative effect on real exchange rates. Chinn and Johnson (1997) show a majority of negative coefficients on *prod* in their models. And Fischer (2004) shows that total factor productivity shock affects the real exchange rate not only through a Balassa-Samuelson-type supply channel but also through an investment demand channel, that is, rising productivity in any sector raises the equilibrium capital stock in the economy and thus raises investment demand which in turn increases prices. He argues that, with possible combination of productivity changes across economic sectors, it is very likely that in some periods other economic forces such as capital movements and commodity price booms or busts will dominate the Balassa-Samuelson effect in determining the real exchange rate. Such cases will simply give no evidence in favor of the Balassa-Samuelson effect.

One possible explanation in our case is that productivity growth is mainly promoted by capital inflows to the home countries. How capital inflows affect real exchange rates depends upon the nature of utilization of this capital. If capital inflows are mostly spent on tradable goods, the real exchange rate will depreciate via a deteriorated trade balance. On the contrary, real exchange rate will appreciate if the capital inflows are mostly spent on non-tradable goods. Over different periods, these two possibilities may alternate. This would explain why the elasticity of *reer* E_{prod}^{reer} changes in sign over the sample period. For China, at 4 out of 11 12-quantiles E_{prod}^{reer} is negative, in comparison, the reverse is true for Korea. The reason for this difference may be that, compared with Korea, more capital inflows go into the sector producing nontradables in the Chinese economy, which is still underdeveloped.

Intuitively, openness may bring both benefits and costs to the economy. On the one hand, the more open a country is to international trade, the more integrated it is into the world economy and the less it needs to rely on protectionist commercial policies. Thus greater openness will help the country benefit from integration and promote its economic development, which may lead to an appreciation of the home currency. On the other hand, being open has a price. As Edwards (1994) and Elbadawi (1994) show in their models for developing countries, greater openness means less trade barriers, especially lower tariffs on imports, so countries with greater openness may rely more heavily on real depreciation as an instrument to safeguard their external competitiveness, thus *open* shows a negative impact on the real exchange rate.

The extant empirical evidence on the effect of trade openness on real exchange rate remains mixed. Some studies show that openness has a positive influence on the real exchange rate (Elbadawi, 1994; Connolly and Devereux, 1995). Kim and Korhonen (2005) provide strong evidence in favor of a negative impact of openness on real exchange rates. Li (2004) has shown that real exchange rates usually depreciate after countries totally open their economy to trade, but partial liberalization could lead to short-run real exchange rate appreciation during the early stages of liberalization. The elasticities calculated in this chapter also confirm this mixed results. As can be seen from Table 2.4 and Table 2.5, the elasticity E_{open}^{reer} is mostly negative. For both China and Korea, the elasticity is positive at only two quantiles, indicating that openness exerts a mostly negative impact on *reer*. A possible explanation is that, for both countries, the income effect of openness occasionally works in a positive direction and dominates substitution effect over some periods, so E_{open}^{reer} is positive over a few periods. China is still a developing country that is not totally open to the world economy, rising trade openness is in the form of decreases in tariffs or increases in quotas, especially before its entry to the World Trade Organization in 2001. As argued by Connolly and Devereux (1995), in such case the substitution effect of openness usually dominates the income effect and hence the total effect of openness is more often negative. In contrast, Korea is a more developed country with a small open economy. After its complete trade liberalization, increased income resulted from trade openness may have been spent more on tradables, thus the income effect works often in the same negative direction as the substitution effect, and thus openness often exerts a negative impact on its real exchange rate.

Analogously, according to the linear models, *gexp* has either a positive or a negative impact on the real exchange rate depending on whether the substitution effect dominates the income effect and whether high government spending is a short-term or long-term policy. Our empirical results show that government expenditure does not exert a significant effect on the KRW real exchange rate. According to Table 2.4 for China, $E_{g\exp}^{reer}$ is only positive at four quantiles, but is negative for the rest. The positive elasticity is consistent with the view that a given size of fiscal stimulus boosts aggregate demand when the government expenditure is low and does not crowd out much private consumption, thus leading to real appreciation of the home currency. The negative elasticity suggests that the income effect of *gexp* often dominates the substitution effect. In addition, as government expenditure remains at higher level for a long period, it causes worries about the sustainability of such a high level of government expenditure, which impairs economic growth and hurts the real value of the home currency. As a result, real depreciation tends to be associated with large increases in government spending.

Generally speaking, *NFA* contributes positively to appreciation of a currency, which explains why E_{NFA}^{reer} is positive. Many studies (e.g. Faruqee 1995, and Obstfeld and Rogoff 1995) show empirical results confirming a positive correlation between net foreign assets and the real exchange rate. But our finding is different: for China, 4 out of 11 values of E_{NFA}^{reer} are negative, and 5 elasticity values are negative for Korea (see Table 2.4 and Table 2.5). This may be due to the short-run co-movement of capital flows and the real exchange rate: a rise in *NFA* could result from high current account surplus generated by home currency real depreciation.

Since improvement of the terms of trade has both a negative substitution effect and a positive income effect on the real exchange rate, the overall impact of the terms of trade on the real exchange rate depends on which effect dominates. We can see from Table 2.4 that E_{tot}^{reer} is only positive for 4 out of 11 quantiles, suggesting that for the CNY real exchange rate the substitution effect mostly dominates the income effect. Hence the terms of trade generally exerts a negative effect on the CNY real exchange rate. In comparison, the corresponding empirical finding for Korea suggests the opposite: E_{tot}^{reer} is positive at all except two quantiles, meaning that the positive income effect often dominates the negative substitution effect. This means that strengthening terms of trade for Korea often leads to a real appreciation of the KRW. On average, the elasticity of real exchange rate with respect to the terms of trade is larger than that with respect to other fundamentals, especially so for Korea, confirming that the terms of trade play a more important role in affecting real exchange rates than other fundamentals, as conjectured in the previous subsection.

Usually, in linear cointegration models fundamentals may have either positive or negative effects on the real exchange rate and the elasticity remains constant over time, which is often at odds with reality and hence is the major drawback of linear models. As a matter of fact, in the real economy almost all forces are changing over time, reflecting both endogenous and/or exogenous shocks. In the short run, these forces interact with each other and their influences on the economy may either strengthen or weaken but rarely remain constant until they ultimately fade away. Thus no theory can guarantee that their effects on the economy are constant. Compared to linear models, the nonlinear model represented by Equations (2.5.2) and (2.5.5) actually provides a more flexible explanation. Besides the changes in sign, it is also apparent that the magnitude of the elasticity is changing over time. Take E_{prod}^{reer} in Table 2.4 for example, at the first quantile (corresponding to 1986Q3), its value is 0.802, meaning that a 1 percent increase in productivity differential can lead to a 0.802 percent appreciation of the CNY real exchange rate. At the second quantile (1990Q4), the elasticity is 2.488, meaning that the effect of *prod* becomes much stronger than before. Then at the third quantile (1995Q4), a smaller elasticity (0.676) indicates a weakened effect. Thus the changing elasticity seems to reflect the real economy more reasonably than constant elasticity.

As indicated by the coefficients in equations (2.5.2), (2.5.3), (2.5.5) and (2.5.6), Table 2.4 and Table 2.5 show that for CNY, $|E_x^{reer}|<|E_x^{neer}|$ (*x*=*prod*, *open*, *gexp*, and *NFA*) but $|E_{tot}^{reer}|>|E_{tot}^{neer}|$, meaning that the CNY nominal exchange rate usually responds more strongly to all of the individual fundamentals except the terms of trade. The case is a little different for KRW: $|E_x^{reer}|>|E_x^{neer}|$ (x=*prod*, *open*, *tot*) but $|E_{NFA}^{reer}|\le|E_{NFA}^{neer}|$, and compared to CNY, the differential between the elasticity of *reer* and that of *neer* is much smaller. Of course the overall effect of all the fundamentals depends on both the magnitude and sign of the elasticity，we sum up the elasticity and find that on average the magnitude of the elasticity of *neer* is larger than that of *reer* for both CNY and KRW, indicating that the nominal exchange rate responds more strongly than the real exchange rate to fundamentals at the overall level. This may explain why the nominal exchange rate is usually more volatile than the real exchange rate. Through further comparison, we also find that the magnitude of both the sum of E_x^{reer} and the sum of E_x^{neer} of CNY is larger than their counterparts for KRW at 8 out of 11 quantiles, suggesting that overall effects of fundamentals are stronger on the CNY exchange rates than on the KRW exchange rate, which may lend support to the view that real exchange rates are more stable in a flexible exchange rate regime than in a less flexible regime. The above results suggest that the behavior of the KRW exchange rate is different from that of CNY, though both of them are nonlinearly related to fundamentals.

2.6 Summary and Conclusions

In theory, there may exist nonlinear cointegration between real exchange rates and economic fundamentals. However, the existing literature pays little attention to the nonlinear case. Actually, no economic theories can guarantee that the relationship between economic variables must be linear. Ignoring the nonlinear case may lead to misleading conclusions that no cointegration exists between exchange rates and fundamentals. Therefore this chapter attempts to explore the potential evidence of nonlinear cointegrating relationships for Chinese yuan and Korean won using quarterly data over the period 1980-2009.

The nonlinear cointegration test is employed to test for the potential nonlinearity among the variables of interest. The results show that for both CNY and KRW there exists a nonlinear cointegrating relationship between real exchange rates and productivity, terms of trade, net foreign assets, openness of the economy and government expenditure. There are several implications of these results. First, in order to avoid misleading conclusions, we have to take into consideration the possibility of nonlinearity when investigating the cointegrating relationship among variables of interest; second, the elasticity of *reer* with respect to fundamentals is changing substantially, not only in magnitude but also in direction over time. This result is in sharp contrast with the conventional equilibrium exchange rate theory, which suggests that both the magnitude and sign of the elasticity is constant over time. So compared with the linear cointegration model, the nonlinear model depicts a more complex picture of the long-term relationship between the real exchange rate and fundamentals and to some extent it provides more flexibility in explaining real exchange rate issues. Finally, the results suggest that the behavior of the KRW exchange rate is different from that of CNY, though both of them are nonlinearly related to fundamentals.

The most important implication for policy making is that, given that the relationship between exchange rates and fundamentals may be nonlinear, policymakers should not take for granted the constant elasticity implied by the linear cointegrating model. Instead, they should keep in mind that suitable policies should be made adjustable to the specific economic context, not only because the magnitude of impact on the exchange rate of fundamentals is changeable, but also because the direction of impact may be reversed if the context changes.

Chapter 3 Nonlinear Relationship between Real Exchange Rate and Economic Fundamentals Revisited: Evidence from the EMU

3.1 Introduction

Chapter 2 has shown that the real exchange rates of Chinese yuan and Korean won are nonlinearly cointegrated with economic fundamentals. A natural question to ask is whether the evidence found for these two emerging-market currencies is valid for currencies in advanced economies. In order to examine the generality of the nonlinear real exchange rate-fundamentals relationship, this chapter examines the real exchange rates of the euro and 10 former currencies of EMU member countries.[17]

As well as the methods employed in Chapter 2, linear and nonlinear Granger-causality tests are also used in this chapter to explore the causal relationship between the variables of interest in the short term. We find evidence of nonlinear relationships between real exchange rates and economic fundamentals. In the long term there exist nonlinear cointegrating relationships between the real exchange rates of the German Mark and Austrian schilling and fundamentals, and in the short term some fundamentals Granger-cause the real exchange rates in a nonlinear fashion in all the cases under consideration.

The remainder of this chapter is organised as follows. Section 3.2 briefly reviews the relevant literature; section 3.3 introduces the empirical specification, variables and data sources; section 3.4 introduces econometric methodologies and the empirical testing procedure; the empirical results are then given and analysed in section 3.5; section 3.6 concludes.

3.2 Literature review

There is a large body of literature on the relationship between real

[17] The ten currencies are German mark, French franc, Italian lira, Spanish peseta, Belgian franc, Irish pound, Dutch guilder, Austrian schilling, Portuguese escudo and Finnish markka. Greece is excluded because it became an EMU member in 2001 and data on some variables are not available.

exchange rates and fundamentals. Here we focus only on the empirical studies relating closely to our empirical analysis. Alberola, et al. (1999) estimate equilibrium real exchange rates for a panel of major currencies using panel unit root and cointegration methods. The sample includes 12 currencies over the period 1980Q1-1998Q4, which ends with the creation of EMU.[18] Their empirical model includes only two explanatory variables (the stock of net foreign assets and a relative sector prices index reflecting the sector productivity differentials across countries). The results show that the four major former EMU currencies (the German mark, French franc, Italian lira and Spanish peseta) locked their parities with the euro at a rate close to equilibrium.

To find the appropriate exchange rates of the European currencies for entry into the EMU and the main determinants of the external value of the euro, Couharde and Mazier (2001) constructs a linear model in the spirit of FEER to estimate the equilibrium real exchange rates of European currencies over the period 1970-1998 using cointegration techniques. They take as determinants of real exchange rates the following four fundamentals: price differential, external performance, growth differentials, and structural characteristics of international specialization in foreign trade. The results suggest that the central parities in force within EMS were satisfactory and would not subsequently cause intra-European tensions.

Maeso-Fernandez, et al. (2002) analyse the determinants of the euro real effective exchange rate and derives synthetic real effective exchange rates of the euro. They apply the BEER and Permanent Equilibrium Exchange Rate (PEER) approach on the basis of synthetic quarterly data for the euro area and its twelve main trading partners from 1975 to 1998. Four specifications are estimated applying Johansen's procedure. Their results indicate that the fundamentals show different significance in different specifications: real interest rate differentials, productivity differentials, the relative fiscal stance and the terms of trade (using the real price of oil as a proxy) may have a significant influence on the euro real effective exchange rates, depending on the specification considered.

[18] The 12 currencies are US dollar, UK sterling, Japan yen, Canada dollar, Denmark krone, Swedish krona, Greek drachma, German mark, French franc, Italian lira, Spanish peseta and the euro.

Detken, et al. (2002) employ four different linear models (including a BEER model) to estimate the equilibrium real exchange rate for the synthetic euro using data aggregated over the period 1973 to 2000. The real exchange rate of the synthetic euro is shown to be significantly and positively correlated with the relative price of non-traded goods versus traded goods and the real interest rate differential vis-a-vis the rest of the world (proxied by the US, UK, Japan and Switzerland). Their results suggest that the estimates for the real effective exchange rates are model-dependent and surrounded by some non-negligible uncertainty. They also point out that their results suggest that the models employed are simply not capable of explaining the path followed by the real exchange rate of euro at the end of the sample period, and alternative variables and models should be sought for that purpose.

The studies mentioned above model and construct the synthetic euro real exchange rate using aggregated data of the euro area, and the longest sample only covers a period up to 2000Q4, which is far from sufficient for understanding the behavior of euro real exchange rates. Furthermore, these studies only focus on the linear relationship between the real exchange rates and fundamentals. This chapter attempts to complement the literature by investigating the nonlinearity in the real exchange rate-fundamentals relationship based on a much longer sample.

3.3 Empirical specification, variables and data Sources

3.3.1 Empirical specification

As in Chapter 2, the empirical specification used in this chapter is also based on Montiel (1999). The real effective exchange rates (REER) of the 11 currencies under consideration are assumed to be determined by a set of economic fundamentals in the following way:

$$REER = f(PROD, TOT, GEXP, OPEN, NFA, R) + \varepsilon \qquad (3.3.1)$$

The right-hand-side variables are the proxies for productivity growth, terms of trade, government expenditure, economic openness, net foreign assets, and interest rate differential, respectively, ε is an error term.[19]

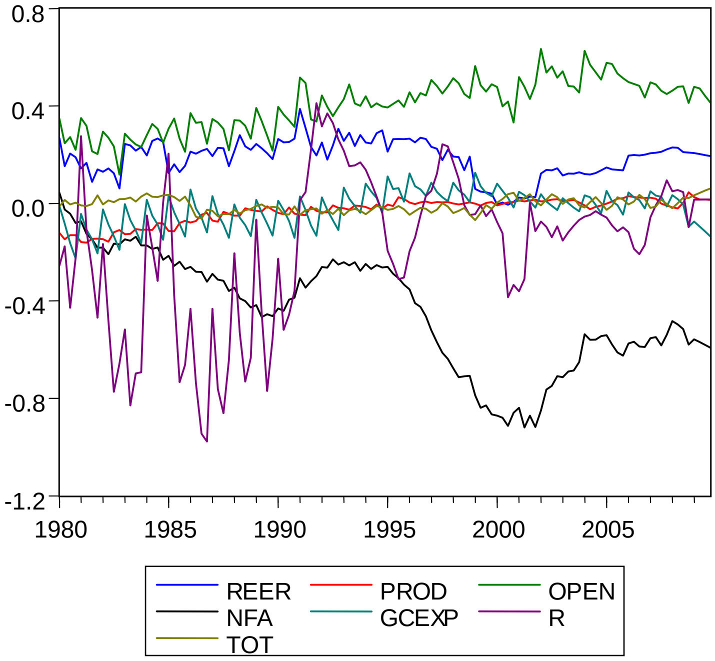
[19] For the case of Belgium, the data needed to calculate *open* are not available, so we estimate model (3.3.1) for Belgium without *open*.

3.3.2 Variables and data sources

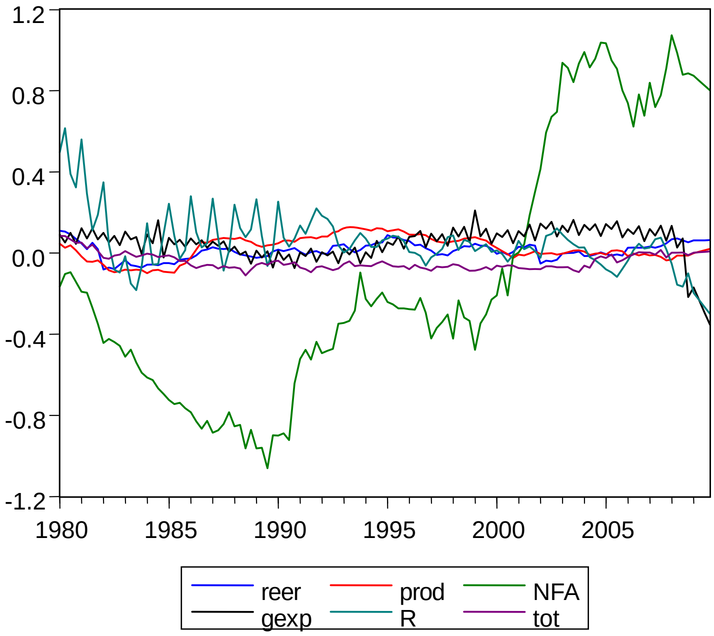
The panel dataset used in this chapter consists of quarterly data on seven variables over the period 1980Q1-2009Q4. For the ten former currencies of EMU countries, the variables are calculated in the same way as in Chapter 2. For the euro, we construct the synthetic series in a way similar to that used by Maeso-Fernandez, et al. (2002). The data is mainly retrieved from the IMF’s Direction of Trade Statistics (DOTS) and International Financial Statistics (IFS). Some data are taken from the OECD's database (see Appendix for details). Data have been seasonally adjusted, where necessary.

During the empirical analysis that follows, all of the variables are expressed in italics and all of them except *R* and *NFA* are expressed in logarithm and denoted by lowercase letters, for example, *reer*=ln(*REER*).

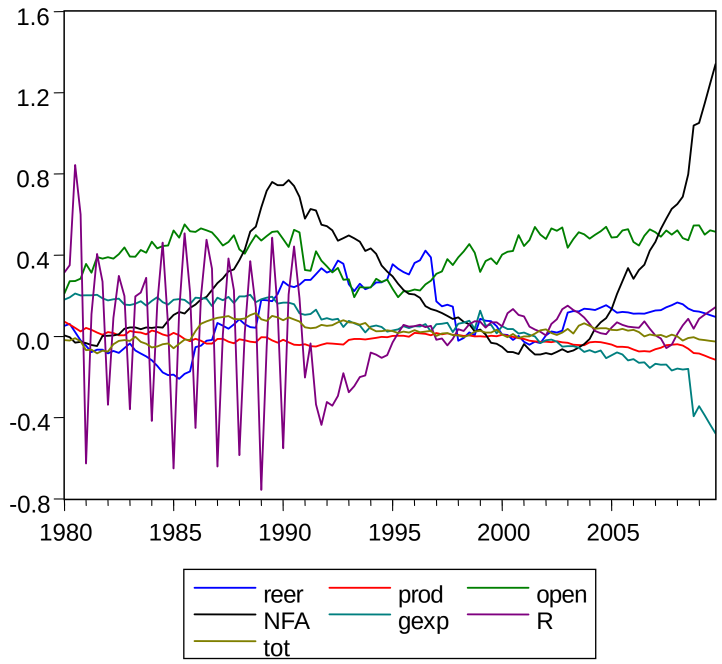
The time series plots of the variables are shown in Figure 3.1. Generally, the variables show different pattern from each other. *R* was very volatile before the introduction of the euro and became more stable since then. Among the variables of interest, *R* is the most volatile one during the sample period, this may explain why it is not cointegrated with the other variables for most of the countries under consideration. The biggest ups and downs are evident for *NFA*. And the other variables usually showed frequent fluctuations during this period.



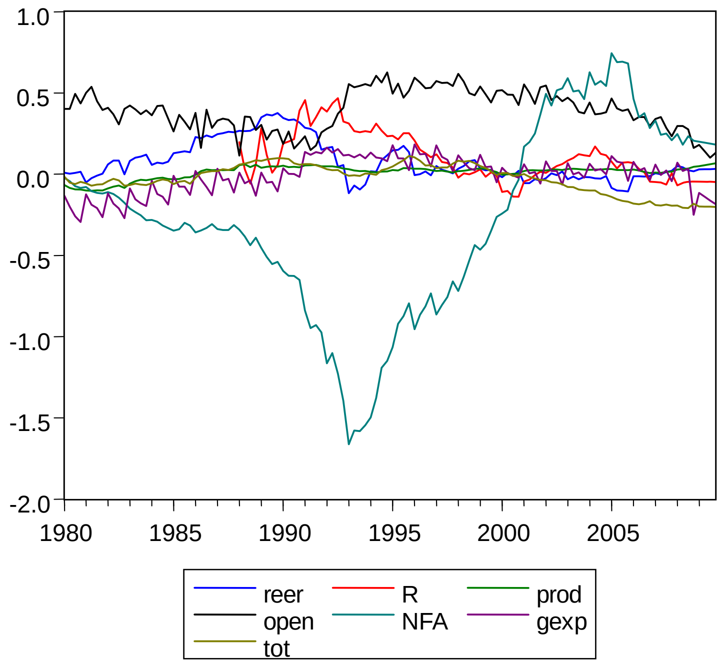
Austria



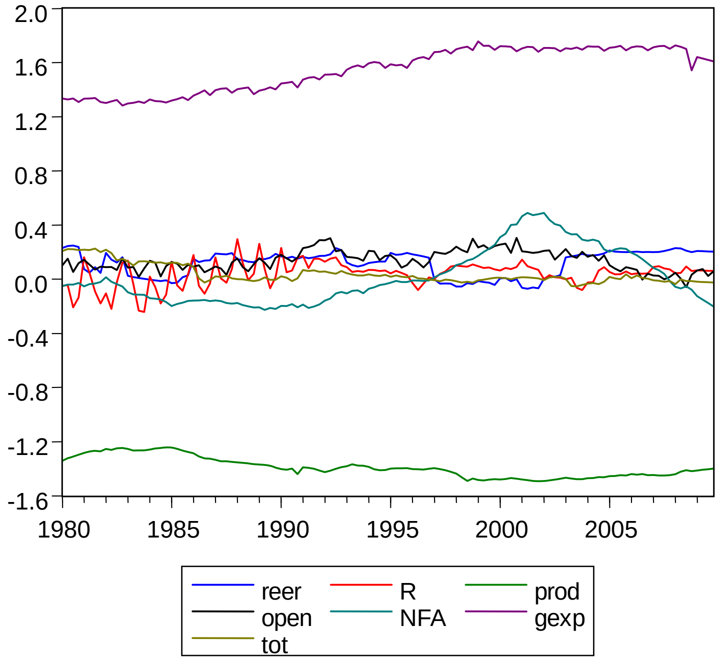
Belgium



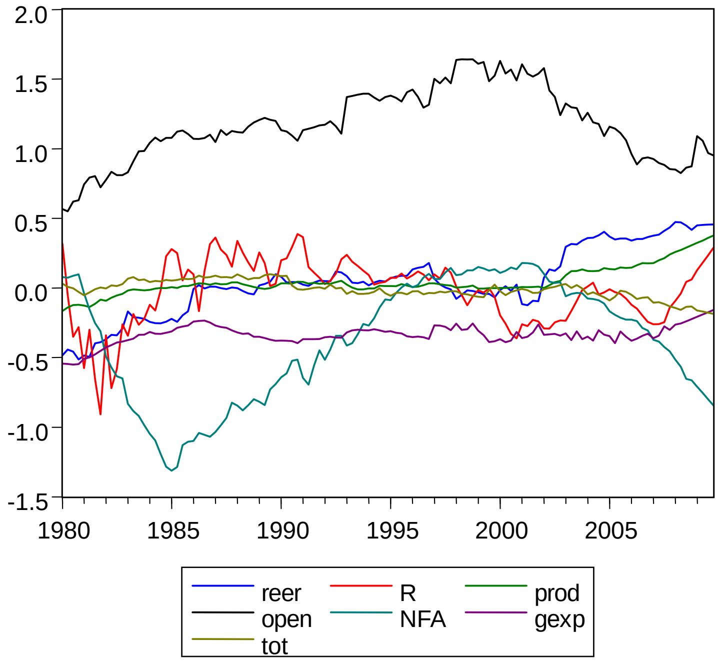
Germany



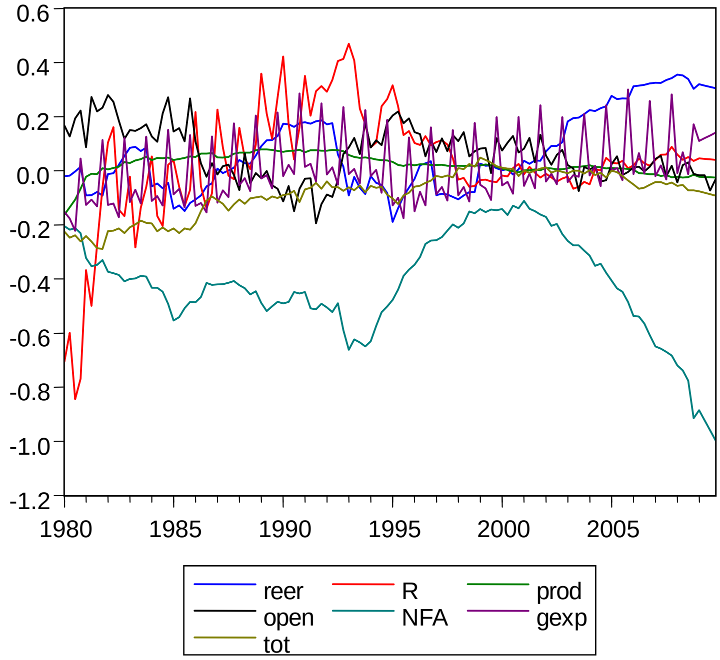
Finland



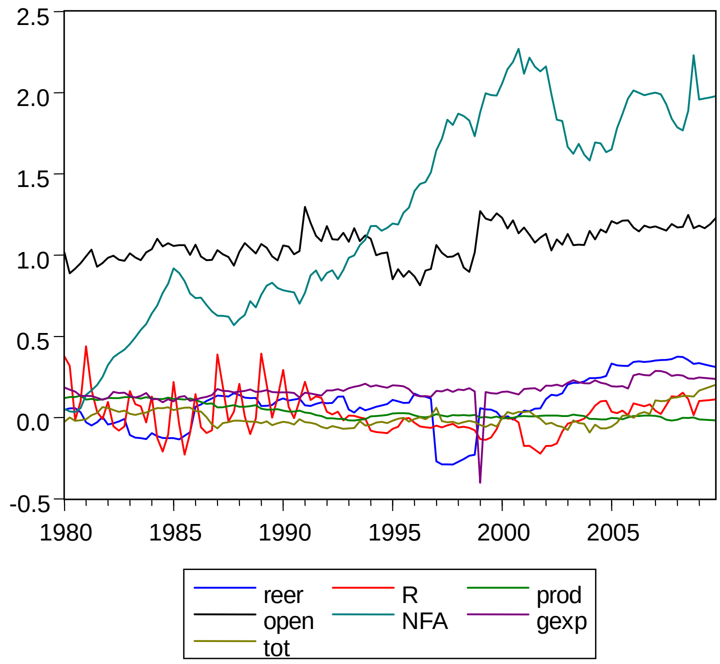
France



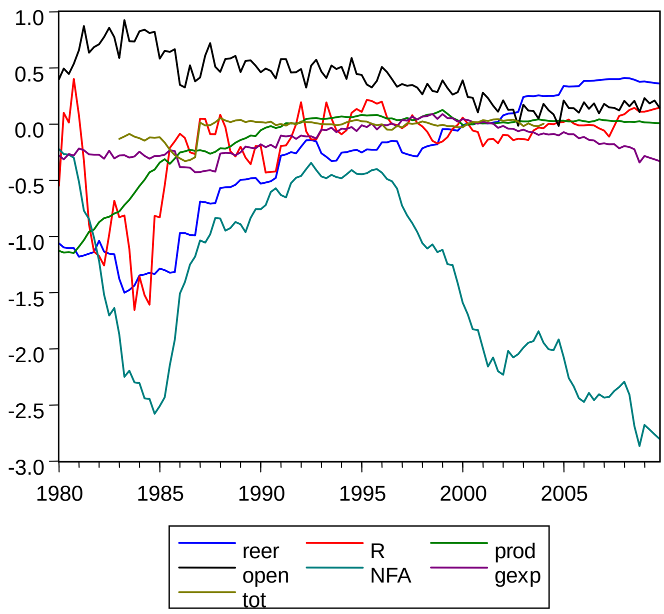
Ireland



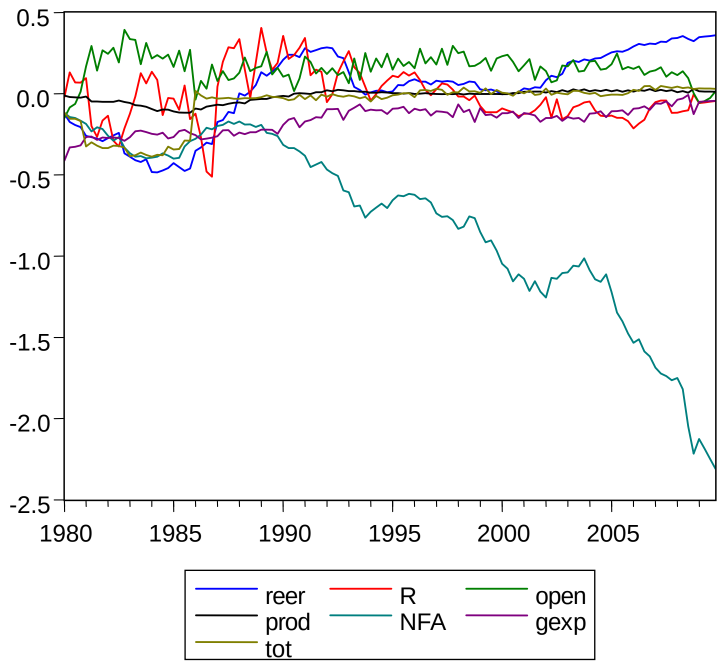
Italy



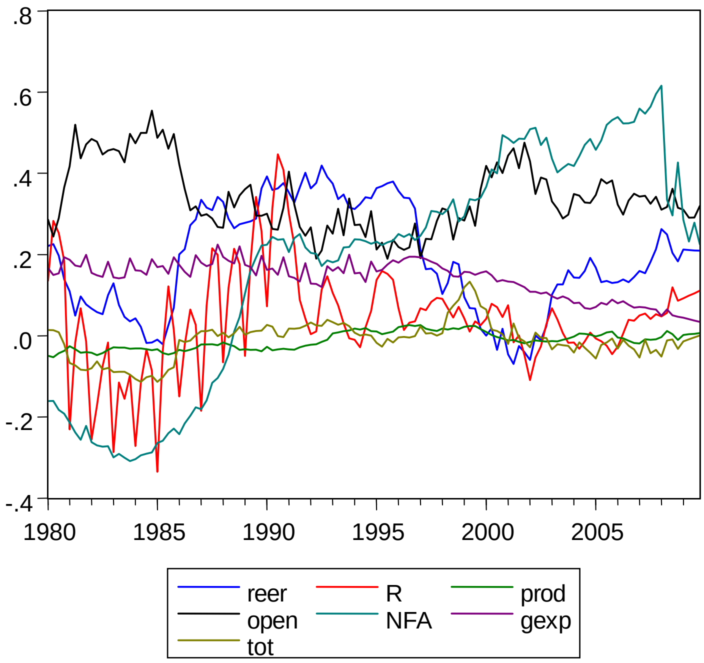
The Nertherlands



Portugal



Spain



Eurozone

Figure 3.1 Time series plots of variables

3.4 Methodologies and testing procedure

As in Chapter 2, techniques such as the ARDL bounds testing approach, the ACE algorithm and the nonlinear cointegration test are used in this chapter. In addition, this chapter employs panel unit root tests and Granger causality tests, which are introduced below.

