Food Prices Convergence:

Disentangling Common and Country-Specific Effects

L. Gutierrez(‡), C. Brasili(*) and R. Fanfani(*)

Abstract

In the paper we show that food prices dynamics can be usefully decomposed into a common component, i.e. aggregate, and an idiosyncratic, i.e. country-specific, component. Using this decomposition, we analyze the relative food prices convergence toward purchasing power parity for a set of food consumer products during the period 1996.1-2008.12 and for two groups of countries located into the "Euro-zone" and "non-Euro-zone" area. The main results are first that food prices convergence varies across products and countries. Second, "Euro-zone" countries have a higher rate of convergence than the "non-Euro-zone" countries. Third, the common component is much more important than the idiosyncratic component in explaining food prices convergence.

Keywords: Food prices, Non stationarity, Common and idiosyncratic components, Half-life.
JEL Classification: C32, C33, Q11.

(‡) L. Gutierrez, Corresponding Author: University of Sassari, Department of Economics and Woody Plant Ecosystems;e-mail: lgutierr@uniss.it
(*) C. Brasili, University of Bologna, Department of Statistics;
(*) R. Fanfani, University of Bologna, Department of Statistics;

Introduction

During the 1990s the process of economic integration among the member states of the European Union was spurred by the start of the Single Market Programme and the European Monetary Union (EMU). The main idea was to eliminate trade barriers between the member states and increase competition by means of free movement of capital, people, goods and services inside the union. The monetary union also allowed some EU member countries to replace their national currencies with a common currency.

The purpose of the paper is to investigate to what extent belonging to the European Monetary Union affects the price of food products. Specifically, we examine the food prices dynamics of two groups of countries. The first includes the group of countries that adopted the Euro currency in January 1999. The second is the group of European countries that have still not adopting the Euro. The aim is to try to identify whether different patterns can be observed for the two areas or, in other words, whether belonging to the European Monetary Union or operating under a different monetary regimes causes different patterns on relative food prices convergence.

Our model is anchored on the Law of One Price (LOP) and the Purchasing Power Parity (PPP). The LOP states that identical goods which are sold in different countries should have identical prices, once the prices are expressed in common currency units. PPP is the notion that this should hold, on average, across goods: similar baskets of goods should cost the same once expressed in common units.

PPP is one of the most extensively researched areas in international economics, as can be seen from Taylor and Taylor's survey (2004). We analyze the "strong" form of PPP, which is mainly based on the analysis of the nonstationary property of the real exchange rate, for a set of food prices collected for 19 European countries. They are taken from the Eurostat harmonized index of food consumer prices database for the period January 1996 and December 2008, and we specifically focus on the COICOP (Classification Of Individual COnsumption by Purpose) four digits food price indexes. Our approach, based on the method originally proposed in Pesaran (2007), computes a statistic $\bar{Z}$ for each food price index. This statistic is given by the proportion of countries for which we can reject the null hypothesis of no adjustment toward PPP for each of all possible $N(N-1)/2$ pairs of countries. It has the advantage of being invariant from base country effects and, more importantly, it provides a simple measure of the extent of convergence toward PPP for each group of countries and single products.

The previous analysis differs only marginally from previous studies that investigate the "strong" form of PPP (see Taylor and Taylor, 2004) and thus can only show the strength of convergence toward PPP. We propose taking the analysis of PPP further by asking which leading sources influence observed food prices convergence, or non-convergence, toward PPP. Following the emerging literature which decompose the dynamic of economic variables into common and idiosyncratic components (see Giannone *et al.* 2004, and more recently Boivin *et al.* 2008; 2009), we provide a methodology that allows one to investigate the impact of the two components on food price dynamics.

To be more precise, we assume the presence of a common component, mainly connected to macroeconomic shocks, that is not specific to a single country or a single product, but influences all prices series. The common component is estimated from a large set of consumer prices that includes more than one thousand of food and non food prices indexes. Since the macroeconomic shocks are common across products and countries, they do not average out and may become the dominant source of variation in food prices. Food prices will be also influenced by an idiosyncratic, i.e. country-specific, component that may be driven by the policies of the government of specific country and thus lead to different prices. Examples of this are tax changes, different institutional structures such as the wage-bargaining system, liberalisation measures and administrative price changes, or finally different exchange rate policies, as these are generally not of the same magnitude and timing across all area countries. This component is simply estimated as the difference between the single food price index and the common component.

Using the previous estimates we are able to measure the impact of the two components on the $\bar{Z}$ statistic. In synthesis, we find that the common component is the main determinant of PPP, while the country-specific effects play a much minor role.

We further analyze the half-life of the PPP deviations. The half-life is a simple measure of the speed of convergence toward PPP. In a survey Rogoff (1996) noted that the consensus estimate of the half-life tends to fall into the three to five years range. We show that the half-life for food products is much lower than the Rogoff's consensus estimates and, as before, this statistic depends on the relative impact of the common and idiosyncratic components on food prices.

A second strand of literature focus on cross-sectional aggregation of a large number of micro-units as the main determinant of the observed importance of common components in determining the dynamics of macrovariables, see Granger (1987), Forni and Lippi (1997) and for an interesting empirical analysis on German food prices v. Cramon-Taubadel *et al.* (2006). In synthesis these works have pointed out that is perfectly consistent that aggregate variables, rather than depending on all the corresponding microvariables, can be represented as driven by a relatively small number of common components plus an idiosyncratic component.

In the paper we will focus on the idea that food prices dynamics are affected by macroeconomics and country-specific shocks. However, the approximate factor analytic model that we will present in the next section is well suited for taking into account the possible presence of aggregation pitfalls, because it allows for cross-correlated idiosyncratic components, i.e it can accommodate a large amount of heterogeneity, while retaining a reasonably parsimonious parameterization, Forni and Lippi (1997).

