# Deconstructing Shocks and Persistence in OECD Real Exchange Rates*

Syed Abul Basher† Josep Lluís Carrion-i-Silvestre ‡

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**Abstract**

We study the Purchasing Power Parity (PPP) hypothesis and the PPP puzzle for a sample of seventeen OECD economies when real exchange rates (RERs) are subject to multiple structural breaks. While several earlier studies have considered structural breaks, the analysis of the persistence of shocks when structural breaks are present in RERs has not yet been considered. Applying recent panel econometric methods, we first show that RERs are found to be I(1) non-stationary processes when the analysis neglects structural breaks, while they are characterized as I(0) stationary stochastic processes when structural breaks are accommodated. This indicates that ignoring structural breaks can lead to model misspecification, which can bias (upward) shocks' persistence measures. After controlling for structural breaks, our half-life point estimates appear below one year for both *idiosyncratic* and *common* measures of persistence of deviation from the changing mean.

*Keywords:* Shock persistence, panel data stationarity tests, multiple structural breaks, cross-sectional dependence

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†Department of Research & Monetary Policy, Qatar Central Bank, P.O. Box 1234, Doha, Qatar. Email: bashers@qcb.gov.qa

‡Corresponding author: AQR-IREA Research Group, Department of Econometrics, Statistics and Spanish Economy, University of Barcelona. Av. Diagonal, 690. 08034 Barcelona. Tel: +34 934024598; Fax: +34 93 4021821. Email: carrion@ub.edu

# 1 Introduction

This paper addresses two key issues in the empirical literature on Purchasing Power Parity (PPP). First, we examine whether the real exchange rates (RERs) show stationary fluctuations around a changing mean for a sample of OECD countries. This issue is related to the branch of the international economics literature that tests whether the PPP hypothesis is satisfied using unit root and stationarity test statistics. Second, we compute the half-life (HL) of the shocks for each real exchange rate, again in the presence of multiple structural breaks.

Accounting for structural breaks is relevant in our context since conclusions can differ depending on whether breaks are accommodated in the analysis or not. For example, when RERs contain structural breaks, conventional unit root and stationarity tests that do not permit for breaks are biased towards concluding in favor of the non-stationarity hypothesis,[1] falsely leading us to conclude that PPP does not hold. It is therefore not surprising that Lopez et al. (2005) found limited evidence of PPP for a sample of industrialized economies, while using the same data but controlling for the presence of structural breaks, Papell and Prodan (2006) found more evidence in favor of the stationarity of the RERs. Similar results are found in Gadea et al. (2004), where it is shown that most of the persistence featured by European real exchange rates is due to comovements in the U.S. dollar during the mid-1980s. Gadea et al. (2004) show that once these effects are isolated, most of the European real exchange rates become stationary. More interestingly and related to our approach, these authors argue that the omission of some structural breaks that affected the behavior of the U.S. dollar real exchange rates during the first half of the 1980's caused the unit root hypothesis not to be rejected, resulting in the apparent lack of evidence in support of PPP.

The presence of structural breaks can be interpreted as (few) real economic shocks affecting time series permanently. As movements in the real exchange rate are tantamount to deviations from PPP, Kim and Enders (1991) argue that these real economic shocks can induce permanent deviations from PPP. Thus, failure to accounting for struc-

[1] See Perron (1989).

tural breaks can lead to upward bias in the autoregressive coefficient of the RERs (and the corresponding upward bias in the persistence measure), prompting to conclude that shocks are more persistent than they really are. A common measure of persistence is the half-life of PPP deviations. Assuming that the deviations of the logarithm of the real exchange rate from its long run value follow an autoregressive process of order 1, half-life can be computed as[2]

$$h = \frac{\ln(0.5)}{\ln(\hat{\alpha})},$$

where $\hat{\alpha}$ is the estimated autoregressive coefficient. Thus, when $\hat{\alpha}$ tends towards 1, the half-life tends towards infinity. The slow speed of reversion to PPP is problematic for model with nominal rigidities, which predict faster convergence to PPP of 1–2 year half-life. The existing point estimate imply instead a half-life in the range of 3–5 years (Rogoff, 1996). The point that we raise in this paper is that lack of accounting for structural breaks in the computation of the half-life is the reason behind higher degree of persistence in the real exchange rate, which helps to explain the puzzle identified in the literature.

Several previous papers have considered structural breaks when testing for the PPP hypothesis in panel data framework – see e.g., Cheung and Lai (2000), Papell (2002), Breitung and Candelon (2005), Im et al. (2005), Harris et al. (2005) and Papell and Prodan (2006). For example, Papell (2002) argued that the rise and fall of U.S. dollar in the 1980s may have changed the slope of dollar-based RERs, which lend evidence of structural change in the data generating process. Not surprisingly, Papell (2002) finds favorable support for PPP once structural breaks have been accounted for in the computation of panel data unit root tests. The use of panel data based statistics aims at getting an improvement in the statistical inference, given that these statistics exploit both the cross-section and time series variation when analyzing the stochastic properties of the real exchange rates.

In this paper, we assess the stochastic properties of RERs by applying the panel data stationary tests of Carrion-i-Silvestre et al. (2005) and Harris et al. (2005), provided that these statistics can handle the presence of multiple structural breaks. As argued

[2]See e.g. Rossi (2005).

by Taylor (2001) and Bai and Ng (2004a), from a conceptual point of view, it is more natural to specify the null hypothesis of I(0) stationarity since, in this case, the theory holds under the null hypothesis and is rejected when there is strong evidence against it.[3]

Unlike Papell (2002), Harris et al. (2005) and Papell and Prodan (2006), we do not impose any restriction on the level of the RER when considering multiple structural breaks. Thus, after a break occurs, our unrestricted approach does not require the level of RER to return to the same level previous to the structural break. Instead, we are interested to examine whether RER is stationary once multiple structural breaks, which affect the level of the time series, are removed from the data. Strictly speaking, the traditional interpretation of Cassel's (1918) PPP hypothesis would not be fitted in our framework, although the presence of (unrestricted) level shifts in RER has been interpreted in Dornbush and Vogelsang (1991) as evidence in favor of the Balassa-Samuelson notion of PPP – see Basher and Carrion-i-Silvestre (2009) for further discussion on the introduction of structural breaks and the interpretation of the PPP hypothesis.

