Another Look at the Null of Stationary Real Exchange Rates: Panel Data with Structural Breaks and Cross-section Dependence

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Abstract
This paper re-examines the null of stationary of real exchange rate for a panel of seventeen OECD developed countries during the post-Bretton Woods era. Our analysis simultaneously considers both the presence of cross-section dependence and multiple structural breaks that have not received much attention in previous panel methods of long-run PPP. Empirical results indicate that there is little evidence in favor of PPP hypothesis when the analysis does not account for structural breaks. This conclusion is reversed when structural breaks are considered in computation of the panel statistics. We also compute point estimates of half-life separately for idiosyncratic and common factor components and find that it is always below one year.

Keywords: Purchasing power parity; Half-lives; Panel unit root tests; Multiple structural breaks; Cross-section dependence

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1 Introduction

In recent years, there has been a great deal of research focusing on the persistence of real exchange rate primarily due to the availability of panel data methods. The long-run purchasing power parity (PPP) requires that the real exchange rate must be stationary, which imply that shocks will only have transitory effects making the real rate a mean-reverting process. Previous PPP studies based on univariate unit root tests are subject to low power, which partly explain the failure of finding evidence for PPP. One way to increase the power of such tests is to use panel-data-based statistics – see Banerjee (1999), Baltagi and Kao (2000), Baltagi (2005), and Breitung and Pesaran (2005) for overview of the field. Several panel studies examine the validity of long-run PPP using panel data tests, most of them specifying the null hypothesis of unit root – see MacDonald (1996), Oh (1996), Wu (1996), Coakley and Fuertes (1997), Papell (1997), Choi (2001), Wu and Wu (2001) and Im, Lee and Tieslau (2005), to mention few. Although these analyses are based on more powerful techniques, existing evidence is not conclusive. For instance, Papell (1997), Cheung and Lai (2000), Wu and Wu (2001), and Chang and Song (2002) are unable to strongly reject the unit root hypothesis suggesting that PPP does not hold. Whereas, Oh (1996) and Wu (1996) find evidence supporting the PPP hypothesis.

Some authors find it more natural specifying the null hypothesis of variance stationarity rather than as the alternative hypothesis when testing the PPP hypothesis, since (i) the stationarity hypothesis is well established in the economist's priors – e.g., Taylor (2001) – and (ii) it should be desirable to ensure that the null of PPP is not rejected as long as there is no strong evidence against it – e.g., Kuo and Mikkola (2001). There are some analyses in the literature that rely on stationarity statistics to test the PPP hypothesis. For instance, Culver and Papell (1999) used the statistic in Kwiatkowski, Phillips, Schmidt and Shin (1992) – hereafter KPSS test – and found evidence in favor of the PPP in the post-Bretton Woods era with quarterly data. Engel (2000) uses the KPSS test when testing for the PPP, although he warns of the low power found in the simulations. Caner and Kilian (2001) also apply the KPSS test and test in Leybourne and McCabe (1994) to the PPP, but advising of the size distortion problems. Finally, Carrion-i-Silvestre and Sansó (2006) test the null hypothesis of PPP hypothesis after showing that size distortions of KPSS test can be reduced if long-run variance is properly estimated. Recently, Kuo and Mikkola (2001) and Bai and Ng (2004a) studied the null of stationary of real exchange rates in the context of panel data.

This paper aims to contribute to the second group of investigations assessing the stochastic properties of the real exchange rates (RER) with panel stationarity statistics. Our analysis simultaneously considers two important features that have not received much attention in previous studies. First, we tackle the issue of cross-section dependence. One important feature that characterizes some of the studies mentioned above is the assumption of cross-section independence among individuals. This assumption is relevant for the analysis since lack of independence among individuals can bias the analysis to conclude in favor of variance stationarity. Thus, O'Connell (1998) shows the importance of cross-section dependence in PPP analyses, since no evidence against the unit root null hypothesis can be found in any of the panels that he considers when cross-section dependence is accounted for. Banerjee, Marcellino and Osbat (2004, 2005) show that panel data unit root statistics tend to conclude in favor of stationarity when cross-section dependence is not considered. These authors warn about the cautions that should be taken when applying panel data statistics to tests the PPP hypothesis.

Second, we allow for the possibility of structural breaks in the RER data. As argued by Perron (1989), erroneous omission of structural breaks in the series can lead to deceptive conclusion when performing the unit root tests using time series data. Since most panel data tests are nothing but simple averages of multiple time series statistics, the problems associated with omitted breaks on the individual time series level can be expected to materialize even in the panel data context – see Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2002). The issue of structural change does not disappear simply because one uses panel data. Furthermore, there are some previous panel data studies that point to the presence of structural breaks in real exchange rates. In this regard, Papell (2002) finds support for the PPP hypothesis using a panel data unit root test that considers the episode of large appreciation and depreciation of the U.S. dollar in the 1980s. Recently, Im, Lee and Tieslau (2005) find overwhelming support for the stationarity in variance of the RER once structural breaks are allowed for using a panel data unit root test. Finally, although Smith, Leybourne, Kim and Newbold (2004) do not consider the presence of structural break when testing the PPP hypothesis, they recognize that they use a shorter time period than the post-Bretton Woods era because of the graphical appearance of structural breaks. Considering this shorter time period, they conclude in favor of the PPP hypothesis. At this point, one important feature has to be discussed. Thus and as argued in Papell and Prodan (2006), the traditional interpretation of the PPP hypothesis requires real exchange rates to be stationary in variance around a constant mean in the long run. Papell and Prodan (2006) tried to concile this view with the presence of structural breaks considering one restricted structural break, so that the long run mean remains constant. Here we do not follow this approach when considering multiple structural breaks, since we do not impose the restriction that the level of the real exchange rates has to be the same as the one previous to the structural break. Therefore, the evidence showed in this paper has to be seen in terms of whether real exchange rates are stationary in variance once the presence of multiple structural breaks that affect the level of the time series are taken into account. Strictly speaking, the traditional interpretation of the PPP hypothesis would not be fitted in our framework. However, the analysis that is performed below shows that the estimated break points for the real exchange rates can be due to some important episodes that affected the European currencies during the 1990s. Thus, although the traditional view of the PPP hypothesis implies that real exchange rates have to evolve around a constant mean in the long run, it can be argued that existence of structural breaks can change the fundamentals of the economies so that the mean do not necessarily have to be remain constant.[1]

Panel data statistics that are able to test the null hypothesis of stationary while simultaneously entertaining the possibility of multiple shifts has recently proposed by Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005), and Harris, Leybourne and McCabe (2005). These tests are flexible enough to account for a large amount of heterogeneity and multiple structural breaks, with breaks locating at different unknown dates and different number of breaks for each individual. In this paper we test the PPP hypothesis focusing on the quarterly real exchange rates used in Smith, Leybourne, Kim and Newbold (2004), and Pesaran (2005) for seventeen developed OECD countries covering the post-Bretton Woods era, who point to the presence of structural breaks affecting the real exchange rates in the recent float period.

