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NEW PANEL UNIT ROOT AND COINTEGRATION TESTS OF PURCHASING POWER PARITY

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Abstract

Purchasing Power parity PPP) is one of the most investigated topics in international finance. The empirical analysis on PPP in the 1980s and 1990s relied on univariate tests such as Dickey Fuller and Augmented Dickey Fuller and cointegration tests. The empirical evidence from these methodologies seemed to produce very little empirical evidence favouring PPP. However, these methodologies have been shown to have low power and be inadequate when used with highly persistent stochastic processes (for unit root tests of the real exchange rate).

One solution followed in the literature to overcome the low power problem was pooling data on two dimensions (i.e. time and cross section dimensions) instead of only one dimension (i.e. time series dimension). Panel unit root tests of PPP have re-affirmed the existence of this parity condition in some studies. However, the empirical evidence favouring PPP in most of the studies using panel unit root tests might be overvalued due to cross section dependence (O'Connell, 1998).

One of the objectives of this thesis is to consider cross section dependence by extending the bootstrap panel unit root proposed by Maddala and Wu (1999) and apply the latter to a panel of twenty OECD real exchange rates. We also use Monte Carlo simulations to examine the size properties of the proposed bootstrap panel test.

If on one hand the literature on testing for PPP by using panel unit root tests is wide, on the other hand very little has been done on testing for cointegration between nominal exchange rate and domestic-foreign prices in a panel context. We shall also address this issue by using some new, heterogeneous, and more powerful panel cointegration tests. Furthermore, we also test for the joint symmetry and proportionality restriction by using likelihood ratio tests extended to a panel context.

As we have pointed out above there exists a large literature on PPP, but most of the analysis conducted has been undertaken on OECD countries. Studies of PPP using data for developing countries are limited. In addition, very few of the studies have used black market exchange rates. One of the main objectives of this thesis is to investigate the validity of PPP in developing countries using black market exchange rates. We construct and use a unique data set consisting of twenty emerging market economies and black market nominal exchange rates, spanning over 1973M1-1993M12. As far as we know such a big data set has never been used in the studies of PPP using black market nominal exchange rates. Furthermore, we use new developed panel unit root and cointegration tests.

Another unresolved puzzle in the PPP literature is the low degree of mean reversion of the real exchange rate towards PPP. In fact, if deviation from PPP were due to monetary factors, one would expect a much faster degree of mean reversion of the real exchange rate towards PPP than what reported in the literature (i.e. 3-5 years). Rogoff called this "the purchasing power parity puzzle". We investigate the PPP puzzle in emerging markets using black market real exchange rates and econometric techniques, such as median unbiased estimation and impulse response function, that have been shown to be more appropriate to measure persistence of the real exchange rate (Murray and Papell, 2002). We also employ non-parametric bootstrap to construct confidence intervals for half-lives.

Chapter 1

Introduction

The concept of purchasing power parity (PPP) is attributable to Cassell who formulated this theory in the 1920s. The PPP hypothesis relies on the idea that goods market arbitrage enforces parity in prices across countries. Most economists have "warm, fuzzy feelings" (Rogoff, 1996) towards this proposition. In fact, until the late 1980s, evidence in support of PPP was quite scant (Frankel, 1979, Frankel, 1981). Economists have now accepted the idea that PPP performs poorly in the short run and as a consequence have looked at PPP as a long-run issue (MacDonald, 1996, Mark, 1990).

There exists a vast literature on testing Purchasing Power Parity (PPP). Any test is conditional on a particular econometric specification, which assumes a set of auxiliary assumptions. Recent developments in time series econometrics, such as unit root, cointegration, and their extensions, have provided appropriate tools to conduct tests of the PPP relationship. Researchers have tested long-run PPP employing a large variety of both univariate and multivariate tests. Early tests such as ADF (Augmented Dickey Fuller), and Johansen maximum likelihood, have indicated little support for long run PPP, especially for the recent floating exchange period. This is mainly due to the relatively small samples employed. However these kind of tests are problematic, because they do not have sufficient power to reject the null hypothesis (Froot and Rogoff, 1995).

Two approaches designed to deal with the power problem have been tried in the literature; one is to look at the number of currencies simultaneously to exploit the cross sectional dimension of the data. The second approach is set-up to look at long-horizon data sets encompassing both pre-and post Bretton Wood data. Many researchers employing longer time series have been able to reject the unit root hypothesis (Lothian and Taylor, 1996). However both these approaches are subject to different drawbacks. In fact, using longer time series it will be likely that the basket used to construct the prices indices is very different at the beginning and at the end of the sample. Moreover, such studies suffer from spanning both fixed and flexible rate regimes. On the other hand, asymptotic distributions of panel estimators are derived under the assumption of no cross section dependence. It is currently well documented in the literature that when that assumption is relaxed the distribution of panel unit root tests is unknown (Maddala and Wu, 1999).

Maddala and Wu (1999) suggest a panel unit root test which permits heterogeneity of the autoregressive root under the alternative hypothesis. They argue that while the Im et al (1997) test relaxes the assumption of homogeneity of the root across the units, several difficulties still remain. In fact, the Im et al (1997) test assumes that T is the same for all the cross units, and hence it requires a balanced panel. Again, Im et al allows for a limited amount of cross correlation across units by allowing for common time effects. Maddala and Wu point out that, practically, the cross correlations are unlikely to take the simple form assumed by Im et al. They proposed the P_λ test and show that this test is more powerful than the Im et al (1997) t-bar test. However, this test, as well as Im et al tests, suffers from cross correlation. Maddala and Wu suggest bootstrap methods to obtain the empirical distribution of the test.

O`Connell (1998) has criticized those panel unit root tests that assume that contemporaneous innovations in different cross sectional units are uncorrelated. Heterogeneous cross sectional dependence can be accommodated in two ways. First, one can express all variables as deviations from time specific means, as in the demeaned version of the Im et al t-bar test. Second, as O` Connell suggests, one can use the feasible GLS (FGLS) estimator to take into account cross sectional dependence. Using such an approach, O`Connell rejects the long run PPP, but his results have been reversed by Higgings and Zakrajsek (2000). They show, by using Monte Carlo method, that O`Connell`s truncation lag selection procedure leads to an over parameterization of the AR and thus to a lack of power.

While most of the empirical literature on PPP, using panel data, focuses on searching for mean reversion in the real exchange rate, little has been done using cointegration tests. The only exceptions are Pedroni (1997) and Canzoneri et al (1999). The literature on testing for cointegration, in panels has taken two directions. The first approach is to take as null that of cointegration and this is the basis of the test proposed by McCosket and Kao (1998). The second is to take as the null hypothesis that of no cointegration (Pedroni, 1997 and 1999). Of these two tests the McCoskey and Kao (1998) has never been applied to long run PPP.

However, all the panel cointegration tests presented above are residual based tests that, using a normalization procedure, restrict the cointegrating vector to be unique. A panel cointegration test that allows for multiple cointegrating vectors is the one proposed by Larsson et al (2001). They proposed a likelihood ratio test in panels, and derive the limit distribution of this test showing that the latter, under an appropriate standardization, is a normal distribution. Again there has been no applications of the Larsson et al (2001) to test PPP.

The above critiques of the econometric methodologies used to test PPP, should be placed in a context where the evidence from panel unit root tests on PPP (and also cointegration tests, see Pedroni, 1997) is mixed. In fact, while some of the studies using panel unit root tests support mean reversion in real exchange rate (Wu, 1996, MacDonald, 1996 and Papell et al, 1988), others challenge this consensus favoring the real exchange rate (O`Connell, 1988, Papell, 1997). The fact that the literature on PPP is mixed constitutes a puzzle, and this is one of the PPP puzzles.

Rogoff (1996) has noted that, even where researchers are able to uncover evidence in favor of long-run PPP, the speed of adjustment appears to be too low (generally 3-5 years). The speed of adjustment of real exchange rates is irreconcilable with the speed of adjustments of nominal variables in response to exogenous shocks in industrialized countries. A related puzzle therefore arises in that, if real exchange rates were driven by financial factors, they should adjust much faster that the empirical literature on exchange rate suggests (Rogoff, 1996). Researchers have explained this low speed of mean reversion by considering productivity factors, sticky prices and transaction costs. One encouraging factor is that some panel unit root methods suggest shorter half-lives that those found in the standard literature. Since movements in the real exchange rate may be viewed as deviations from PPP, Rogoff uses the expression the "purchasing power parity puzzle" (Rogoff, 1996).

Whilst the vast majority of the studies presented above have been concerned with exchange rates in the advanced Western industrialized economies, little attempt has been made to assess the generality of these conclusions for emerging market economies. These countries are characterized by different monetary and exchange rate regimes, higher inflation, capital controls, exchange rate control, trade restrictions and currency crises. Furthermore, in most of these countries the volume of transactions taking place on the unofficial market (black market) is much higher than the volume of transactions taking place on the official market. The distributional properties of black market exchange rates have attracted much attention in the recent years, since these are frequently subject to episodes of pronounced turbulence, partially due to political, economic and financial instability.

There are no studies using black market exchange rates for emerging markets economies in a panel context, except Luintel (2000). In this paper, the author tests PPP using a panel of eight Asian real exchange rates, assuming the US$ as the numeraire currency and using the Im et al (1997) tests only. Also, he allows for cross sectional dependence by using the demeaned procedure as suggested by Im et al (1997). The study finds evidence of mean reversion in the real exchange rate.

This thesis investigates long-run PPP in OECD countries and emerging markets. Its mean objectives are: (a) to review some of the econometric methodologies we have mentioned above and account for what, in our view, are the major issues that have been neglected by the empirical literature on PPP. Since the homogeneity assumption underlying most panel unit root tests (see for example the Levin and Lin ,1993 tests) is too restrictive, especially under the alternative hypothesis, we account for this issue by implementing a new heterogeneous panel unit root test (i.e. the Maddala and Wu, 1999 tests). We also account for cross section dependence; (b) to use new, more powerful and heterogeneous cointegration tests that have never been used to test PPP. In fact, as we pointed out above, empirical evidence on PPP using panel cointegration tests is very limited. (c) To apply these econometric methodologies to two different data sets. Mainly a panel of twenty OECD monthly nominal exchange rates and a panel of twenty black market exchange rates of emerging market economies. This will allow us to compare real exchange rate behavior between developed and developing countries. (d) To investigate half-lives in the real exchange rate of developing countries. In fact, as also highlighted above, if a literature on half-lives in industrial countries does exist, very little has been done on assessing persistence of real exchange rates in emerging markets, and in particular, using black market exchange rates. To achieve this goal we use new, and more appropriate econometric methodologies such as median unbiased estimation, impulse response function, and non parametric bootstrap.

This thesis is arranged in the following order. Chapter 2 is essentially a critical review of the panel data methodology used to test PPP. With regard to PPP we shall show that evidence supporting PPP is mixed, and the issue of whether or not long-run PPP holds is not decisively settled. With regard to panel data econometrics, we attempt to analyse some of the most important open issues of non-stationary panel data, focussing mainly on cross sectional dependence, and between group dependence of innovations. We attempt to characterise different sources that generate cross sectional dependence and consequently non-diagonal covariance matrix. Furthermore, we stress that in the presence of a non-diagonal covariance matrix, size distortion in unit root tests increases the likelihood of type 1 error. Panel tests that assume i.i.d. disturbances suffer from severe size biases. That is, the derived distributions are not valid and should not be used to make inference.

Chapter 3 deals more specifically with cross sectional dependence, between group dependence of innovations and non-diagonal covariance matrix. The econometric techniques, proposed in the literature to deal with cross sectional dependence, do not characterise the source(s) of cross sectional dependence. As far as we know, only two papers have addressed the issue, and these are Bai (2001) and Chang (2002). Chang (2001) models cross sectional dependence as caused by omitted variables correlated with the included regressors, and suggests a panel unit root IV estimation procedure. Bai (2001) models cross section dependence throughout common stochastic trends. He assumes cross section dependence to be caused by common factors correlated with the included regressors. However, as we observed, it is possible that the cause of a non zero covariance matrix is due to an omitted variable that is independent of the included regressors (for example world shocks). If this is the case, removing correlations between different units does not make the covariance matrix diagonal. We believe that in this case bootstrap may still be a valid alternative. Non parametric bootstrap has the advantage, with respect to Monte Carlo methods, that we are not forced to make any assumptions regarding a specific data generating process (DGP) for our data.

We extend the non-parametric bootstrap methodology proposed by Maddala and Wu (1999) and apply the resulting panel unit root test to two OECD panels; Consumer Price Index (CPI) and Wholesale Price Index (WPI). Our proposed bootstrap methodology is based on bootstrapping an AR process while the bootstrap algorithm proposed by Maddala and Wu (1999) is based on bootstrapping a moving average process, requiring in this way an arbitrary choice with respect to the lag truncation. Furthermore, we use Monte Carlo simulation to analyse the size distortion of the proposed bootstrap test.

Chapter 4 analyses the problem of heterogeneity in panels by using new heterogeneous panel cointegration tests (McCoskey and Kao, 1998; Pedroni, 1997; Larsson et al., 2001). The Larsson et al (2001) test allows for multiple cointegrating vectors, so enabling us to investigate the possibility of more than one cointegrating vector in PPP. Furthermore, we investigate the joint symmetry and proportionality restriction with likelihood ratio tests extended to a panel context. The latter will permit us to shed some light on the empirical validity of a restriction that is implicitly imposed on the unit root tests of the real exchange rate. In fact, the non rejection of the unit root null may be due to the violation of the joint symmetry and proportionality restriction.

Chapter 5 deals with black market exchange rates (US$ based exchange rates). The main contribution of this chapter is to construct and use a unique panel of monthly black market exchange rates, for twenty emerging market economies, in order to test for PPP. In fact, despite the huge amount of empirical works on PPP using OECD official data, very little has been done to test PPP using black market data and emerging market economies. This chapter is an attempt to fill this gap in the PPP literature. Additional contributions come from using a battery of panel unit root and cointegration tests to test PPP. We also test for the joint symmetry and proportionality restriction using likelihood ratio inference extended to panel context.

Chapter 6 investigates persistence in the black market real exchange rate. We calculate half-lives of the black market real exchange rate in emerging market economies. Following Murray and Papell (2002), we allow for serial correlation in the structure of our data, and use different methodologies (i.e. median unbiased estimation, bootstrap and impulse response function). We also support our point estimates of half-lives with bootstrap confidence intervals. However, we implement the bootstrap methodology used in Murray and Papell (2002) by using non-parametric bootstrap. These econometric methodologies will allow us to investigate the persistence of the real exchange rate in developing countries. The main contributions of this chapter consist of the fact that there is no other empirical study assessing persistence in the black market real exchange rate in emerging markets. Furthermore, we implement and use more appropriate econometric techniques to measure persistence in the black market real exchange rate. An additional contribution is the use of Monte Carlo simulation to construct quantiles of the median function which can be used by other studies applying exact median unbiased estimator.

Finally, Chapter 7 summarises the main findings of this thesis and Chapter 8 considers future research and extensions.

CHAPTER 2

ECONOMETRIC APPROACHES TO TESTING PPP

2.1 Introduction

The concept of Purchasing Power Parity (PPP) is attributable to Cassel who formulated this theory in 1920s. Fundamentally, PPP rests on the notion that the exchange rate depends on relative price levels. Researchers have tested long run PPP employing a large variety of both univariate and multivariate tests. Early tests such as the ADF (augmented Dickey Fuller) and Johansen maximum likelihood methods have indicated little support for relative PPP. The problem with these tests is that they do not have sufficient power to reject the null hypothesis.

The power problem in unit root tests is very important and is still an open issue. In fact, while Froot and Rogoff (1995) suggest that unit root tests fail to reject the null hypothesis because of the lack of data, Ng and Perron (1999) suggest that the low power problem in unit root tests is to be attributed to the model under consideration. If the model is highly persistent, that is, its dominant root is close to, but not exactly equal to unity, unit root tests will tend to lack power. However, the lack of data remains a genuine problem. In order to improve the power of time series tests, researchers have suggested using panel unit root tests and have found some evidence supporting mean reversion in real exchange rate. Of these procedures, those developed by Levin and Lin (1993) have been widely used. However, tests using the Im et al (1997) procedure are becoming more popular. New multivariate tests have been proposed recently by Larsson et al (2001) and Pedroni (1997).

Although panel unit root tests and panel cointegration tests have improved the power of unit root and cointegration tests, nevertheless, it became clear to researchers that they are not the "panacea" they had hoped. In fact, the asymptotic distributions of many panel unit root and panel cointegration tests are based on the assumption that error terms are not cross-correlated. When this assumption is violated the asymptotic distributions of these tests are no longer valid. Maddala and Wu (1999) and Pedroni (1999) made an important contribution to the debate on cross sectional dependence. Maddala and Wu suggest using the bootstrap distribution to make inference, while Pedroni advices using GLS-based corrections.

Also, the hypothesis of homogeneity across sectional units assumed by many tests is too restrictive in many cases. For example, in the case of PPP, the homogeneity hypothesis would imply, under the alternative hypothesis of stationary, that the speed of convergence to PPP is the same for each country in the panel. This assumption is too restrictive because even if each real exchange rate in the panel converges to PPP, it would be incredible to think that they all converge at the same rate. The papers by Im et al (1997) and Pedroni (1999) make an important contribution to this issue. In fact, they allow for heterogeneity across the sectional units.

A further issue, which is worthy of further investigation, is that many cointegration tests do not allow for multiple cointegrating vectors because the cointegrating vector is considered to bê unique. One of the papers attempting to address this issue, is Larsson et al (2001). The issue of multiple cointegrating vectors may also be relevant when we test PPP using panel cointegration methods.

The aim of this chapter is critically to review some of the most common econometric methodologies used in the literature to test long run PPP, with the focus being mainly on panel unit root and cointegration tests. However, in reviewing these econometric techniques this chapter will also summarise some empirical works, which have made an important contribution to the PPP debate. Papell (2002) made one of these contributions. He presented evidence that panel unit root tests fail to reject the unit root null hypothesis when the US dollar is the numeraire currency because of the presence of structural change. If this is the case, then we need to construct unit root tests, which account for structural changes. In addition, these tests should be also consistent with long-run PPP.

This chapter is organised as follows. Section 2 discusses the PPP doctrine. Section 3 applies some unit root and cointegration tests in order to test PPP. Section 4 discusses unresolved issues in unit root and panel unit root tests. Section 5 concludes.

2.2 **Purchasing Power Parity (PPP)**

PPP suggests that, once converted to a common currency, national and foreign price levels should be equal. This concept relies on the idea that goods market arbitrage enforces parity in prices across countries. The doctrine of PPP can be illustrated by making a distinction between absolute and relative PPP.

2.2.1 **Absolute PPP**

The starting point for most derivations of PPP is the law of one price (LOP), which states that for any good i

$$P_i = SP_i^* \tag{2.1}$$

where P_i is the domestic currency price of good i, P_i^* is the foreign currency price, and S is the domestic currency price of foreign exchange. Equation (1) states that the domestic price of good i is equal to the price of the same good abroad multiplied by the nominal exchange rate (S).

Absolute PPP states that the exchange rate is a ratio of domestic price level and foreign price level:

$$S = P / P^* \tag{2.2}$$

where S is the nominal exchange rate as defined above, P is the domestic price level and P^* is the foreign price level. Often equation (2.2) appears in logarithmic form as:

$$s = p - p^* \tag{2.2A}$$

where lower case letters denote natural logarithms.

The question of an appropriate measure for PPP is a very important issue. Governments do not construct indices for an internationally standardised basket of goods, and only domestic indices are available, which are constructed differently. Furthermore, government price data are constructed in the form of indices relative to a base period. Because the indices give no indication of how large absolute PPP deviations were for the base period, one must assume that absolute PPP held on average over that period. On a practical level, relative PPP is used to overcome these problems. Thus, even if countries use different price weights, changes in relative price levels will be reflected in the relative price index.

2.2.2 **Relative PPP**

Relative PPP requires that changes in relative price levels be offset by changes in the nominal exchange rate:

$$\Delta p_t = \Delta p_t^* + \Delta s_t \tag{2.3}$$

One of the most important task researchers face when testing PPP by using, for example, equation (2.3), is the choice of a price index to measure the nominal exchange rate. The choice of an appropriate price index is very important, since defining the exchange rate in one way rather than another we reach different conclusions[1]. Broadly speaking we can generalise the issue saying that if the exchange rate is considered as the relative price of traded commodities the appropriate

[1] For example, the empirical evidence of stationarity of the CPI based real exchange rate is much stronger than WPI real exchange rate. This is because the CPI index contains a larger proportion of tradable goods.

price index should include only traded goods. If the exchange rate is considered as an asset price and a broad price level index is adopted, this will include both traded and non-traded goods and services. However, if the exchange rate, as an asset price, is the relative price of two currencies, the appropriate price index is a broader one such as the gross national product (GNP) deflator or the consumer price index (MacDonald, 1994).

2.3 **Econometric Techniques to Test for PPP**

As we have mentioned in the introduction, different methodologies have been used to test long-run PPP. In this section we present some of the main econometric techniques[2] and highlight the empirical evidence they have provided. For reason of space, after a brief introduction of univariate methodologies, we focus mainly on panel unit root and cointegration tests, summarising the empirical evidence provided by these tests.

2.3.1 **Dickey-Fuller and Augmented Dickey-Fuller Tests**

Consider the following model:

$$q_t = \alpha + \beta q_{t-1} + u_t \tag{2.4}$$

[2] Note: For reason of space we only focus on panel tests of PPP, and we do not consider tests based on the Markov regime-switching model for the exchange rate Klaassen (1999) as well as tests that account for non-linearity.

where q_t is the log real exchange rate. Let us take q_{t-1} away from each side of (2.4):

$$\Delta q_t = \alpha + \beta^* q_{t-1} + u_t \qquad \beta^* = \beta - 1 \tag{2.5}$$

We test H₀: $\beta = 0$ against H$_A$: $\beta < 0$ in (2.5). This test is known as a unit root test. The problem is that if we apply the t-ratio to the (2.5) under the null hypothesis of non-statiorarity, the t-ratio has a non-normal distribution, and so conventional critical values are not valid. Dickey and Fuller performed simulation studies to tabulate the small-sample distribution of the t-ratio under the null hypothesis.

In the above discussion we have assumed that the time series can be modelled as a first order AR process. Suppose now to regress q_t on a constant and lagged changes in q_{t-1}:

$$q_t = \alpha + \beta q_{t-1} + \theta(L)\Delta q_{t-1} + u_t \tag{2.6}$$

where L is the lag operator, θ(L) is a pth order polynomial in L, and u_t is a white noise. Equation (2.6) represents the augmented Dickey Fuller equation. We test the null hypothesis H_0: $\beta = 1$ against the alternative hypothesis H_A: $\beta < 1$.

Most of the literature on PPP in the 1980`s was based on this methodologies (i.e. DF-ADF tests). To understand the reason, consider the following model of the real exchange rate:

$$q_t = s_t - p_t + p_t^* \tag{2.7}$$

where s_t is the logarithm of the nominal exchange rate, p_t the logarithm of the domestic price levels and p_t^* the logarithm of the foreign price levels. In the above model, the real exchange rate can be viewed as deviations from PPP. In fact, if we compare (2.7) with (2.2A), we note that for PPP to hold the real exchange rate should be zero. This means that any shocks on the real exchange rate should die out in the long-run, so that the real exchange rate reverts to its long run equilibrium that is given by PPP. It is on the basis of this that researchers have used unit root tests of the real exchange rate to test long-run PPP. The null hypothesis becomes that the real exchange rate follows a random walk (has a unit root), the alternative hypothesis is that PPP holds in the long run. The null hypothesis that real exchange rate follows a random walk is according to Rogoff: "a sensible null hypothesis because real exchange rate changes, like changes in asset prices, should not be predictable if foreign exchange markets are efficient".

The basic result in the empirical literature is that researchers failed to reject the null of a unit root during the recent float period for bilateral rates against the US dollar, but not for European currencies against the Deutsche mark, (see for example Mark 1990, Meese and Rogoff 1988). The difficulties researchers had in rejecting the null hypothesis are something of an embarrassment. In fact, even if one assumes a monetary shock, and there are short-term rigidities in domestic nominal prices, long-term monetary neutrality implies that any effects on the real exchange rate should die out in the long run. The major concern with unit root tests and is that they lack sufficient power to reject the null hypothesis. In fact, the post Bretton Woods period is too short to reject the random walk hypothesis (data is not sufficient to reject the random walk null hypothesis). In order to deal with low power in unit root tests researchers have proposed two different approaches. One is to use longer time series and the other to use panel data.

Frankel (1986) uses 116 years of data for the dollar/pound real exchange rate. He finds that the first order autoregression yields a coefficient of 0.85, which implies that PPP deviations have an annual decay rate of 14% and a half life of 4.6 years. Lothian and Taylor (1996) using 100 years of annual data find evidence of mean reversion with an average half-life of 4 years. Lothian and Taylor`s results have been challenged by Cuddington and Liang (1997). They show that the AR(1) stationary model proposed by Lothian and Taylor is misspecified. In general, Cuddington and Liang (CL) propose a procedure based on GTS methodology (from general-to-specific) in choosing both the optimal lag length and the correct model.

Consider the following model:

$$\Delta q_t = \alpha_0 + \alpha_1 t + \gamma q_{t-1} + \sum_{i=1}^{p} \beta_i \Delta q_{t-i} + \varepsilon_t \qquad (2.8)$$

The above model includes both the intercept and time trend. In fact, according to Cuddington and Liang, it is important to allow for the possibility of a deterministic trend in the real exchange rate since non-stationarity can take the form of unit root, structural break or deterministic trend. If PPP holds, we reject the unit root hypothesis and the trend should not be significant. On the other hand, if the null hypothesis of a unit root is not rejected, in the general model, then the significance of the trend and intercept can be tested to see if they can be omitted. They also use the GTS methodology to select the lag length (p). The procedure is the following: we start with a large number of lags, examine the t-statistic on the last lag, if it is not significant, drop the last lag and rerun the test on the above equation. Based on this procedure CL show that the long-run PPP does not hold for the dollar-sterling exchange rate.

However the literature on PPP presented above, as well as the methodologies they use, suffer for different problems. In fact, using longer time series it will be likely that the basket used to construct the price indices is very different at the beginning and at the end of the sample. Again, such studies suffer from spanning both fixed and flexible rate regimes. Considering these reasons many researchers have suggested using panel methods.

2.3.2 **Panel Unit Root Tests**

An alternative approach to improving power is to extend the number of cross sectional units. In particular, researchers have suggested using panel data. A standard panel framework for PPP is:

$$s_{it} = \alpha + \beta(p_{it} - p_{it}^{*}) + (\Sigma_i D_i) + (\Sigma_t \delta_t D_t) + u_{it} \qquad (2.9)$$

where the i is the data cross sectional dimension and D_i and D_t are dummy variables, which denote, respectively, country specific and time series specific effects. A panel offers a certain number of advantages over traditional time series data. The most obvious advantage is that the number of observations is much larger in panel data.

Panel data may alleviate the problem of multicollinearity. In fact, when the explanatory variables vary in two dimensions they are less likely to be correlated. Panel data reflect long-run behaviour while time series data emphasise short run behaviour. Again, panel data may alleviate spurious regression problems (Phillips and Moon, 1999) .

Levin and Lin (1993) (LL) have started a growing literature on panel data. They developed two tests (LL1 and LL2). Levin and Lin consider the following model:

$$\Delta q_t = \alpha_i + \phi_t + \beta q_{t-1} + c_i t + \xi_{it} \qquad (2.10)$$

The model allows for fixed effects and unit-specific time trends in addition to common time effects. It is a direct extension of a univariate DF test to panel data setting. It restricts the speed of convergence to long run equilibrium under the alternative of stationarity to be the same for all countries. Furthermore, errors are assumed to be independent across the units and follow an invertible ARMA process:

$$\xi_{it} = \sum_{j=1}^{\infty} \theta_{ij} \xi_{it-j} + \varepsilon_{it} \qquad (2.11)$$

LL consider the use of pooled cross-section time series data, to test the null hypothesis that each individual time series contains a unit root, against the alternative hypothesis that each time series is stationary. Since β is assumed to be the same for all observations this is the same as testing the following null and alternative hypotheses:

$$H_0: \beta_1 = \beta_2 = ...\beta_N = 1$$

$$H_1: \beta_1 = \beta_2 = ...\beta_N < 1$$

The fact that β is assumed to be the same for all observations represents a very important limitation of the LL1 test (Maddala and Kim 1998). Furthermore both N and T are assumed to be sufficiently large, and T increases faster than N such that $N/T \to 0$ as both N and T $\to \infty$[3].

Finally, since the test requires that the data are generated independently across individuals, LL show that this assumption can be relaxed to allow for limited degree of dependence via time-specific effects. The influence of these effects can be removed by subtracting the cross-section average $y_t^A = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ from the observed data.

The removal of cross section averages from the data does not affect the limiting distributions of the panel unit root and cointegration test statistics.

The strong assumptions described in the LL1 test have led those authors to develop a second test (LL2) with fewer restrictions. Levin and Lin show that the assumption of no serial correlation, for example, can be relaxed. In fact they show that adding lags of Δq into a DF regression does not affect the limiting distribution of the test. Furthermore, thw LL2 test allows autoregressive parameter under the alternative hypothesis to vary across individual countries. The model corresponds to an unrestricted ADF model:

$$\Delta q_{it} = \alpha_i + \beta_i q_{i,t-1} + \sum_{k=1}^{m(i)} \lambda_{i,k} \Delta q_{i,t-k} + u_{i,t} \qquad \text{i=1,..N t=1,..T} \qquad (2.12)$$

Three steps are required to obtain the test statistic t_B^* .

Step 1: Estimating $\hat{t}_B$ by partitioning (2.12) as follows .

$$\Delta q_{it} = \alpha_i + \sum_{k=1}^{m(i)} \lambda_{i,k} \Delta q_{i,t-k} + e_{i,t} \Rightarrow e_{i,t}^*$$

$$q_{it-1} = \alpha_i + \sum_{k=1}^{m(i)} \lambda_{ik} \Delta x_{it-j} + v_{it-1} \Rightarrow v_{it-1}^*$$

The regression of e_{it}^* on v_{it-1}^* is estimated to derive β_i^* :

$$\hat{e}_{it}^* = \beta_i v_{it-1}^* + u_{it}$$

Since residual in the partitioned regression above may display a large variance due to the heterogeneity of series used, LL suggest the following adjustment:

$$\bar{e}_{it} = \frac{e_{it}^*}{\sigma_{ui}^*} \qquad \text{and} \qquad \bar{v}_{it-1} = \frac{v_{it-1}^*}{\sigma_{ui}^*}$$

where $\hat{\sigma}_{ei}^* = (T - m_i - 1)^{-1} \sum_{t=m_i+2}^{T} (e_{it}^* - \beta_i^* v_{it-1})^2$

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[3] Harris and Tzavalis (1999) derive the limiting properties of unit root tests when T is fixed, that allows the derivation of exact moment of the distribution.

Step 2: For each series, compute the long run variance: .

$$\sigma_{qi}^{*2} = (T-1)^{-1}\sum_{t=2}^{T}\Delta q_{it}^{2} + 2\sum_{L=1}^{K}\omega K_{L}(\frac{1}{T-1}\sum_{t=2+L}^{T}\Delta q_{it}\Delta q_{it-L})$$

$$\omega = \frac{1-L}{K+1} \qquad \text{and} \qquad K = 3.21T^{1/3}$$

Using the long run variance compute the ratio of the estimated long run variance and standard deviation:

$$s_{i}^{*} = \frac{\sigma_{qi}^{*}}{\sigma_{ei}^{*}} \qquad \text{and} \qquad S_{N}^{*} = \frac{1}{N}\sum_{i=1}^{N}s_{i}^{*}$$

Step 3: Estimate the panel regression (for all i and t) and compute the test statistic:

.

$$\bar{e}_{it} = \beta \bar{v}_{it} + u_{it}$$

$$t_{B=0} = \frac{\beta^{*}}{RSE(\beta^{*})} \tag{2.13}$$

where

$$RSE(\beta^{*}) = \sigma_{u}^{*}[\sum_{i=1}^{N}\sum_{t=mi+2}^{T}\bar{v}_{it-1}^{2}]^{1/2}$$

$$\sigma_{u}^{*2} = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=mi+2}^{T}(\bar{e}_{it} - \beta^{*}\bar{v}_{it-1})^{2}$$

The LL adjustment of (2.13) is given by:

$$t_{\beta*} = \frac{t_{\beta=0} - NTS_N^{*}\sigma_u^{*-2}RSE(\beta^{*})\mu_{mT}}{\sigma_{mT}}$$

where μ_{mT} and σ_{mT} are mean and standard deviation adjustments computed by Monte Carlo and tabulated in their paper.

As with the LL1 test, homogeneous cross sectional dependence can be accommodated by expressing all variables as deviations from their time specific means[4].

In summary, the Levin and Lin tests contain more or less all the elements that are font of discussion in the literature. For example, the necessity of focusing on the rate at which T and N are permitted to tend to infinity, homogeneity versus heterogeneity across i, the assumption that the error terms are independent across i, and the correction required in the presence of serial correlation.

Im et al (1997) proposed a unit root test for heterogeneous dynamic panels based on the mean-group approach. The Im et al unit root test is similar to LL2 test, in the sense that it allows for heterogeneity across-sectional units. The heterogeneous panel data model is the following:

[4] Researchers have largely employed the methodology developed by Levin and Lin and found support for the validity of long run PPP (MacDonald 1996, Wu 1996 and Oh 1996). O`Connell (1998) extends the results of Levin and Lin. He demonstrates the importance of accounting for cross-sectional dependence among real exchange rates when testing for long-run PPP. He suggests using a feasible GLS (FGLS) estimator. Using such an approach he finds a blanket rejection of long-run PPP but his results have been reversed by Higgins and Zakrajsek (2000). They show, using Monte Carlo methods, that the O`Connell truncation lag selection procedure leads to an overparameterisation of the AR and thus a lack of power.

$$\Delta q_{it} = \alpha_i + \beta_i q_{i,t-1} + \sum_{k=1}^{p} \phi_{i,k} \Delta q_{i,t-k} + \gamma_i t + u_{it} \qquad (2.14)$$

i=1,...,N; t=1,...T

The model allows the speed of convergence to long run equilibrium to vary across countries[5]. The relevant hypotheses are:

H_0: $\beta_i = 0$, H_1: $\beta_i < 0$ i=1, ...N_1 ; $\beta_i = 0$, i=N_1+1, N_1+2,...N

Then, instead of pooling the data, we can perform separate unit root tests for the N cross units. Consider the t-test for each cross-section unit based on T observations. Let t_i, i=1,2...N denote the t-statistics for testing unit roots, and let $E(t_i)=u$ and $var(t_i)=\sigma^2$ then:

$$\sqrt{N}\frac{t-u}{\sigma} \qquad (2.15)$$

Since, the problem one faces in using (2.15) is computing u and σ^2. Im et al computed them by Monte Carlo. Assuming that the cross sections are independent, Im et al derived the following standardised t-bar statistic:

$$t^* = \frac{\sqrt{N(T)}(t_T - E(t_T))}{\sqrt{VAR(t_T)}} \qquad (2.16)$$

[5] Since the Levin and Lin work, there has been a growing interest in the literature on panel data for heterogeneous panels.

where t_T is the average t-statistic performed on each individual unit. $E(t_T)$ and $Var(t_T)$ are mean and variance of the average t statistic that they tabulated in their paper.

Im et al state that the standardardized t-bar statistic converges in probability to a standard normal distribution as T, N→∞ with a rate of convergence equal to $\sqrt{N}$. Therefore we can compare the t-statistic obtained to the critical values from the lower tail of the normal distribution.

Since the main result obtained by Im et al (1997) requires observations to be generated independently across sections, and this assumption is likely to be violated, they propose the following adjustment. Assume that the error term in equation (2.14) is composed of two random components:

$$u_{it} = \vartheta_t + \varepsilon_{it} \tag{2.17}$$

where ϑ_t is a stationary, time specific common effect and ε_{it} is an idiosyncratic random effect. To deal with cross sectional dependence in disturbances they propose subtracting cross sectional means from the observed data.[6]

Im et al also provide a second test that is called LM-bar statistic (Lagrange Multiplier):

[6] This procedure is the same as the one we have mentioned for LL1 and LL2.

$$LM = \frac{\sqrt{N(T)}(LM_T - E(LM_T))}{\sqrt{VAR(LM_T)}} \tag{2.18}$$

where E(LM) and VAR(LM) are the asymptotical values of mean and the variance of the average LM statistics tabulate by Im et. al.[7]

Monte Carlo experiments on the Im et al (1997) test have shown that generally, the t-bar test tends to have low power for small T. Furthermore, in comparison with the LL2 test, it is very sensitive to the order of the underlying ADF regressions. Size distortion appears to be a serious matter when the order of the ADF regression is underestimated. However, when the order is overestimated its empirical size is much closer to the nominal size. In contrast, the LL2 test tends to over-reject the null hypothesis in many cases and the problem worsens as N increases. Finally it seems to be affected more by a rise in T than a rise in N (see for example Im et al, 1997, Maddala and Wu, 1999, Karlsson and Lothgren, 2000).

Recently, Karlsson and Lothgren (2000) have demonstrated how the power of panel unit root tests (LL1, LL2, t-bar and LR-bar) depends on the number N of series in the panel, on the number T of time series dimension in each individual series, and on the proportion of stationary series in the panel. For a given proportion of stationary series in the panel, the power increase due to a rise in T is larger than that due to a corresponding increase in N. This means that the probability of rejecting the null hypothesis increases with T. As a consequence for large T we may reject the null even

[7] Tests using the Im et al. procedure have also been used to test PPP (Coakley and Fuertes, 1997). Coakley and Fuertes, applying the Im et al. procedure to a panel of 19 OECD countries in the 1973-96 period found results which support the stationarity of real exchange rate.

if this is not true. On the other hand, for small T we may accept the null when this is false.