As real economic shocks induce permanent deviations from PPP, the computation of half-life is likely to get impacted by the presence of structural breaks. One possible way to deal with this problem is by isolating the influence of structural breaks (occasional permanent shocks) from that of recurrent transitory shocks affecting the level of RER. In so doing, we have implemented the approximate factor model of Bai and Ng (2004a) that allows us to estimate both the common and idiosyncratic components of the model and thereby gaining a better understanding of non-stationarity sources in the data. Besides, the factor structure has shown to be a useful way to model cross-sectional dependence in panel data.

The use of panel data based methods allow us to gain some insight in the sources of persistence that exhibit the real exchange rates. As both (nominal and real) exchange rates usually exhibit high variability within each country over time as well as strong co-movement across countries, decomposing the shock persistence of RER in common and country-specific (idiosyncratic) components might be useful in understanding the

[3]The specification of the null hypothesis of unit root implies that the theory is false, which is contrary to the notion of PPP.

evolution of real exchange rate dynamics. Consequently, we compute both common and idiosyncratic half-life measures of persistence of real exchange rate. To the best of our knowledge this decomposition has not been previously considered in the literature.

Briefly, our main results are summarized as follows. We find limited evidence supporting the stationarity of RERs in the OECD panel when structural breaks are ignored. This conclusion is reversed once multiple structural breaks are accommodated, which lead us to obtain half-life point estimates that 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. Section 2 describes the econometric methodology used throughout the paper. Section 3 presents the data and reports the results of the analysis. Section 4 discusses the measurement of half-life. Finally, Section 5 concludes the paper.

# 2 Econometric methodology

## 2.1 Panel data stationarity tests

Let $y_{i,t}$ denotes a stochastic process with data generating process given by:

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

where $DU_{i,k,t} = 1$ for $t > T_{b,k}^i$ and 0 elsewhere, with $T_{b,k}^i$ denoting the $k$-th date of the break for the $i$-th time series, $k = 1, ..., m_i$, $m_i \geq 1$, $t = 1, ..., T$ and $i = 1, ..., N$. The model in (1) includes individual effects and individual structural break effects. The framework entails a high degree of heterogeneity as it considers multiple structural breaks, where the number and position of the structural breaks are allowed to vary across units. It is worth mentioning that the case of no structural breaks covered by Hadri (2000) is embedded in our analysis if $\theta_{i,k} = 0$ $\forall i, k$. Further, it is possible that some time series are not affected by the presence of structural breaks, in which case $\theta_{i,k} = 0$ $\forall k$ for some

$i$. The test statistic in Carrion-i-Silvestre et al. (2005) is constructed by estimating (1) using ordinary least squares (OLS) for every member of the panel and then averaging the $N$ individual stationarity test statistics à la Kwiatkowsky, Phillips, Schmidt and Shin (1992) – hereafter, the KPSS test $\eta_i(\lambda_i)$. The general expression of the test statistic is

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

with $\eta_i(\lambda_i) = \hat{\omega}_i^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}_{i,t}^2$, where $\hat{S}_{i,t} = \sum_{j=1}^{t} \hat{\varepsilon}_{i,j}$ is the partial sum process obtained using the estimated OLS residuals of (1). The term $\hat{\omega}_i^2$ denotes a consistent estimate of the long-run variance of the error $\varepsilon_{i,t}$, which is estimated following the procedure in Sul, Phillips and Choi (2005) using the Quadratic spectral kernel. In (2), $\lambda$ is defined as the vector of break fractions $\lambda_i = (\lambda_{i,1}, ..., \lambda_{i,m_i})' = (T_{b,1}^i/T, ..., T_{b,m_i}^i/T)'$, which indicates the relative position of the date of the breaks on the entire time period for the $i$-th times series. Note that for the test in Hadri (2000) $\lambda_i = 0 \ \forall i$, since there are no structural breaks.

Assuming cross-sectional independence, Hadri (2000) and Carrion-i-Silvestre et al. (2005) show that under the null hypothesis of panel data stationary with multiple structural breaks, the $LM(\lambda)$ statistic converges to

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

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 et al. (2005). It is also possible to compute the Harris et al. (2005) panel data stationarity test statistic defined by:

$$\hat{S}_k = \frac{\hat{C}_k + \hat{c}}{\hat{\omega}\left\{\hat{a}_{k,t}\right\}}, \tag{3}$$

with $\hat{C}_k = T^{-1/2} \sum_{t=k+1}^{T} \hat{a}_{k,t}$ the autocovariance of order $k$, where $\hat{a}_{k,t} = \sum_{i=1}^{N} \hat{\varepsilon}_{i,t}\hat{\varepsilon}_{i,t-k}$ and $\hat{\varepsilon}_{i,t}$ denoting the OLS residuals in (1). The term $\hat{c} = (T-k)^{-1/2} \sum_{i=1}^{N} \hat{c}_i$, being $\hat{c}_i$ a correction term defined in Harris et al. (2005) and, $\hat{\omega}^2\left\{a_{k,t}\right\}$ is a consistent estimate of the long-run variance of $a_{k,t}$, which is estimated following the approach in Sul et al. (2005) as above. Under the null hypothesis of I(0) stationarity and assuming cross-sectional independence, the statistic $\hat{S}_k \rightarrow N(0,1)$.

In order to estimate the number and position of the structural breaks, Carrion-i-Silvestre et al. (2005) follow the procedure developed by Bai and Perron (1998), which proceeds in two steps. First, the breakpoints are estimated by globally minimizing the sum of squared residuals for all permissible values of $m_i \leq m^{\max}$, $i = 1, ..., N$. Second, the sequential testing procedure[4] suggested in Bai and Perron (1998) is applied 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 unit.