3.4.1 Panel unit root tests

Generally speaking, panel unit root tests have greater power than unit root tests based on individual time series. We conduct two panel unit root tests to examine the stochastic characteristics of the series: one is the LLC test (Levin, Lin and Chu, 2002), and the other is the IPS test (Im, Pesaran and Shin, 2003).

The LLC panel test is based on the following basic ADF specification:

$$\Delta y_{it} = \alpha_i y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X_{it}^{'} \delta + \varepsilon_{it} \tag{3.4.1}$$

where i=1,...,N, t=1,...,T and ε_{it} ~i.i.d with 0 mean, and variance σ_i. The LLC test assumes a common coefficient on y_{it-1}, that is, $\alpha_i = \alpha$, but allows the lag order for the difference terms, p_i, to vary across cross-sections. The null and alternative hypotheses for the tests may be written as H_0: $\alpha = 0$ and H_1: $\alpha < 0$. Under the null hypothesis there is a unit root, while under the alternative there is no unit root.

The hypothesis that the autoregressive parameters are common across individual cross-sections is pretty restrictive, so some researchers extend the LLC test to allow for heterogeneity in the autoregressive coefficient under the alternative hypothesis. Unlike the LLC test, which assumes that all series are stationary under the alternative hypothesis, the IPS test is consistent under the alternative that only a fraction of the series are stationary. Specifically, in the IPS test, Im, Pesaran and Shin (2003) specify a separate ADF regression for each cross section *i*. The null hypothesis may be written as: H_0: $\alpha_i = 0$, for all *i*, while the alternative hypothesis is given by:

$$H_1 : \begin{cases} \alpha_i = 0 & for \ \ (i = 1, 2, ..., N_1) \\ \alpha_i < 0 & for \ \ (i = N_1 + 1, N_1 + 2, ..., N) \end{cases} \tag{3.4.2}$$

Thus, under the alternative hypothesis, some series may be characterized by a unit root, while the other series can be stationary.

3.4.2 Linear and nonlinear Granger causality

(1) Linear Granger causality

Granger (1969) causality is a very useful notion for characterizing dependence relations between economic variables. Assume that $\{X_t\}$ and $\{Y_t\}$ are two scalar-valued strictly stationary time series. Intuitively we say X Granger causes Y if past and current values of X_t contain additional information on future values of Y_t. Put another way, let $\Omega_{X,t}$ and $\Omega_{Y,t}$ denote the information sets consisting of past observations of X_t and Y_t up to and including time t, and let '～' denote equivalence in distribution. Then $\{X_t\}$ is not Granger-causing $\{Y_t\}$ if

$$(Y_{t+1}, ..., Y_{t+k}) \big| (\Omega_{X,t}, \Omega_{Y,t}) \sim (Y_{t+1}, ..., Y_{t+k}) \big| \Omega_{Y,t} \tag{3.4.3}$$

In practice, k=1 is usually used, that is, testing for Granger non-causality is equivalent to testing for the conditional independence with respect to $\Omega_{X,t}$ of the one-step-ahead conditional distribution of $\{Y_t\}$.

The linear Granger causality is usually tested using a vector autoregression (VAR) model. A bivariate VAR model may be given as follows:

$$X_t = A(L)X_t + B(L)Y_t + \varepsilon_{Xt} \tag{3.4.4}$$

$$Y_t = C(L)X_t + D(L)Y_t + \varepsilon_{Yt} \tag{3.4.5}$$

where t=1,2,…,N. L is the lag operator. A(L), B(L), C(L) and D(L) are all polynomials of L with all roots outside the unit circle. ε_{Xt} and ε_{Yt} follow i.i.d. processes with zero mean and constant variance. To test whether Y strictly Granger-causes X, we only need to test the joint exclusion restriction that all the coefficients of the lag polynomial B(L) are zero. Granger causality is accepted if the joint exclusion restriction is rejected. If Y Granger-causes X but not vice versa, then the causality is unidirectional from Y to X, if Y Granger-causes X and vice versa, then the causality is bidirectional between X and Y. Since the bivariate VAR is in linear form, this type of causality is called linear Granger causality.

(2) Nonlinear Granger causality

It is likely that two time series are nonlinearly related to each other, say, in a bivariate VAR model represented by equations (3.4.4) and (3.4.5), X_t and Y_t may be replaced by nonlinear functions, $f(X_t)$ and $g(Y_t)$, respectively. The finding of nonlinear causality implies a nonlinear dynamic relationship between the variables under consideration. This justifies the investigation of nonlinear Granger causality. Baek and Brock (1992) propose a nonparametric statistical method for detecting nonlinear causal relations between two time series. This method was modified by Hiemstra and Jones (1994) to allow each series to display weak temporal dependence. Diks and Panchenko（2005) show that this modified Baek and Brock method can severely over-reject the null hypothesis of no nonlinear Granger causality when the null hypothesis is true. To overcome this problem, Diks and Panchenko (2006) propose a new test statistic, which we call the DP test in what follows.

Let $X_t^{\ell_x} = (X_{t-\ell_x+1},...,X_t)$ and $Y_t^{\ell_y} = (Y_{t-\ell_y+1},...,Y_t)$ ($\ell_x, \ell_y \geq 1$). Then the null hypothesis that X_t does not nonliearly Granger-cause Y_t can be put as follows:

$$H_0 : Y_{t+1} \left| (X_t^{\ell_x}; Y_t^{\ell_y}) \sim Y_{t+1} \right| Y_t^{\ell_Y} \tag{3.4.6}$$

For strictly stationary time series X_t and Y_t, let $W_t = (X_t^{\ell_X}, Y_t^{\ell_Y}, Z_t)$, where Z_t=Y_{t+1}. The null hypothesis (3.4.6) is actually a statement about the invariant distribution of the vector W_t. With this fact, it won't cause confusion to drop the time index to keep the notation compact. Without loss of generality, we assume $\ell_X = \ell_Y = 1$. Hence, the null hypothesis states that the conditional distribution of Z given (X,Y)= (x,y) should be the same as that of Z given Y=y, that is to say, the joint probability density function $f_{X,Y,Z}$(X,Y,Z) and its marginals must satisfy the following relationship:

$$\frac{f_{X,Y,Z}(X,Y,Z)}{f_Y(Y)} = \frac{f_{X,Y}(X,Y)}{f_Y(Y)} \bullet \frac{f_{Y,Z}(Y,Z)}{f_Y(Y)} \tag{3.4.7}$$

This explicitly states that X and Z are independent conditional on Y = y for each fixed value of y. Diks and Panchenko (2006) show that (3.4.7) implies:

$$q \equiv E[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)] = 0 \tag{3.4.8}$$

Let $\hat{f}_W(W_i)$ denote a local density estimator of a d_W-variate random vector W at W_i, it is defined as $\hat{f}_W(W_i) \equiv \frac{(2\varepsilon_n)^{-d_W}}{n-1} \sum_{j,j\neq i} I_{ij}^W$, where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon_n)$, I(x) denotes the indicator function that equals 1 when x is true and zero otherwise, ε_n is the bandwidth depending on the sample size n. For given $\hat{f}_W(W_i)$, Diks and Panchenko (2006) propose the following test statistic, which is the sample version of equation (3.4.8):

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \bullet \sum_i (\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i))$$

for $\ell_X = \ell_Y = 1$, Diks and Panchenko (2006) prove that, if $\varepsilon_n = Cn^{-\beta}(C > 0, \frac{1}{4} < \beta < \frac{1}{3})$, the test statistic $T_n(\varepsilon_n)$ satisfies:

$$\sqrt{n} \bullet \frac{T_n(\varepsilon_n) - q}{S_n} \xrightarrow{D} N(0,1)$$

where D denotes convergence in distribution and S_n is an estimator of the asymptotic variance of $T_n(\bullet)$.

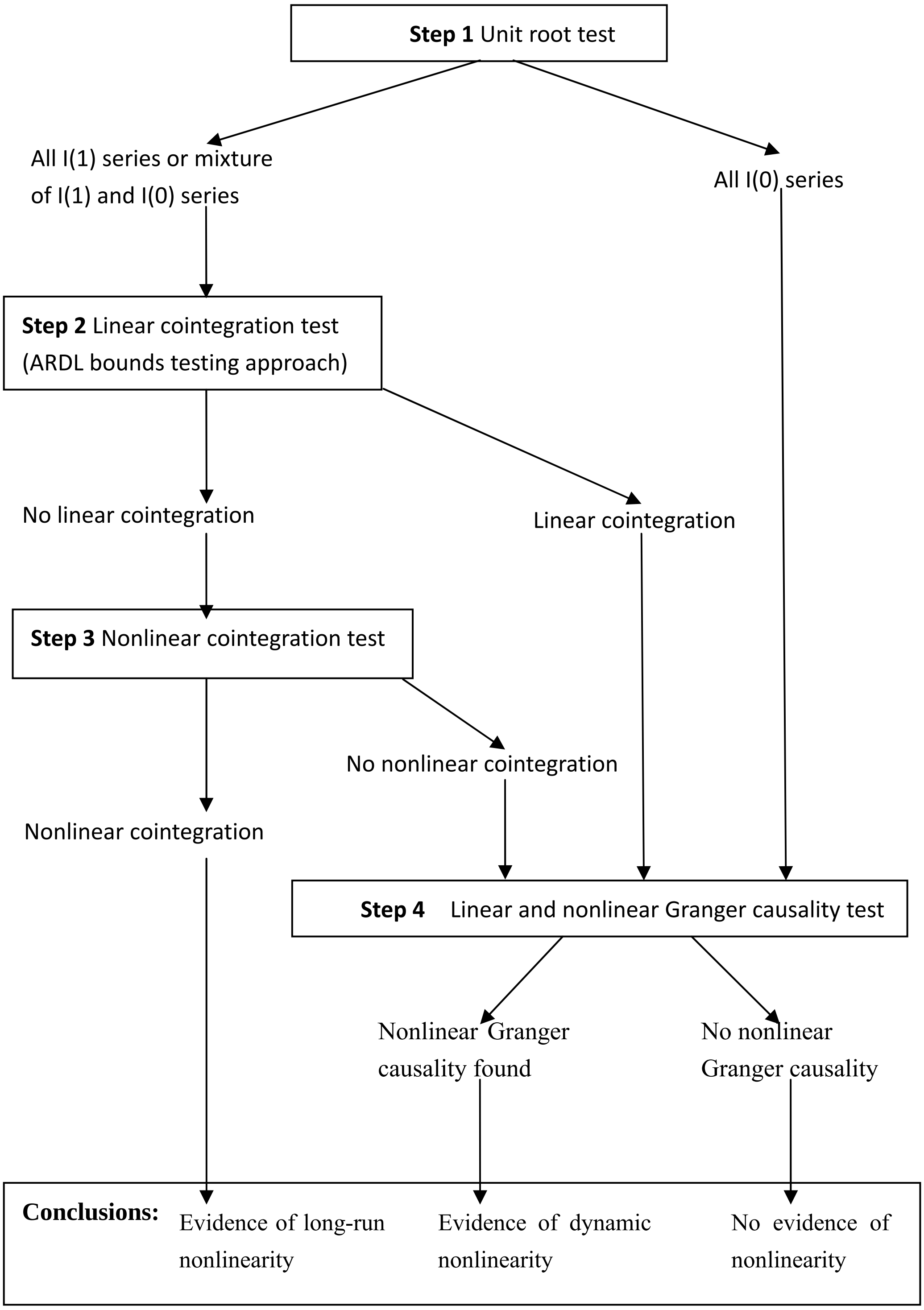


Figure 3.2 Testing procedure

3.4.3 Testing procedure

We follow a testing procedure similar to that of Ma & Kanas (2000) which involves the following four steps to finish the empirical analysis: (1) panel unit root tests; (2) linear cointegration tests; (3) nonlinear cointegration tests; and (4) linear and nonlinear Granger causality tests. More specifically, as the first step, we test for the stochastic properties of the series under consideration using panel unit root tests. If the series are nonstationary or a mixture of stationary and nonstationary series, then we proceed to step 2 to test for linear cointegration between the real exchange rates and fundamentals using the ARDL bounds testing approach. If all of the series are stationary, we go straight to step 4 to test for Granger causality. If no linear cointegration is found at step 2, then we proceed to the third step to test for nonlinear cointegration, otherwise we proceed to the fourth step. If nonlinear cointegration exists, it can be taken as strong evidence of a nonlinear long-run relationship. Our procedure is different from that of Ma & Kanas (2000) in three aspects: First, we use panel unit root test in step one instead of the conventional unit root test based on individual time series. Second, we use the ARDL approach instead of the conventional cointegration tests. Third, at step 4 we use the DP test to test for nonlinear Granger causality instead of the modified Baek and Brock method. Figure 3.2 illustrates the road map for the empirical tests.

3.5 Empirical Results

3.5.1 Unit root tests (step 1)

We conduct the LLC test and the IPS test to examine the stochastic characteristics of the series of interest. Table 3.1 reports the results of panel unit root tests for each of the series. The test results show that all series except *R* and *open* contain a unit root. For *R* and *open*, the IPS test shows that the null of a unit root is rejected, suggesting that these two series are stationary for some countries. Unit root tests on the first difference series show that no series is integrated of order 2 or above. In this context the traditional cointegration test and panel cointegration tests are not applicable. In order to ensure robust results, we use the ARDL bounds testing approach in the cointegration analysis that follows.

Table 3.1 Panel unit root tests

	reer	R	prod	NFA	gexp	open	tot
LLC	0.364 (0.642)	0.895 (0.815)	-0.288 (0.387)	0.895 (0.815)	2.275 (0.989)	-0.028 (0.489)	-0.011 (0.496)
IPS	-1.052 (0.147)	-4.249 (0.000)***	0.396 (0.654)	1.572 (0.942)	0.317 (0.624)	-1.835 (0.033)**	-0.922 (0.178)

Notes: (1) Selection of exogenous variables: except tests on prod assume individual effects and individual linear trends, tests on the other variables assume individual effects. Lag length is selected based on SIC and Bartlett kernel. (2) LLC test takes common unit root process as its null. IPS test takes individual unit root process as its null. (3) The p-values are in parenthesis, * , ** and *** denote significance at 10%, 5% and 1% level respectively.

3.5.2 Linear cointegration tests (step 2)

We now apply the ARDL bounds testing approach to each of the currencies in our sample. The estimation results are reported in Table 3.2. We find that there is linear cointegrating relationship between the real exchange rates and fundamentals for six currencies, including the former currencies of Finland, Spain, Belgium, Portugal, the Netherlands and the euro, but no linear cointegration for the remaining 5 currencies.

To check the stability of the cointegrating vectors, we perform cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests based on the residuals from the estimated ARDL models. If the graphs of CUSUM and CUSUMSQ stay between the two straight lines that represent critical bounds at 5% significance level, the cointegrating vector is stable, otherwise it means that the cointegrating vector is unstable. Figures 3.3 -3.10 illustrate the test results. We can see that most of the graphs of CUSUM and CUSUMSQ stay between the two straight lines, indicating the stability of the coefficients in the long-run relationships. The two exceptions are the graphs of CUSUMSQ for the Netherlands and Portugal, which go across the straight line over certain period, suggesting that there is structural change in the long-run relationship.

To ensure the robustness of the empirical results, we also perform four diagnostic tests to test for no residual serial correlation, no functional form mis-specification, normal errors and homoscedasticity, respectively. The results are presented in the last four columns of Table 3.2. We can see that all the regressions fits reasonably well and pass the diagnostic tests, except that, for the Netherlands and Portugal, the diagnostic test for normal error series failed, confirming the instability of the cointegrating relationships.

Table 3.2 Summary of ARDL test results

	Estimated model	F Statistic	ECM	$x_{SC}^2(4)$	$x_{FF}^2(1)$	$x_N^2(2)$	$x_H^2(1)$
Finland	ARDL(4,7,1,0,0,2,0)	$F(7,55)=3.952^{**}$	-0.355 $[0.002]^{***}$	0.716 [0.949]	2.291 [0.130]	2.644 [0.212]	0.819 [0.365]
Spain	ARDL(6,6,5,4,7,7,7)	$F(7,55)=5.406^{***}$	-0.287 $[0.001]^{***}$	5.159 [0.271]	2.077 [0.150]	2.194 [0.334]	3.133 $[0.077]^{*}$
Belgium	ARDL(1,1,0,0,0,0)	$F(6,98)=3.780^{**}$	-0.308 $[0.000]^{***}$	2.539 [0.638]	0.271 [0.603]	3.252 [0.127]	0.000 [0.982]
Ezone	ARDL(1,0,0,5,0,6,5)	$F(7,55)=3.633^{**}$	-0.123 $[0.022]^{**}$	1.423 [0.840]	2.096 [0.148]	3.902 $[0.092]^{*}$	0.213 [0.644]
Portugal (1980-2009)	ARDL(1,3,1,3,0,0,3)	$F(7,84)=4.458^{***}$	0.073 $[0.046]^{**}$	3.114 [0.539]	0.092 [0.761]	87.344 $[0.000]^{***}$	3.082 $[0.079]^{*}$
Portugal (1980-1998)	ARDL(7,6,4,1,6,7,7)	$F(7,11)=5.223^{***}$	-0.823 $[0.000]^{***}$	2.952 [0.125]	2.464 [0.109]	0.395 [0.821]	2.699 [0.100]
Netherlands (1980-2009)	ARDL(1,1,0,2,4,2,0)	$F(7,63)=4.103^{**}$	-0.043 [0.271]	3.067 [0.547]	0.299 [0.585]	1821.8 $[0.000]^{***}$	0.872 [0.350]
Netherlands (1980-1998)	ARDL(1,0,0,0,0,0,0)	$F(7,3)=6.266^{***}$	-0.334 $[0.000]^{***}$	2.278 [0.131]	2.272 [0.122]	2.805 [0.183]	1.046 [0.307]
Autria Ace-transformed	ARDL(4,2,0,1,3,4,1)	$F(7,71)=3.263^{*}$	-0.585 $[0.000]^{***}$	1.3069 [0.860]	2.106 [0.118]	3.457 $[0.075]^{*}$	0.182 [0.670]
Germany Ace-transformed	ARDL(1,0,0,1,0,0,0)	$F(7,103)=4.174^{**}$	-0.612 $[0.000]^{***}$	5.384 [0.250]	0.570 [0.450]	2.296 [0.263]	0.392 [0.531]

Notes: 1. All ARDL models are selected based on Akaike Information Criterion; 2. For Belgium, the number of regressors is 5, the critical bounds for F Statistics are (2.26,3.35), (2.62,3.79) and (3.41,4.68) at 10% , 5% and 1%, respectively; For the other countries, the number of regressors is 6, the critical bounds for F Statistics are (2.12,3.23), (2.45,3.61) and (3.15,4.43) at 10% , 5% and 1%, respectively; 3. ECM denotes the error correction term; 4. Diagnostic test results are presented in the last four columns, $x_{SC}^2(4)$, $x_{FF}^2(1)$, $x_N^2(2)$ and $x_H^2(1)$ denote chi-squared statistics to test for no residual serial correlation, no functional form mis-specification, normal errors and homoscedasticity, respectively, with p-values given in []; 5. *, ** and *** denote the 10%, 5% and 1% significance level respectively.

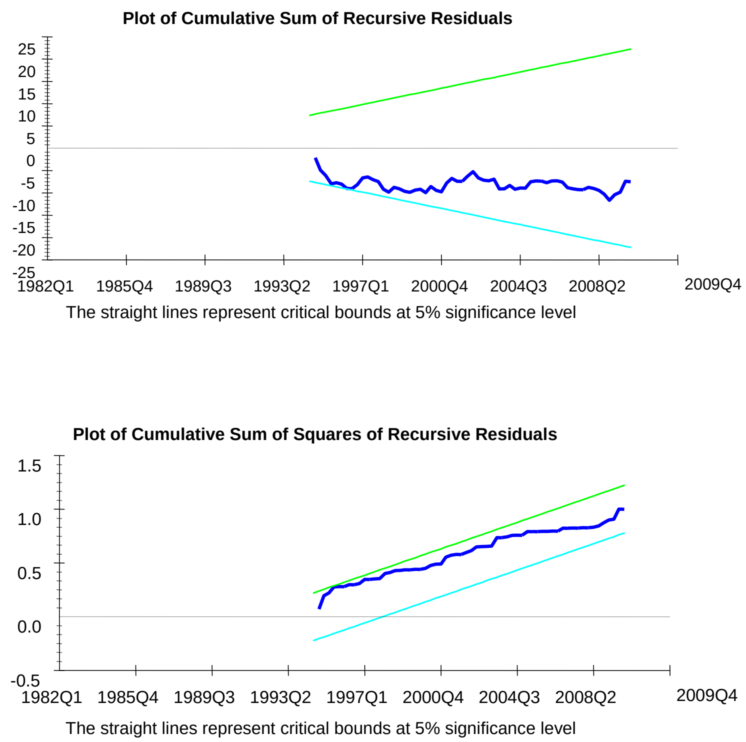


Figure 3.3 Plots of CUSUM and CUSUMSQ (Spain)

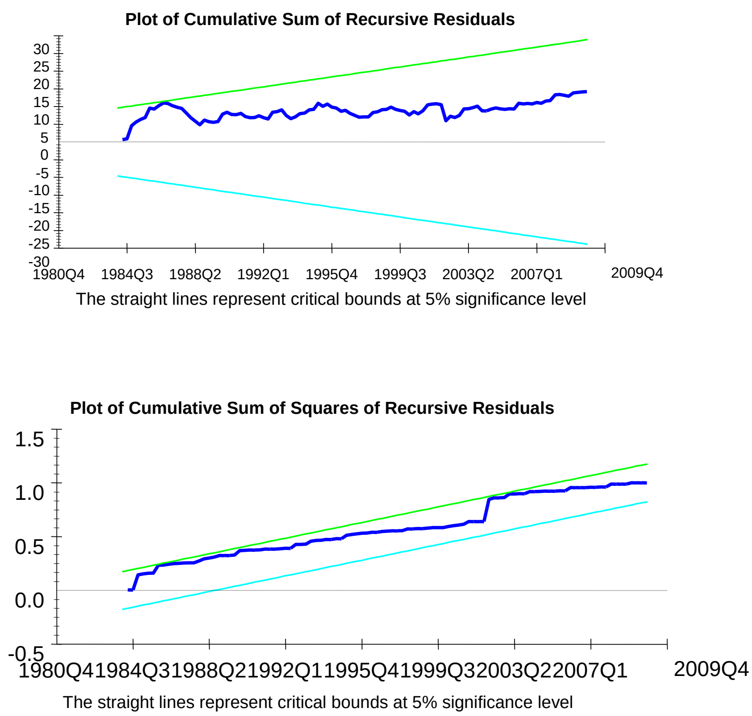


Figure 3.4 Plots of CUSUM and CUSUMSQ (Belgium)

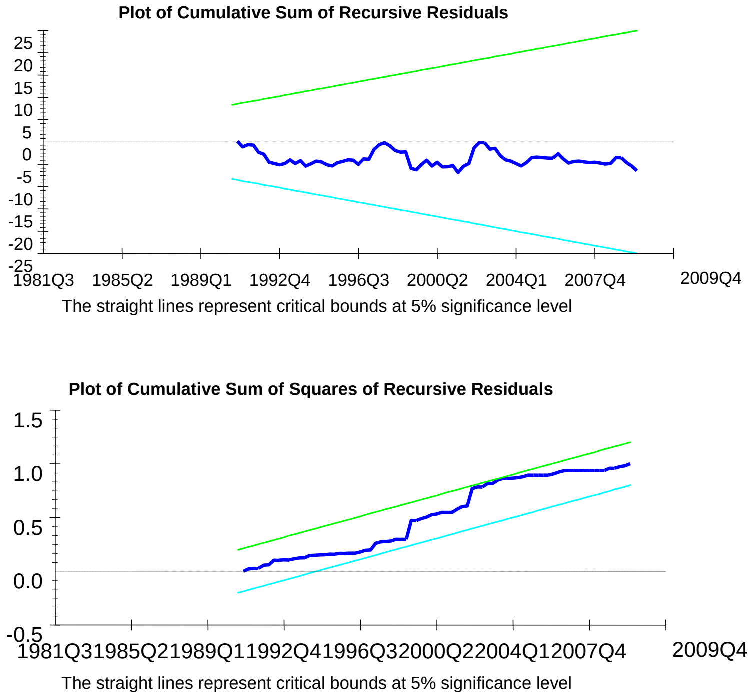


Figure 3.5 Plots of CUSUM and CUSUMSQ (Austria)

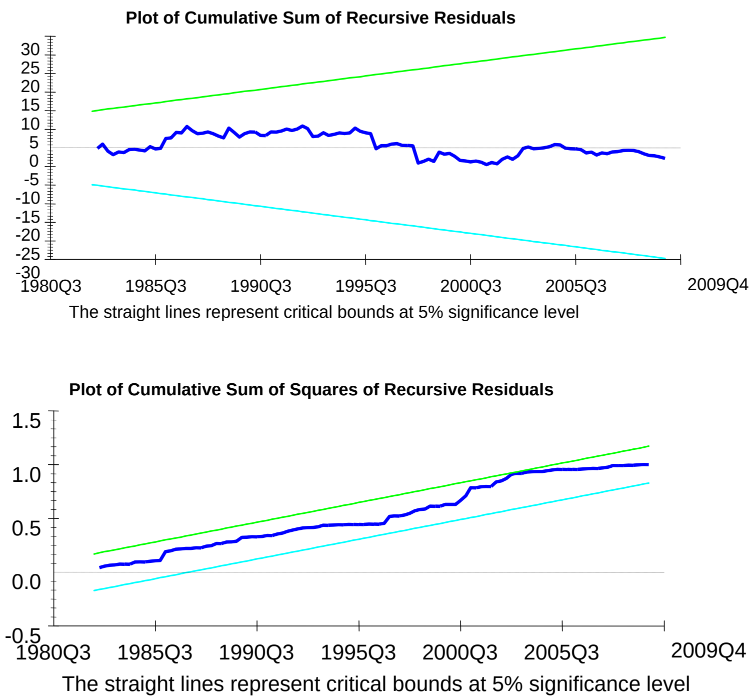


Figure 3.6 Plots of CUSUM and CUSUMSQ (Germany)

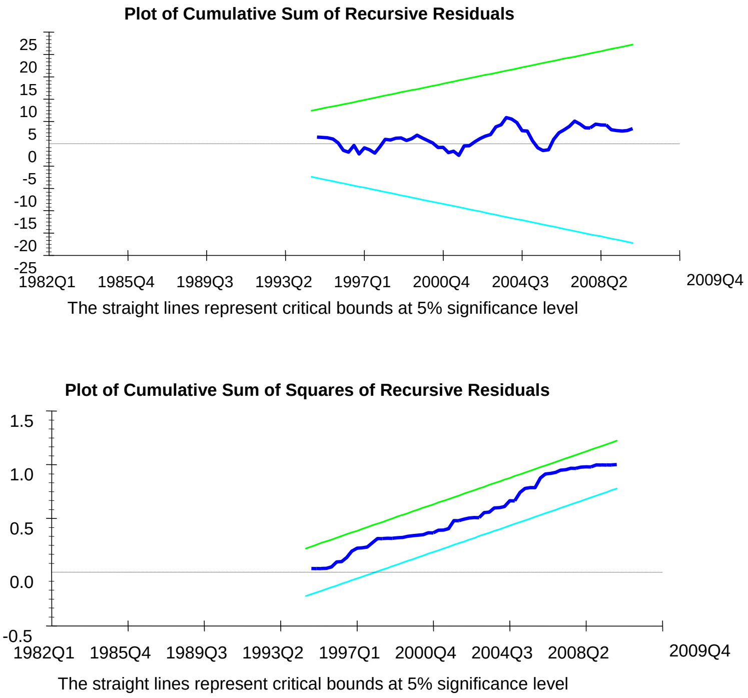


Figure 3.7 Plots of CUSUM and CUSUMSQ (finland)

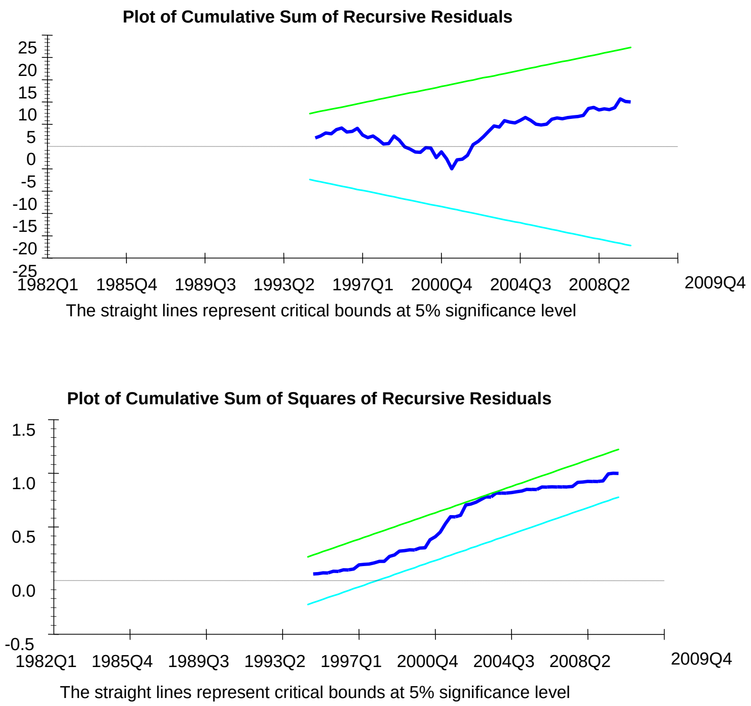


Figure 3.8 Plots of CUSUM and CUSUMSQ (euro zone)

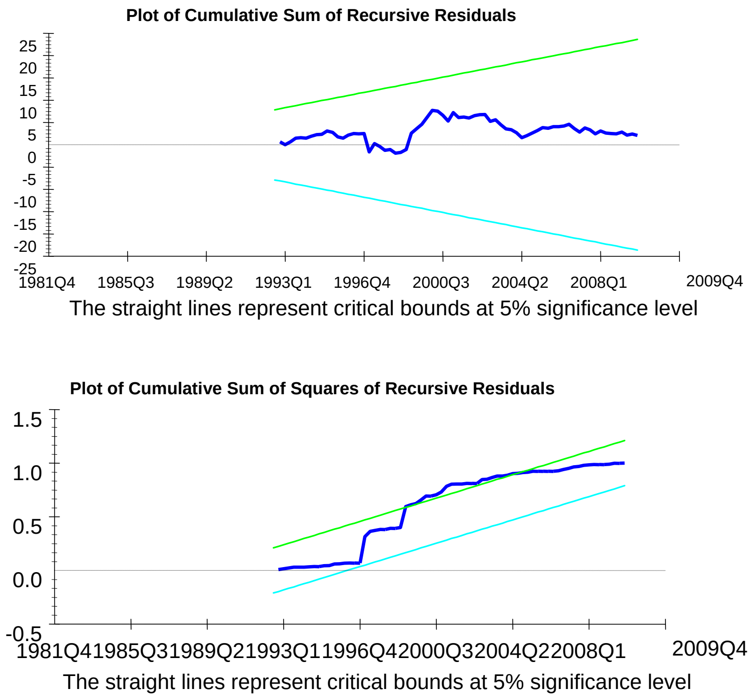


Figure 3.9 Plots of CUSUM and CUSUMSQ (Netherlands)

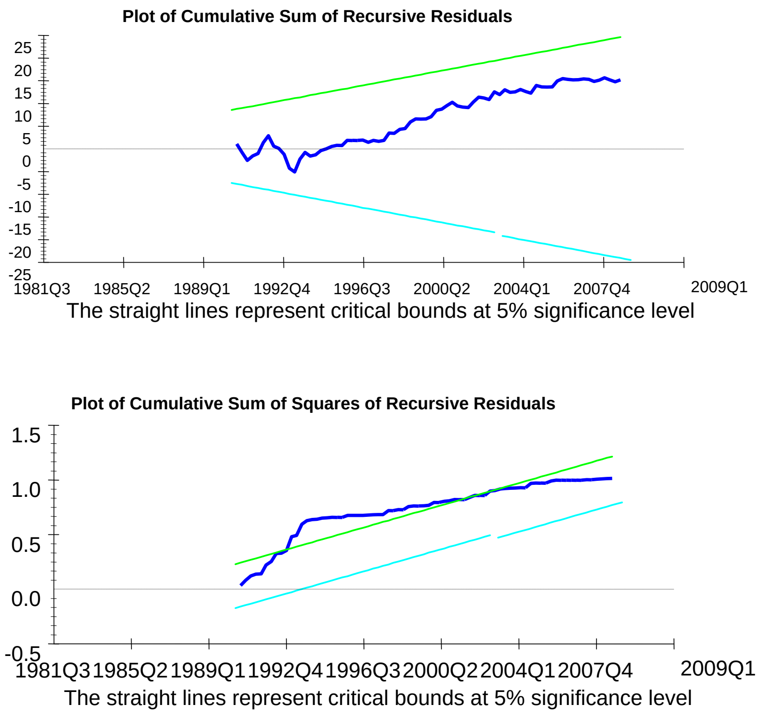


Figure 3.10 Plots of CUSUM and CUSUMSQ (Portugal)

Specifically, for the Finnish markka, Spanish peseta, Belgian franc and the euro, the long-run relationships between the real exchange rates and fundamentals are represented by equations (3.5.1)-(3.5.4), respectively.

$$\underset{}{reer_t} = \underset{(0.061)^{***}}{-0.172 prod_t} - \underset{(0.152)^{***}}{0.428 open_t} - \underset{(0.184)^{*}}{0.350 gexp_t} - \underset{(0.026)}{0.022 NFA_t} + \underset{(0.183)^{***}}{0.662 tot_t} - \underset{(0.032)}{0.020 R_t} + \underset{(0.068)}{0.061} \tag{3.5.1}$$

$$reer_t = \underset{(0.836)^{**}}{2.038 prod_t} - \underset{(0.271)^{*}}{0.461 open_t} - \underset{(0.841)^{***}}{2.463 gexp_t} + \underset{(0.074)^{***}}{0.284 NFA_t} + \underset{(0.515)^{***}}{1.679 tot_t} + \underset{(0.014)^{***}}{0.058 R_t} - \underset{(0.159)^{***}}{3.232} \tag{3.5.2}$$

$$reer_t = \underset{(0.112)^{***}}{0.590 prod_t} + \underset{(0.068)}{0.011 gexp_t} + \underset{(0.009)^{**}}{0.019 NFA_t} + \underset{(0.200)^{***}}{0.546 tot_t} - \underset{(0.005)}{0.004 R_t} - \underset{(0.009)^{***}}{2.226} \tag{3.5.3}$$

$$reer_t = \underset{(0.280)^{*}}{0.528 prod_t} - \underset{(0.757)}{0.202 open_t} - \underset{(1.214)^{**}}{2.605 gexp_t} + \underset{(0.266)^{***}}{0.715 NFA_t} + \underset{(0.647)}{0.782 tot_t} + \underset{(0.034)^{***}}{0.093 R_t} - \underset{(0.503)^{***}}{1.851} \tag{3.5.4}$$

where the values in parentheses are the standard errors of the coefficients, the symbols *, ** and *** denote the 10%, 5% and 1% significance levels respectively, and these notations extend to equations (3.5.5)-(3.5.8) too.