A new unit root test has been proposed recently by Koedijk et al. (1998), which tests for absolute PPP. The relevant characteristic of this test is that results are invariant to the choice of a numeraire currency. Assume that PPP does not hold equally well for all currencies in the panel. For each country in the panel we can investigate whether the value of its currency moves proportionally to the price level in that country:

$$q_{ij} = (c_i - c_j) + (\delta_i - \delta_j)t + \beta_i p_i(t) - \beta_j p_j(t) - u_{ij}(t) \qquad (2.19)$$

where c is a constant term, q_{ij} is the real exchange rate, p_i and p_j , denote the log of the domestic consumer price index for country i,j and t is a time trend. Koedijk et al estimate the above equation simultaneously as a system of N equations for N exchange rates assuming that currency j=0 is the common numeraire currency. Furthermore, to circumvent unit root and spurious regressions they consider the hypothesis of relative PPP:

$$\Delta_k q_{ij}(t) = \beta_i \Delta_k p_i(t) - \beta_j \Delta_k p_j(t) + u_{ij}(t) \qquad (2.20)$$

Since all the exchange rates are expressed in terms of a common base currency, in order to obtain more efficient estimates they use a GLS estimator. However, constructing a GLS estimator requires assumptions about the error term, then they assume that the error term in the exchange rate equation is the difference between the error term for country i and the error term for country j:

$$u_{i0} = u_i(t) - u_0(t) \tag{2.21}$$

Furthermore, they assume that country-specific shocks are uncorrelated and have constant variance equal to $\sigma^2/2$:

$$\Sigma = \frac{1}{2}\sigma^2(\mathrm{I} + \Psi^{\prime}) \tag{2.22}$$

with I the identity matrix and $\psi^{\prime}$ the (N×1) vector of ones. Since, under the above assumptions, the covariance matrix is completely specified, a GLS estimator can be used. The covariance structure in (2.22) assumes that all exchange rates in the panel have equal variance and a correlation between exchange rates is ½. The structure of the covariance matrix also ensures that all results are invariant with respect to the numeraire currency (Koeijk and Schotman, 1990)[8].

[8] They apply their procedure to a panel of 17 currencies (1972-1996) and show that evidence favouring PPP is stronger for the German mark and much weaker for the US dollar. However, the Koedijk et al. GLS estimator relies on very simplistic assumptions. Generally the assumption that the country-specific shocks are uncorrelated is a utopia. Shocks across sections (countries), very often, are correlated and are unlikely to be of weak-memory variety (Phillips and Moon, 1999). Coakley and Fuertes (2000) use a different approach. They employ a panel of 19 OECD currencies (1973-1997) and different panel unit root tests to investigate the issue that the base currency effect can be attributed to neglect cross sectional dependence. They found no evidence of the base currency effect if we account for cross

A common element of the unit root tests presented above is that they are invalid in the presence of cross correlation between sections[9]. Bai and Ng (2002b)[10] use a decomposition of data into common components and idiosyncratic components to construct panel unit root tests that are robust to cross sectional dependence. Assume that the observed series q_{it} is generate as follows:

$$q_{it} = D_{it} + \lambda_i' F_t + e_{it} \quad \text{i=1,2,...,N, t=1,2,...,T} \tag{2.23}$$

the observed series is decomposed into three components, a deterministic component (D_{it}), an unobservable factor (F_t) and an idiosyncratic element (e_{it}). The presence of the common factor in (2.23) implies correlations between different groups. Thus pooled tests based on q_{it} are invalid. However, as it is generally assumed in factor analysis the idiosyncratic component is cross sectional uncorrelated, so panel unit root tests can be developed focusing on this latter. For example, the Im et al, 1997 tests on q_{it} would be invalid in this case, but the same tests on e_{it}^* (i.e. the estimate of e_{it} obtained by principal components) is valid. Furthermore, they allow F_t and e_{it} to be integrated of different order. They refer such Panel Analysis of Non-stationary in the Idiosyncratic and Common Components as PANIC (Bai and Ng, 2002b). The basic structure of their methodology can be summarized as follows. Assume data are generated as in (2.24):

sectional dependence. The result is important since it goes in same way to challenging the previous results obtained in a panel context by the empirical literature on PPP.

[9] Note: even the t-bar test is invalid, and this is the reason Im et al proposed a demeaning procedure. But, as we shall see, this procedure is particularly restrictive.

[10] Although there is no application of this methodology on PPP, because of the importance of this test, we shall briefly discuss it in this section.

$$F_{mt} = \alpha_m F_{mt-1} + u_{mt} \qquad m=1,\ldots,k \qquad (2.24)$$
$$e_{it} = \rho_i e_{it-1} + \varepsilon_{it} \qquad i=1,\ldots,N$$

where u_{mt} and ε_{it} are iid and mutually independent. The factor m will not be stationary if $\alpha_m = 1$, on the other hand the idiosyncratic component will be stationary if $\rho_i < 1$. As a consequence they suggest testing the following null and alternative hypotheses

$$H_0 : \rho_i < 0, \text{ for all i}$$
$$H_0 : \rho_i = 1 \text{ for some i}$$

They show that the above null and alternative hypothesis can be tested using the KPSS test developed in Kwiatkowsky et al (1992) on the estimates of the two components (i.e. F^*_{mt} and e^*_{it})obtained by using principal components on equation (2.23).

Furthermore, they also proposed another panel unit root test, based on the SB statistic developed in Sargan and Bhargava (1983), that they call modified SB (MSB). The procedure is the same as before. The test is applied on the estimates of F_{mt} and e_{it} obtained by the method of principal components on equation (2.23), but the null hypothesis being tested now is $\rho_i = 1$ for every i, that implies a unit root null hypothesis.

Monte Carlo simulations on both the panel tests proposed reveals large size distortion for the KPSS test even when it is used to test F_{mt} and e_{it} separately. Thus, this test rejects the stationarity null hypothesis too often. On the other hand the MSB test has good size and good power when it is used to test the components separately[11].

The panel unit root test literature has recently been subjected to a critique by Taylor and Sarno (1998), who show that such tests may have a high probability of rejecting the null hypothesis of joint nonstationarity of real exchange rates when just one real exchange rate series in the panel is mean reverting[12]. The null hypothesis tested by many panel unit root tests is that all of the series are realisations of I(1) processes. Taylor and Sarno (1998) suggested an alternative multivariate unit root test (Johansen JLR test), where the null hypothesis is rejected only if all the series are generated by mean reverting processes.

Consider the following VAR representation:

$$\Delta q_t = \Gamma + \Pi q_{t-1} + \sum_{j=1}^{L} \varphi_i \Delta q_{t-j} + \nu_t \quad \text{t=1,...T} \qquad (2.25)$$

where $q_t = (q_{1t}, q_{2t}, ..., q_{Nt})'$, Γ is an N×1 vector of constants, Π is a N×N long-run multiplier matrix and ν_t is an N×N vector of disturbances and $\nu_t \sim$ i.i.d. $N(0,\Omega)$.

[11] They use this methodology to identify the source of non-stationarity in a panel of 21 quarterly real exchange rates and they find that a large number of exchange rates in the panel have a non-stationary idiosyncratic component.

[12] According to Taylor and Sarno, given the null hypothesis underlying panel unit root tests, the only possible alternative hypothesis is that at least one unit is a stationary process. The consequence of this is that we may end up rejecting the null, even if only one series is stationary. However this is not completely true since the alternative hypothesis underlying panel unit root tests are different and they all depend, crucially, on the degree of heterogeneity we assume. For example, in the LL1 test (that is a homogeneous test), the alternative hypothesis implies that all of the series are stationary processes. If we increase the degree of heterogeneity under the alternative, we may also have that each series as a panel is a

If each of the series is I(1) and no cointegration vector exists the rank of Π is equal to zero. If Π is of full rank this implies that all the series q_t are realisations of stationary processes. The rank of a matrix is equal to the number of non-zero latent roots. In this context, stationarity of all the series means that Π has full rank and so N non-zero latent roots. Taylor and Sarno suggested testing the null that at least one series has a unit root and the alternative that they all are stationary. This is the same as testing the null that Π has less than full rank. Essentially this is a special case of Johansen's likelihood ratio test for cointegration. The Johansen likelihood ratio (JLR) statistic is:

$$JLR = -T \ln(1-\lambda_N) \tag{2.26}$$

They show that the JLR statistic has a known χ^2 distribution with one degree of freedom under the null hypothesis, and that the empirical distribution of the JLR statistic is quite close to the asymptotic distribution for T>100.[13] However, this test is reliable only if it is applied to panel a with small cross sectional dimension.

An alternative test is the one proposed by Maddala. Fisher (1932), developed the original idea for this test, known as the P_λ test. Maddala and Wu (1999) show that this test is more powerful than a t-bar test. The disadvantage of this test is that the significance levels have to be derived by Monte Carlo simulations. Maddala and Wu argue that while Im et al (1997) tests relax the assumption of homogeneity of the root

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stationary process, and also as in the Im et al (1997) test, that some units are stationary while others are not. The most heterogeneous test is the Maddala and Wu (1999) test.

across units, several difficulties still remain. In fact, Im et al. assume that T is the same for all the cross-section units and hence the t-test requires a balanced panel or complete panel, (i.e. where the individuals are observed over the sample period). Again, the Im et al allow for a limited amount of cross correlation across units, by allowing for common time effects. Maddala and Wu point out that, practically, the cross correlation is unlikely to take this simple form. They propose the following test and show that this test is more powerful than the Im et al. t-bar test. Suppose there are N unit root tests. Let π_i be the observed significance level (p-value)[14] for the ith test. The P_λ test has a χ^2 distribution with d.f 2N, $P_\lambda = \sum_{i=1}^{N}(-2\ln\pi_i)$. The advantage of P_λ test is that it does not require a balanced panel. However, this test as well as the Im et al tests, suffer from cross sectional dependence. The important contribution of Maddala and Wu is that they suggest a further statistical procedure to deal with cross–section dependence and between group dependence of innovations. In fact, they suggest bootstrap methods.[15]

[13] Taylor and Sarno apply the JLR test to a small panel of OECD countries (1973-1996) and find significant evidence of mean reversion in each of the real exchange rates.

[14] This is a crucial point, since it distinguishes the Fisher test which is based on combining the significance levels of the different tests and the t-test which relies on combining the test statistics.

[15] However, despite the growing amount of new panel unit root tests, many researchers have simply extended the DF and the ADF tests to a panel context (Lothian, 1997, Frenkel and Rose, 1996, Papell, 1997 and 1998). Papell (2002), in order to consider the larger swings in the US dollar during the 1980, extends the unit root tests in the presence of restricted structural change. Though the results confirm that unit root tests fail to reject the null hypothesis (particularly when the US dollar is assumed as numeraire) because of the presence of structural breaks, they are still mixed.

2.3.3 **Cointegration Tests**

A number of researchers have focused on the application of cointegration to testing PPP by estimating an equation such as:

$$s_t = \alpha + \beta_0 p_t + \beta_1 p_t^* + u_t \qquad (2.27)$$

or when symmetry between domestic and foreign prices was imposed, an equation such as:

$$s_t = \alpha + \beta(p_t - p_t^*) \qquad (2.28)$$

Early applications of cointegration methods to test PPP were based on the following procedure. Considering (2.27), if s_t, p_t, and p_t^*, are integrated of order one, I(1), and residuals are stationary I(0), then weak form PPP exists. Strong form PPP exists if the joint symmetry and proportionality restrictions are also satisfied; $\beta_0 = -\beta_1 = 1$[16]

There has been a plethora of empirical works using cointegration to test PPP and they reached two important conclusions[17]. First, tests based on CPI price levels reject PPP

[16] Taylor (1988) presented an empirical analysis of long-run PPP, for five major exchange rates, using monthly data for the period 1973-1985. He tests strong PPP and shows that this condition is too stringent, in the sense that it implies that 1 percent increase in the relative price will lead to a 1 percent long run depreciation of the exchange rate, and it does not consider measurement error and transportation costs. Taylor, using Engle and Granger (1987) cointegration, obtained results very unfavourable to the PPP hypothesis. The exchange rate and relative prices did not appear to be cointegrated for any of the countries he examined. However, Taylor and MacMahon (1988), using Engle and Granger (1987) cointegration, test PPP during 1920s for a number of bilateral exchange rates, and find support for long-run PPP.
[17] One of the drawbacks of the literature using cointegration is that they restrict the cointegrating vector to be unique. If we consider 2.28 it is easy to see that this is the case.

less frequently than tests based on WPI. Second, the hypothesis of cointegration is more often rejected if we assume the US dollar as a numeraire currency instead of the German Mark DM.

However, the Engle and Granger approach is known to have low power against the null hypothesis of non-cointegration. To increase the power of cointegration tests researchers have used multivariate procedures. Some of the most widely used cointegration tests are due to Johansen. The Johansen procedure identifies the cointegration space and not the unique cointegrating vectors. Once we have determined the cointegrating vectors, we see if they belong to the same space[18].

Johansen proposes two cointegration tests: the trace test and the maximum eigenvalue test. The trace test tests the hypothesis that there are at most r cointegrating vectors. The maximum eigenvalue test tests the hypothesis that there are r+1 cointegrating vectors versus the hypothesis that there are r cointegrating vectors. The maximum of the likelihood function is given by:

Suppose, now, we have a set of k variables y_t which are all I(1) and $\beta' y_t = u_t$ is I(0), then the cointegrating vector is no longer unique. Furthermore, if we assume that we have two cointegrating vectors β_1 and β_2 so that $\beta_1 y_t = u_{1t}$ and $\beta_2 y_t = u_{2t}$ are both I(0), then any linear combination of these vectors is also a cointegrating vector because linear combinations of I(0) variables are I(0). There is an identification problem. In this case, which vector represents the long run relationship. This is an economic matter rather then an econometric one. In fact, econometric theory has very little to say about this point (we shall consider this point in this thesis). In this context the goal of cointegration tests is no longer to identify the long run relationship. One contribution of the cointegration tests is in modelling VAR systems if we are interested in forecasting in VAR systems. In fact, in this case we check the data for the presence of unit roots and cointegration. We may wont to consider this before using cointegration.

[18] For a detailed description of Johansen procedure refer to Stewart and Gill (1998).

$$-2\log L_{\max} T \sum_{i=r+1}^{n} \ln(1-\lambda_i) \tag{2.29}$$

The LR (likelihood ratio) test statistic for the hypothesis of at most r cointegrating vectors is:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\lambda_i^*) \tag{2.30}$$

where $\lambda^*_{r+1},\ldots\lambda^*_n$ are the (n-r) smallest eigenvalues of the determinant equation:

$$\left| S^{-1}_{11} S_{10} S^{-1}_{00} S_{01} - \lambda I \right| = 0$$

The asymptotic distribution of this statistic is given by the trace of the stochastic matrix:

$$\int_0^1 (dW)W'\left(\int_0^1 WW'dr\right)^{-1} \int_0^1 W(dW)' \tag{2.31}$$

where W is a (n-r) dimensional Brownian motion. If we assume a constant and/or a time trend in the VAR model the above equation is replaced in the following way:

$$\int_0^1 (dW)W^{*'}\left(\int_0^1 W^*W'dr\right)^{-1} \int_0^1 W^*(dW)' \tag{2.32}$$

where W* is the demeaned or detrended Brownian motion.

A second test due to Johansen is the maximum eigenvalue test. To test the null hypothesis of r+1 cointegrating vectors versus the alternative of r cointegrating vectors the LR test statistic is:

$$\lambda_{max} = -T \ln (1-\lambda^*_{r+1}) \qquad (2.33)$$

The asymptotic distribution of this statistic is given by the maximum eigenvalue of the stochastic matrix described above[19].

2.3.4 **Panel Cointegration Tests**

While some researchers have applied cointegration to test PPP, others have extended these techniques to a panel framework. The literature on testing for cointegration in panels has taken two directions. The first approach is to take as null that of cointegration and this is the basis of the test proposed by McCoskey and Kao (1998). The second is to take as null hypothesis of no cointegration (Pedroni, 1997, 1999).

McCoskey and Kao (1998) propose a residual based Lagrange Multiplier test for the null hypothesis of cointegration in panel data, to analyse the nuisance parameters

[19] Example of empirical works using Johansen tests to test PPP are Enders and Falk (1998), Coakley and Fuertes (1998) and MacDonald and Marsh (1994). Enders and Falk (1988) use Johansen tests to test long-run PPP between US/Canada, US/Germany, US/France, US/Japan, Germany/France but they do not find strong evidence of weak-PPP. Coakley and Fuertes (1997) apply the Johansen tests to investigate PPP. The results they obtain are quite mixed and these results seem to be consistent with the greater power of multivariate tests over univariate tests.

issue in a single equation model. The model is similar the ones used by Pedroni (1997) and Im et al (1997). Assume that y_{it} is generated as follows:

$$y_{i,t} = \alpha_i + \beta_i x_{i,t}^{'} + e_{i,t} \tag{2.34}$$

where $e_{i,t} = \theta \sum_{j=1}^{t} u_{i,j} + u_{i,t}$

The model allows for varying slopes and intercepts. Residuals are serial correlated. Furthermore, regressors $(x_{i,t}^{'})$ are assumed to be endogenous and generate as follows $x_{i,t} = x_{i,t-1} + \omega_{i,t}$, but non cointegrated (i.e the assumption of no cointegration amongst regressors is maintained). Under the null hypothesis $H_0{:}\theta = 0$ $e_{it} = u_{it}$ and the equation above is a system of cointegrated regressors. McCoskey and Kao (1998) show that the test statistic is an LM type statistic given by (2.35) below:

$$LM = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} S_{it}^2}{s^2} \tag{2.35}$$

where $S_{i,t}$ is the partial sum of the residuals, i.e $S_{it} = \sum_{j=1}^{t} e_{i,j}^{*}$ and s^2 is a consistent estimator of σ^2_u. If we allow for correlation in the error processes[20], s^2 can be estimated using dynamics OLS estimator (DOLS) or the fully modified estimator (FMOLS)[21].

[20] The serial correlation element could be particularly relevant in many empirical applications included applications on PPP.

Define the test statistic based on the FM estimator with LM^F as:

$$LM^F = \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T} S^{F\,2}_{it}}{\varpi^{F2}} \tag{2.36}$$

where $S^F{}_{it} = \sum_{j=1}^{t} e^F_{ij}$

and the long-run covariance matrix as:

$$\varpi^F = \begin{bmatrix} \varpi^F_{11} & \varpi^F_{12} \\ \varpi^F_{21} & \varpi^F_{22} \end{bmatrix}$$

McCoskey and Kao (1998) show that the asymptotic distribution of the LM test in (2.35) is given by:

$$\sqrt{N}(LM^F - u_v) \Rightarrow N(0, \delta_v^2) \tag{2.37}$$

If we estimate s^2 using DOLS estimators we can construct an LM test similar to (2.35) whose limiting distribution is the same as the one given in (2.37). As in Im et al (1997) u_v and σ^2_v can be obtained by simulation. The important result is that the asymptotic distribution above is free of nuisance parameters. Also, the LM^F test seems to be robust to heteroschedasticity.

McCoskey and Kao (1998) study the small sample properties of these tests using Monte Carlo simulation, and they find these tests to perform better, in terms of power,

[21] Generally how we shall see the DOLS estimator performs better than FM estimator.

for large T. Also, when N and T are very close (i.e N=50, T=50) and there is a negative moving average component, the LM-DOLS test has the greatest power, while the LM-FM test has the lowest power.

Pedroni (1996), uses the fully modified OLS principles to deal with the problems of asymptotic bias and nuisance parameter dependency, associated with cointegrating vector estimates in a single equation model, and applies the statistics to test the hypothesis that strong PPP holds for a panel of countries for the post Bretton Woods period[22]. This relationship (strong PPP) is expected to be such that the variables move one-to-one in the long run. Thus the single equation model is:

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it} \qquad (2.38)$$

where y_{it} is the log U.S. nominal exchange rate, and x_{it} is the log aggregate price ratio in terms of the CPI between the two countries[23].

Pedroni (1997) proposes seven different panel cointegration tests. The construction of such tests is complicated, because residuals may depend on the distribution of the estimated coefficients. He allows for considerable heterogeneity in the panel. In fact, he assumes a heterogeneous slope coefficient, fixed effects and individual specific

[22] In the single equation case, although ordinary least squares estimates of the cointegrating vector are superconsistent, the corresponding distribution are asymptotically biased and dependent on nuisance parameters associated with the serial correlation properties of the data (see also McCoskey and Kao, 1998)

[23] Given 2.39 Pedroni tests the null hypothesis H_0:β_i=1 and finds evidence supporting weak PPP but not strong PPP. One of the most recent papers using cointegration methods to test PPP is due to Canzoneri et al. (1999). They use traded goods price and the panel cointegration test proposed by Pedroni (1996) to test if the log of the nominal exchange rate and the log of the PPP exchange rate are cointegrated. Using DM as reference currency, the results are more supportive of long run PPP.

deterministic trends. The model considered is a more general one than the model represented in 2.34:

$$y_{it} = \alpha_i + \delta_i t + \beta_i x'_{i,t} + e_{i,t} \qquad \text{t=1,2....T; i=1,...,N} \quad \text{m=1,...M} \qquad (2.39)$$

where $\beta_i = (\beta_{1i}, \beta_{21}, ..., \beta_{Mi})'$, $x_i = (x_{1it}, x_{2it}, ..., x_{Miit})'$, T refers to the number of observations over time, N refers to the number of individual members in the panel, and M refers to the number of regression variables.

An important assumption discussed by Pedroni is the one regarding the cross-member panel-wide properties of the data. Specifically, he requires that the idiosyncratic error terms are independent across individual members of the panel and proposes GLS-based correction to allow for feedback across individual members of the panel[24]. Of these seven tests, four are based on within-dimension approach and three are based on between-dimension approach. In the first group we sum both the numerator and the denominator terms over the N dimension. In the second group, we, first, divide the numerator by the denominator prior to summing over the N dimension separately.

We shall describe the construction of test seven, which is a parametric one.

1) Estimate the panel cointegration regression (2.39) and collect the residuals $e^*_{i,t}$

[24] Note that both Maddala and Pedroni in their papers have made an important start in dealing with the problem of cross-sectional dependence and group dependence between innovations. Maddala and Wu (1999) use bootstrap methods, Pedroni (1997, 1999) uses GLS-based corrections.

2) Difference the panel regression; $\Delta y_{i,t} = \beta'_i \Delta x_{i,t} + \eta_{i,t}$ t=1,2…,T; i= 1,..N and compute the residuals.

3) Calculate the long-run variance of η*, $L_{11i}^{*2} = \Omega_{11i}^{*} - \Omega_{21i}^{*} \Omega_{22i}^{*-1} \Omega_{21i}^{*\prime}$

4) Using the residuals e*it estimate $e_{i,t}^{*} = \gamma_i^{*} e_{i,t-1}^{*} + \sum_{K=1}^{Ki} \gamma_{i,k}^{*} \Delta e_{i,t-k}^{*} + \mu_{i,t}^{*}$ and get the residuals to compute the simple variance of μ_{it}^{*} denoted s_i^{*2}. The panel t-statistic is then given as follows:

$$N^{-1/2} Z_{tN,T}^{*} = N^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} s_i^{*2} e_{i,t-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} e_{i,t-1}^{*} \Delta e_{i,t}^{*} \qquad (2.40)$$

This statistic can be viewed as analogous to the Levin and Lin panel unit root test statistic applied to the estimated residuals of a cointegration regression. Let $z_{it} = (y_{it}, x_{it})'$ be such that the process z_{it} is generated as follows $z_{it}=z_{i,t-1}+\varsigma_{it}$, for $\varsigma_{it} = (\varsigma_{it}^{y}, \varsigma_{it}^{x})'$. Assume that (A) the process $\varsigma_{it} = (\varsigma_{it}^{y}, \varsigma_{it}^{x})'$ can be characterised in terms of standard Brownian motion. In this case, all we need to determine the complete distribution of the process above is its covariance structure Ω_i. (i.e we need just the first two moments of the process). (B) error terms are independent across individual members of the panel. As consequence, under the assumptions (A) and (B), the central limit theorem holds for each individual series as T grows large. The statistic described above can subsequently be standardised, relaying on the moments of the Brownian motion function. If we define with Θ* and Ψ*, the vector of means and covariance matrix of the vector functional, the asymptotic distribution of the statistic above can be written as follows: $N^{-1/2}z^*_{t,N,T}-\Theta^*_2\sqrt{N} \Rightarrow N(0,\Psi^*_{22})$. This result is important because it tells us that the standardised statistic converges to a normal distribution whose moments depend on Ψ^* and Θ^*.

These moments can be obtained by Monte Carlo simulation and used to re-write the asymptotic distribution above as follows:

$$\frac{k_{N,T} - u\sqrt{N}}{\sqrt{v}} \Rightarrow N(0,1) \qquad (2.41)$$

where $k_{N,T}$ is the panel cointegration statistic and u and ν are function of the moments of the Brownian function (i.e broadly speaking expected mean and variance).

Pedroni performs Monte Carlo simulation to study the small sample properties (power and size) of these 7 statistics. He finds that the size distortions for all of the proposed panel cointegration statistics are small, provided that there is not a negative moving average component in the DGP. In terms of power, Pedroni finds that the power of the panel cointegration statistics is very high when T=100 and T=250. Also, size distortions are smaller for T=250 and larger for smaller T. In summary, in terms of size distortion, the panel-rho statistic seem to exhibit the least distortions among the seven statistics. The group ADF exhibits the largest size distortions. In terms of power, the group ADF does very well, followed by the panel ADF and the panel-rho.

All the panel cointegration tests presented above are residual based tests. One major drawback of these tests is that they do not allow for the possibility of multiple cointegrated vectors. An important cointegration test has been recently proposed by Larsson et al (2001). They propose a likelihood-based test of cointegrating rank in heterogeneous panels and give an important contribution to the empirical literature on panel cointegration tests. Assume that the data generating process for each of the groups is represented by the following VAR (k_i)[25]:

$$y_{it} = \sum_{k=1}^{k_i} \Pi_{ik} y_{i,t-k} + \varepsilon_{it} \qquad i=1,\ldots,N \qquad (2.42)$$

following (Engle and Granger, 1987) the error representation of (2.42) can be written as follows:

$$\Delta y_{it} = \Pi_i y_{i,t-1} + \sum_{k=1}^{ki} \Gamma_{ik} \Delta y_{i,t-k} + \varepsilon_{it} \qquad i=1,\ldots N \qquad (2.43)$$

where Π_i is of order $p \times p$ (p are the number of variables in each group). The matrix Π_i can be decomposed in $\Pi_i = \alpha_i \beta_i'$ where α_i and β_i are matrices of order $p\times r_i$ representing the long-run coefficient and the adjustment parameter. Consider the following null and alternative hypotheses :

$$H(r): \text{rank}\ (\Pi) \leq r$$

[25] In what follows, one may think of y_{it} as being the real exchange rate.

$$H(p) : \text{rank } (\Pi) = p$$

Under the null and alternative hypotheses, as in Johansen (1988), the likelihood ratio test[26](the trace statistic) can be written as follows:

$$-T\sum_{i=r+1}^{p}\ln(1-\lambda_i^*) = -2\ln Q_T(H(r) \mid H(p)) \qquad (2.44)$$

Since we are interested in testing the hypothesis that all of the N groups in the panel have the same number of cointegrating relationship ($r=r_i$) the following hypothesis is considered:

$$H_0: \text{rank}(\Pi_i)=r_i \leq r \qquad \text{for all } i=1\ldots N$$

and the alternative

$$H(p) : \text{rank } (\Pi_i) = p \quad \text{for all } i=1\ldots N$$

The LR-bar statistic can be defined as the average of the N individual trace statistics LR_{iT} (H(r) ¦ H((p)) in the following way[27]:

$$LR_{NT}(H(r) \mid H(p)) = 1/N\sum_{i=1}^{N} LR_{iT}(H(r) \mid H(p)) \qquad (2.45)$$

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[26] Note that the trace statistic refers to each group i.
[27] This test is based on the approach suggested by Im et al. (1997) for the univariate unit root panel test statistic.

Using a standardization procedure on (2.45), the standardised LR –bar statistic for the panel cointegration becomes:

$$\gamma_{LR-bar}(H(r) \mid H(p)) = \frac{\sqrt{N}(LR_{NT}(H(r) \mid H(p)) - E(Z_K))}{\sqrt{Var(Z_k)}} \tag{2.46}$$

where $E(Z_K)$ and $Var(Z_K)$ is the mean and variance of the asymptotic trace statistic.

The original contribution made by Larsson et al. is that they show that every study performed in a non-panel context can be extended to a panel framework. Furthermore, Larsson et al, by proposing the panel data analogue of the Johansen maximum likelihood method, study the case of multiple cointegrating vectors in panels[28].

An important hypothesis that is considered in Larsson et al (2001) is the hypothesis of a common cointegrating rank. However, the authors assume this hypothesis but they do not test it. For example, assume that the number of cointegrating vectors is two (r=2). Since we know that any linear combinations of cointegrating vectors are themselves cointegrated, we expect these new vectors to share some common properties with the initial ones. But we do not know if across the vectors one common feature exists. This hypothesis needs to be tested. Larsson and Lyhagen (2000) propose the following way to test the hypothesis of a common cointegrating rank.

[28] As we pointed out, one of the problems with the panel cointegration tests presented above (i.e. Pedroni, and McCoskey,) is that they are residual based tests and restrict the cointegrating vector to be unique across different sections. In applied work this assumption is likely to be violated.

First, they use the LR-bar statistic of Larsson et al. (2001) and get the maximum rank amongst the N individual ones. The second stage is to test against one cointegrating less relation. They derive a panel test (PC-bar) which tests the hypothesis of r cointegrating vectors against r-1. The new test is based on the test proposed by Harris (1997). If the two tests coincide, the null of the same number of cointegrating relations cannot be rejected otherwise the null hypothesis is rejected and the alternative accepted.

Recently, Larsson and Lyhagen (1999) have developed a new test. They propose a panel-VAR with cointegrating restrictions and derived two test statistics; a likelihood ratio rest for cointegrated rank and a likelihood ratio test of common cointegrating space. To understand the model, let i=1,...N be the index the groups, t=1,...T the sample time period and j=1,...p the variables in each group, then y_{ijt} denotes the ith group, the jth variable at time t. Assume the following model:

$$\Delta y_t = \pi y_{t-1} + \sum_{k=1}^{m-1} \Gamma_k \Delta y_{t-k} + \varsigma_t \qquad (2.47)$$

where $y_t = (y'_{1t}, y'_{2t}, \ldots y'_{Nt})'$ is the Np vector of the panel of observations available at time t on the p variables for the N groups and $\varsigma = (\varsigma'_{1t}, \ldots \varsigma'_{Nt})'$ with $\varsigma \sim N(0, \Omega)$. π and Γ can be divided into submatrices π_{ij} and Γ_{ij} i,j=1,...N. If we assume the matrix π of rank Σr_i where $0 \le r_i \le p$, we write π as $\pi = AB'$ where A and B are two matrices of order $Np \times \Sigma r_i$, and A contains the short run coefficients α_{ij} and B the long run coefficients β_{ij}, each of rank r_i. At this point an important restriction is discussed by Larsson and Lyhagen. They assume that $\beta_{ij} = 0$ but $\alpha_{ij} \neq 0$. In this way, the model allows short run dependence between the panel groups. But there is no long run dependence between the panel group. The off diagonal elements in $\pi = AB'$ that is $\pi_{ij} = \alpha_{ij}\beta_j'$ represent the short run dependencies of the changes in the series for group i due to long-run equilibrium deviations in group j. These assumptions enable Larsson and Lyhagen to re-write the model (2.47) in the following form:

$$\Delta y_t = AB' y_{t-1} + \sum_{k=1}^{m-1} \Gamma_k \Delta y_{t-k} + \varsigma_t \qquad (2.48)$$

Given the model and two homogeneity restrictions, B=Diag(β_{ii}) and B= ($I_N \otimes \beta$), model B= ($I_N \otimes \beta$) is tested against B=Diag(β_{ii}). They derive the distribution of the test for cointegrating rank and for common cointegrating space, and show that the distribution of the test for cointegrating rank is equal to the convolution of a Dickey-Fuller type distribution and an independent χ^2 variate and the distribution of the test for common cointegrating space is a χ^2 distribution, and the number of degree of freedom is (N-1)r(p-r)[29].

2.3.5 **Some Unresolved Issues in Panel Unit Root and Panel Cointegration Tests.**

Several issues remain which are worthy of further investigation. Some empirical research has presented Monte Carlo evidence to point out the size distortion and low power of the commonly used unit root tests[30]. The distribution of the most common

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[29] Note that although the empirical literature on testing PPP using unit root tests and cointegration tests is wide, very few empirical works have used panel cointegration tests.

[30] The low power problem should be kept distinct from the size problem (Ng and Perron, 1999). In fact, low power arises when the dominant root is near but not exactly unity. Size

unit root tests is far different from the reported distributions in the presence of negative moving average errors. In this case, the implementation of unit root tests often necessitates a large autoregressive truncation lag (k). Monte Carlo simulations have demonstrated an association between k and the severity of size distortion[31] (Ng and Perron, 1999). If the moving average components are small, a small k is adequate. On the other hand, if the moving average components are large, a large value of k is required. However, such a strategy may not be feasible since selecting a large k may lead to an overparameterization and consequently in a loss of power. The most common tests to select a value of k are the Akaike Information Criterion (AIC), and the Schwarz Information Criterion (SIC). These all belong to the class of information based rules (IC). The problem with these methods is that they tend to select a value of k which is too small. Again, the bias in the estimated sum of the autoregressive coefficients (β^{*}_{0}) might depend on k in the presence of a negative moving average component. To see the problem, assume the following data generating process (DGP):

$$y_t = d_t + u_t \tag{2.49}$$

$$d_t = \varphi' z_t$$

where z_t is a set of deterministic components

$$\begin{aligned} u_t &= \alpha u_{t-1} + v_t \\ v_t &= e_t + \phi e_{t-1} \end{aligned} \tag{2.50}$$

distortion may arise, for example, when the underlying distribution contains a negative moving average component. However, in panel data, size distortion may also arise in the presence of cross sectional dependence.

[31] Simulations for T=100 and 250 have provided evidence that the size issue in the negative moving average case is not a small sample problem. In this case, the consequence is over-rejection of the unit root hypothesis (Ng and Perron, 1999).

The Dickey-Fuller test (1979) is the t statistic for β_0 in the autoregression:

$$\Delta y_t = d_t + \beta_0 y_{t-1} + \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + u_{tk} \tag{2.51}$$

Select k using the AIC or the SIC methods. They all belong to the class of information based tests rules (IC) where the value of k is k_{ic} = arg. $\min_k$ IC (k):

$$IC(k) = \log(\delta_k^{*2}) + (k)C_t/T \tag{2.52}$$

with $\delta_k^{*2} = T^{-1} \sum_{t=k+1}^{T} u_{tk}^{2*}$, $C_t/T \to 0$ as $T \to \infty$ and $C_t > 0$ where C_t is the weight applied to overfitting.

We select k* such that $\lim_{t\to\infty} E(T(k-k^*))=0$, Gourieroux and Monfort (1995). That is, we select k* to minimise the objective function (2.52). However, this methodology does not consider the possibility that the bias in the estimated sum of the autoregressive coefficients:

$$\pi_T(k) = (\delta_k^{*2})^{-1} \beta_0^{*2} \sum_{t=k+1}^{T} y_{t-1}^{*2} \tag{2.53}$$

might depend on k in the presence of a negative moving average component. The reason is that the bias in the estimated sum of the autoregressive coefficients is very high for small values of k. Unless k is very large this bias persists and becomes highly dependent on k[32].

[32] The problem of size distortion of univariate and multivariate unit root tests in the presence of negative moving average components is very relevant, and different methodologies to deal

Another very important issue in panel unit root and cointegration tests is the assumption made on the covariance matrix. In fact, this is generally assumed to be diagonal. As pointed out by Im et al (1997) this assumption requires observations to be generated independently across different groups, that is, no cross sectional dependence. There are currently two strands of the literature dealing with non-diagonal covariance matrix. The first strand has focused mainly on correlation occurring between group of observations, while the second has focused on group dependence of innovations. As we shall stress below, correlations between a group of observations (cross section dependence) and correlations between a group of innovations are generally close related each other.

Panel data refers to the pooling of observation on a cross-section of households, countries, firms, over several time periods. This can be achieved by surveying a number of households or individuals and following them over time. We have a combination of time series and cross section data. But why the concern with cross sectional dependence? Recall that the properties of all tests described in the previous sections are based on the assumption that data in one group are generated independently by data in another group. In other words, that there is no dependence

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with this problem have been suggested. For example, Carner and Kilian (1999) report extreme size distortions for the Leybourne and McCabe (1994) test and the KPSS test. They consider a highly persistent model, under the null of stationarity and a unit root process under the alternative. They overcome the size distortions using appropriate adjusted finite sample critical value and demonstrate that such corrections inevitably result in a dramatic loss of power in the resulting tests. However, the above results should be interpreted with caution. In fact the data generating process assumed is an AR(1) process with root ρ and NID (0,1) innovations. Furthermore, they select the number of lagged terms (l) using a procedure for fixed l as function of T, i.e $l= \text{int}\,(C(T/100)^{1/d})$ with c=12 and d=4 . This procedure for fixing l as a function of T might lead to an overparameteration and as a consequence in loss power. Furthermore, they derive the finite sample critical values from a parametric model and this, clearly, violates the nonparametric spirit of the KPSS test.

between different group of observations. Provided that this assumption holds, one can use the central limit theorem and derive the asymptotic distribution for a particular panel estimator[33]. Essentially, there are different kinds of cross sectional correlation: homogeneous, quasi heterogeneous and heterogeneous. If we consider the relationship between the French and German[34] real exchange rates, and we use the US dollar as a base currency, then the French and Germany real exchange rates will be correlated. In fact by construction they contain two common elements, independent variation in the value of the dollar and independent variation in the US price index (O` Connell, 1998). Consider the following real exchange rate model:

$$\Delta q_{i,t} = \beta_i q_{i,t-1} + u_{i,t} \tag{2.54}$$

$$u_{i,t} = \theta_t + \varepsilon_{i,t} \tag{2.55}$$

where θ_t is a stationary time-specific common effect across groups and q_t is the real exchange rate (US dollar is the numeraire currency). The effect of the omitted global variable is, as shown by (2.55), entirely captured by innovations. Equation (2.55) assumes a homogeneous form of cross sectional dependence, as the dependence induced by independent variation in the value of the dollar and US price is the same for all exchange rates and, in this case, the covariance matrix, of innovations, can be assumed of the following type (see O` Connell, 1998):

[33] Note that in extremis one could still use the central limit theorem in the case of dependent random variables, however this would require a finite variance to establish convergence (see for example White, 2001).

[34] Obviously, this is only given as an example since, today, both Germany and France use the Euro.

$$\Omega=\begin{bmatrix} 1 & \omega & \dots & \omega \\ \omega & 1 & \dots & \omega \\ . & . & . & . \\ \omega & \omega & \dots & 1 \end{bmatrix} \qquad \omega<1 \qquad (2.56)$$

where ω is the contemporaneous correlation between real exchange rate innovations[35].

If the covariance matrix is not diagonal, we can correct the bias by subtracting cross sectional means from the observed series. This is the procedure suggested by Im et al (1997).[36] This procedure can be described in the following way. Consider the following DGP for the real exchange rate q_{it}:

$$q_{i,t} = \beta_i q_{it-1} + u_{i,t} \qquad i = 1,\dots,N \quad t = 1,\dots,T \qquad (2.57)$$

Equation (2.57) consists of i countries observed t times. It is convenient for our purpose to stack (2.57) into N equations as follows:

$$q_t = \beta q_{t-1} + u_t \qquad (2.58)$$

with each of the N equations consisting of T observations. Define by $i' = [1,\dots,1]$ a vector that contain columns of ones. Then $ii' = N \times N$. Also define the covariance

[35] Note that as equations 2.54 and 2.55 show it is the correlation between the French and Germany real exchange rates that cause between group dependence in innovations and a non-diagonal covariance matrix (see 2.56).