The approach followed in this paper is interesting since there are few contributions in the literature that address the PPP hypothesis testing using panel stationarity tests and structural breaks. One exception is Harris, Leybourne and McCabe (2005), who have used the monthly data

[1] In the univariate case, Hegwood and Papell (1998) made a similar attempt.

set in Papell (2002) to re-evaluate the PPP hypothesis in the presence of structural change. Harris, Leybourne and McCabe (2005) consider cross-sectional dependency in the panel and find significant evidence against the PPP hypothesis with a panel data stationarity test, even after structural breaks are considered. Instead of using the restricted specification in Papell (2002), we have proceeded to test the null hypothesis of PPP in an unrestricted framework. The results that are obtained throughout this paper indicate that there is little evidence in favor of the PPP hypothesis when the analysis does not account for structural breaks. This conclusion is reversed when they are considered in the computation of the statistics. Thus, our results are in sharp contrast with those in Harris, Leybourne and McCabe (2005), which can be due to the use of unrestricted models and to the use of different data frequency.

Finally, we extend our analysis to estimate the half-life of RER deviations, which is considered as one of the most puzzling empirical regularities in international macroeconomics – see, e.g., Rogoff (1996) and Taylor (2001), among others. Besides allowing for the possibility of multiple structural breaks, we compute the common factor and the idiosyncratic components separately, which to our knowledge has not been previously implemented in the literature. Results show that half-life point estimates are below one year for both the idiosyncratic and the common components. This finding is compatible with the constructed confidence intervals of half-life estimates.

The rest of the paper is organized as follows. In Section 2 we describe the methodology that is applied. Section 3 presents the data set that is used and reports the results of the analysis. Section 4 discusses the measurement of half-life. Finally, Section 5 concludes.

2 Methodology

This section briefly discusses the panel stationarity tests proposed in Hadri (2000), Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005), and Harris, Leybourne and McCabe (2005). These statistics are the ones applied in the paper to investigate the PPP hypothesis. Then, we briefly discuss about the effects of cross-section dependence when assessing the stochastic properties of panel data sets. Finally, we present two statistics to formally test the hypothesis of cross-section independence. All these statistics are used throughout the paper.

2.1 Panel stationarity tests

Hadri (2000) proposes an LM panel data stationarity test without structural breaks, while Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005) extend the analysis to account for the presence of multiple structural breaks. Since the latter proposal encompasses the former one, we proceed to present the approach in Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005). Let $y_{i,t}$ be the data generating process for real exchange rate which is given by

$$y_{i,t} = \alpha_i + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{i,k} DT^*_{i,k,t} + \varepsilon_{i,t} \tag{1}$$

where $t = 1, ..., T$ and $i = 1, ..., N$ indexes the time series and cross-sectional units, respectively. The dummy variables $DU_{i,k,t}$ and $DT^*_{i,k,t}$ are defined as $DU_{i,k,t} = 1$ for $t > T^i_{b,k}$ and 0 elsewhere, and $DT^*_{i,k,t} = t - T^i_{b,k}$ for $t > T^i_{b,k}$ and 0 elsewhere, with $T^i_{b,k}$ denoting the k-th date of the break for the i-th individual, $k = 1, ..., m_i, m_i \geq 1$, and α_i and β_i are the parameters of the constant and time trend, respectively, and $\varepsilon_{i,t}$ denotes the disturbance term. Note that the proposal in Hadri (2000) follows from setting $\theta_{i,k} = \gamma_{i,k} = 0 \ \forall i, k$ in (1). The model in (1) includes individual effects, individual structural break effects (i.e., shift in the mean caused by the structural breaks known as temporal effects where $\beta_i \neq 0$) and temporal structural break effects (i.e., shift in the individual time trend where $\gamma_i \neq 0$). In addition, the specification given by (1) considers multiple structural breaks, which are located at different unknown dates and where the number of breaks are allowed to vary across the members of the panel. The test statistic is constructed by running individual KPSS regression for every member of the panel and then averaging the N individual statistic. The general expression for the test statistic is

$$LM(\lambda) = N^{-1} \sum_{i=1}^{N} \eta_i(\lambda_i), \tag{2}$$

with $\eta_i(\lambda_i) = \hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}^2_{i,t}$, where $\hat{S}_{i,t} = \sum_{j=1}^{t} \hat{\varepsilon}_{i,j}$ is the partial sum process that is obtained using the estimated OLS residuals of (1). $\hat{\omega}_i^2$ denotes a consistent estimate of the long-run variance of the error $\varepsilon_{i,t}$, which has been estimated following the procedure in Sul, Phillips and Choi (2005) – we use the Quadratic spectral kernel. In (2), λ is defined as the vector $\lambda_i = (\lambda_{i,1}, ..., \lambda_{i,m_i})' = \left(T^i_{b,1}/T, ..., T^i_{b,m_i}/T\right)'$, which indicates the relative position of the dates of the breaks on the entire time period, T, for each individual i – note that for the test in Hadri (2000) $\lambda_i = 0 \; \forall i$, since there is no structural breaks. Assuming that individuals are cross-section independent, Hadri (2000) and Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005) show that $LM(\lambda)$ reaches the following sequential limit under the null of stationary panel with multiple shifts

$$Z(\lambda) = \frac{\sqrt{N}(LM(\lambda) - \bar{\xi})}{\bar{\varsigma}} \rightarrow N(0,1),$$

where $\bar{\xi}$ and $\bar{\varsigma}$ are the cross-sectional average of the individual mean and variance of $\eta_i(\lambda_i)$, which are defined in Hadri (2000) and Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005).

In order to estimate the number of breaks and their locations, Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005) follow the procedure developed by Bai and Perron (1998), which proceeds in two steps.[2] First, the breakpoints are estimated by globally minimizing the sum of squared residuals for all permissible values of $m_i \leq m^{\max}, i = 1, ..., N$ – throughout the paper we specify the maximum number of structural breaks at $m^{\max} = 5$. Second, we use the sequential testing procedure suggested in Bai and Perron (1998) to estimate the number of structural breaks. As a result, we obtain the estimation of both the number and position of the structural breaks. This procedure is then repeated N times to obtain the estimated number of breaks and their locations for each individual. Monte Carlo simulations indicate that the test has good size and power in finite sample.