For the Netherlands and Portugal, as can be seen from Figure 3.9 and Figure 3.10, the CUSUMSQ goes beyond the critical bounds over a period around 1999, indicating that there is a structural break in the long-run relationship between the real exchange rate and fundamentals, probably caused by the introduction of the euro. So we apply the ARDL approach to the subsample over the period 1980Q1-1998Q4. We obtain the following cointegrating equations for the Netherlands and Portugal, respectively.

$$reer_t = \underset{(1.056)^{**}}{-2.518 prod_t} - \underset{(0.259)^{***}}{1.000 open_t} - \underset{(1.045)^{**}}{2.110 gexp_t} + \underset{(0.078)^{***}}{0.452 NFA_t} - \underset{(1.274)}{2.042 tot_t} - \underset{(0.018)}{0.014 R_t} - \underset{(0.390)^{***}}{2.903} \tag{3.5.5}$$

$$reer_t = \underset{(0.065)^{***}}{0.459 prod_t} - \underset{(0.219)^{***}}{0.653 open_t} - \underset{(0.141)^{**}}{0.800 gexp_t} + \underset{(0.038)^{***}}{0.183 NFA_t} + \underset{(0.276)^{***}}{0.932 tot_t} - \underset{(0.089)}{0.016 R_t} - \underset{(0.103)^{***}}{2.344} \tag{3.5.6}$$

We can see from equations (3.5.1)-(3.5.6) that the cointegrating relationships display currency-specific characteristics. The real exchange rates of different currencies are not cointegrated with the same set of fundamentals. *NFA* and *R* are not statistically significant in equation (3.5.1), meaning that *NFA* does not significantly affect the real exchange rate of Finland. In equation (3.5.3) both *gexp* and *R* are insignificant, indicating that government expenditure and interest rate differential do not contribute significantly to the change in real exchange rates of Belgian franc. Equation (3.5.4) shows that *open* and *tot* do not have a substantial impact on the euro real exchange rates. Equation (3.5.5) tells us *tot* and *R* do not exert significant effects on the real exchange rates of the Dutch guilder, and equation (3.5.6) shows that R does not have significant effects on the real exchange rate of the Portuguese escudo.

The coefficients on *prod* are positive in all of the linear cointegrating equations except Finland and the Netherlands. A positive coefficient on *prod* is consistent with the Balassa-Samuelson theory, but a negative coefficient is hard to explain from the Balassa-Samuelson perspective. In the existing empirical literature, there are many studies that are not supportive of the Balassa-Samuelson effect (see Chinn 1997, Chinn and Johnson, 1997 and Fischer 2004). One possible explanation for the negative effect of *prod* is that, for small economies such as Finland and the Netherlands, productivity growth may be mainly promoted by capital inflows, and the capital inflows are mostly spent on tradable goods, leading to deterioration in trade balance, which in turn leads to the real exchange rate depreciation.

The extant empirical evidence on the effect of trade openness on real exchange rate remains mixed in the literature (see Elbadawi, 1994; Connolly and Devereux, 1995; Kim and Korhonen, 2005 and Li, 2004). Our results show that openness exerts a negative impact on real exchange rates of Finland, Spain, the Netherlands and Portugal (see equations 3.5.1, 3.5.2, 3.5.5 and 3.5.6), indicating that the substitution effect of openness dominates the income effect in these four countries. The results also show that government expenditure exerts significant negative effects on the real exchange rates of Finland, Spain, Portugal, the Netherlands and euro. A possible reason for the negative effect is that government expenditure has to be financed by taxes, which results in a decline of disposable income and a fall in demand for nontradables. Thus the income effect of *gexp* dominates the substitution effect, resulting in depreciation of the real exchange rates.

The coefficients on NFA in equations (3.5.2)-(3.5.6) are all positive, suggesting that an increase in net foreign assets leads to an appreciation of these real exchange rates. In equations (3.5.1), (3.5.2), (3.5.3) and (3.5.6), the coefficients on *tot* are all positive. This is because the positive income effect of *tot* dominates the negative substitution effect, so strengthening terms of trade leads to a real appreciation of the real exchange rate. The coefficients on *R* are significant and positive in equation (3.5.2) and (3.5.4). This is consistent with theoretical expectation that an increase in the interest rate differential would lead to appreciation of domestic real exchange rate. But *R* is insignificant in the other 4 equations, suggesting that the interest rate differential does not play a significant role in affecting the real exchange rates of Finland, Belgium, the Netherlands and Portugal.

3.5.3 Nonlinear cointegration test (step 3)

For the currencies for which we do not find linear cointegrating relationships, we proceed to test for potential nonlinear cointegration. To this end, we first transform the variables using the ACE algorithm. The transformed variables are indicated by a superscript *A*. Unit root tests show that all of the ACE-transformed variables are integrated of order less than 2.[20] We then apply the ARDL bounds testing approach to the ACE transformed series. We find cointegrating relationship among the transformed series for Austria and Germany, meaning that there exist nonlinear relationship between the real exchange rates of the German Mark and Austrian schilling and fundamentals. The results are presented in the last two rows of Table 3.2.

The cointegrating equations for Austria and Germany are (3.5.7) and (3.5.8), respectively.

$$\underset{}{reer_t^A} = \underset{(0.162)^{***}}{1.167\,prod_t^A} + \underset{(0.253)^{***}}{0.673\,open_t^A} + \underset{(0.588)^{***}}{1.600\,gexp_t^A} + \underset{(0.043)^{***}}{0.974\,NFA_t^A} + \underset{(0.636)^{***}}{2.367\,tot_t^A} + \underset{(0.589)}{0.918\,R_t^A} - \underset{(0.039)}{0.002} \qquad (3.5.7)$$

[20] Detailed unit root test results are omitted to save space.

$$\underset{}{reer_t^A} = \underset{}{0.961} \underset{(0.089)^{***}}{prod_t^A} + 0.887 \underset{(0.088)^{***}}{open_t^A} + 1.033 \underset{(0.0.152)^{***}}{gexp_t^A} + 1.077 \underset{(0.082)^{***}}{NFA_t^A} + 1.162 \underset{(0.129)^{***}}{tot_t^A} + 1.166 \underset{(0.735)}{R_t^A} - \underset{(0.028)}{0.001} \tag{3.5.8}$$

We can see from equation (3.5.7) and (3.5.8) that all of the transformed explanatory variables except R^A have a positive effect on the transformed real exchange rate. Because the ACE transformation is nonparametric and has no simple functional representation, the relationship between the original and the transformed variables is difficult to comprehend. To better understand the effect of the ACE transformation on the variables, we present scatter plots of the transformed versus the original variables in Figure 3.11 and 3.12. If the plot demonstrates a straight line, it means that the transformed variable has a linear relationship with the original variable, so there is no need for transformation. We can see clearly from Figure 3.11 and 3.12 that, as none of the plots shows a straight line, the relationship between transformed and original variables are all nonlinear.

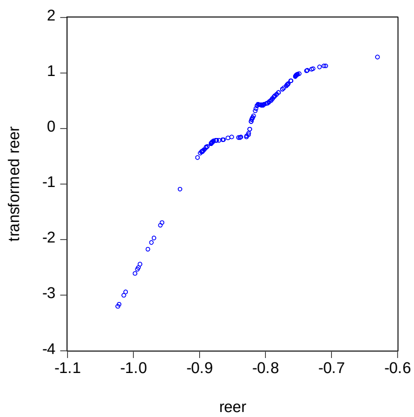
It is difficult to interpret the nonlinear cointegrating equations (3.5.7) and (3.5.8) because the ACE algorithm does not show the functional forms of the nonlinear relationships between the original and the transformed variables. To get a rough view of the qualitative impact of the original explanatory variables on the real exchange rates, we turn to the scatter plots of the raw variables against the transformed ones. In Figure 3.11 for example, *prod* is positively correlated with $prod^A$, which is positively correlated with $reer^A$. In turn $reer^A$ is positively correlated with *reer*, therefore *prod* is positively correlated with *reer*. This suggests that productivity has a positive effect on the real exchange rates. Similar reasoning shows that *open* and *NFA* are also positively correlated with *reer*, and *gexp* is negatively correlated with *reer*. In comparison, the scatter plot for *tot* is much more irregular, indicating that the direction of the effects of *tot* is changing over time. Put differently, *tot* exerts positive and negative effects on the real exchange rates alternately over the sample period, depending on the specific economic context.[21] Besides the changes in direction of the effects on *reer* of the fundamentals, the nonlinear

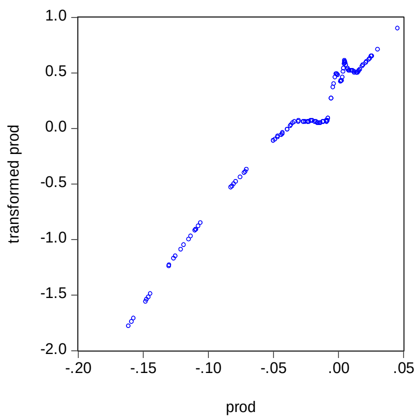
[21] Caution should be taken when interpreting the graphs since the horizontal axis is scaled by the variable's value rather than by time.

relationship also indicates that the magnitude of the effects is changing over time.

Usually, in linear cointegrating equations (3.5.1)-(3.5.6), the fundamentals have either positive or negative effects on real exchange rate and the coefficients remain constant over time, meaning that the effects of the fundamentals on the real exchange rates are constant. This is in sharp contrast with the nonlinear cointegration models (3.5.7) and (3.5.8), where both the direction and magnitude of the effects of fundamentals may change over time. The nonlinear relationships can be explained as follows. In the real economy almost all forces may change over time and interact with each other. It is likely that in one period some economic forces dominate the others but the reverse may be true in another period in affecting the real exchange rates. The ultimate influences of the forces on the economy depend on which forces dominate. In our case, the fundamentals such as *open*, *gexp* and *tot* have both income effects and substitution effects on *reer*, and the dominator alternates over time, hence resulting in changing ultimate effects of the fundamentals on real exchange rates.

For the remaining 3 countries, namely, France, Ireland and Italy, however, we do not find any evidence of nonlinear cointegrating relationship. Therefore there is neither linear nor nonlinear long-run relationship in these three cases. It is noteworthy that having no cointegrating relationship does not rule out the possible Granger causality between the real exchange rates and fundamentals. This issue will be investigated in subsection 3.5.4.





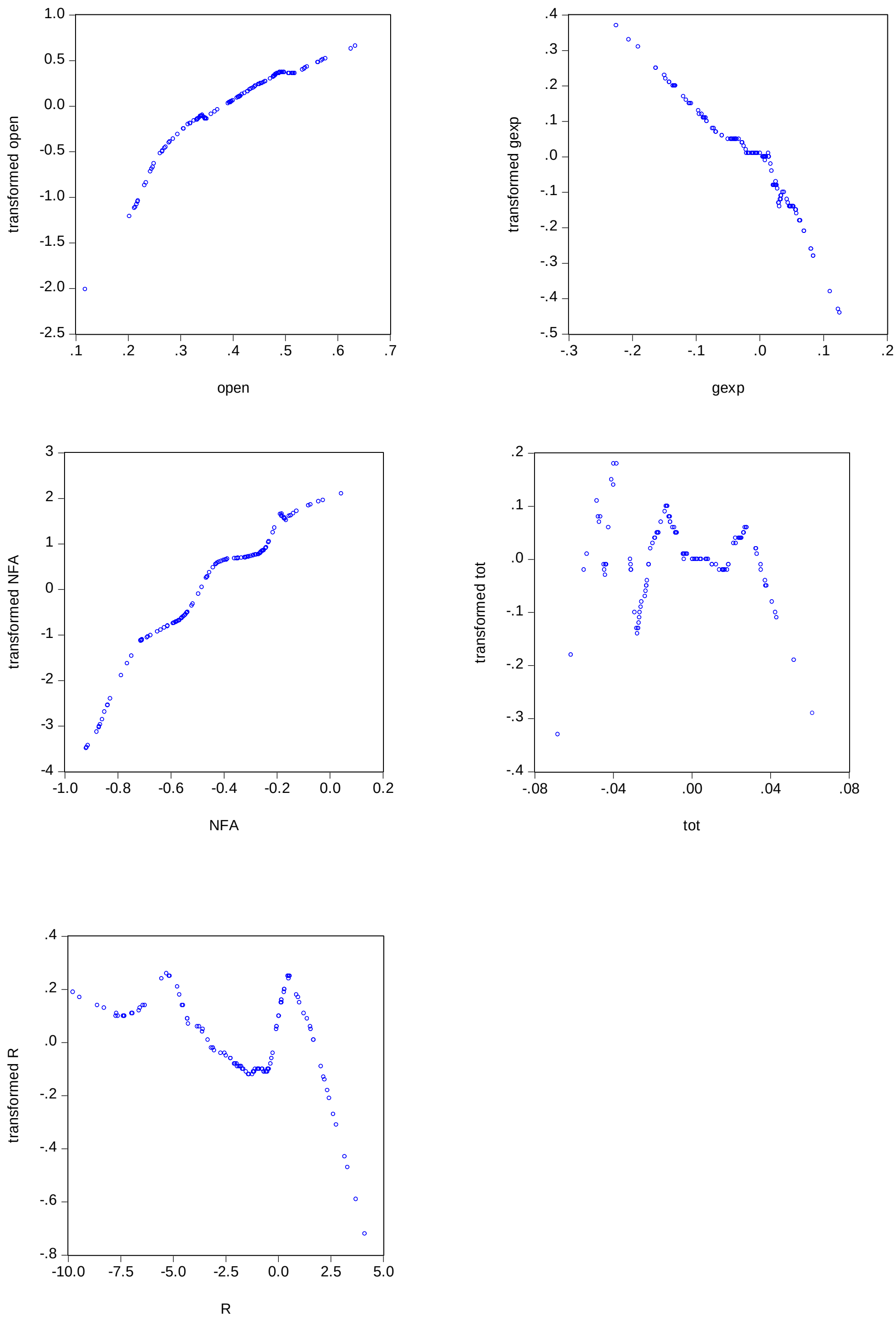
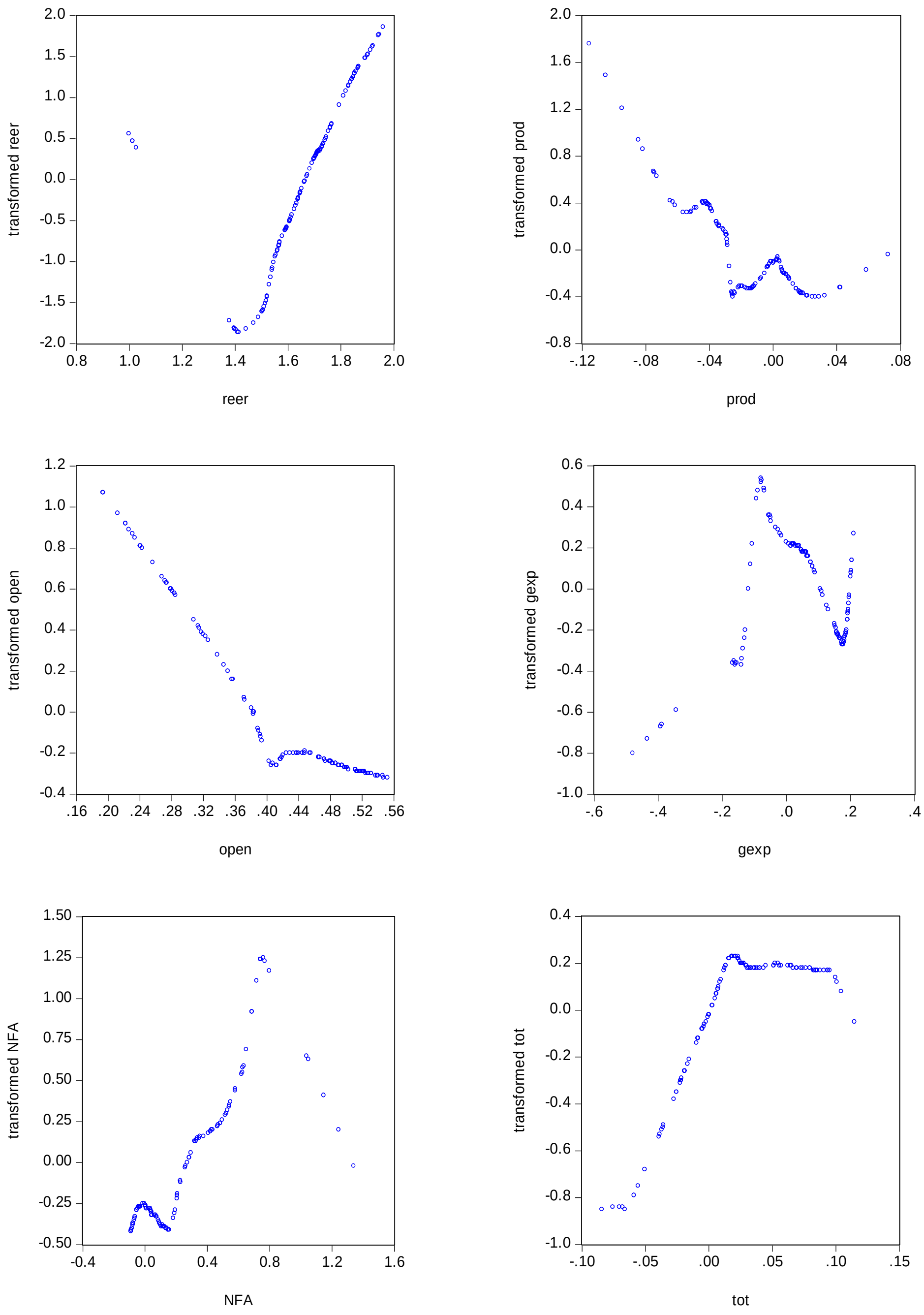


Figure 3.11 Scatter plots of raw variable versus transformed variable (Austria)


transformed reer
reer
transformed prod
prod
transformed open
open
transformed gexp
gexp
transformed NFA
NFA
transformed tot
tot

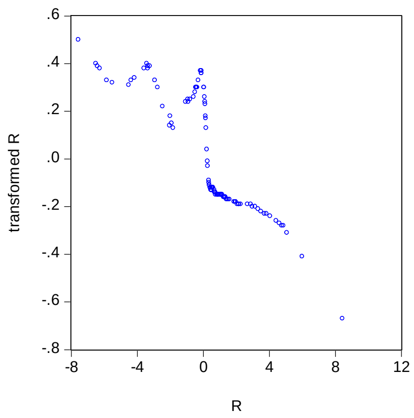


Figure 3.12 Scatter plots of raw variable versus transformed variable (Germany)

3.5.4 Linear and nonlinear Granger causality tests (step 4)

First we test for linear Granger causality between real exchange rates and fundamentals based on VAR models. For the cases where the variables are cointegrated, the VAR is constructed by variables in level based on the cointegrating relationship. For the cases where the variables are not linearly cointegrated, we specify a VAR model with variables in first differences. The lag lengths of the VAR specification were selected using the likelihood ratio (LR) test.

We next test for nonlinear Granger causality between the real exchange rate and fundamentals using the DP test. To remove all linear causality among the variables so as to ensure robust results, we apply the DP test to the residuals from the previously estimated VAR. Following the usual practice, we choose lags $\ell_X = \ell_Y = 1$ to implement the DP test, and as suggested by Diks and Panchenko (2006), the optimal bandwidth value is set equal to 1.5.[22] The test results are summarized in Table 3.3.

[22] Diks and Panchenko (2006) suggest $\varepsilon_n = \max(Cn^{-2/7}, 1.5)$ for small samples. The constant C for the bandwidth is set at 8.0 and the sample size n=120 in this paper, this suggests choosing the optimal bandwidth value of 1.5.

Table 3.3 Granger causality test results (to be continued)

country	x	Linear Granger causality	Nonlinear Granger causality
		H_0: x does not linearly Granger-cause reer	H_0: x does not nonlinearly Granger-cause reer
Finland	prod	72.206(0.000)***	-1.173(0.880)
	open	42.392(0.000)***	-0.365(0.642)
	NFA	37.731(0.000)***	1.752(0.046)**
	gexp	61.098(0.000)***	-0.615(0.731)
	tot	53.995(0.000)***	-0.302(0.619)
	R	46.306(0.000)***	-0.385(0.650)
Spain	prod	34.327(0.000)***	-0.467(0.680)
	open	17.629(0.014)**	0.470(0.319)
	NFA	17.761(0.013)**	1.276(0.100)*
	gexp	13.350(0.064)*	0.722(0.235)
	tot	17.675(0.014)**	-0.534(0.703)
	R	15.072(0.035)**	-0.009(0.504)
Belgium	prod	13.996(0.082)*	-0.277(0.609)
	NFA	24.301(0.002)***	-1.165(0.878)
	gexp	27.207(0.001)***	1.551(0.068)*
	tot	26.042(0.001)***	0.423(0.336)
	R	10.360(0.241)	0.361(0.359)
Euro zone	prod	12.473(0.063)*	1.443(0.075)*
	open	20.993(0.004)***	-1.615(0.947)
	NFA	25.487(0.001)***	0.270(0.394)
	gexp	15.778(0.027)**	-3.255(0.999)
	tot	3.623(0.822)	1.425(0.080)*
	R	25.259(0.001)***	0.730(0.233)

Notes: 1. The lag lengths of VAR specification are selected using the LR criterion; 2. for the linear Granger causality tests, x^2 statistics are reported, for the nonlinear causality tests, t statistics are reported, the P-values are in parenthesis; 3. there is also Granger causality from *reer* to some fundamentals in some cases, the results are not reported in this table. 4. *,** and *** denote significance level of 10%, 5% and 1% respectively.

Table 3.3 Granger causality test results (continued)

France	prod	9.610(0.008)***	0.486(0.313)
	open	2.376(0.305)	-0.257(0.601)
	NFA	6.813(0.072)*	-2.112(0.983)
	gexp	6.341(0.081)*	-1.075(0.859)
	tot	6.292(0.093)*	-0.851(0.803)
	R	1.845(0.398)	1.579(0.065)*
Ireland	prod	11.263(0.004)***	1.858(0.032)**
	open	1.377(0.502)	0.404(0.343)
	NFA	7.42(0.025)**	0.143(0.443)
	gexp	0.056(0.972)	0.783(0.217)
	tot	5.118(0.062)*	0.026(0.490)
	R	5.814(0.055)*	-0.212(0.584)
Italy	prod	8.509(0.075)*	-1.623(0.948)
	open	4.582(0.333)	-1.970(0.976)
	NFA	0.981(0.913)	1.758(0.038)**
	gexp	8.904(0.067)*	-1.303(0.904)
	tot	8.862(0.058)*	-0.439(0.670)
	R	8.115(0.087)*	-0.262(0.603)
Netherlands	prod	5.005 (0.062)*	-0.814(0.792)
	open	0.090(0.764)	0.332(0.370)
	NFA	3.206(0.073)*	0.063(0.475)
	gexp	9.234(0.056)*	1.646(0.056)*
	tot	2.530(0.011)**	-1.009(0.843)
	R	0.435(0.510)	0.284(0.388)
Portugal	prod	14.898(0.005)***	0.597(0.275)
	open	7.781(0.092)*	1.894(0.029)**
	NFA	8.376(0.081)*	-0.795(0.787)
	gexp	7.564(0.100)*	0.010(0.496)
	tot	4.761(0.313)	1.734(0.041)**
	R	6.882(0.142)	0.531(0.298)

For simplicity, we use symbols, $\xrightarrow{L}$ and $\xrightarrow{N}$, to denote "linearly Granger-cause" and "nonlinearly Granger-cause", respectively. The linear causality tests show that for all the countries under consideration most of the economic fundamentals linearly Granger-cause real exchange rates. For example, for Finland and Spain, all of the economic fundamentals $\xrightarrow{L}$ the real exchange rates. For Belgium, *prod, NFA*, *gexp* and *tot* $\xrightarrow{L}$ *reer*. For euro zone, all fundamentals except *tot* $\xrightarrow{L}$ *reer*. More importantly, the nonlinear Granger causality tests show that some economic fundamentals nonlinearly Granger-cause real exchange rates in all of the cases. To give a few examples, for euro, both *prod* and *tot* $\xrightarrow{N}$ reer; for Portugal, both *open* and *tot* $\xrightarrow{N}$ *reer*.

As shown in the previous subsection, for France, Ireland and Italy, the real exchange rates are not cointegrated with the fundamentals. However, the Granger causality tests show that for these three countries some fundamentals do Granger-cause the real exchange rates, either linearly or nonlinearly. Specifically, for France, all of the fundamentals except *open* and *R* $\xrightarrow{L}$ *reer*, and *R* $\xrightarrow{N}$ *reer*. For Ireland, *prod*, *NFA*, *tot* and *R* $\xrightarrow{L}$ *reer*, and *prod* $\xrightarrow{N}$ *reer*. For Italy, *prod*, *gexp*, *tot* and *R* $\xrightarrow{L}$ *reer*, and *NFA* $\xrightarrow{N}$ *reer*.

To sum up, both of the linear and nonlinear Granger causality tests show that the past values of all of the fundamentals contain important information about the present and future real exchange rates. In other words, all of the fundamentals can serve as predictors of real exchange rates. More importantly, the existence of nonlinear Granger causality indicates that there is a nonlinear dynamic relationship between real exchange rates and some fundamentals in the short term.

3.6 Summary and conclusions

Based on quarterly data over the period 1980Q1-2009Q4, this paper attempts to investigate the linear and nonlinear relationship between real exchange rates and fundamentals for the euro and 10 former currencies of EMU countries. We employ the ARDL bounds testing approach together with two nonparametric testing approaches (the nonlinear cointegration test and the nonlinear Granger-causality test) to test for the dynamic relationship between the real exchange rates and fundamentals. The empirical results show that for Finland, Belgium, Spain and the euro, real exchange rates are linearly cointegrated with various set of fundamentals. There is a structural break in the long-run relationships between the real exchange rate and fundamentals for the Netherlands and Portugal. We find that there exists nonlinear cointegration between the real exchange rates and fundamentals for Austria and Germany, which can be interpreted as evidence of a long-run nonlinear relationship between the variables for these two countries. For the remaining currencies, no cointegration is evident.

For all the cases where no nonlinear cointegration is found, we perform both linear and nonlinear Granger causality tests to investigate the causal relation between the real exchange rates and fundamentals. The results show that there is linear Granger causality from fundamentals to the real exchange rates, and more importantly, we also find evidence of nonlinear Granger causality from some fundamentals to the real exchange rates in all the cases.

To sum up, the empirical analysis shows that there exists a nonlinear relationship between real exchange rates and economic fundamentals. The nonlinear cointegrating relationship found for some currencies indicate the existence of long-term nonlinearity in the real exchange rate-fundamentals relationship. The nonlinear Granger causality from fundamentals to real exchange rates indicates that there also exists a short-term dynamic nonlinear relationship between real exchange rates and fundamentals.

Appendix:

1 **Construction of synthetic time series for the EMU**

Since the euro has only a short history, a medium-term analysis of real effective exchange rate requires the construction of historical time series for the euro by aggregating the data of the individual EMU member countries (Greece is excluded for reason of data availability and its late membership). We construct the synthetic series along the lines of Maeso-Fernandez, et al. (2002). These synthetic time series are computed based on quarterly data over the period 1980Q1-2009Q4.

Each time series for the EMU (X^E) is computed as a geometric weighted average of the individual EMU countries series, using the weights (w_j) of each EMU member country j in total trade of the EMU. The rest of the world (ROW) for EMU consists of its top ten trading partners, including the United Kingdom, Sweden, Denmark, the United States, Japan, Canada, Australia, Switzerland, Norway, and Korea. The weights (g_i) for compiling the data of ROW are based on trade flows data averaged over the sample period, the time series are calculated using the formula $X_t^E = \sum_{j=1}^{10} w_j X_t^j$ and $X_t^{ROW} = \sum_{i=1}^{10} g_i X_t^i$.

Correspondingly, the 'synthetic' nominal effective exchange rates (NEER) of the euro is calculated as $NEER^E = \sum_{j=1}^{10} (w_j \sum_{i=1}^{10} g_i E_t^{ij})$, where E_{ij} is the exchange rate of the currency of partner i against each former EMU currency j (e.g. US dollar/Deutsche Mark), which implies that an increase in $NEER^E$ reflects an appreciation of the synthetic euro in effective terms. The real effective exchange rate is defined as the nominal effective exchange rate adjusted for differences between home and foreign consumer price indices, that is $REER_t^E = NEER_t^E \bullet P_t^E / P_t^{ROW}$.

2 Data sources

The EMU member countries include France, Spain, Germany, Austria, Italy, Portugal, Belgium, the Netherlands, Ireland and Finland. The top ten trading partners of each of these EMU member countries are changing over time. In a few cases, quarterly data are not available, so annual data are transformed into quarterly data using a spline method.

Table 3.A Data sources

Data	sources
Nominal exchange rate	International Financial Statistics(IMF)
Government bond rate(long-term)	International Financial Statistics(IMF)
Consumer Price Index (CPI)	International Financial Statistics(IMF), OECD
Percent change of CPI	International Financial Statistics(IMF)
Total foreign assets	International Financial Statistics(IMF)
Total foreign liability	International Financial Statistics(IMF)
Exports	Direction of Trade Statistics(IMF)
Imports	Direction of Trade Statistics(IMF)
Export unit value	International Financial Statistics(IMF)
Import unit value	International Financial Statistics(IMF)
Government consumption expenditure	International Financial Statistics(IMF), OECD
GDP	International Financial Statistics(IMF)
Population	International Financial Statistics(IMF)

Chapter 4 Forecasting Volatility of Euro Exchange Rates

4.1 Introduction

The volatility of exchange rates is very important for investment analysis, the pricing of derivative securities and risk management. However, exchange rate volatility is still very difficult to forecast, despite a large amount of research output on this issue.