[36] However, under these assumptions and if cross sectional dependence is of weak-memory variety, the central limit theorem, so important to derive the asymptotic distribution, may continue to apply, but, when there are strong correlations in a cross section (as there will be in the presence of global shocks.) we may expect failure in the central limit theorem (Phillips and Moon, 1999).

matrix as $\Omega = E(u_t u_t^{'})$. Finally consider two different cases for Ω^*. In the first case the covariance matrix is assumed to be diagonal. In the second case it assumes the form given in 2.56. By using the demeaning procedure the covariance matrix reduces to:

$$\Omega = (u_t - u_t^{AV})(u_t - u_t^{AV})' \text{ where } u_t^{AV} \text{ is the average of } u_t \qquad (2.59)$$

Define the following idempotent symmetric matrix $P = I - \frac{1}{N} ii'$ and $i' = [1,..,1]$

$$P_{N \times N} = \begin{pmatrix} 1-\frac{1}{N} & -\frac{1}{N} & -\frac{1}{N}. & -\frac{1}{N} \\ & 1-\frac{1}{N} & -\frac{1}{N} & -\frac{1}{N} \\ & & 1-\frac{1}{N} & -\frac{1}{N} \\ & & & 1-\frac{1}{N} \end{pmatrix} \qquad (2.60)$$

Using the general expression of the covariance given above and (2.60), we have :

$$Pu_t (Pu_t)' = \Omega^*$$

$$\Omega^* = Pu_t u_t^{'} P'$$

$$\Omega^* = P \Omega P' \qquad (2.61)$$

Equation 2.61 represents the covariance matrix after the demeaning procedure. It is straightforward to see that it is no longer diagonal. This result is not surprising since it is the subtracting cross sectional means, after all, that determines cross sectional dependence. In other words we are subtracting a common element (same information) from each cross unit[37].

Let us consider the case when the covariance matrix is not diagonal and of the form given in (2.56)[38]. By using (2.56) in conjunction with (2.60) we have:

$$\Omega = (1-\omega)I + \omega ii'$$

$$P\Omega P' = (I - \frac{1}{N}ii')[(1-\omega)I + \omega ii']P \tag{2.62}$$

after some algebra (2.62) reduces to[39]:

$$P\Omega P' = (1-\omega)P \tag{2.63}$$

Then, in the presence of cross sectional dependence the covariance matrix depends on the parameter ω that measures the degree of cross section dependence. It is clear from (2.63) that the demeaning procedure is not effective even for very large N. In fact, as $N \to \infty$, the parameter ω still appears in the expression (2.63).

The sort of correlation considered above, assumes that the degree of dependence is the same for all group of observations (i.e. that cross section dependence is

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[37] However, by subtracting a common element across units we may end up losing important information. One way out of this is to model the cause of dependence between group of innovations.

[38] Note that we are considering only a limited case of cross section dependence, that is homogeneous cross section dependence. Modelling the covariance matrix in the case of heterogeneous cross section dependence is much more complicated.

homogeneous). In fact, it may well be that in the presence of global shocks some units may respond in one way while others may respond in a different way. In the extreme case some units may well not be affected at all. However, in this instance as proposed by O`Connell (1998), equation 2.55 can be re-written as follows:

$$u_{i,t} = r_i \theta_t + \varepsilon_{i,t} \tag{2.64}$$

The covariance matrix that describes the correlation between real exchange rate innovations is still not diagonal, but now it is also heterogeneous. This is a form of heterogeneous cross sectional correlation (see Maddala and Wu, 1999, Higgings and Zakrajsek, 2000). For example, between any two countries (and real exchange rates), in addition to the base currency effect, there might be other sources of correlation between real exchange rate innovations, that is generated by exogenous global shocks.

One way out of this problem is to use GLS based corrections as proposed by Pedroni (1999) and O`Connell (1998). In fact the use of GLS based techniques produces an estimator, with critical values invariant to the cross sectional correlation among real exchange rates. A second way is to use the bootstrap method to get the empirical distributions of the tests to make inference (Maddala and Wu, 1999).

The problem with the use of FGLS techniques to deal with cross section dependence, is that, generally, FGLS requires the imposition of a homogeneous serial correlation structure (the autoregressive parameter is assumed to be the same across i) and the selection of a same lag length. O`Connell (1998), and Higgins and Zakrajsek (1999

[39] I wish to thank Joseph Pearlman for his advice given to me in helping to achieve the final

and 2000), follow this line. This imposition is too restrictive for two reasons. First, if the serial correlation pattern is heterogeneous the invariance property of FGLS breaks down. Second, the selection of a same lag length, generally, is not supported empirically (Papell and Theodoridis, 2000). Furthermore, the consistence of the FGLS estimator relies on the consistence of the estimator used to estimate the covariance matrix. Generally, the estimator used to obtain estimates of the covariance matrix is the Pooled Least Square Estimator (POLS). Coakley et al (2002) show that, under cross sectionâl dependence, this estimator is inconsistent[40].

Another strand of literature has preferred to focus on between group correlation of innovations. In fact, we could have a situation where a non-diagonal covariance matrix is caused by an omitted variable, that is completely uncorrelated with the included regressors. In this case, there could be no correlations between different groups of observations, but because the effect of the omitted variable is captured by innovations, the covariance matrix will not be diagonal. SURE procedures have been recommended in this case. The logic behind such an approach is that since the efficiency of the SURE estimator increases, the larger the correlation between innovations with respect correlation between group of observations, one should gain in efficiency by using SURE estimation. However, since the SURE approach in panels consists in a multivariate FGLS procedure, all the drawbacks we pointed out above also apply in this case. Furthermore, if the cause of a non zero diagonal covariance matrix is due to an omitted global variable, that is correlated with included

result.

[40] Phillips and Soul, 2003 also show that, under cross sectional dependence, the POLS as well as FGLS estimators are biased. However we may always estimate the covariance matrix by using a non-parametric approach.

regressors (that is when we have cross sectional dependence), then the SURE estimator is not necessarily superior to the OLS estimator (Maddala, 2002).

Recently Banerjee et al (2001) noticed that in addition to cross sectional dependence there is an additional source of size distortion in panel unit root and cointegration tests. In fact, these methodologies suffer from large size distortion in the presence of cointegration between different groups[41]. They perform Monte Carlo simulations on some of the most common panel unit root and cointegration tests (i.e. LL ,1993, Im et al, 1997 and Maddala and Wu, 1999), and show that they all suffer from size distortion when different groups are cointegrated[42]. The panel unit root test that suffers from less size distortion is the LL2 (1993) test. The implication for applied work is the same as in the presence of cross sectional dependence. That is, one ends with rejecting the null hypothesis too often.

The paper by Banerjee et al (2001) provides an important contribution to the empirical literature on panel estimators. However, their Monte Carlo experiment might be biased towards the LL test. Banerjee et al (2001) compare, in terms of size and power, the Im et al (1997), the LL2 (1993) and the Maddala and Wu (1999) tests. This comparison may not be totally appropriate. Can we compare two tests based on different hypotheses? Remember that the Im et al (1997) test is a heterogeneous test whose alternative is that some units are stationary while some others are not. On the other, hand the LL is a homogeneous test with the alternative being that all units are

[41] The issue of cross cointegration can be viewed as long run cross correlation between different groups. The cointegration could be due, for example, to a common stochastic trend driving different groups. In this respect, the issue of cointegration between groups has been analysed in the literature by Bai and Ng (2001a), and larsson and Lyhagen (2000).

stationary. Furthermore, their Monte Carlo experiment is entirely calibrated on the LL test[43]. As a consequence it is of little surprise that, in their Monte Carlo simulation, the LL test performs better than the others in the presence of cointegration between groups. We believe that their results may be due to their Monte Carlo design.

2.4 **Exchange rates Persistence and Half-lives**

An interesting issue in PPP literature is the half-lives of PPP deviations, defined as the amount of time that it takes a shock to the real exchange rate to revert 50 percent back to its mean value. This can be also viewed as a measure of mean reversion in real exchange rates. The issue of half-lives is very closely related to the Rogoff' s purchasing power parity puzzle, since the problem is how to reconcile high short term volatility of real exchange rates with extremely slow convergence to purchasing power parity (shocks appear to dump out at 15% per year). The empirical literature on PPP surveyed by Rogoff (1996) seems to find consensus of 3-5 year half-lives of PPP deviations. Some authors attempt to solve the PPP puzzle considering non-linear mean reversion, and they show that once we allow for nonlinearities, the speed of adjustment to real exchange rate shocks may be greater than what is reported with linear models (Taylor et al, 2001).

However, the 3-5 year half lives reported in Rogoff (1996), come primarily from papers whose main concern is to investigate unit roots in real exchange rates, and not specifically half-lives. Murray and Papell (2002) point out that there are three major

[42] Lyhagen (2000) studies the size of different panel unit root and cointegration tests in the presence of cointegration across units. He finds the McCoskey and Kao (1998) test to perform better than the Im et al (1997) test in the presence of cointegration between groups.
[43] In fact they follow the same Monte Carlo design as in Levin and Lin, 1993.

drawbacks with the econometric approach used in these studies. First, it is well documented that the LS estimator suffer from size distortion in small samples. Murray and Papell suggest using median unbiased estimation. Second, most of the studies on half-lives, use the DF test (see Section 3) and the half life is calculated from the coefficient on the lagged real exchange rate ($\ln(0.5)/\ln(\phi^*)$). This procedure is valid provided that there is not serial correlation in the real exchange rate series. In fact, if there is serial correlation an AR(1) specification may not be appropriate. For a higher order AR model there are two alternatives: (a) calculate the half- life using approximate median unbiased estimation. (b) Calculate the half-life directly from the impulse response function (Murray and Papell, 2002). Finally, studies on half-lives generally only present point estimates of half-lives, giving in this way an incomplete picture of the persistence of the real exchange rate. Murray and Papell (2002) suggest to support point estimates of half-lives with bootstrap confidence intervals. For example, if the confidence interval is {3.51, 34.31} we say that we are 95% confident that the lower bound is 18% per year and the upper bound is 2% per year (Murray and Papell, 2002). This procedure allows us to avoid the arbitrariness of the point estimate of half-lives as a measure of persistence[44].

2.5 Conclusions

This chapter provides a critical review of the major panel unit root/cointegration tests used in the literature to test long run PPP. We have presented the Levin and Lin

[44] An interesting result on half-lives come from Higgin and Zakrajsek, 2000. They use a large panel of 36 countries and CPI real exchange rates and report half-lives for this sample of more than 85 years. However, since the main focus of this paper is on testing for PPP and not half-lives of the real exchange rate, the econometric techniques used are unlikely to be appropriate.

(1993) tests and pointed out their limitations, the Im et al (1997) test, the Taylor and Sarno (1998) test, the Fisher test. We have also discussed some panel cointegration tests such as the one proposed by Larsson et al (2001), Pedroni (1997) and McCoskey and Kao (1998). We have considered (i) the role of ADF regressions as a way of allowing for serially dependent and heteroskedastic residual processes; (ii) the problem of heterogeneity in panel unit root and cointegration tests and its implication for applied works on PPP; (iii) the problem of endogeneity in cointegration tests, (iv) the low power and size distortion of unit root tests in the presence of a negative moving average. A common important element of all of the tests presented in this chapter is that their asymptotic distributions were derived under the assumption of no correlation between groups of observations, and therefore a diagonal covariance matrix. We have pointed out that this assumption is often violated, and therefore asymptotic distributions of panel estimators may no longer be reliable. Different approaches have been suggested in the literature to deal with cross sectional dependence and non diagonal covariance matrix. However, the research in this area is evolving and more work needs to be done.

The previous literature on PPP has used univariate unit root tests to test mean reversion in the real exchange rate. One of the problems with this literature is the low power of such tests. As an alternative, researchers have used panel unit root and cointegration tests. Using panels, researchers have noted that PPP holds more often for DM-based bilaterals. Recently, Coakley and Fuertes (2000) challenged this point. However, the empirical evidence from panel unit root tests on PPP is mixed, while very little has been done using panel cointegration tests.

What have we learned from this review of panel unit root tests and panel cointegration tests to long run PPP? Size distortion in unit root tests increases the likelihood of type 1 error. Panel tests that assume i.i.d. disturbances suffer from severe size biases. That is, the derived distributions are not valid and should not be used to make inference. FGLS or SURE techniques are unlikely to provide a solution to the problem. The assumption of a homogeneous slope parameter is too restrictive in many applied works and in particular in PPP.

Summing up, given that panel estimators are subject to the above drawbacks and considering that empirical evidence supporting PPP is mixed, the issue of whether or not long-run PPP holds is not yet decisively settled.

CHAPTER 3

THE CROSS SECTIONAL DEPENDENCE PUZZLE

3.1 Introduction

The analysis of unit roots and cointegration in non-stationary panel data is becoming a growing research area. A number of issues have been raised in the literature. Most of the relevant asymptotic theory for panel data was developed for large cross sectional dimension (N), but small time series (T). However, recently there has been an increase of the number of observations, and this raises a number of issues. First, most economic time series are known to be non-stationary. The issue here is to develop asymptotic properties of panel estimators when data are non-stationary. Second, since we have large (N) and large (T), there is the question of how to do the asymptotic analysis of N,T rather just N. Third, since we have large T, it is possible to estimate each group separately. The latter raises the possibility that parameters may vary across groups. If this is the case, then we have heterogeneous panels. Finally, all the panel unit root/cointegration tests assume individual cross sections are independent from each other. However, as noted by O\`Connell (1998), this assumption is unlikely to hold practically (for example in Purchasing Power Parity). If this is the case, the assumption underlying most of the panel unit root/cointegration tests, that is $E(\varepsilon_t \varepsilon_t^{'}) = \Omega$ is diagonal (i.e. no correlation between different groups of innovations), breaks down and their asymptotic distributions are no longer valid.

As we have seen in the previous chapter, Im et al (1997) recognise that there are cases where disturbances may be correlated across units. This may happen when observations are not generated independently across groups, and they propose subtracting cross sectional means from the observed data. Although this procedure might be appropriate when there is one main source of dependence across units (homogeneous cross sectional dependence), it should be avoided in practice.

Pedroni (1997) and O'Connell (1998) use feasible GLS corrections to deal with non i.i.d. error terms. But Phillips and Su (2002) show that under cross section dependence the GLS estimator is likely to be biased downwards.

Maddala and Wu (1999) suggest bootstrap. In fact, if the error terms are not i.id, because of cross sectional dependence, the asymptotic distributions of unit root/cointegration tests are unknown. Maddala and Wu (1999) suggest, in this case, using the bootstrap distribution to make inference.

Following Maddala and Wu (1999), Wu and Wu (2001) use bootstrap to deal with cross correlated errors. They propose a methodology that allows for heterogeneous serial correlation and arbitrary contemporaneous correlation of innovations across countries, thus addressing the limitations of O`Connell (1998). Wu and Wu (2001) use SURE method to obtain the bootstrap sample, but they do not provide any analysis of the size distortion of their bootstrap panel unit root statistic.

Although all the above mentioned papers use different approaches to deal with between group correlation of errors, they do not attempt to characterise it. That is, they try to remove group dependency but they do not model the cause of group dependency.

Chang (2002) models cross sectional dependence caused by omitted variables and she uses instruments generated by a non-linear instrument generating function. However, the methodology suggested by Chang is likely to be valid, provided that cross sectional dependence is caused by an omitted variable that is correlated with the included regressors. Strictly speaking when there is one main common source of dependence.

Bai (2001) uses a different approach. He models cross sectional dependence through common stochastic trends. He assumes cross sectional dependence to be caused by common factors correlated with the included regressors.

The original contributions of Chang and Bai are a very important step in the right direction. However, as we shall see, they only consider the case when a non-zero covariance matrix is the consequence of cross section dependence. But non-zero covariance matrix can also be due to an omitted variable that is independent of the included regressors. We notice a sort of puzzle, and following Maddala and Wu (1999), suggest bootstrap. We implement the bootstrap procedure suggested by Maddala and Wu (1999) in different ways and apply the resulting unit root test to the long-run Purchasing Power Parity hypothesis. The test cannot reject the unit root null hypothesis in the real exchange rate. Monte Carlo simulations on the test confirm very little evidence of size distortion.

3.2 **Cross Section Dependence and Between Group Dependence of Innovations**

A very important issue in panel unit root and cointegration tests is the assumption made on the covariance matrix Σ. In fact, it is generally assumed that the latter is diagonal. This would imply no correlation between different groups of innovations. The assumption of zero off diagonal elements of the covariance matrix in panel data, is made for identifiability reasons so that estimation can proceed. However, this assumption requires observations to be generated independently across units (i.e. no cross section dependence). If this assumption is relaxed, the derived distributions of panel unit root and cointegration tests are no longer valid. In the above context, the distribution of unit root and cointegration tests will not be asymptotically non-stochastic.[1]

As noted in chapter 2, cross sectional dependence can be caused by different factors:

(a) Omitted variables correlated with the included regressors, whose effect is captured by innovations causing a non-zero off-diagonal elements of the variance-covariance matrix

(b) Stochastic trends correlated with the included regressors, whose effect is the same as in (a)

[1] Here, we prefer using the term "non correlated" rather than " independent". In fact, it is important to differentiate non-correlation from independence. Let X and Y be two random variables. If for any functions $v=\Phi(X)$ and $z=\vartheta(Y)$; $f(\Phi(X),\vartheta(Y))=f_v(\Phi(X)\bullet\vartheta(Y))$, for each $(v,z)\in R$, the two random variables are said to be independent. This means that if X and Y are independent, then any functions of these random variables are also independent. On the other hand, correlation is a different issue. Broadly speaking, it defines a measure of linear dependence only. Hence, the general conclusion we reach is that if variables are independent, they are non-correlated. On the other hand, if they are non-correlated, this does not imply that

(c) For real exchange rates cross sectional dependence can occur by assuming the same base currency

As a consequence, cross sectional dependence can be due to either model miss-pecification or global shocks.

In general, researchers have largely neglected modelling cross-sectional dependence, which is often very complicated, since individual observations across sections display no natural ordering[2]. Nevertheless, many researchers (see Phillips and Moon 1999, Banerjee, 1999) have called for major research effort in this direction.

3.3 **Review of the Literature.**

One of the first papers, which explicitly attempt to deal with between group dependence, is Im *et al* (1997). In this paper the authors, explicitly say that their procedure is no longer applicable when observations are not generated independently across groups. This is because correlation between groups of observations produces a non-diagonal covariance matrix[14]. In order to restore a diagonal matrix, Im et al, 1997 suggest a demeaning procedure. Consider the following model:

$$\Delta y_{it} = a_i + \beta_i y_{i,t-1} + u_{it} \qquad i=1,\ldots,N, \qquad t=1,\ldots,T \quad (3.1)$$

they are independent. However, for simplicity in this paper we focus on non correlated error terms.

[2] However, modelling cross sectional dependence is not always an easy task. For example, Peasaran and Smith (1995) modelled cross sectional dependence by including, amongst the regressors an additional variable which accounted for cross sectional dependence. However, this way is not always feasible (e.g in the case of Purchasing Power Parity).

if we assume that the error term is composed of two components:

$$u_{it} = \theta_t + \varepsilon_{it} \tag{3.2}$$

a stationary time specific effect and a random effect, which is independent across the sections, then to remove the effect of the common component in equation (2), we subtract cross sectional means from both sides of equation (1), that is:

$$a_i^* = a_i - N^{-1}\sum_{j=1}^{N} a_j\ ,\ \ y_{it}^* = y_{it} - N^{-1}\sum_{j=1}^{N} y_{it}\ , \tag{3.3}$$

However, equation (3.2) is in general, of little practical use[3], since it only considers a homogeneous form of cross section dependence. Furthermore, this procedure may not allow one to deal with the case when non diagonal covariance matrix is due to omitted variables uncorrelated with the included regressors.

O` Connell, 1998, considers a more general form of (3.2):

$$u_{it} = r_i\theta_t + \varepsilon_{it} \tag{3.4}$$

In the presence of heterogeneous cross sectional dependence, O`Connell (1998) shows that feasible GLS (FGLS) estimator can restore orthogonality across the units.

[14] Correlation between observations could be due to an omitted global variable.

[3] Another weakness of the demeaning approach is that by removing the mean we may well lose some important information.

The cross sectional effect is captured by the off-diagonal element of the covariance matrix Ω, namely ω, and FGLS is invariant with respect to ω (see O`Connell, 1998 for details). Based on this procedure O`Connell proposes a panel unit root test. Many researchers, following O`Connell, use FGLS procedure to deal with cross sectional dependence (Higgins and Zakrajsek, 2000; Coakley and Fuertes, 2000). However, as observed in Chapter 2 such a corrections are likely to be invalid for large N. Also, this methodology requires the common component to be stationary across individual cross sections. Finally, Phillips and Su (2002) show that the GLS estimator is biased downwards under cross section dependence.

Maddala and Wu (1999) suggest an alternative way of dealing with non diagonal covariance matrix. In fact, if error terms are correlated across the units, the derived distributions of many unit root and cointegration tests are no longer valid, or more precisely, they are unknown. In this case, Maddala and Wu (1999) propose using the bootstrap distribution to make inferences. They propose a modified panel version of the Fisher (1932) test where p-values are obtained by bootstrap (refer to chapter 2 for a detailed description of this test).

The bootstrap method is a resampling method. It works as follows: Let $(x_1, x_2, \ldots, x_n)$ be the original sample. Draw a sample of size n[4] from this sample with replacement, say $B_j=(x^*_1, x^*_2, \ldots, x^*_n)$. This is the bootstrap sample. Each x^*_i is randomly drawn from the given sample. If we do this many times and compute the estimator θ_j^* from each of the bootstrap sample B_j, we have a realisation of θ^*, and we use it to draw inferences. Of course we may alternatively decide to bootstrap residuals or bootstrap data. Assuming that we decide an bootstrap procedure based on bootstrapping residuals, and that our data generating process consists of the following:

$$\Delta y_{it} = \eta_i \Delta y_{i,t-1} + e_{it} \qquad (3.5)$$

since there are cross correlations among innovations $e_{it}^{\oplus}$, instead of resampling $e_{it}^{\oplus}$, we resample $e_t^{\oplus} = [e_{1t}^{\oplus}, e_{2t}^{\oplus}, ..., e_{Nt}^{\oplus}]'$. This procedure consists of resampling $e_{it}^{\oplus}$ keeping the cross sectional dimension fixed, that is, resampling a full column of the $[e_{it}^{\oplus}]$ matrix at a time.

However, it should be kept in mind that although the bootstrap often provides better finite sample critical values for test statistics than does first-order asymptotic theory, bootstrap values are still approximations and are not exact. That is why we need Monte Carlo evidence on the numerical performance of the bootstrap as a means of reducing differences between the true and the nominal levels of tests[5]. Finally, as noted by Li and Maddala, (1996) "it is easy to jump on the computer and mechanically apply a certain bootstrap procedure when in fact the structure of the model suggests some other procedure for bootstrap data generation. It is also important to think about what statistic to bootstrap which depends on the particular

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[4] We may also decide to draw a sample of size m<n. The validity of an m out of n bootstrap sample is well documented.

[5] Monte Carlo analysis of bootstrap tests is highly time consuming. However, Davidson and MacKinnon (2000) suggest a Monte Carlo approach that is relatively cheap, under the conditions of asymptotic independence of the bootstrapped statistic and the bootstrap data generating process.

problem and procedure for studentization. For this reason it is important to avoid some ready available canned programs".

Following Maddala and Wu (1999), Wu and Wu (2001) use bootstrap to deal with non-diagonal covariance matrix. They propose a bootstrap methodology based on the Maddala and Wu (1999), but consider a different DGP. In fact, they use SURE to exploit the existing correlation between different groups of innovations. In this way one should gain, in terms of efficiency, the higher the correlation between groups of innovations. However, if correlations are due to omitted variables correlated with the included regressors (as it may happen with cross section dependence), SURE estimation is not necessarily superior to OLS. In fact, if correlation among regressors is stronger than that among innovations, or the regressors in one block of equations are a subset of those in another, the SURE estimates collapse to the OLS estimates. Furthermore Wu and Wu (2001) do not provide any Monte Carlo analysis of the size of their bootstrap estimator.

The main focus of the literature presented above is dealing with non-diagonal covariance matrix. However, they do not try to model the cause of non-diagonal covariance matrix. Since one of the causes may be due to cross section dependence, in what follows, we shall present some of the most recent papers that have tried to model and deal with cross section dependence.

Chang (2002), proposes a unit root test for panels with cross sectional dependence. Consider the following regression:

$$y_{it} = a_i y_{it-1} + u_{it} \qquad i=1,\ldots,N;\ t=1,\ldots,Ti \qquad (3.6)$$

where i is the cross sectional unit and t the time period. Since T can differ across i, unbalanced panels are allowed. The hypotheses under consideration are that $a_i=1$ for all y_{it}`s in the above equation, against $a_i<1$ for some y_{it}. The error in the above equation is modelled assuming an AR(p_i) process as follows:

$$a^i(L)u_{it} = \varepsilon_{it} \qquad (3.7)$$

where L is the lag operator. If the linear filter of the above process is given by:

$$a^i(z) = 1 - \sum_{k=1}^{p_i} a_{i,k} z^k \qquad (3.8)$$

then, model (3.6) can be re-written as follows:

$$y_{it} = a_i y_{i,t-1} + \sum_{k=1}^{p_i} a_{i,k} u_{i,t-k} + \varepsilon_{it} \qquad (3.9)$$

Since under the unit root null hypothesis we have $\Delta y_{it} = u_{it}$, equation (3.9) becomes:

$$\Delta y_{it} = a_i y_{i,t-1} + \sum_{k=1}^{p_i} a_{i,k} \Delta y_{i,t-k} + \varepsilon_{it} \qquad (3.10)$$

Using equation (3.10), Chang (2002) constructs a unit root test based on IV estimation procedure. Strictly speaking the test is based on the ADF regression for each individual cross section, using as instruments non-linear transformations of the lagged levels. He shows that such a test is simply the standardised sum of the individual IV t-ratios. To deal with cross sectional dependence, he uses instruments generated by a non-linear instrument generating function defined as $F(y_{i,t-1})$. The main result is that the limit distributions of the IV t-ratio statistics, that is proved to be normal, are cross-sectionally independent, since the non linear instruments $F(y_{i,t-1})$ and $F(y_{j,t-1})$ are asymptotically uncorrelated[6]. This independence will carry over to the covariance matrix.

The main difference between the panel unit root test proposed by Chang (2002) and the others proposed in the literature is that Chang's test achieves asymptotic normality without imposing independence across sectional units, but relies instead on the asymptotic orthogonalities of the non-linear instruments, with the latter obtaining asymptotic normality under the assumption of no cross sectional dependence.

Two considerations are necessary on the described procedure. First, instruments for the lagged differences (i.e. $(\Delta y_{i,t-1},\ldots,\Delta y_{i,t-1-p_i})$), are generated using only the dependent variable. For all regressors the instruments are $(F(y_{i,t-1}), \Delta y_{i,t-1},\ldots,\Delta y_{i,t-p_i})'$. This procedure is valid provided that $\text{cov}(\Delta y_{i,t-1},\ldots,\Delta y_{i,t-p_i},\varepsilon_{it}) = 0$, that is there must be no correlation between the instruments and the error term. In practice, this

[6] However, this test is found to be very sensitive to the specification of the cross sectional and time series dimensions. Furthermore, it produces ambiguous results if the autoregressive parameter is restricted to be homogeneous across individual units.

assumption is likely to be violated. This could be a further explanation of why the test produces ambiguous results when the sample size is small.[7]

Bai (2001) uses a different approach. Based on Hall *et al* (1999a, b), he models cross sectional dependence through common stochastic trends. That is, he assumes cross sectional dependence to be caused by common factors (global shocks) correlated with the included regressors and he shows that if this is the case, it is possible to estimate the common stochastic trends as well as the shocks themselves.

Consider the following model:

$$X_{it} = \lambda_i^{'} F_t + e_t \tag{3.11}$$

where F_t are the common stochastic trends, λ_i is a vector of cointegrating coefficients, and $\lambda_i^{'} F_t$ the common components of X_{it}. Only X_{it} is observable and (X_{it}, F_t) are cointegrated. Call r the number of the true common trends, and assume that r is known. Then, for a single time series, equation (3.11) can be re-written as follows:

$$\underset{(T\times 1)}{\underline{X}_i} = \underset{(T\times r)}{F^0} \; \underset{(r\times 1)}{\lambda_i^0} + \underset{(T\times 1)}{\underline{e}_i} \tag{3.12}$$

[7] Chang (2002) applies the non-linear IV method to test for PPP. When she applies the test to IFS and PWT data, she gets contradictory results. In fact, the test appears to support PPP only when the sample size is large. It may well be that the independence condition, required by the test, is violated.

For the panel data:

$$\underset{(T\times N)}{X} = \underset{(T\times r)}{F^0}\ \underset{(r\times N)}{\Lambda^0} + \underset{(T\times N)}{e} \qquad (3.13)$$

where $X=(\underline{X}_1,\ldots,\underline{X}_N)$. The goal, here, is to estimate r, F^0 and Λ^0.[8] To achieve this goal, Bai`s methodology relies on 4 assumptions: (a) common stochastic trends, (b) heterogeneous cointegrating coefficients[9], (c) time series and cross section dependence and heteroskhedasticity and (d) weak dependence between common trends and idiosyncratic errors. We do not intend to go into details here, because this would be beyond the aim of this chapter. The reader interested in more details is therefore referred to Bai`s paper.

Estimates of F_t^k and Λ^k (here r is assumed given and equal to k) are obtained as follows: let the covariance matrix of X be Σ[10]. Then, the variance of a linear combination, say $\Psi' X$ is $\Psi'\Sigma\Psi$. Maximising this with respect to Ψ subject to a normalisation rule $\Psi'\Psi / I_r$, gives Ψ as the eigenvector of $|X - \Psi I_r| = 0$. If $v_1, v_2, \ldots, v_k$ are the eigenvalues of Σ and $\Psi_1, \Psi_2, \ldots, \Psi_k$ are the corresponding eigenvectors then Ψ_k are mutually orthogonal and $Var(\Psi_k' X) = v_k$. If we order v_k in

[8] Note that in this chapter we only describe the procedure used to estimate common trends and the true cointegrating coefficients. For the estimation of the number of trends (r), see Bai (2001) and Bai and Ng (2002a).

[9] An important feature should also be noted. Once cross sectional dependence is introduced explicitly in the model, it could make sense restricting the slope parameter to be homogeneous across sectional units. In fact, it is the common stochastic trend that may impart homogeneity across the units of the panel.

[10] Note that to make the subject more simple, we assume $\Sigma=(\Sigma_\Lambda\ \ \Sigma_F)$, this would imply that the random matrix $(\Sigma_\Lambda\ \ \Sigma_F)$ has the same eigenvalues. Of course this is not the assumption made by Bai. In fact, he assumes that the eigenvalues of the described r×r matrix are distinct

descending order, $v_1 > v_2 > .. v_k$, then we get the principal components as $\Psi_1^{'}X, \Psi_2^{'}, ..., \Psi_k^{'}X$. Thus the principal components corresponding to the lowest v_k give the cointegrating vectors and those corresponding to the largest v_k give the common stochastic trends. Clearly, the above proposed methodology is the method of principal components. However, there are a number of drawbacks with this procedure as well. For example, the principal components often do not have economic meaning, so, the first problem would be how to interpret them. Furthermore, once we have estimated the common factors we have to determine which of these factors are important. To do this, it is necessary to establish the consistency property of the estimated common factors when both N and T are large. Although Bai (2001) derives the limiting distribution for the estimated common-stochastic trends, cointegrating coefficients, and common components, more work is needed on this issue. Recently, Bai and Ng (2002a) developed a panel criteria to select the number of factors. However the proposed methodology is applicable to large panels only. Finally, λ_i in equation (3.11) is assumed not to be random. If λ_i is random and is correlated with the common factors, Bai`s result will no longer hold.

Is cross section dependence the only source of non-zero covariance matrix? Bai (2001) models shocks via factor analysis and in this way he removes correlation between sections, restoring a diagonal covariance matrix. However, it could well be that the cause of between group dependence in the covariance matrix is due to global shocks that are uncorrelated with the included regressors. For example, the dot.com bubble has lasted years before busting. If we use stock prices over that period, we would probably notice no correlations between groups of stocks. However, the

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with probability 1.

omitted variable would be likely to produce correlation between groups of innovations. Neither the Chang (2002) nor Bai (2001) methodologies allow for this possibility. That is, global shocks uncorrelated with the included regressors whose effect is captured by the innovations. If this is the case, bootstrap may still be the appropriate response. Furthermore, using bootstrap, we do not eliminate, from our data, the information contained in the data.

3.4 **Bootstrap Methodology**

In this section we present the bootstrap methodology used to obtain p-values for the Maddala and Wu (1999) panel unit root test. The objective is to simulate the empirical distribution of an ADF test and calculate probabilities values. In doing this we shall also take into account the possibility of cross sectional dependence and/or correlation between innovations as implied by equation (3.4).

Consider the following panel data model:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{k_i} \rho_j \Delta y_{i,t-j} + e_{i,t} \qquad (3.14)$$

We generate our bootstrap distribution assuming the following data generating process (DGP):

$$\Delta y_{i,t} = \eta_i \Delta y_{i,t-1} + e_{i,t} \tag{3.15}$$

The individual equations of the DGP in (3.15) are estimated by least squares and the OLS residuals $e_{it}^{\oplus}$ are computed.

The bootstrap innovations e_{it}^{*} are obtained by resampling with replacement from the empirical residuals keeping the cross sectional dimension fixed.. We get the N-dimensional vector of bootstrap innovations $e_{it}^{*} = (e_{1t}^{*}, e_{2t}^{*}, ..., e_{NT}^{*})'$ which are free from cross sectional dependence

We next generate pseudo-data by employing the scheme

$$u_{i,t}^{*} = \eta_i^{*} u_{i,t-1}^{*} + e_{i,t}^{*} \tag{3.16}$$

where η_i^{*} is computed from estimation of equation (3.15) and e_{it}^{*} are bootstrap innovations.

Application of scheme (3.16) requires an initial value for u_0^{*}. The procedure suggested by Maddala and Wu (1999) to build up u_0^{*} is to pick it up from the estimated moving average (MA) representation. However the suggested procedure encounters two practical difficulties. First it is well known that estimation of MA time series models is not as straightforward as the estimation of the AR models. Second it requires the truncation of an infinite sum (see Berkowitz and Kilian, 2000). These problems can be avoided by adopting an alternative procedure suggested by

Berkowitz and Kilian (2000). This involves selecting arbitrary values for $u_{i,0}^{*}$ in the recursion $y_{it}^{*} = \eta_i^{*} y_{it-1}^{*} + e_{it}^{*}$.

The bootstrap sample is generated by using the following scheme:

$$y_{i,t}^{*} = y_{i,t-1}^{*} + u_{i,t}^{*} \quad \text{with } y_{i,t}^{*} = 0 \tag{3.17}$$

In this case it makes sense to set the initial value of $y_{i,t}^{*} = y_{i,0}$. In fact as Dickey and Fuller show, if the DGP contains a unit root the test, statistic depends on $y_{i,0}$, and α (if intercept is included) (see Dickey and Fuller, 1981, for more details).The proposed resample scheme is the sampling scheme S_2 suggested by Maddala and Kim (1998) and Li and Maddala (1996).

Using the boostrap sample, we estimate the regression model (3.14) to produce the empirical distribution of the unit root test. The number of bootstraps is replicated B times to form the bootstrap distribution of the test statistic under the null hypothesis of a unit root in the panel, which allows for cross sectional dependence[13]

3.5. Empirical Results

In this section we use two different methodologies to account for cross-sectional dependence. To have a benchmark against which we can evaluate our test statistic, we use the widely used t-bar test proposed by Im *et al* (1997), with and without the adjustment described above. We then apply the bootstrap methodology outlined in the previous section to obtain *p*-values for the Maddala and Wu test (see chapter 2 for a detailed description of this test). We apply these tests to two different panels of real exchange rates to test the long-run Purchasing Power Parity hypothesis (PPP).

Our data consist of monthly observations on bilateral exchange rates (using the US$ as numeraire) and the consumer price (CPI) and wholesale price (WPI) indices used for constructing the real exchange rates (RER). For the CPI data set, we use G20 countries. For the WPI data set, we use a smaller panel of only G10 countries, due to the unavailability of data. Furthermore, the two panels span through two different periods. While the CPI series span the period January 1973 to January 2000, the WPI series span the period January 1981 to October 1999. Nominal exchange rates are end-of-period. All data were obtained from Datastream.

Following Papell (2000), we do not include a time trend in the ADF regression, because such an inclusion would be inconsistent with long-run PPP. Also, we use the recursive t-statistic procedure as described by Campbell and Perron (1991), to select the lag length in the ADF specification.

The t-bar statistics for the CPI- and WPI-based real exchange rates are respectively –1.90 and –0.52 (5% critical value is –1.64). If we use the adjustment described in Section 3, the t-bar statistics for the CPI- and WPI-based real exchange rates are –4.41 and –2.17 respectively. These results reject strongly the unit root hypothesis in both the panels, and are in line with the findings on PPP by Wu (1996) and Oh (1996). Taken as a whole, the above findings seem to suggest that the real exchange rate is mean reverting in the long-run.

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[13] The proposed algorithm is programmed in Matlab 5.0, B is set equal to 2000.

Is mean reversion due to effective stationarity of the real exchange rate or is it due to neglecting cross-sectional dependence? To answer this question we use a panel unit root where the p-values have been calculated using the bootstrapping procedure described in Section 4, which is robust to cross sectional dependence. The empirical results are reported in Tables 3.1 and 3.2.

Table 3.1

Panel Unit Root Test: CPI-RER

Country	Lags	t-statistic	p-value (π_i)	$\ln(\pi_i)$
Austria	1	-2.2529	0.176	-1.7344
Denmak	2	-2.0037	0.282	-1.2658
Belgium	2	-1.6792	0.427	-0.8509
France	0	-1.9015	0.315	-1.1536
Germay	1	0.4896	0.989	-0.0111
Italy	0	-1.8212	0.334	-1.0951
Netherland	2	-1.9587	0.314	-1.1584
Norway	2	-2.1575	0.228	-1.4784
Portugal	6	-1.4244	0.548	-0.6015
Spain	2	-1.0304	0.463	-0.77
Canada	6	-1.8574	0.329	-1.1117
Sweden	6	-1.3339	0.629	-0.4628
Switzerland	6	-1.9834	0.252	-1.3783
UK	1	-2.4869	0.13	-2.0402
New Zel.	6	-2.1704	0.215	-1.5348
Japan	0	-2.0106	0.19	-1.6607
Greece	4	-1.71	0.425	-0.8557
Finland	0	-1.7968	0.393	-0.9339
Ireland	4	-2.3964	0.148	-1.9045
Mexico	6	-3.0131	0.04	-3.2189
SUM ln(p)				-25.220
P_λ test				50.441
χ^2 (40)-1%		63.7		
χ^2(40)-5%		55.8		
χ^2(40)-10%		51.8		

Note: CPI-RER denotes the real exchange rate based on consumer price

We note that using the individual ADF statistics we cannot reject the null hypothesis of a unit root for all CPI-, and WPI-based real exchange rates, except for Mexico (CPI-RER).