## 2.2 Cross-sectional dependence

The preceding discussion is based on the assumption that time series in the panel data are cross-sectional independent, which is very unlikely to hold in the present context. In fact, the case of cross-sectional dependence comes naturally into RERs analyses due to the definition of the base country. Thus, as pointed by O'Connell (1998), the use of U.S. as a base country automatically introduces two common components in the observed data, namely, independent variation in the value of the dollar and independent variation in the U.S. price index. In addition to the base country effect, there may be other unobserved common factors – e.g., due to oil price shocks or common economic policies – that tend to make exchange rates and prices co-move across countries. Neglect of the cross-sectional dependence has adverse effects on the properties of estimators and is known to cause severe size distortions that can render the power gain from panel dimension entirely fictitious – see Lyhagen (2000) and Banerjee et al. (2004, 2005), among others.

Although cross-sectional dependence comes naturally into RERs applications, recent

[4]Note that the sequential approach in Bai and Perron (1998) can be used here since under the null hypothesis we have that the units are I(0). Consequently, the consistency on the specification of the number and position of the structural breaks is warranted. Furthermore, the test remains consistent against the alternative hypothesis of I(1) as shown, for instance, in Lee, Huang and Shin (1997), Kurozumi (2002) and Carrion-i-Silvestre (2003).

developments in the literature offer the possibility of testing for the presence of cross-sectional dependence in a panel of observed data. Two recently proposed tests are Pesaran (2004) and Ng (2006). Pesaran's (2004) CD statistic tests the null hypothesis of cross-sectional independence against the alternative hypothesis of dependence. The CD statistic is based on the average of pairwise Pearson's correlation coefficients of the residuals obtained from autoregressive (AR) regression equations for each cross unit. However, it is not clear whether a rejection of the null hypothesis is due to a small or large number of units. In this regard, Ng (2006) proposes a uniform spacing method to test the correlation of units when possibly some, but not necessarily all, units are correlated. The idea is to look at a transformation of the ordered (from the smallest to the largest) correlation pairs instead of looking at the correlation themselves. Under the null hypothesis that all the correlations are zero, Ng's (2006) proposal allows to gain insight about the extent of the correlation in the data when it is not known a priori how many and which series are correlated. Undoubtedly, the use of these statistics will help researchers to decide which panel unit root or stationarity statistic should be used for statistical inference.

In this paper we account for cross-sectional dependence when computing the panel data stationarity test statistics in three alternative ways. First, we follow the suggestion in Levin, Lin and Chu (2002) and proceed to remove the cross-sectional mean. This approach of dealing with cross-sectional dependence is simple, although its main drawback is that it is equivalent to the situation where the cross-sectional dependence is driven by one stationary common factor that has the same effect on all units. Second, we follow Maddala and Wu (1999) and compute the empirical distribution by means of parametric bootstrap. These two approaches are applied to all test statistics described above. Finally, we apply the factor structure in Bai and Ng (2004a) to account for cross-sectional dependence in the panel. The factor structure is specified for the $\varepsilon_{i,t}$ disturbance term in (1)

$$\varepsilon_{i,t} = F_t' \pi_i + e_{i,t}, \tag{4}$$

where $F_t$ denotes the $(r \times 1)$ vector of common factors, $\pi_i$ the factor loadings and $e_{i,t}$ is the idiosyncratic disturbance term. Note that this decomposition permits assessing the stochastic properties of the observed $y_{i,t}$ variable in terms of idiosyncratic and common factor components.

The estimation of these components is carried out using principal components method – see Bai and Ng (2004a) for further details. Harris et al. (2005) use the same framework as Bai and Ng (2004a) to allow cross-sectional dependence among individuals in the panel and propose a test statistic ($\hat{S}_k^F$) that tests the null hypothesis of joint I(0) stationarity of the common and idiosyncratic components – under the null hypothesis it is shown that $\hat{S}_k^F \rightarrow N(0,1)$.

# 3 Empirical results

## 3.1 Data and preliminary results

We use the same data set used by Pesaran (2007), 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.[5] The logarithms of the real exchange rates ($y_{i,t}$) are computed against the U.S. dollar as the benchmark.

Before progressing any further, it is useful to review the case without any structural breaks in the data. To save space we do not present these results, but these are available from the corresponding author on request. As predicted, both Pesaran (2004) and Ng (2006) statistics provide significant evidence of cross-sectional dependence amongst the individuals in the panel data set. We get mixed results after controlling for the cross-sectional dependence in the data. For instance, when cross-sectional demeaned data is used, we strongly reject the null hypothesis of stationarity using Hadri's (2000) statistics, while it is not rejected when using the $\hat{S}_k$ statistic in Harris et al. (2005). When cross-sectional dependence is accommodated using the bootstrap[6] distribution, we get favorable

[5] We are thankful to Takashi Yamagata for making the data available to us. We include the observations for 1973 in our analysis, while Pesaran (2007) starts at 1974.

[6] Following Maddala and Wu (1999), we have computed the bootstrap empirical distribution of the

results for the PPP hypothesis, regardless of the type of statistic that is used. When common factor[7] framework in Bai and Ng (2004a) is used, we are unable to find support for the PPP hypothesis. This result is consistent with the findings by Bai and Ng (2004a) and Wagner (2008), who also document limited evidence of PPP when the cross-sectional dependence is modeled using the factor structure. Overall, we do not find much evidence for the PPP hypothesis.

These results, however, are conditional to the assumption that the parameters of the deterministic component of the model are stable throughout the sample period. Consequently, we address the robustness of the above results in the presence of multiple structural breaks using the statistics described in Section 2.

## 3.2 Panel data stationarity tests with structural breaks

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 – in our analysis this maximum was never attained for any of the time series. The number of break points has been selected with the sequential approach in Bai and Perron (1998) working at the 5% level of significance. The results in Panel A in Table 1 indicate that at least one structural break has been detected for each unit, which shows the potential bias on the estimation of shock persistence measures that neglect the presence of structural breaks. The estimated break points are used to compute the statistics in Carrion-i-Silvestre et al. (2005) and Harris et al. (2005).