The euro is the second most widely traded international currency. Figures 4.1-4.4 plot the volatility of the exchange rate of the euro against four currencies, the US dollar (USD), British pound (GBP), Japanese yen (JPY) and Canadian dollar (CAD). As can be seen from these figures, the euro appears to be more volatile during the recent crisis than before. As shown by Hamilton and Lin (1996), the volatility of stock prices is higher during recessions than in normal times. Hence a natural conjecture is that euro volatility may exhibit different dynamics during economic crises compared with normal times. Put differently, the volatility of euro exchange rates may follow a nonlinear process. If so, using a dummy variable to indicate the more volatile period may capture the nonlinearity in volatility and may enhance forecasting accuracy during this period. Another way to model nonlinear volatility is to use nonlinear volatility model such as the regime-switching GARCH model. The regime-switching GARCH (RS-GARCH) models have aroused great interest lately since they are shown to have an advantage over the traditional GARCH models in accounting for the fact that financial markets react differently to large and small shocks. In addition, the RS-GARCH models have not been compared to the stochastic volatility (SV) models in forecasting exchange rate volatility, so it is interesting to forecast the volatility of euro exchange rates using both the regime-switching GARCH model and the SV model. This study will try to complement the literature by modelling and forecasting the volatility of euro exchange rates over the period from January 1999 to March 2011.

This chapter fits 8 single-regime GARCH models, one regime-switching

GARCH model and one SV model to the euro exchange rates. These ten models include short-memory and long-memory models, single-regime and regime-switching models, linear and nonlinear volatility models, and deterministic and stochastic volatility models. For the purposes of comparison and based on graphical observation of the volatility series, the whole sample period is divided into a normal period (before 1 January 2008) and a volatile period (after this date). The forecasting performance of the models is evaluated and compared over these two subperiods. By comparing the single-regime model with the regime-switching model, we investigate whether exchange rate volatility displays regime-switching behavior. Furthermore, by comparing the GARCH models with and without a dummy variable indicating the volatile period, we explore whether including a dummy in the models can capture the possibly different volatility dynamics during the volatile period. In addition, comparing short-memory models with long-memory models allows for examination as to whether considering the long-memory property of the volatility process can improve the forecast accuracy.

The remainder of this chapter is arranged as follows. Section 4.2 reviews the relevant literature. Section 4.3 describes the data and their properties. In section 4.4 the models utilized in this study are specified. Section 4.5 presents the estimation results. Section 4.6 forecasts volatility of the exchange rate series out-of-sample and compares the forecasting performance of the models according to different statistical criteria. Finally, a summary and conclusions are presented in section 4.7.

4.2 Literature Review

There is a vast literature on modeling and forecasting the volatility of financial assets (for detailed surveys, see Poon and Granger, 2003 and 2005). In this section, we restrict our attention to the studies that are closely related to this chapter.

Various models have been developed to model and forecast time-varying volatility processes. The ARCH-type models are among the most popular ones. Hansen and Lunde (2005) compare 330 ARCH-type models out-of-sample using data on the DM/$ exchange rate and IBM stock returns. They find no evidence that a GARCH(1,1) is outperformed by more sophisticated models in their analysis of exchange rates, though the

GARCH(1,1) does worse than models that can accommodate a leverage effect in their analysis of IBM stock returns.

Some studies show that long-memory models outperform short-memory models in forecasting volatility, for example, Li (2002) investigates the volatility of exchange rates of the German mark, Japanese yen and British pound. He finds that the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model gives a better fit to volatility behavior than alternative models and that it beats option implied volatility substantially in the standard tests of forecasting performance. Andersen, et al. (2003) show that long-memory models outperform traditional short-memory models such as the IGARCH and GARCH in forecasting exchange rate volatility. Pong et al. (2004) forecast the volatility of the British pound, German mark and Japanese yen exchange rates against the US dollar using ARMA, ARFIMA, GARCH models and option implied volatilities. They find that the ARFIMA and ARMA forecasts generally perform better than option implied volatilities for short forecast horizons while implied volatilities produce more accurate forecasts for longer forecast horizons. They also find that the GARCH forecasts are the least accurate for most of the evaluations.

Klaassen (2002) shows that volatility forecasts given by GARCH models are too high in volatile periods due to the high persistence of shocks in GARCH forecasts. He develops a Markov regime-switching GARCH model to obtain more flexibility regarding volatility persistence. His empirical result shows that the regime-switching GARCH model yields significantly better out-of-sample volatility forecasts than the single-regime GARCH model.

The SV model was first developed by Taylor (1986). It has been considered a competitive alternative to the GARCH models for forecasting volatility. For instance, Shephard (1996) conducts a survey on the use of the ARCH and the SV models in finance and finds that the SV models have some strengths in comparison with the ARCH models. However, some studies show mixed evidence on the comparative forecasting performance of the SV models. For example, Lopez (2001) and Yu (2002) find evidence supporting the superiority of the SV model among volatility models, while Dunis, et al. (2001) find evidence against it.

Since the euro has a relatively short history, the literature on modeling and forecasting the volatility of euro exchange rates is still very limited. Malik (2005) uses GARCH, FIGARCH, and the SV models to estimate the volatility of the British pound and the euro based on both hourly and daily data over the period December 2001 to March 2002. His results suggest that the euro is considerably more volatile compared to the British pound. However he does not forecast exchange rate volatility using these models. Bauwens and Sucarrat (2010) employ a general-to-specific econometric methodology to model the weekly volatility of the NOK/euro exchange rate and evaluate its forecasting performance over the period 8 January 1993–25 February 2005. Their findings suggest that this method produces unbiased *ex post* and *ex ante* forecasts and performs relatively well at all horizons.

Chortareas, et al. (2011) employ traditional volatility models, including GARCH, FIGARCH, ARFIMA and the SV model, to forecast the volatility of euro exchange rates using high frequency data spanning the period from 4 January 2000 to 31 October 2004. Their results show that using high frequency data and considering long memory can enhance forecasting performance significantly and that the FIGARCH model outperforms all the other traditional models considered for almost all of the exchange rate series in question.

4.3 Data and their Properties

The four currency-pairs to be examined are USD, GBP, JPY and CAD vis-a-vis the euro. The original data set consists of daily closing spot exchange rates of EUR/USD, EUR/GBP, EUR/JPY and EUR/CAD over the period from 1 January 1999 to 15 March 2011 collected from the ECOWIN database. Actually, it is the return rate series that is modeled in this study and 2 and 3 January 1999 are holidays, so the actual sample considered in this study is from 4 January 1999 to 15 March 2011. The return rate, r_t, is calculated as follows:

$$r_t = \ln p_t - \ln p_{t-1} \tag{4.2.1}$$

where p_t is the spot exchange rate at time t.

Finding an appropriate proxy for volatility is important in volatility forecasting. Before the study by Andersen and Bollerslev (1998), the majority of the time series volatility models use squared daily return as a proxy for daily volatility. However, Davidian and Carroll (1987) show that absolute return is more robust against asymmetry and non-normality of volatility process. Other studies, such as Ding, et al. (1993), McKenzie (1999), Ederington and Guan (2004) etc., find empirical evidence that models using absolute return as a proxy produce better volatility forecasts than models based on squared return. Correspondingly, we use the absolute return of the exchange rate, $|r_t|$, as a volatility measure. Andersen and Bollerslev (1998) suggest that measuring daily volatility using high frequency data can substantially improve the forecasting performance of a GARCH model. Due to data availability, we use daily data on exchange rates.

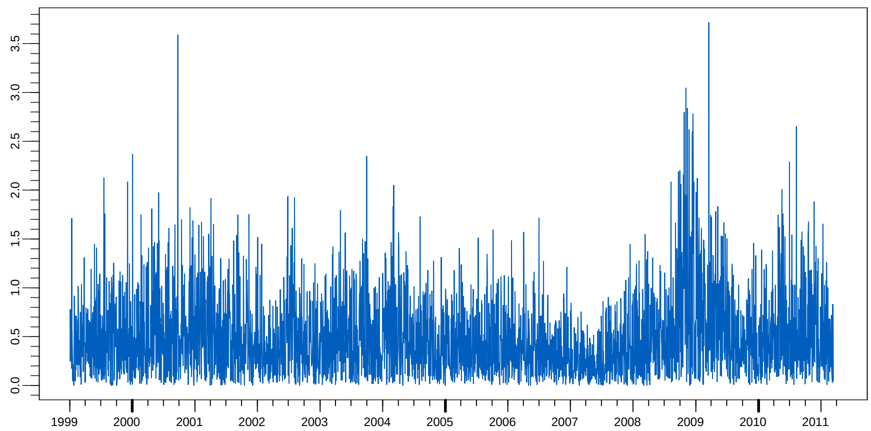


Figure 4.1 Volatility of EUR/USD

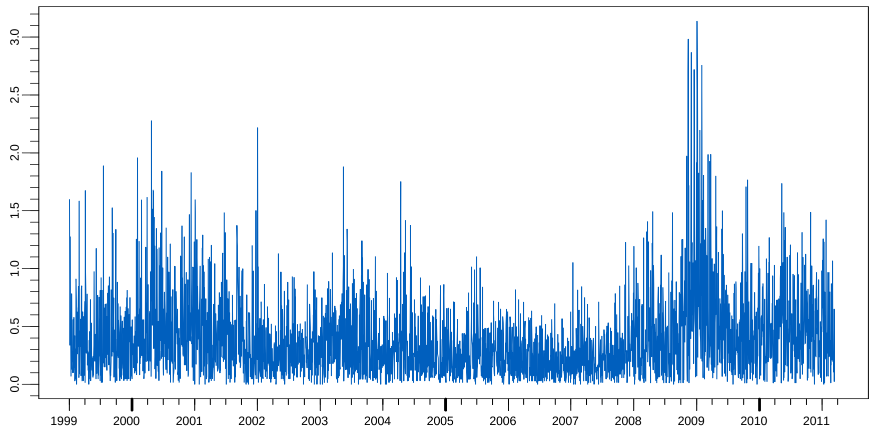


Figure 4.2 Volatility of EUR/GBP

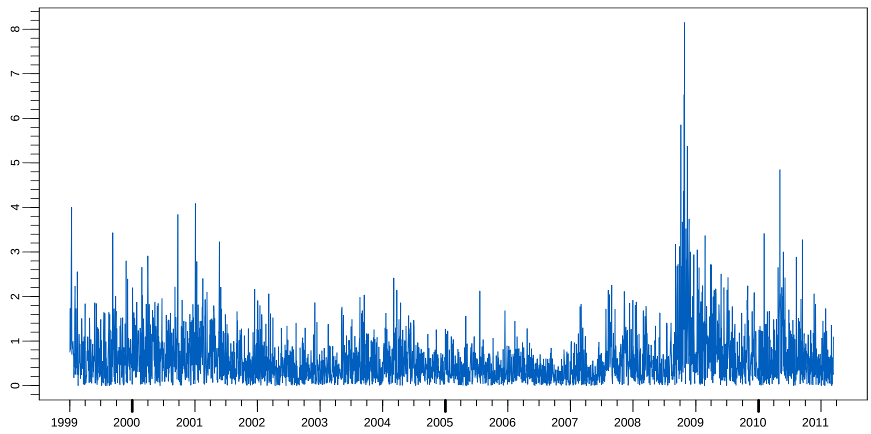


Figure 4.3 Volatility of EUR/JPY

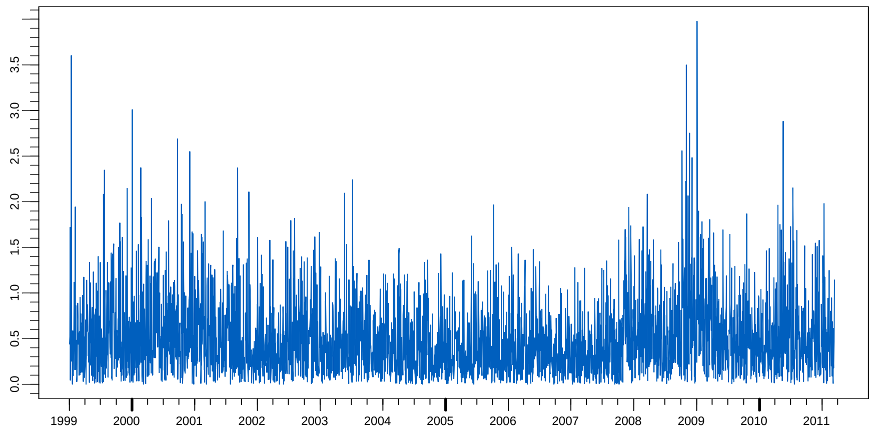


Figure 4.4 Volatility of EUR/CAD

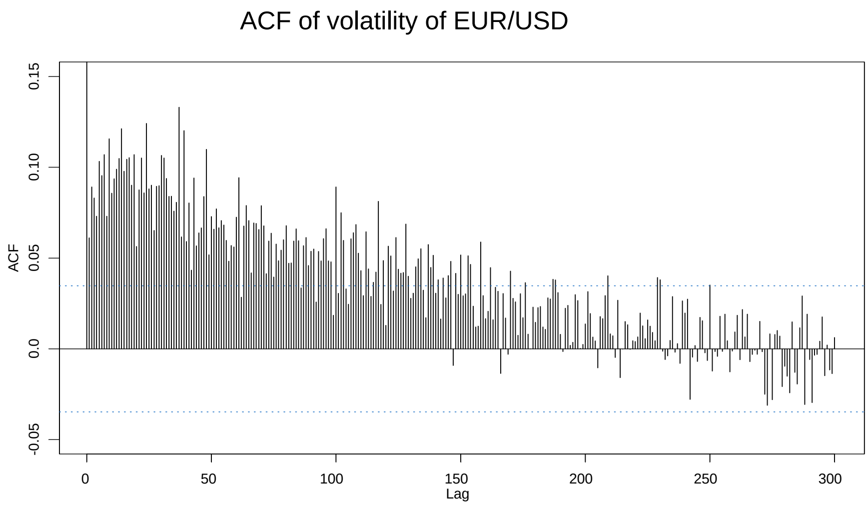


Figure 4.5 ACF of volatility of EUR/USD

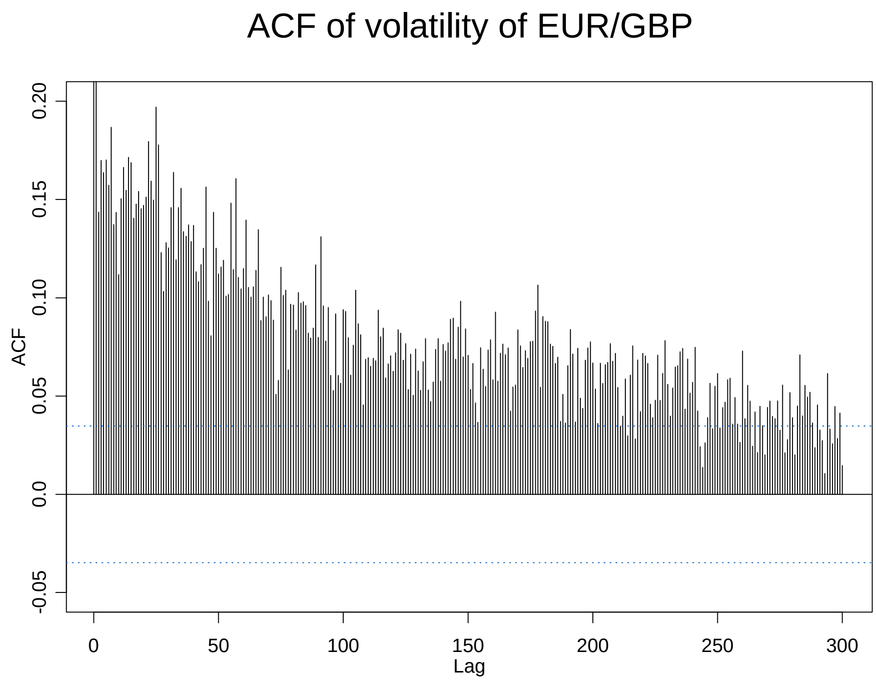


Figure 4.6 ACF of volatility of EUR/GBP

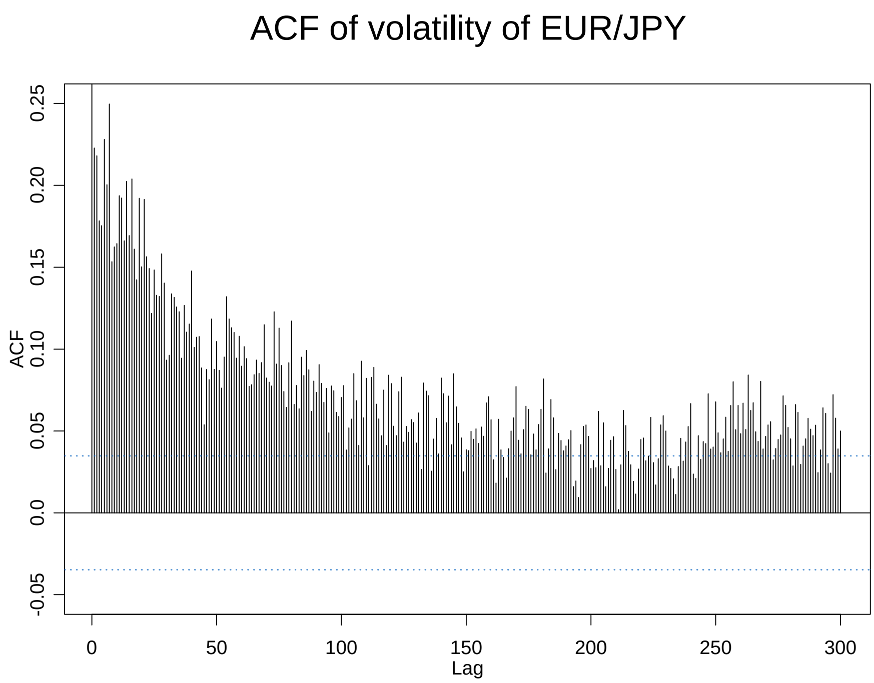


Figure 4.7 ACF of volatility of EUR/JPY

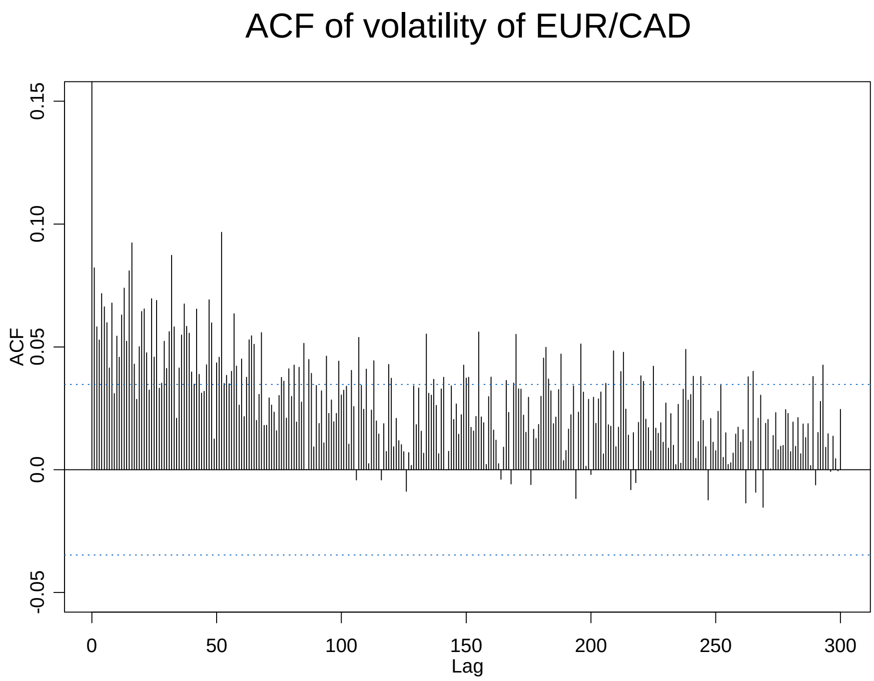


Figure 4.8 ACF of volatility of EUR/CAD

Table 4.3.1 Summary statistics of the returns series

	mean	standard deviation	skewness	kurtosis
EUR/USD	0.006	0.649	0.200	4.605
EUR/GBP	0.007	0.527	0.131	5.756
EUR/JPY	-0.005	0.828	-0.158	10.703
EUR/CAD	-0.008	0.664	0.189	4.644

Table 4.3.1 reports the summary statistics of the distribution of the returns series for each of the four euro exchange rate series. The kurtosis values of these series are all greater than that of the normal distribution, indicating that these returns series have fat tailed distributions. We can also see that all of the returns series are slightly skewed and the means of the series are all approximately zero.

Figures 4.1-4.4 show that large volatilities are usually followed by large ones and small volatilities are usually followed by small ones. Put differently, large volatilities tend to cluster together, and so do small ones. This pattern is typical of many financial time series, and this phenomenon of volatility clustering indicates the time-varying conditional heteroskedasticity of volatility behavior. The seminal work by Engle (1982) constructs the Autoregressive Conditional Heteroskedasticity (ARCH) model to capture this stylized fact.[23] This work led to a huge literature on numerous extensions of ARCH-type models.

Another relevant stylized fact is the remarkable volatility persistence called long memory in the literature. The long-memory process exhibits strong autocorrelation but less than an I(1) process. In other words, it lies between a stationary I(0) process and a non-stationary I(1) process. Figures 4.5-4.8 present the autocorrelation function (ACF) of the volatility series up to 300 lags (the autocorrelation at lag zero, which is always 1, is dropped in the graphs). We can see that the autocorrelation of these series exhibits strong persistence because the autocorrelation is still significant even beyond hundreds of lags. The long-memory character will be confirmed by empirical tests in section 4.5 (see Table 4.5.1).

4.4 Model specifications

4.4.1 The GARCH-type model

(1) The GARCH(p,q) model

According to Engle (1982), for time series y_t, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH(p,q)) model can be written as follows:

$$y_t = c + \varepsilon_t \tag{4.4.1}$$

$$\varepsilon_t = z_t \sigma_t \tag{4.4.2}$$

$$\sigma_t^2 = a_0 + a(L)\varepsilon_t^2 + b(L)\sigma_t^2 \tag{4.4.3}$$

where c is mean of y_t , t = 1, · · · , T, $\sigma_t^2 = \text{var}_{t-1}(\varepsilon_t)$ is the variance of ε_t conditional on information at time t−1, z_t follows i.i.d process with mean zero and unit variance. a(L) and b(L) are polynomials in the lag operator L ($L^i x_t = x_{t-i}$) of order p and q, respectively, that is, $a(L) = \sum_{i=0}^{p} a_i L^i$,

[23] Many stylized facts of the volatility behavior of financial time series have been observed, for detailed review see Bollerslev, Engle and Nelson,1994.

$b(L)=\sum_{j=1}^{q} b_j L^j$, therein coefficients a_i (i = 0, · · · , p) and b_j (j = 1, · · · , q) are all assumed to be positive to ensure positive conditional variance. Note that if we allow for b(L)=0, the GARCH model nests the ARCH model as a special case.

It is worth noting that it is a well-known stylized fact that, as indicated by Table 4.3.1, financial time series usually have fatter tails than a normal distribution, so it may be more desirable to use a distribution with fat tails, such as the t-distribution and Generalized Error Distribution (GED) proposed by Nelson (1991). If a random variable u_t follows a GED with mean zero and unit variance, its probability density function (PDF) can be written as:

$$f\left(\varepsilon_t\right)=\frac{\upsilon \exp[-(1/2)\left|u_t/\lambda\right|^{\upsilon}]}{\lambda 2^{(\upsilon+1)/v}\Gamma(1/\upsilon)} \tag{4.4.4}$$

where $\lambda=\left\{\Gamma(1/v)/4^{1/v}\Gamma(3/v)\right\}^{1/2}$ and ν is a positive parameter governing the thickness of the tails of the distribution. When ν = 2, the PDF reduces to the standard normal PDF; when ν < 2, the distribution has fatter tails than the normal distribution; and when ν > 2, the distribution has thinner tails than the normal distribution.

In general, the basic GARCH model presented above can meet reasonably well the need for analyzing and estimating conditional volatility of financial time series. However, in order to better capture the characteristics and dynamics of a particular time series, ARMA terms of y_t and ε_t and other exogenous explanatory variables (x_t) can be added into the conditional mean equation. The most general form for the conditional mean equation is:

$$y_t=c+\sum_{i=1}^{r}\phi_i y_{t-i}+\sum_{j=1}^{s}\theta_j\varepsilon_{t-j}+\sum_{m=0}^{k}\beta_m' x_{t-m}+\varepsilon_t \tag{4.4.5}$$

where x_t is a k×1 vector of weakly exogenous variables, and β_m is the k×1 vector of coefficients.

Since exogenous variables may have an impact on conditional volatility too, we can also extend the GARCH model by adding exogenous explanatory variables into the conditional variance equation. In this case the conditional variance equation would be as follows:

$$\sigma_t^2 = a_0 + a(L)\varepsilon_t^2 + b(L)\sigma_t^2 + c(L)x_t \qquad (4.4.6)$$

where, of terms not previously defined, c(L) is polynomials in the lag operator *L*.

Assume that a_i , b_i are non-negative for all *i≥1*, expression (4.4.3) can be written in the form of an ARMA(max (*p*,*q*),*q*) model of squared residuals series:

$$\phi(L)\varepsilon_t^2 = a_0 + \left[1 - b(L)\right]\mathrm{v}_t^2 \qquad (4.4.7)$$

where $v_t^2 \equiv \varepsilon_t^2 - \sigma_t^2$, $\phi(L) = 1 - a(L) - b(L)$ and b(L)=0 have roots outside unit circle.

(2) The long-memory GARCH models

If a time series y_t is an I(0) process, observations far apart in time are essentially independent and its ACF declines fast at a geometric rate. Conversely, if y_t is an I(1) process, observations far apart in time are not independent and its ACF declines at a linear rate. In between I(0) and I(1) process is the so-called fractionally integrated process denoted by I(d) (0<d<1). The ACF of a fractionally integrated process declines at a hyperbolic rate, implying that observations far apart in time may exhibit weak but non-zero correlation. This weak correlation between observations far apart is often referred to as long memory in the literature. Correspondingly I(0) processes are said to have short memory.

Technically, a time series y_t is said to have long memory if its autocorrelation function ρ(k) approaches $c_\rho k^{-\alpha}$ infinitely as k approaches infinity ∞, where c_ρ is a positive constant, and α is a real number between 0 and 1. So the autocorrelation function ρ(k) of a long-memory process decays slowly at a hyperbolic rate such that the autocorrelations are actually not summable, that is, $\sum_{k=-\infty}^{\infty} \rho(k) = \infty$. Both Granger and Joyeux (1980) and Hosking (1981) show that, if y_t is a long-memory process, then it can be modeled parametrically by a fractionally integrated process as follows:

$$(1 - \mathrm{L})^{\mathrm{d}}(\mathrm{y}_t - \mu) = \mathrm{u}_t \qquad (4.4.8)$$

where d is the fractional difference parameter, 0<d<1, μ is the expectation of

y_t, and u_t is a stationary short-memory disturbance with zero mean. If we allow d to be 0 and 1, then equation (4.4.8) contains I(0) and I(1) processes as special cases.

One limitation of the traditional GARCH model for exchange rate studies is that the GARCH model is a short-memory model, in which a volatility shock decays (at a geometric rate) much faster than in long-memory models. In comparison, the integrated GARCH (IGARCH) model proposed by Engle and Bollerslev (1986):

$$\phi(L)(1-L)\varepsilon_t^2 = a_0 + \left[1-b(L)\right]v_t^2 \tag{4.4.9}$$

has infinite memory, that is, a volatility shock affects the path of volatility at all horizons. This permanent characteristic does not fit the reality well either, thus the IGARCH model is not a very satisfactory description of exchange rate volatility. In reality it is often the case that a volatility shock does not decay as fast as in the GARCH model nor does it behave like in the IGARCH model, but lies between these two extremes. In order to capture this fact, Baillie, et al. (1996) introduce a long-memory GARCH model--the fractionally integrated GARCH (FIGARCH) model as follows:

$$\phi(L)(1-L)^d\varepsilon_t^2 = a_0 + \left[1-b(L)\right]v_t^2 \tag{4.4.10}$$

where $0<d<1$ is the fractional difference parameter, assuming all the roots of $\phi(L)=0$ and b(L)=0 lie outside unit circle. The FIGARCH model allows for great flexibility in modeling conditional variance, and the covariance stationary GARCH model (*d*=0) and the IGARCH model (*d=1*) can be taken as special cases nested in the FIGARCH model. In the FIGARCH model, the coefficients in the polynomials $\phi(L)$ and *b(L)* capture the short run dynamics of volatility, while the fractional difference parameter d reflects the long run properties of volatility. The FIGARCH model holds that a volatility shock is persistent but the impact of a shock dies out at a hyperbolic rate and thus the process will eventually revert to the long-run steady state.

(3) The regime-switching GARCH model

Some studies, such as Wong and Li (2001) and Lanne and Saikkonen (2003), show that the existence of shifts in the variance process over time can induce volatility persistence. Generally, standard GARCH models cannot account for this kind of persistence. Hence the estimates of GARCH models may suffer from an upward bias in the persistence parameter. Therefore, allowing parameters in the GARCH models to change over time may be better for modelling volatility. Efforts taken in this direction have resulted in a large literature on regime-switching volatility models. For example, Hamilton and Susmel (1994) and Cai (1994) introduce an ARCH model with regime-switching parameters. Gray (1996) develops a tractable Markov-switching GARCH model, which is further modified by Klaassen (2002).

Generally, a regime-switching GARCH model with two regimes takes the following form:

$$y_t = \mu_{s_t} + \varepsilon_t \tag{4.4.11}$$

$$\varepsilon_t = z_t \sigma_t \tag{4.4.12}$$

$$\sigma_t^2 = \alpha_{s_t} + \beta_{s_t} \sigma_{t-1}^2 + \gamma_{s_t} \varepsilon_{t-1}^2 \tag{4.4.13}$$

where $z_t \sim i.i.d(0,1)$, $s_t \in \{0,1\}$ denotes the variance regime at time t, $\alpha_{s_t}, \beta_{s_t}, \gamma_{s_t} \geq 0$ for $s_t \in \{0,1\}$, and transition of s_t follows a Markov chain with fixed transition probabilities. The transition probabilities are set as $Pr(s_t = 0 | s_{t-1} = 0) = p$, $Pr(s_t = 1 | s_{t-1} = 1) = q$. We can see that the parameters in this model are different in each regime, hence by construction, it can account for the possibility that the volatility process undergoes changes over the sample period.

4.4.2 The SV model

The GARCH models define the time-varying variance as a deterministic function of past squared innovations and lagged conditional variances, hence they can be called deterministic volatility models. Unlike the deterministic volatility models, the stochastic volatility models take the variance as an unobserved component that follows some stochastic process. The most popular version of the SV model defines volatility as a logarithmic AR(1) process. A simple SV model due to Taylor (1986) takes the following form:

$$y_t = \mu + \varepsilon_t \tag{4.4.14}$$

$$\varepsilon_t = z_t \sigma_t \tag{4.4.15}$$

$$\ln \sigma_t^2 = \alpha + \beta \ln \sigma_{t-1}^2 + \sigma_{0,u} u_t \tag{4.4.16}$$

where $\sigma_t^2 = E_{t-1}\left(\varepsilon_t^2\right)$, $|\beta| < 1$, $z_t \sim \text{i.i.d}N\left(0,1\right)$, $u_t \sim \text{i.i.d}N\left(0,1\right)$. The logarithm of conditional variance, $\ln \sigma_t^2$, is modeled as an unobserved AR(1) process.

4.5 Estimation results

In this section, various conditional volatility models are used to estimate the volatility of euro exchange rates over the full sample period.

Before estimating volatility models, the long-memory property of the four returns series are examined. Hurst (1951) proposes the range over standard deviation (R/S) statistic to test for long memory of time series. Geweke and Porter-Hudak (1983) propose a semi-parametric approach (GPH test) to test for long memory. We carry out both the modified R/S test and GPH test. The test results, presented in Table 4.5.1, suggest that all of the returns series under consideration have long memory. Hence the results provide support to the long-memory GARCH models.

Table 4.5.1 Long-memory test results

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
R/S test statistic	3.5968*	4.0224*	3.2956*	3.703*
GPH test statistic	7.5627*	7.3743*	3.6311*	6.3671*

Note: * means that the statistic is significant at 1% level.