Table 3.2

Panel Unit Root Test: WPI-RER

Country	Lags	t-statistic	p-value (π_i)	$\ln(\pi_i)$
Austria	1	-1.68	0.4385	-0.8244
Belgium	0	-2.15	0.2055	-1.58231
Denmark	0	-1.38	0.5495	-0.59875
Germany	0	-1.35	0.598	-0.51416
Italy	0	-1.49	0.518	-0.65778
Ireland	2	-1.44	0.5345	-0.62642
Netherland	0	-1.05	0.6845	-0.37907
Norway	2	-2.17	0.207	-1.57504
Spain	0	-1.4	0.5395	-0.61711
Switserland	0	-1.51	0.517	-0.65971
SUM ln(p)				-8.03475
P_λ -test				16.06949
χ^2 (40)-1%	37.6			
χ^2(40)-5%	31.4			
χ^2(40)-10%	28.4			

Note: WPI-RER denotes the real exchange rate based on wholesale prices

The panel test statistic is shown at the bottom of the final columns in Tables 3.1 and 3.2 (50.44 for CPI-based real exchange rate and 16.07 for WPI-based real exchange rate). As Maddala and Wu (1999) show, this is a nonparametric test given by

$$P_\lambda = -2\sum_{i=1}^{N} \ln(\pi_i) \quad \Rightarrow \chi^2(2\text{N}) \qquad (3.18)$$

where π_i are the probabilities of the test statistic for a unit root in unit i, and P_λ has a χ^2(2N) distribution on the null.

For our panels we have $\chi^2(40)$ and χ^2 (20) respectively, with the respective 5% and 1% critical values shown in Tables 1 and 2. The reported panel unit root statistics are considerably smaller than their corresponding 5% and 1% critical values. Consequently, we cannot reject the null hypothesis of a unit root in the real exchange for all countries in the panel,[15] irrespective of the price index employed for constructing the real exchange rate.

Our empirical findings based on the bootstrap methodology contrast sharply with those obtained with the Im *et al* (1997) test that is used widely in the literature. This result is not a surprise. In fact, O`Connell (1998) talked about "overvaluation of PPP". He argued that evidence favouring PPP is mainly due to the fact of neglecting cross sectional dependence. He concluded that once we account for cross sectional dependence, evidence favouring PPP disappears. We confirm that result.

Finally, our results would appear to contrast with Wu and Wu (2001), who state that they found evidence supporting long-run PPP. Closer inspection of their bootstrap results, however, shows that the Maddala and Wu (1999) test rejects the unit root null in the panel of 20 countries, only at the 10% significance level. Besides using a different bootstrap algorithm, differences in the sample period and frequency of data, as shown in section 3.6, may also account for this difference in our results.

15 Wu and Wu (2001) using their bootstrap methodology were able to reject the unit root null

3.6. Size Analysis

In Section 3.3 we presented different econometric procedures for dealing with cross sectional dependence and we highlighted for each of them some pitfalls. With regard to bootstrap, we stressed the necessity of running Monte Carlo simulations in order to analyse the size distortion of a bootstrap test. However such an experiment is very time-consuming, because each replication requires the calculation of B+1 test statistics if B bootstrap samples are used. Davidson and MacKinnon (1998) show that it is possible to estimate the size distortion of a bootstrap test by running a simpler Monte Carlo simulation, provided that the condition of asymptotic independence of the bootstrapped statistic and the bootstrap data generating process (DGP) holds. In this section, after a brief presentation of the Monte Carlo analysis suggested by Davidson and MacKinnon (DM)[16], we use the suggested statistical methodology to analyse the size distortion of the bootstrap test presented in this paper.

The fundamental idea of Davidson and MacKinnon is based on the fact that we can estimate the size distortion of a bootstrap test using Monte Carlo experiments, relying on two simple concepts, respectively "error in rejection probability" (ERP) and "rejection probability" (RP) of the bootstrap test. The former represents the size distortion of a bootstrap test, the latter gives the rejection probability of the asymptotic test.

Consider a data-generating process (DGP), with a set of DGPs forming what we call a model M. A generic element, or DGP, of a model M will be denoted as μ. A test

hypothesis only at 10% significance level.

statistic λ is said to be asymptotically pivotal if its distribution is the same for each DGP $\mu \in M$. We denote by λ^* the realisation of λ calculated from data generated by some unknown DGP μ_0. The DM procedure works as follows. For each of M replications indexed by m, draw a sample from μ_0 and use this sample to draw a realisation of the statistic λ and the bootstrap DGP μ_m^*. Now, draw another sample from μ_m^*, and use it to compute a realisation of λ_m^*. The quantile $Q(\alpha, \mu_0)$ is estimated by $Q_0^*(\alpha)$, the α quantile of the drawings of λ. If we perform m replications the simulated estimate of RP and the corresponding ERP are given by:

$$RP_2^* = 2\alpha - \frac{1}{M}\sum_{m=1}^{M} I(\lambda_m^* < Q_0^*(\alpha)) \quad \text{and} \quad ERP_2^* = \alpha - \frac{1}{M}\sum_{m=1}^{M} I(\lambda_m^* < Q_0^*(\alpha)) \qquad (3.19)$$

However, since the above estimator of the rejection probability is not guaranteed to be positive, DM suggest using a more accurate estimate in which λ and λ* are interchanged. The procedure is the same as the one described above but the (ERP) is estimated as the proportion of drawings of λ less than $Q^*(\alpha)$, the α quantile of λ^*, minus α:

$$RP_1^* = \frac{1}{M}\sum_{m=1}^{M} I(\lambda_m < Q^*(\alpha)) \quad \text{and} \quad ERP_1^* = \frac{1}{M}\sum_{m=1}^{M} I(\lambda_m < Q^*(\alpha)) - \alpha \qquad (3.20)$$

[16] For more details on this statistical technique see Davidson and MacKinnon (1998,2000).

As suggested in DM (2000), it makes sense to compute both, since substantial differences between the two estimated ERPs may indicate that neither of them is accurate.

The DGP used, in this experiment, is the following linear AR equation:

$$\Delta y_{i,t} = \alpha_i + p_i y_{i,t-1} + \varepsilon_{i,t} \tag{3.21}$$

We consider the above model, assuming that p=0.998[17], 0.75, 0.50. We use different values of T, that is we consider our test when T= 325 and T=100. For each combination of (p,T) the number of replication is set to 2000. The nominal significance level (α) is set to 0.05. The size estimates from the DM approach are reported in Tables 3.3 (A, B, C) and 3.4 (A, B, C).[18] The empirical size of the test should not greatly exceed the nominal significance level. To allow for some random variation we form a confidence interval of the simulated size having length α $\pm 1.96 \cdot \delta_\alpha$, with $\delta_\alpha = \sqrt{\alpha(1-\alpha)/M}$. Since M=2000 and α = 0.05 the confidence interval is {0.04; 0.059}. Appendix 1, Tables 3.3 and 3.4 show that most of those values fall within these limits. With T=325, the empirical size of the test seems to be reasonable regardless of the value of p. With T=100, the test seems to suffer of very small size distortion when p = 0.998, but the size distortion increases the smaller the value of p. Since T = 100 corresponds to the frequency of data in Wu and Wu (2001), we believe that this may be the main reason for the empirical result they obtain.

[17] Since 0.998 is statistically indistinguishable from 1, in this case we assume that the process under consideration contains a unit root. However, we also consider our test statistic when the process contains roots that lie outside the unit circle.

[18] Algorithm is programmed in Matlab 5.0, B is set equal to 2000

This experiment suggests that the empirical size of our test matches the nominal size pretty well. Given that the size of the sample used in our econometric application is close to 325, our reported bootstrap statistics for the panel unit root test are free from significant size distortions. We therefore believe that the results provided by our test can be reasonably trusted.

3.7 Concluding Remarks

This chapter focuses on between group dependence of innovations and cross sectional dependence. We believe that although one of the causes of between group dependence of innovations is cross sectional dependence, there is also an interesting case in which the cause of a non-zero covariance matrix is due to a global variable non-correlated with the included regressors.

Following Maddala and Wu (1999), we propose bootstrap as a way of dealing with the problem. We believe that, in many practical cases, this methodology is still a valid response. We use Monte Carlo simulations to investigate the size distortion of the bootstrap test statistic. The panel unit root test is then applied to the long-run Purchasing Power parity (PPP) using a dynamic panel of monthly data for twenty OECD countries over the post-Bretton Woods period. We find no evidence favouring long-run PPP, irrespective of the price index employed for constructing the real exchange rates.

Our results contrast sharply with those obtained with the widely used Im *et al* (1997) test. We believe that the Im *et al* panel unit root test fails to reject long-run PPP essentially because it does not fully account with group dependency in the innovations. The latter is likely to increase the probability of a type 1 error.

Our findings also contrast with those obtained by Wu and Wu (2001), though their rejections of the unit root null is rather weak. However, in contrast to the Wu and Wu test, our Monte Carlo simulations do not reveal size distortions for the proposed bootstrap test statistic for moderate and large samples, as used in our empirical investigation, thus enabling us to draw valid inferences.

Appendix 1: MacKinnon Size Test for T=325 and p = 0.998

Table 3.3

(A) McKinnon-size test	
DM-simulation	p = 0.998
RP2	0.057
ERP2	0.007
RP1	0.059
ERP1	0.009

(B) McKinnon-size test	
DM-simulation	p = 0.75
RP2	0.06
ERP2	0.001
RP1	0.06
ERP1	0.001

(C) McKinnon-size test	
DM-simulation	p = 0.50
RP2	0.04
ERP2	-0.008
RP1	0.04
ERP1	-0.008

(Appendix 1 continued), MacKinnon Size Test for T=100

Table 3.4

(A)	
McKinnon-size test	
DM-simulation	p=0.998
RP2	0.05
ERP2	0.011
RP1	0.06
ERP1	0.009

(B)	
McKinnon-size test	
DM-simulation	p = 0.75
RP2	0.06
ERP2	0.014
RP1	0.06
ERP1	0.013

(C)	
McKinnon-size test	
DM-simulation	p = 0.50
RP2	0.07
ERP2	0.017
RP1	0.07
ERP1	0.016

CHAPTER 4

SYMMETRY, PROPORTIONALITY AND PURCHASING POWER PARITY: EVIDENCE FROM PANEL COINTEGRATION TESTS

4.1 **Introduction**

Although most of the studies examining long-run PPP are based on unit root tests of the real exchange rates, there is also another strand testing for cointegration between the nominal exchange rate and the domestic and foreign prices. However, the number of studies is limited[1]. While time series cointegration for individual countries provide conflicting evidence (e.g. Taylor, 1988; Mark, 1990, Sarantis and Stewart, 1993; Cheung and Lai, 1993; Ender and Falk, 1998; Coakley and Fuertes, 2000), studies applying panel cointegration are scarce. To our knowledge Pedroni (1997) and Canzoneri et al (1999) are the only studies that apply panel cointegration (but only the Pedroni tests) to PPP, though their evidence for PPP is mixed.

One important issue, that has been largely neglected by the studies cited above, is the possibility of more than one cointegrating vector in PPP. In fact, all (panel) cointegration tests used to test PPP are residual based tests that, by using a normalisation rule, restrict the cointegrating vector to be unique. Such a restriction is valid provided that the

[1] A major advantage of the cointegration approach to PPP, is that it relaxes the restrictive conditions of symmetry and proportionality imposed by unit root tests of the real exchange rate (Sarno and Taylor, 2002).

symmetry restriction holds. A part the symmetry restriction, the proportionality restriction is also important. In fact, unit root tests of the real exchange rate are based on that assumption. Consequently, the failure of unit root tests to find evidence favouring PPP may be due to the failure of the proportionality restriction.

An important contribution of this chapter is that we employ some recently developed heterogeneous panel cointegration tests (i.e. MacCoskey and Kao, 1998; Pedroni 1997; Larsson et al, 2001) that have not been previously applied to PPP. Furthermore, we investigate symmetry and proportionality conditions using likelikehood-based inference as suggested by Johansen (1995), but with likelihood ratio tests extended to a panel context. An additional contribution comes from the issue of multiple cointegrating vectors in PPP. We test for multiple cointegrating vectors in PPP using a new panel cointegration test proposed by Larsson et al. (2001) and attempt to give an economic meaning to the cointegrating vectors.

4.2 **Theoretical Framework**

PPP suggests that the exchange rate depends on relative price levels:

$$s_t = \alpha + \beta_0 p_t - \beta_1 p_t^* \tag{4.1}$$

where s_t is the log of nominal exchange rate, and p_t, p_t^* are, respectively the log of domestic and foreign prices.

Imposing the symmetry condition $\beta_0 = -\beta_1$ on prices in equation (4.1), we can re-rewrite (4.1) as:

$$s_t = \alpha + \beta(\; p_t - p_t^*) \qquad (4.2)$$

If we also impose the proportionality condition on the relative price coefficient in equation (4.2) , then $\beta = 1$. Equation (4.2) can only have one single cointegrating vector and this result from the symmetry condition.[2] In this chapter we examine these two assumptions because of their empirical relevance. First we test whether there is one unique cointegration vector in PPP. Next we examine the symmetry and proportionality assumptions. Rejections of these restrictions can be explained by reference to measurement errors, common trend in the relative prices of traded/non traded goods (Froot and Rogoff, 1995) barriers to trade and other economically unimportant factors (see Sarno and Taylor, 2002; Taylor, 2001).

4.3 **Panel Cointegration Tests for Testing PPP**

This section presents the panel cointegration tests used in this chapter[3]. We apply three panel cointegration tests. Two of them are residual based tests (McCoskey and Kao, 1998, and the Pedroni, 1997) where the cointegrating vector is subject to a normalisation

[2] The assumption $\beta = 1$ is also relevant for unit root tests. In fact, only if we are ready to assume that the proportionality and symmetry condition hold, we can justify the use of unit root tests to test for PPP, otherwise PPP tests based on real exchange rates would be biased. Hence the reasons for causing the failure of PPP may be also due to the failure of the proportionality restriction, imposed in unit root tests of real exchange rate.

rule. One (Larsson et al, 2001) is an extension of the Johansen method to a panel data framework.

Let $\{y_t, x_t\}$ be I(1) variables and consider the following model:

$$x_t = x_{t-1} + \varepsilon_t$$

$$e_t = \theta \sum_{j=1}^{T} u_j + u_t$$

$$y_t = \alpha + \beta x_t' + e_t \tag{4.3}$$

where x_t' is a vector of I(1) variables, $\theta = 0$ and the cointegrating vector is (1, $-\beta$`). The above model can be estimated using two different methods: (1) single equation methods, (2) system methods. We shall now consider the single equation method first.

The model represented in the equation (4.3) has been normalised with respect to y_t, and this normalisation rule allows the researcher to focus only on one cointegrating vector. That is, β' is unique. Stock et al (1993) show that the estimator of β, say β*, in this

[3] In this section, we present, briefly, the tests used in this chapter. For more details the reader is referred to chapter 2.

model, is superconsistent[4]. Although β* is superconsistent, Banerjee et al (1986) show that there is a substantial small sample biases. Furthermore, the distribution of the OLS estimates depends on nuisance parameters associated with the serial correlation properties of the data. This problem has been overcome in the literature using the following procedures: the fully modified OLS (FMOLS) of Phillips and Hansen (1990) which uses nonparametric corrections to the OLS estimator β*. Dynamic OLS (DOLS) as proposed by Saikkonen (1991), Phillips and Loretan's (1991) nonlinear least squares, Stock and Watson' (1993) dynamic GLS (DGLS) and Johansen maximum likelihood method.

The model (4.3.) constitutes the base on which McCoskey and Kao (1998) develop their panel cointegration test. McCoskey and Kao (1998) develop a residual based Lagrange Multiplier test for the null hypothesis of cointegration in panel data. The model they consider allows for varying slopes and intercepts across units:

$$y_{i,t} = \alpha_i + \beta_i x_{it}^{'} + e_{it} \qquad (4.4)$$

where $e_{it} = \theta \sum_{j=1}^{t} u_{ij} + u_{it}$

We test the null hypothesis $H_0 : \theta = 0$ against the alternative $H_0 : \theta \neq 0$. Under the null hypothesis we have $e_{it} = u_{it}$ and the equation above is a system of cointegrated regressors.

[4] β* is a superconsistent estimator of β, if β*→β as T→∞ at a rate T instead of $\sqrt{T}$. Intuitively, this happens because y_t and x_t are both I(1). Moreover, the variance will increase rapidly as the sample size increases.

The test statistic is then given by the following LM statistic:

$$LM = \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T}S_{it}^{+2}}{s^{+2}} \tag{4.5}$$

where S_{it}^{+2} is the partial sum of estimated residuals:

$$S_{it}^{+} = \sum_{j=1}^{t} e_{ij}^{*+} \text{ and } s^{+2} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}^{*+2}$$

The residuals e_{it}^{*} can be estimated using DOLS, FMOLS or any one of the methodologies discussed above. McCoskey and Kao (1998) show that under appropriate standardisation the LM-statistic in (4.5) becomes:

$$LM* = \frac{[\sqrt{N}(LM - u_v)]}{\sigma_v} \Rightarrow N(0,1) \tag{4.6}$$

where u_v and σ_v are obtained by Monte Carlo simulation and tabulated by the authors (see McCoskey and Kao, 1998, table 1).

Pedroni (1997) uses the same heterogeneous model as the one represented by the equation (4.4), but he also assumes individual specific deterministic trends. However, his null hypothesis is that there is no cointegration:

$$y_{i,t} = \alpha_i + \varphi_i t + \beta_i x_{it}^{'} + e_{it} \tag{4.7}$$

Based on the above model, he proposes seven panel cointegration statistics. Specifically, four are based on within-dimension approach, and three are based on between-dimension approach. In the first group we sum both the numerator and the denominator terms over the N dimension. In the second group we first divide the numerator by the denominator, prior to summing over the N dimension separately. Pedroni (1997) shows that the asymptotic distribution of these statistics, under an appropriate standardisation, is a normal distribution:

$$k = \frac{k_{N,T} - u\sqrt{N}}{\sqrt{v}} \Rightarrow N(0,1) \tag{4.8}$$

where $k_{N,T}$ is the panel cointegration statistic and u and v are the moments of the Brownian function (i.e. broadly speaking expected mean and variance) that are computed in Pedroni (1999).

One weakness of the tests considered above is that they assume the cointegrating vector to be unique. Such an assumption may be too strong. In fact, as we stressed at the beginning of this section, it constrains the researcher to choose a normalisation rule and, it is still unclear on the basis of what criterion this choice is made. To overcome this problem, system estimation methods have been suggested.

Larsson et al (2001) propose a panel cointegration test analogue of the Johansen maximum likelihood method. In this way, they allow for multiple cointegrating vectors. Although the use of this methodology resolves the issue of multiple cointegrating vectors, other problems may arise[5].

Assume that the data generating process for each of the groups is represented by the following VAR (k_i):

$$y_{it} = \sum_{k=1}^{k_i} \Pi_{ik} y_{i,t-k} + \varepsilon_{it} \qquad i = 1,\ldots,N \qquad (4.9)$$

The error correction representation of the above model can be written as follows:

$$\Delta y_{it} = \Pi_i y_{i,t-1} + \sum_{k=1}^{k_i} \Gamma_{ik} \Delta y_{i,t-k} + \varepsilon_{it} \qquad i=1,\ldots,N \qquad (4.10)$$

where Γ_i is of order p×p (p is the number of variables in each group), y_i is a p×1 vector of variables and Π_i a p×p long run matrix. We estimate equation (4.10) for each individual group using maximum likelihood methods and calculate the trace statistic. The LR (likelihood ratio)-bar statistic can be obtained as the average of the N individual trace statistics $LR_{iT}(H(r) \mid H(p))$.

[5] One of the problems arising in this context is the identification problem. We discuss the identification problem involved with panel cointegration tests based on Johansen procedure in the next section.

The null and alternative hypotheses are:

$$Ho : rank(\Pi_i) = r_i \leq r \quad \text{for all i = 1,...N}$$

$$H_1 : rank(\Pi_i) = p \quad \text{for all i = 1,...N}$$

The standardised LR-bar statistic for the panel cointegration test is:

$$Y_{LR}(H(r) \mid H(p)) = \frac{\sqrt{N}(LR_{NT}(H(r) \mid H(p)) - E(Z_k))}{\sqrt{Var(Z_K)}} \Rightarrow N(0,1) \quad (4.11)$$

where $E(Z_k)$ and $Var(Z_k)$ are the mean and variance of the asymptotic trace statistic. Larsson et al (2001) report the values for the moments of Z_k, and these can be used to calculate the test statistic.

Using Monte Carlo simulations the authors demonstrate that the probability of falsely choosing a too large rank from the standardised panel trace test approaches to zero as the sample increases. For the DGP with true rank $r = 1$ and $r = 2$, the power of rejecting the false hypothesis approaches unity as N and T increase. It is shown that the power of the panel trace test for this hypothesis is in fact close to unity for $T \geq 25$ and $N \geq 10$. Since our study employs a sample of 20 countries with 336 time observations, we believe this test should have a sufficient power.

4. 4 **Empirical Results from Panel Unit Root Tests**

The panel data set contains monthly data for twenty OECD countries over the period 1973-2000. Nominal exchange rates are end-of-period US$, while prices are measured by the consumer price index. Data were obtained from Datastream.

First we examine the stationarity properties of the individual time series. Table 4.1 shows the result from the ADF test. Following Papell (1997), we do not include a time trend in PPP equation. In fact, the inclusion of a time trend would be inconsistent with PPP because the real exchange rate would be trend stationary. The individual ADF statistics for nominal exchange rates (ER) show little evidence of stationarity. In fact the null hypothesis of a unit root in the nominal exchange rate is rejected for Italy and Sweden only.

The panel unit root test, reported at the bottom of Table 4.1, confirms the evidence of a unit root in the nominal exchange rate and domestic prices (DP).

Table 4.1

Im et al (1997) t-bar Test

	s_t	p_t^*
AUST	-2.83	-2.87
BELG	-1.6	-2.26
CAN	-1.25	0.34
DAN	-0.96	1.1
GERM	-2.59	-2.03
FRA	-0.65	1.99
ITA	-3.22	-3.7
NL	-2.27	-0.61
NORW	-2.54	0.33
PORT	-2.76	-3.77
SWITZ	-2.79	-1.97
IR	-0.76	-0.6
MEX	-0.67	0.17
FINL	-1.39	1.88
GRE	-0.84	-1.49
NZ	-2.61	-1.55
JAP	-0.36	1.19
SPA	-1.88	1.49
UK	-0.57	-0.67
SWED	-2.96	0.6
AVE(t)	**-1.77**	**-0.62**
t-bar	**-1.27**	**4.71**
CV(5%)	**-1.65**	**-1.65**
CV(1%)	**-2.33**	**-2.33**

We also use the bootstrap panel unit root test proposed in chapter 3. Table 4.2 reports the π values. The individual π_i values cannot reject the null hypothesis of unit root in the exchange rate and domestic price for any country. The panel test statistic is smaller than its critical values for both variables, thus suggesting that the exchange rate and the domestic price are I(1) stochastic processes for the whole panel of OECD countries. The ADF test for the US consumer price p_t^* over the same period was -3.123. This implies a stationary process at 5% level. Given the international evidence of non-stationarity of consumer price and the borderline value of the unit root statistic, we treat the US-CPI as an I(1) process.

Table 4.2

Bootstrap Panel unit root Test (π_i values)

	s_t	$s_t - \log(\pi_i)$	p_t	$p_t - \log(\pi_i)$
AUST	0.147	-1.91732	0.245	-1.4065
BELG	0.36	-1.02165	0.321	-1.13631
CAN	0.695	-0.36384	0.421	-0.86512
DAN	0.49	-0.71335	0.11	-2.20727
GERM	0.199	-1.61445	0.643	-0.44161
FRA	0.562	-0.57625	0.421	-0.86512
ITA	0.558	-0.5834	0.445	-0.80968
NL	0.215	-1.53712	0.187	-1.67665
NORW	0.517	-0.65971	0.521	-0.65201
PORT	0.507	-0.67924	0.486	-0.72155
SPA	0.609	-0.49594	0.122	-2.10373
SWED	0.6	-0.51083	0.345	-1.06421
SWITZ	0.064	-2.74887	0.432	-0.83933
IR	0.347	-1.05843	0.231	-1.46534
MEX	0.629	-0.46362	0.121	-2.11196
FINL	0.194	-1.6399	0.213	-1.54646
GRE	0.505	-0.6832	0.435	-0.83241
JAP	0.481	-0.73189	0.234	-1.45243
NZ	0.521	-0.65201	0.08	-2.52573
UK	0.142	-1.95193	0.123	-2.09557
SUM		**-20.6029**		**-26.819**
P_λ		**41.20589**		**53.63801**
χ^2(40)-1%	**63.69**	**χ^2(40)-5%**	**55.76**	

4.5 Empirical Results from Panel Cointegration Tests

On the basis of the empirical results obtained in the previous section, we apply the panel cointegration tests reviewed in section 4.3 to our data set. To calculate the McCoskey and Kao LM-statistic, we specify the following DOLS:

$$s_{it} = \alpha_i + \beta_0 p^{d}_{t-1} - \beta_1 p^{us}_{t-1} + \sum_{j=-k}^{k_i} \phi_{ij} \Delta p^{d}_{i,t-j} + \sum_{j=-k}^{k_i} \Delta p^{us}_{i,t-j} + u_{it} \tag{4.12}$$

i =1,…N, k_i = leads and lags of $\Delta p^{d}_{i,t-1}$ and $\Delta p^{us}_{i,t-1}$, p^{d} = domestic prices, p^{us} = US prices.

However, in the presence of autocorrelation, we re-specify the DOLS equation above by adding AR processes. Table 4.3 reports the results for the DOLS and DGLS estimator, used to calculate the McCoskey and Kao LM-statistic. We start with a reasonable number of leads and lags (i.e. 7) and use the AIC information criteria to select the final number of leads and lags to be included. The number of leads and lags in most cases is equal to two, except for UK, Italy and France, where it is 4. Furthermore, since we noticed evidence of autocorrelation in six countries out of twenty (i.e. France, Italy, Netherlands, Norway, Ireland and Japan), we apply the DGLS method[6].

[6] It is interesting note that Maddala and Kim (1998) using Monte Carlo simulations demonstrate that the DOLS/DGLS estimator provides the best choice amongst single equation methods for cointegration.

Table 4.3
Long-Run Equilibrium PPP (DOLS-DGLS) Estimates

	α_i	p_t	p_t^*	$AdjR^2$	$Akaike$	$\Pr[Fa]$
AUST	35.43 [3.71]	6.7 [23.3]	-2.3 [-19.1]	0.981	0.135	0.321
BELG	11.87 [6.19]	8.1 [23.1]	-2.7 [-17.9]	0.972	0.219	0.112
CAN	5.89 [1.06]	0.7 [19.6]	-0.2 [-13.4]	0.897	0.128	0.182
DAN	8.98 [6.04]	0.8 [4.1]	-0.4 [-2.1]	0.789	-0.781	0.232
GERM	56.98 [2.74]	1.2 [20.6]	-1.1 [-18.5]	0.705	1.12	0.099
FRA	4.15 [22.46]	0.08 [1.99]	-1.17 [-10.13]	0.58	1.75	0.231
ITA	1.01 [5.46]	-1.03 [-8.52]	2.04 [2.26]	0.739	-0.656	0.541
NL	14.82 [12.03]	1.85 [12.7]	-0.19 [-3.54]	0.628	-0.923	0.189
NORW.	0.17 [1.52]	-1.49 [-13.05]	1.81 [15.58]	0.498	-1.47	0.298
SWITZ	61.79 [2.76]	1.5 [29.6]	-1.4 [-27.1]	0.758	1.645	0.195
PORT	32.74 [1.89]	0.3 [14.7]	0.7 [27.1]	0.879	-0.132	0.169
SPA	21.76 [3.95]	1.3 [18.2]	-0.2 [-2.9]	0.867	-0.124	0.193
SWED	48.93 [4.05]	-0.5 [-7.1]	1.1 [12.7]	0.689	1.211	0.231
IR	4.15 [22.46]	0.08 [1.9]	-1.17 [-10.13]	0.58	1.76	0.561
MEX	56.05 [3.71]	0.9 [146.1]	-0.5 [-60.8]	0.897	-0.213	0.311
FINL	29.36 [1.97]	0.4 [0.2]	-3.6 [-1.1]	0.489	-0.871	0.508
GRE	8.78 [3.56]	0.3 [24.3]	0.9 [63.7]	0.945	-0.741	0.987
JAP	2.09 [2.04]	3.7 [13.5]	-2.4 [-21.8]	0.765	-0.598	0.334
NZ	20.12 [3.56]	0.6 [20.7]	-0.5 [-16.1]	0.887	-0.656	0.674
UK	25.66 [5.23]	0.3 [6.4]	-0.4 [-7.7]	0.952	-0.54	0.988

Note: numbers in brackets below regression are t values based on HAC standard errors. Akaike is the information criterion used to determine the number of leads and lags in the model. Pr[Fa] is the probability value of an F version of the Breusch-Godfrey test for the first order autocorrelation. The equations for France [AR(1)], Italy [AR(2)], Netherland [AR(2)], Norway [AR(1)], Ireland [AR(1)], and Japan [AR(1)], were estimated using DGLS. All other estimates are DOLS

The Pr values indicate that all of the series are free from autocorrelation, while the coefficient of determination suggest good explanatory power for most countries. The intercept (α_i) appears to be significant (at 10% significance level) for almost all countries in the panel except Canada. Domestic prices appear to be significant in all countries except Finland and display the anticipated sign in all countries but three (Italy, Norway and Sweden). The coefficient on the foreign price is also significant in all countries except Finland, though it has the wrong sign in five countries (Italy, Norway, Portugal, Sweden and Greece). The McCoskey and Kao (1998) panel cointegration test based on the estimates of Table 4.3 is reported in Table 4.4

Table 4.4

(a)Pedroni (1999) Panel Cointegration Tests

Panel v-statistic	-0.9057
Panel rho-statistic	1.1454
Panel pp-statistic	1.9786
Panel ADF-statistic	-2.1477
Group-rho statistic	2.0573
Group pp- statistic	2.7175
Group ADF-statistic	-2.9453
(b)McCoskey and Kao (1998) Panel Cointegration Test	
LM*	1.21

Note: (a) The MacCoskey and Kao (1998) LM statistic is one-sided with critical values of 1.64. Therefore large values (LM*>1.64) suggest rejection of the null hypothesis. The mean and the variance used to calculate the LM statistic are respectively 0.0850 and 0.0055 (MacCoskey and Kao, 1998, Table 2).*
(b)The Pedroni (1997) statistics are one-sided tests with critical values of -1.64 ($k < 1.64$ suggest rejection of the null) except for the v statistic that has a critical value of 1.64 ($k > 1.64$ suggests rejection of the null).Note that the means and variances used to calculate the Pedroni statistics are reported in Pedroni (1999, Table 2), with heterogeneous intercept included.

Since LM* is smaller than the critical value, we cannot reject the null hypothesis of cointegration for the panel as a whole. The statistics for the Pedroni panel cointegration test are reported in the same table. Five statistics out of seven cannot reject the null of non-cointegration. However Pedroni (1997) shows that the panel-ADF and the group-ADF have better small sample properties than the other statistics and hence they are more reliable.

The LM* is one-sided with a critical value of 1.64. Therefore large values suggest rejection of the null hypothesis.[7] The Pedroni statistics are one-sided tests with a critical value of –1.64. Hence, large values imply rejection of the null of non- cointegration.[8] Taking as a whole, the above results show that there is long-run evidence of cointegration between nominal exchange rate and relative prices, but it is not completely unambiguous. As we have mentioned in the previous sections, the tests presented so far are residual based test that restrict the cointegration vector to be unique, and the uniqueness is reached through normalisation rule. A panel cointegration test that allows for multiple cointegrating vectors is the one proposed by Larsson et al (2001) and based on Johansen cointegration trace statistics. The trace statistics are reported in Table 4.5. The lag length of the VAR was chosen on the basis of the AIC information criteria. An intercept was included. The individual trace statistics indicate the presence of two cointegrating vectors.[9] This result is confirmed by the panel cointegration test (Y_{LR}) shown at the bottom of the table. In fact, the largest rank in the panel is $r_i = 2$. Hence the Larsson test

[7] Note that the mean and variance to calculate the LM* statistic are respectively 0.0850 and 0.0055 (MacCoskey and Kao, 1998)

[8] Note that for the means and variances used to calculate the statistics presented in Table 4.4.2 refer to Pedroni (1999) Table 2, heterogeneous intercept included, number of regressors (i.e.m) equal to two.

[9] A similar result was obtained by Coakley and Fuertes (2000) for a panel of 19 OECD countries over the period 1973-1996, using German mark as the numeraire currency.

suggests the presence of two cointegrating vectors between the nominal exchange rate and domestic and foreign prices for the full panel of OECD countries.

Table 4.5

Larsson et al (2001) Panel Cointegration Test

Country	Lag	r=0	R=1	R=2	Rank,ri
Aust	5	37.43121	7.262255	0.356479	1
Belg	3	63.004	22.11346	2.972761	2
Can	2	69.63771	8.27306	0.081483	1
Dan	6	29.28871	9.379702	2.925927	1
Germ	3	46.0645	5.456459	0.963623	1
Fra	4	45.30611	17.33128	2.225056	2
Ita	5	36.71795	14.9697	0.689368	2
NL	6	23.99649	3.751779	0.367481	0
Norw	6	39.08324	10.415	0.296676	1
Port	2	82.44046	13.57342	0.024311	2
Spa	6	38.79391	4.897133	0.209494	1
Swed	3	81.64645	7.751423	0.22209	1
Switz	3	41.85091	9.544353	1.56124	1
IR	4	41.30592	7.022778	2.297074	1
Finl	4	53.36104	16.16923	3.202354	2
Gre	5	69.67991	21.01656	4.061353	3
Mex	4	73.33212	28.74585	0.058538	2
Jap	3	87.28403	40.47651	0.136095	2
NZ	2	69.98683	15.32998	0.404149	2
UK	2	79.05629	14.84021	3.373594	2
LR_{NT}		**55.46339**	**13.91601**	**1.321457**	
Y_{LR}		**36.42**	**10.79**	**0.55**	

Note: The critical values for the trace statistic at 95% significance level are 34.91 $(r=0)$; 19.96 $(r=1)$; 9.24 $(r=2)$. 41.07 $(r=0)$; 24.60 $(r=1)$; and 12.97 $(r=2)$ at 99%. The critical values for $E(Z_k)$ and $Var(\hat{Z}_k)$ were obtained from Larsson et al (2001, Table 1). These are respectively 14.955 and 24733 for $r=0$; 6.086 and 10.535 for $r=1$; 1.137 and 2.212 for $r=2$

4.6 **The Identification Issue in Cointegrating Relationships**

The Johansen multivariate framework in the previous section, can be also used to attempt to interpret the cointegrating vectors. We use the likelihood ratio test to test the validity of the joint symmetry/proportionality restriction[10] $\beta_1 = 1$ and $\beta_0 = -1$ which implies that one of the cointegrating vectors is (1, -1, 1). Furthermore, since there is no theoretical reason for not believing that the relative prices of traded and nontraded goods may share the same common stochastic trend, we impose this restriction on the second cointegrating vector. This restriction would imply that US CPI, forms itself a co integrating vector.[11] Following Johansen (1995) we test the following restrictions:

$$\beta = (H_1 \vartheta_{1,} H_2 \vartheta_2) \tag{4.13}$$

where for i = 1,2 H_i ($p \times s_i$) is known, and ϑ_i ($s_i \times r_i$) is the parameter to be estimated with $r_i \le s_i \le p$ and $r_1 + r_2 = r$.

[10] Note: On the basis of the result that we obtain from the Larsson et al. test (i.e. r = 2), we decide to fix the number of cointegrating vectors to 2 for all cross units. However, this result should be taken with caution since we found the Larsson et al test to be very sensitive to the lag length, inclusion of an intercept in the VAR and the span of data. We believe that this test tends to select a higher number of co integrating vectors than there really are.

[11] There is no empirical evidence suggesting it could not be the case. Furthermore, by graphical inspection we noticed the presence of a damped-trend in the US-CPI. We take into account these elements to decide the restriction on the second co-integrating vector. Furthermore we noticed that after having run an DF and ADF tests on the natural log of the US-CPI, the latter appeared to be stationary . It should be stressed that the result from DF/ADF tests on US-CPI, the presence of a common stochastic trend in the price of traded non traded goods and the presence of a damped trend, all imply that there has been no inflation in the US over the sample period under consideration. However, we have been unable to give an explanation to this puzzle.

Where H_1 and H_2 are given by :

$$H_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; \quad H_2 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \tag{4.14}$$

The test statistic follows a χ^2 with $v = \sum(pl - r - s_i)$, where pl is the number of freely estimated parameters in β_i and the maximum rank, in our case, is equal to two. Furthermore, assuming independence across i, for i = i,...N; we can extend the above test to a panel context. The panel test will be given by $\sum_{i=1}^{N} NQ_i(r) \sim \chi^2_N$. Where $Q_i(r)$ is the likelihood ratio test performed on each individual i for i = 1,...N[12]. The results are displayed in Table 4.6.

Table 4.6
Johansen (1995) LR Test

AUST	0.46
BELG	13.03
CAN	9.63
DAN	18.25
GERM	0.43
FRA	18.22
ITA	0.15
NL	6.39
NORW	0.28
PORT	8.97
SPA	21.04
SWED	1.98
SWITZ	0.63
IR	13.68
MEX	8.38
FINL	0.18
GRE	9.68
JAP	10.36
NZ	4.55
UK	12.13
PLR	**163.42**
$\chi^2(2)$-1%	**9.21**
$\chi^2(2)$-5%	**5.99**

Note: The individual country statistic follows a χ^2 with 2 degree of freedom. The panel PLR test follows a χ^2 distribution with 2N degree of freedom, where N is the cross section dimension

Since $\chi_2^2 = 5.99$ at 5% and 9.21 at 1%, we reject the null for twelve countries out of twenty at 5% and nine out of twenty at 1%. The panel statistic strongly rejects the null hypothesis that at least one of the restrictions is valid using both 5% and at 1% critical value. The evidence of the rejection of the symmetry and proportionality conditions is in line with similar results obtained by other studies using time series cointegration tests

[12] Note that as we pointed out, by testing the validity of the joint symmetry/proportionality restriction which is implicitly imposed in unit root test on the real exchange rate, one indirectly tests the plausibility of using unit root tests to test PPP.