Harris, Leybourne and McCabe (2005) have proposed a panel stationarity test statistic that extends the approximation in Harris, McCabe and Leybourne (2003) to panel data framework. Their specification is based on the following model

$$\begin{aligned} y_{i,t} &= x_{i,t}\beta + z_{i,t} \\ z_{i,t} &= \phi_i z_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $x_{i,t}$ collects deterministic regressors in a general way – regressors such as constant, linear time trend or broken trends. We can obtain the OLS estimated residuals in (3) and, assuming

[2] Note that the sequential approach in Bai and Perron (1998) can be used here since under the null hypothesis of the statistic we have that the units are stationary in variance.

cross-section independence, compute the statistic given by

$$\hat{S}_k = \frac{\hat{C}_k + \hat{c}}{\hat{\omega}\left\{\hat{a}_{k,t}\right\}}, \tag{4}$$

with $\hat{C}_k = T^{-1/2}\sum_{t=k+1}^{T}\hat{a}_{k,t}$ the autocovariance of order k, where $\hat{a}_{k,t} = \sum_{i=1}^{N}\hat{z}_{i,t}\hat{z}_{i,t-k}$, and $\hat{z}_{i,t}$ denotes the OLS residuals in (3). $\hat{c} = (T-k)^{-1/2}\sum_{i=1}^{N}\hat{c}_i$, being $\hat{c}_i$ a correction term defined in Harris, Leybourne and McCabe (2005) and, $\hat{\omega}^2\left\{a_t\right\}$ is a consistent estimate of the long-run variance of $\{a_t\}$, which is estimated following the approach in Sul, Phillips and Choi (2005) as above. Under the null hypothesis of joint variance stationarity of the common and idiosyncratic components the statistic $\hat{S}_k \rightarrow N(0,1)$. In this paper we follow Harris, Leybourne and McCabe (2005) and use $k = \left[(3T)^{1/2}\right]$.

2.2 Cross-section dependence

So far, the presentation of the panel statistics has assumed that individuals are cross-section independent. However, this assumption might be restrictive in practice since the analysis of macroeconomic time series for different countries are affected by similar major events that might introduce dependence among individuals in the panel data set. There are different approximations in the literature to deal with cross-section dependence. In this paper we account for cross-section dependence in three ways. First, we follow the suggestion in Levin, Lin and Chu (2002) and proceed to remove the cross-section mean, which is equivalent to include temporal effects in the panel data set. Second, we follow Maddala and Wu (1999) and compute the empirical distribution by means of parametric bootstrap. These two approaches are applied for all test statistics described above. Finally, it is possible to specify approximate factor models to account for cross-section dependence as in Bai and Ng (2004a, b). Thus, Bai and Ng (2004a) generalize the statistic in Hadri (2000) for the case where cross-section dependence is driven by common factors. The factor structure is specified for the $\varepsilon_{i,t}$ disturbance term in (1), which permits assessing the stochastic properties of the observed $y_{i,t}$ variables in terms of idiosyncratic and common factor components. The estimation of these components is carried out using principal components – see Bai and Ng (2004a, b) for further details. Harris, Leybourne and McCabe (2005) use the same framework as Bai and Ng (2004a, b) to allow dependence among individuals in the panel data set – this statistic is denoted as $\hat{S}_k^F$. Note that the set up in Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005) does not accommodate for common factors to model cross-section dependence.[3]

2.3 Testing for cross-section independence

Recent developments in the literature offer the possibility of testing for the presence of cross-section dependence among individuals. Pesaran (2004) designs a test statistic based on the average of pair-wise Pearson's correlation coefficients $\hat{p}_j$, $j = 1, 2, \ldots, n$, $n = N(N-1)/2$, of the residuals obtained from ADF-type regression equations. The CD statistic in Pesaran (2004) is given by

$$CD = \sqrt{\frac{2T}{n}} \sum_{j=1}^{n} \hat{p}_j \rightarrow N(0,1).$$

This statistic tests the null hypothesis of cross-section independence against the alternative of dependence.

Besides, Ng (2006) relies on the computation of spacings to test the null hypothesis of independence. In brief, the procedure in Ng (2006) works as follows. First, we get rid of autocorrelation pattern in individual time series through the estimation of an AR model. As for the test in Pesaran (2004), this allows us isolating cross-section regression from serial correlation. Taking the estimated residuals from the ADF-type regression equations as individual series, we compute the absolute value of Pearson's correlation coefficients ($\bar{p}_j = |\hat{p}_j|$) for all possible pairs of individuals, $j = 1, 2, \ldots, n$, where as above $n = N(N-1)/2$, and sort them in ascending order. As a result, we obtain the sequence of ordered statistics given by $\left\{\bar{p}_{[1:n]}, \bar{p}_{[2:n]}, \ldots, \bar{p}_{[n:n]}\right\}$. Under the null hypothesis that $p_j = 0$ and assuming that individual time series are Normal distributed, $\bar{p}_j$ is half-normally distributed. Furthermore, let us define $\bar{\phi}_j$ as $\Phi\left(\sqrt{T}\bar{p}_{[j:n]}\right)$, where Φ denotes the cdf of the standard Normal distribution, so that $\bar{\phi} = \left(\bar{\phi}_1, \ldots, \bar{\phi}_n\right)$. Finally, let us define the spacings as $\Delta\bar{\phi}_j = \bar{\phi}_j - \bar{\phi}_{j-1}$, $j = 1, \ldots, n$.

Second, Ng (2006) proposes splitting the sample of (ordered) spacings at arbitrary $\vartheta \in (0,1)$, so that we can define the group of small (S) correlation coefficients and the group of large (L) correlation coefficients. The definition of the partition is carried out through minimization of the

[3] Other proposals in the literature that deal with cross-section dependence are O'Connell (1998), who estimates a SUR specification, and Moon and Perron (2004), and Pesaran (2005), who use common factor models as in Bai and Ng (2004a, b).

sum of squared residuals

$$Q_n(\vartheta) = \sum_{j=1}^{[\vartheta n]} \left(\Delta\bar{\phi}_j - \bar{\Delta}_S(\vartheta)\right)^2 + \sum_{j=[\vartheta n]+1}^{n} \left(\Delta\bar{\phi}_j - \bar{\Delta}_L(\vartheta)\right)^2,$$

where $\bar{\Delta}_S(\vartheta)$ and $\bar{\Delta}_L(\vartheta)$ denotes the mean of the spacings for each group respectively. Consistent estimate of the break point is obtained as $\hat{\vartheta} = \arg\min_{\vartheta\in(0,1)} Q_n(\vartheta)$, where definition of some trimming is required – we follow Ng (2006) and set trimming at 0.10.

Once the sample has been splitted, we can proceed to test the null hypothesis of non-correlation in both sub samples. Obviously, rejection of the null hypothesis for the small correlations sample will imply rejection for the large correlations sample provided that the statistics are sorted in ascending order. Therefore, the null hypothesis can be tested for the small, large and the whole sample using the Spacing Variance Ratio $SVR(\eta)$ in Ng (2006), with $\hat{\eta} = \left[\hat{\vartheta} n\right]$ being the number of statistics in the small correlations group. Ng (2006) shows that under the null hypothesis that a subset of correlations is jointly zero, the standardized statistic $svr(\eta) \to N(0,1)$.

One advantage of the approach in Ng (2006) is that it allows us gaining some insight about the kind of cross-section dependence in terms of how pervasive and strong is the cross-section correlation. The use of these statistics will help us to decide in which panel stationarity statistic we should most base the statistical inference.

3 Data and Empirical Results

We use the same data set used by Pesaran (2005), which consists of quarterly real exchange rates covering the periods 1973Q1 to 1998Q4 ($T = 104$) for 17 OECD countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom.[4] The logarithms of the real exchange rates are computed against the U.S. dollar. First, we present the results for the non-break case. Then, the exposition considers the presence of multiple structural breaks.