Since euro exchange rate volatility appears to be relatively more volatile from 2008 onward, in order to compare the forecasting performance of the models over different time periods, we divide the whole sample period into two subperiods. Period 1 is from 4 January 1999 to 1 January 2008 and period 2 is from 1 January 2008 to 15 March 2011. The dummy variable, denoted by D, indicates the relatively more volatile period from 1 January 2008 onwards. It takes a value of 1 from 1 January 2008 onwards and 0 before this date.

We first fit 8 alternative single-regime GARCH-type models to each of the four exchange rate returns series, and then we fit an RS-GARCH model and an SV model to the full sample. The single-regime GARCH-type models include: (1) three GARCH(1,1) models with normal-distributed, t-distributed and GED-distributed error terms, denoted by GARCH.N, GARCH.T and GARCH.GED, respectively;[24] (2) three GARCH(1,1) models with the aforementioned error terms and an extra dummy variable indicating the volatile period in the conditional variance equation, denoted by GARCH.N.D, GARCH.T.D and GARCH.GED.D, respectively; and (3) an FIGARCH(1,d,1) model, and an FIGARCH(1,*d*,1) model with dummy variable in the conditional variance equation, denoted by FIGARCH.D.

The estimation results of single-regime GARCH models are reported in Tables 4.5.2-4.5.5. We can see from Table 4.5.2 for EUR/USD that for all of the models, the constant terms (C) in the mean equations are insignificant at a 5% level, indicating that the exchange rate returns series have nearly mean zero, which is consistent with the mean statistics reported in Table 4.3.1. The estimated ARCH parameters are highly significant in all of the short-memory GARCH models, but are significant only at a 10% significance level in two long-memory GARCH models, the estimated GARCH parameters are highly significant in all of the models, and fractional difference parameters are also highly significant in the long-memory GARCH models. This is consistent with the long-memory test results given in Table 4.5.1. It is worth noticing that the dummy variable is significant and its coefficient is positive in all of the cases under consideration, confirming that the volatility of euro exchange rates is higher in period 2 than in period 1. Results for the other currency-pairs are qualitatively similar to that for EUR/USD (Tables 4.5.3-4.5.5).

Estimation results for the RS-GARCH model and the SV model are

[24] Hansen and Lunde (2005) find no evidence that a GARCH(1,1) is outperformed by more sophisticated models in their analysis of exchange rates. As is the convention in the existing literature, we choose an order pair of (1,1) for the models.

reported in Table 4.5.7 and Table 4.5.8 respectively. These two tables show that μ is insignificant in all of the cases, due to the fact that the returns series of exchange rates usually have a near zero mean. In Table 4.5.7, most of the estimates for σ, β and γ are at least significant at a 10% level, the two exceptions being β_1 for EUR/CAD and γ_1 for EUR/GBP. For all the cases the sum of β and γ is less than 1 in both regimes, meaning that both regimes are stable. Additionally, the relatively high values of transition probabilities, p and q, indicate that it is more likely for the exchange rate volatility at date t to stay in the same regime as at date t-1. This result reflects the persistence of volatility. Table 4.5.8 shows that except for α for EUR/GBP and EUR/CAD, which are insignificant, the other estimated σ, β and $\sigma_{0,u}$ are all significant.

If the GARCH models are successful at modelling the serial correlation structure in the conditional mean and conditional variance, then there should be no autocorrelation left in the standardized residuals and squared standardized residuals. Furthermore, there should be no ARCH effects left in the standardized residuals if the GARCH model successfully models the volatility series. To investigate these issues, we carry out the Ljung-Box test for the standardized residuals and squared standardized residuals, and we also apply the ARCH test on the standardized residuals to see if there are any ARCH effects left. The diagnostic test results for all the models are reported in Table 4.5.6, we can see that for all the models the null hypotheses are not rejected, therefore all the models fit the volatility series reasonably well.

We can see the advantage of the RS-GARCH model over the GARCH.N model in capturing the persistence of shocks in volatility by comparing the GARCH parameters in these models. For example, in the GARCH.N model for EUR/CAD, the GARCH parameter is 0.966, meaning that the volatility of exchange rate of EUR/CAD is very persistent in the whole sample period. In contrast, the RS-GARCH model displays more flexibility, the volatility process switches between regime 0 and regime 1, while in regime 0 (low-persistence regime) the GARCH parameter is 0.752, in regime 1 (high-persistence regime) the GARCH parameter is 0.854 (see Table 4.5.5 and Table 4.5.7). The driving force behind the regime switches may be the alternating showing up of good news and bad news in the market. As an established finding in many existing studies, bad news usually has stronger and more persistent effects on economy than good news. Consequently, the volatility of exchange rates would be more persistent when bad news hits the economy than it would be when good news shows up. This flexibility of the RS-GARCH model explains why the RS-GARCH model provides more accurate volatility forecasts than the other single-regime GARCH models, as is shown in section 4.6.

Table 4.5.2 Estimation Results of single-regime GARCH models (EUR/USD)

MODEL	GARCH.N					GARCH.T					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)		
	0.016	0.001	0.031	0.966		0.014	0.001	0.031	0.966		
	(0.113)	(0.014)**	(0.000)***	(0.000)***		(0.165)	(0.069)*	(0.000)***	(0.000)***		
MODEL	GARCH.GED					GARCH.N.D					
COEF.	C	A	ARCH(1)	GARC0H(1)		C	A	ARCH(1)	GARCH(1)	DUMMY	
	0.014	0.001	0.030	0.967		0.017	0.001	0.029	0.968	0.01	
	(0.170)	(0.073)*	(0.000)***	(0.000)***		(0.095)*	(0.034)**	(0.000)***	(0.000)***	(0.038)**	
MODEL	GARCH.T.D					GARCH.GED.D					
COEF	C	A	ARCH(1)	GARCH(1)	DUMMY	C	A	ARCH(1)	GARCH(1)	DUMMY	
	0.014	0.001	0.029	0.968	0.02	0.013	0.001	0.028	0.968	0.01	
	(0.173)	(0.110)	(0.000)***	(0.000)***	(0.042)**	(0.178)	(0.104)	(0.000)***	(0.000)***	(0.048)**	
MODEL	FIGARCH					FIGARCH.D					
COEF	C	A	ARCH(1)	GARCH(1)	FRACTION	C	A	ARCH(1)	GARCH(1)	FRACTION	DUMMY
	0.014	0.001	0.059	0.938	0.864	0.014	0.0001	0.059	0.940	0.365	0.02
	(0.072)*	(0.024)**	(0.082)*	(0.000)***	(0.000)***	(0.072)*	(0.088)*	(0.075)*	(0.000)***	(0.000)***	(0.043)**

Notes: 1. In the output, C corresponds to the constant c in the conditional mean equation (4.4.1). A, ARCH(1), GARCH(1) and FRACTION correspond respectively to a_0, a_1, b_1 and the differencing parameter d in the conditional variance equations (4.4.3) and (4.4.10). Dummy is an exogenous variable indicating the crisis period in the conditional variance equation; 2. *,** and *** denote significance level of 10%, 5% and 1% respectively; 3. p-values are in the parentheses. These notes apply to Tables 3.5.3-3.5.5 too.

Table 4.5.3 Estimation Results of single-regime GARCH models (EUR/GBP)

MODEL	GARCH.N					GARCH.T					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)		
	0.005	0.001	0.048	0.948		0.002	0.001	0.044	0.951		
	(0.537)	(0.004)***	(0.000)***	(0.000)***		(0.796)	(0.022)**	(0.000)***	(0.000)***		
MODEL	GARCH.GED					GARCH.N.D					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)	DUMMY	
	-0.000	0.001	0.046	0.950		0.001	0.001	0.034	0.960	0.02	
	(0.994)	(0.018)	(0.000)***	(0.000)***		(0.223)	(0.310)	(0.000)***	(0.000)***	(0.063)*	
MODEL	GARCH.T.D					GARCH.GED.D					
COEF	C	A	ARCH(1)	GARCH(1)	DUMMY	C	A	ARCH(1)	GARCH(1)	DUMMY	
	0.001	0.001	0.042	0.951	0.02	-0.000	0.001	0.043	0.950	0.02	
	(0.870)	(0.013)	(0.000)***	(0.000)***	(0.019)**	(0.975)	(0.011)**	(0.000)***	(0.000)***	(0.030)**	
MODEL	FIGARCH					FIGARCH.D					
COEF	C	A	ARCH(1)	GARCH(1)	FRACTION	C	A	ARCH(1)	GARCH(1)	FRACTION	DUMMY
	0.004	0.004	0.127	0.768	0.472	0.003	0.005	0.139	0.804	0.450	0.02
	(0.085)*	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.072)*	(0.088)*	(0.075)*	(0.000)***	(0.000)***	(0.051)*

Table 4.5.4 Estimation Results of single-regime GARCH models (EUR/JPY)

MODEL	GARCH.N					GARCH.T					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)		
	0.020	0.005	0.073	0.921		0.035	0.004	0.061	0.934		
	(0.071)*	(0.000)***	(0.000)***	(0.000)***		(0.001)***	(0.004)***	(0.000)***	(0.000)***		
MODEL	GARCH.GED					GARCH.N.D					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)	DUMMY	
	0.035	0.004	0.066	0.929		0.031	0.003	0.039	0.946	0.01	
	(0.001)***	(0.003)***	(0.000)***	(0.000)***		(0.084)*	(0.031)**	(0.000)***	(0.000)***	(0.053)*	
MODEL	GARCH.T.D					GARCH.GED.D					
COEF	C	A	ARCH(1)	GARCH(1)	DUMMY	C	A	ARCH(1)	GARCH(1)	DUMMY	
	0.034	0.004	0.063	0.930	0.04	0.035	0.005	0.067	0.923	0.06	
	(0.001)***	(0.003)***	(0.000)***	(0.000)***	(0.067)*	(0.001)***	(0.002)***	(0.000)***	(0.000)***	(0.050)*	
MODEL	FIGARCH					FIGARCH.D					
COEF	C	A	ARCH(1)	GARCH(1)	FRACTION	C	A	ARCH(1)	GARCH(1)	FRACTION	DUMMY
	0.021	0.011	0.364	0.615	0.457	0.013	0.012	0.361	0.620	0.373	0.01
	(0.028)**	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.057)*	(0.000)*	(0.055)*	(0.000)***	(0.000)***	(0.061)*

Table 4.5.5 Estimation Results of single-regime GARCH models (EUR/CAD)

MODEL	GARCH.N					GARCH.T					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)		
	-0.008	0.003	0.027	0.966		-0.015	0.003	0.025	0.969		
	(0.484)	(0.004)***	(0.000)***	(0.000)***		(0.170)	(0.038)**	(0.000)***	(0.000)***		
MODEL	GARCH.GED					GARCH.N.D					
COEF.	C	A	ARCH(1)	GARCH(1)		C	A	ARCH(1)	GARCH(1)	DUMMY	
	-0.016	0.004	0.027	0.965		0.015	0.001	0.041	0.952	0.01	
	(0.135)	(0.021)**	(0.000)***	(0.000)***		(0.095)*	(0.034)**	(0.000)***	(0.000)***	(0.042)**	
MODEL	GARCH.T.D					GARCH.GED.D					
COEF	C	A	ARCH(1)	GARCH(1)	DUMMY	C	A	ARCH(1)	GARCH(1)	DUMMY	
	-0.015	0.004	0.025	0.964	0.02	-0.015	0.004	0.026	0.964	0.02	
	(0.164)	(0.021)**	(0.000)***	(0.000)***	(0.038)**	(0.154)	(0.020)**	(0.000)***	(0.000)***	(0.053)*	
MODEL	FIGARCH					FIGARCH.D					
COEF	C	A	ARCH(1)	GARCH(1)	FRACTION	C	A	ARCH(1)	GARCH(1)	FRACTION	DUMMY
	-0.008	0.023	0.254	0.643	0.302	0.016	0.0001	0.258	0.638	0.304	0.01
	(0.219)	(0.024)**	(0.042)**	(0.000)***	(0.000)***	(0.073)*	(0.088)*	(0.075)*	(0.000)***	(0.000)***	(0.059)*

Table 4.5.6 Diagnostic test results

LB test	GARCH.N	GARCH.T	GARCH.GED	GARCH.N.D	GARCH.T.D	GARCH.GED.D	FIGARCH	FIGARCH.D
LB test for ε/σ	14.820 (0.252)	15.340 (0.220)	12.810 (0.318)	10.470 (0.252)	11.354 (0.345)	9.157 (0.302)	8.632 (0.502)	8.123 (0.572)
LB test for (ε/σ)	14.041 (0.298)	14.782 (0.276)	11.734 (0.369)	9.044 (0.308)	10.614 (0.287)	8.976 (0.268)	8.042 (0.549)	14.04 (0.597)
ARCH test	14.766 (0.255)	15.016 (0.260)	12.174 (0.329)	10.274 (0.260)	11.846 (0.375)	10.042 (0.315)	9.016 (0.550)	14.766 (0.585)

Note: 1. LB test denotes Ljung-Box test, ε/σ denotes the standardized residuals; 2. Null Hypothesis for Ljung-Box test: no autocorrelation, Null Hypothesis for ARCH test: no ARCH effects; 3. P-values are reported in parentheses.

Table 4.5.7 Estimation results of RS-GARCH model

	Regime 0				Regime 1				p	q
	μ_0	α_0	β_0	γ_0	μ_1	α_1	β_1	γ_1		
EUR/USD	0.004 (0.198)	0.075 (0.049)**	0.889 (0.020)**	0.078 (0.046)**	-0.063 (0.258)	1.351 (0.004)***	0.948 (0.043)**	0.023 (0.079)*	0.874	0.751
EUR/GBP	0.003 (0.105)	0.092 (0.054)*	0.622 (0.074)*	0.364 (0.085)*	-0.045 (0.325)	1.150 (0.071)*	0.826 (0.037)**	0.129 (0.225)	0.823	0.764
EUR/JPY	0.002 (0.370)	0.168 (0.032)**	0.813 (0.025)**	0.157 (0.074)*	-0.065 (0.144)	1.068 (0.053)*	0.917 (0.056)*	0.037 (0.043)**	0.697	0.842
EUR/CAD	0.011 (0.257)	0.474 (0.044)**	0.752 (0.011)**	0.239 (0.064)*	-0.121 (0.650)	0.947 (0.048)**	0.854 (0.125)	0.120 (0.078)*	0.716	0.753

Notes: 1. μ, σ, β and γ correspond to parameters in equations 3.4.11-3.4.13; 2.*, ** and *** denote significance level of 10%, 5% and 1% respectively; 3. p-values are in the parentheses.

Table 4.5.8 Estimation results of the SV model

	μ	α	β	$\sigma_{0,u}$
EUR/USD	0.016 (0.168)	-0.365 (0.024)**	0.946 (0.000)***	0.173 (0.054)*
EUR/GBP	0.032 (0.225)	-0.315 (0.174)	0.542 (0.014)**	0.323 (0.025)**
EUR/JPY	0.025 (0.105)	-0.268 (0.043)**	0.347 (0.005)***	0.117 (0.043)**
EUR/CAD	0.061 (0.650)	0.407 (0.114)	0.824 (0.011)**	0.244 (0.067)*

Notes: 1. μ, σ, β and $\sigma_{0,u}$ correspond to parameters in equations 3.4.11-3.4.13; 2. *, ** and *** denote significance level of 10%, 5% and 1% respectively; 3. p-values are in the parentheses.

4.6 Comparison of the out-of-sample forecasting performance

In order to test for and compare the forecasting performance of the models, we carry out rolling estimation and forecasting in the following way. For each of the four currency-pairs, we take the period between 4 January

1999 and 11 January 2005 as the first subsample, in which there are 1572 observations in total. We then roll the subsample forward by 10 steps, keeping the width of the subsample unchanged; this makes a second subsample. We keep rolling forward in this way until the 160th subsample, which ends on 15 February 2011. Ten volatility models are fitted to these 160 subsamples, and we then make one-step-ahead forecasts of the exchange rate volatility based on these in-sample estimations. Thus, for each of the four currency-pairs, we obtain 160 one-step-ahead forecasts using each of the models. Among the 160 subsamples, the first 78 subsamples fall into period 1, and the remaining 82 subsamples fall into period 2. It is noteworthy that the dummy variable can only be included in the models for the latter 82 subsamples, which cover observations over the second period.

The existing literature shows that different criteria for evaluating forecasting performance may favour different models. To avoid bias, we compare the models using three criteria, namely, forecast error, the regression test and the Diebold-Mariano (DM) test. In what follows, the three criteria are first introduced, and then the models are compared over the two periods using these criteria.

4.6.1 Measures of forecasting accuracy

(1) Forecast error

One basic way to measure forecasting accuracy is to compare the true volatility with the forecasted value and calculate the forecast error. A smaller absolute value of forecast error means a better forecast. Various forecast error statistics have been used in the existing literature, and there is no standard to decide which one is the best. In this study, we choose one of the most commonly used statistics, mean squared error (MSE), to carry out the comparison. The forecast error for the h-step-ahead forecast at time t is $\hat{\varepsilon}_{t+h|t} = \sigma_{t+h} - \hat{\sigma}_{t+h|t}$, where σ_{t+h} is the true volatility at time t+h, and $\hat{\sigma}_{t+h|t}$ is the h-step-ahead forecasted volatility at time t. MSE is calculated using the following formula:

$$MSE(h) = \frac{1}{T-n-h+1}\sum_{t=n}^{T-h}\hat{\varepsilon}^2_{t+h|t} \tag{4.6.1}$$

Generally speaking, the smaller the absolute values of the forecast errors are, the better the model forecasts. The forecast error statistic can provide a rough comparison of the models.

(2) The regression test

The regression test is proposed by Mincer and Zarnowitz (1969) and is further studied by Hatanaka (1974). It is used to compare forecasting performance in many studies, such as Anderson and Bollerslev (1998), Martens, et al. (2002) and Pong, et al. (2004). The basic idea of this approach is to regress the true volatility on a constant and forecasted volatility in order to examine whether the forecast value has explanatory power for the true volatility. The regression equation is as follows:

$$\sigma_{t+h} = \alpha + \beta \hat{\sigma}_{t+h|t} + e_t \tag{4.6.2}$$

where σ_{t+h} is the true volatility, proxied by absolute return at time t+h, and $\hat{\sigma}_{t+h|t}$ is the h-step-ahead forecasted volatility at time t, and e_t is the error term.

The determination coefficient R^2 from the above regression can be used to compare the forecasting performance of our models. A larger R^2 is interpreted as a stronger forecasting ability of the corresponding model.

(3) The Diebold-Mariano Test

From a statistical point of view, a smaller forecast error does not necessarily mean that the corresponding model is significantly superior to other models. The difference between two forecasts might be insignificantly different from zero, though the forecast errors are different. Therefore the comparison given by forecast error statistics may not be statistically robust. In order to test for the statistical significance of forecast differential, Diebold and Mariano (1995) propose a test to compare two competing models.

The basic idea of the Diebold-Mariano (DM) test is as follows. Let L(•) denote a specified loss function. $\left\{\hat{\varepsilon}^{(1)}_{t+h|t}\right\}$ and $\left\{\hat{\varepsilon}^{(2)}_{t+h|t}\right\}$ denote the two h-step-ahead forecast error series resulting from model 1 and model 2, respectively. The loss differential is given by $d_t = L(\hat{\varepsilon}^{(1)}_{t+h|t}) - L(\hat{\varepsilon}^{(2)}_{t+h|t})$. The null hypothesis of the DM test is that the two models forecast equally well, that is, H_0: $E(d_t)=0$. If the null is rejected, it means that the model with smaller loss is significantly superior to the other model. The DM test statistic is defined as follows:

$$DM = \bar{d} / \sqrt{\widehat{LRV}(\bar{d})} \tag{4.6.3}$$

where $\bar{d} = \frac{1}{N}\sum_{t=1}^{N} d_t$, N is the number of h-step-ahead forecasts, and $\widehat{LRV}(\bar{d})$ is a consistent estimate of the long-run asymptotic variance of $\bar{d}$. Diebold and Mariano show that the DM statistic follows, asymptotically, a standard normal distribution under the null hypothesis of equal predictive accuracy. The DM test has become the most widely used method for comparing forecasting performance of different models.

4.6.2 Comparison using MSE

We rank the models over periods 1 and 2 according to MSE of the forecasts. The ranking of models over the two periods are reported in Table 4.6.1 and Table 4.6.2, respectively (see Table 4.A.1 and Table 4.A.2 in Appendix for detailed data on MSE). We can see from Table 4.6.1 that RS-GARCH is ranked the best for EUR/USD, EUR/GBP and EUR/JPY, and it is ranked second-best for EUR/CAD. The SV model is the second-best model for EUR/USD and EUR/GBP and is the third-best model for EUR/JPY and EUR/CAD. The long-memory GARCH model, FIGARCH, is ranked the best for EUR/CAD, second-best for EUR/JPY and third-best for EUR/USD. It always outperforms the three short-memory GARCH models, GARCH.N, GARCH.T and GARCH.GED.

By comparing Table 4.6.2 with Table 4.6.1, we can see that the ranking of the models is different over period 2. Somewhat surprisingly, Table 4.6.2 shows that FIGARCH.D is the best model for all of the four currency-pairs. RS-GARCH is ranked third-best for EUR/GBP and ranked second-best for the other three currency-pairs. The performance of SV and FIGARCH is similar; they both perform better than the short-memory models. The GARCH models with a dummy variable all forecast better than the GARCH models without a dummy variable. It is also worth noticing that GARCH.GED generally outperforms GARCH.T and GARCH.N over the two periods.

4.6.1 Ranking of models by MSE (period 1)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	6	6	5	6
GARCH.T	5	4	6	5
GARCH.GED	4	5	4	4
FIGARCH	3	3	2	1
RS-GARCH	1	1	1	2
SV	2	2	3	3

Table 4.6.2 Ranking of models by MSE (period 2)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	10	10	9	9
GARCH.T	9	9	10	10
GARCH.GED	8	8	8	8
GARCH.N.D	6	6	5	6
GARCH.T.D	7	5	7	7
GARCH.GED.D	5	7	6	5
FIGARCH	4	3	4	3
FIGARCH.D	1	1	1	1
RS-GARCH	3	2	2	2
SV	2	4	3	4

4.6.3 Comparison using the regression test

Now we compare the models according to the R^2 from the regression test (see Table 4.A.3 and Table 4.A.4 in Appendix for detailed data on R^2). Table 4.6.3 and Table 4.6.4 summarize the ranking of models over period 1 and period 2, respectively. Table 4.6.3 shows that in period 1 RS-GARCH is ranked the best for all of the four currency-pairs. The SV model is the third-best model for EUR/USD and is the second-best model for the other three currency-pairs. The performance of FIGARCH is similar to that of SV, ranked second-best for EUR/USD and EUR/JPY and third-best for the other two currency-pairs.

By comparing Table 4.6.4 with Table 4.6.3, we can see that the ranking of the models is slightly different over period 2. For example, RS-GARCH no longer ranks the best, it ranks fourth-best for EUR/USD and second-best for the other three currency-pairs. FIGARCH.D outperforms RS-GARCH and becomes the best model for all of the four currency-pairs, the same as ranked by MSE over period 2. Like in period 1, in period 2 SV and FIGARCH still forecast similarly and both perform better than the short-memory models.

Table 4.6.3 Ranking of models by the regression test (period 1)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	5	6	4	5
GARCH.T	6	5	5	6
GARCH.GED	4	4	3	4
FIGARCH	2	3	2	3
RS-GARCH	1	1	1	1
SV	3	2	2	2

Table 4.6.4 Ranking of models by the regression test (period 2)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	9	10	9	9
GARCH.T	10	9	8	9
GARCH.GED	8	8	8	8
GARCH.N.D	6	5	5	7
GARCH.T.D	5	6	6	6
GARCH.GED.D	7	7	7	5
FIGARCH	2	4	4	3
FIGARCH.D	1	1	1	1
RS-GARCH	4	2	2	2
SV	3	3	3	4

By comparing Table 4.6.3 with Table 4.6.1 and comparing Table 4.6.4 with Table 4.6.2, we find that the regression test provides a different overall ranking from that given by MSE. However, these two criteria agree with each other on the following points: First, RS-GARCH is the best model in period 1 and FIGARCH.D is the best one in period 2. Second, the long-memory GARCH models generally forecast better than the short-memory GARCH models over both of the two periods. Third, the GARCH models with a dummy variable generally forecast better than those without a dummy variable. Finally, GARCH.GED generally outperforms GARCH.T and GARCH.N over both of the two periods.

4.6.4 Comparison using the DM Test

As mentioned earlier, the comparison given by forecast error statistics may not be statistically robust, so this subsection focuses on comparing the models using the DM test. To simplify the comparison, we first compare the single-regime GARCH models, and then we compare the best single-regime GARCH model with the regime-switching GARCH model and the SV model.

(1) Comparison of the single-regime GARCH Models

When comparing model performance using the DM test, higher priority is given to the model with the smallest forecast error. The tests are performed for the competing model-pairs. We use MSE as the loss functions for the DM test. For each currency-pair, we rank the models according to the DM test results (see Table 4.A.5 and Table 4.A.6 in Appendix for detailed data). The ranking of models is summarized in Table 4.6.5 and Table 4.6.6, which correspond to period 1 and period 2 respectively.

From Table 4.6.5 for period 1, we can see that for all of the currency-pairs, FIGARCH is ranked the best. GARCH.GED is the second-best model and it always forecasts better than GARCH.N and GARCH.T. For EUR/USD and EUR/CAD, GARCH.N and GARCH.T forecast equally well. However, in Table 4.6.7 for period 2, the ranking is different. FIGARCH.D now becomes the best model. For EUR/USD, FIGARCH performs as well as FIGARCH.D. It is ranked second-best for the other three currency-pairs. Table 4.6.7 also shows that the short-memory GARCH models with a dummy variable all outperform those without a dummy variable.

Table 4.6.5 Ranking of 4 single-regime GARCH models by the DM test (period 1)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
1	FIGARCH	FIGARCH	FIGARCH	FIGARCH
2	GARCH.GED	GARCH.GED	GARCH.GED	GARCH.GED
3	GARCH.N/GARCH.T	GARCH.T	GARCH.N	GARCH.N/GARCH.T
4		GARCH.N	GARCH.T	

Table 4.6.6 Ranking of 8 single-regime GARCH-type models by the DM test (period 2)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
1	FIGARCH.D/ FIGARCH	FIGARCH.D	FIGARCH.D	FIGARCH.D
2	GARCH.T.D	FIGARCH	FIGARCH/GARCH.N.D	FIGARCH
3	GARCH.N.D/ GARCH.GED.D	GARCH.GED.D	GARCH.GED.D/ GARCH.T.D	GARCH.GED.D/ GARCH.T.D
4	GARCH.GED	GARCH.N.D/GARCH.T.D	GARCH.GED	GARCH.N.D
5	GARCH.N/GARCH.T	GARCH.GED	GARCH.N	GARCH.GED
6		GARCH.N/GARCH.T	GARCH.T	GARCH.N/GARCH.T

(2) Comparison of the RS-GARCH, SV and long-memory GARCH models

As mentioned in the literature review, both the RS-GARCH model and the SV model have been shown to forecast better than the traditional GARCH models in the existing literature. However the relative performance of these two models has not been compared. In this subsection we compare them together with FIGARCH and FIGARCH.D, which are shown in the previous subsection to be the best models over period 1 and period 2, respectively. The ranking of models is summarized in Table 4.6.7 and Table 4.6.8 (see Table 4.A.7 and Table 4.A.8 in the appendix for details). We can see from Table 4.6.7 that the RS-GARCH model forecasts better than SV, which in turn performs better than FIGARCH for EUR/GBP and EUR/CAD and forecasts equally well as FIGARCH for EUR/USD and EUR/JPY. However, Table 4.6.8 shows that over the second period FIGARCH.D turns out to be the best model. It performs better than the SV model for EUR/USD and forecasts better than RS-GARCH for EUR/JPY. It also forecasts equally well as RS-GARCH for EUR/GBP and EUR/CAD. It is worth noticing that RS-GARCH generally forecasts better than the SV model over both of the two periods, with only one exception in the case of EUR/USD over period 2.

Table 4.6.7 Ranking of models using the DM test (period 1)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
1	RS-GARCH	RS-GARCH	RS-GARCH	RS-GARCH
2	SV/FIGARCH	SV	SV/ FIGARCH	SV
3		FIGARCH		FIGARCH

Table 4.6.8 Ranking of models using the DM test (period 2)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
1	FIGARCH.D	FIGARCH.D/ RS-GARCH	FIGARCH.D	FIGARCH.D/ RS-GARCH
2	SV	SV	RS-GARCH	SV
3	RS-GARCH		SV	

Overall, by comparing the models using three criteria over the two periods, we find that the relative performance of these models is changing across different periods, and the three criteria provide different overall ranking from each other. However, the comparative analysis confirms the following existing findings. First, the long-memory GARCH models generally forecast better than the short-memory GARCH models over both of the two periods, suggesting that modelling the long memory of the volatility series can improve forecasting performance. Second, GARCH.GED tends to outperform GARCH.T and GARCH.N, indicating that the generalized error distribution assumed in the model fits the fat tails of the returns series better than the normal distribution and t distribution.

In addition, our analysis provides two new findings. First, the RS-GARCH model is the best model in period 1. It also performs reasonably well over period 2, implying that the volatility of euro exchange rates do exhibits regime-switching behavior and taking this behavior into consideration can improve the forecast. Second, FIGARCH.D is the best model in period 2, and the GARCH models with a dummy variable generally forecast better than those without a dummy variable, implying that the dummy variable makes good contribution to the forecasting performance of the models.

4.7 Summary and Conclusions

This chapter fits ten volatility models to four daily euro exchange rate series over the period from 4 January 1999 to 15 March 2011. The sample is divided into period 1 (before 1 January 2008) and period 2 (after 1 January 2008). The out-of-sample forecasting performance of these models is compared over the two periods using the forecast error statistic, the regression test and the DM test, respectively. The in-sample estimation results show that the volatility of the four euro exchange rates has long memory and is higher in period 2 than in period 1. The out-of-sample comparison shows that the relative performance of these models changes across different periods, and the three criteria provide different overall ranking of the models.

The following conclusions can be drawn. First, the regime-switching GARCH model generally forecasts better than the single-regime GARCH models and the SV model in period 1. It is only outperformed by FIGARCH.D in period 2, implying that euro exchange rate volatility displays regime-switching nonlinearity and accounting for this behavior can improve the forecast. Second, FIGARCH.D turns out to be the best model over period 2, and the GARCH models with a dummy variable generally perform better than those without a dummy variable, confirming the nonlinearity in the volatility process. In addition, this study also confirms the following established findings in the existing literature. First, the long-memory GARCH models generally perform better than the short-memory ones, indicating that incorporating long memory into modeling practice can improve the predictive ability of the models. Second, over both period 1 and 2, GARCH.GED tends to outperform GARCH.T and GARCH.N, implying that the generalized error distribution assumed in the model fits the fat tails of the returns series better than the normal distribution and t distribution. Third, the performance of the models may change across different time periods and the ranking of the models may differ according to different criteria, hence great caution should be taken when comparing the forecasting performance of different models.

Volatility forecasting is still a challenging task. Many issues remain open and need to be further investigated in the future. The advantage of FIGARCH.D over FIGARCH and other models in period 2 is actually gained by using ex post control, because the dummy variable is a predetermined variable taking account of possible different volatility dynamics in period 2. This result has an important implication for future research. Volatility forecasting techniques that can account for structural breaks from an ex ante perspective might provide more accurate forecasts than the traditional models. Furthermore, some studies show that some exogenous variables are significantly related to volatility. For example, Bittlingmayer (1998) show that political events are important causes of volatility; Spiro (1990) and Glosten et al. (1993) show that interest rates are positively related to volatility; and Bollerslev and Jubinski (1999) find a positive relationship between trading volume and volatility. Therefore an avenue for the future research is whether and to what extent using such exogenous variables can improve forecasting accuracy. In addition, it may be fruitful to develop more sophisticated models, such as regime-switching long-memory GARCH model which can account for both long memory and regime-switching properties of volatility. It is noteworthy that there does not seem to be a one-for-all model that is superior for forecasting volatility of all the financial assets at all times, different models can perform differently depending on the time period, the asset class, the forecast horizon and even many other factors, therefore combination of various volatility forecasting techniques might yield more insightful results. Some efforts have been taken in this promising direction, but more extensive research is needed to explore the potential of this approach in the future.