(Cheung and Lai, 1993; Wu, 1996), and tell us that the joint symmetry and proportionality restriction may be too restrictive.

We also test the validity of the symmetry condition $\beta_0 = -\beta_1$. Results are reported in Table 4.7. We are unable to reject the null hypothesis in only seven countries out of twenty. The panel test strongly rejects the null. This result tells us that the imposition of one single cointegrating vector may be too restrictive.

Table 4.7
LR Test: Symmetry Restriction

Austria	3.18
Belgium	6.26
Canada	3.04
Denmark	16.83
Germany	19.94
France	23.78
Italy	0.26
Netherl.	26.1
Norway	3.84
Portugal	5.24
Spain	10.65
Sweden	9.09
Switzerl.	2.45
Ireland	18.52
Mexico	0.13
Finland	16.61
Greece	8.94
Japan	19.38
New Zel.	3.6
UK	5.69
PLR	**161.4**

Note: See note to Table 4.6 for information on the distribution of the statistics

On the basis of the results obtained above, and also considering that the Larsson et al (2001) test, since it is based on the Johansen multivariate cointegration procedure, may tend to overestimate the true number of cointegrating vectors, we decide to fix a common rank r = 1 across different units and test the joint symmetry-proportionality restriction by using a LR test for over-identifying restrictions. The results are reported in Table 4.8. On the basis of individual LR statistics, we reject the null in fifteen countries out of twenty at 1% and in eighteen out of twenty at 5%. significance level. The panel test strongly rejects the null hypothesis of valid restrictions for the whole panel of OECD countries. These findings are similar to those reported above for the case of two cointegrating vectors. The result is also in line with other empirical results such as Wu (1996).

Table 4.8

LR Test Joint Symmetry/Proportionality Restriction

AUST	15.61
BELG	2.25
CAN	41.28
DAN	30.17
GERM	26.69
FRA	2.13
ITA	12.18
NL	24.94
NORW	16.95
PORT	54.83
SPA	27.27
SWED	4.1
SWITZ	4.01
IR	26.03
MEX	24.92
FINL	11.9
GRE	25.01
JAP	11.19
NZ	22.49
UK	5.1
PLR	**389.05**

Note: The individual countries LR statistic follows a χ^2 *distribution with 2 d.f., while the panel statistic (PLR) follows a* χ^2 *distribution with 2N d.f. Critical values are* $\chi^2(2) - 5\%$ *5.99;* $\chi^2(2) - 1\%$ *9.21.*

4.7 **Conclusions**

This chapter examines the validity of Purchasing Power Parity as a long run equilibrium condition in a dynamic panel of twenty OECD countries during the post Bretton Woods floating period. We use recently developed heterogeneous panel cointegration tests that have not been previously applied to test for PPP before and find evidence of cointegration.

This chapter represents the first attempt to investigate the possibility of more than one long run equilibrium in PPP between nominal exchange rate, domestic and foreign prices. To examine this issue we use the new panel cointegration test proposed by Larsson et al (2001) and find two cointegrating vectors in PPP. Using likelihood ratio test we find that the joint symmetry and proportionality restriction, imposed on the unit root tests of the real exchange rate, is not consistent with our data. We claim that its imposition may bias unit root tests of the real exchange rate towards finding no mean reversion.[13] This result is in line with empirical works such as Taylor (1988), and Froot and Rogoff (1995) that explain the failure of the proportionality restriction, due to the presence of measurement errors and transaction costs. Furthermore, it is also in line with other empirical works, (see Wu, 1996).

[13] The methodology we have used in this paper to test for PPP (i.e. testing for cointegration in a trivariate PPP framework and testing for joint symmetry/proportionality restriction by likelihood ratio test) could be, in our view, an ideal way of compromise between that part of the literature that opts for testing for PPP using the real exchange rate and that which prefers an unrestricted cointegrating framework.

We also find that the symmetry condition is rejected both for most individual countries and for the full panel of OECD countries. Our empirical findings imply that prices are important determinants of the exchange rate in the long-run, but the coefficients do not necessarily comply with the restrictive conditions imposed by the strong PPP hypothesis. What the empirical evidence supports is weak form of the long run PPP. Hence one important issue for future research would be to investigate the economic factors that account for the failure of the symmetry and proportionality conditions.

CHAPTER 5

DOES THE PURCHASING POWER PARITY HOLD IN EMERGING MARKETS? EVIDENCE FROM BLACK MARKET EXCHANGE RATES

5.1 Introduction

Most of the literature has focused on testing for PPP in OECD countries. The consensus amongst practitioners seems to be mixed (see, for example Sarno and Taylor, 2002; O`Connell, 1998; Papell, 1997; Pedroni, 1997; Lothian, 1997; Frankel and Rose, 1996).

However, if a large literature on PPP using OECD countries does exist, little work has been done for emerging market economies. More importantly, very few papers investigate black market exchange rates behaviour in emerging market economies. Phylaktis et al (1994), Phylaktis (1994) and Speight and McMillan (1998) who use time series, and Luintell (2000), who use panel data, are the few examples that consider black market exchange rates, although they cover only a small number of countries.

These countries tend to have some form of a fixed exchange rate system combined with foreign trade and capital restrictions., they suffer from high inflation and large external deficits, and are often faced with currency crises. Hence, persistent deviations from PPP can be caused not only by macroeconomic disequilibrium, but also resource misallocation and income redistribution.. It might therefore be argued that evidence on the PPP hypothesis is even more crucial for developing than developed countries. The unique features of developing economies have led to the development of black markets for foreign exchange in these countries.

Black market exchange rates are unofficial rates, in the sense that their transactions do not take place in official markets. Most of the countries of the present study have a long black market tradition and in many cases these markets have also been supported by governments. In fact, in many cases the volume of transactions in these markets were much larger than the official market.

Although black market exchange rates play such a major role in the developing economies, it is surprising to note that very few papers use this major source of information to investigate the PPP hypothesis in developing countries. Baghestani (1997) covers just one country, namely India. Phylaktis and Kassimatis (1994) and Luintel (2000) look at the experience of seven countries in the Pacific Basin region, while Diamandis (2003) examines four Latin America countries. Besides their limited country cover, all these papers use tradition time series unit root or cointegration tests, which are known to have limited power due to the small sample employed. The only exception is the paper by Luintel (2000) that addresses this problem by using panel unit root tests.

The data set used in this study includes twenty countries and spans over twenty one years. To our knowledge, empirical investigation of the real exchange rate using black market rates of this dimension has not been previously undertaken. Thus this study extends the test of PPP into new directions.

Another contribution of this chapter comes from using a battery of new multivariate panel unit root and cointegration tests that the literature on panels considers having greater power than the existing tests used in the literature to test PPP. In addition, we examine the symmetry and proportionality conditions within the context of both time series and panel methods.

Froot and Rogoff (1995) posits that rich countries have higher exchange rates than poor countries, which means that if we test PPP between rich and poor countries, the real exchange rate will not be mean reverting. That is, deviations from PPP between rich and poor countries tend to be persistent. This can be explained by considering cross country productivity differences and the Balassa-Samuelson effect, an issue we shall We shall also address.

Furthermore, two stereotypical views seem to be common when we test PPP using emerging markets data. First, nominal exchange rates in those countries are more volatile than exchange rates in OECD countries. Second, in those countries, monetary growth tends to overshadow real factors such that the relative price ratios exhibit excessive volatility. The latter may bias evidence in support of PPP. We try to shed some light on the above issues in this chapter.

This chapter is organised as follows. Section 5.2 discusses the PPP doctrine and the econometric framework. Sections 5.2 and 5.3 present the data used in this study. This is a unique set of data that has not been previously used in the literature. Section 5.4 deals with exchange rates and relative price ratio volatility. We investigate the issue of real exchange rate volatility in high-inflationary countries. Sections 5.5 and 5.6 review the panel tests used in this chapter. Empirical results are presented in sections 5.7, 5.8 and 5.9. A separate section concludes.

5.2 Purchasing Power Parity

PPP is one of the most important conditions in international finance because many models are built on the assumption that it holds. Under absolute PPP the nominal exchange rate is proportional to a ratio of domestic to foreign price levels. In a logarithmic form:

$$s_t = \alpha + \beta_0 p_t - \beta_1 p_t^* \qquad (5.1)$$

where s_t is the nominal exchange rate, and p_t, p_t^* are, respectively domestic and foreign prices, all measured in logs.

Equation 5.1 is known as a trivariate relationship. A bivariate relationship between the nominal exchange rate and the domestic to foreign price ratio is given by:

$$s_t = \alpha + \beta(p_t - p_t^*) + u_t \tag{5.2}$$

This PPP framework does impose an a-priori restriction on the cointegrating vector. The difference between the PPP framework represented by equation 5.1 and 5.2, is that in the latter the symmetry condition on the price coefficients has been imposed.

There is also a further specification of PPP, more commonly used in unit root tests:

$$q_t = s_t - p_t + p_t^* \tag{5.3}$$

Where q_t is the real exchange rate. The PPP equation in 5.3 requires $\beta = 1$. This also implies $\beta_1 = -\beta_0$, that is the joint symmetry/proportionality restriction holds. Since all unit root tests on the real exchange rate assume, implicitly, that such a restriction holds, a failure of these tests to find evidence favouring mean reversion in the real exchange rate, may be caused by a failure of such a restriction.

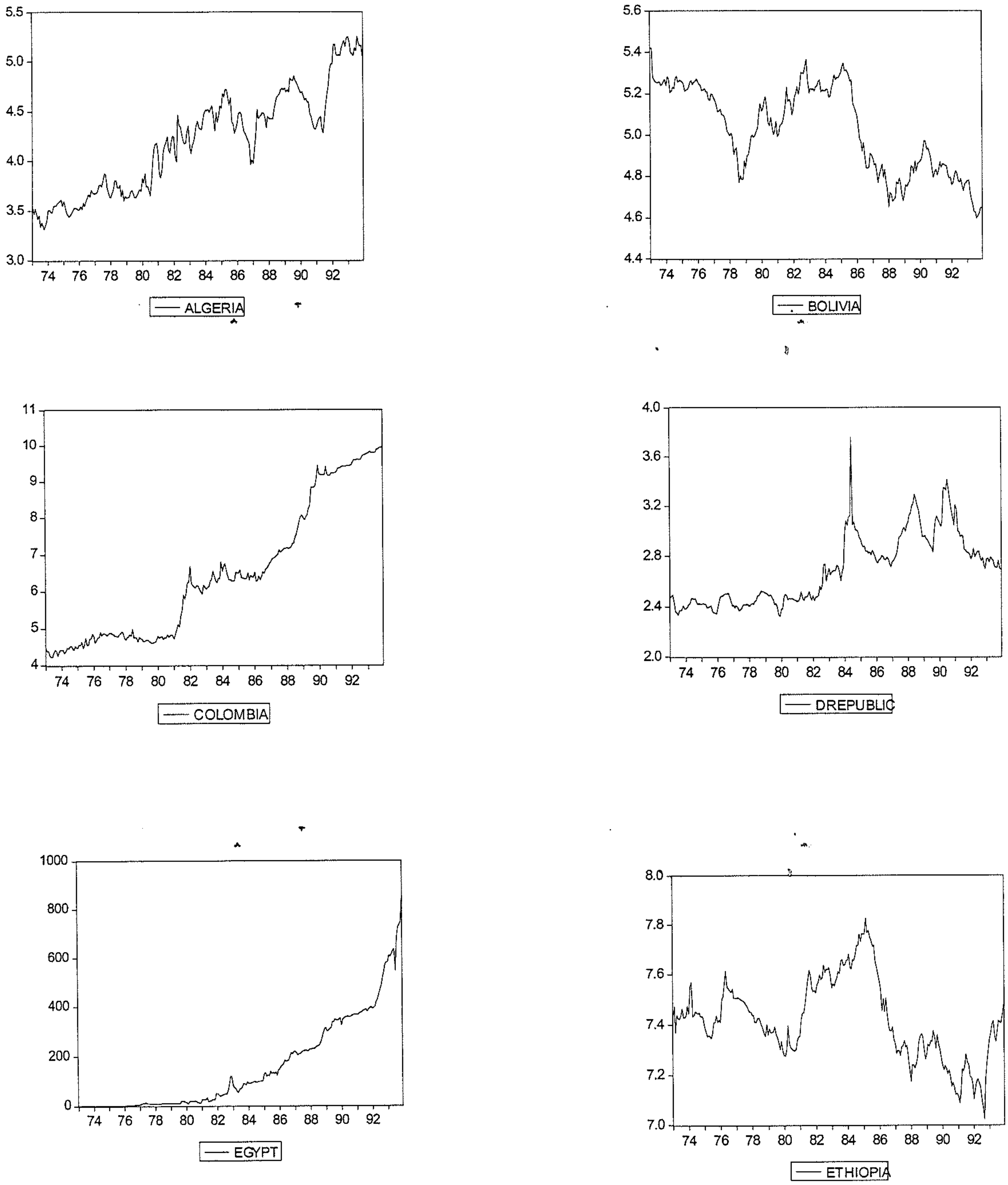
Why may β not be equal to one? Different economic explanations have been suggested in the literature. For example, Froot and Rogoff (1997) consider as a possible explanation the presence of a trend in the relative prices of traded/non-traded goods. Taylor (1988), offers a different explanation and suggests that it may be due to measurement error.

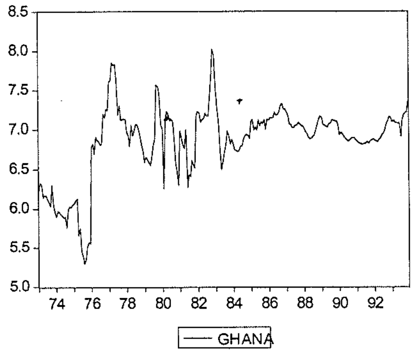
5.3 **An Overview of the Data**

We use monthly data on the black market exchange rates for a panel of twenty emerging market countries (Nepal, Pakistan, Philippines, Thailand, Kenya, Korea, Malaysia, Ethiopia, Ghana, Hungary, India, Algeria, Bolivia, Colombia, Dominica Republic, Egypt, Venezuela, Turkey, Indonesia and Sri Lanka) over the period 1973M1-1993M12. The US Dollar will be employed as numeraire currency. The black market exchange rates are obtained from Pick's currency yearbook in various publications. The tonsumer price index (CPI) is used as price index. These are the standard sources for black market exchange rate data. Black market exchange rates are unofficial rates, in the sense that their price is not set by the official market (see section 5.4 for details). Generally, the black market currency is defined as the private dealings of foreign currency bank notes and/or nonblank transfer abroad. We have only twenty currencies in our panel because of the lack of data on CPI (over the period 1973-1993) for most emerging markets. Furthermore, 1993 was chosen as the span of our set of data because the unavailability of data spanning beyond that year. All the exchange rate series are plotted in Figure 5.1.

Figure 5.1

Black Market Exchange Rates





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6.5
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5.0
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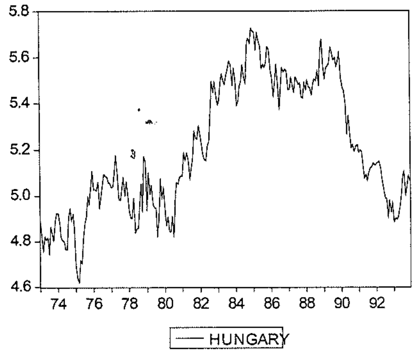
GHANA



5.8
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5.2
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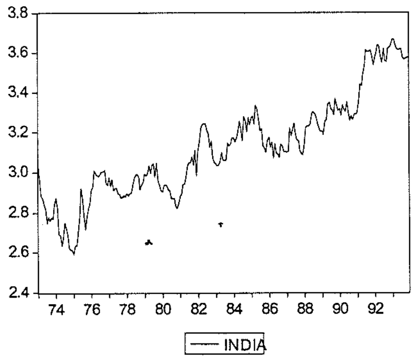
4.8
4.6
74 76 78 80 82 84 86 88 90 92
HUNGARY



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3.2
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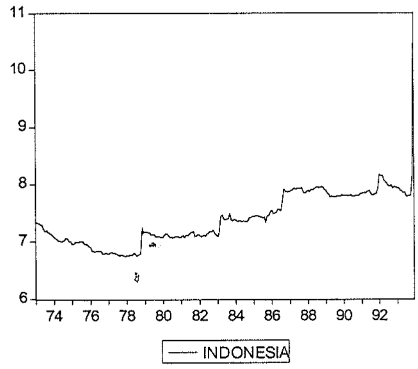
2.6
2.4
74 76 78 80 82 84 86 88 90 92
INDIA



11
10
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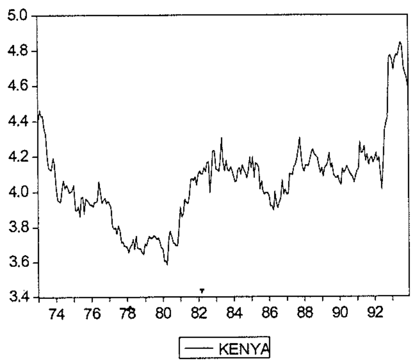
74 76 78 80 82 84 86 88 90 92
INDONESIA



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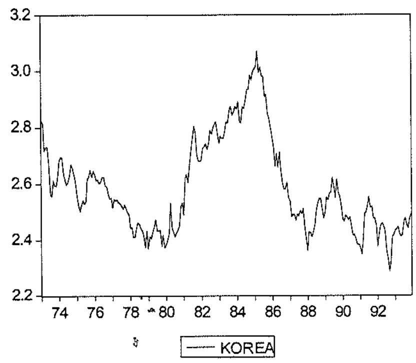
74 76 78 80 82 84 86 88 90 92
KENYA



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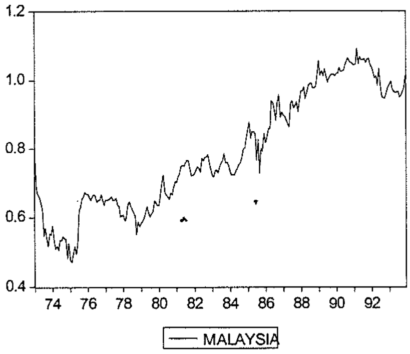
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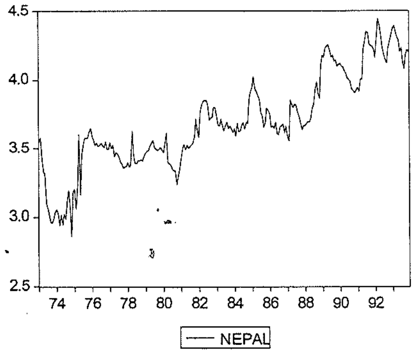
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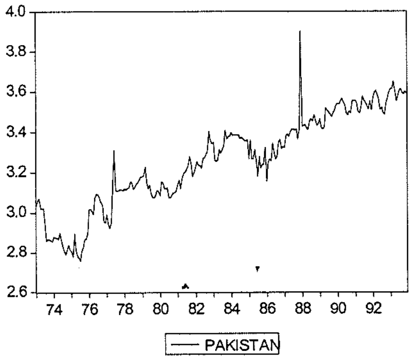
NEPAL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2.8
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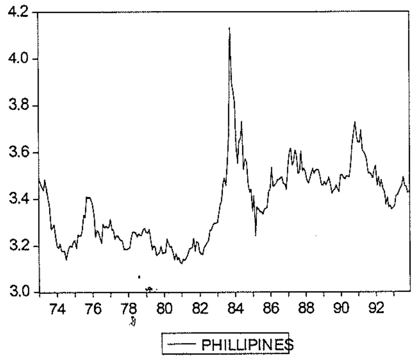
74 76 78 80 82 84 86 88 90 92
PAKISTAN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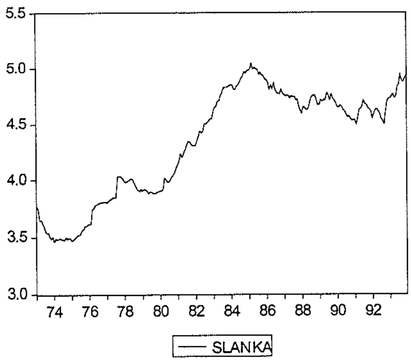
74 76 78 80 82 84 86 88 90 92
PHILLIPINES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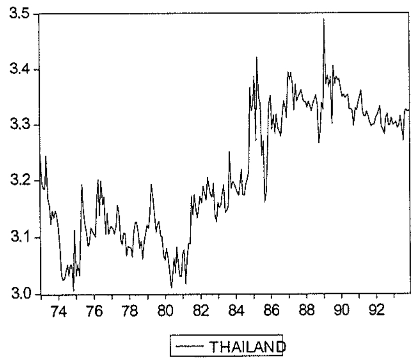
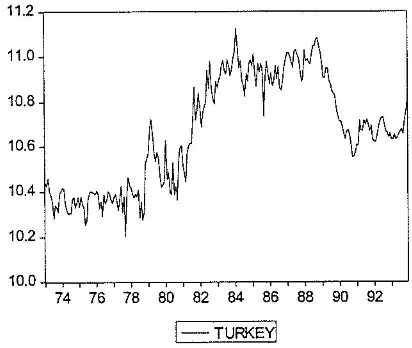
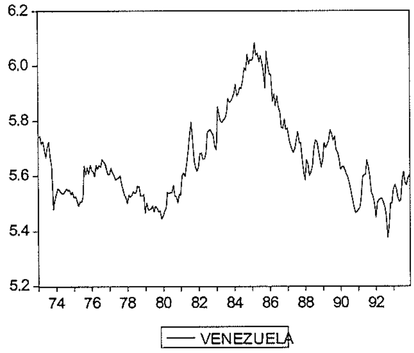
74 76 78 80 82 84 86 88 90 92
SLANKA


3.5
3.4
3.3
3.2
3.1
3.0
74 76 78 80 82 84 86 88 90 92
THAILAND





The above graphs seem to indicate segmented trends for some countries. However, for some of these countries, Luintel (2000) performed formal tests of structural breaks and he reported fewer structural breaks than appear by graphical inspection.[1]

5.4 **An Overview of Exchange Rate Policies in the Sample Countries**

Nepal

The Nepalese Rupee (NRe), divided into 100 Pice, was devalued in December 11, 1967, from the official rate of NRs 7.619 to NRs 10.125 per US Dollar. At the same time the traditional relationship with the Indian Rupee was changed from NRs 101.55 to NRs 135.00 per 100 Indian Rupee.

In 1971, following the floating of the US exchange rate, the official Rupee remained unchanged vis-a`-vis the American unit.

On February 20, 1973 following the US Dollar devaluation by 10% in terms of gold, the Nepalese Rupee`s gold content was reduced to 13.7%.

During the US Dollar crisis, the black market activity of the Nepalese Rupee increased considerably, and the black market of the US unit declined. The improvement of the Nepalese unit against the US Dollar continued in the second quarter of the 1973, however, increasing imports and sharply raising food prices pushed the Rupee to lower levels again.

During 1977, the rupee fluctuated in a range between NRs 14.55 and 13.35 per US Dollar. In March the Nepalese unit was up-valued and then partially devalued.

After different up and down movements, the rupee unit finally fell to NRs 70.00 per US Dollar in early 1992, but recovered later during 1993.

[1] Luintel (2000) includes in his panel five of the countries covered by the present study.

Pakistan

Black market activities in Pakistan Rupees reached PRs 10 million a month and more than PRs 20 million a month during domestic crisis and periods of international tensions and domestic crises.

With the banknote demonetization in June 1971, the Pakistan Rupee nosedived to a record of PRs 25.00 per US Dollar. Rising volume of capital flight pushed the black market rate for the Rupees to month-end lows as the US Dollar devaluation in early 1973.

The unit`s quotation strengthened during the second half of 1979 and early 1980. During 1985 and 1986 the Pakistan Rupee swung wildly. From then on through mid-1991, the Rupee gradually declined. By the end of August 1993 it fell to PRs 31.50 per US Dollar.

Philippines

The black market exchange rate, in the case of Philippines, is defined as the private dealings of foreign currency bank notes and/or nonbank transfer abroad.

In the early Seventies, because of fears of US Dollar devaluation there was an huge amount of black market transactions. During the first half of 1974, the black market activities declined a bit. In mid-1976 the black market was down to P7.45 per US Dollar. For the remainder of the 70s the black market for the Peso was erratic.

Social and political unrest pushed down the Peso from one new low to another in the early 1980s. By mid-October 1983 a new record low of P26.00 per US Dollar was reached. The currency ended the 1980s with some recovery, however, in 1987, new low levels of P24.00 per US Dollar were reached during.

The unit then stabilized and traded at P 22.00/P23.75 per US Dollar through the mid 1990

Sri-Lanka

The black market is defined here as unauthorized dealings of foreign currency banknotes and/or unlicensed transfers abroad.

Following the US devaluation in early 1973, the Rupee appreciated vis-a`-vis the Us Dollar. Black market transactions maintained a high volume of activity in this period. Corruption and bankruptcy pushed the Rupee down in the black market, in the Spring 1975. Some improvement followed. The break with the Pound Sterling in May 1976 led no effect on the black market quotation for the Rupee.

Some improvement followed in the 1980s, that is 1985 and carried into 1986 when the unit was Rs 25.70 per US Dollar.

With the civil war dragging the economy down, the Rupee fell to a record low of Rs 55.00 per US Dollar by the end of 1993.

Thailand

Thailand`s unofficial exchange rate markets are centered domestically in Bangkok and abroad in Hong Kong and Singapore. Unlicensed transactions via payments in Bangkok operated principally through Hong Kong. The US Dollar`s premium in such black market transactions all but disappeared and, in fact, the US unit at times listed at a sight discount from the Official Rate, reflecting the decline in unofficial dealings. This trend continued early into 1971.The devaluation of the US Dollar in 1971, and the devaluation of the Baht itself, generated some weakness in the unit. The political turmoil of 1976 weakened the unit as low as B21.00 per US Dollar in October. Despite domestic difficulties of the US Dollar in 1978, the Baht remained quite stable.

In the 1980s the Baht continued firm despite two devaluations in 1981. But some weakening set in during 1982 and in the late 1983, falling to 25.00 per US Dollar. In April 1985 the Baht reached a new record low of B28.25 per US Dollar after that followed a sharp recovery.

After hitting B28.00 per US Dollar at the end of the 1980s, the Baht moved within a narrower range of B25.25-B26.75 through mid-1993.

Turkey

Black markets in Turkey, with an uninterrupted existence for over 35 years, had become an integral part of the country`s economic organisation.

After the decline of the US Dollar in 1973 the Lira rose sharply. It reached LT 3.00 per US Dollar and successive government crises resulted in a sharp weakening of the rate to LT 15.10 in January 1974. The invasion of Cyprus led to capital flight, pushing the Lira to LT 14.90. The currency started to drop from one historical low to another after the 1977, as commercial enterprises turned to the black market for currency to pay the necessary imports.

The 1980s were also worse with the Lira falling against the US Dollar. It reached LT 315 per US Dollar in 1983. In early 1984 all foreign exchange controls were removed and the black market disappeared.

The early 1990s saw the Lira in the street to reach new record lows of LT 14,990 per US Dollar.

Venezuela

The Bolivar was free from black markets until the end of 1959, when foreign exchange controls were imposed. With the institution of the exchange market control there was an increasing black market activity. In 1983, the revamping of the exchange rate structure all but wiped out black market activities.

Throughout the late seventies and the early eighties, the Bolivar remained firm and constant at Bs4.30 per US Dollar. However, rumours of foreign exchange controls and currency devaluation, coupled with debt problems, dropped Venezuela`s unit to a record low of Bs 5.50 per US Dollar. Continued slides took the Bolivar to Bs30.00 at the end of November 1986, reaching Bs44.50 per US Dollar at the start of 1989.

By mid-1991 the currency was at a new low of Bs59.00 per US Dollar, falling to Bs110.00 per US Dollar by the end of 1993.

Indonesia

Black market activities have persisted since the early 1940`s. Except for a few short-lived recoveries , the corruption-ridden Rupiah was subject to a continued depreciation. Black market rates for the Rupiah in their heyday were often nominal and disparate, the subject of a case to case basis.

The Dollar devaluation in 1973 raised the Rupiah to Rp404 per US Dollar and as a consequence there was a flight from the Rupiah into gold. By mid-1975 the Rupiah was down to Rp447 per US Dollar, as funds fled in the face of devaluation rumours. During 1977 and 1978 the Rupiah intermittently improved as rumours of an revaluation of the currency circulated from time to time. However after the massive devaluation in November, the Rupiah dropped to Rp683 per US Dollar.

Some improvements in the Rupiah followed in the early 1980s, but chronic corruption and continuing capital flight forced the Rupiah to new lows. By early 1987, a new low was reached Rp1,900 per US Dollar, and a new low in July 1988 with Rp2,100 per US Dollar.

The Rupiah showed renewed strength in 1990 when most transactions were shifted to a freely fluctuating Interbank Rate. In 1992 after pushing towards Rp3,000, the Rupiah appreciated, rising to Rp2,150 per US Dollar.

Kenya

Black markets have functioned in the East African countries since World War II, but have been a rather limited and concentrated affair.

Following the January devaluation, Kenyans found their overseas havens for their money menaced by the so called "energy crisis", and began some capital repatriations. US Dollars were also being hoarded and shifted into Shillings for gold coin purchases. Consequently the shilling strengthened to Ksh8.00 per US Dollar. Fluctuations remained erratic during the last semester of 1974 and the first half of 1975. The Shilling strengthened through early 1978 when it reached Ksh8.10 per US Dollar.

Economic malaise in the 1980`s brought on more capital flight and a new low of Ksh18.50 per US Dollar. It was only in April 1986 that the Shilling moved up to Ksh17.10. In the spring of 1987, Kenyan`s currency weakened again as social unrest mounted over restrictions on foreigners and economic prospects dimmed. After reaching Ksh20.80 per US Dollar in early 1989, the Shilling fell to new record lows, the rate of depreciation accelerating in late 1992 and 1993 with the unit at Ksh 100.00 per US Dollar at mid-1993.

South Korea

Black market activities in Korea traditionally reflected currency debasement and capital flight as well as the widespread, wholesale corruption which dominated almost all sectors of political and economic life. Japanese yen became a big item in Seoul`s tolerated black market.

Sharp oscillations dominated during the last semester of 1973, as abrupt capital flight and capital inflows tugged at the rate. But during the first half of 1974, the illicit outflow of capital gained the upper hand, as the black Won deteriorated in anticipation of a long devaluation that took place in December. Some improvement followed in early 1976, but the Won again slid back to a new record low of W545 per US Dollar. As the US Dollar began its worldwide decline in 1977, the Won strengthened despite the persistent devaluation rumours. By February 1978 the currency reached W498 per US Dollar.

The new decade solved no problems for the Won as the currency plummeted from one low to another. By October 1982, the unit was W940 per US Dollar. The US Dollar weakness in 1985 and 1986 led the Won to W754.30 per US Dollar. The Won improved gradually in 1987, 1988 and the first half of 1989, as foreign exchange controls were being phased out and the black market currency was more of a free market.

By mid-1991 the Won was W765 per US Dollar, falling to W885 in April 1992 then moving up to W800 at the beginning of 1993.

Malaysia

Black Markets in Malaysia have been in existence since 1939.

The devaluation of the US Dollar in 1971-1973 generated an appreciation of the black market rate. In mid-1973 Kuala Lumpur`s unit reached M$2.33 per US Dollar. During the last semester the unit dropped to RM2.50 per US Dollar. With the approaching defeats in Laos, Cambodia, and South Viet Nam, capital flight from Indochina triggered an appreciation of the black market rate, which continued into 1975. As the US Dollar collapsed worldwide, the Malaysian unit hit a historical high of RM2.17.

The 1980s saw the Malaysian unit weaken against the US Dollar. It reached RM2.45 per US Dollar in May 1987, and worsened at the start of 1989 when it reached RM2.80 per US Dollar. It improved partially by mid-1989 to RM2.67.

The 1990s started with a drop in the Malaysia currency to RM2.85 per US Dollar. It strengthened through 1993 fluctuating between RM2.52-RM2.80 per US Dollar.

Ethiopia

Black markets in local currency have been important at various time, attracting traders, dealers and others who wish to export funds in excess of permitted limits.

Following the replacement of the Ethiopia Dollar by the Ethiopia Birr in September 1976, black market dealings became hectic, as war with the Eritrean rebels pushed money out of the country. In September 1977 the Birr was Br5.65 per US Dollar. The 1970s ended with an appreciation of the Birr that reached Br3.15 per US Dollar.

After strengthening to Br2.70 per US Dollar at the start of 1980s, the currency fluctuated narrowly through the remainder of the 1980s, between Br3.70 and Br2.70 per US Dollar. Continued economic problems pushed the Birr to a record low of Br7.05 in 1988 followed by some improvements in 1989.

The Birr then weakened again in 1991 anticipating the, forthcoming devaluation on October 1, 1992. A record of Br14.00 per US Dollar was reached at the end of 1992.

Ghana

Following the US Dollar devaluation in February 1973, Ghana's Cedi had a discount of only 15% from its new official rate of C1.15 per US Dollar. The Cedi began a gradual upward rise during 1974, touching C1.35 per US Dollar in March 1975. Intense capital flight in the face of a soaring price inflation, shortages and widespread hoarding, increased the competition for hard currency among black marketers, professionals and new amateurs, pushed the Cedi by early 1977 to C12.50 per US Dollar. The Cedi showed very little improvement for the remainder of the year and into 1978.

As a result of the decline of the Dollar in the same year, the West German Mark became the preferred hard currency in Accra. With the economy in total collapse all currency transactions shifted to the black market.

By the end of 1982 a new record low was set to C120.00 per US Dollar, following the drastic depreciation of the Effective Rate by 90%. The unit underwent further devaluation in 1984, 1985 and 1986, and the black market rate continued to decline, hitting C220.00 per US Dollar in 1987. By the end of 1990 the unit was buying C370 on the unofficial market, reaching C399 by the end of 1991. In 1992 and 1993 it hit one record low after another.

Hungary

The increasing troubles of the US Dollar did not fully penetrate the Hungarian black market during the last half of 1971. However, following the US Dollar devaluation in December, the Forint started to depreciate, reaching Ft37.05 per US Dollar by May 1972. The currency gained in strength under the impact of the February devaluation of the US Dollar. The popularity of gold coins waned considerably during 1975. Towards the end of the year, the Forint weakened substantially, plagued by the Western disease of price inflation. This weakness continued throughout the first semester of 1977, but with the decline of the American Dollar during the latter part of the year, quotations began to strengthen, reaching Ft29.40 per US Dollar by April 1978.

A continuing weak economy and price inflation again depressed the Forint through 1981, 1982 and 1983, with the unit falling to Ft57.00 per US Dollar. After hitting Ft70.10 per US Dollar in the Spring of 1985, it showed renewed strength in 1986.

In 1987 the Forint began a steady decline that carried it to a three decade low of Ft88.00 per US Dollar. The Forint gained against the Dollar through the first half of 1991, declined through mid-1992, and after recovering for the rest of the year, began a fall which took it to Ft115.00 per US Dollar at the end of August 1993.

India

Black market activities have continued on a large scale, celebrating their 50th year of uninterrupted existence. Black market transactions in US Dollar or Swiss Francs averaged about Rs100-Rs110 million a month, and were centralised in Bombay.

Illegal trading of hard currency amounted to about 70% of the currency in circulation. With the disappearance of most gold buyers, the smuggling operators of Bombay turned to more lucrative fields. The big items being "imported" from Dubai all originated in Japan; namely, textiles, transistor radios and, watches of Swiss imitation. Payment for this contraband was partially made by silver exports to Dubai, and Foreign exchange losses through the black market were estimated at Rs4.75 billion annually.

The start of 1980s swept Mrs Ghandi back into office and it wasn`t long before the Rupee tumbled, after only improving to Rs8.20 per US Dollar in 1980. By the end of 1983 the black market Rupee was down to Rs13.40 per US Dollar before falling to Rs15.20 in August 1984. During 1986, India`s Rupee hit a high of Rs13.00 per US Dollar, which widened in 1987 and 1988 as the Rupee steadily declined.

With political and social conditions as they were, the Rupee continued to slide to still another low of Rs26.00 per US Dollar by mid-1991. In 1992 and 1993 the Rupee moved from partial to full convertibility while falling to new lows.

Algeria

With oil revenue falling in 1980, and import restrictions made tighter, Algerians, with money-making mentalities began to make heavy purchases of hard currency on the black market for trips abroad, as the Dinar plugged to a new low during 1981. Residents who needed money to stay abroad started to buy hard currencies on the black market, at DA2.50-Da3.00 per French Franc, compared with the official rate of DA1.00-F1.00. After illicit transactions resumed during the last semester of 1982, the unit recovered temporarily, only to fall again to still another record low of DA29.00 per US Dollar. From the first half of 1988, the Dinar began to fall from one low to another, reaching a record of DA28.75 per US Dollar near the year ending in 1990.

The rise of the Islamic fundamentalist movement and a depreciation of the Effective Rate, pushed the black rate to record lows in 1991, 1992 and 1993.

Bolivia

Following the devaluation of the US Dollar in October 1972 and February 1973, the Peso registered new lows of $b26.50 per US Dollar. Contraband traffic of underpriced Bolivian goods into neighbouring kept free market dealings active through most of 1973, as the Peso strengthened to $b21.00 per US Dollar. Devaluation rumours at the end of 1974 set another run out of the currency. In 1976, the repatriation of capital flight and the fluctuation of the Peso in free dealings remained minimal. Following the revolutionary seizure of the government in July 1978, and the deterioration of the Peso in free dealings in 1979, the regime had to devalue in November.

With the cocaine trade beginning to prosper in the hands of a corrupt military junta, the profit from the drug trade leaving the country depressed the currency to new lows during 1980. The soaring inflation price at a triple-digit level, coupled with the exhaustion of monetary reserves and an overload of foreign debt, activated foreign exchange controls in July 1981, and rejuvenated the black market. With the devaluation of November 1982, the black market was still in business listing the Peso, at a year end at a new low of $b350.00 per US Dollar. In August 1985 it reached $b1,000 per US Dollar. The black market was then legalised with the introduction of a Parallel Market Rate which exceeded $b2,000,000 per US Dollar in 1986. The introduction of the Boliviano on January 1, 1987 to replace the Peso at 1,000,000 old units for one new unit moved to decimal point. By mid-1993 the new Boliviano had lost 54.9% of its value and was at a record low of Bs4.32 per US Dollar, the equivalent of 4,320,000 Pesos or 4,320,000 old Bolivianos.