As a preliminary analysis, we first compute individual stationary statistics to obtain the fraction of the cross-section units that are stationary. Panel A in Table 1 offers the values for the individual KPSS 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 provided, since this statistic converges to the standard Normal distribution.

statistics using 20,000 replications – we offer the percentiles of interest in Table 1.

[7]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.

Inspection of the individual statistics reveals that the null hypothesis of I(0) 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-sectional independent, we conclude that the null hypothesis of panel stationarity cannot be rejected with either version of the $Z(\lambda)$ test, although it is rejected by the $S_k$ test – see Panel B in Table 1. However, as discussed above, strong cross-sectional dependence is present by construction.

Table 2 reports the cross-sectional correlations based on Pesaran (2004) and Ng (2006). We have estimated an AR regression equation that includes dummy variables to account for the presence of the level shifts.[8] As can be seen, the $CD$ statistic strongly rejects the null hypothesis of independence. As for the statistics in Ng (2006), the p-values of the whole $\left(svr^W(\hat{\eta})\right)$ and small $\left(svr^S(\hat{\eta})\right)$ sample indicate that the null hypothesis of independence cannot be rejected at the 5% level of significance, while the null hypothesis of independence is strongly rejected for the cross-section units in the large group $\left(svr^L(\hat{\eta})\right)$. Moreover, the estimated break point $(\hat{\eta} = 14)$ suggests that the fraction of units in the $S$ group is small $\left(\hat{\vartheta} = 0.103\right)$ compared to the correlation coefficients in the $L$ group, which leads us to conclude that strong cross-sectional correlation among cross-section units is also present when structural breaks are considered in the analysis.

When cross-sectional dependence is addressed, either through cross-sectional demeaning or computing the empirical distribution by means of parametric bootstrap, all panel data statistics indicate that the null hypothesis of I(0) stationarity cannot be rejected at the 5% level of significance – see the results reported in the columns labeled as 'CS demeaned' and 'Bootstrap distribution' in Table 1. This conclusion is reinforced by the $\hat{S}_k^F$ statistic, which uses the common factor approach in Bai and Ng (2004a) to model the cross-sectional dependence. Therefore, we have found strong evidence of I(0) stationarity of the RERs for the set of countries that have been considered.[9]

[8] The AR 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.

[9] Our results are qualitatively different from Harris et al. (2005) who are unable to find favorable support for the PPP hypothesis when applying panel stationary test with cross-sectional dependence

### 3.3 Structural breaks and real rigidities

Panel A in Table 1 reports the estimated break points, which are depicted in Figure 1. Except for New Zealand, at least three breaks are found for each country with all breaks occurring during the period 1976Q3 to 1993Q2. From an historical point of view, the estimated break points are in accordance with events such as oil price shocks, the rise and fall of U.S. dollar in the 1980s 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 1 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 1973-74 and 1978. It is possible that events such as the oil embargo or shocks affecting the technological process may change the productivity of cross-section units in different ways, so that differences in productivity can be reduced or increased after the shocks, which may imply a change in the level around which the RERs would show stationary fluctuations. In this regard, Alexius (2005) finds that productivity shocks explain about 60–90% of the permanent movements for five out of the six OECD real exchange rates that he examined.

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. The competitiveness approach emphasizes that real exchange rate depreciations accelerate productivity growth in certain circumstances. For example, a positive demand shock (i.e., RER depreciation) can increase the measured productivity growth in the tradable goods sector through increased factor utilization, learning-by-doing effects or increasing returns to scale. While these effects are consistent with models of endogenous growth in open economies, there is a related literature arguing the opposite link between cycles and productivity. This strand of the literature identifies reorganization or cleansing recession

and structural breaks. One possible reason for the discrepancy of research conclusions is the constrained framework imposed in Papell (2002) and maintained in Harris et al. (2005). As mentioned, our results are based on an unconstrained set-up that does not restrict the RERs to return to the levels previous to the structural change.

as reasons that a cyclical downturn could lead to productivity increases – e.g. Saint-Paul (1993). However, empirical results from both sides appear mixed and there is an active empirical debate regarding how permanent the productivity consequences of demand shocks are – see Basu (1998) and Harris (2001) for useful discussion in the productivity-exchange rate debate.

Few countries (mostly European) experienced a fourth break occurring at the beginning of 1990s, which can be explained by the German reunification and/or the formation of the 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.

In summary, we provide statistical evidence supporting real exchange rates I(0) stationarity hypothesis for a sample of OECD economies once multiple structural breaks are accounted for. Overall, our results provide a serious warning against the use of conventional panel data unit root and stationary tests without proper consideration of underlying breaks in the data generating process. Neglecting such structural breaks will clearly lead to a model misspecification. Therefore, modeling the structural breaks is not only important for correct specification of the model, it is also plays a critical role in measuring the persistence of RER, an issue that we examine in the next section.

# 4 Shock's decomposition and their persistence measurement

In this section we take a fresh look at the "PPP puzzle" using the panel data framework developed above. Briefly, PPP puzzle is the apparent contradiction between the enormous short-term volatility of real exchange rates and the high degree of persistence of shocks to real exchange rate (about 3–5 years) – see Rogoff (1996) for further details. While PPP is compatible with the very high short-term volatility of RERs, the much slow speed of mean reversion is very difficult to reconcile with PPP. This feature has provoked a flurry of papers addressing the PPP puzzle.[10]

Two recent studies using panel data include Murray and Papell (2005) and Choi et al. (2006). Murray and Papell (2005) employ the approximate median-unbiased (MU) estimator of Andrews and Chen (1994) to measure the persistence of the deviations of RERs from their changing mean for 20 industrialized economies. Using post-1973 data, the authors find a median half-life of 3.55 years, with the 95% confidence interval of 2.48–4.09 years. Similarly, Choi et al. (2006) use post-1973 data of 21 OECD countries and obtain a point estimate of unbiased half-life of 3 years with a 95% confidence interval of 2.3–4.2 years. As can be seen, these results fall exactly within Rogoff's (1996) consensus range of 3–5 years. However, both studies restrict the autoregressive coefficients to be identical across all cross-section units, which is implausible in applied work since it implies that each RER reverts to its respective mean over time at the same speed. Additionally, as shown by Papell (2002), post-1973 dollar-based RERs were impacted by structural breaks on several episodes in the 1980s. The upshot of all these studies is that ignoring structural breaks might induce misleading conclusions, and hence, may not work too well at describing the PPP puzzle.