[4] We are thankful to Takashi Yamagata for making the data available to us. We include the observations for 1973 in our analysis, while Pesaran (2005) starts at 1974.

3.1 Panel data stationarity tests without structural breaks

Table 1 reports the Hadri (2000) statistics – assuming either that long-run variance is homogeneous or heterogeneous – and the $\hat{S}_k$ statistic in Harris, Leybourne and McCabe (2005). When the individuals are assumed to be cross-section independent, both versions of Hadri's statistics lead to reject the null hypothesis of variance stationarity at the 5% level of significance, while the $\hat{S}_k$ statistic does not. Therefore, the application of these panel stationarity statistics produces contradictory results. However, it should be beard in mind that these results are based on the fact that individuals are independent. Computations in Pesaran (2005) reveal that this assumption is far from being satisfied. Thus, Pesaran (2005) computes the statistic in Pesaran (2004) and obtains strong evidence that points to existence of cross-section dependence. As noted above, this might bias the analysis leading to obtaining wrong conclusions.

To get a feeling of the size of the cross-sectional dependence problem in the RER data, we have proceeded to compute the statistics in Pesaran (2004) and Ng (2006) to test the null hypothesis of independence among individuals. The ADF-type regression equation in which the statistic is based uses the t-sig criterion in Ng and Perron (1995) to select the order of the autoregressive correction with up to ten lags. The computation of the CD statistic in Pesaran (2004) gives $CD = 68.043$, which leads to reject the null hypothesis of independence. As for the statistic in Ng (2006), the whole sample of spacings can be splitted in two groups, where the break point is estimated at $\hat{\eta} = 15$. The $svr(\eta)$ statistic for the whole sample – $svr^W(\hat{\eta}) = 5.179$, with p-value 0.000 – and for the large sample – $svr^L(\hat{\eta}) = 4.065$, with p-value 0.000 – indicate that the null hypothesis of non-correlation is strongly rejected. The statistic computed for the small sample reveals that the null hypothesis cannot be rejected at the 5% level of significance – $svr^S(\hat{\eta}) = 5.179$, with p-value 0.785. Therefore, we can see that there is evidence of cross-section correlation among the individuals of the panel data set. Furthermore, the fact that the break point is estimated at $\hat{\eta} = 15$ implies that the proportion of correlation coefficients that form the S group $\left(\hat{\vartheta} = 0.10\right)$ is small compared to correlation coefficients in the L group, which indicates that pervasive cross-correlation is present amongst the individuals in the panel data sets, so that approximate factor models as suggested in Bai and Ng (2004a) can capture the cross-section dependence in better way.

These elements indicate that results based on the assumption of independent individuals can lead to erroneous conclusions, so that cross-section dependence has to be accounted for when testing the null hypothesis of panel stationarity. As mentioned above, in this paper we have dealt with cross-section dependence in three different ways. First, we have removed the cross-section mean, which does not change previous conclusions, i.e. we strongly reject the null hypothesis of variance stationarity using the Hadri (2000) statistics while it is not rejected when using the $\hat{S}_k$ statistic – see results reported in the columns labelled as CS demeaned in Table 1. Note that this approach is equivalent to assuming that there is one stationary common factor that affects the individuals in the same way, which might be restrictive in practice. Second, we have computed the Bootstrap empirical distribution of the statistics following Maddala and Wu (1999) using 20,000 replications – we offer the percentiles of interest in Table 1. In this case, we find strong evidence in favor of the PPP hypothesis when using the (homogeneous long-run variance) Hadri's statistic and the $\hat{S}_k$ statistic, since the null hypothesis of variance stationarity cannot be rejected even at the 10% level of significance. When heterogeneous long-run variance is assumed in the computation of the Hadri (2000) statistic, the null hypothesis cannot be rejected at the 5% level, although it does at the 10% level. However, the statistic in Ng (2006) has shown that cross-section dependence among individuals is pervasive, so cross-section dependece should be better captured using approximate common factor models.

Finally, Table 1 presents the panel data stationarity statistics in Bai and Ng (2004a), and Harris, Leybourne and McCabe (2005) that consider the presence of common factors to model the cross-section dependence. In both cases, the number of common factors (r) has been estimated using the panel BIC information criterion in Bai and Ng (2002) with up to six common factors. The approach in Bai and Ng (2004a) allows us to investigate the source of stationarity separately, i.e. we can test the null hypothesis of stationarity for the idiosyncratic and estimated common factors. In contrast, the proposal in Harris, Leybourne and McCabe (2005) tests the null hypothesis of joint stationarity in both common factors and idiosyncratic disturbance terms. Note that in both situations the estimated number of common factors ($\hat{r}$) achieves the maximum number permitted – we increased the maximum number of common factors, but it was reached as well. We essayed other information criteria than the panel BIC in Bai and Ng (2002), i.e., $IC_{p_2}(k)$ and $IC_{p_2}(k)$ in Bai and Ng (2002), and the number of estimated common factors always reached the maximum allowed. When the usual BIC information criterion, denoted as $BIC_3(k)$ in Bai and Ng (2002), was used, the estimated number of common factors was less than the maximum permitted. However and as noted in Bai and Ng (2002), this information criterion may perform well for some but not all configurations of the parameters. Given the number of individuals that is considered in our study we have decided to use six common factors in the analysis, although the number of common factors might has been over-estimated by the panel BIC information criterion. Let us first focus on the Bai and Ng (2004a) statistic. The KPSS statistic applied to each estimated common factor reveals that there are $\hat{r}_1 = 4$ common stochastic trends, since the null hypothesis of variance stationarity can be rejected at the 5% level of significance. The other two common factors are characterized as variance stationary. The panel data variance stationarity statistic computed using the idiosyncratic disturbance terms indicates that the null hypothesis is strongly rejected – the mean and variance required to compute this statistic are obtained by simulation. Therefore, both idiosyncratic and common factor components lead to reject the PPP hypothesis. This conclusion is also reached when using the $\hat{S}_k^F$ statistic, since the joint null hypothesis of variance stationarity of the idiosyncratic and common factor components is rejected at the 5% level of significance.

To sum up, the computations that have been carried out indicate that contradictory results are obtained depending on the way that cross-section dependence is accounted for. When cross-section demeaned data is used, the Hadri (2000) and $\hat{S}_k$ statistics report contradictory results. Nevertheless, in our case the application of cross-section demeaning has been shown to be useless, provided that it implies assuming that there is only one stationary common factor, when in fact we have find more than one. The use of the bootstrap distribution points to the fulfilment of the PPP hypothesis, regardless of the statistic that is used. Notwithstanding, this conclusion might be affected by the presence of common factors, which now is known to bias the analysis to conclude in favor of variance stationarity – see Banerjee, Marcellino and Osbat (2004, 2005). When common factor framework is used, we have not been able to find support for the PPP hypothesis fulfilment. This result is in accordance with most of previous evidence in the literature cited above, which implies that the PPP hypothesis is not satisfied for the seventeen OECD countries that have been considered in the analysis.