Colombia

Cocaine and Marijuaña became Colombia`s "growth" industries in the mid-Seventies and were soon the nation`s biggest extralegal export with earnings of US$1.5-US$3 billion. Some 60% remained abroad in foreign banks and in American in real estate, partially concentrated in Florida. The remaining 40% of profit were laundered through the black market.

In 1976, with the emergence of a dual economy-coffee and drugs, transactional volumes in the black Peso soared and the unit, in waves of capital flight, dropped from one historical low to another. Although the black Peso depreciated in 1976, the growing surplus of US Dollars in the black market began to push the black Peso to more reasonable quotations. In 1978 Bogota` resumed the devaluation of the Official Certificate Market Rate, and this pushed the currency in the black market to Col$41.30 per US Dollar. By mid-1979 another new low at Col$43.00 per US Dollar was set.

In 1983 the continued devaluation of the Official Certificate Market Rate kept the Peso on the decline with new lows. By November 1990 the Peso was at a low of Col$670.00 per US Dollar. A further decline in 1993 dropped the Peso to a record low of Col$890.00 per US Dollar.

Dominican Republic

The black market for the Peso has become a quite open affair, with dealings in such a parallel mart passively tolerated by authorities since 1970.The US Dollar devaluation in 1971 and 1973 had little effect on the Peso. Towards mid-1973 the US Dollar weakened in Santo Domingo, the Peso posting its best listing in thirty-one months. The unit softened in late 1974 and early 1975. After a slight recovery, the Peso fell back to RD$1.39 per US Dollar by mid-1976. Fluctuations were minimal during 1977 and into

1978. But in November, the Peso dropped to RD$1.43 per US Dollar. The Peso improved to RD$1.29 per US Dollar one year later.

In 1983 the Dominican Peso reached RD$1.85 per US Dollar. Austerity demands and calls for exchange rate unification by the IMF, forced the Peso to landslide to a new low of RD$3.13 per US Dollar. The peso was quite stable during 1986 and 1987, fluctuating between RD$3.20-RD$3.35 per US Dollar. The end of the 1980s saw the Dominican Peso reaching new lows at RD$8.20 per US Dollar in July 1988 and RD$10.50 per US Dollar by the end of 1989.

The Peso tumbled from one record low to RD$20.00 per US Dollar in 1991. The unit improved following the introduction of a freely floating Interbank Rate and it reached RD$13.00 per US Dollar by the end of 1992, before slipping in the first half of 1993.

Egypt

Despite all the attempts at currency freedom, the active black market has continued to undersell all categories of the Official Egyptian Pound. With the legalisation of foreign currency holdings in 1976, along with the simplification of the exchange rate structure, the volume of black market dealings dropped, and the Pound strengthened as Cairo sought peace negotiations with Israel. The unit remained firm during the first half of 1978, but weakened when proposals were made to revise the exchange rate structure. By mid-1979, the currency had steadied to around US$1.33, with Cairo talking of completely legitimising the black market.

With exchange reserves dwindling in late 1980 through 1981, and US Dollars scarce on the official free market, the Pound began to slide. By the end of 1983 it was US$0.49. The 1980s ended with the Pound reaching US$0.32. The unit recovered during the remainder of the year and through 1990 to over US$0.40, however, by the end of 1991 and early 1992 a new record low of US$0.28 per Egyptian Pound was reached.

5.5 **Volatility of Exchange Rates and Relative Prices**

One of the most important results in the PPP literature is that this parity condition seems to hold much better for high inflationary countries, than for those countries whose rate of inflation has been relatively low over the sample period under analysis. This is why monetary growth in the former case is likely to overshadow real factors, and that may bias evidence towards PPP (see Lothian and Taylor, 1996). Since the panel data set used in this study contains developing countries data, and these countries may have experienced high inflation rates, we calculate the volatility of the relative price and exchange rates. Results are displayed in Table 5.1. Comparison of the volatility of the nominal exchange rate with that of the relative price shows that the relative price ratios are less volatile than the nominal exchange rate. That is, the monthly absolute rate of change of the nominal exchange rate, is always greater than the monthly absolute rate of change of the relative price ratios, except Turkey. Following Lothian and Taylor (1996), our result means that the volatility of relative prices in our set of data should not provide a source of bias towards PPP

Table 5.1

Exchange Rates and Relative Price Volatility

Country		Δq_t		Δs_t		$\Delta(p_t-p^*_t)$
	Mean	**Stdv.**	**Mean**	**Srdv.**	**Mean**	**Stdv.**
Nepal	0.015	0.018	0.051	0.066	0.013	0.011
Pakistan	0.009	0.015	0.029	0.053	0.008	0.009
Phil.	0.009	0.001	0.029	0.047	0.008	0.012
S.Lanka	0.013	0.075	0.421	0.181	0.009	0.01
Thail.	0.008	0.008	0.025	0.028	0.005	0.005
Turkey	0.004	0.004	0.005	0.049	0.035	0.076
Venez.	0.006	0.013	0.035	0.088	0.013	0.018
Indon.	0.005	0.019	0.062	0.569	0.008	0.098
Kenya	0.010	0.011	0.041	0.044	0.01	0.015
Korea	0.006	0.020	0.041	0.119	0.006	0.007
Malaysia	0.023	0.026	0.016	0.018	0.005	0.038
Etiopia	0.037	0.057	0.064	0.122	0.019	0.0171
Ghana	0.014	0.024	0.095	0.237	0.039	0.047
Hungary	0.012	0.008	0.05	0.04	0.01	0.013
India	0.011	0.094	0.032	0.029	0.008	0.007
Algeria	0.014	0.013	0.054	0.061	0.02	0.02
Bolivia	0.01	0.057	0.088	0.295	0.065	0.15
Colomb.	0.003	0.036	0.023	0.028	0.014	0.009
D.Rep.	0.012	0.021	0.033	0.08	0.014	0.016
Egypt	0.151	0.41	0.071	0.16	0.017	0.017

Note: where, Δq_t is the monthly rate of change in the real exchange rate (in log), Δs_t is the monthly absolute rate of change of the nominal exchange rate and $\Delta(p_t-p^*_t)$ is the monthly absolute rate of change of the relative price ratios[1].

One proposition often presented in the literature is that real exchange rates in developing countries have been more volatile than exchange rates in OECD countries. We compare the results on the real exchange rate (Δq_t), displayed in the Table 5.1 above (means and

[1] We calculate, here, means and standard deviations.

standard deviations), with those referring to a panel of twenty OECD countries over the same sample period (Table 5.2):

Table 5.2

Real Exchange Rate Volatility in OECD Countries

Country	Mean	Stdv
Aust.	0.011	0.009
Dan	0.014	0.011
Belg.	0.008	0.006
Fra.	0.015	0.013
Germ.	0.054	0.049
Ita.	0.003	0.003
NL	0.045	0.038
Norw.	0.012	0.01
Port.	0.005	0.004
Spa.	0.006	0.006
Swed.	0.013	0.012
Switz.	0.071	0.074
Can.	0.029	0.026
UK	0.034	1.58
NZ	0.043	0.05
Jap.	0.005	0.005
Gre.	0.005	0.004
Finl.	0.016	0.015
IR	0.006	0.005
Mex.	0.027	0.066

On average, the black market real exchange rates are characterised by lower standard deviations than the real exchange rates in OECD countries. In fact, the increment between these two data sets is 3.84. However this result is completely biased by just one country, the UK, whose exchange rate has been very volatile over the sample period under consideration. In fact, the standard deviation, in this case, is 1.58. If we drop this country from our panel, the increment now falls to 0.18. This means that in terms of volatility in the real exchange rate there is very little difference between these two data sets.

5.6 **Testing for a Unit Root in Heterogeneous Panels**

In this section we use some new heterogeneous panel unit root tests and the PPP framework given by equation (5.3), to investigate whether or not the black market real exchange rate has been stationary over the sample period under consideration.[2]

Im et. al. (1997) proposed a unit root test for heterogeneous dynamic panels based on the mean-group approach. This test is valid in the presence of heterogeneity across-sectional units and is given by the following equation: (see chapter 1 for discussion of this test and definition of the variables)

$$t - bar = \frac{\sqrt{N(T)}(t_T - E(t_T))}{\sqrt{VAR(t_T)}} \qquad (5.4)$$

Im. et al. (1997) state that the standardardized t-bar statistic converges, in probability, to a standard normal distribution as T, N$\rightarrow\infty$. Therefore we can compare the t-statistic

[2] For a formal description of the tests and variables used in this and next section, refer to Chapter 2 and Chapter 3.

obtained to the critical values from the lower tail of the normal distribution. We shall be using the demeaned version of the above t-bar test in this chapter.

While the Im et al (1997) t-bar test relaxes the assumption of homogeneity of the root across units, several difficulties still remain. In fact, Im et al. assume that T is the same for all the cross-section units and hence the t-bar test requires a balanced panel or complete panel, (i.e. where the individuals are observed over the sample period).

Maddala and Wu (1999) suggest an alternative way. Suppose there are N unit root tests. Let π_i be the observed probability level for the ith test. The P_λ test has a χ^2 distribution with d.f 2N:

$$P_\lambda = -2\sum_{i=1}^{N} \ln(\pi_i) \qquad \Rightarrow \chi^2(2N) \tag{5.5}$$

The test presented above is due to Fisher (1932). Maddala and Wu (1999) extend it to a panel context and, to obtain a distribution free from cross sectional dependence, they suggest obtaining p_i-values by using bootstrap methods. However, the bootstrap methodology suggested by Maddala and Wu (1999) is extremely time consuming, and furthermore, it relies on bootstrapping a moving average process. In Chapter 2 we suggested bootstrapping π_i for the test in (5.5), by using a simpler and less time consuming bootstrap algorithm, and by Monte Carlo simulation we showed that it is affected by very negligible size distortion. We shall use this bootstrap algorithm in this chapter to obtain p-values for the test given above.

5.7 **Testing for Cointegration in Heterogeneous Panels**

In this section, we present the panel cointegration tests applied in this Chapter. Since, the small sample properties of these tests have already been discussed in chapter 2, we only report here their distributions.

McCoskey and Kao (1998) developed a residual based Lagrange Multiplier test for the null hypothesis of cointegration in panel data.

The standardised version of this test is given by:

$$LM^* = \frac{[\sqrt{N}(LM - u_v)]}{\sigma_v} \Rightarrow N(0,1). \qquad (5.6)$$

where u_v and σ_v are obtained by Monte Carlo simulation and tabulated by the authors and LM* is the standardized LM-statistic as defined in the previous chapters.

Pedroni (1997) developed heterogeneous tests of the null hypothesis of no cointegration. He proposed seven panel cointegration statistics and showed that the asymptotic distribution of these statistics, under an appropriate standardisation, is a normal distribution:

$$k = \frac{k_{N,T} - u\sqrt{N}}{\sqrt{v}} \Rightarrow N(0,1) \tag{5.7}$$

where $k_{N,T}$ is the panel cointegration statistic and u and v are the moments of the Brownian function that are computed in Pedroni (1999).

However, the above panel cointegration tests assume the presence of one single cointegrating vector and this is, in many practical cases, a strong assumption. A panel cointegration test that relaxes that assumption is the one proposed by Larsson et al (2001).

Larsson et al. (2001) propose a likelihood-based test of cointegrating rank in heterogeneous panels which tests for multiple cointegrating vectors.

The standardised LR–bar statistic for the panel cointegration is:

$$\gamma_{LR-bar}(H(r) \mid H(p)) = \frac{\sqrt{N}(LR_{NT}(H(r) \mid H(p)) - E(Z_K))}{\sqrt{Var(Z_k)}} \tag{5.8}$$

where $E(Z_k)$ and $Var(Z_k)$ is the mean and variance of the asymptotic trace statistic (refer to chapters 2 and 3 for further details on the variables)

5.8 Results from Panel Unit Root Tests

We perform standard ADF tests on each real exchange rate in the panel. The number of lags in the ADF specification is chosen using the procedure suggested by Campbell and Perron (1991). The results are displayed in Table 5.3

Table 5.3

Im et al (1997) t-bar Test

Country	Lag	t-stat
Algeria	4	-0.87
Colomb.	6	-0.67
D.Repub	5	-2.07
Egypt	5	0.89
Ethiopia	1	-1.85
Ghana	5	-2.29
Hungary	6	-1.65
India	0	-0.78
Indon.	1	1.14
Kenya	0	-0.98
Korea	5	-3.86*
Malaysia	1	-0.55
Nepal	5	-1.5
Pakistan	1	-1.69
Philip.	1	-2.29
S.Lanka	4	-3.38*
Thayl.	1	-1.71
Turk.	4	-1.42
Venez.	6	-1.35
Boliv.	0	-0.74
t-bar		**2.04**

On the basis of individual ADF statistics we are able to reject the unit root null hypothesis in only two countries (Korea and Sri Lanka), out of twenty

The demeaned version of the t-bar test, as suggested by Im et al. (1997), is 2.04. This indicates that the black market real exchange rate is non stationary for the whole panel. We also apply the panel unit root test proposed in chapter 2 with the p-values obtained by the bootstrap method, as explained in the same chapter. The results are displayed in the table below:

Table 5.4

Bootstrap Panel Unit Root Test (p -values)

Country	π_i	$In(\pi_i)$
Alger.	0.671	-0.39899
Boliv	0.701	-0.35525
Colomb	0.7965	-0.22753
D.Rep	0.2585	-1.35286
Egyp.	0.9585	-0.04239
Ethio.	0.3005	-1.20231
Ghana	0.177	-1.73161
Hung.	0.451	-0.79629
India	0.754	-0.28236
Indon.	0.981	-0.01918
Kenya	0.788	-0.23826
Korea	0.0105	-4.55638
Malaysia	0.2075	-1.57262
Nepal	0.5065	-0.68023
Pakistan	0.7245	-0.32227
Philip.	0.1785	-1.72317
S.Lank.	0.018	-3.57555
Thai.	0.423	-0.86038
Turk.	0.504	-0.68518
Venez.	0.5615	-0.57714
		-21.1999
P_λ		**42.3998**
CV5%		55.76

The individual p-valûes in Table 5.3 reject the unit root hypothesis in only two countries (Korea and Sri Lanka) out of twenty. The panel unit root test is 42.40. This statistic is below both 5% and 1% critical values, providing strong evidence that the black market exchange rate in emerging markets is an I(1) stochastic process.

Taken together, the above results indicate a much stronger acceptance of the null hypothesis of a unit root, than the ones obtained in Chapter 2 for OECD countries. Furthermore, these results also contrast with the ones obtained by Luintel (2000). However, that study included only eight countries in its panel and only five of them are also included in the present investigation. Finally, they posit strong evidence of the "difference in productivity" (i.e. the Balassa Samuelson effect) issue raised by Froot and Rogoff (1995).

5.9 **Test for Structural Breaks**

The detection of a unit root by ADF test could have been due to the effects of structural changes within our sample period. In this section we develop a unit root test for structural breaks based on some of the most common methodologies proposed in the literature, i.e. Perron (1989), Banerjee et al. (1992) and Zivot et al. (1992). These methodologies, because of their simplicity, are simpler to implement than others. Perron`s procedure is a conditional test given a known break point. Since the break point is assumed to be known it raises the problem of pre-testing the break data. That is we select the break data exogenously. Consider the following models:

$$\text{(A)} \quad y_t = \alpha + D(TB)_t + y_{t-1} + e_t \tag{5.9}$$

$$\text{(B)} \quad y_t = \alpha_1 + y_{t-1} + (\alpha_2 - \alpha_1)DU_t + e_t$$

$$\text{(C)} \quad y_t = \alpha_1 + y_{t-1} + D(TB)_t + (\alpha_2 - \alpha_1)DU_t + e_t$$

$D(TB)_t = 1$ if $t = T_B + 1$, 0 otherwise; and T_B $(1 < T_B < T)$ is when the break occurs.

$DU_t = 1$ if $t > T_B$, 0 otherwise.

We test the null hypothesis represented by models (A)-(C), against the alternative of trend stationary represented by the following models:

$$\text{(A1)} \quad y_t = \alpha_1 + Bt + (\alpha_2 - \alpha_1)DU_t + e_t \tag{5.10}$$

$$\text{(B1)} \quad y_t = \alpha + \beta_1 t + (\beta_2 - \beta_1)DT_t^* + e_t$$

$$\text{(C1)} \quad y_t = \alpha_1 + \beta_1 t + (\alpha_2 - \alpha_1)DU_t + (\beta_2 - \beta_1)DT_{\ t} + e_t$$

$DT_t^* = t - T_B$ and $DT_t = t$ if $t > T_B$ and zero otherwise.

Model (A) refers to the crash model which allows one time change in the intercept of the trend function. In this case, the unit root hypothesis would imply a dummy variable that takes on a value equal to one when the break occurs (see A). Under the alternative we have the one of trend stationary, implying a shift in the intercept of the trend function (see A1).

Model (B) is the "changing growth" model. In this case, the null would imply a shift of the parameter α at time T_B, while the alternative is a change in the slope of the trend function. Finally, model (C) allows a change in both the intercept and slope of the trend function (under the alternative hypothesis).

We can implement tests of unit root by incorporating dummy variables in the following ADF function:

$$y_t = \alpha + \beta t + \delta y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{i-1} + e_t \tag{5.11}$$

such that we have:

$$y_t = \alpha^A + \theta^A DU_t + \beta^A t + \tau^A D(TB) + \delta^A y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.12}$$

$$y_t = \alpha^B + \theta^B DU_t + \beta^B t + \eta^B DT_t^* + \delta^B y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.13}$$

$$y_t = \alpha^C + \theta^C DU_t + \beta^C t + \eta^C DT^* + \tau^C D(TB)_t + \delta^C y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.14}$$

The above models have been obtained by adding dummy variables and nesting models (A)-(C). The null hypothesis would imply the following restrictions: model (A), $\alpha^A = 1, \beta^A = 0, \theta^A = 0,$ model (B), $\alpha^B = 1, \tau^B = 0; \beta^B = 0$, and finally model (C), $\alpha^C = 1, \lambda^C = 0, \beta^C = 0$.

The distribution of the tests (5.12)-(5.14) is different from the one derived by Dickey and Fuller, (it depends on π where $\pi = T_B/T$, the ratio of the pre-break sample size to the total sample size). Perron (1989) tabulates critical values for the models above, for different values of π. The critical values obtained are much larger , in absolute value, than the ones tabulated by Dickey and Fuller. This means that by using the latter one would not be able to reject the null hypothesis. The asymptotic distribution of $t_{\delta^A} and_c\, t_{\delta^c}$ in (5.12) and (5,14) are the same, meaning that we can use the tabulated critical values to make inference. However, the asymptotic distribution of the model in (5.13) is not. Perron (1989) suggests in this case using the following model:

$$y_t = \alpha^B + \beta^B t + \eta^B DT_t^* + \delta^B y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-1} + e_t \qquad (5.15)$$

In this section we investigate the presence of structural breaks by using a two stage approach. In the first stage we exogenously select T_B and estimate models (5.16)-(5.18). Once the best model has been selected, we construct dummy variables, and incorporate the latter into models 5.12-5.14 (it depends on the model that has been chosen). Finally, following Perron (1998), we estimate the ADF models. The first stage, then, consists of estimating the models presented below:

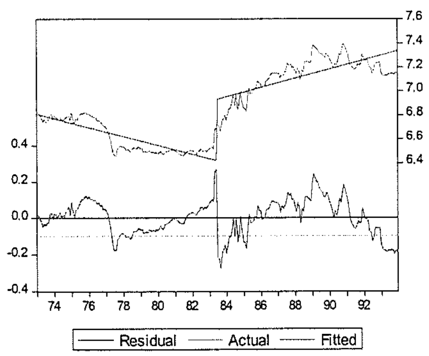
$$y_t = \alpha_t + \theta DU + \beta t \tag{5.16}$$

$$y_t = \alpha + \beta t + \eta DT_t^* \tag{5.17}$$

$$y_t = \alpha + \theta_1 DU_t + \beta t + \tau_2 DT_t \tag{5.18}$$

We report an example of the described procedure below. In this example $T_B = 126$ and the selected model is (5.18), that allows for both a shift in the mean and intercept of the time trend. Model and data break were chosen on the basis of the regression results displayed below. The procedure is a slight implementation of the one recommended by Perron (1989). It should be noticed that we do not treat the data break as data dependent, otherwise we could not use the critical valued tabulated in Perron (1989). The estimated coefficients are reported in the graph below:

Figure 5.2: Colombia

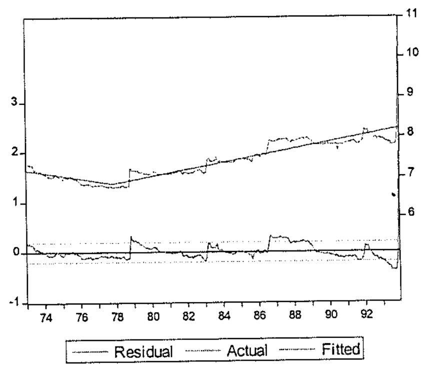


α'	θ_1	β	τ_2
6.89	-0.28	-0.003	0.05
[394.9]	[-5.8]	[-12.97]	[18.76]
$R^2 = 0.9$			

The above graph shows evidence of a shift in the mean and intercept of the time trend on 1983:06, that is, the period of the devaluation of the Official Certificate Rate. This might be the cause of a structural break occurring on that data. The second step consists of incorporating the structural break in a Dickey-Fuller framework, as described above, and testing for a structural break.

Another example is taken from Indonesia. In this case we select $T_B = 71$ and model (5.17) that only allows for a shift in the slope of the trend function. The graph and the estimated coefficients of (5.17) are reported below:

Figure 5.3: Indonesia



α	β	η
7.18	-0.006	0.01
[156.5]	[-5.9]	[11.4]
$R^2 = 0.8$		

As the above graph shows, in this case there could be a shift in the slope of the trend function. The significance of the coefficients and the fit also confirm model (5.17) as the most appropriate one.

5.10 Sequential Tests of the Unit Root and Trend-Break Hypothesis

The methodology presented in the previous section assumes that the location of the break is known a priori. This assumption has been criticised in the literature by Christiano (1992). In fact, as he stresses, in many cases the break date is correlated with the data. A number of studies have proposed methodologies where the choice of the data break is data dependent, (see Perron (1996), Volgelsang and Perron (1998), Banerjee et al (1992) and Zivot and al. (1992)). All these methodologies are based on the same strategy, that consists in applying Perron`s (1989) methodology for each possible break data in the sample and constructs a sequence of t-statistics. Based on this sequence different "t-minimum" statistics can be constructed.

In this section we develop unit root tests for structural breaks following the methodologies proposed by Banerjee et al. (1992) and Zivot et al. (1992).

Null and alternative hypothesis are the same as described in the previous section, that is models A-C, null hypothesis, A1-C1, alternative hypothesis. One can nest the null and the appropriate alternative as follows:

$$y_t = \alpha^A + \theta^A DU_t(\lambda T) + \beta^A t + \delta^A y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.19}$$

$$y_t = \alpha^B + \beta^B t + \eta^B DT_t^*(\lambda T) + \delta^B y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.20}$$

$$y_t = \alpha^C + \theta^C DU_t(\lambda T) + \beta^C t + \eta^C DT^*(\lambda T) + \delta^C y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \tag{5.21}$$

where λ is the break data. The true break is assumed to be in the interval $\Psi = [\lambda_0, 1-\lambda_0]$, where λ_0 is the initial start up sample defined as $\lambda_0 = \gamma_0 T$ and γ_0 the trimming parameter. Equations (5.19)-(5.21) are estimated for break dates $[\lambda_0 T]$, $[\lambda_0 T] + 1, \ldots, T-[\lambda_0 T]$ and the sequence of ADF statistics for $H_0 : \delta = 1$ denoted as $t^i_{ADF}(T_b)$ for $T_b = [\lambda_0 T]$ up to $T-[\lambda_0 T]$ with i = A, B and C, computed. The minimum sequential ADF statistic as suggested in Banerjee et al (1992) and Zivot et al. (1992) is given by the statistic that maximises the evidence against the unit root null hypothesis. In this section we select the break point using this methodology

However, an important issue will be raised subsequently when we incorporate the break into ADF models. While all these procedures assume that the location of the break point is unknown, they also assume that its specification is known. In fact, they do not require specification of the break under the alternative hypothesis. In other words, once the data break has been selected, which of the above alternative specifications (i.e. 5.19, 5.20 5.21) is to be preferred? Sen (2000) shows that a misspecification of the model under the alternative hypothesis leads to lower power of the test proposed by Banerjee et al (1992) and Zivot (1992). What he recommends is using the mixed model under the alternative hypothesis, unless prior information about the nature of the break is known. We shall use this approach in this chapter, consisting of two stage. In the first stage (pre-test stage) we select the break date. Once the break date has been selected we estimate the mixed model with break date as selected in the previous stage.

5.10 **Empirical Results**

We apply the test statistics presented in the previous section to our set of data. π is the ratio of pre-break data to the total number of observations. k is the lag length used in the ADF framework. We have used the Campbell and Perron (1991) procedure, starting from a max of 8 lags, to select k. The remaining parameters are as specified in (5.12)-(5.14). The results are reported in the Table 5.4.

Table 5.4

Tests for Structural Breaks (Model A)

Country	π	K	α	θ	β	τ	δ	R^2
Algeria	0.86	0	0.33	0.01	0.0006	0.4	0.92	0.98
			[3.51]	[0.13]	[2.8]	[0.01]	[-3.48]	
Egypt	0.27	5	0.48	0.18	-0.0007	-0.001	1.01	0.98
			[-0.0005]	[3.03]	[-1.16]	[-0.8]	[2.16]	
Philp.	0.5	2	0.53	-0.04	-0.8	0.09	0.84	0.9
			[4.3]	[-0.82]	[-0.86]	[1.84]	[-4.4]	
Turkey	0.84	4	0.58	-0.008	0.0002	-0.011	0.94	0.94
			[1.57]	[-0.13]	[1.03]	[-0.18]	[-1.55]	
Venez.	0.5	3	0.19	-0.0006	0.0003	0.03	0.96	0.98
			[1.58]	[-2.09]	[1.49]	[0.9]	[-1.71]	
Korea	0.15	4	0.57	-0.55	-0.15	-0.15	0.74	0.43
			[1.22]	[-5.6]	[-6.6]	[-6.6]	[-4.13]	
Bolivia	0.67	0	-1.72	0.14	-0.003	2.05	1.12	0.98
			-0.64	0.16	-2.01	0.76	0.69	

Note: Numbers in the brakets are t-values.Tthe 5% critical values are: Algeria, -3.69, Egypt, -3.76, Philippines and Venezuela, -3.76, Turkey, -3.75, Korea, -3.68, Bolivia, -3.80.

Table 5.5

Tests for Structural Breaks (Model B)

Country	π	K	α	θ	β	η	δ	R^2
Colom.	0.5	1	0.62	0.21	0.002	-0.008	0.9	
			[3.2]	[0.39]	[3.01]	[-3.7]	[-4.7]	
Hungary	0.59	3	0.52	0.32	0.0006	-0.001	0.89	0.95
			[3.62]	[0.93]	[3.11]	[-3.3]	[-3.59]	
India	0.58	2	0.31	0.38	0.0003	0.0002	0.89	0.97
			[3.92]	[2.04]	[3.11]	[1.07]	[-3.93]	
Indon.	0.28	1	1.29	-0.21	-0.001	0.003	0.82	0.91
			[2.6]	[-0.91]	[-1.86]	[2.56]	[-3.98]	
Pakist.	0.73	2	0.66	-0.29	0.0007	-0.0003	0.77	0.95
			[4.6]	[-0.84]	[4.5]	[-1.7]	[-4.6]	
S.Lanka	0.15	2	2.12	-0.02	0.002	-0.007	0.42	0.32
			[6.43]	[-0.32]	[4.2]	[-2.8]	[-2.08]	
Thai.	0.15	1	0.41	0.28	0.0001	0.23	0.87	0.91
			[3.4]	[0.99]	[0.47]	[0.05]	[-3.55]	

Note 5% critical values are: Colombia, -3.69, Hungary and India, -3.95, Indonesia, -3.87, Pakistan, -3.85, S. Lanka and Thailand, -3.6.

Table 5.6

Tests for Structural Breaks (Model C)

Country	π	K	α	θ	β	τ	η	δ	R^2
D.Rep	0.18	1	0.219	0.66	0.0005	0.679	-0.68	0.9	0.95
			[3.37]	[10.59]	[3.23]	[11.01]	[-11.02]	[-3.61]	
Ethiopia	0.5	1	0.181	0.042	0.0009	-0.11	-0.0004	0.89	0.88
			[3.01]	[0.33]	[0.52]	[-0.81]	[-0.23]	[-3.01]	
Ghana*	0.12	0	0.96	0.48	-0.002	-0.28	0.002	0.84	0.87
			[4.79]	[2.74]	[-0.63]	[-1.52]	[0.64]	[-5.11]	
Kenya	0.36	0	0.33	-0.03	-0.0003	0.05	0.0006	0.92	0.91
			[3.03]	[-0.47]	[-1.1]	[0.91]	[1.63]	[-3.23]	
Malaysia	0.12	1	0.03	-0.01	0.0004	0.019	-0.0002	0.91	0.98
			[1.54]	[-0.46]	[0.71]	[0.77]	[-0.39]	[-3.02]	
Nepal*	0.2	4	0.58	-0.07	0.003	-0.01	-0.002	0.79	0.95
			[5.12]	[-0.87]	[3.41]	[-0.16]	[-2.69]	[-5.36]	

Note 5% critical values are: D. Republic, -3.99, Ethiopia, -4.24, Ghana and Malaysia, -3.75, Kenya, -4.22, Nepal, -3.99.

Table 5.4 presents the results of the estimated model (i.e. model A). The lag length k has been selected using the procedure suggested by Campbell and Perron (1991). We focus on t_δ first. To evaluate the significance of t_δ, we compare it with the critical values tabulated in Table IV.B, V.B and VI.B by Perron, 1989. We are able to reject the unit root null, at 5% significance level, in only two countries; Philippines and Korea. Now we can assess the significance of the other coefficients, taking into account that the asymptotic distribution of their t-values is a standard normal distribution. In the case of Philippines, α and τ are significant while θ and β are not. On the other hand, Korea has all the coefficients significant except α. Taken as a whole, these results do not constitute strong evidence of structural break in the countries under investigation.

Consider Model (B) now. Again, we can reject the null hypothesis in only two countries (Colombia and Pakistan) out of seven. Furthermore, all the estimated coefficients are significant. This result suggests that for these two countries, the relevant process is a trend stationary process.

Finally Model (C). Ghana and Nepal have a significant t_{δ}. However, results for all the other coefficients are very mixed, and in this case, as for Model (A), there is very little evidence favouring structural breaks.

Taken as a whole the above results do not constitute significant evidence of structural breaks. In fact, for only two countries (i.e. Colombia and Pakistan) out of twenty we can conclude that the relevant process is a trend stationary process. As we have already mentioned in the previous section, the above methodology assumes that the data break is selected exogenously. This assumption has been the object of criticism in the literature. Amongst

the cited methodologies that assume the break data to be date dependent the most known and widely used are the one proposed by Banerjee et al (1992) and Zivot et al (1992).

Table 5.7 presents the sequential t^{i}_{ADF} statistics for models 5.19-5.21. Critical values for these statistics are reported at the bottom of table 5.7. The mean shift model and the trend shift model were both analysed in Banerjee et al (1992), and the critical values used for these models are taken from Banerjee et al (1992) Table 2. The mixed model was analysed in Zivot et al (1992) and the critical value has been taken from Zivot et al (1992) Table 4. The trimming parameter γ_0 is set to 0.15 and the number of lags, as suggested in Banerjee et al (1992), set to four.

Table 5.7
Sequential Tests of Structural Breaks

Country	Mean-shift	Trend-shift	Mean-Trend shift
Algeria	-2.12 [82:04]	-2.78 [80:08]	-3.11 [76:01]
Bolivia	-14.4*** [86:11]	-2.46 [82:05]	-13.84*** [86.11]
Colombia	-2.39 [85:01]	-2.02 [75.12]	-2.31 [75:12]
Dom.Rep.	-3.42 [85:01]	-3.67 [83:07]	-3.81 [83:11]
Egypt	-3.09 [85:01]	-3.87 [80:12]	-3.71 [80:12]
Ethiopia	-3.99 [78:12]	-4.0 [80:12]	-4.23 [75:12]
Ghana	-7.21*** [75:12]	-4.81** [78:02]	-7.52*** [75:12]
Hungary	-3.91 [89:12]	-3.29 [86:01]	-4.03 [82:05]
India	-4.12 [86:11]	-3.98 [89:12]	-4.58 [86:01]
Indonesia	-2.26 [75:12]	-1.57 [78:02]	-2.65 [78:02]
Kenya	-3.16 [89:12]	-3.64 [89:12]	-3,71 [89:12]
Korea	-4.6* [82:05]	-4.67** [87:07]	-5.02* [85:01]
Malaysia	-4.27 [86:01]	-4.34 [89:12]	-4.52 [86:01]
Nepal	-4.62* [85:01]	-4.76** [75:12]	-4.93* [86:01]
Pakistan	-4.44** [75:12]	-4.90** [78:02]	-4.97* [85:01]
Philippines	-4.81 [82:05]	-3.81 [89:12]	-4.63 [82:05]
S. Lanka	-4.75* [78:02]	-5.38*** [78:02]	-5.39** [78:02]
Thailand	-4.63 [83:11]	-4.23 [89:12]	-4.2 [86:11]
Turkey	-2.67 [80:12]	-3.38 [83:11]	-3.51 [82:05]
Venezuela	-3.84 [82:05]	-2.63 [87:07]	-3.73 [2:05]
CV 1%	**-5.34**	**-4.93**	**-5.57**
CV 5%	**-4.80**	**-4.42**	**-5.08**
CV 10%	**-4.58**	**-4.11**	**-4.82**

*Note: The critical values (CV) for min t_{ADF} are taken from Zivot and Andrews (1992), Table 2-4. The symbols ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. Numbers within brackets denote the date of the break chosen by sequential procedure.*

Consider the mean shift model first. We can reject the null hypothesis of unit root in only three countries, namely Ghana, Philippines and Bolivia. There is weaker evidence (at 10% level) against the unit root null for Korea, Nepal, S. Lanka and Thailand. It is interesting that Philippines was also selected using Perron`s methodology. In the case of trend shift model, the unit root null hypothesis is rejected in five countries (i.e. Ghana, Korea, Nepal, Pakistan and S. Lanka) at 5% or 1% levels, and in two countries (i.e. Malaysia and Thailand) at 10% level. Finally, the mixed (mean and trend shift) model suggest rejection of the unit root null at 1% level for Ghana and Bolivia, at 5% level for S.Lanka, and at 10% for Korea, Nepal and Pakistan[3]. It seems that Ghana, Korea, Nepal and S.Lanka are the most frequently selected countries. Ghana was also selected using the Perron`s methodology. Out of nine countries where the unit root null hypothesis is rejected, the weakest evidence is for Malaysia, Thailand and Philippines.

In cases where the unit root null is rejected, we can determine the significance of the other coefficients given that their t-values are normally distributed (see Perron, 1989; Sen, 2000). For countries where the unit root null is rejected for more than one specification of the break, we report estimates of the model with the highest significance level of the null hypothesis. If the highest significance level is the same for two models, then we report estimates of the model with the lowest. Table 5.8 presents results for the mean shift model. The constant and the mean shift dummy are highly significant in all three countries, while the trend is significant in two countries (Bolivia and Thailand).

[3] Our results contrast with Papell`s (2002) evidence against break-trend stationary in the real exchange rate for all individual industrial countries (except France), and with Luintel`s (2000)

Table 5.8

Estimates of the Mean-Shift Model

Country	T_b	α	θ	β	δ	$S(e)$
		7.064	-6.861	0.003	0.527	
Bolivia	1986:11	[13.86]	[-14.37]	[2.40]	[-14.4]	0.657
		0.512	0.053	-7E-05	0.842	
Philippines	1982:05	[4.80]	[3.34]	[-0.79]	[-4.81]	0.052
		0.684	0.031	0.0001	0.778	
Thailand	1983:11	[4.61]	[2.81]	[1.89]	[-4.63]	0.034

Note: Statistics in brackets in the Table 5.8-5.10 are t-values. $S(e)$ *is the standard error of the regression*

The trend shift model is chosen for most of the countries that experienced structural breaks and its estimates are reported in Table 5.9:

Table 5.9

Estimates of the Trend-Shift Model

Country	T_b	α	β	η	δ	S(e)
		2.493	0.0004	-0.002	0.63	
Korea	1987:07	[4.65]	[2.17]	[-2.63]	[-4.67]	0.109
		0.063	0.0004	-0.0004	0.867	
Malaysia	1989:12	[4.19]	[4.40]	[-2.42]	[-4.34]	0.023
		0.484	0.002	-0.002	0.83	
Nepal	1975:12	[4.44]	[2.44]	[-1.78]	[-4.76]	0.075
		0.747	0.002	-0.001	0.726	
Pakistan	1987:02	[4.78]	[4.42]	[-2.94]	[-4.90]	0.054
		1.957	0.008	-0.008	0.399	
S.Lanka	1978:02	[5.23]	[3.80]	[-3.48]	[-5.38]	0.314

---

findings for eight Asian countries (except for Malaysia and Thailand).

It is interesting to note that the constant, trend and the dummy, for the shift in the slope of the trend, are highly significant in all five countries, with the trend displaying a downwards shift. The mixed model is only chosen for Ghana and the estimates are reported in Table 5.10

Again all coefficients in Table 5.10 are significant. An interesting observation is that the trend has a positive coefficient in seven countries out of the nine countries where there is evidence of trend-break stationarity, thus implying rising real appreciation over time. The break dates differ across countries, suggesting that they are likely to be country-specific. Taken together, the above results suggests that there is certain evidence (in six countries) of structural break in the black market real exchange rate. This evidence may have implications for unit root tests of the real exchange rate[4].

Table 5.10

Estimates of the Mean-Shift and Trend-Shift-Model

Country	T_b	α	θ	β	η	δ	$S(e)$
		2.001	0.483	-0.007	0.007	0.681	
Ghana	1975:12	[7.21]	[5.72]	[-2.00]	[1.97]	[-7.52]	0.163

[4] However, we have also re-applied the panel unit root tests used in section 5.8 after having excluded from our panel countries with strong evidence of structural breaks. But results remained qualitatively unchanged.