There are different approximations in the literature to estimate the autoregressive model that constitutes the half-life measurement. When time series are thought to be highly persistent, approaches such as the ones in Pesavento and Rossi (2006) can be employed since these approximations model the time series as a local-to-unity process. When time series are far from the local-to-unity framework, other approaches such as Andrews and Chen (1994), Kilian (1998) and Hansen (1999) can be used. Since, first, the results reported in the previous section reveal that time series are I(0) and, second, the initial OLS estimation of the autoregressive models for both components – not reported

[10] See Taylor and Taylor (2004) for discussion related to the PPP puzzle.

here to save space – reveal that the largest root of the characteristic polynomial is not close to unity, we have proceeded to compute the HL estimates using the proposal in Andrews and Chen (1994). This procedure also permits to obtain confidence intervals for the autoregressive parameters, and therefore confidence intervals for the idiosyncratic and common HLs can be established as well.

We follow Murray and Papell (2005) to measure the persistence of the shocks, but allow the autoregressive parameters to vary across all cross-section units. The estimation of the HLs depends on the order of the autoregressive model that is used.[11] Using the method in Andrews and Chen (1994), 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 median-unbiased autoregressive parameter. However, when the order of the autoregressive model is $p > 1$ the HL estimate has to be obtained from the impulse response function (IRF) that derives from the estimation of the AR($p$) model:

$$e_{i,t} = \phi_1 e_{i,t-1} + \cdots + \phi_p e_{i,t-p} + v_{i,t}, \tag{5}$$

where $e_{i,t}$ denotes the idiosyncratic disturbance term in (4). Besides the analysis of the idiosyncratic disturbance term, we may also be interested in investigating the persistence coming from each element of the common factor vector $F_t = (F_{1,t}, \ldots, F_{r,t})'$ in (4), or the effects considering the whole common factor component that affects each individual – i.e. $w_{i,t} = F_t'\pi_i$ in (4) – or the whole stochastic component – i.e. $\varepsilon_{i,t} = F_t'\pi_i + e_{i,t}$ in (4). In these cases, autoregressive models such as the one given in (5) have been estimated replacing $e_{i,t}$ by $F_{j,t}$, $j = 1, \ldots, r$, $w_{i,t}$, or $\varepsilon_{i,t}$, respectively.

Table 3 presents estimates of the autoregressive parameter $\alpha$ and the HL measures that are obtained using the median-unbiased method of Andrews and Chen (1994). In addition to the point estimates, we report the 95% confidence interval for $\hat{\alpha} = \sum_{j=1}^{p} \hat{\phi}_j$, where $\hat{\phi}_j$ denotes the estimated coefficients in (5), and the corresponding HL measures.

Panels A to D in Table 3 report the computations for the idiosyncratic stochastic

[11] 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.

component ($e_{i,t}$), the stochastic component due to the common factor component ($w_{i,t}$), the analysis for each of the common factors ($F_{j,t}, j = 1, \ldots, r$) and the whole stochastic component ($\varepsilon_{i,t}$), respectively. Looking first at the idiosyncratic component (Panel A in Table 3) we find that, although the half-lives vary between countries, all are considerably smaller than one year with a mean of 0.407 years and a median of 0.382 years. For countries such as Sweden and Denmark, real exchange rate variations are apparently dominated by the idiosyncratic components. The common factor estimates (Panel B in Table 3) are very similar but the point estimates of the persistence are very often smaller (with a mean of 0.304 years and a median of 0.265 years) than that of the idiosyncratic component. We also see that for most European countries the common shocks are less lasting than their non-European counterparts, which appears consistent with the supposedly lower persistence among integrated European economies. If we analyze the effect of each common factor separately we see that their effects are always lower than one year – see Panel C in Table 3. Turning to the estimates for the whole component $\varepsilon_{i,t}$ in Panel D of Table 3, the half-life estimates are roughly in similar magnitude to the previous components, but with a slightly higher mean of 0.421 years and median of 0.396 years. According to these results, real exchange rates' persistence is much smaller than the consensus of 3 to 5 years established by the literature. Note that, save for Austria, in all these situations the confidence intervals are quite narrow and informative when compared to previous estimates in the literature – e.g., Murray and Papell (2005).

To see whether our results are sensitive to the choice of estimation methods, we have also applied the bootstrap method in Kilian (1998) and the grid bootstrap procedure in Hansen (1999) to compute the HLs – these results are not reported to conserve space, although they are available upon request in a companion appendix. We find that the results are quite similar to those based on the median-unbiased estimator. In all cases, the coefficients of the $\alpha$ parameter and the half-life are below unity. Moreover, except for Austria and Denmark when using the Hansen's (1999) method, the confidence interval remains very informative.

Taken together, the above results suggest very rapid adjustments of OECD real exchange rates, faster than the consensus view in the literature. This is interesting and, as suggested in Rogoff (1996), this may indicate that the adjustment to shocks affecting real exchange rate responds to the existence of nominal rather than real market rigidities. In particular, our results emphasize that neglecting structural breaks in the model can lead to upward bias in the autoregressive parameters, leading to conclude that shocks are more persistent than they really are.[12] This is not surprising if we notice that, by definition, structural changes can be seen as few *occasional* shocks having permanent effects on the time series. The methods that usually are employed in the literature to estimate the persistence of shocks investigate the effects of *recurrent* shocks on time series, which is clearly different from occasional shocks. Thus failing to distinguish between these shocks will bias the measures of the shock persistence.[13]

# 5 Conclusions

We show that conflicting results can arise depending on whether structural breaks are accommodated in the analysis. If structural breaks are present in the data, they must be clearly modeled to avoid misspecification errors, which will lead to obtain biased persistence measures. Although this feature is well known to happen when practitioners