3.2 Panel data stationarity tests with structural breaks

Previous analysis has not considered the presence of structural breaks, which might imply misleading conclusions about the stochastic properties of the panel data set. In this section we consider this feature. There are some proposals in the literature that allow for the presence of structural breaks when testing the PPP hypothesis – see Perron and Vogelsang (1992), Hegwood and Papell (1998), and Papell (2002). In this section we address the robustness of previous conclusions in the presence of multiple structural breaks using the statistics described in Section 2.

We have estimated the number and position of the structural breaks using the procedure in Bai and Perron (1998) setting $m^{\max} = 5$ as the maximum number of structural breaks – this maximum was never attained. The number of break points has been selected with the sequential approach in Bai and Perron (1998) – the level of significance is set at the 5% level. The estimated break points are used to compute the statistics in Carrion-i-Silvestre, del Barrio-Castro and López-Bazo (2005), and Harris, Leybourne and McCabe (2005). Panel A in Table 2 offers the values for the individual $KPSS_i$ and $S_{i,k}$ statistics, as well as the estimated break points. We have also included the simulated critical values at the 10% and 5% level of significance for the individual KPSS statistic. Note that critical values for the $S_{i,k}$ test are not required, since this statistic converges to the standard Normal distribution. Inspection of the individual statistics reveals that the null hypothesis of variance stationarity cannot be rejected in any case for the individual KPSS statistic, while it is rejected in seven cases when using the individual $S_{i,k}$ test at the 5% level of significance. If we combine this information to define panel data statistics and assume that individuals are cross-section independent, we conclude that the null hypothesis of panel stationarity cannot be rejected with either version of the $Z(\lambda)$ test, whereas it is rejected if we base on the S_k test – see Panel B in Table 2. Notwithstanding, evidence of strong cross-section dependence has been found in the previous analysis, so that we should check if this assumption holds in this case.

In order to test the null hypothesis of cross-section independence we have computed the tests in Pesaran (2004) and Ng (2006). We have estimated an ADF-type regression equation that includes dummy variables to account for the presence of level shifts – the order of the autoregressive correction is selected as described above. The CD statistic computed with the estimated residuals of the ADF equations indicates that the null hypothesis of cross-section independence is strongly rejected, since $CD = 64.586$. The computation of the statistic in Ng (2006) gives $svr^{W}(\hat{\eta}) = -1.147$ (p-value 0.874), $svr^{L}(\hat{\eta}) = 6.423$ (p-value 0.000) and $svr^{S}(\hat{\eta}) = -0.587$ (p-value 0.722), for the whole sample, and large and small groups, respectively, with $\hat{\eta} = 14$. The statistics for the whole and small sample indicate that the null hypothesis of independence cannot be rejected at the 5% level of significance. However, the hypothesis is strongly rejected for the individuals in the large group. Provided that the fraction of individuals in the small sample is small $\left(\hat{\vartheta} = 0.103\right)$, we have to conclude that cross-section correlation among individuals is pervasive, so that it should be taken into account when assessing the stochastic properties of the panel data set.

When cross-section dependence is addressed, either through cross-section demeaning or computing the empirical distribution by means of parametric bootstrap, all panel data statistics indicate that the null hypothesis of variance stationarity cannot be rejected at the 5% level of significance – however, note that the null hypothesis is rejected at the 10% level of significance for the $\hat{S}_k$ statistic. This conclusion is reinforced by the $\hat{S}_k^F$ statistic when working at the 5% level of significance, although the null hypothesis is rejected at the 10% level – as above, the analysis allows for up to six common factors. Therefore, we have found strong evidence of stationarity in variance of the RER for the set of countries that have been considered using both versions of the $Z(\lambda)$ test. In addition, stationarity in variance of the RER is supported by the $\hat{S}_k$ and $\hat{S}_k^F$ statistics when the level of significance is set at the 5% level, although the null hypothesis of variance stationarity is rejected at the 10% level of significance.

Our results are qualitatively different from Harris, Leybourne and McCabe (2005), who find no evidence of PPP hypothesis when applying panel stationary test with cross-section dependence and structural breaks. Nevertheless, we should bear in mind that their evidence and ours are based on the use of time series of different frequency. One possible reason for the discrepancy of research conclusions is the constrained framework imposed in Papell (2002), and maintained in Harris, Leybourne and McCabe (2005). Thus, our results are based on an unconstrained set up that does not restrict the real exchange rates to return to the levels previous to the episode of appreciation and depreciation of the U. S. dollar in the 1980s. Therefore, it would be the case that even in the case that real exchange rates were only affected by one episode affecting the dollar, the level to which RER returned after the episode ended was not necessarily the same as the previous one. It is worth mentioning that our framework retains the possibility that RER returned to similar (although not equal) values to those previous to the dollar episode in the 1980s, since it accommodates the presence of multiple structural breaks. Furthermore, the investigation that has been conducted here reveals that RER are affected by other features than the dollar appreciation and depreciation episode, features that should be taken into account when assessing their stochastic properties.

Panel A in Table 2 reports the estimated break points obtained from the Bai and Perron (1998) procedure, which are depicted in Figure 1. At least three breaks are found for each country (except New Zealand) with all breaks occurring during the period 1976Q3 to 1993Q2. From an historical point of view, this seems very reasonable with events such as oil price shocks, the rise and fall of U.S. dollar and the formation of European Monetary System (EMS). In fact, Papell (2002) identified graphically three major regimes that are likely to have impacted the slopes of real and nominal exchange rates during the post-1973 era. The results in Table 2 reveal that in most cases, the first break occurred during the period 1976Q3 to 1978Q3, which may have resulted due to the oil price shocks in 1974. The second break took place at the beginning of 1980s (between 1981Q1 and 1982Q2), which clearly mimics the start of dollar's appreciation. The third break confirms the transition of dollar's appreciation to depreciation during the period 1986Q2 to 1988Q1.[5] Few countries (mostly European) experienced a fourth break occurring at the beginning of 1990s, which can be explained by the German reunification and the formation of EMS. Thus European countries involved in the EMS carried out progressive abolition of any remaining capital controls among the European countries by 1990. In addition, the EMS crisis in September 1992 explains the estimated break points at the beginning of the 1990s. Thus, the exits of Italy and the UK from the exchange rate mechanism of the EMS reflect the detected structural breaks on the fourth and third quarter of 1993 for these countries, respectively. Furthermore, in August 1993 exchange rate bands of the EMS were increased to $\pm 15\%$, which was followed to the adherence of the prospective euro members to the Maastricht conditions on nominal convergence.

As can be seen, the procedure that has been applied in this paper allows the detection of the structural breaks that corresponds with the dollar episode in the middle of the 1980s, as well as it captures important features that have affected most countries in the panel data set in the early

[5] For further discussion on the rise and fall of U.S. dollar and the determination of possible breaks in the slopes, we make reference to Papell (2002).

1990s. These elements were not taken into account in previous analyses where testing for the stationarity in variance of the RER using panel data techniques was the main aim.