5.11 **Results from Panel Cointegration Tests**

Before using cointegration analysis to test for long-run relationship between nominal exchange rate and relative prices, we performed unit root tests on each variable entering in the cointegrating vector.[5] The results are displayed in the Table 5.11:

Table 5.11

Im et al (1997) Unit Root Tests

Country	s_t	p_t
Alger.	0.36	1.38
Boliv	-1.83	0.25
Col.	1.26	0.031
D.Rep	-0.08	2.63
Egypt	-2.58	0.76
Ethi.	-1.83	-1.38
Ghana	-1.17	-2.52
Hung.	-0.51	5.37
India	0.32	-0.71
Indon.	1.77	-2.06
Kenya	2.01	2.27
Korea	-3.98	-1.38
Malay.	-2.84	-4.79
Nepal	-0.39	0.28
Pak.	-1.21	-3.28
Philip.	-0.55	-2.48
S.Lanka.	-5.92	0.64
Thai.	-2.54	-5.17
Turk.	1.87	4.06
Venez.	0.83	7.50
t-bar	**3.55**	**8.35**

[5] We drop here the US-CPI for the same reasons we mentioned in Chapter 3. That is, after having run DF and ADF tests on the latter we found it to be stationary. We then performed a graphical inspection. By graphical inspection the stochastic process under consideration appeared to have a damped-trend. We strongly suspect the results of DF and ADF tests to be biased by the presence of a common stochastic trend driving the price of traded non-traded goods. However, we shall stress, once again, that we do not believe the US-CPI to be an I(0) process, so we treat it as non-stationary.

The t-bar test in Table 5.11 suggests that both nominal exchange rate and domestic price are non-stationary. We also apply the bootstrap panel unit root test that we have proposed in chapter 2. Results are displayed in the Table 5.12

Table 5.12

Bootstrap Panel Unit Root Test (p -values)

	s_t	ln-s_t	p_t	ln-p_t
Alger.	0.429	-0.846	0.223	-1.501
Boliv	0.429	-0.846	0.598	-0.514
Col.	0.901	-0.104	0.516	-0.662
D.Rep	0.842	-0.172	0.858	-0.153
Egypt	0.332	-1.103	0.845	-0.168
Ethiopia	0.429	-0.846	0.223	-1.501
Ghana	0.324	-1.127	0.142	-1.952
Hung.	0.842	-0.172	0.994	-0.006
India	0.919	-0.084	0.416	-0.877
Indon.	0.391	-0.942	0.152	-1.884
Kenya	0.999	-0.001	0.953	-0.048
Korea	0.039	-3.244	0.223	-1.501
Malaysia	0.146	-1.924	0.011	-4.605
Nepal	0.858	-0.153	0.671	-0.401
Pakistan	0.588	-0.531	0.042	-3.171
Philip.	0.736	-0.306	0.147	-1.917
S.Lank.	0.005	-5.298	0.718	-0.331
Thai.	0.311	-1.172	0.009	-4.710
Turk.	0.408	-0.897	0.968	-0.032
Venez.	0.957	-0.044	0.993	-0.0070
		-19.82		-25.941
P_λ		**39.625**		**51.881**
CV5%		55.76		

The individual p-values on the nominal exchange rates displayed in the above table show that nominal exchange rates are not stationary. The same result holds for individual CPI with the exception of Malaysia and Thailand. The panel test confirms that result. Furthermore it confirms the result obtained by the Im et al (1997) test, that both the nominal black market exchange rate and the domestic price are I(1) stochastic processes.

The estimates of the long-run PPP relationship (1) obtained with the DOLS/DGLS estimators are exhibited in Table 5.113. Leads and lags in the DOLS/DGLS were obtained using the Akaike and Schwartz Information Criteria. Since we have often obtained contradictory results from these two Information Criteria, we only report the Akaike statistics. Number in parentheses are t-values. Pr[F_a] is the probability value of an F version of the Breusch-Godfrey test for first order autocorrelation. The equations for Venezuela [AR(1), Indonesia [AR(1)], Ethiopia [AR(2)] and Ghana [AR(1)] were estimated with the DGLS method. All other estimates are DOLS.

Table 5.13

Long-Run Equilibrium PPP:DOLS/DGLS Estimates

Country	α	βo	β_1	$AdjR^2$	Akaike	$Pr[F_a]$	Lead/Lag
Nepal	1.61	1.45	-0.86	0.985	-1.23	0.96	2
	[7.57]	[23.50]	[-8.92]				
Pak.	1.16	1.2	-0.66	0.977	-0.74	0.54	1
	[8.27]	[17.7]	[-7.36]				
Philipp.	3.38	1.17	-1.13	0.988	-0.56	0.38	2
	[12.89]	[24.29]	[-11.18]				
S.Lanka	-0.69	0.44	0.6	0.798	0.87	0.23	3
	[-1.09]	[3.18]	[2.36]				
Thai	2.1	-0.78	1.06	0.899	1.12	0.57	1
	[36.39]	[-6.56]	[8.48]				
Turkey	4.66	0.84	0.46	0.965	0.99	0.78	1
	[12.28]	[62.81]	[5.13]				
Venez	-3.01	0.58	1.16	0.995	-2.31	0.22	2
	[-0.49]	[2.05]	[0.76]				
Indon.	3.13	-0.94	1.625	0.947	1.01	0.908	1
	[0.27]	[-0.97]	[0.532]				
Kenya	5.81	1.52	-1.77	0.947	0.96	0.97	2
	[14.97]	[22.53]	[-12.96]				
S.Korea	7.1	0.98	-1.02	0.937	1.27	0.87	3
	[16.24]	[7.19]	[-4.47]				
Malay.	1.49	-0.49	0.38	0.862	-1.13	0.21	1
	[4.80]	[-2.65]	[3.16]				
Ethiopia	-2.53	0.106	0.91	0.924	-1.35	0.89	2
	[-1.01]	[0.26]	[1.15]				
Ghana	-25.2	-0.13	7.12	0.993	-0.59	0.34	2
	[-3.01]	[-0.43]	[3.36]				
Hung.	2.1	0.39	0.23	0.942	1.56	0.981	1
	[12.01]	[12.74]	[4.39]				
India	1.33	1.41	-0.92	0.911	0.871	0.898	3
	[11.02]	[29.05]	[-14.27]				
Alger.	1.2	0.59	-1.1	0.891	-0.91	0.68	3
	[1.34]	[3.21]	[-1.56]				
Bolivia	10.15	-0.043	-1.49	0.641	-0.881	0.871	1
	[2.27]	[-0.633]	[-1.41]				

Col.	11.56	1.53	-2.38	0.932	-0.78	0.58	1
	[22.64]	[38.45]	[-16.68]				
D.Rep.	0.99	-0.51	0.72	0.899	1.34	0.75	1
	[45.09]	[-7.61]	[3.03]				
Egypt	-0.45	-0.913	0.67	0.897	-0.845	0.75	1
	[-1.34]	[-20.64]	[6.13]				

Note: numbers in brackets below regression are t values based on HAC standard errors. Akaike is the information criterion used to determine the number of leads and lags in the model. Pr[Fa] is the probability value of an F version of the Breusch-Godfrey test for the first order autocorrelation. The equations for France [AR(1)], Italy [AR(2)], Netherland [AR(2)], Norway [AR(1)], Ireland [AR(1)], and Japan [AR(1)], were estimated using DGLS. All other estimates are DOLS.

The intercept is significant in almost all countries except five (Sri-Lanka, Venezuela, Ethiopia, Ghana, Egypt). It is interesting to notice that the log. of the US-CPI appears not to be significant in six countries out of twenty. On the other hand, the coefficient of the domestic price displays the expected sign in most countries and is significant in thirteen countries out of twenty, and is insignificant in five countries. The results from the McCoskey and Kao (1998) test and the Pedroni (1997) tests are reported in Table 5.14

Table 5.14
Panel Cointegration Tests

Pedroni (1997)-Statistics	
Panel v-stat.	4.99
Panel rho-stat.	-2.43
Panel pp-stat.	-1.79
Panel ADF-stat.	-2.61
Group rho-stat.	-5.93
Group pp-stat.	-3.57
Group ADF-stat.	-4.86
McCoskey and Kao (1998)	
LM*	-3.41

Note: (a) The MacCoskey and Kao (1998) LM statistic is one-sided with critical values of 1.64. Therefore large value (LM*>1.64) suggest rejection of the null hypothesis. The mean and the variance used to calculate the LM statistic are respectively 0.0850 and 0.0055 (MacCoskey and Kao, 1998, Table 2). (b)The Pedroni (1997) statistics are one-sided tests with critical values of -1.64 ($k < 1.64$ suggest rejection of the null) except the v statistic that has a critical value of 1.64 ($k > 1.64$ suggests rejection of the null).Note that the means and variances used to calculate the Pedroni statistics are reported in Pedroni (1999, Table 2), with heterogeneous intercept included.*

The LM* test is one sided with critical value of 1.64 (i.e. LM*>1.64 implies rejection of the null hypothesis of cointegration). The mean and variance used for calculating the McCoskey and Kao (1998) statistic are respectively 0.0850 and 0.0055. The mean and variance for calculating the Pedroni statistics were obtained from Pedroni (1999, Table 2). The number of truncations was set to 1. The Pedroni tests are one sided test. All statistics, with the exception of the v-statistic, have a critical value of -1.64. The v-statistic has a critical value of 1.64.

The Pedroni and the McCoskey and Kao statistics are considerable larger, in absolute value, than their respective critical values. Hence, the panel cointegration tests strongly support cointegration between nominal black market exchange rate and relative prices in emerging markets.[6] These results, favouring PPP, are sharply in contrast with the results obtained by panel unit root tests for the real exchange rate.

Finally, we test for cointegration by using the new panel contegration test suggested by Larsson et al (2001). We include an intercept in the VAR to account for potential measurement errors, as in equation 1. The number of lags for each country was chosen on the basis of the Akaike criterion.

[6] Results seem to be more supportive of cointegration between nominal exchange rate and relative price than the ones obtained in chapter 3 for the OECD countries.

The results are reported in Table 5.15.

Table 5.15

Larsson et al (1998) Test

Country	Lags	r=0	R=1	R=2	r_i
Algeria	7	21.39	9.44	0.131	0
Col.	7	73.18	13.91	5.63	3
D.Rep.	3	66.42	26.37	0.29	2
Egypt	4	85.37	35.47	5.45	3
Ethiopia	2	53.46	10.53	0.0126	1
Ghana	6	40.08	9.25	0.095	1
Hung.	5	51.62	16.2	1.04	2
India	3	40.87	14.31	0.871	2
Indon.	2	80.07	8.36	1.91	1
Kenya	2	61.12	28.98	1.91	2
Korea	7	29.11	13.47	0.83	2
Malay.	4	32.6	8.758	0.109	1
Nepal	6	37.05	14.16	1.98	2
Pakistn	3	49.67	14.58	0.028	2
Phili.	3	47.39	14.44	0.57	2
S.Lanka	3	88.21	38.6	1.56	2
Thail.	2	63.98	20.56	2.65	2
Turk.	2	55.49	22.67	0.045	2
Venez.	4	57.36	26.83	2.23	2
Boliv.	2	89.15	26.99	0.11	2
		56.1795	18.6939	1.37258	
LR-bar		**37.07**	**10.07**	**0.71**	

Note: The critical values for the trace statistic at 95% significance level are 34.91 ($r=0$); 19.96 ($r=1$); 9.24 ($r=2$). 41.07 ($r=0$); 24.60 ($r=1$); and 12.97 ($r=2$) at 99%. The critical values for $E(Z_k)$ and $Var(Z_k)$ were obtained from Larsson et al (2001, Table 1). These are respectively 14.955 and 24733 for $r=0$; 6.086 and 10.535 for $r=1$; 1.137 and 2.212 for $r=2$

As the Johansen trace test shows, for most of the countries in the panel, the maximum rank is two. The null of no cointegration is rejected only for Algeria. The Larsson et al (2001) panel cointegration test, shown at the bottom of the table, suggests the presence of two cointegrating vectors amongst the variables in equation (1)[7] for the full panel of emerging market economies.

5.12 **Interpreting Cointegrating Vectors.**

As we have obtained two cointegrating vectors from our PPP framework, we would like to give them an economic meaning by imposing a structure on them. We proceed with doing exactly what we have done in Chapter 3. We impose a structure on the cointegrating vectors by imposing some restrictions and use likelihood ratio test, as suggested by Johansen (1995), to test for such restrictions. Namely, we impose a structure on the two cointegrating vectors in the following way. We impose the joint symmetry and proportionality restriction i.e. (1, -1, 1). We also impose a structure on the second cointegrating vector by assuming the log. US-CPI to be an I(0) process, that is (0, 0, 1). In this case log US-CPI would be itself a cointegrating vector.

Finally, we use a likelihood ratio test as in Johansen (1995) to test for the validity of these restrictions and following Larsson et al (2001), we extend that test to a panel context[8].

[7] However, this test may tend to over-estimate the true number of cointegrating vectors.
[8] Results from this test should be taken with caution since it requires cross section independence.

The results are displayed in the Table 5.16:

Table 5.16

Johansen (1995) Likelihood Ratio Test

Country	LR-test
Algeria	10.0101
Col.	0.87196
D.Rep.	0.6911
Egypt	22.2445
Ethiopia	6.5263
Ghana	7.9276
Hung.	1.8144
India	10.0597
Indon.	1.1491
Kenya	3.2395
Korea	14.04
Malay.	7.6194
Nepal	7.3967
Pak.	8.8372
Phili.	7.1733
S.Lanka	6.3645
Thai.	12.268
Turk.	6.3615
Venez.	12.6794
Boliv.	9.2603
PLRtest	**156.53**
χ2-5%	5.99

Note: The individual country statistic has a χ^2 with 2 degree of freedom. The panel PLR test has a χ^2 distribution with 2N degree of freedom, where N is the cross section dimension.

The individual LR test statistics reject the null of valid restriction in five countries out of twenty. The panel test (PLR) displayed at the bottom of Table 5.16 suggests that the null hypothesis of valid restrictions is strongly rejected. The rejection of the null here confirms our believes that US-CPI , is probably a unit root process. We also reject the joint symmetry and proportionality restriction, indicating that the latter is likely to be too restrictive. Taking into account these results, and the fact that the Larsson et al (2001) test tends to over-estimate the true number of cointegrating vectors, we decide to restrict the rank to be the same and equal to one across different countries.

We impose a structure on the cointegrating vector by imposing the joint-symmetry and proportionality restriction and use a likelihood ratio test for over-identifying restrictions. Furthermore, we extend such a test to a panel context. The results are reported in the table 5.17.

Table 5.17
LR-Test for Over-Identifying Restrictions

Country	LR-test
Nepal	3.02*
Pakistan	16.16
Philip.	15.03
S.Lanka	25.49
Thai	12.27
Turkey	3.99*
Venez	1.41*
Indon.	40.25
Kenya	4.11*
S.Korea	3.88*
Malaysia	17.59
Ethiopia	16.74
Ghana	17.59
Hungary	7.93
India	8.42
Alger.	4.57*
Bolivia	18.35
Col.	0.88*
D.Rep.	17.51
Egypt	40.89
PLR-test	276.08

*Note: * indicates we accept the null. The above test follows a χ^2 distribution with d.f. of 2. (i.e.5.99). The panel test would then follow a χ^2 distribution with d.f. of 40.*

The individual country statistics imply acceptance of the null in seven out of twenty countries. But the panel statistic again strongly rejects the null hypothesis of valid restriction for the panel of emerging market economies.

The result we have obtained by panel LR tests has noticeable implications for applied work. In fact, we strongly rejected the joint symmetry and proportionality restriction. Since this restriction is implicitly imposed on the unit root tests of the real exchange rate, our conclusion is that this could be one of the reasons why unit root tests fail to reject the unit root hypothesis. However, this conclusion needs further investigation and we leave this on the agenda for future research.

5.8 **Conclusions**

This chapter examines PPP using a panel of twenty black market exchange rates for emerging market economies. We use a battery of new heterogeneous panel unit and cointegration tests that have been found to have greater power than the tests used by the standard literature on PPP.

The empirical evidence on PPP from panel unit root tests does not favour mean reversion in the real exchange rate. This supports the Balassa- Samuelson hypothesis. Furthermore these results are in line with those obtained in Chapter 2 for OECD countries. However, all panel cointegration tests strongly support cointegration between nominal exchange rate and relative prices, thus providing some support for the PPP hypothesis in the full panel of developing economies. Estimates of the long run PPP relationship for individual countries are significant and display the anticipated sign for most countries, though the price coefficients appear to be different from unity for most cases. These results contrast with the ones for OECD countries.

We also tested for the joint symmetry/proportionality restriction using likelihood ratio tests and found this restriction not to be supported by our set of data. This is probably due to the presence of trade barriers, and measurement errors, in prices in many developing countries. As we stressed in Chapter 3, this result has noticeable relevance for applied research on PPP. In fact, since unit root tests on the exchange rate implicitly impose this restriction, failure of this restriction could be one of the reasons why unit root tests fail to reject the unit root hypothesis in the real exchange rate. Therefore, unit root tests on the real exchange rate may be biased towards finding no mean reversion.

The overall empirical findings from the black market exchange rates seem to provide support for the weak form but not the strong form of the PPP hypothesis, in developing countries. The support for the weak form of PPP implies the absence of persistently over-valued or under-valued black market exchange rates. This contrasts with the official exchange rate that tends to be chronically over-valued or under-valued (as can be seen from the large and fluctuating black market premium) for many developing countries, with damaging effects on economic growth and the allocation of resources. Hence from a policy perspective, short of moving to a flexible exchange rate system, monetary authorities in developing countries should be using the black market rather than the official exchange rate both in the construction of the long-run equilibrium exchange rate and in the formulation of monetary and exchange rate policies.

Finally, some stylised facts are always put forwards when testing PPP using emerging market economies exchange rates. First nominal exchange rates, in these economies, are more volatile. Second, relative price ratios are more volatile. There is little evidence supporting these issues in our set of data.

Chapter 6

Purchasing Power Parity Persistence in Emerging Markets

6.1 Introduction

An important issue in the literature on PPP is the low speed of adjustment to equilibrium of the real exchange rate (generally 3-5 years). This result, in conjunction with the very high short run volatility of the real exchange rates, generates the so-called Rogoff (1996) "Purchasing Power Parity Puzzle". Half-life deviation of the real exchange rate from purchasing power parity (PPP) is a very important measure of persistence of the real exchange rate. This measure enables one better to understand exchange rate behavior and to interpret results produced by unit root tests. Let us assume that unit root tests discover evidence favoring PPP, but half lives are excessively long , for example 15-20 years or longer. How much does it matter to know that PPP holds if a half of a shock on the real exchange rate takes 15-20 years to die out?

Although most of the studies on real exchange rate persistence report half-lives that are in line with the Rogoff (1996) consensus of 3-5 years (for example Frankel, 1986, Abuaf and Jorion, 1990; Cheung and Lai, 1994; and others), there are also some other studies reporting half-lives that in some cases are below 3 years (see for example Taylor et al, 2001; and Wu 1996). A remarkable line of these studies is that most of them are based on AR (1) models that do not account for serial correlation. Furthermore, they calculate half-lives on the basis of the estimate of the unit root parameter. One major problem with these half lives is that the least squares (LS) estimates of the half-lives are biased downwards. Finally, they only provide point estimates of half-lives which give an incomplete picture of the speed of convergence. As we highlight in the following sections, it is important to support point estimates with confidence intervals.

In a recent paper, Murray and Papell (2002) criticize the previous literature on half-lives, on the basis that in most of them the focus is mainly on the rejections of unit root in the real exchange rate. Therefore, they do not use appropriate techniques to measure the degree of persistence in the real exchange rate. Murray and Papell (2002) identify four issues involving the use of these half-lives: confidence intervals, serial correlation, impulse response functions, and small sample bias of LS estimators.

Based on Murray and Papell (2002), we investigate the speed of adjustment of the real exchange rate towards PPP by estimating half-lives in the black market real exchange rate in twenty emerging markets economies. We consider different data generating processes (DGP) and different econometric and statistic techniques. First, as suggested in Murray and Papell (2002) we use both AR(1) and AR(p) models, and estimate half-lives in the real exchange rates using both LS estimates and a number of other methodologies such as impulse response function and the exact median unbiased estimator as in Andrews (1993). Furthermore, we support our point estimates of half-lives by constructing bootstrap confidence intervals.

One of the contributions of this chapter is the adoption of more appropriate methodologies to measure the speed of adjustment to PPP. The other contribution is the application of these methodologies to a unique data set consisting of twenty emerging market economies and black market real exchange rates. Furthermore, by comparing our results with Murray and Papell (2002), we try to shed some light on the cross country persistence in real exchange rates.

The chapter is organized as follows Sections 6.2-6.4 describe the econometric methodologies that we employ. Sections 6.5-6.6 present the empirical results. Conclusions are reported in section 6.7. Finally the appendix provides exact critical values for our sample size.

6.2 The Empirical Literature on Half-Lives.

Half-life deviations from purchasing power parity play an important role in the debate about the validity of PPP as an international parity condition. The validity of PPP has been largely assessed by using unit root tests on the real exchange rate. However, although the validity of PPP is an important theoretical issue, what does matter from an economic perspective is the degree of mean reversion in the real exchange rate. Indeed, as we stressed in the introduction, it is of very little "economic" interest to know that PPP holds if the degree of mean reversion in the real exchange rate is "infinitely" long.

Half-lives of Purchasing Power Parity (PPP) come mainly from studies using long-horizon data and the data collected by Lee (1976), consisting of WPI real exchange rates between the US and eight industrial countries over the period 1900-1972. Abuaf and Jorion (1990) report average half-lives of 3.3 years. Cheung and Lai (1994) extend the data through 1987-1992 and find similar average half-life. Frankel (1986) reports half-lives of 4.6 years, while Lothian and Taylor (1996), using two centuries of data, report half-lives of 4.5 years[1]. Wu (1996) use a different data set of quarterly data for post 1973 floating exchange rates and CPI prices and find an average half-life of 2.5 years[2].

Surveying these papers, Rogoff (1996) noticed that such a wide range of half-lives are difficult to reconcile with the PPP theory. In fact, according to that theory, deviations from PPP are attributed to transitory disturbances, such as monetary shocks. Thus while PPP is compatible with large short run variability of the real exchange rate (because in the short run wages and prices are sticky), it also suggests that deviations should be very short-lived, since they can only occur during the time when wages and prices are sticky (generally no longer than two years). These larger than expected half lives of PPP led to the "Rogoff's purchasing power parity puzzle".

Recent empirical studies have attempted to re-solve this purchasing power parity puzzle using different econometric and statistical techniques. The most influential work on half-lives is Cheung and Lai (2000a). Cheung and Lai (2000a) investigate half-lives of PPP in five OECD countries, using impulse response function and find point estimates of half-lives of about two years. In some countries such as for example UK and Italy, they find half-lives of 1.77 and 1.92 years, that is well below two years. This result, together with the median lower bound of their bootstrap confidence interval below 0.79 years, leads them to conclude that there is no PPP

[1] Note that these are only some examples of empirical studies on half-lives. For more complete reference please refer to Rogoff (1996).

puzzle. However their upper bound, 5.34 years, is still incompatible with price rigidity.

Cheung and Lai (2000b) investigate half-lives in PPP using a data set consisting of 94 developed and developing countries vis a vis the US$ from April 1973 to December 1994[3]. They use impulse response function and obtain half-lives for developing countries generally lower than the ones reported for industrial countries. In fact, half-lives were generally below two years. They conclude that persistence in developing countries is lower than industrial countries.[4] We shall try to shed some light on this issue in the next sections.

Taylor et al (2001) calculate half-lives of PPP for four OECD countries using an impulse response obtained by Monte Carlo integration. They point out that because of non linearity in the real exchange rates, the half-lives of shocks to real exchange rates vary both with the size of the shock and the initial conditions. For example, for small shocks occurring when the real exchange rate is near to PPP, half-lives of PPP fall in the range of three to five years. However, either when shocks are much larger or when the real exchange rate is far away from PPP (in this case even allowing for a much smaller shock) they discover much shorter half-lives (generally two years) than the ones reported in the literature.

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[2] The main contribution of these papers is on testing PPP rather than measuring the degree of mean reversion of the real exchange rate.

[3] Most of these countries are either low income countries or developing countries.

[4] They also report a sort of negative correlation between the frequency of rejection of the unit root null hypothesis and the persistence in PPP. In fact, they point out that since low income countries and developing countries are more likely to have lower persistence, this pattern may account for the higher unit root rejection observed for lower income and developing countries.

Recently, Murray and Papell (2002) noticed that the focus of most of the papers surveyed by Rogoff (1996), and mentioned above, was essentially on testing for mean reversion in the real exchange rate. Therefore, the general consensus of half-lives between 3-5 years is calculated from the autoregressive coefficient on the lagged real exchange rate. They identify three main drawbacks with this methodology: the absence of confidence intervals, serial correlation and small sample bias. For example, Papell (1997),Wu (1996), Lothian and Taylor (1996) and Cheung and Lai (1994, 2000a) only present point estimates of half-lives. This measure of persistence provides an incomplete picture of the degree of convergence of the real exchange rate. In fact, point estimates of half-life should be supported by confidence interval estimates. Furthermore, in some of these empirical works, estimates of half-lives are obtained from the estimates of the unit root parameter in an AR(1) type regression (i.e using generally DF regressions). The problem with this methodology is that the least squares estimator of the unit root parameter is known to be biased downward with the bias increasing the greater the persistence in the real exchange rate. Murray and Papell (2002) suggest that the problem of small sample bias can be overcome using exact median unbiased estimation, as suggested in Andrews (1993). Finally, studies using the DF test assume that real exchange rates can be represented by an AR(1) process. In this way these studies explicitly neglect the presence of autocorrelation in the data. This may have important implications for the calculation of half-lives. In this respect, Murray and Papell suggest calculating half-lives directly from impulse response function in an AR(p+1) model.

Murray and Papell (2002) use two different data sets, mainly the annual data collected by Lee (1976), and a second data set consisting of twenty consumer price index real exchange rates for industrial countries spanning from 1973:01 to 1998:2. They use median unbiased estimation and impulse response and report half-lives that are not encouraging for PPP. In fact, while point estimates of half-lives are reasonably low to be compatible with nominal price rigidity, confidence interval estimates are too wide to of any use.

6.3 Modeling Persistence in the Real Exchange Rate: AR (1) Model.

As mentioned in the previous section a large part of the empirical evidence on half-lives is obtained from AR(1) models. As stressed in Murray and Papell (2002), these models provide incorrect information of persistence in the real exchange rate since the estimator used (least squares) is downwards biased. In this section we present some of the methodologies that have been suggested in the literature to overcome the problem of small sample bias.

6.3.1 Median Unbiased Estimator

Consider the following AR(1) model:

$$q_t = \alpha + b_{LS} q_{t-1} + u_t \tag{6.1}$$

with $u_t \sim iidN(0,\sigma^2)$, initial value $q_0 \sim N(0,\sigma^2/(1-b^2))$ and AR parameter lying within the interval (-1,1).

Define b_{LS}^{*} as the least square estimator of b_{LS}. It is well known that, in small samples, b_{LS}^{*} is biased downward with the size of this bias increasing for large values of b_{LS} (see for example Andrews, 1993).

The problem of small sample bias of b_{LS}^{*} is of particular relevance, especially in empirical works dealing with half-lives, since the calculation of the latter relies on a biased parameter. Different methodologies have been proposed in the literature. For example, it is well known that the Jackknife estimator of b is mean unbiased of order 1/T for T→ ∞. One problem with this estimator is that it is not clear if the result holds for values of the AR parameter lying in the region of a unit root.

Another way of approaching the problem is by using median unbiased estimation. Following Andrews (1993) we define the median z of a random variable X as

$$P(X \geq z) \geq 1/2 \quad \text{and} \quad P(X \leq z) \leq 1/2 \qquad (6.2)$$

Assume that b_{LS}^{*} is an estimator of b_{LS}. By definition b_{LS}^{*} is a median unbiased estimator of b_{LS} if the true parameter b_{LS} is a median unbiased for b_{LS}^{*} for each b_{LS} in the parameter space. In other words b_{LS}^{*} is a median unbiased estimator if the distance between b_{LS}^{*} and the true parameter being estimated is on average the same as that from any other value in the parameter space. Suppose there are two candidates as population parameters b_{LS} and $b_{LS}^{'}$ then $E_b \mid b_{LS}^{*} - b_{LS} \mid \leq E_b \mid b_{LS}^{*} - b_{LS}^{'} \mid$ for all

b_{LS} and b'_{LS} in the parameter space. In this way, the probability that b^*_{LS} will overestimate the true parameter is the same to that it will underestimate it.

We define b^*_U as the median unbiased estimator of b_{LS} as follows:

$$b^*_U = 1 \text{ if } b^*_{LS} > z(1) \tag{6.3}$$

$$b^*_U = z^{-1}(b^*_{LS}) \text{ if } z(-1) < b^*_{LS} \leq z(1) \tag{6.4}$$

$$b^*_U = -1 \quad \text{if} \quad b^*_{LS} \leq z(-1) \tag{6.5}$$

where $z(-1) = \lim_{b \to -1} z(b_{LS})$ and z^{-1} is the inverse function of $z(.) = z_T(.)$ so that $z^{-1}(z(b_{LS})) = b_{LS}$. b^*_U can be easily computed given that $z(.)$ is known.

Appendix 1 shows quantiles of the median function $z(b_{LS})$ for different values of b_{LS} $\in$ {-1,1} and our particular sample size obtained by Monte Carlo simulation as in Andrews (1993). The appendix has been constructed using a simple AR(1) model as a DGP and increasing the value of b_{LS} by 0.01. The number of Monte Carlo replicates was set to 3000. In what follows, we report a simple example demonstrating how to use the tables in the Appendix 1. Suppose $z(1) = 0.9968$, then any values of $b^*_{LS} \geq 0.9968$ corresponds to $b^*_U = 1$. In the same way we calculate b^*_U when $z(-1)$. For example, if $z(-1) = -0.9955$, then, for any values of $b^*_{LS} \leq -0.9955$, $b^*_U = -1$. Finally if $-0.9955 \leq b^*_{LS} \leq 0.9968$ one finds b^*_U by looking at the 0.5 quantile column as follows: $b_{LS}^* = 0.7482$, then $b_U^* = 0.75$. For values of b_{LS}^* no contained in the 0.5 quantile column, interpolation is required.

Using the same approach an in Andrews (1993), we can also construct confidence for the median unbiased estimator. For example the $100(1-p)\%$ confidence intervals (c) for c_u can be constructed as follows:

$$c_u^L = 1 \text{ if } b_{ls}^* > lu(1) \tag{6.6}$$

$$c_u^L = lu^{-1}(b_{LS}^*) \text{ if } lu(-1) < b_{LS}^* \leq lu(1) \tag{6.7}$$

$$c_u^L = -1 \text{ if } b_{ls}^* \leq lu(-1) \tag{6.8}$$

where c_u^L is the lower confidence interval and $lu(.)$ is the upper quantile. Using the same approach we can also construct upper confidence interval as follows:

$$c_u^u = 1 \text{ if } b_{ls}^* > lL(1) \tag{6.9}$$

$$c_u^u = lL^{-1}(b_{LS}^*) \text{ if } lL(-1) < b_{LS}^* \leq lL(1) \tag{6.10}$$

$$c_u^u = -1 \text{ if } b_{ls}^* \leq lL(-1) \tag{6.11}$$

where c_u^u is the upper confidence interval and $lL(.)$ the lower quantile. The 100(1-p)% confidence interval for b_{LS} is $c_u^L \leq c_u \leq c_u^u$.

For example, consider the two-sided 95% confidence interval for c_u. Assume that $b_{LS}^{*} = 0.9943$ then, using the 0.975 quantile column, $IL = 0.98$, while $lu = 1$,using the 0025 quantile column.

6.3.2 **The Bootstrap Percentile Method.**

An alternative way of obtaining point estimates of b_{LS} consists of using bootstrap methods. Furthermore, by extending such a methodology one can also construct confidence intervals. Papell and Murray (2002) use a parametric percentile bootstrap approach based on generating bootstrap samples from an iid normal distribution. This approach does not allow for deviations from normal distribution. To consider deviations from the normal distribution, we implement that procedure by using non-parametric bootstrap. We construct confidence interval for b_{LS} as follows:

Suppose that b_{LS}^{*} is a consistent estimator of b_{LS}, and $b_{LS}^{\oplus}$ is the bootstrap estimator. Assume also that B is the number of bootstrap replications. We generate the bootstrap distribution of $b_{LS}^{\oplus}$ by drawing repeated samples with replacement from empirical residuals $(u_1^{*}, u_2^{*}, ..., u_T^{*})$ such that we can obtain $(u_1^{\oplus}, u_2^{\oplus}, ..., u_T^{\oplus})$, that is the bootstrap innovations. Using the bootstrap innovations we generate the bootstrap samples $(q_1^{\oplus}, q_2^{\oplus}, ..., q_T^{\oplus})$.We use the bootstrap sample to obtain $b_{LS}^{\oplus}$. Finally, repeating this B times we obtain the bootstrap distribution. A two sided (100-2α) confidence interval for b_{LS} is $b_{LS}^{*} - L_{1-\alpha}^{*} . b_{LS}^{*} + L_{\alpha}^{*}$ where L_{α}^{*} is the $100\,\alpha$ percentile.

One major problem of the bootstrap approach described above is that if $b_{LS} = 1$ and $\alpha = 0$, Basawa et al (1991) show that the bootstrap confidence interval is asymptotically invalid.

6.4. Modeling Persistence in the Real Exchange Rate: AR(p) Model

The major drawbacks with the methodologies described above is that they only consider AR(1) models. AR(1) models are appropriate when there is no serial correlation in the data set used. If there is serial correlation, it should be taken into account by using higher order processes. In one particular case, the model in (6.1) is replaced by:

$$q_t = a + bq_{t-1} + \sum_{i=1}^{p} \theta_i \Delta q_{t-1} + \mu_t \qquad (6.12)$$

As we shall see in section 6.6, neglecting serial correlation may have noticeable consequences on the estimates of half-lives.

Half-lives calculated from b in (6.12) assume shocks to real exchange rates decay monotonically. Murray and Papell (2002) point out that while this is appropriate in the case of an AR(1) model, it is no longer so in the case of an AR(p) model. Murray and Papell (2002), following Inoue and Kilian (2002), suggest obtaining point estimates of half-lives directly from impulse response function. In this section, we present the approach to the problem suggested by Inoue and Kilian (2002) .

6.4.1 Impulse Response Function

Consider the following AR(p) DGP:

$$\phi(\Psi)q_t = \alpha + \mu_t \tag{6.13}$$

with Ψ being a lag operator. Assume the process q_t is written as follows:

$$q_t = \alpha + bq_{t-1} + \theta_1 \Delta q_{t-1} + \theta_2 \Delta q_{t-2} + ... + \theta_{p-1} \Delta q_{t-1+1} + \mu_t \tag{6.14}$$

with $b = \phi_1 + \phi_2 + ... + \phi_p = 1$, $\theta(1) = 1 - \theta_1 - \theta_2 - ... - \theta_{p-1}$

Inoue and Kilian (2002) point out that the level representation (6.13) of the autoregressive process in (6.14) , can be written as a linear combination of b and θ_i. Specifically, $\phi_1 = b + \theta_1$, $\phi_j = \theta_j - \theta_{j-1}$ and $\phi_p = -\theta_{p-1}$. Hence, they show that although when $b = 1$ and $\alpha = 0$, the bootstrap is not valid for the unit root parameter b in (6.14), nevertheless, it is asymptotically valid for the slope parameters ϕ_i in its level representation . This is why although the bootstrap estimator has a random limit distribution, the rate at which the latter converges is so fast (i.e. $T^{3/2}$), that any linear combination of bootstrap estimators on the coefficients of the lagged difference variables will be consistent[5]. This result is important for empirical works focusing on half-life and using AR(p) models. In fact, in this case the parameter of interest is not b or θ_i but linear combinations of the latter i.e. ϕ_i. Hence the bootstrap point estimates and confidence intervals of half-life based on the impulse response functions are asymptotically valid.

In section 6.6 we shall use the following specification of the AR(p) model:

$$q_t = \alpha + \sum_{i=1}^{p+1} \phi_i q_{t-i} + \mu_t \qquad (6.15)$$

with $\phi_1 = b + \theta_1$, $\phi_j = \theta_j - \theta_{j-1} \dots \phi_{p+1} = -\theta_p$ for $j = 2,\dots,p$, and calculate half-lives and confidence intervals in the real exchange rate based on impulse function (i.e $\phi_{1,}\phi_2,\dots,\phi_{p+1}$).

6.5. Empirical Results from AR(1) Models

We shall use monthly data on the black market exchange rates for a panel of twenty emerging market countries over the period 1973M1-1993M12. The US Dollar is used as numeraire currency. The black market exchange rates are obtained from Pick`s currency yearbook various publications. The consumer price index (CPI) is used as the price index. Half lives are calculated from b^*_{LS} in (6.1) as ln(0.5)/ln(b_{LS}). Point and 95% bootstrap confidence interval estimates of half-lives (in years) from an AR(1) model are reported in Table 1.

[5] See Inoue and Kilian (2002) for a mathematical proof.

Table 6.1

OLS Half-Lives in DF Regressions

Country	b^*_{LS}	95% CI	HL_{LS}	95%CI
Algeria	0.991	[0.987 1.0]	6.39	[4.41 ∞]
Colombia	0.995	[0.993 1.0]	11.52	[8.82 ∞]
D.Rep	0.975	[0.973 1.0]	2.28	[2.11 ∞]
Egypt	0.987	[0.985 1.0]	4.41	[3.82 ∞]
Etiopia	0.941	[0.939 1.0]	0.95	[0.92 ∞]
Ghana	0.925	[0.923 0.991]	0.74	[0.76 6.39]
Hungary	0.971	[0.968 1.0]	1.96	[1.78 ∞]
India	0.992	[0.989 1.0]	7.19	[5.22 ∞]
Indonesia	1	[0.997 1.0]	∞	[19.2 ∞]
Kenya	0.977	[0.975 1.0]	2.48	[2.28 ∞]
Korea	0.542	[0.539 0.608]	0.094	[0.09 0.12]
Malaysia	0.993	[0.990 1.0]	8.22	[5.75 ∞]
Nepal	0.977	[0.975 1.0]	2.48	[2.28 ∞]
Pakistan	0.969	[0.966 1.0]	1.83	[1.67 ∞]
Philip.	0.946	[0.945 1.0]	1.04	[1.02 ∞]
S.Lanka	0.425	[0.421 0.487]	0.07	[0.06 0.08]
Thailand	0.945	[0.944 1.0]	1.02	[1..0 ∞]
Turkey	0.967	[0.966 1.0]	1.72	[1.67 ∞]
Venez.	0.988	[0.986 1.0]	4.78	[4.09 ∞]
Bolivia	0.994	[0.990 1.0]	9.59	[5.75 ∞]

Note: *95% CI represents the 95% bootstrap confidence interval.*
HL_{LS} indicates half-lives based on OLS estimates.