[12] Empirical estimates of the half-life of shocks to the RER may also be biased upward due to (i) temporal aggregation in the data and (ii) nonlinear adjustment of RERs (see Taylor (2001) for further details). However, the possibility of nonlinear adjustment could arise due to the presence of structural breaks, which has been cogently addressed in our work. Whereas, the time aggregation problem is difficult to deal with since one would require long-spans of high frequency data, which may not always be available in panels. Another source of aggregation bias, that might induces a positive bias in persistence estimates, may result from aggregating across different sectors of the economy (Imbs et al. (2005)). However, assuming that sectors can be represented as heterogenous AR processes and the number of sectors is sufficiently large, Mayoral (2007) shows analytically that standard impulse response function computed as the aggregate level equals the average of the sectoral impulse responses to a common shock. This implies that the average persistence of a common shock remains constant, regardless of the level of aggregation at which data is reported. Thus, no aggregation bias arises if aggregate data and appropriate techniques are employed. See also Gadea and Mayoral (2009) for an empirical application of this result on a sample of aggregate RERs.

[13] As the presence of structural breaks gives rise to nonlinear adjustment in real exchange rates, our results are also relevant to a strand of literature that uses nonlinear models to analyze mean-reversion of real exchange rates – see e.g., Sarno and Taylor (2002, pp. 68-73) for a list of related papers. These models support the view that real exchange rates are driven by an arbitrage process, such that the speed of reversion to PPP is an increasing function of the scale of the shock and hence of the divergence from equilibrium. Applying different classes of nonlinear models both Taylor et al. (2001) and Peltonen et al. (2010) observe a substantial reduction in half-life persistence, compared to what was found using linear PPP models. Our results therefore encompass previous empirical work in this area.

analyze the order of integration of time series, it seems to be neglected in those papers that analyze the persistence of real exchange rates deviations. Our paper stresses the fact that, if multiple structural breaks are present, they should be taken into account when estimating the models in which the computation of half life measures are based on. From an economic point of view, structural breaks represent occasional but permanent changes in the deterministic specification of the model – i.e., real exchange rate can evolve around a different deterministic component due to changes in the fundamentals of the economies – so that they should be taken apart from those recurrent and transitory shocks that are investigated when analyzing the persistence of real exchange rates deviations.

In line with earlier studies, we find more evidence that the RERs are I(0) once structural breaks are accommodated in the analysis. We have also measured the persistence of the idiosyncratic and common shocks to the real exchange rates through the computation of the half-life measure. The half-life point estimates 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. These results are interesting in view of recent research that purport to shed light on PPP by exploiting recent advances in panel data econometrics. Overall, our results provide a serious warning against the use of conventional panel data unit root and stationary tests without proper consideration of underlying breaks in the data generating process.

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Table 1: Individual and panel data stationarity tests with multiple structural breaks

**Panel A:** Individual statistics

| | $KPSS_i$ | Critical values 10% | 5% | $S_{i,k}$ | $T^i_{b,1}$ | $T^i_{b,2}$ | $T^i_{b,3}$ | $T^i_{b,4}$ |
|---|---|---|---|---|---|---|---|---|
| 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 | $\hat{r}$ | $\hat{r}_1$ |
|---|---|---|---|---|
| $\hat{S}^F_k$ | 1.519 | 0.064 | 6 | - |

Notes: $KPSS_i$ and $S_{i,k}$ report individual test statistic in Kwiatkowsky et al. (1992) and Harris et al. (2005), respectively. $Z(\lambda)$ Hom. and $Z(\lambda)$ Het. report the panel statistics in Carrion-i-Silvestre et al. (2005), while $\hat{S}_k$ represents the panel stationary statistics in Harris et al. (2005). The column CS demeaned refers to the cross-sectional demeaned procedure in Levin et al. (2002), while the column independence refers the case where cross-section units are independent. $T^i_{b,k}$ denote the $k$-th date of the break for $i$-th individual. $\hat{r}$ denotes estimated number of common factors.

Table 2: Cross-sectional correlation tests

| | Test statistic and p-value |
|---|---|
| $CD$ Statistic | 64.586 (0.000) |
| | |
| $\hat{\eta}$ | 14 |
| $svr^{W}(\hat{\eta})$ | -1.147 (0.874) |
| $svr^{L}(\hat{\eta})$ | 6.423 (0.000) |
| $svr^{S}(\hat{\eta})$ | -0.587 (0.722) |

Notes: All the statistics in the table specify the null hypothesis of cross-sectional independence. $CD$ refers to the test statistic proposed in Pesaran (2004). $svr^{W}(\hat{\eta})$, $svr^{L}(\hat{\eta})$, and $svr^{S}(\hat{\eta})$ report Ng's (2006) spacing variance ratio for the whole, large, and small sample, respectively. P-values between parentheses. $\hat{\eta}$ indicates the estimated break point in the sample. We use the $t-sig$ criterion in Ng and Perron (1995) to select the order of the autoregressive correction with up to ten lags.

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 | | |
|---|---|---|---|---|---|---|---|
| | | | 95% CI | | | 95% CI | |
| | Lags | Point | Lower | Upper | Point | Lower | Upper |
| 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 | | |
|---|---|---|---|---|---|---|---|
| | | | 95% CI | | | 95% CI | |
| | Lags | Point | Lower | Upper | Point | Lower | Upper |
| Australia | 3 | 0.628 | 0.417 | 0.780 | 0.347 | 0.214 | 0.662 |
| Austria | 4 | 0.523 | 0.249 | 0.688 | 0.265 | 0.166 | 0.424 |
| Belgium | 4 | 0.516 | 0.284 | 0.684 | 0.260 | 0.175 | 0.417 |
| Canada | 7 | 0.353 | 0.055 | 0.506 | 0.193 | 0.132 | 4.784 |
| Denmark | 4 | 0.538 | 0.281 | 0.706 | 0.275 | 0.174 | 0.447 |
| Finland | 3 | 0.552 | 0.331 | 0.721 | 0.292 | 0.187 | 0.517 |
| France | 4 | 0.493 | 0.226 | 0.668 | 0.246 | 0.162 | 0.399 |
| Germany | 4 | 0.520 | 0.276 | 0.685 | 0.263 | 0.173 | 0.419 |
| Italy | 4 | 0.347 | 0.029 | 0.553 | 0.192 | 0.129 | 0.297 |
| Japan | 1 | 0.699 | 0.537 | 0.850 | 0.442 | 0.275 | 0.981 |
| Netherlands | 4 | 0.509 | 0.257 | 0.682 | 0.256 | 0.168 | 0.415 |
| New Zealand | 5 | 0.734 | 0.523 | 0.896 | 0.538 | 0.268 | 1.433 |
| Norway | 3 | 0.535 | 0.308 | 0.691 | 0.277 | 0.181 | 0.456 |
| Spain | 4 | 0.382 | 0.089 | 0.571 | 0.202 | 0.137 | 0.310 |
| Sweden | 0 | 0.700 | 0.530 | 0.869 | 0.486 | 0.273 | 1.230 |
| Switzerland | 1 | 0.667 | 0.496 | 0.817 | 0.391 | 0.248 | 0.748 |
| UK | 3 | 0.492 | 0.241 | 0.660 | 0.246 | 0.165 | 0.383 |