4 Half-life measurement

The PPP puzzle, which has intrigued researchers for many years and has devoted huge amount of contributions in the literature, is the apparent contradiction between the high persistence of shocks to RER (three to five years) and the high short-term volatility that exhibit (nominal and real) exchange rates. This feature has been investigated in a flurry of papers, which in most of them the persistence of the shocks is approximated by mean of half-life (HL) measures – the HL is usually defined as the number of time periods required for a unit impulse to dissipate by one half. The extent to which a shock to the RER lasts is a crucial question in the context of sticky-price versions of New Open Economy Macroeconomics models, since theories typically imply a length of half-life between one and two years. Rogoff (1996), while reviewing the empirical literature, reached to the consensus estimate of 3-5 year half-lives of PPP deviations.

Most of the empirical illustrations of HL calculation for RER are concerned with the time series estimation,[6] and only few recent ones deal with panel data methods. For example, Choi, Mark and Sul (2006) focus on CPI-based annual real exchange rates and find that the HL to be 5.5 years (with a 95% confidence interval ranges from 4.3 to 7.3 years) for a panel of 21 OECD countries during the post-1973 period. Murray and Papell (2005) put the HL to 3.55 years (with a 95% confidence interval of 2.48 and 4.09 years) for 20 OECD countries during the post-1973 period applying the approximate median-unbiased (MU) estimation method in Andrews and Chen (1994). These analyses are based on the estimation of panel data models that restrict the autoregressive coefficient to be homogeneous for all individuals in the panel data set.[7] The main conclusion of these recent panel studies is that the findings of univariate methods are confirmed, so that the PPP puzzle remains unsolved.

In this section we shed light on the PPP puzzle using the panel data framework developed in the earlier sections. To the best of our knowledge, no previous studies have examined this issue

[6] See Murray and Papell (2002) for a recent account based on univariate method.

[7] Although Choi, Mark and Sul (2006) and Imbs, Mumtaz, Ravn and Rey (2004) have both pointed out that inappropriate pooling across cross-sectional units may result in an upward bias in the estimated half-life, Chen and Engel (2005) find that it is not an important source of bias.

in a panel data framework while simultaneously considering the pervasive source of cross-sectional dependence and multiple structural breaks. Furthermore, the approach that has been followed here allows us to distinguish two different stochastic components, i.e. the idiosyncratic and the common factor components. This permits the computation of both idiosyncratic HL and common HL measures of persistence, which has not been previously calculated in the literature.

We have followed Murray and Papell (2002, 2005) in order to measure the persistence of the shocks. Thus, we have estimated an autoregressive specification for the estimated idiosyncratic disturbance terms and the common factors, which are the ones that have been obtained from the model that incorporates multiple structural breaks. As above, the selection of the order of the autoregressive model is done using the t-sig information criterion in Ng and Perron (1995) with up to ten lags. It is well known that the OLS estimation method of autoregressive models produces biased estimates, which in turn causes biased measures of HL. In order to account for this estimation bias, we have estimated the parameters of the autoregressive models using the MU estimation method in Andrews and Chen (1994). In addition, the application of this procedure allows us to obtain confidence intervals for the parameters, so that confidence intervals for the idiosyncratic and common HLs can be established. The estimation of the HLs depends on the order of the autoregressive model that is used. When we are dealing with an AR(1) model the HL estimate can be directly computed as $HL = \ln(0.5) / \ln(\hat{\alpha}_{MU})$, where $\hat{\alpha}_{MU}$ denotes the autoregressive parameter. However, when the order of the autoregressive model is greater than one, the HL estimate has to be obtained from the impulse response function – see Murray and Papell (2002) for further details. In this case, α_{MU} will denote the sum of the autoregressive parameters.

Table 3 presents the MU estimates of α_{MU} as well as the HL measures based on these MU estimates for each individual. Despite of the point estimates, we report the 95% confidence interval for $\hat{\alpha}_{MU}$ and the corresponding HL measures. Panel A in Table 3 reports the computation for the idiosyncratic disturbance terms, while Panel B offers the results for the common factors. Some remarks are in order. First, the estimates that have been obtained for α_{MU}, either for the idiosyncratic or the common components, are lower than the ones obtained in the literature. Furthermore, we can see that the upper limit of the 95% confidence intervals is below one in all cases. This is because the approach that has been followed here distinguishes two sources of shocks – idiosyncratic and common shocks – as well as it considers the presence of multiple structural breaks. Therefore, we account for two important features when estimating the autoregressive parameters that are well known to be potential sources of bias estimation. Second, the HL point estimates are below one year for both the idiosyncratic and the common components. This is in sharp contrast with most of previous estimates, where HLs computed using similar data set were estimated around 3 to 5 years. Moreover and except for Denmark, the confidence intervals indicate that HL estimates are below 1.356 years for the idiosyncratic component, and below 1.573 years if we focus on the common factor component. Note that in all situations, the confidence intervals are quite narrow and informative when compared to previous estimates in the literature (e.g., Murray and Papell (2002, 2005)).

One may argue that finding evidence of shorter half-lives is not an interesting result since by allowing break points in the autoregressive framework inherently reduce the persistence measures. However, doing so will imply to assume that previous investigations on the stationarity in variance of the real exchange rates are based on misspecified models. In this regard, previous literature that do not consider the presence of such breaks are obtaining biased estimates of the autoregressive parameters – see Perron and Vogelsang (1992) for an early example of the potential problem. Therefore, our results reflect the potential pitfall in which PPP panel data analyses that do not consider the presence of pervasive cross-section dependence and multiple structural breaks can simultaneously incur. More interestingly, our framework shed light on the PPP puzzle, as described by Rogoff (1996), the enormous short-term volatility of the real exchange rates with the extremely slow rate at which shocks appear to damp out.

To sum up, the evidence that has been reported in this section indicates that PPP panel data analyses focusing on post-Bretton Woods era should consider the presence of cross-section dependence as well as multiple structural breaks when computing HL measures. Otherwise, the estimated measures of persistence might be upper biased, leading to conclude that shocks are more persistent than they really are.

5 Conclusions

In this paper, we re-examine the null of stationary of RER for a panel of seventeen OECD developed countries taking into account both the presence of cross-section dependence and multiple structural breaks. The approach that is followed throughout the paper is flexible enough to accommodate large degree of heterogeneity with respect to the presence of multiple structural breaks. We have investigated the maintained assumption of cross-section independence in which most previous panel data RER analyses rely on. The statistics that have been computed show that pervasive cross-section correlation is present among individuals, which indicates that a factor structure might help to capture the cross-section dependence. Nevertheless, the analysis has applied different approaches to account for the presence of cross-section dependence to study the robustness of the conclusions.

Results depend on whether structural breaks are considered or not, i.e., we find evidence supporting the stationarity in variance of the RER when structural breaks are allowed for, while non-stationarity in variance is found when structural breaks are omitted. As a by-product we have measured the persistence of the idiosyncratic and common shocks to the RER through the computation of half-life measure. Our point estimates of half-life shed light on the PPP puzzle since they turn out to be less than one year for both the idiosyncratic and common factor components used in the analysis. Our results may be interesting in view of recent research that purport to shed light on PPP by exploiting recent advances in panel data econometrics.