The average half-life of 3.6 years falls within Rogoff's 3-5 year estimate. The median half life is, instead, 2.3 years. The median half-life is much smaller than the average half-life. This may be probably due to the presence of outliers affecting the average. It should be noticed that in nine countries out of twenty point estimates of half-lives are below two years.[6] It is interesting to notice that Murray and Papell (2002), using OECD countries and quarterly data, report a median value of half lives for their point estimate that is very similar to ours (i.e. 2.52). As in Murray and Papell (2002), we support our point estimates of half-lives with interval estimates obtained using bootstrap. We use non-parametric percentile method described in section 6.3 to

[6] In Murray and Papell (2002) in only three countries.

construct a 95% confidence interval with B set equal to 3000 . The median lower bound of our confidence interval is 2.1 (average 3.8) and is larger than in other empirical studies reporting interval estimates of half-life. For example, the lower bound in Murray and Papell (2002) using quarterly data is around 0.64. The median upper bound is [∞], much larger than that reported in other empirical studies reporting confidence intervals of half-lives. In Murray and Papell (2002) the upper bound is 4.95 years.

As we have mentioned in section 6.3.2, if $b_{LS} = 1$ and $\alpha = 0$, the bootstrap is invalid so confidence interval based on bootstrap will be invalid. Furthermore, point estimates are invalid because the LS estimator is biased in small sample.[7] Taking into account these issues and following Murray and Papell (2002), we use the exact median unbiased estimations as suggested in Andrews (1993).

Least square median unbiased point estimates (in Table 2) are generally higher than the ones presented in Table 1. The median point estimate of half is 2.7. Contrary to what reported in Murray and Papell (2002), we do not note a very significant increase in the median point estimate. In fact, Murray and Papell (2002) report a median estimate of 5.69 that is much larger than the least squares estimates. However, it is important to notice that the difference in average point estimates in our case is very significant. In fact, while the least squares average estimate is 3.8 years, the median unbiased average estimate is 5.9. The median lower bound is 1.1 (average 3.7), and

[7] Note that even when one has a reasonable large sample, the problem still remains. In fact the bias is likely to approach to zero as the sample size increases, but does not disappear completely. This problem is substantially relevant when dealing with high persistent processes. In this case the LS estimator yields spurious low estimates even when the sample is reasonable large (Andrews, 1993)

the upper bound is infinite. These bounds are in line with Murray and Papell (2002). Considering individual country estimates we notice that there are still six countries for which point estimates of half-lives are below two years and for three other countries point estimates indicate a half-life of two years.[8]

Table 6.2

Exactly Median Unbiased Half-Lives in DF Regressions

Country	b_U^*	95%-CI	HL_{MU}	95% CI
Algeria	0.995	[0.989 1.0]	11.523548	[5.22 ∞]
Colombia	0.997	[0.998 1.0]	19.225193	[28.85 ∞]
D.Rep	0.977	[0.95 1.0]	2.4824097	[1.126 ∞]
Egypt	0.992	[0.97 1.0]	7.1913633	[1.896 ∞]
Etiopia	0.945	[0.941 1.0]	1.0210696	[0.949 ∞]
Ghana	0.93	[0.887 1.0]	0.7959448	[0.482 ∞]
Hungary	0.975	[0.945 1.0]	2.2814876	[1.02 ∞]
India	0.994	[0.975 1.0]	9.5981341	[2.281 ∞]
Indonesia	1.0	[0.985 1.0]	∞	[3.822 ∞]
Kenya	0.981	[0.955 1.0]	3.0111457	[1.254 ∞]
Korea	0.545	[0.455 0.705]	0.095165	[0.073 ∞]
Malaysia	0.997	[0.971 1.0]	19.225193	[1.963 ∞]
Nepal	0.981	[0.955 1.0]	3.0111457	[1.254 ∞]
Pakistan	0.972	[0.938 1.0]	2.0339202	[0.902 ∞]
Philip.	0.95	[0.915 1.0]	1.1261173	[0.65 ∞]
S.Lanka	0.423	[0.327 0.6]	0.0671355	[0.052 ∞]
Thailand	0.948	[0.915 1.0]	1.0816746	[0.65 ∞]
Turkey	0.978	[0.938 1.0]	2.5965693	[0.902 ∞]
Venez.	0.992	[0.97 1.0]	7.1913633	[1.896 ∞]
Bolivia	0.997	[0.997 1.0]	19.225193	[19.22 ∞]

Note: 95%-CI represents the 95% bootstrap confidence interval. HL_{MU} Indicates half-lives based on median unbiased estimates..

6.6 Empirical Results from AR(p) Models

Since serial correlation could be a problem when using monthly data, we extend the simple AR(1) model to account for possible autocorrelation in disturbances. We extend the simple AR(1) model represented in (6.1) by including p lags of the first difference of the dependent variable on the right hand side, and applying the ADF test

[8] In Murray and Papell (2002) there is only one country for which point estimates indicate half-life below two years.

and impulse response function. We select the number of lags in the ADF regression, using the lag selection criterion suggested by Ng and Perron (1995). We start with reasonable maximum number of lags of 8. We calculate point estimates and confidence intervals of half-lives in different ways. First, using OLS point estimates of the unit root parameter in an AR(p) model. Second, impulse response function as in Murray and Papell (2002). In terms of confidence intervals, we use two different approaches, namely, the bootstrap and the delta method[9]. The model we consider is given in (6.12). Point estimates and confidence intervals of the half-lives are reported below

Table 6.3
Half-Lives in ADF Regressions

Country	K	b^*_{LS}	95%-CI	HL_{LS}	95%-CI	D.M.	HL_{IRF}	95%-CI
Algeria	4	0.991	[0.933,1.0]	6.39	[0.83 ∞]	[0 20.5]	2.446	[1.38 ∞]
Colombia	5	0.996	[0.925,1.0]	14.41	[0.74 ∞]	[0 65.9]	0.423	[0.36 ∞]
D.Rep	5	0.963	[0.928,1.0]	1.53	[0.77 ∞]	[0.1 2.7]	0.465	[0.39 ∞]
Egypt	4	0.994	[0.939,1.0]	9.59	[0.92 ∞]	[0 60.9]	2.52	[1.36 ∞]
Etiopia	1	0.959	[0.931,1.0]	1.38	[0.81 ∞]	[0 20.9]	0.453	[0.37 ∞]
Ghana	5	0.927	[0.927,1.0]	0.76	[0.76 ∞]	[0 21.3]	2.034	[1.37 ∞]
Hungary	4	0.974	[0.927,1.0]	2.19	[0.76 ∞]	[0 4.71]	0.432	[0.36 ∞]
India	0	0.992	[0.989 1.0]	7.19	[5.22 ∞]	[0 26.3]	7.19	[0.43 ∞]
Indonesia	1	0.992	[0.941,1.0]	7.19	[0.95 ∞]	[0 48.3]	0.558	[0.45 ∞]
Kenya	0	0.977	[0.975 1.0]	2.48	[2.28 ∞]	[0 5.75]	2.48	[2.28 ∞]
Korea	5	0.843	[0.926,1.0]	0.34	[0.75 ∞]	[0.15 0.5]	0.445	[0.41 ∞]
Malaysia	1	0.995	[0.931,1.0]	11.52	[0.81 ∞]	[0 51.6]	2.459	[1.38 ∞]
Nepal	5	0.978	[0.926,1.0]	2.6	[0.75 ∞]	[0. 6.0]	0.447	[0.36 ∞]
Pakistan	1	0.979	[0.927,1.0]	2.72	[0.76 ∞]	[0 6.8]	1.45	[0.98 ∞]
Philip.	1	0.953	[0.930,1.0]	1.21	[0.79 ∞]	[0.15 2.3]	0.474	[0.41 ∞]
S.Lanka	4	0.754	[0.940,1.0]	0.2	[0.93 ∞]	[0.06 0.3]	0.524	[0.40 ∞]
Thailand	1	0.966	[0.887,1.0]	1.67	[0.48 ∞]	[0 3.64]	0.418	[0.35 ∞]
Turkey	4	0.977	[0.930,1.0]	2.48	[0.79 ∞]	[0 5.9]	0.431	[0.36 ∞]
Venez.	6	0.986	[0.921,1.0]	4.09	[0.70 ∞]	[0 55.7]	0.468	[0.38 ∞]
Bolivia	0	0.994	[0.990 1.0]	9.59	[5.7 ∞]	[0 36.6]	9.59	[0.48 ∞]

Note: HL_{LS} and HL_{IRF} represent point estimates of half-lives (in years) from OLS and the impulse response function presented in section 6.4.1. 95% bootstrap confidence intervals are presented in the columns six and eight.

[9] Note that to follow the previous literature, in Table 3, we present estimation of half-lives using OLS, bootstrap and delta method. However, as highlighted in the previous sections, these are not the correct methodologies. As shown in Murray and Papell (2002), point estimates and confidence interval estimates of half-lives in AR(p) models should be obtained from impulse response function.

The second column in Table 6.3 (K) represents the number of lags. At least one lag was chosen for each country except for India, Kenya and Bolivia, where the maximum lag is zero. The third column (b_{LS}^*) presents the least squares point estimates of the unit root parameter in (6.12). The median point estimate of half-lives, using OLS, is 2.5 which is not very different than what obtained from DF test on the AR(1) model. But the average of 4.5 years is larger. In Murray and Papell (2002) the median point estimate is 1.77. The median lower bound is 0.80 (average 1.33) which is much lower than the median lower bound in the case of an AR(1) model. On the other hand upper bounds are still infinite. In Murray and Papell (2002) the median lower bound is 0.64, which is analogous to ours, and the median upper bound, 3.12.

We also construct confidence intervals for OLS estimates of half-lives using a delta approximation (D.M.) based on normal sampling distribution, as in Rossi (2002). A conventional two side 95% confidence interval for half-lives (HL_{b*}) is:

$$HL_{b*} \pm 1.96\delta_{b*}^{*}\left(\frac{\ln(0.5)}{b*}[\ln b*]^{-2}\right) \qquad (6.16)$$

where δ_{b*}^{*} is an estimate of the standard deviation of b. The only constraint we need to apply delta approximation is that the half-life cannot be negative[10].

Confidence intervals using delta approximation are reported in the seventh column of Table 3. These estimates appear somewhat to be much smaller that the ones obtained

[10] Note: all the estimates that is b^*, δ_{b*}^{*} are obtained from the OLS estimation of b in 6.1.

by bootstrap. We notice that in eight countries out of twenty, these estimates (i.e.the upper bound) fall within the Rogoff range of three-five years. The median upper bound is 5.94 while the average is 20.45. The upper bound estimates obtained by bootstrap are, in each country, much wider than the ones using delta approximation.

However, these estimates are of little use since they are based on the assumption that shocks to the real exchange rate decay monotonically (Murray and Papell, 2002). In this specific case with an AR(p) model, this is a rather strong assumption. In fact, there is no reason why shocks to the real exchange rate should decay at a constant rate when the model considered is a AR(p) model. Again, in this particular case (i.e. AR(p) models) Inoue and Kilian (2002) show that although the bootstrap method is asymptotically invalid for the unit root parameter in (6.12), nevertheless, it is valid for the individual slopes in the level representation (6.14)[11]. In what follows we shall use the impulse response function presented in section 6.4.1 to calculate half-lives[12].

In columns eight and nine of Table 3, we report point and confidence interval estimates of half-lives calculated from impulse response function (i.e $\phi_{1,}\phi_2,...,\phi_{p+1}$). The median of half-lives calculated from the impulse response function is 0.50 (average 1.78). These are much lower than the ones obtained from ADF-OLS test and the AR (1) model. Murray and Papell (2002) report median estimates of half-life of

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[11] Note that, as we pointed out, the bootstrap is invalid when $\alpha = 0$ and $b = 1$ in 6.12. The consequence of this is that our interval estimates of half-lives in column six are questionable.
[12] Note that, as shown in section 6.4.1, the cumulative impulse response function (see equation 6.15) used in this section is obtained from smooth functions of the autoregressive parameters. Therefore, half-life is also assumed to be smooth (there might be small alteration of parameters that generate jumps). However, since there is no closed form solution for half-life, we may conjecture that bootstrap can be used to calculate cumulative impulse response function and therefore half-life in many practical cases (included exchange rates). We thank Lutz Kilian for his comment on this point.

2.15. There is clearly a different behavior in the degree of persistence of the real exchange rate in OECD countries and emerging market economies. Individual countries estimates suggest a half-life below two years, in thirteen countries out of twenty. The result is in line with Cheung and Lai (2000b) who discover average half-lives for developing countries less than three years, and in most cases in the range 0-1 year[13]. However, Cheung and Lai do not report confidence intervals.

Taking this result into account, one would be tempted to conclude that the PPP puzzle is solved. However, when interval estimates are considered, these latter are so wide as to make point estimates completely unreliable. In fact, although the lower bound is 0.41 (average 0.73), the upper bound is [∞]. In Murray and Papell (2002) these are, respectively, 1.14 and 4.04. We believe that results obtained from point estimates, as well as lower bound estimates of half-lives, are consistent with the presence of large misalignments from PPP in developing countries. On the other hand, upper bound estimates of half lives are consistent with anything, even unit root processes.[14]

6.7 Conclusions

The adjustment dynamics of the real exchange rate to shocks has been largely investigated in the literature on PPP. Prior studies use data for industrial economies and generally they obtain half-lives falling in Rogoff's range of three-five years. However, these studies suffer from serious drawbacks. Recently Murray and Papell (2002) questioned the previous literature on half-lives showing that they have ignored

[13] See Cheung and Lai (2000b) p.g. 389, plot of half-life estimates (a), (c), and (f).

small sample bias, serial correlation and confidence intervals. Using median unbiased estimation they show that the degree of persistence of the real exchange rate is much wider than what previously reported.

This chapter extends Rogoff's (1996) puzzle in new directions. It provides an extensive analysis of PPP reversion, using a unique data set consisting of twenty emerging market economies and black market real exchange rates. We have addressed the problems of small sample bias and serial correlation, by using exact median unbiased estimation and calculating half-lives from impulse response function and ADF model. In addition, we have constructed bootstrap confidence intervals. We use a non-parametric approach while Papell and Murray (2002) rely on a parametric approach. Confidence intervals seem, somehow, to be sensitive to the frequency of data and model specification, the higher the frequency of data used, the wider the confidence intervals. An additional contribution of this chapter is the construction of exact quantiles of least squares estimator for our sample size.

We focus on our preferred specification (i.e. ADF regression) and methodology (i.e. impulse response function). The median point estimate of half-lives is 0.5. This confirms the existence of a much lower persistence in the real exchange rates of developing countries, confirming, in this way, the empirical results reported in Cheung and Lai (2000b). Murray and Papell (2002), using the same methodological approach (i.e. impulse response function), report a median point estimate of half-life for OECD countries of 2.15 years. Our result seems to confirm the hypothesis of different behaviors of real exchange rates between industrial countries and developing

[14] Note that this result is consistent with results from unit root tests reported in Chapter 5.

countries. We believe a possible explanation for our result could be due to large misalignment from PPP in emerging market economies. In developing countries, large policy shocks could induce large misalignments implying that the real exchange rate is more often likely to be far from its equilibrium value (i.e. PPP). The consequence of this is that one would observe a much faster rate of mean reversion.

On the basis of our point estimates of half-lives, one would tempted to conclude that there is no longer a PPP puzzle. However, interval estimates tell us a different story. In fact, confidence intervals of half-lives are so wide that they contain very little information. These half-lives are consistent both with models based on nominal rigidities, and with a unit root in the real exchange rate. Therefore, when confidence interval estimates are considered, the different behavior of real exchange rates between industrial countries and developing countries becomes less pronounced.

Appendix 2: Quantiles of the Median Function $z(b_{LS})$ when T+1 =228

B_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
-0.999	-0.9583	-0.9671	-0.9955	-1.0044	-1.0059
-0.989	-0.9458	-0.954	-0.9859	-0.9976	-0.9995
-0.979	-0.9255	-0.9362	-0.9745	-0.9916	-0.9935
-0.969	-0.9132	-0.9235	-0.9653	-0.9856	-0.9879
-0.959	-0.9013	-0.9123	-0.955	-0.9776	-0.9809
-0.949	-0.8918	-0.9024	-0.9462	-0.9716	-0.9744
-0.939	-0.8734	-0.8863	-0.9344	-0.9637	-0.9675
-0.929	-0.8594	-0.8739	-0.9249	-0.957	-0.9611
-0.919	-0.8499	-0.8616	-0.9155	-0.9504	-0.9552
-0.909	-0.8333	-0.8492	-0.9058	-0.9428	-0.9475
-0.899	-0.8239	-0.837	-0.8958	-0.9357	-0.9412
-0.889	-0.8084	-0.8217	-0.8857	-0.9273	-0.9324
-0.879	-0.8006	-0.8182	-0.8749	-0.9163	-0.9228
-0.869	-0.7784	-0.7929	-0.856	-0.9017	-0.9091
-0.859	-0.7812	-0.7937	-0.8553	-0.9009	-0.9074
-0.849	-0.7676	-0.7833	-0.8463	-0.8918	-0.8993
-0.839	-0.7539	-0.7675	-0.8347	-0.8845	-0.8927
-0.829	-0.7401	-0.7561	-0.8251	-0.8763	-0.8833
-0.819	-0.7332	-0.7486	-0.8162	-0.8677	-0.8753
-0.809	-0.721	-0.7366	-0.8062	-0.8594	-0.8664
-0.799	-0.6826	-0.7023	-0.7749	-0.8338	-0.844
-0.798	-0.7054	-0.7222	-0.7963	-0.8475	-0.8555
-0.797	-0.7052	-0.7212	-0.7936	-0.8502	-0.8602
-0.796	-0.7022	-0.7192	-0.7917	-0.8477	-0.8557
-0.795	-0.7064	-0.7213	-0.7923	-0.8477	-0.8558
-0.794	-0.7005	-0.7183	-0.7901	-0.8461	-0.8564
-0.793	-0.7001	-0.7158	-0.7916	-0.8427	-0.8508
-0.792	-0.6991	-0.7155	-0.7886	-0.8459	-0.856
-0.791	-0.6973	-0.7136	-0.7869	-0.8434	-0.856
-0.781	-0.6892	-0.7065	-0.7781	-0.8355	-0.8439
-0.771	-0.6787	-0.6939	-0.7682	-0.827	-0.8365
-0.761	-0.6626	-0.6836	-0.757	-0.818	-0.8289
-0.751	-0.6507	-0.6698	-0.7496	-0.8064	-0.8161
-0.741	-0.6444	-0.6583	-0.7377	-0.8025	-0.8122

b_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
-0.731	-0.6293	-0.6484	-0.7279	-0.793	-0.8056
-0.721	-0.6168	-0.6352	-0.716	-0.7795	-0.7904
-0.711	-0.611	-0.6262	-0.7098	-0.7778	-0.7904
-0.701	-0.5978	-0.6158	-0.6982	-0.766	-0.7765
-0.691	-0.5865	-0.6049	-0.6871	-0.7555	-0.7667
-0.681	-0.5801	-0.5999	-0.6786	-0.7476	-0.7583
-0.671	-0.5659	-0.5822	-0.6692	-0.7382	-0.7519
-0.661	-0.5528	-0.574	-0.6563	-0.7296	-0.7439
-0.651	-0.5431	-0.5609	-0.6471	-0.719	-0.7313
-0.641	-0.5378	-0.5573	-0.6383	-0.7114	-0.7231
-0.631	-0.5224	-0.5405	-0.6292	-0.703	-0.7182
-0.621	-0.509	-0.5306	-0.6161	-0.6935	-0.7092
-0.611	-0.4995	-0.5176	-0.6102	-0.6815	-0.6953
-0.601	-0.4924	-0.5062	-0.5988	-0.678	-0.693
-0.591	-0.4733	-0.4972	-0.5879	-0.6656	-0.6783
-0.581	-0.466	-0.4855	-0.5767	-0.6559	-0.6699
-0.571	-0.4584	-0.4766	-0.5703	-0.6533	-0.6669
-0.561	-0.4493	-0.4665	-0.5582	-0.6386	-0.6524
-0.551	-0.4405	-0.4598	-0.548	-0.626	-0.6406
-0.541	-0.4287	-0.4507	-0.5387	-0.626	-0.6406
-0.531	-0.4134	-0.4352	-0.5305	-0.6096	-0.6287
-0.521	-0.4064	-0.4224	-0.5172	-0.6019	-0.6195
-0.511	-0.3939	-0.4143	-0.508	-0.5897	-0.6019
-0.501	-0.3876	-0.4094	-0.4991	-0.5832	-0.5969
-0.491	-0.3712	-0.3939	-0.4906	-0.573	-0.5735
-0.481	-0.3636	-0.3844	-0.4781	-0.5608	-0.5735
-0.471	-0.358	-0.3785	-0.469	-0.553	-0.5688
-0.461	-0.3425	-0.362	-0.4604	-0.5448	-0.5605
-0.451	-0.3318	-0.3497	-0.4477	-0.5389	-0.5537
-0.441	-0.321	-0.3375	-0.4401	-0.5251	-0.5443
-0.431	-0.3138	-0.3295	-0.4276	-0.5232	-0.5391
-0.421	-0.2973	-0.3183	-0.4195	-0.5084	-0.5237
-0.411	-0.2923	-0.3113	-0.4074	-0.4966	-0.5174
-0.401	-0.2786	-0.3031	-0.3981	-0.485	-0.4982
-0.391	-0.276	-0.2938	-0.3897	-0.4804	-0.4962
-0.381	-0.2606	-0.2787	-0.3799	-0.4701	-0.4866

b_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
-0.371	-0.2481	-0.2674	-0.3672	-0.4623	-0.4789
-0.361	-0.236	-0.2539	-0.3603	-0.4505	-0.4716
-0.351	-0.2321	-0.2489	-0.349	-0.4481	-0.4628
-0.341	-0.2154	-0.2341	-0.3397	-0.4309	-0.4491
-0.331	-0.2083	-0.2305	-0.3277	-0.418	-0.4325
-0.321	0.2025	-0.2202	-0.3197	-0.4161	-0.4302
-0.311	-0.1892	-0.2066	-0.3099	-0.4046	-0.4205
-0.301	-0.1786	-0.1967	-0.2987	-0.3949	-0.4133
-0.291	-0.1684	-0.1903	-0.2885	-0.3798	-0.394
-0.281	-0.1619	-0.1802	-0.2801	-0.3776	-0.3921
-0.271	-0.1488	-0.165	-0.2697	-0.3655	-0.3831
-0.261	-0.1368	-0.1571	-0.2589	-0.3566	-0.3764
-0.251	-0.1253	-0.142	-0.2495	-0.3478	-0.3668
-0.241	-0.1216	-0.1385	-0.239	-0.3424	-0.3607
-0.231	-0.1036	-0.1242	-0.2307	-0.3271	-0.342
-0.221	-0.1004	-0.1165	-0.2181	-0.3188	-0.3357
-0.211	-0.0864	-0.1064	-0.2109	-0.3124	-0.3327
-0.201	-0.0738	-0.0966	-0.1978	-0.2979	-0.3146
-0.191	-0.0688	-0.0878	-0.1884	-0.2835	-0.3011
-0.181	-0.0632	-0.0799	-0.1814	-0.28	-0.2983
-0.171	-0.0463	-0.065	-0.1689	-0.2709	-0.2932
-0.161	-0.0412	-0.0595	-0.161	-0.2617	-0.2813
-0.151	-0.0281	-0.0454	-0.1486	-0.252	-0.269
-0.141	-0.018	-0.034	-0.1414	-0.2398	-0.2606
-0.131	-0.0082	-0.0307	-0.1276	-0.2264	-0.2476
-0.121	0.0045	-0.0189	-0.1218	-0.2217	-0.2405
-0.111	0.0111	-0.0074	-0.1118	-0.2127	-0.2338
-0.101	0.0218	0.003	-0.101	-0.2039	-0.2212

b_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
0.2	0.3184	0.2982	0.1962	0.0966	0.0724
0.21	0.3263	0.3082	0.2118	0.1095	0.0891
0.22	0.3338	0.3171	0.2182	0.1164	0.0967
0.23	0.3459	0.3267	0.2286	0.1255	0.1047
0.24	0.3478	0.3308	0.2373	0.1362	0.1169
0.25	0.3594	0.3436	0.2495	0.1496	0.1313
0.26	0.3741	0.3565	0.2604	0.1582	0.1362
0.27	0.3851	0.3668	0.269	0.1648	0.15
0.28	0.3916	0.3712	0.2794	0.178	0.1532
0.29	0.3969	0.3831	0.2895	0.1905	0.1713
0.3	0.4147	0.3942	0.2996	0.2003	0.1774
0.31	0.4152	0.4025	0.3092	0.211	0.1921
0.32	0.4337	0.4137	0.3194	0.2203	0.1966
0.33	0.4414	0.4232	0.3287	0.2269	0.2103
0.34	0.4472	0.4281	0.3384	0.2408	0.2158
0.35	0.4589	0.4442	0.3494	0.2447	0.2243
0.36	0.4639	0.4492	0.3556	0.2549	0.2331
0.37	0.4771	0.4583	0.3699	0.2725	0.2569
0.38	0.4876	0.4694	0.3786	0.2808	0.2618
0.39	0.5025	0.4786	0.3873	0.2839	0.2671
0.4	0.5091	0.4912	0.3991	0.301	0.2754
0.41	0.5129	0.4982	0.4108	0.3139	0.2914
0.42	0.5232	0.506	0.4182	0.3234	0.2959

b_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
0.43	0.5294	0.516	0.4284	0.3345	0.3134
0.44	0.5447	0.527	0.4386	0.3431	0.3204
0.45	0.5558	0.5365	0.4492	0.3541	0.3339
0.46	0.5569	0.5419	0.4574	0.3657	0.341
0.47	0.5705	0.5565	0.4694	0.3664	0.3491
0.48	0.5751	0.5632	0.4759	0.3772	0.3561
0.49	0.5885	0.5725	0.4899	0.3952	0.3791
0.5	0.5979	0.5827	0.497	0.4041	0.3863
0.51	0.6114	0.5934	0.5067	0.4099	0.3929
0.52	0.6173	0.6018	0.5189	0.4267	0.3997
0.53	0.6238	0.6104	0.5287	0.4364	0.4162
0.54	0.6345	0.6195	0.5385	0.4487	0.4257
0.55	0.6407	0.6287	0.5495	0.4577	0.4345
0.56	0.6467	0.6362	0.5575	0.4709	0.4533
0.57	0.6624	0.6481	0.5681	0.4771	0.4558
0.58	0.6721	0.6562	0.578	0.4887	0.4716
0.59	0.674	0.6616	0.5867	0.4997	0.4815
0.6	0.6891	0.6783	0.5989	0.5053	0.4877
0.61	0.6951	0.6821	0.6063	0.5143	0.4938
0.62	0.7054	0.6905	0.6193	0.5308	0.5121
0.63	0.7183	0.703	0.6267	0.5403	0.5228
0.64	0.7264	0.7116	0.6366	0.5479	0.5298
0.65	0.7345	0.7196	0.6476	0.5635	0.538
0.66	0.7406	0.729	0.6572	0.5749	0.5556
0.67	0.75	0.738	0.668	0.5846	0.5697
0.68	0.7562	0.7458	0.6787	0.5955	0.5741
0.69	0.7694	0.7582	0.6876	0.5985	0.5805
0.7	0.7775	0.6983	0.7653	0.6171	0.6028
0.71	0.7849	0.7729	0.707	0.6311	0.6142
0.72	0.7958	0.7832	0.7178	0.6368	0.6186
0.73	0.8011	0.79	0.7275	0.6463	0.6339
0.74	0.8045	0.7973	0.7359	0.661	0.646
0.75	0.8206	0.8117	0.7482	0.668	0.6539

b_{LS}/Quantile	0.975	0.95	0.5	0.05	0.025
0.76	0.8287	0.8268	0.7567	0.6867	0.6718
0.77	0.8376	0.8267	0.7672	0.6908	0.6739
0.78	0.8428	0.8335	0.7775	0.7018	0.6877
0.79	0.8475	0.8401	0.7856	0.7167	0.7021
0.8	0.8626	0.8537	0.7989	0.7236	0.7094
0.81	0.87	0.8596	0.8067	0.7408	0.7253
0.82	0.8785	0.8694	0.8175	0.7489	0.7297
0.83	0.8839	0.8764	0.8268	0.7573	0.7434
0.84	0.8893	0.883	0.8361	0.7719	0.7578
0.85	0.9037	0.8955	0.8481	0.7795	0.7685
0.86	0.9081	0.9009	0.8549	0.7904	0.7778
0.87	0.9168	0.9095	0.8671	0.804	0.7906
0.88	0.9259	0.918	0.8749	0.8158	0.8009
0.89	0.9302	0.9251	0.8858	0.8283	0.8138
0.9	0.9409	0.9349	0.8966	0.8396	0.8261
0.91	0.9483	0.9427	0.9069	0.8511	0.839
0.92	0.9544	0.949	0.9164	0.8622	0.8495
0.93	0.9605	0.9569	0.9256	0.8754	0.8665
0.94	0.9689	0.9652	0.9368	0.8872	0.8739
0.95	0.9753	0.9728	0.9463	0.8998	0.8884
0.96	0.8719	0.979	0.9565	0.9107	0.8995
0.97	0.9883	0.9858	0.9662	0.9262	0.9156
0.98	0.9943	0.9927	0.9766	0.9407	0.9306
0.99	1.001	0.9986	0.9854	0.9532	0.9421
1	1.0061	1.0051	0.9968	0.9668	0.9576

Chapter 7

Conclusions and Suggestions for Future Research

This study has examined the Purchasing Power Parity (PPP) theory from a long-run perspective. While the first part of this thesis has followed the empirical literature in using panel data for OECD countries and official exchange rates, the second part addressed the issue of validity of PPP in emerging markets, using a panel of black market exchange rates.

Despite the enormous amount of empirical research on PPP, there is still mixed evidence that PPP is a valid international parity condition (see for example, O`Connell, 1998 and Papell, 1998). Univariate tests have been recognized as having low power and being inadequate for testing long run PPP. As a consequence, researchers have suggested using panel data, have been able to find some evidence favouring PPP. However the increasing evidence towards long run PPP from panel estimators may be due to size distortion in panel estimators under cross section dependence[1]. This is one of the points analyzed in this thesis.

We have extended the bootstrap panel unit root test due to Maddala and Wu (1999), and used it to test long run PPP in OECD countries and emerging markets using black market exchange rates. Following Berkowitz and Kilian (2000), we propose an alternative method of selecting the initial value when bootstrapping a non-stationary AR process. Furthermore, we use Monte Carlo simulation to analyse the size

[1] This point is particularly relevant for panel unit root tests.

distortion of the proposed bootstrap test, and find it to have a good size for our span of data.

With regard to the empirical results on PPP from our bootstrap unit root test, we found that while the Im et al (1997) test supported evidence of stationarity of the real exchange rate in OECD countries, our panel test failed to find any significant evidence favoring mean reversion. This finding is in line with O`Connell (1998) that considers cross section dependence as the main source of "overvaluation" of PPP.

Another important element that is common in panel data methodology used to test PPP, is the homogeneity null and alternative hypotheses. In fact, most of the panel unit root tests used to investigate long run PPP are homogeneous tests.[2] We pointed out that the homogeneity assumption may be too restrictive, in particular, when testing for PPP by unit root tests of the real exchange rate. Our bootstrap panel unit root tests allows for a greater amount of heterogeneity than the existing panel unit root tests.

While there has been a considerable proliferation of panel unit root tests to investigate PPP, relatively little work has been done using panel cointegration tests. We use a battery of new, heterogeneous and more powerful panel cointegration tests, that have never been applied to PPP before, including the McCoskey and Kao (1998) and the Larsson et al (2001). Using a panel cointegration approach we have found greater evidence favoring PPP in OECD countries. In fact, six out of the nine cointegration tests we have used support cointegration between the nominal exchange rate and

[2] Generally these are either LL1 (1993) test or extended version of this.

domestic-foreign prices. These empirical results contrast with the ones obtained from panel unit root tests. Since panel unit root tests on the real exchange rate implicitly impose the joint symmetry and proportionality restriction, we decided to test for such a restriction by using likelihood ratio tests extended to panel context. As already documented in the literature[3], we have found very little empirical evidence favoring the joint symmetry and proportionality restriction. We have highlighted that panel unit root tests of the real exchange rate may be biased towards finding no mean reversion because of the invalidity of the joint symmetry and proportionality restriction.[4] We believe that panel cointegration is a more appropriate methodology than panel unit root tests.

An important contribution of this thesis is the construction and use of a unique panel data on black market exchange rates for twenty emerging market economies, the largest ever used for black market exchange rates. We test for PPP by using a battery of heterogeneous panel unit root and cointegration tests.[5] Panel unit root tests do not provide any evidence for stationarity of the black market real exchange rate. We have also allowed for structural breaks, and found support of the hypothesis that real exchange rates are break-trend stationary in nine emerging markets out of twenty. Panel cointegration tests, on the other hand, do find strong evidence of cointegration amongst nominal exchange rate, domestic and foreign prices. The empirical evidence

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[3] See for example Coakley and Fuertes (2000), and Wu (1999).

[4] The joint symmetry and proportionality restriction, together with cross section dependence, constitutes a sort of puzzle when testing PPP using unit root tests. In fact, if we accept the unit root null hypothesis (i.e. PPP does not hold), this may be due to the failure of the symmetry and proportionality restriction. On the other hand if we reject the null hypothesis (i.e. PPP holds), this may be due to size distortion caused by cross section dependence. It is also on the basis of this ambiguity that we suggest using cointegration to test long-run PPP.

[5] Note that when testing PPP in emerging markets one should allow for heterogeneity, since these exchange rates are likely to be very heterogeneous (see Cheung and Lai, 2000a). Homogeneous tests are likely to produce miss-leading results in this context.

here is much stronger than in OECD countries. This result seems to be in line with Cheung and Lai (2000), who report empirical evidence for PPP to be much stronger in developing countries than developed ones.[6] We have also tested for the validity of the joint symmetry and proportionality restriction and found no empirical support for it in the black market for foreign exchange.

Finally, following Murray and Papell (2002) and Cheung and Lai (2000a,b), we investigate real exchange rate persistence, using black market real exchange rates for twenty emerging market economies. We use a new and more appropriate econometric technique (i.e. median unbiased estimation and impulse response function) and report half-lives that are noticeably smaller (i.e. 6 months) than the ones generally obtained for OECD countries. This result is in line with Cheung and Lai (2000a). However, bootstrap confidence intervals give us a different picture of the persistence in the black market real exchange rates. In fact, confidence intervals are so wide as to be of little use to interpret the source of dynamics of the black market real exchange rates. It seems that the greater the sophistication of the econometric techniques used to solve Rogoff's "Purchasing Power Parity Puzzle", the further we are from solving it.

What are the main implications of our empirical findings for modeling the long run PPP hypothesis? Is PPP a valid international parity condition? As we have previously discussed, the unit root methodology may not be an appropriate tool after all. First, problems with multivariate unit root tests are likely to make inference in a panel

[6] Note that the empirical result in Cheung and Lai (2000a) refers to unit root tests and not cointegration tests. We have also performed univariate and multivariate unit root tests using a different sample period, that is 1973M1-1988M1 with the sample ending just after the dollar fell. There is clear evidence, in this case, favoring long-run PPP.

context much more complicated than in a univariate context[7]. Second, the joint symmetry and proportionality restriction imposed on unit root tests of the real exchange rate is likely to be violated. Therefore, we believe that a proper procedure to test long run PPP is to use cointegration methods, and then test for the validity of the joint symmetry and proportionality restriction by likelihood ratio tests. Third, when testing the degree of PPP persistence, it is essential to use methods which allow for serial correlation and small sample bias.

What are the policy implications of our empirical results? As we have already pointed out in Chapter 5, in most emerging countries, black market exchange rates are supported by local governments. This is because they help to immunize domestic economy (i.e. prices) from the effect of a devaluation (Kiguel et al, 1995)[8]. The black market exchange rate in developing countries can be considered as the equilibrating exchange rate (Baghestani, 1997). In fact, although in the presence of a shock both the official and the black market exchange rates respond to the shock, the speed of response to a shock is much faster in the case of black market exchange rate. For example, Baghestani, (1997), estimates that while 63% of the deviation from PPP is corrected within a quarter, by a fall in the black market exchange rate, only 17.6% of the deviation is corrected by the official exchange rate over the same period (i.e. a quarter). This result indicates that the black market exchange rate, in most emerging markets, should be the exchange rate used by authorities to set monetary and exchange rate policies.

[7] For example, in a panel context, small sample bias of most estimators is likely to work jointly with cross section dependence making inference in panels very difficult.
[8] Here the black market exchange rate limits the effect of a devaluation on domestic prices.

One major result coming our from the analysis on PPP, undertaken in this thesis, is that empirical evidence of PPP is much stronger in emerging markets than OECD countries. This result has important policy implications for those economies. Firstly, developing countries are often subject to financial crises. If PPP holds in those countries then a divergence of the nominal exchange rate from its PPP level may indicate that a currency crisis is imminent. Then PPP may constitute a reliable indicator of currency crisis in these countries. Furthermore, if countries decide to peg their currencies against another one, say US$, it would be useful for policy-makers in those countries to know whether PPP holds amongst countries participating to the peg-regime. Finally, our results on PPP for developing markets imply that purchasing power measures of income should be based on black market exchange rates, when comparing the welfare and income inequality amongst developing and developed countries (Allsopp A, and Ralf, Z., 2003).

Before concluding this section it is essential to provide some indications of the different ways the research in this thesis could be extended. Firstly, cross section dependence and between group dependence of innovations are separate issues, but they often work together (i.e. cross section dependence may be the cause of between group correlations in disturbances). The implications for panel estimators of relaxing the assumption of a zero off diagonal covariance matrix is still an unresolved issue. We believe that future research should be essentially focusing on two points: testing for between group dependence and modelling the cause of a non-zero off covariance matrix. This goal could be achieved by imposing a factor structure on the covariance matrix[9] and principal component to analyze the source that generates a non-zero covariance matrix[10].

Second, although the issue of cross section dependence in unit root tests has been addressed in the literature, very little work has been done on this issue for panel cointegration tests.

Third, another important research aspect, worthy of further investigation, is the potential presence of structural breaks in real exchange rates in emerging markets. The methodology used in this thesis does not consider the possibility of multiple breaks and co-breaks. Furthermore, investigation needs to be made on the effect of structural breaks in panel cointegration tests. However, the main drawback of these methodologies extended to a panel context is that they result in imposing restrictions on the degree of heterogeneity. These may be too restrictive in a panel data set as ours, where exchange rates are shown to display very different dynamics.

Fourth, half-lives in emerging markets. We have calculated half-lives from the impulse response function, because the bootstrap estimator is proved to be asymptotically invalid under certain conditions (see Chapter 6 for details). However, impulse response is not the only methodology. One could use, for example, a double-bootstrap approach or Jack Knife bootstrap. It could be of interest to check the sensitivity of our results with respect to different methodologies.

[9] After all, both cross section dependence and between group correlation of innovations will cause a non-zero covariance matrix. That is, in either case the effect will captured by the covariance matrix.

[10] Note that by using factor analysis and principal components one would also address the issue of cross sectional cointegration.

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