Table 3 (Cont.): Autoregressive parameter and Half-life (in years) estimates for the idiosyncratic, common and whole stochastic components

**Panel C: Analysis of common factors**

| | | $\hat{\alpha}_{MU}$ parameter | | | HL estimates | | |
|---|---|---|---|---|---|---|---|
| | | | 95% CI | | | 95% CI | |
| Factor | Lags | Point | Lower | Upper | Point | Lower | Upper |
| 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 |

**Panel D: Whole stochastic component**

| | | $\hat{\alpha}_{MU}$ parameter | | | HL estimates | | |
|---|---|---|---|---|---|---|---|
| | | | 95% CI | | | 95% CI | |
| | Lags | Point | Lower | Upper | Point | Lower | Upper |
| Australia | 0 | 0.613 | 0.412 | 0.785 | 0.354 | 0.196 | 0.716 |
| Austria | 5 | 0.755 | 0.500 | 0.973 | 0.670 | 0.250 | 12.555 |
| Belgium | 1 | 0.594 | 0.409 | 0.764 | 0.327 | 0.212 | 0.611 |
| Canada | 0 | 0.725 | 0.542 | 0.873 | 0.539 | 0.283 | 1.276 |
| Denmark | 5 | 0.686 | 0.402 | 0.913 | 0.484 | 0.209 | 3.482 |
| Finland | 3 | 0.683 | 0.521 | 0.821 | 0.452 | 0.267 | 0.790 |
| France | 5 | 0.679 | 0.473 | 0.818 | 0.382 | 0.237 | 0.692 |
| Germany | 3 | 0.720 | 0.552 | 0.882 | 0.524 | 0.294 | 1.527 |
| Italy | 4 | 0.084 | -0.266 | 0.326 | 0.137 | 0.099 | 0.185 |
| Japan | 0 | 0.730 | 0.552 | 0.884 | 0.550 | 0.292 | 1.406 |
| Netherlands | 4 | 0.640 | 0.440 | 0.786 | 0.391 | 0.223 | 0.711 |
| New Zealand | 3 | 0.657 | 0.494 | 0.792 | 0.396 | 0.247 | 0.646 |
| Norway | 0 | 0.582 | 0.341 | 0.738 | 0.320 | 0.161 | 0.571 |
| Spain | 1 | 0.752 | 0.595 | 0.886 | 0.541 | 0.321 | 1.300 |
| Sweden | 0 | 0.709 | 0.534 | 0.844 | 0.505 | 0.276 | 1.025 |
| Switzerland | 3 | 0.510 | 0.289 | 0.681 | 0.257 | 0.176 | 0.422 |
| UK | 0 | 0.593 | 0.361 | 0.754 | 0.332 | 0.170 | 0.614 |

Notes: The number of lags is obtained using the $t$-sig information criterion of Ng and Perron (1995). $\hat{\alpha}_{MU}$ denotes the median-unbiased estimate of Andrews and Chen (1994). HL indicates half-life which is computed as $HL = \ln(0.5) / \ln(\hat{\alpha}_{MU})$.