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Table 1: Panel data variance stationarity test statistics without structural breaks

	Independence		CS demeaned		Bootstrap distribution			
	Test	p-val	Test	p-val	90%	95%	97.5%	99%
Homogeneous	3.311	0.000	11.381	0.000	3.845	5.980	8.154	10.839
Heterogeneous	5.064	0.000	7.763	0.000	3.849	5.932	8.054	10.564
$\hat{S}_k$	-0.451	0.674	1.059	0.145	1.283	1.607	1.849	2.150
	Panel statistics with common factors							
	Test	p-val	$\hat{r}$	$\hat{r}_1$				
Bai-Ng	8.082	0.000	6	4				
$\hat{S}_k^F$	2.025	0.021	6	-				

Table 2: Individual and panel data stationarity tests with multiple structural breaks

Panel A: Individual statistics

	$KPSS_i$	Critical values 10%	5%	$S_{i,k}$	$T_{b,1}^i$	$T_{b,2}^i$	$T_{b,3}^i$	$T_{b,4}^i$
Australia	0.0213	0.059	0.069	-0.284	1976Q4	1984Q2	1988Q1	1992Q2
Austria	0.0305	0.100	0.126	2.326	1977Q2	1981Q1	1986Q2	
Belgium	0.0362	0.063	0.076	1.838	1976Q3	1981Q1	1986Q2	1990Q1
Canada	0.0314	0.054	0.062	0.843	1978Q2	1984Q1	1987Q4	1993Q2
Denmark	0.0228	0.100	0.126	3.051	1977Q2	1981Q1	1986Q2	
Finland	0.0365	0.076	0.091	1.017	1982Q2	1986Q4	1992Q3	
France	0.0283	0.099	0.124	1.391	1977Q2	1981Q2	1986Q2	
Germany	0.0369	0.062	0.074	2.341	1977Q1	1981Q1	1986Q2	1990Q2
Italy	0.0373	0.071	0.083	0.654	1981Q1	1986Q2	1992Q4	
Japan	0.0422	0.100	0.128	-0.711	1977Q1	1981Q2	1986Q1	
Netherlands	0.0372	0.101	0.127	1.987	1976Q3	1981Q1	1986Q2	
New Zealand	0.0163	0.117	0.143	0.127	1983Q1	1986Q4		
Norway	0.0283	0.055	0.062	0.706	1976Q3	1982Q2	1986Q4	1992Q4
Spain	0.0248	0.056	0.065	0.708	1978Q2	1982Q1	1986Q2	1993Q2
Sweden	0.0442	0.055	0.063	1.703	1976Q3	1981Q4	1986Q4	1992Q4
Switzerland	0.0253	0.099	0.125	2.053	1977Q2	1981Q1	1986Q2	
UK	0.0406	0.055	0.063	0.153	1978Q3	1982Q2	1987Q1	1992Q3

Panel B: Panel Stationarity Tests

	Independence		CS demeaned		Bootstrap distribution			
	Test	p-val	Test	p-val	90%	95%	97.5%	99%
$Z(\lambda)$ Hom.	-2.237	0.987	-1.689	0.954	6.780	7.888	8.874	10.279
$Z(\lambda)$ Het.	-1.983	0.976	-1.921	0.973	6.313	7.464	8.548	10.002
$\hat{S}_k$	1.965	0.025	-0.253	0.600	1.639	1.974	2.264	2.575

Panel Stationarity test with common factors

	Test	p-val	$\hat{r}$	$\hat{r}_1$
$\hat{S}_k^F$	1.519	0.064	6	-

Table 3: Median-unbiased-based autoregressive parameter and Half-life (in years) estimates for the idiosyncratic and common components

Panel A: Idiosyncratic component

		$\hat{\alpha}_{MU}$ parameter			HL estimates		
			Confidence interval (95% level of confidence)			Confidence interval (95% level of confidence)	
	Lags	Point estimate	Lower limit	Upper limit	Point estimate	Lower limit	Upper limit
Australia	0	0.625	0.457	0.819	0.369	0.221	0.868
Austria	3	0.702	0.530	0.853	0.484	0.275	1.003
Belgium	1	0.480	0.310	0.660	0.241	0.181	0.388
Canada	0	0.711	0.521	0.856	0.508	0.266	1.115
Denmark	8	0.775	0.524	0.931	0.703	0.271	3.187
Finland	3	0.709	0.527	0.851	0.501	0.273	1.006
France	3	0.647	0.455	0.791	0.370	0.229	0.685
Germany	3	0.653	0.475	0.806	0.382	0.238	0.744
Italy	4	0.329	0.022	0.531	0.186	0.128	0.273
Japan	0	0.699	0.556	0.880	0.484	0.295	1.356
Netherlands	0	0.722	0.527	0.858	0.532	0.271	1.132
New Zealand	0	0.591	0.372	0.754	0.330	0.175	0.614
Norway	7	0.300	-0.040	0.508	0.179	0.120	0.257
Spain	1	0.735	0.593	0.870	0.499	0.320	1.138
Sweden	0	0.738	0.564	0.878	0.571	0.303	1.332
Switzerland	3	0.569	0.361	0.734	0.305	0.196	0.534
UK	0	0.541	0.240	0.674	0.282	0.122	0.439

Panel B: Common factor component

		$\hat{\alpha}_{MU}$ parameter			HL estimates		
			Confidence interval (95% level of confidence)			Confidence interval (95% level of confidence)	
Factor	Lags	Point estimate	Lower limit	Upper limit	Point estimate	Lower limit	Upper limit
1	4	0.485	0.239	0.662	0.243	0.164	0.396
2	3	0.637	0.485	0.762	0.361	0.243	0.559
3	1	0.682	0.531	0.825	0.398	0.269	0.743
4	0	0.702	0.533	0.859	0.490	0.275	1.142
5	0	0.689	0.586	0.896	0.466	0.325	1.573
6	4	0.366	0.050	0.574	0.197	0.132	0.320

The column labelled as Lags denotes the number of lags that has been included in the ADF-type regression equation that is used to obtain the MU parameter estimates.