Appendix:

Table 4.A.1 MSE (period 1)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	0.234	0.089	0.125	0.123
GARCH.T	0.215	0.085	0.131	0.121
GARCH.GED	0.198	0.086	0.122	0.121
FIGARCH	0.194	0.074	0.093	0.108
RS-GARCH	0.182	0.064	0.084	0.116
SV	0.187	0.071	0.101	0.119

Table 4.A.2 MSE (period 2)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	0.224	0.137	0.253	0.177
GARCH.T	0.223	0.135	0.278	0.178
GARCH.GED	0.222	0.132	0.239	0.176
GARCH.N.D	0.182	0.12	0.183	0.173
GARCH.T.D	0.22	0.119	0.201	0.175
GARCH.GED.D	0.179	0.131	0.184	0.171
FIGARCH	0.177	0.116	0.171	0.164
FIGARCH.D	0.161	0.108	0.105	0.152
RS-GARCH	0.168	0.112	0.143	0.158
SV	0.172	0.118	0.161	0.169

Table 4.A.3 R^2 from the regression test (period 1)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
GARCH.N	0.202	0.634	0.478	0.206
GARCH.T	0.191	0.646	0.472	0.201
GARCH.GED	0.226	0.658	0.568	0.215
FIGARCH	0.230	0.665	0.631	0.221
RS-GARCH	0.249	0.689	0.652	0.246
SV	0.229	0.675	0.631	0.233

Table 4.A.4 R^2 from the regression test (period 2)

	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
FIGARCH.D	0.243	0.602	0.463	0.241
RS-GARCH	0.226	0.599	0.455	0.239
FIGARCH	0.241	0.574	0.442	0.229
SV	0.232	0.582	0.449	0.221
GARCH.GED.D	0.212	0.561	0.429	0.216
GARCH.T.D	0.221	0.567	0.431	0.214
GARCH.N.D	0.214	0.568	0.440	0.209
GARCH.GED	0.165	0.549	0.386	0.204
GARCH.N	0.158	0.516	0.382	0.197
GARCH.T	0.157	0.517	0.386	0.197

Table 4.A.5 The DM test statistics for comparing 4 single-regime GARCH models (period 1)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
FIGARCH vs GARCH.GED	8.342***	5.016***	3.546***	4.132***
GARCH.GED vs GARCH.N	2.672***	2.023**	2.761***	2.314**
GARCH.N vs GARCH.T	0.756	-1.814*	3.145***	1.246
GARCH.GED vs GARCH.T	2.361**	3.715***	2.141**	2.596***

1. The table reports the DM test statistics based on MSE, the tests are performed for the competing models pair by pair. The models are sorted in terms of increasing MSE and then the test statistics are calculated from consecutive pairs of models, starting with the two models having the smallest MSE; 2. Symbols *,** and *** mean that the difference between the two models is significant at the 10%, 5% and 1% level, respectively; 3.These notes apply to Tables 4.A.6-4.A.8 too.

Table 4.A.6 The DM test statistics for comparing 8 single-regime GARCH models (period 2)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
FIGARCH.D vs FIGARCH	1.012	2.845***	3.046***	4.647***
FIGARCH vs GARCH.T.D	4.451***	5.181**	3.487***	4.302***
FIGARCH vs GARCH.GED.D	3.421***	2.157**	2.689***	3.212***
FIGARCH vs GARCH.N.D	3.431***	2.824***	0.897	2.178**
GARCH.N.D vs GARCH.GED.D	0.845	-2.561**	2.389**	2.421**
GARCH.N.D vs GARCH.T.D	-2.123**	1.234	2.184**	-2.225**
GARCH.GED.D vs GARCH.T.D	-3.254***	2.104**	0.794	1.256
GARCH.GED.D vs GARCH.GED	2.432**	3.874***	2.067**	3.241***
GARCH.N.D vs GARCH.N	3.614***	4.012***	6.225***	3.364***
GARCH.T.D vs GARCH.T	5.216***	2.665***	3.571***	2.784***
GARCH.GED vs GARCH.N	2.042**	2.443**	3.726***	1.987**
GARCH.N vs GARCH.T	1.351	0.674	2.147**	1.472

Table 4.A.7 The DM test statistics for comparing RS-GARCH, SV and FIGARCH (period 1)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
RS-GARCH vs SV	6.245***	5.384***	4.861***	5.226***
RS-GARCH vs FIGARCH	5.846***	7.261***	4.652***	6.442***
SV vs FIGARCH	1.145	2.237**	0.852	2.176**

Table 4.A.8 The DM test statistics for comparing RS-GARCH, SV and FIGARCH.D (period 2)

Rank	EUR/USD	EUR/GBP	EUR/JPY	EUR/CAD
FIGARCH.D vs RS-GARCH	5.249***	1.115	3.567***	0.884
FIGARCH.D vs SV	6.227***	4.158***	3.664***	5.046***
RS-GARCH vs SV	-2.217**	3.335***	4.918***	2.318**

Chapter 5 Impact of Exchange Rate Volatility on Exports: Evidence from the EMU

5.1 Introduction

During the on-going economic crisis in Europe, both the euro and exports from EMU member countries to other countries have been more volatile than was typical previously. A natural question to ask is whether euro exchange rate volatility has a substantial effect on the exports of the EMU member countries. Economic theory supports both the possibility of positive and of negative effects of exchange rate volatility on exports and empirical studies also show highly mixed results. So far, no consensus has been reached as to whether exchange rate volatility stimulates or depresses exports.

In the existing literature, many studies find evidence of a linear cointegrating relationship between foreign trade and exchange rate volatility, assuming implicitly that the adjustment of the deviations of foreign trade towards the long-run equilibrium is made linearly. In theory, there is no reason why adjustment could not be in a nonlinear manner. Actually the existence of transaction costs implies that adjustment will occur only when costs (benefits) of deviations from equilibrium are larger than the transaction costs, and hence adjustment may not always immediately follow economic shocks. Even in highly liquid markets, deviations of asset prices are sometimes too small to trigger profitable arbitrages, so the so-called neutral band of no arbitrage exists. As far as the trade-volatility relationship is concerned, trade need not adjust immediately when economic shocks hit. It may be the case that economic agents adjust their production plans only when the costs (benefits) caused by economic shocks are larger than the costs of adjustment. In other words, the adjustment does not occur until the deviation exceeds some critical threshold. Therefore it is possible that the adjustment of foreign trade follows a nonlinear process. However this possibility has not been explored in the existing literature. This chapter attempts to fill this gap.

This chapter uses both linear and threshold cointegration techniques to examine how exchange rate volatility affects the exports from ten EMU member countries to the US and the UK. The ten EMU member countries are: Austria, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. Belgium and the other member states are excluded due to unavailability of data. The empirical results show that exchange rate volatility tends to depress exports. In addition, the exports of some countries follow a nonlinear adjustment process, with adjustment speed differing in different regimes.

The remainder of this chapter is organized as follows. The second section provides a brief overview of the existing literature on the relationship between exchange rate volatility and international trade. Section 5.3 introduces the model specification and data sources. Then section 5.4 introduces the econometric methods used in this chapter. The empirical analyses of exports to the US and the UK are carried out in Section 5.5 and section 5.6, respectively. Finally, section 5.7 concludes this chapter.

5.2 Literature Review

There is a large literature concerned with how exchange rate volatility affects international trade. McKenzie (1999) and Bahmani-Oskooee and Hegerty (2007) provide a comprehensive overview of the relevant literature. We will focus on the studies that are closely related to this chapter. Theoretical studies give both reasons for positive and negative impacts of exchange rate volatility on exports. On the one hand, some studies argue that exchange rate volatility tends to impede trade flows because higher exchange rate volatility means higher costs for risk-averse traders and hence results in less foreign trade (see Ethier, 1973; Hooper and Kohlhagen, 1978; Broll, 1994). On the other hand, there are also studies arguing that higher volatility might enhance foreign trade. For example, De Grauwe (1988) argues that an increase in exchange rate volatility raises the expected marginal utility of export revenue and hence induces exporters to increase exports if they are sufficiently risk averse. Therefore the dominance of income effects over substitution effects can lead to a positive trade effect of exchange rate volatility. Franke (1991) derives conditions under which higher exchange rate volatility may lead to more exports. He argues that disadvantaged firms can benefit from exchange rate volatility as it gives them leeway to set prices more freely.

The existing empirical studies also show mixed evidence of the trade effects of volatility. One strand of the empirical literature uses gravity models to investigate the impact of exchange rate volatility on trade. For example, Thursby and Thursby (1987) use a gravity model to study the export values of 17 countries using annual data over the period 1974-1982. They find that uncertainty depressed trade flows for 10 out of 17 countries. Brada and Mendez (1988) test the export values of 30 developed and less-developed countries as a function of foreign income, population, distance, and the existence of preferential trade agreements between each pair of nations. They also find that uncertainty depressed trade flows. The previous two studies use OLS methods to estimate gravity models. Dell'Ariccia (1999) applies pooled OLS as well as fixed and random effects panel data and two-stage least squares models to study the 15 countries of the European Union, plus Switzerland, over the period 1975-1994. He finds that the effect of uncertainty is significantly negative.

As noted by Mátyás (1997), the traditional cross-section approach to gravity models may suffer from a severe problem of misspecification. Thus OLS estimates of gravity model are very likely to result in inconsistent estimates, so the previous findings from estimating gravity models may not be reliable. Tenreyro (2007) also argues that there are several estimation problems that cause biased results in previous studies that use OLS method to estimate gravity models. She corrects for relevant biases when employing a gravity model to analyze bilateral trade among 104 countries over the period from 1970 to 1997. She finds that nominal exchange rate volatility has no significant effect on trade. By and large, gravity models do not seem to provide clear-cut conclusions on the issue of trade effects of volatility, though they are successful in modeling other aspects of international trade.

Another strand of empirical literature examines the trade effects of exchange rate volatility using cointegration techniques. More specifically, many studies attempt to find out whether there is a cointegrating relationship between exports (or imports) and exchange rate volatility, the income of trading partner and relative prices. For example, Chowdhury (1993) examines the impact of exchange rate volatility on the trade flows of the G-7 countries using cointegration technique and shows that the exchange rate volatility exerts a significant negative impact on exports. Aristotelous (2001) uses the Engel-Granger cointegration method to investigate the impact of exchange rate volatility on UK exports to the United States using annual data over the period 1889–1999. The empirical findings suggest that neither exchange rate volatility nor the different exchange rate regimes that spanned the last century had effects on export volumes. Interestingly, however, Aristotelous (2002) finds a completely different result in his study of the exports from the US to Canada, Japan, Germany and the UK over the period 1959:1-1997:4 using cointegration techniques. In that study, volatility has significant short and long-run effects, and the floating exchange rate regime has a negative effect on US trade.

Arize (1996) examines the impact of exchange rate volatility on the exports of eight European countries using an error-correction model over the period 1973-1992. The results show that the volatility of the exchange rate exerts a significant negative effect on exports in both the short run and the long run. Arize (1998) investigates the long-run relationship between imports and exchange rate volatility in the same 8 European countries over the period 1973Q2-1995Q1 using cointegration techniques. Exchange rate volatility is shown to have a significant negative effect on the volume of imports of six countries, but the effect is significantly positive for Greece and Sweden. Arize, et al. (2000) examine the impact of exchange rate volatility on the export flows of 13 less-developed countries over the period 1973-1996 using cointegration techniques. Their results show that increases in the volatility of the real effective exchange rate have a significant negative effect on export demand in both the short run and the long run in each of the 13 countries. Following the same approach, Arize, et al. (2008) investigate volatility-exports relationship for 8 Latin American countries over the period 1973-2004 and draw the same conclusion that exchange rate volatility depresses exports. De Vita and Abbott (2004a) investigate the impact of exchange rate volatility on the exports from the UK to the remainder of the EU. They find that short-term exchange rate volatility has no effect on exports whereas long-term volatility has a significant negative effect. De Vita and Abbott (2004b) employ the bounds testing approach in their study of US exports. They find significantly negative effects of volatility for Germany, the UK, and Mexico, but significantly positive results for Japan.

Ćorić and Pugh (2010) perform a meta-regression analysis of 49 studies on the relationship between exchange rate volatility and international trade. Their results suggest that there is a negative link between exchange rate volatility and trade, especially for less developed countries where financial markets are much less developed than those of industrial countries. Furthermore, they show that it is more likely for the studies that use cointegration techniques to find a negative link between exchange rate volatility and trade, and the choice of the volatility measure rarely affects the results.

However, there are few studies that investigate the potential nonlinear relationship between exchange rate volatility and foreign trade. An exception is a study by Baum et al. (2004), which investigates the impact of exchange rate volatility on real international trade flows using a dataset of monthly bilateral real exports for 13 countries during the period 1980–1998. They find that the effect of exchange rate volatility on trade flows is nonlinear depending on its interaction with the importing country's volatility of economic activity, and that it varies considerably over the set of country pairs considered.

5.3 Model specification and data

As mentioned in the previous section, various models have been used to examine the trade effects of exchange rate volatility in the existing literature. Based on international trade theory, many studies model demand for exports as a function of income, the exchange rate and exchange rate volatility **(**see Chowdhury, 1993; Arize, et al. 2000; Aristotelous, 2002; McKenzie and Brooks, 1997). Following these studies, we choose a widely used model specified as follows:

$$EX_{ijt} = \alpha_{ij0} + \alpha_{ij1} Y_{jt} + \alpha_{ij2} RER_{jt} + \alpha_{ij3} VOL_{jt} + \varepsilon_{ijt} \qquad (5.3.1)$$

where i denotes home country (10 EMU countries), j denotes the trading partner (the US and the UK), t denotes time period. EX_{ij} denotes the real exports from country i to country j, Y_j denotes the aggregate income of country j (proxied by real GDP here), RER_j is bilateral real exchange rate expressed as price of the euro in terms of the currency of country j, VOL_j is the volatility of the euro exchange rate against the currency of country j, and

ε is the error term. The variables are expressed in logarithms. Data on GDP are not available at monthly frequency, so we first deflate quarterly nominal GDP by the GDP deflator to get quarterly real GDP, and then convert the quarterly real GDP into monthly real GDP using the quadratic interpolation method. To get real exports, we first use the Census-X12 procedure to adjust for seasonal effects in nominal exports and then deflate the seasonally adjusted exports by the exports price index.[25] *RER* is computed as the product of the bilateral euro exchange rate and the ratio of national CPI of EMU member countries to the CPI of country *j*. In theory, rising income of the trading partner should stimulate demand for exports from home countries, so α_{i1} is expected to be positive. Real appreciation of the exchange rate is likely to depress exports, so α_{i2} is expected to be negative. The sign of α_3 is ambiguous according to the theoretical and empirical results in the literature.

With the development of econometric techniques, the methods of measuring volatility have evolved over time. The specific construction of the measures differs from study to study. Besides the moving standard deviation approach, there are some other volatility measures. For example, the ARCH approach developed by Engle and Granger (1987) is also a popular measure of exchange-rate volatility. While some measures are more popular than others, none of them is clearly dominant (see Bahmani-Oskooee and Hegerty, 2007), and Ćorić and Pugh (2010) show that the choice of the volatility measure rarely affects the empirical results. In addition, both nominal and real exchange rate are used in volatility measures in the literature, and there is no standard to decide which one is better. Since many studies (such as Thursby and Thursby (1987), Qian and Varangis (1994), McKenzie and Brooks (1997) etc.) show that distinction between real or nominal volatility makes no substantial difference to the results, we only consider nominal exchange rate volatility.

We measure exchange rate volatility as the moving standard deviation of the changes in the nominal exchange rate *e*, it is defined as follows:

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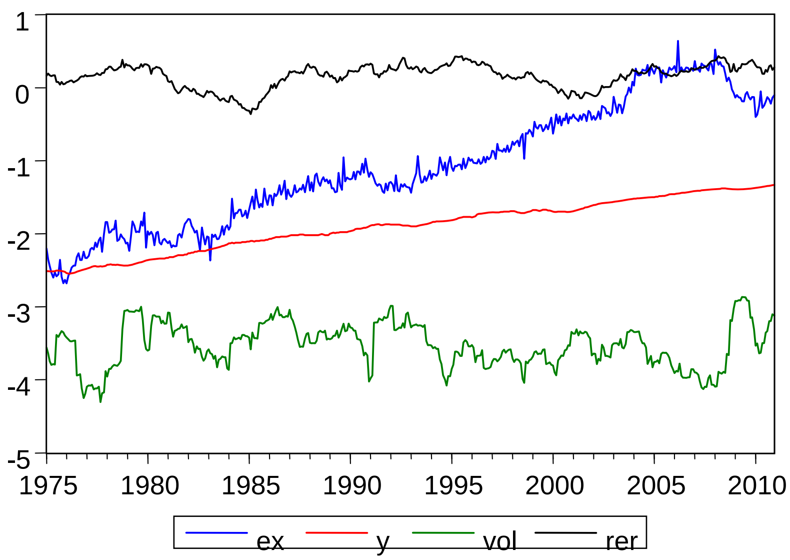
[25] For Austria, France and Portugal, export price indices are not all available in the whole sample period, so I use CPI instead.

$$VOL_t = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(e_{t+i-1} - e_{t+i-2})^2} \tag{5.3.2}$$

where m denotes the horizon used in calculating moving average.[26]

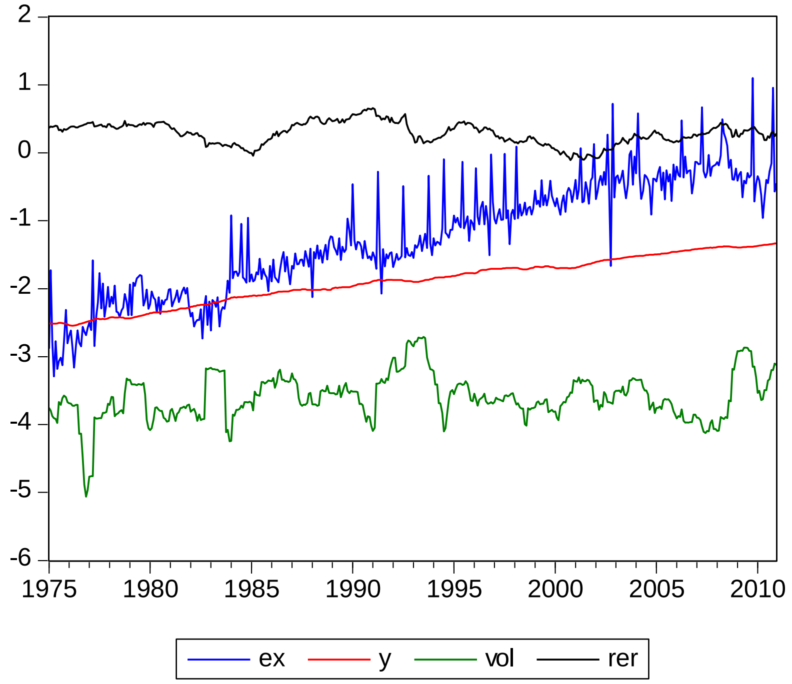
As indicated in model (5.3.1), the dataset used in this study consists of monthly data on bilateral exports from ten EMU member countries to the US and the UK, bilateral exchange rates between euro and USD and GBP, GDP of the US and the UK, CPI and trade price indices, over the period between January 1975 and December 2010. The data are retrieved from the IMF's *Directions of Trade Statistics* (DOTS) and from the IMF's *International Financial Statistics* (IFS).

The time series plots of the variables are shown in Figure 5.1. We can see that the variable *y* (real GDP of the US) rose steadily in the sample period. For all of the EMU countries under consideration except for Greece and Portugal, the real exports exhibited an upward trend though frequent fluctuations were evident over the sample period. And the variables *rer* and *vol* fluctuated substantially.

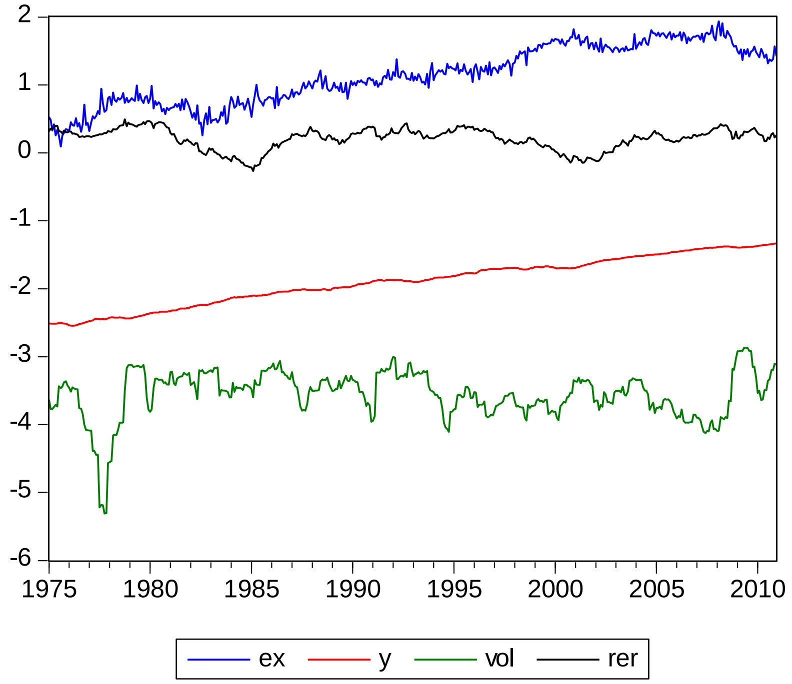


Austria

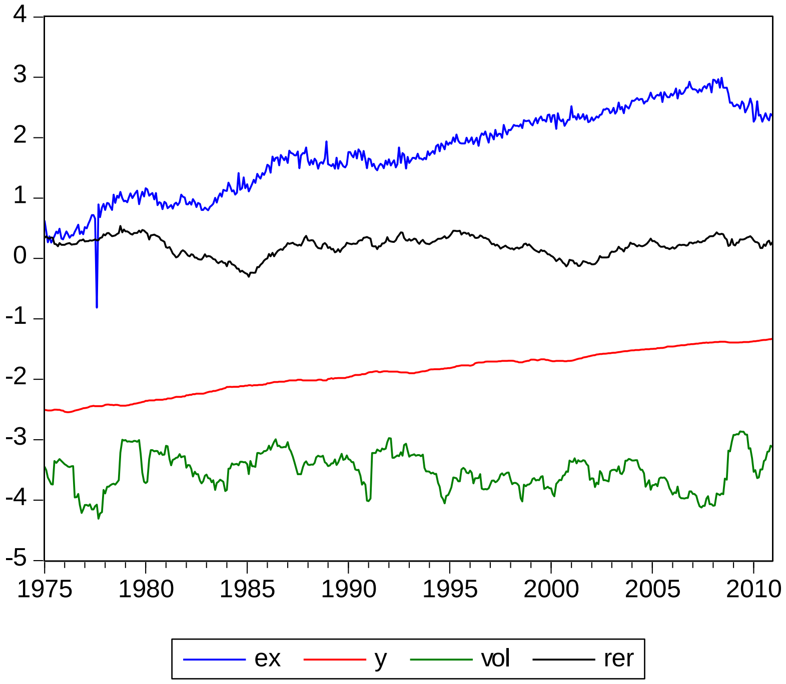
[26] We calculate this moving standard deviation at three horizons (m=8, 12 and 16 months) to check for robustness and to avoid an arbitrary choice of m. Since the choice of m does not alter the results, we use m=12 in the empirical analysis.



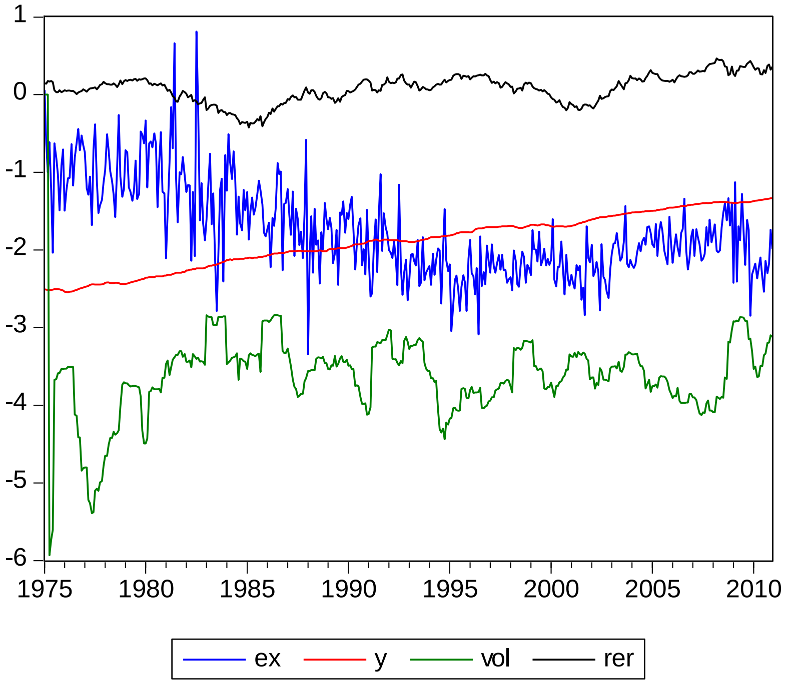
Finland



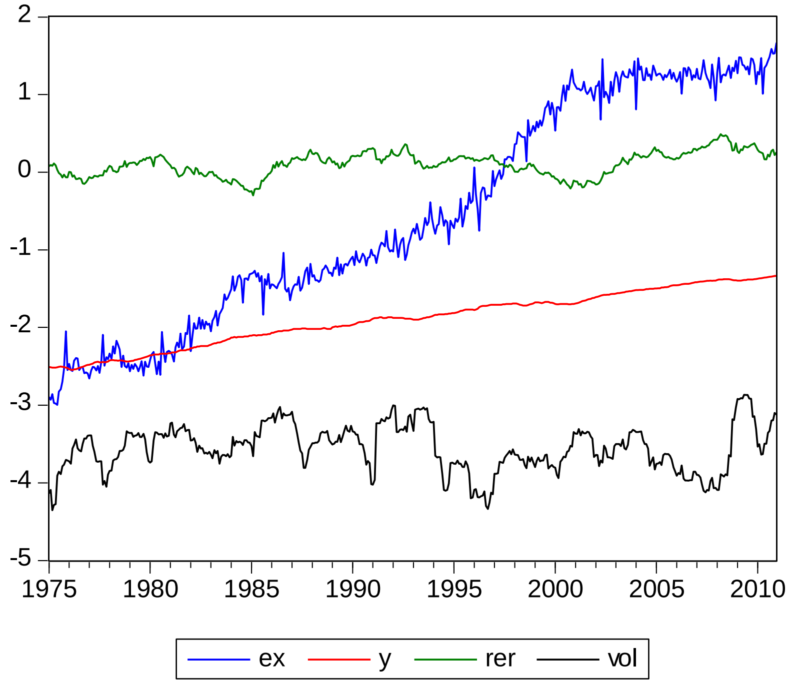
France



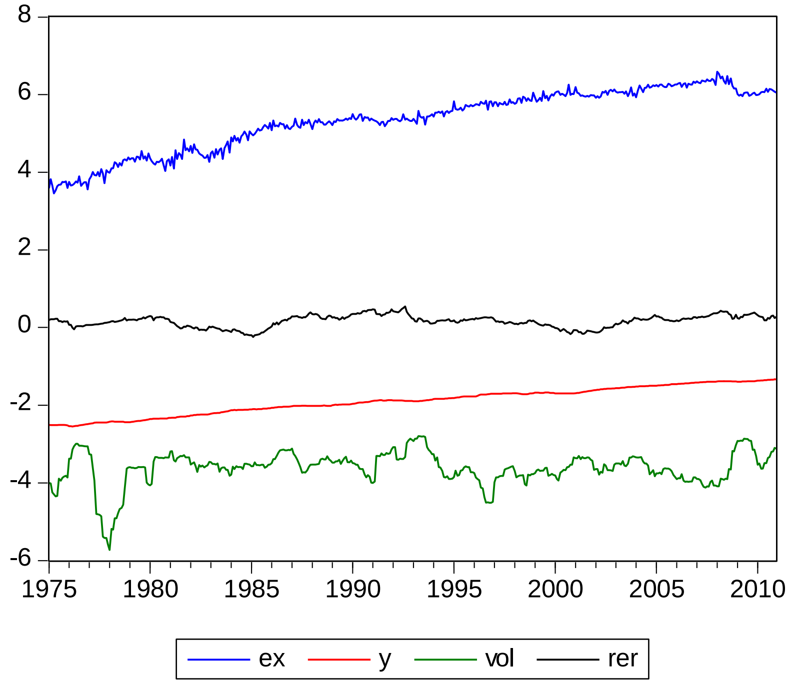
Germany



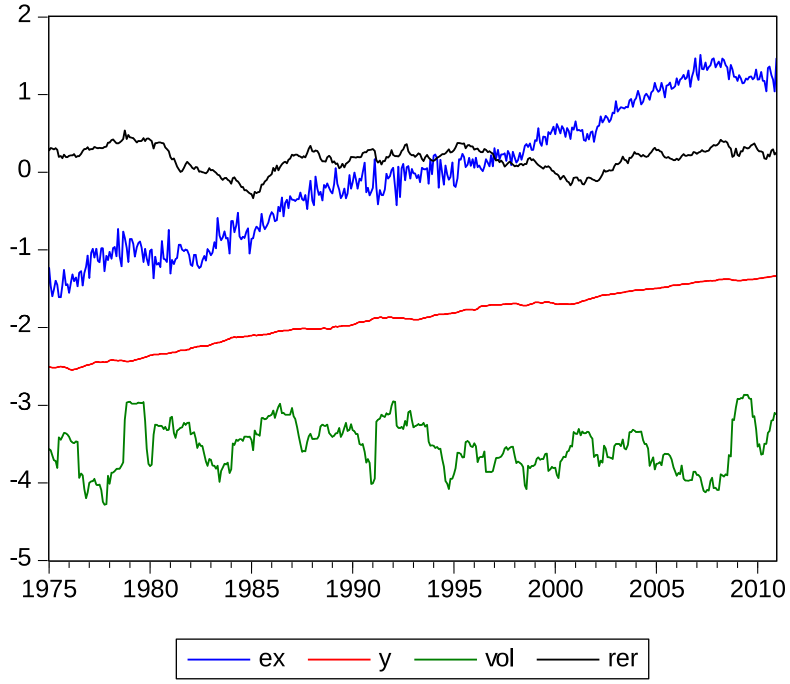
Greece



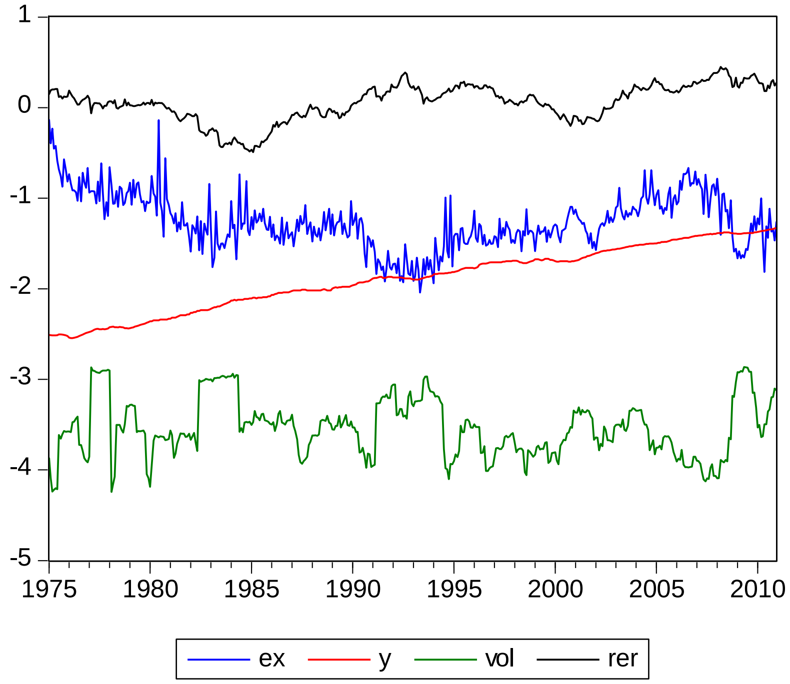
Ireland



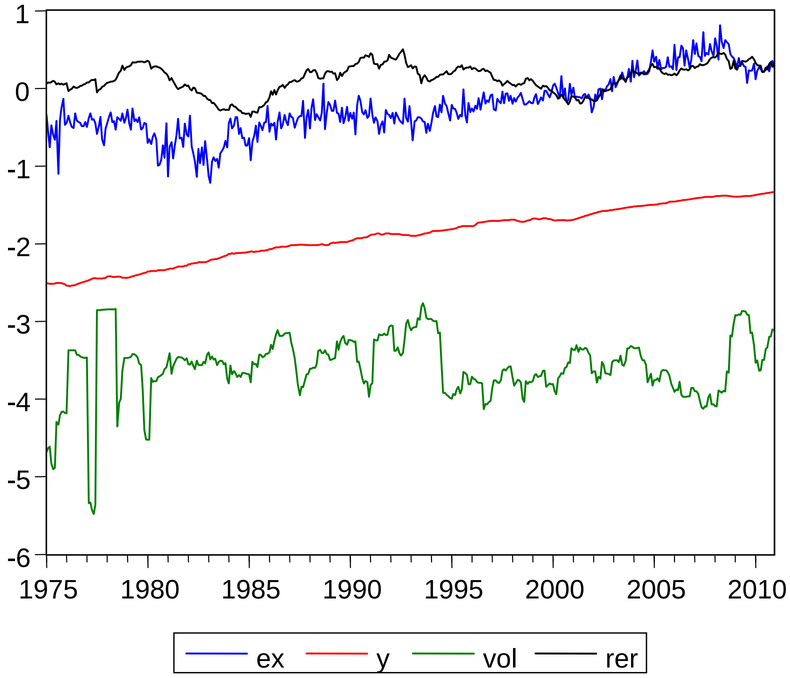
Italy



The Netherlands



Portugal



Spain

Figure 5.1 Variables of ten EMU member countries

5.4 Econometric methodology

In order to identify the long-run relationship between the economic variables under consideration, both linear cointegration and threshold cointegration tests are employed in this chapter. The two testing methods are briefly outlined as follows.