Figure 1. Real exchange rates and the estimated structural breaks

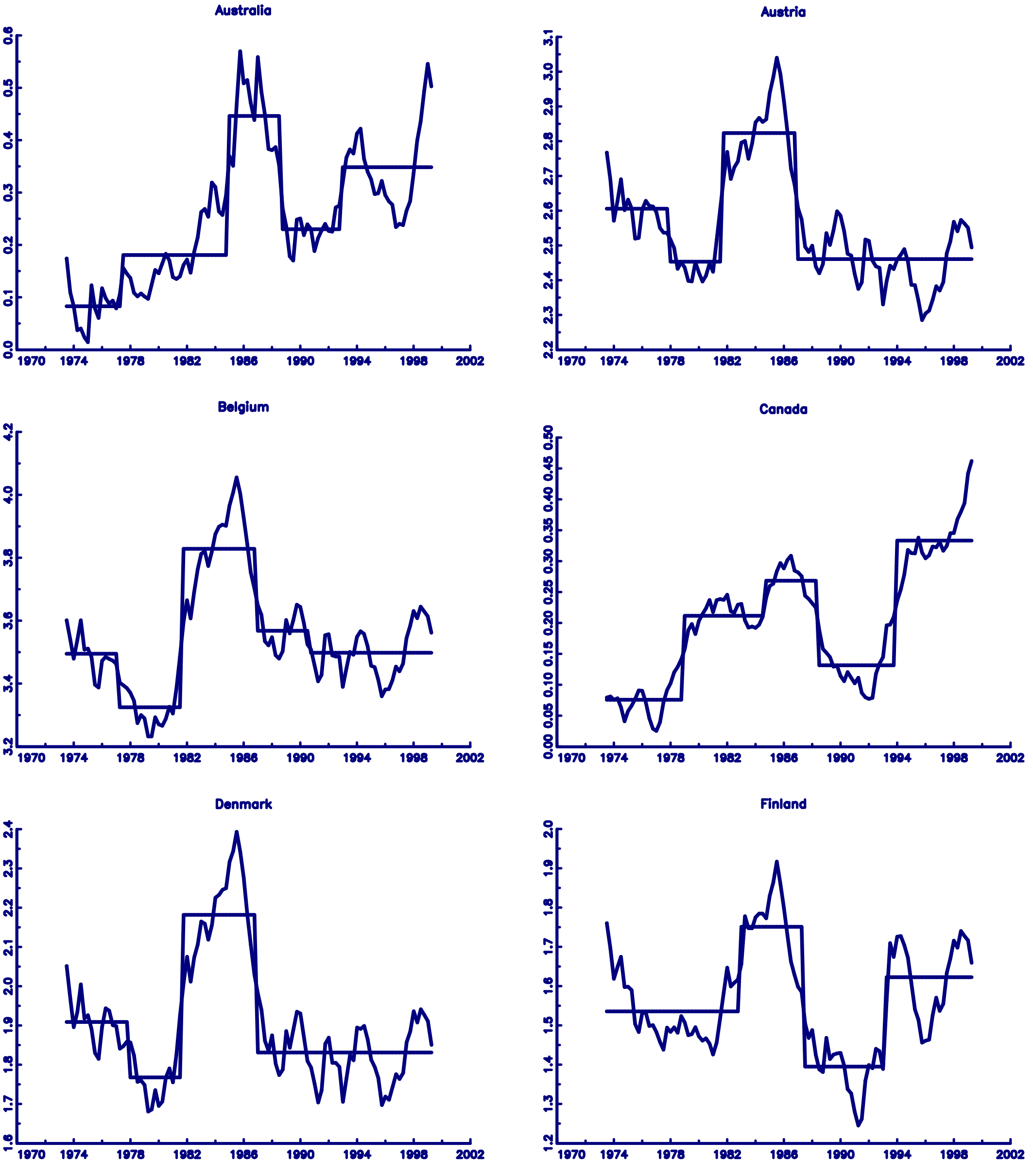

Figure 1 (Cont). Real exchange rates and the estimated structural breaks

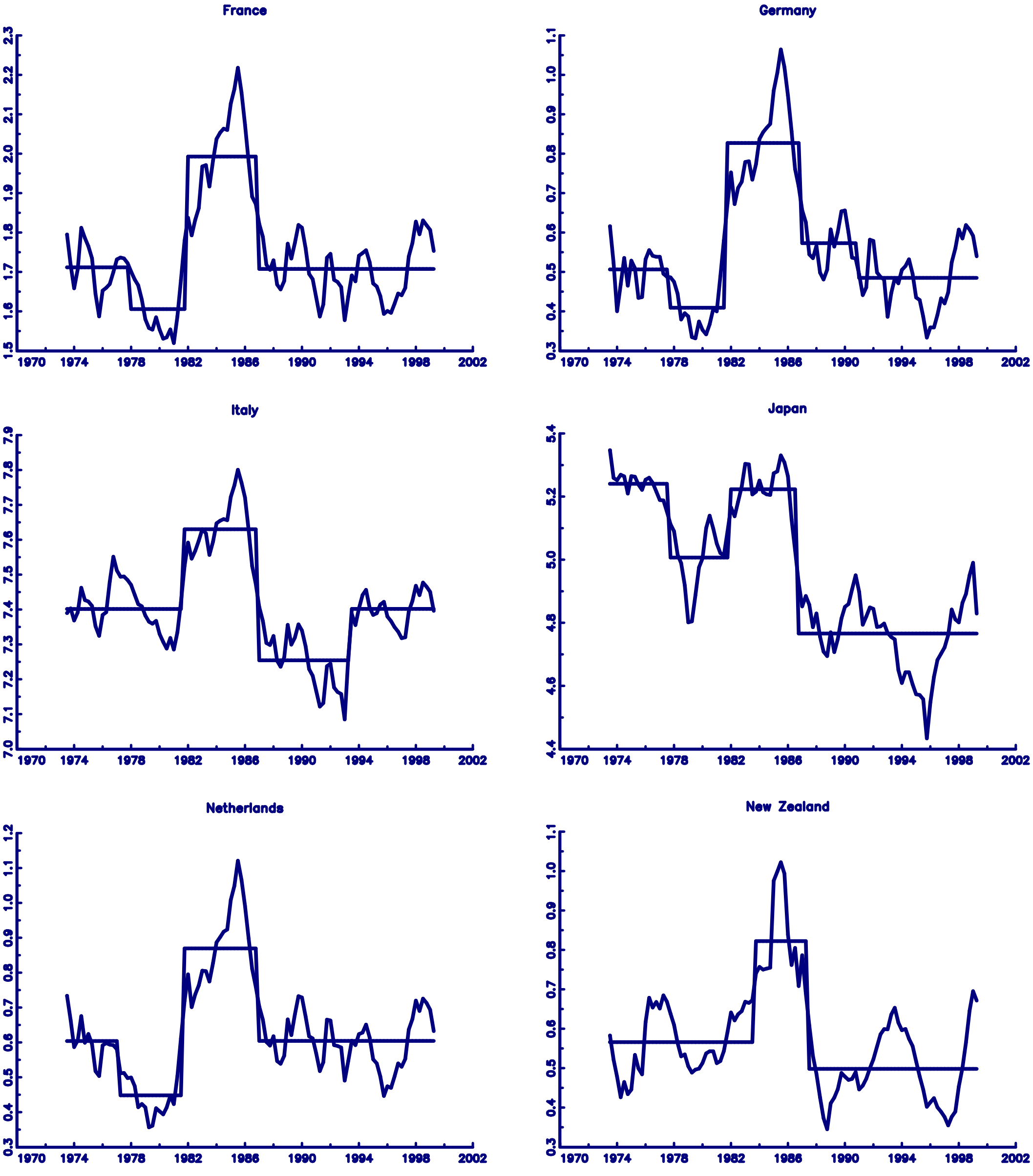

Figure 1 (Cont). Real exchange rates and the estimated structural breaks