Figure 1. Real exchange rates and the estimated structural breaks

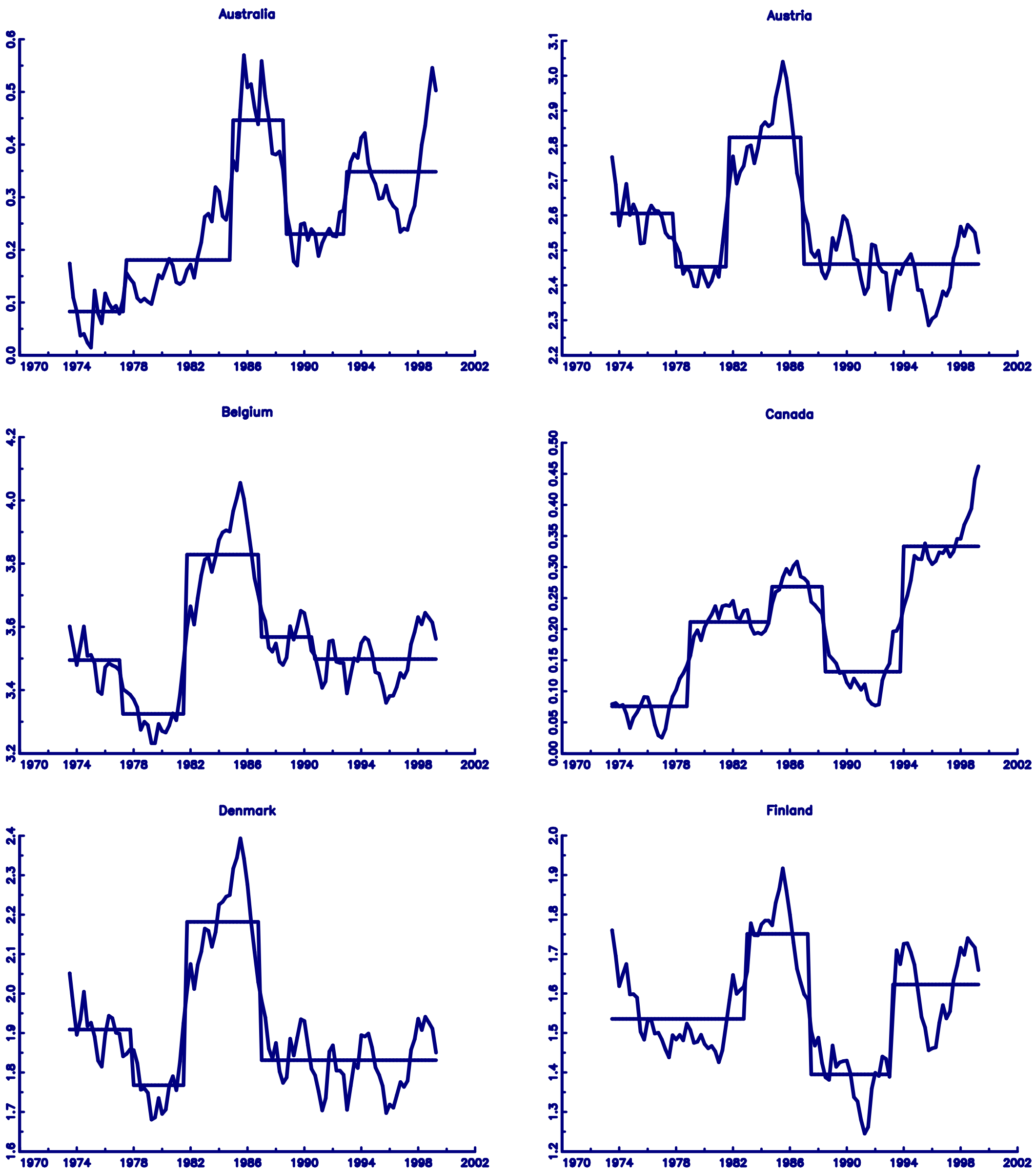

Figure 1 (Cont). Real exchange rates and the estimated structural breaks

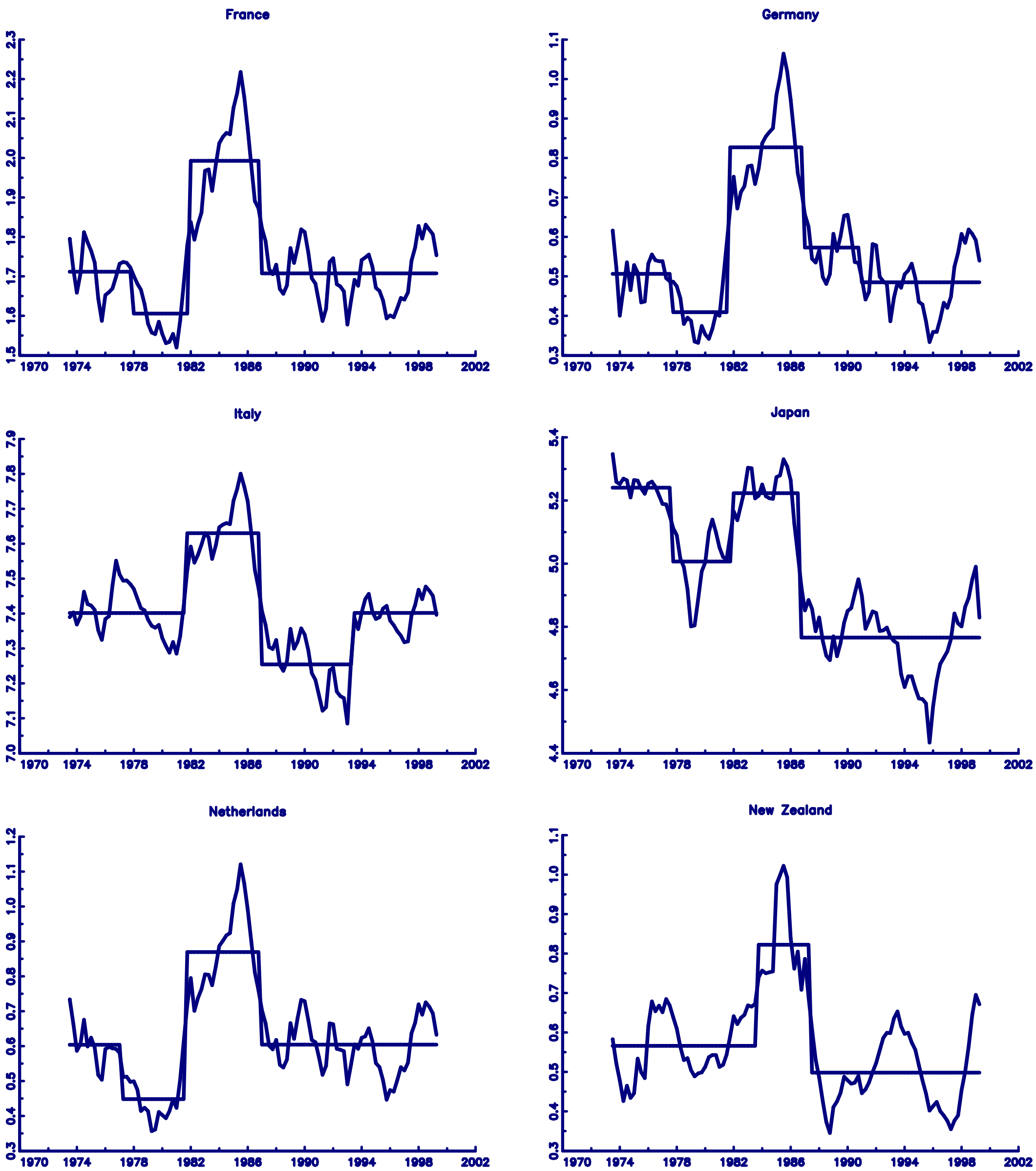

Figure 1 (Cont). Real exchange rates and the estimated structural breaks