5.4.1 Testing methods for linear cointegration

According to Engle and Granger (1987), if a linear combination of two or more non-stationary series (I(1) series) is stationary, the non-stationary time series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and it can be interpreted as a long-run equilibrium relationship among the non-stationary series.

The cointegration test developed by Johansen (1995) is the most widely used method of testing for cointegration. It is based on a vector autoregression (VAR(p)) model specified as follows.

Let x denote a $n \times 1$ vector of variables, and assume that it has a representation of vector autoregression of order p, VAR(p):

$$x_t = \eta + \sum\nolimits_{i=1}^{p} \prod\nolimits_i x_{t-i} + \varepsilon_t \qquad (5.4.1)$$

where η is a n×1 vector of deterministic terms, ε is a n×1 vector of white noise disturbance terms, with mean zero and covariance matrix Ω. Equation 5.4.1 may be rewritten into the error correction representation as:

$$\Delta x_t = \eta + \sum\nolimits_{i=1}^{p-1} \Phi_i \Delta x_{t-i} + \prod x_{t-1} + \varepsilon_t \qquad (5.4.2)$$

where Δ denotes the first difference operator, $\Phi_i = -\sum\nolimits_{j=i+1}^{p} \prod\nolimits_j$ is an n×n coefficient matrix, and $\prod = -(\mathrm{I} - \sum\nolimits_{i=1}^{p} \prod\nolimits_{\mathrm{i}})$ (I is an identity matrix) is an n×n matrix whose rank determines the number of cointegrating vectors. If the rank of Π is either n or zero, there will be no cointegrating relationship amongst the variables in the long run. If, however, the rank is r (0<r<n), then there will exist n×r matrices α and β such that Π=αβ′, where β is the matrix whose columns are the linearly independent cointegrating vectors and α is interpreted as the adjustment matrix, indicating the speed with which the system responds to last period’s deviation from the equilibrium level of *x*. The error correction representation 5.4.2 is often called the Vector Error Correction Model (VECM). According to the Granger Representation Theorem, the existence of cointegration implies the existence of the VECM, and vice versa.

5.4.2 Testing method for threshold cointegration

The drawback of conventional linear cointegration is that it assumes implicitly that the adjustment of the deviations towards long-run equilibrium is made linearly at each period and hence ignores the potential nonlinearity. Threshold cointegration can address this problem and capture nonlinearity in the adjustment process of the deviations towards long-run equilibrium.

Balke and Fomby (1997) introduce the concept of threshold cointegration as an extension of linear cointegration. In their framework, the adjustment does not occur until the deviation exceeds some critical threshold. They base their adjustment process on the self-exciting threshold autoregressive model (SETAR) introduced by Chan (1993). In the SETAR model, the autoregressive coefficients take different values depending on whether the previous value is above or below a certain threshold value, thus exhibiting regime-switching dynamics.

Suppose Y_t and $X_t = (x_{1t}, x_{2t}, \cdots, x_{kt})'$ are cointegrated with $(1, \alpha')$ as the cointegrating vector, where $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_k)'$. The long-run relationship can be written as

$$Y_t + \alpha' X_t = \varepsilon_t \tag{5.4.3}$$

where ε_t is the deviation from equilibrium, which is also called the equilibrium error in the literature.

The conventional linear cointegration assumes that ε_t follows a linear autoregressive (AR) process:

$$\varepsilon_t = \rho \varepsilon_{t-1} + u_t \tag{5.4.4}$$

In contrast, threshold cointegration proposed by Balke and Fomby (1997) assumes that ε_t follows a SETAR process as:

$$\varepsilon_t = \begin{cases} \mu_1 + \rho_1(L)\varepsilon_{t-1} + u_{1t} & \text{if } \varepsilon_{t-d} \le \theta_1 \\ \mu_2 + \rho_2(L)\varepsilon_{t-1} + u_{2t} & \text{if } \theta_1 < \varepsilon_{t-d} \le \theta_2 \\ \cdots\cdots & \cdots\cdots \\ \mu_m + \rho_m(L)\varepsilon_{t-1} + u_{mt} & \text{if } \varepsilon_{t-d} > \theta_{m-1} \end{cases} \tag{5.4.5}$$

where subscripts $i = 1, 2, \ldots, m$ refer to the *i*-th regime, μ_i are intercepts, $\rho_i(L)$ is a polynomial of the lag operator *L*, and u_{it} is random disturbance with zero mean and standard deviation σ_i , θ_i is the threshold, and integer *d* represents the delay in the error correction process, meaning that economic agents react to the deviation from equilibrium with a time lag of *d* periods.[27]

It is worth noting that threshold cointegration is very different from the concept of nonlinear cointegration in Chapter 2. In the case of nonlinear

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[27] Note that if we use an external variable x_{t-d} instead of the equilibrium error ε_{t-d} as a transition variable, the SETAR model becomes a TAR model.

cointegration, the variables are not cointegrated directly with each other but through some nonlinear functions, the nonlinearity lies in the cointegrating relationship. This form of nonlinearity needs to be examined after linear cointegration is tested and rejected. In contrast, in the case of threshold cointegration suggested by Balke and Fomby (1997), the cointegrating relationship is still assumed to be linear, and only the equilibrium error series is assumed to follow a SETAR process. In other words, it is not the cointegrating relationship that exhibits nonlinearity, only the adjustment process towards equilibrium exhibits nonlinearity. Threshold nonlinearity should be examined on the basis of linear cointegration found between the variables of interest. Therefore it is important to distinguish this two types of cointegration.

Testing for threshold cointegration in this chapter is motivated by the specific issue under consideration. As mentioned in the introduction section, foreign trade need not necessarily adjust when economic shocks hit due to the existence of transaction costs. As a matter of fact, the adjustment of trade may not occur until the deviation from equilibrium exceeds certain critical threshold. Therefore it is important to consider the possibility that the adjustment of foreign trade follows a nonlinear process.

As argued by Balke and Fomby (1997), the threshold nonlinearity of error terms, ε_t, does not affect the order of integration of the variables under consideration because the cointegrating relationship is still linear and only the equilibrium error series is assumed to follow a SETAR process. As a result, standard time series analyses used for linear cointegration are still asymptotically valid for the case of threshold cointegration. Following the approach of Balke and Fomby (1997), we carry out the analysis in two steps. In step one, we first use Johansen's cointegration test to identify the long-run cointegrating relationships between exports and three explanatory variables and then obtain the residual series to be used for the test of threshold behaviour. In step two, we use the test method proposed by Hansen (1999) to determine the number of regimes. Specifically, we test the null hypothesis of linear AR process, also labelled SETAR(1), against the alternative of SETAR with 2 regimes (SETAR(2)) or SETAR with 3 regimes (SETAR(3)). If the null hypothesis is rejected, we then proceed to estimate the threshold and parameters by conditional least squares (CLS).

5.5 Empirical analysis of exports to the US

We first carry out panel unit root tests to investigate the order of integration of all the series in question using LLC and IPS test (see subsection 3.4.1 in chapter 3 for details). Table 5.5.1 summarizes the test results. All of the series are non-stationary. We use the Johansen cointegration method to test whether a long-run relationship exists among the variables of interest. The Johansen cointegration test statistics are reported in Table 5.5.2. Both the trace statistics and the max-eigen statistics show that for Austria, Portugal and Spain, there is no cointegration between the variables under consideration. However, for the other 7 EMU member countries, there is only one cointegrating relationship between the variables, that is to say, the real exports from these 7 countries to the US are cointegrated with foreign income (US GDP), the real exchange rate and the volatility of exchange rates.

The cointegrating equations are shown in Table 5.5.3. To check the stability of the cointegrating vectors, we perform the cumulative sum of recursive residuals (CUSUM) test and the cumulative sum of squares of recursive residuals (CUSUMSQ) test based on the residuals from the estimated models. If the graphs of CUSUM and CUSUMSQ stay between the two straight lines representing critical bounds at 5% significance level, the cointegrating vector is stable, otherwise it means that the cointegrating vector is unstable. Figures 5.2-5.8 illustrate the test results. We can see that the graphs of CUSUM and CUSUMSQ all stay between the two straight lines, indicating the stability of the coefficients in the long run relationships.

Table 5.5.1 Panel unit root test results (exports to the US)

	EX	Y	RER	VOL
LLC	6.925 (0.842)	-0.138 (0.445)	-0.341 (0.306)	-0.788 (0.216)
IPS	-1.186 (0.117)	-0.063 (0.475)	0.874 (0.587)	-0.214 (0.415)

Notes: (1) Selection of exogenous variables: tests on EX and Y assume individual effects and individual linear trends, tests on the other two variables assume individual effects. Lag length is selected based on SIC and Bartlett kernel. (2) LLC test takes common unit root process as its null. IPS test takes individual unit root process as its null. (3) The p-values are in parenthesis, * , ** and *** denote significance at 10%, 5% and 1% level respectively.

Table 5.5.2 Johansen cointegration test statistics (exports to the US)

	Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	Prob.	Max-Eigen Statistic	0.05 Critical Value	Prob.
Austria	None	40.454	47.856	0.146	21.532	27.584	0.192
	At most 1	20.435	29.797	0.394	8.956	21.132	0.836
	At most 2	11.479	15.495	0.184	8.220	14.265	0.357
Finland	None	69.894	54.079	0.001*	29.380	28.588	0.003*
	At most 1	40.514	35.193	0.012*	21.637	22.300	0.052
	At most 2	18.877	20.262	0.077	12.759	15.892	0.973
France	None	60.737	47.856	0.002*	40.958	27.584	0.001*
	At most 1	19.780	29.797	0.438	9.978	21.132	0.747
	At most 2	9.802	15.495	0.296	5.637	14.265	0.660
Germany	None	47.030	47.856	0.040*	29.856	27.584	0.025**
	At most 1	17.173	29.797	0.627	9.252	21.132	0.812
	At most 2	7.921	15.495	0.474	5.938	14.265	0.621
Greece	None	55.643	40.175	0.001*	26.346	24.159	0.025*
	At most 1	29.297	24.276	0.107	22.977	17.797	0.760
	At most 2	6.320	12.321	0.398	5.619	11.225	0.395
Ireland	None	92.449	54.079	0.000*	51.888	28.588	0.000*
	At most 1	40.560	35.192	0.120	25.863	22.299	0.152
	At most 2	14.697	20.261	0.244	11.522	15.892	0.215
Italy	None	100.811	40.174	0.000*	56.779	24.159	0.000*
	At most 1	44.031	24.275	0.171	31.907	17.797	0.254
	At most 2	12.123	12.320	0.539	6.533	11.224	0.292
Netherlands	None	50.125	47.856	0.030*	29.893	27.584	0.041*
	At most 1	23.231	29.797	0.235	12.183	21.131	0.529
	At most 2	11.047	15.494	0.209	7.4136	14.264	0.441
Portugal	None	47.541	49.214	0.124	21.745	28.588	0.291
	At most 1	27.347	33.193	0.164	17.362	22.150	0.176
	At most 2	14.430	22.324	0.418	9.017	16.287	0.461
Spain	None	49.375	52.276	0.094	21.227	25.647	0.186
	At most 1	15.924	32.287	0.198	16.146	23.327	0.287
	At most 2	13.085	21.745	0.371	10.541	16.354	0.458

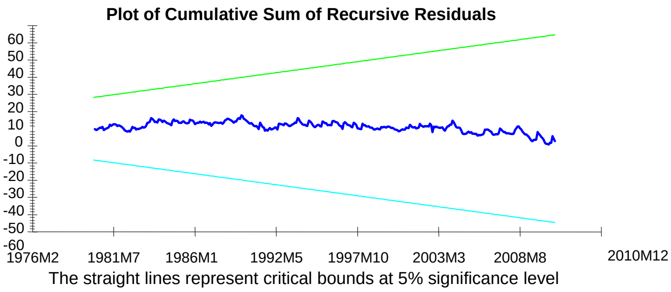
Notes: 1. *CE(s)* denotes cointegrating equation(s); 2. * means that the statistic is significant at significance level of 1% or 5%.

Table 5.5.3 shows that all of the coefficients are significant and the signs of the coefficients on variables *Y* and *RER* are in line with the theoretical prediction that appreciation of the real exchange rate depresses exports and that rising income of the US stimulates exports. The sign of the coefficient on volatility is consistently negative in all of the seven cases, indicating that exchange rate volatility unambiguously depresses exports of the seven EMU member countries. This result is consistent with the findings of previous studies by Arize (2000, 2008) and DeVita and Abbott (2004a). We can see from Table 5.5.3 that the estimates of volatility elasticity range from -0.394 to -1.250. It is worth noting that for Finland and Ireland the coefficients on volatility are -1.054 and -1.250, respectively, larger than that for the other countries, implying that the exports of these two countries are more sensitive to exchange rate volatility than that of the other countries.

Table 5.5.3 Cointegrating equations (exports to the US)

	Dependent variable	Independent variables			
	EX	Y	RER	VOL	C
Finland	1	1.801 (0.180)***	-0.641 (0.304)**	-1.054 (7.040)*	-30.800 (5.101)***
France	1	0.698 (0.118)***	-0.931 (0.258)***	-0.394 (6.450)***	
Germany	1	1.215 (0.230)***	-1.231 (0.463)***	-0.462 (11.444)***	
Greece	1	0.800 (0.046)***	-4.593 (1.877)**	-0.653 (36.263)***	
Ireland	1	4.057 (0.460)***	-3.124 (1.073)***	-1.250 (17.280)***	-91.607 (12.929)***
Italy	1	1.029 (0.022)***	-2.170 (1.184)*	-0.538 (18.316)***	
Netherlands	1	1.369 (0.487)***	-3.738 (1.123)***	-0.864 (24.556)***	

Notes: 1. The values in parentheses are standard errors; 2. Choice of trend assumption is based on AIC; 3. VAR Lag Order is selected according to LR; 4. ***, ** and * indicate significance level of 1%, 5% and 10%, respectively.



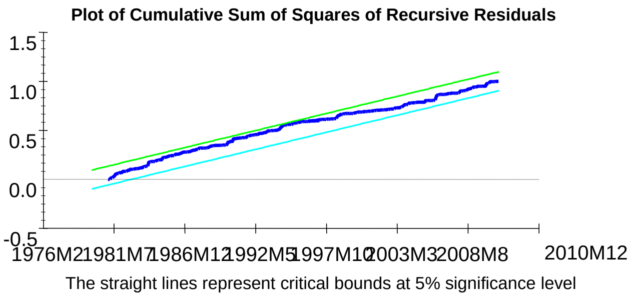
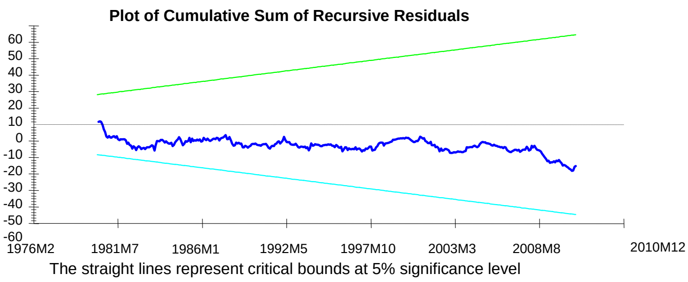


Figure 5.2 Plots of CUSUM and CUSUMSQ(Finland)



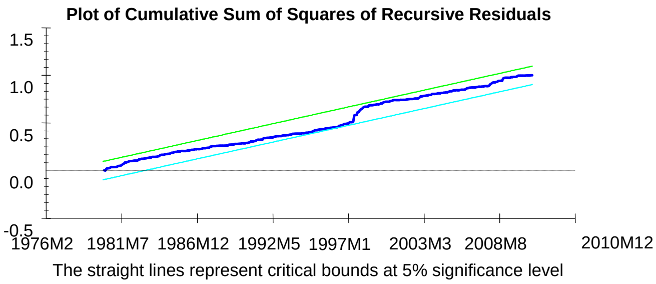


Figure 5.3 Plots of CUSUM and CUSUMSQ (France)

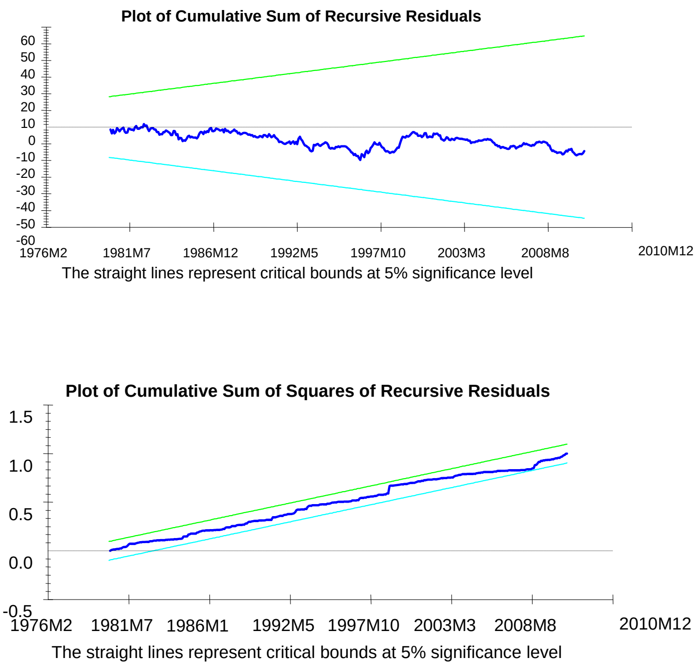
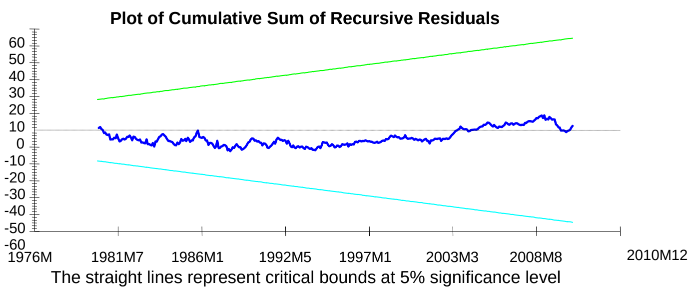


Figure 5.4 Plots of CUSUM and CUSUMSQ(Germany)



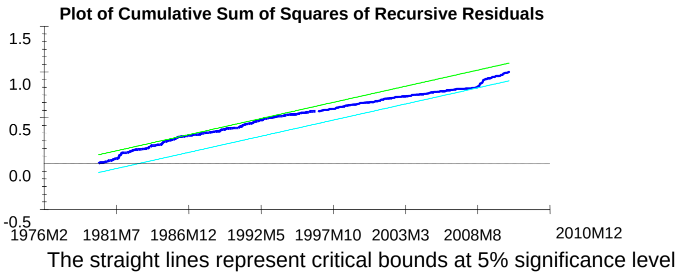
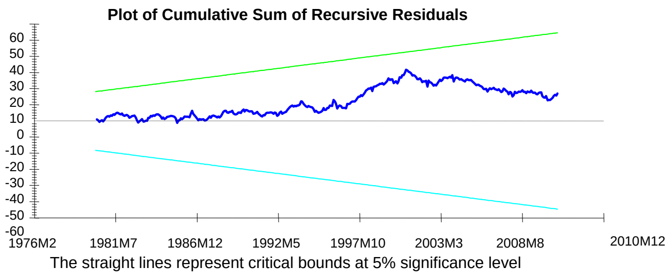


Figure 5.5 Plots of CUSUM and CUSUMSQ (Greece)



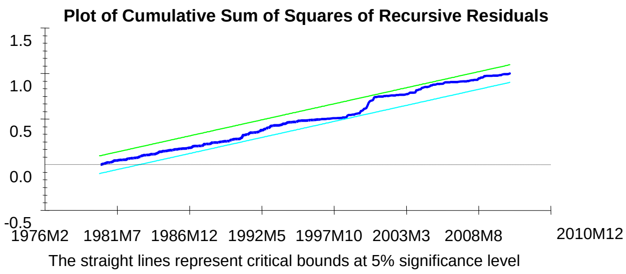
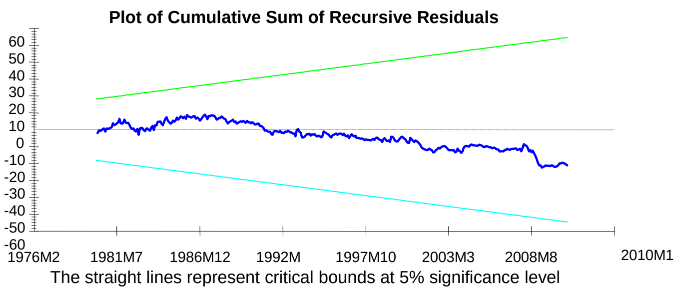


Figure 5.6 Plots of CUSUM and CUSUMSQ (Ireland)



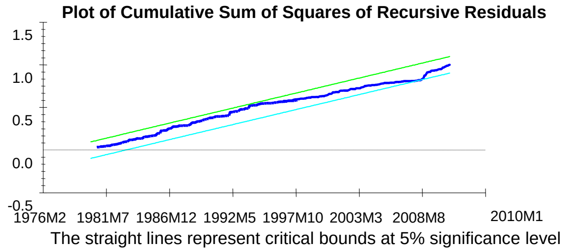
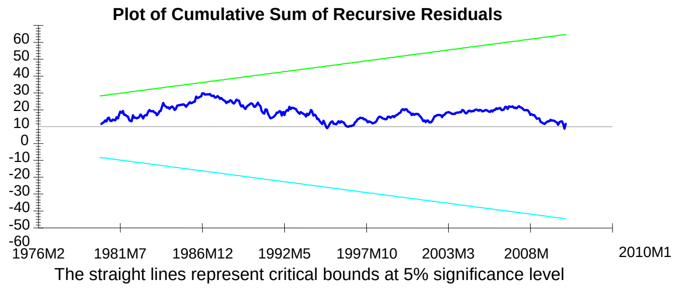


Figure 5.7 Plots of CUSUM and CUSUMSQ (Italy)



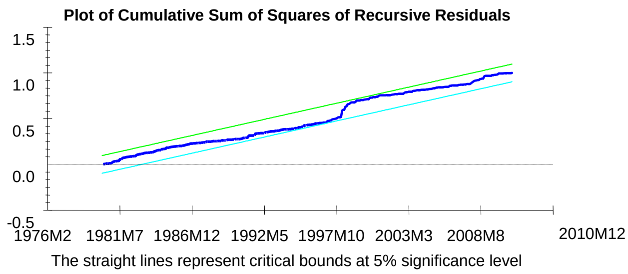


Figure 5.8 Plots of CUSUM and CUSUMSQ (the Netherlands)

Table 5.5.4 Hansen sup-LR nonlinearity test results (exports to the US)

	Finland	France	Germany	Greece	Ireland	Italy	Netherlands
Threshold	-0.0225	0.0701	-0.0681	0.081	-0.0037	-0.0814	-0.0233
F-statistic	21.917	14.680	15.954	10.073	27.667	13.019	11.978
P-value	0.014*	0.159	0.123	0.527	0.000**	0.212	0.352

Notes: 1. Null Hypothesis: no threshold; 2. Number of Bootstrap Replications is 1000; 3.Trimming percentage is 0.15; 4. ** and * indicate significance level of 1%, 5%, respectively.

Table 5.5.5 Tests of SETAR(1) against SETAR(2), SETAR(1) against SETAR(3), and SETAR(2) against SETAR(3) (exports to the US)

	Finland		Ireland	
	Test statistic (p-value)	Critical values (5%)	Test statistic (p-value)	Critical values (5%)
SETAR(1) vs SETAR(2)	21.917 (0.027)*	19.941	27.667 (0.004)**	19.360
SETAR(1) vs SETAR(3)	39.245 (0.029)*	36.746	44.691 (0.003)**	35.410
SETAR(2) vs SETAR(3)	16.442 (0.234)	22.439	15.978 (0.255)	21.030

Notes: 1. SETAR(1), SETAR(2) and SETAR(3) refer to linear AR process, SETAR with 2 regimes, and SETAR with 3 regimes, respectively; 2. Null hypothesis is the former model for all of the tests; 3.Number of bootstrap replications is 1000; 3. P-values are in parentheses; 4. Lags are chosen according to Akaike Information Criterion; 5. **, and * indicate significance level of 1%, respectively.

Table 5.5.6 Estimation of the SETAR(2) models for Finland and Ireland (exports to the US)

			Estimate	Std. Error	t value	Threshold value
Finland	Regime L	Const	-0.077	0.031	-2.466	-0.0225
		$\rho_1(L)$	-0.204	0.101	-2.018	
	Regime H	Const	0.086	0.026	3.353	
		$\rho_1(H)$	-0.209	0.082	-2.570	
Ireland	Regime L	Const L	-0.052	0.013	-4.077	-0.0137
		$\rho_1(L)$	-0.329	0.099	-3.335	
		$\rho_4(L)$	-0.165	0.065	-2.518	
	Regime H	Const H	0.029	0.012	2.364	
		$\rho_1(H)$	-0.183	0.090	-2.033	

Notes: 1. $\rho_i(m)$ refers to the coefficient on the ith lag in regime m, m=L, H; 2. The lag order of AR in each regime is chosen according to the AIC.

To test whether the equilibrium error series follow a SETAR process, we first perform the Hansen sup-LR nonlinear test for each of the seven residual series obtained from the cointegrating equations. If threshold nonlinearity is found, then we proceed to test for the number of regimes and the threshold values. Let SETAR(m) denote a SETAR model with m regimes, we need to test the null hypothesis of SETAR(1) (linear AR process) against the alternative of SETAR(2), the null of SETAR(1) against SETAR(3), and the null of SETAR(2) against SETAR(3). At last we estimate the SETAR(m) model with the previously found threshold(s) using the Hansen SETAR test. Nonlinearity test results are reported in Table 5.5.4 and the results show that the adjustment processes of the exports of five countries (France, Germany, Greece, Italy and the Netherlands) towards equilibrium are linear. In contrast, threshold behavior is evident for Finland and Ireland.

The linear error correction models are represented by the following equations.

France:

$$\Delta EX_t = -0.094ECT_{t-1} - \sum_{i=1,2,3,4,6,12} \alpha_i \Delta EX_{t-i} + \sum_{j=5,7} \beta_j \Delta Y_{t-j} - 0.272\Delta RER_{t-6} - \sum_{k=7,8} \gamma_k \Delta VOL_{t-k} \quad (5.5.1)$$

where $ECT_{t-1} = EX_{t-1} - 0.698Y_{t-1} + 0.931RER_{t-1} + 39.405VOL_{t-1} - 2.902$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_6, \alpha_{12}) = (0.692, 0.487, 0.294, 0.178, 0.150, 0.241)$,

$(\beta_5, \beta_7) = (2.971, 2.339)$, $(\gamma_7, \gamma_8) = (6.242, 4.357)$.

Germany:

$$\Delta EX_t = -0.068ECT_{t-1} - \sum_{i=1}^{5} \alpha_i \Delta EX_{t-i} - 0.841\Delta RER_{t-1} - 0.528\Delta RER_{t-7} - \sum_{k=1,6,10} \beta_k \Delta VOL_{t-k} \quad (5.5.2)$$

where $\mathrm{ECT}_{t-1} = \mathrm{EX}_{t-1} - 1.215Y_{t-1} + 1.231RER_{t-1} + 46.165VOL_{t-1} + 10.710$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5) = (0.778, 0.539, 0.389, 0.374, 0.194)$, $(\beta_1, \beta_6, \beta_{10}) = (5.742, 4.244, 4.967)$.

Greece:

$$\Delta EX_t = -0.052ECT_{t-1} - \sum_{i=1}^{12} \alpha_i \Delta EX_{t-i} + 9.897\Delta Y_{t-1} - \sum_{j=5,10} \beta_j \Delta RER_{t-j} - \sum_{k=4,13,15,16} \gamma_k \Delta VOL_{t-k} \quad (5.5.3)$$

where

$ECT_{t-1} = EX_{t-1} - 0.800Y_{t-1} + 4.953RER_{t-1} + 165.266VOL_{t-1}$,

$(\alpha_1, \alpha_2, \ldots, \alpha_{12}) = (0.733, 0.725, 0.628, 0.635, 0.628, 0.557, 0.531, 0.435, 0.421, 0.424, 0.370, 0.461)$,

$(\beta_5, \beta_{10}) = (1.371, 1.697)$, $(\gamma_4, \gamma_{13}, \gamma_{15}, \gamma_{16}) = (16.224, -12.969, 13.648, 16.428)$.

Italy:

$$\Delta EX_t = -0.013ECT_{t-1} - \sum_{i=1}^{4} \alpha_i \Delta EX_{t-i} + 2.178\Delta Y_{t-5} \qquad (5.5.4)$$

where $ECT_{t-1} = EX_{t-1} - 1.029Y_{t-1} + 2.170RER_{t-1} + 53.799VOL_{t-1}$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.755, 0.453, 0.244, 0.126)$.

The Netherlands:

$$\Delta EX_t = -0.026ECT_{t-1} - \sum_{i=1,5,8,12} \alpha_i \Delta EX_{t-i} + \sum_{j=7,11} \beta_j \Delta Y_{t-j} - \sum_{k=1,3,4,12,} \gamma_k \Delta RER_{t-k} - 7.237\Delta VOL_{t-4} + 0.040 \qquad (5.5.5)$$

where $ECT_{t-1} = EX_{t-1} - 1.369Y_{t-1} + 3.738RER_{t-1} + 86.433VOL_{t-1} + 15.197$,

$(\alpha_1, \alpha_5, \alpha_8, \alpha_{12}) = (0.745, 0.157, 0.145, 0.164)$, $(\beta_7, \beta_{11}) = (3.111, 3.438)$,

$(\gamma_1, \gamma_3, \gamma_4, \gamma_{12}) = (0.679, 0.383, -0.362, 0.466)$.

In the above equations, ECT denotes the error correction term, Δ is the first difference operator, and we only include in the models the terms that are significant at a 5% significance level. From these equations we can see that the first difference of *EX*, ΔEX, exhibits strong negative autocorrelation, especially for France, Greece and the Netherlands. In the case of France, for example, the change in exports 12 months ago (ΔEX_{t-12}) still has an impact on the present adjustment of exports (ΔEX_t), indicating that changes in exports are strongly autoregressive. Thus an export shock may exert persistent impact on later exports and it may take a long time for exports to recover from the shock. The results also show that the adjustment coefficients on the error correction terms (ECT_{t-1}) for the five countries are all negative, meaning that if exports deviate from the equilibrium level over the previous period, they will adjust in the opposite direction in the present period. The error correction equations also show that changes in foreign income, real exchange rate and exchange rate volatility have significant short-term effects on exports, in addition to their long-term effects. This finding is generally consistent with that of Arize (1996) and De Vita and Abbott (2004a).

It is worth noting that in the adjustment process of Italy's exports to the US, short-term volatility changes have no significant impact on the adjustment of exports.[28] For the other four countries (France, Germany, Greece and the Netherlands), however, the short-term changes in exchange rate volatility do have significant effects on the adjustment of exports.

The first difference terms of the three explanatory variables show significant effects at relatively long lags on the adjustment of exports (see ΔY_{t-i}, ΔRER_{t-j}, and ΔVOL_{t-k} in equations 5.5.1-5.5.5), signifying that it takes a long time for the changes in *Y*, *RER* and *VOL* to affect exports and for their effects to fade out. This is not surprising because there is usually a time lag between the occurrence of economic shocks and their effects on exports, with the effects often being of sustained duration. As far as the trade effects of volatility are concerned, the international trade market is riskier if exchange rates become more volatile since pre-existing trade contracts have to be honoured anyway. Thus the strategy exporting firms follow is either to hedge the risk in financial markets where possible, to adjust their production schedule or to "wait and see". As a matter of fact, risk can never be completely hedged even in advanced financial markets because hedging strategies themselves cause transaction costs and hedging is not easy in a very volatile market. In addition, sunk costs play a significant role in the decision-making on whether to adjust the production schedule. In order to adapt their products to the export market, exporting firms have to make substantial investment to change production facilities specifically designed for export markets and to set up new marketing and distribution networks. The adjustment is time-consuming, even if it is profitable. So in the face of an expected short-term shock to the exchange

[28] De Vita and Abbott (2004a) find that short-term volatility changes do not significantly affect the adjustment of the UK's exports to the other EU countries.

rate, the consideration of costs tends to make firms cautiously adopt a “wait and see” strategy. In the long run, if the firms expect the volatile situation to last a long time, adjustment will be inevitable. We can also see that the time lag differs across variable as well as across countries. This may be explained by the specific economic structure, especially the trade industry structure in different economies.

For Finland and Ireland, the adjustment processes of the two residual series can be characterized as SETAR(2) processes. The test results are reported in Tables 5.5.5 and 5.5.6. The SETAR(2) models for Finland and Ireland can be represented by Equations 5.5.6 and 5.5.7, respectively:

$$ECT_t = \left(-0.077 - 0.204ECT_{t-1} + \mu_t\right) I\left(ECT_{t-1} < -0.0225\right) + \left(0.086 - 0.209ECT_{t-1} + \mu_t\right) I\left(ECT_{t-1} \geq -0.0225\right) \tag{5.5.6}$$

$$ECT_t = \left(-0.052 - 0.329ECT_{t-1} - 0.165ECT_{t-4} + \mu_t\right) I\left(ECT_{t-1} < -0.0037\right) + \left(0.029 - 0.183ECT_{t-1} + \mu_t\right) I\left(ECT_{t-1} \geq -0.0137\right) \tag{5.5.7}$$

where ECT denotes the error correction term for the export adjustment, *I(x)* is an indicator function taking a value of 1 if x is true and zero otherwise. We label the regime with $ECT_{t-1} < threshold\,value$ as regime L and that with $ECT_{t-1} \geq threshold\,value$ as regime H. In Equation 5.5.6, both regime L and H have only 1 lagged term of ECT_t, but in Equation 5.5.7, regime L has 2 lagged terms of ECT_t, namely the first and the fourth lagged term of ECT_t, and regime H has only 1 lagged term of ECT_t. For Finland, the share of observations falling in regime L and regime H is 51.1% and 48.9%, respectively, and for Ireland it is 49.9% and 50.1%, therefore the error correction terms are asymmetrically located in the two regimes.

Unlike the conventional linear error correction model, where the speed of adjustment is the same no matter how large the disequilibrium in the previous period, in the SETAR(2) models 5.5.6 and 5.5.7 the equilibrium error evolves according to different regime specification and the adjustment speed is different across regimes, indicating that the adjustment process of exports is asymmetric. Our estimates of the threshold values for Finland and Ireland are -0.0225 and -0.0137, respectively. Thus, for Finland, the adjustment process of exports switches between regime L and regime H, depending on whether exports deviate from equilibrium by more than 2.25%.

The adjustment speed in regime L is a little lower than in regime H, thus the share of observations falling in regime L is a little larger than that in regime H. For Ireland, the regime-switching adjustment is activated when exports deviate from equilibrium by more than 1.37%, which is smaller than the absolute threshold value for Finland, indicating that Ireland's exports to the US are more sensitive to shocks than that of Finland. In addition, the two threshold values are both negative, indicating that decreases in exports trigger a stronger reaction by economic agents than increases in exports. This nonlinear adjustment mechanism is driven by the comparative costs of adjustment relative to the losses caused by economic shocks. Generally speaking, the trading firms prefer not to adjust their strategies and production plans if the adjustment costs are larger than the losses. The adjustment will only be activated when the losses are larger than the costs of adjustment.

The reason why the nonlinear adjustment of exports occurs for Finland and Ireland but not for other countries under consideration may be that Finland and Ireland rely on foreign trade more heavily than the other countries and exports of these two countries are more sensitive to economic shocks. From a microeconomic point of view, the exporting firms in small open economies are on average much smaller than those in large economies in terms of capital stock and investment. The smaller size of firms means lower sunk cost associated with adjustment on the one hand and higher risk aversion on the other hand. Higher risk aversion and lower sunk cost tend to lead small firms to adjust more frequently than larger firms in the face of shocks. Thus, on aggregate, the level of exports of small economies appears to be more sensitive to shocks than those of large economies.

As pointed out in chapter 2, theoretically, there may be a general form of nonlinear cointegration among variables of interest, even though no linear cointegration nor threshold cointegraton is found for them. Put differently, even if there is no linear cointegration or threshold cointegraton between variables, say, y and x_i (i=1,2,...,n), it is still possible for nonlinear functions of these variables, f(y) and $g_i(x_i)$, to be cointegrated. Thus it is necessary to take a further step to test for this general form of nonlinear cointegration for the cases of Austria, Portugal and Spain. To this end, we first transform the variables in consideration using the ACE algorithm and then test for linear cointegrating relationship between these ACE-transformed variables. Since the unit root test results show that *VOL* become stationary after transformation, the ARDL bounds testing approach is applied here. It turns out that no evidence of nonlinear cointegration can be found for these three countries.[29]

5.6 Empirical analysis of exports to the UK

The previous section examined exports to the US. We now carry out a parallel analysis using data on exports from the EMU countries to the UK. Table 5.6.1 summarizes the results from panel unit root tests. We can see that the series are all non-stationary at a 5% significance level. Table 5.6.2 reports the test statistics of the cointegration tests using Johansen's method. The test results are qualitatively similar to those reported in Table 5.5.2 for the case of exports to the US. There are cointegrating relationships among the variables of interest for Austria, Finland, Germany, Greece, Ireland, Italy and the Netherlands, but no long-run relationships exist for France, Portugal and Spain.[30]

Table 5.6.1 Panel unit root test results (exports to the UK)

	EX	Y	RER	VOL
LLC	-0.418 (0.338)	0.234 (0.593)	0.045 (0.518)	-0.877 (0.190)
IPS	-1.022 (0.153)	0.566 (0.714)	-0.784 (0.217)	-0.342 (0.305)

Notes: (1) Selection of exogenous variables: tests on EX and Y assume individual effects and individual linear trends, tests on the other two variables assume individual effects. Lag length is selected based on SIC and Bartlett kernel. (2) LLC test takes common unit root process as its null. IPS test takes individual unit root process as its null. (3) The p-values are in parenthesis, * , ** and *** denote significance at 10%, 5% and 1% level respectively.

[29] For details about ACE algorithm and the ARDL approach see Chapter 1. The ARDL test results are not reported for brevity.

[30] For France, Portugal and Spain, further analysis shows no evidence of the general form of nonlinear cointegration mentioned at the end of section 5.5.

Table 5.6.2 Johansen cointegration test statistics (exports to the UK)

	Hypothesized No. of CE(s)	Trace Statistic	0.05 Critical Value	Prob.	Max-Eigen Statistic	0.05 Critical Value	Prob.
Austria	None	62.689	54.079	0.007*	28.561	28.588	0.050*
	At most 1	34.127	35.193	0.065	22.224	22.300	0.051
	At most 2	11.903	20.262	0.458	8.785	15.892	0.457
Finland	None	47.701	40.175	0.007*	26.518	24.159	0.024*
	At most 1	21.182	24.276	0.117	16.535	17.797	0.077
	At most 2	4.648	12.321	0.618	4.596	11.225	0.536
France	None	43.463	54.079	0.310	19.230	28.588	0.473
	At most 1	24.232	35.193	0.448	13.462	22.300	0.512
	At most 2	10.770	20.262	0.564	7.560	15.892	0.601
Germany	None	58.219	54.079	0.020*	29.527	28.588	0.038*
	At most 1	28.692	35.193	0.212	18.242	22.300	0.168
	At most 2	10.450	20.262	0.596	7.118	15.892	0.655
Greece	None	89.393	63.876	0.000*	63.553	32.118	0.000*
	At most 1	25.840	42.915	0.746	12.383	25.823	0.848
	At most 2	13.457	25.872	0.702	7.227	19.387	0.885
Ireland	None	65.019	40.175	0.000*	51.095	24.159	0.000*
	At most 1	13.924	24.276	0.544	8.673	17.797	0.631
	At most 2	5.251	12.321	0.533	5.132	11.225	0.459
Italy	None	41.102	40.175	0.040*	25.781	24.159	0.030*
	At most 1	15.322	24.276	0.430	8.126	17.797	0.692
	At most 2	7.196	12.321	0.306	5.845	11.225	0.368
Netherlands	None	61.048	54.079	0.011*	23.907	28.588	0.177
	At most 1	37.142	35.193	0.030*	20.840	22.300	0.079
	At most 2	16.301	20.262	0.161	11.556	15.892	0.213
Portugal	None	51.488	54.079	0.084	21.745	28.588	0.291
	At most 1	29.743	35.193	0.172	17.414	22.300	0.209
	At most 2	12.329	20.262	0.420	8.810	15.892	0.454
Spain	None	51.962	54.079	0.076	23.074	28.588	0.216
	At most 1	28.887	35.193	0.204	15.914	22.300	0.304
	At most 2	12.974	20.262	0.366	9.092	15.892	0.424

Note: * means that the statistic is significant at least at significance level of 5%.

Table 5.6.3 Cointegrating equations (exports to the UK)

	Dependent variable	Independent variables			
	EX	Y	RER	VOL	C
Austria	1	1.677 (0.181)***	-2.016 (0.440)***	-0.622 (0.328)***	-24.079 (4.645)***
Finland	1	0.764 (0.004)***	-1.414 (0.279)***	-0.864 (0.450)***	
Germany	1	0.999 (0.101)***	-2.235 (0.208)***	-0.371 (0.171)***	-3.477 (1.588)**
Greece	1	1.001 (0.161)***	-0.481 (0.192)***	-0.462 (0.072)**	
Ireland	1	0.581 (0.031)***	-11.791 (2.621)***	-0.912 (2.215)*	
Italy	1	0.824 (0.006)***	-1.326 (0.598)**	-0.348 (0.518)***	
Netherlands	1	2.089 (0.734)***	-1.736 (1.583)	-0.725 (0.133)***	-31.529 (15.862)**

Notes: 1. The values in parentheses are standard errors; 2. Choice of trend assumption is based on AIC and BIC; 3. VAR Lag Order is selected according to LR; 4. ***, ** and * indicate significance level of 1%, 5% and 10%, respectively.

The cointegrating equations estimated using the Johansen tests are reported in Table 5.6.3.[31] Similar to the results in Table 5.5.3, all of the coefficients on the variables are significant with only one exception – the coefficient on *RER* for the Netherlands is insignificant. The coefficients on variables *Y* and *RER* also show the expected sign. As in the case of exports to the US, the coefficients on exchange rate volatility are also negative, indicating negative effects of exchange rate volatility on exports from the seven EMU member countries to the UK. However, interestingly, the volatility elasticity is smaller in magnitude than that in the case of exports to the US, indicating that the exports from these countries to the UK is less sensitive to exchange rate volatility than their exports to the US.

[31] The results from CUSUM and the CUSUMSQ tests based on the residuals from the estimated ARDL models show that the coefficients in the long run relationships are all stable.

Now we are in a position to examine whether the adjustment process of the equilibrium error is linear or nonlinear. Following the same procedure for testing for nonlinearity as in section 5.5, we test for the nonlinearity of the equilibrium error series from the cointegrating equations reported in Table 5.6.3. The test results are reported in Table 5.6.4. We can see that, as in the case of exports to the US, the adjustment processes of exports to the UK towards equilibrium for Germany, Greece, Italy and the Netherlands are linear, and for Finland and Ireland threshold behavior is evident. There is a difference in that the adjustment process of exports for Austria now exhibits threshold behaviour.

The error correction models corresponding to the linear cointegrating equations are represented by equations 5.6.1-5.6.4 as follows.

Germany:

$$\Delta EX_t = -0.059 ECT_{t-1} - \sum_{i=1}^{4} \alpha_i \Delta EX_{t-i} - \sum_{j=1}^{3} \beta_j \Delta RER_{t-j} - 12.392 \Delta VOL_{t-1} - 5.176 \Delta VOL_{t-14} \quad (5.6.1)$$

where $\mathrm{ECT}_{t-1} = \mathrm{EX}_{t-1} - 0.999 Y_{t-1} + 2.235 RER_{t-1} + 2.127 VOL_{t-1} + 3.477$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.824, 0.469, 0.254, 0.153)$, $(\beta_1, \beta_2, \beta_3) = (0.785, 0.733, 0.409)$.

Greece:

$$\Delta EX_t = -0.034 ECT_{t-1} - \sum_{i=1}^{4} \alpha_i \Delta EX_{t-i} + \sum_{j=4,7,12} \beta_j \Delta Y_{t-j} - 2.814 \Delta RER_{t-2} - 1.456 \Delta RER_{t-4} - 2.057 \Delta RER_{t-8} \quad (5.6.2)$$

wher $ECT_{t-1} = EX_{t-1} - 1.677 Y_{t-1} + 2.016 RER_{t-1} + 1.022 VOL_{t-1} - 24.079$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.452, 0.413, 0.714, 0.154)$, $(\beta_4, \beta_7, \beta_{12}) = (2.423, 1.478, 1.041)$.

Italy:

$$\Delta EX_t = -0.024 ECT_{t-1} - \sum_{i=1}^{5} \alpha_i \Delta EX_{t-i} + 0.372 \Delta \mathrm{Y}_{t-1} + 0.624 \Delta \mathrm{Y}_{t-2} + 0.517 \Delta \mathrm{Y}_{t-3} \quad (5.6.3)$$

where $ECT_{t-1} = EX_{t-1} - 0.824 Y_{t-1} + 1.326 RER_{t-1} + 1.548 VOL_{t-1}$,

$(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5) = (0.512, 0.475, 0.358, 0.431, 0.416)$.

The Netherlands:

$$\Delta EX_t = -0.031ECT_{t-1} - \sum_{i=1,3,4,10} \alpha_i \Delta EX_{t-i} + \sum_{j=2,5,7} \beta_j \Delta Y_{t-j} - 0.021\Delta VOL_{t-2} \quad (5.6.4)$$

where $\mathrm{ECT}_{t-1} = \mathrm{EX}_{t-1} - 2.089Y_{t-1} + 1.736RER_{t-1} + 1.108VOL_{t-1} + 31.529$,

$(\alpha_1, \alpha_3, \alpha_4, \alpha_{10}) = (0.422, 0.157, 0.317, 0.224), (\beta_2, \beta_5, \beta_7) = (2.125, 1.074, 2.431)$.

By comparing the above 4 equations with equations 5.5.1-5.5.5, it can be seen that exports from EMU countries to the UK have similar error correction mechanisms to those to the US, supporting the findings in the previous section. For example, ΔEX_{t-i} also exhibits strong negative autocorrelation, suggesting that export shocks in the past exert persistent effects on adjustment of exports in the present period. Generally, the first difference terms of the explanatory variables, ΔY_{t-i}, ΔRER_{t-j}, and ΔVOL_{t-k}, with relatively large *i*, *j* and *k* respectively, have significant effects on ΔEX_t, indicating that there is generally a long time lag between the economic shocks and their effects on exports.

SETAR tests show that for Finland and Ireland the adjustment of exports towards equilibrium still follow SETAR(2) processes and this is also the case for Austria. The test results are reported in Tables 5.6.5 and 5.6.6. With the same notation used in Equations 5.5.6 and 5.5.7, the SETAR(2) models for Austria, Finland and Ireland can be written as Equations 5.6.5, 5.6.6 and 5.6.7, respectively, as follows:

$$ECT_t = (-0.437 - 0.341ECT_{t-1} + \mu_t) I(ECT_{t-1} < -0.0314) + (0.175 - 0.304ECT_{t-1} + \mu_t) I(ECT_{t-1} \geq -0.0314) \quad (5.6.5)$$

$$ECT_t = (-0.156 - 0.218ECT_{t-1} + \mu_t) I(ECT_{t-1} < -0.0421) + (0.172 - 0.234ECT_{t-1} + \mu_t) I(ECT_{t-1} \geq -0.0421) \quad (5.6.6)$$

$$ECT_t = (-0.047 - 0.276ECT_{t-1} + \mu_t) I(ECT_{t-1} < -0.0352) + (0.048 - 0.264ECT_{t-1} + \mu_t) I(ECT_{t-1} \geq -0.0352) \quad (5.6.7)$$

In comparison with Equations 5.5.6 and 5.5.7, the absolute threshold value estimated in Equations 5.6.5, 5.6.6 and 5.6.7 are larger, especially for

Ireland, implying that the exports from Finland and Ireland to the UK are less sensitive to economic shocks than their exports to the US. This may be because Finland, Ireland and the UK are all EU member countries and are located far more closely to each other than to the US, with the result that the trade cost and hence trade risk for exports to the UK is much lower than to the US. Therefore, in face of shocks, these countries' exports to the UK do not adjust as frequently as their exports to the US.

The shares of observations lying within regime L and regime H are respectively 47.1% and 52.9% for Austria, 51.8% and 48.2% for Finland, and 48.9% and 51.1% for Ireland. Interestingly, as in the case of exports to the US, for Finland the adjustment speed of exports to the UK in regime L is still lower than that in regime H. The opposite is true for Ireland, implying that, compared with Ireland, exports of Finland are more difficult to adjust when they deviate from equilibrium. In addition, the absolute threshold value for Ireland is still smaller than that for Finland, confirming that exports of Ireland are more sensitive to shocks than those of Finland.

Table 5.6.4 Hansen sup-LR nonlinearity test results (exports to the UK)

	Austria	Finland	Germany	Greece	Ireland	Italy	Netherlands
Threshold	0.0415	-0.0314	-0.0547	-0.0421	-0.0352	-0.0431	-0.0324
F-statistic	19.347	18.807	10.954	14.273	21.587	11.019	14.978
P-value	0.037*	0.042*	0.453	0.175	0.012*	0.402	0.154

Notes: 1. Null Hypothesis: no threshold; 2. Number of Bootstrap Replications is 1000; 3.Trimming percentage is 0.15; 4. ** and * indicate significance level of 1%, 5%, respectively.

Table 5.6.5 Tests of SETAR(1) against SETAR(2), SETAR(1) against SETAR(3), and SETAR(2) against SETAR(3) (exports to the UK)

	Austria		Finland		Ireland	
	Test statistic (p-value)	Critical values (5%)	Test statistic (p-value)	Critical values (5%)	Test statistic (p-value)	Critical values (5%)
SETAR(1) vs. SETAR(2)	22.354 (0.020)**	19.473	25.478 (0.018)**	20.604	26.517 (0.013)**	20.942
SETAR(1) vs. SETAR(3)	40.245 (0.012)**	35.241	39.754 (0.032)**	36.140	41.247 (0.008)***	34.324
SETAR(2) vs. SETAR(3)	12.202 (0.413)	19.391	13.726 (0.425)	21.430	14.442 (0.359)	20.751

Notes: 1. SETAR(1), SETAR(2) and SETAR(3) refer to linear AR process, SETAR with 2 regimes, and SETAR with 3 regimes, respectively; 2. Null hypothesis is the former model for all of the tests; 3.Number of bootstrap replications is 1000; 3. P-values are in parentheses; 4. Lags are chosen according to Akaike Information Criterion; 5. ***, ** and * indicate significance level of 1%, 5% and 10%, respectively.

Table 5.6.6 Estimation of the SETAR(2) model for Austria, Finland and Ireland (exports to the UK)

			Estimate	Std. Error	t value	Threshold value
Austria	Regime L	Const	-0.437	0.029	-15.069	-0.0314
		$\rho_1(L)$	-0.341	0.141	-2.418	
	Regime H	Const	0.175	0.032	5.469	
		$\rho_1(H)$	-0.304	0.075	-4.053	
Finland	Regime L	Const	-0.156	0.034	-4.588	-0.0421
		$\rho_1(L)$	-0.218	0.094	-3.383	
	Regime H	Const	0.172	0.034	5.059	
		$\rho_1(H)$	-0.234	0.073	-4.575	
Ireland	Regime L	Const L	-0.047	0.021	-2.238	-0.0352
		$\rho_1(L)$	-0.276	0.084	-3.286	
	Regime H	Const H	0.048	0.018	2.667	
		$\rho_1(H)$	-0.264	0.085	-3.106	

Notes: 1. $\rho_i(m)$ refers to the coefficient on the ith lag in regime m, m=L, H; 2. The lag order of AR in each regime is chosen according to the AIC.

5.7 Summary

This chapter investigates how exchange rate volatility affects bilateral exports from ten EMU member countries to the US and to the UK using a monthly dataset covering the period 1975-2010. Both linear and nonlinear cointegration tests are employed to test for the potential long-run relationship amongst the variables of interest.

The empirical analysis suggests that, for most of the countries, real exports to the US are cointegrated with the level of GDP in the US, the real exchange rate and the volatility of exchange rates. *GDP* and the real exchange rate contribute positively and negatively to exports, respectively, in line with the theoretical prediction that an appreciation of the real exchange rate depresses exports and that rising income of the trading partner stimulates exports. Exchange rate volatility is shown to unambiguously depress exports of most of the EMU member countries. In addition, it is found that for Finland and Ireland the adjustment of exports towards equilibrium follows a nonlinear process. More specifically, the adjustment process of exports switches between two regimes, depending on whether the deviation of exports from equilibrium is larger than some threshold value. The adjustment speed is different across the two regimes. The negative threshold value indicates that decreases in exports trigger a stronger reaction of economic agents than increases in exports. The driving force of this nonlinear adjustment mechanism is the comparative costs of adjustment relative to the losses caused by economic shocks.

A parallel analysis of the exports from these EMU member countries to the UK generally supports the above findings. It is found that exports from these countries to the UK is less sensitive to exchange rate volatility than those to the US. In addition, it is shown that the absolute threshold values of the threshold cointegrating equations for Finland and Ireland are larger than those in the case of the exports to the US, particularly for Ireland, implying that the exports from Finland and Ireland to the UK are less sensitive to economic shocks than their exports to the US. One possible explanation for this is that Finland, Ireland and the UK are all EU member countries and are far more closely located to each other than they are to the US, with the result that the trade cost and hence trade risk for exports to the UK are much lower than that for the exports to the US. Therefore, in the face of shocks, their exports to the UK do not adjust as much as their exports to the US.

The empirical results in this chapter have some important implications for policy making. First, the finding that real appreciation of exchange rates and exchange rate volatility tend to depress exports and that exports are strongly autoregressive imply that it is important to maintain stable euro exchange rates. Second, the finding that exchange rate volatility tends to depress exports also lends some support to the trade benefits associated with joining the EMU because it has eliminated exchange rate risk inside the currency union. Finally, the exchange rate and its volatility affect exports differently across countries. The small open economies tend to be more sensitive to economic shocks than larger economies. Hence in comparison with big economies, it is more important and beneficial for the small economies to keep exchange rates stable. However, as a member of the EMU, the individual country sacrifices exchange rate policy as a tool to protect its economy from external shocks. Therefore it is important for small economies to build trade industries that are resilient to economic shocks and to implement more flexible commercial policies to protect exports from external shocks.

This chapter finds evidences of both linear and nonlinear effects of volatility on exports from ten EMU member countries to the US and the UK. The threshold cointegration found between the variables of interest in this study is just one form of nonlinearity. It is likely for volatility to affect international trade in other nonlinear ways. These possibilities need to be explored more extensively in the future.

Chapter 6 Summary and Conclusions

6.1 Summary of the empirical findings

To explore the potential nonlinear relationship between real exchange rates and fundamentals, chapter 2 examines two emerging-market currencies (CNY and KRW) using quarterly data over the period 1980Q1-2009Q4. Methodologically, the ARDL bounds testing approach is employed to test for linear cointegrating relationships, and the Alternating Conditional Expectation algorithm is employed to test for nonlinearity among the variables of interest. The results show that for both CNY and KRW there exists a nonlinear cointegrating relationship between real exchange rates and fundamentals such as productivity, terms of trade, net foreign assets etc. The elasticity analysis of the nonlinear cointegrating relationships found suggests that the elasticity of real exchange rates with respect to fundamentals changes substantially not only in magnitude but also in direction over time, being in sharp contrast with the implications of linear cointegration.

To examine the generality of the nonlinear real exchange rate-fundamentals relationship, chapter 3 examines the real exchange rates of euro and 10 former currencies of EMU member countries. Besides the methods used in chapter 2, the nonlinear Granger causality test is also employed to test for the dynamic nonlinear causal relationship between the real exchange rates and fundamentals. The empirical analysis confirms the finding in chapter 2 that there is nonlinear relationship between real exchange rates and fundamentals. The main empirical findings can be summarized as follows. First, there are linear cointegrating relationships between the real exchange rates and fundamentals for currencies of Finland, Belgium, Spain and euro, and there is structural break in the long-run relationships between the real exchange rates and fundamentals for the Netherlands and Portugal, for which linear cointegration is evident over the subperiod before the introduction of euro. Second, there exists nonlinear cointegration between the real exchange rates and fundamentals for Austria, Germany. Third, nonlinear Granger causality tests show that there is nonlinear causality from some fundamentals to real exchange rates in all of the cases under consideration.

All in all, the empirical analyses in the first two chapters lead to a robust conclusion that there does exist nonlinearity in the relationship between real exchange rates and fundamentals. In the long term real exchange rate may be nonlinearly cointegrated with fundamentals. In the short term there always exists nonlinear Granger causality from some fundamentals to the real exchange rates.

To capture the volatility dynamics of euro exchange rates, chapter 4 estimates and forecasts the volatility of four daily euro exchange rates over the period from 4 January 1999 to 15 March 2011 using ten volatility models. These models include short-memory and long-memory GARCH models, single-regime and regime-switching GARCH models, and deterministic volatility models and stochastic volatility model. The out-of-sample forecasting performance of these models is compared using different criteria and is also compared over different time periods. By comparing forecasting performance of these ten models using forecast error statistics (MSE), regression test and DM test, it is shown that performance of these models can be evaluated differently, depending on the specific criterion used. By comparing forecasting performance of these models over different time periods, it is shown that these models perform differently across different periods: the regime-switching GARCH model performs best in normal times, it forecasts slightly better than the SV model, which in turn performs better than the FIGARCH model. A somewhat surprising result from this comparison is that FIGARCH.D turns out to be the best model over the volatile period.

To sum up, chapter 4 provides some important new findings. First, the regime-switching GARCH model generally performs better than single-regime GARCH models and the SV model. Second, FIGARCH.D performs the best among all the models over the volatile period, it forecasts better than FIGARCH and also performs better than RS-GARCH and SV. Furthermore, GARCH models with a dummy variable generally perform better than those without a dummy over the volatile period, confirming the conjecture that the volatility of exchange rates displays different dynamics during volatile period than during normal period.

In addition, chapter 4 also confirms some established findings in the existing literature. First, the long-memory GARCH models generally perform better than short-memory ones, indicating that incorporating long memory into modeling practice can improve the predictive ability of the models. Second, the performance of the models may change across different time periods, and different criteria may evaluate models differently, hence great caution should be taken when comparing the performance of different models. Finally, GARCH.GED outperforms GARCH.T and GARCH.N at all times, indicating that the generalized error distribution assumed in the model fits the fat tails of the returns series better than the normal distribution and t distribution.

Chapter 5 examines how exchange rate volatility affects exports. Monthly data over the period 1975-2010 for exports from ten EMU member countries to the US and the UK are used. Cointegration techniques are employed to test for the potential long-run relationship among the variables of interest.

For most of the ten EMU countries real exports are cointegrated with GDP of their trading partner, the real exchange rate and the volatility of exchange rates. The results show that appreciation of real exchange rate depresses exports and rising income of the importing partner stimulates exports, which is consistent with theory. Exchange rate volatility is shown to depress exports. More importantly, while the adjustment of exports from some countries towards equilibrium follows a linear error correction process, for other countries (Finland and Ireland in both cases and Austria in the case of exports to the UK) the adjustment process of exports follows a nonlinear SETAR process with 2 regimes. Specifically, the adjustment process of the exports from these countries to the US/UK switches between two regimes, H and L, depending on the size of the deviation of exports from equilibrium. If deviation from equilibrium is less than the threshold, then the adjustment process is governed by regime L, otherwise the adjustment process switches to regime H. The adjustment speed in regime L is generally different than that in regime H, and the negative threshold value indicates that decreases in exports trigger a stronger reaction of economic agents than increases in exports. This threshold adjustment mechanism is driven by the comparative costs of adjustment relative to the losses caused by economic shocks.

Generally, the trading firms will not adjust their strategies and production plans if the adjustment costs are larger than the losses, and the adjustment will be activated only when the losses are larger than the costs of adjustment.

In addition, comparison of the two analyses shows that in the case of exports to the UK the absolute threshold values of the threshold cointegrating equations for Finland and Ireland are larger than that in the case of exports to the US, especially so for Ireland, implying that the exports from Finland and Ireland to the UK is less sensitive to economic shocks than their exports to the US. One possible explanation for this is that Finland, Ireland and the UK are all EU member countries and are far more closely located to each other than they are to the US, as a result, the trade cost and hence trade risk of exports to the UK is much lower than that of exports to the US, therefore in face of shocks their exports to the UK do not adjust as much as their exports to the US.

6.2 Implications of the findings

The findings in this dissertation have some important implications for both policymakers and practitioners in financial markets. Chapter 2 and 3 reveal the possible nonlinear cointegrating relationship between the real exchange rate and the fundamentals, implying that both magnitude and direction of the effects of fundamentals on the exchange rate may change over time, depending on the specific economic context. Therefore policymakers should take into consideration the likely nonlinear relationship between exchange rates and fundamentals and make policies adjustable according to the specific economic context.

In chapter 4, the relative good performance of the regime-switching GARCH model implies that euro exchange rate volatilities do display regime-switching characteristic and accounting for the regime-switching behavior of volatility can improve the forecasting accuracy. Furthermore, the finding that GARCH models with a dummy variable generally perform better than those without a dummy over the volatile period implies that using exogenous variables based on ex ante judgment can enhance forecasting performance. In addition, the finding that the performance of the models may change across different time periods implies that no model is a clear winner at all times in forecasting volatility of exchange rate, hence great caution should be taken when choosing models to forecast volatility in practices of risk management and financial assets pricing.

The empirical results in chapter 5 provide the following important implications for policy making. First, it is important to maintain stable euro exchange rates and keep exports stable by making flexible trade policies because real appreciation of exchange rates and exchange rate volatility tend to depress exports and economic shocks exert persistent effects on exports. Second, the finding that exchange rate volatility tends to depress exports implies trade benefit of joining the EMU because it has eliminated exchange rate risk inside the currency union. Finally, exchange rate and volatility influence exports differently across countries, the small open economies are generally more sensitive to economic shocks than large economies, hence it is important for small countries of EMU to focus more attention on building trade industry that is resilient to economic shocks and to implement more flexible commercial policies to protect exports from external shocks.

6.3 Avenues for future research

Chapter 2 and 3 find evidences of nonlinear cointegration between real exchange rate and economic fundamentals using the ACE algorithm, but the nonlinear methods do not show us the specific functional form of the nonlinearity, this problem make it difficult to interpret the nonlinear relationship identified statistically. Hence an important avenue for future research is to take more efforts to investigate the functional form of nonlinearity in the relationships between real exchange rate and economic fundamentals.

Chapter 4 shows that including a dummy variable accounting for possible different volatility dynamics in volatile period can improve forecasting power. Its implication for future research is that volatility forecasting techniques that can account for structural breaks from ex ante perspective might provide more meaningful forecasts than the traditional models. Furthermore, whether using other exogenous variables related to volatility based on ex ante judgment can improve forecasting power deserves more investigation in the future. In addition, it may be fruitful to develop more sophisticated models, such as regime-switching long-memory GARCH model, which can account for both long memory and regime-switching properties of volatility. It is worth noting that there does not exist a one-for-all model superior for forecasting volatilities of all the financial assets at all times, different models can perform differently depending on the time period, the asset class, the forecast horizon and even many other factors, therefore combination of advantages of various volatility forecasting techniques might yield more insightful results. Some efforts have been taken in this promising direction, but more extensive research is needed to explore the potential of this approach in the future.

From a perspective of cointegration, chapter 5 finds evidences of both linear and nonlinear effects of volatility on exports from ten EMU member countries to the US and the UK. The threshold cointegration found between the variables of interest in this study is just one form of nonlinearity. It is likely for volatility to affect international trade in other nonlinear ways. These possibilities need to be explored more extensively in the future.

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