The outline is designed as follows. Section 2 describes the methodology that we used. Section 3 presents the data and the empirical results. Section 4 contains some concluding comments.

Methodology

For each country $i = 1, 2, ..., N$, and observations $t = 1, 2, ..., T$, we define the logarithm of the food prices q_{it} in the currency 0 as

$$q_{it} = q_{0it} = e_{0it} + p_{it}, \tag{1}$$

where e_{0it} is the log of the nominal exchange rate (units of currency 0 per unit of currency i), and p_{it} is the log of food prices defined using the own currency i . We assume that the large set of observable food price series q_{it} is related to k common components or factors $F_t = \left(F_{1t}, \ldots, F_{kt}\right)'$, with $k < N$, as

$$q_{it} = d_i + \sum_{j=1}^{k} \lambda_{ij} F_{tj} + \varepsilon_{it} = d_i + \lambda_i' F_t + \varepsilon_{it}, \tag{2}$$

where d_i is a deterministic component, $\lambda_i = \left(\lambda_{i1}, \ldots, \lambda_{ik}\right)'$ indicates the vector of loadings and ε_{it} is an idiosyncratic, i.e. country-specific, component. Note that the right-hand side variables in (2) are not observable and only q_{it} is observable.

In classical factor analysis, see for example Anderson (1984), F_t and ε_{it} are mutually uncorrelated and independent and identically distributed (i.i.d.) sequences of random variables. Defining the $N \times T$ matrices $Q_t = \left(q_{1t}, ..., q_{Nt}\right)'$ and $V_t = \left(\varepsilon_{1t}, ..., \varepsilon_{Nt}\right)'$, from (2) we have that

$$E\left(Q_t Q_t'\right) = E\left(\lambda_i' F_t F_t' \lambda_j\right) + E\left(V_t V_t'\right) = \lambda_i' \Sigma_F \lambda_j + \Sigma_V, \tag{3}$$

i.e. in classical factor analysis the covariance $E\left(Q_t Q_t^{'}\right)$ between food prices only arises from the covariance of common factors, Σ_F , and from the factor loadings λ_i, given that the covariance of the idiosyncratic terms is, by assumption, the diagonal matrix Σ_V .

The approximate factor models (see Geweke, 1977; Chamberlain and Rothschild, 1983; Connor and Korackzyk, 1986; Forni *et al.* 2000; and Stock and Watson 2002), weaken the assumptions of F_t and ε_{it} are mutually uncorrelated and i.i.d. by allowing for weak cross sectional and temporal dependence in the series. The only constraint is that sample averages satisfy laws of large numbers with the same limits as those that would obtain in classical factor analysis.

There is a body of empirical evidence that the approximate factor model, with a small number of factors, captures the main comovements of macroeconomic time series data (see among others Stock and Watson 2002, Giannone *et al.* 2004 and more recently Boivin *et al.* 2008; 2009). Moreover, when *N* and *T* are large, the factor model (2) has proved useful because relatively simple methods can be used for estimation and inference. For example, simple penalized function as Akaike criteria can be used to consistently estimate the number of factors, (Bai and Ng, 2002), Principal Components can be used to consistently estimate factors (Stock and Watson, 2002), and finally the estimation error in the estimated factors is sufficiently small that it can be ignored., (Stock and Watson , 2002).

Thus equation (2) may be well suited for decomposing the fluctuations of each food price series into a common and a country-specific (idiosyncratic) component. In synthesis, the decomposition allow us to disentangle the fluctuations of food prices due to the macroeconomic factors, represented here by the common components F_t which may have a diffuse effect on all data series, from those due to country-specific conditions, represented by the term ε_{it} . Finally note that since F_t is a vector which may contain elements with very different dynamics and the vectors of loadings λ_i may differ across countries, each country-specific food price index may show different dynamics in its response to a common macroeconomic shock.

Interestingly, the decomposition (2) has been also used for the analysis of possible aggregation bias, Granger (1987), Forni and Lippi (1997) and v. Cramon-Taubadel *et al.* (2006). These works have pointed out that is perfectly consistent that aggregate variables, rather than depending on all the corresponding microvariables, can be mainly driven by a small number common components plus an idiosyncratic components. The approximate factor analytic model (2) can take into account the aggregation bias because it allows for cross-correlated idiosyncratic components, i.e it can accommodate a large amount of heterogeneity, while retaining a reasonably parsimonious parameterization, Forni and Lippi (1997).

Using (2) it is simple to write the relative food prices, i.e the real exchange rate between any pair of countries, r_{ijt}, for $i, j \neq 0$, as

$$r_{ijt} = q_{it} - q_{jt} = \left(d_i - d_j\right) + \left(\lambda_i - \lambda_j\right)' F_t + \left(\varepsilon_{it} - \varepsilon_{jt}\right). \tag{4}$$

Adherence to the PPP is tipically assumed to be satisfied if r_{ijt} is a stationary variable. Looking at (4) we can see that r_{ijt} is a stationary variable or, in other words, $q_{it} - q_{jt}$ are cointegrated variables with a cointegrating vector equal to $[1 \ -1]$, if either the common factors F_t are I(0), i.e they are stationary variables, or if F_t is nonstationary, i.e. $I(1)$, but $\left(\lambda_i - \lambda_j\right) = 0$ and the difference $\left(\varepsilon_{it} - \varepsilon_{jt}\right)$ is $I(0)$. Finally, r_{ijt} will be a stationary variable, if both F_t and $\left(\varepsilon_{it} - \varepsilon_{jt}\right)$ are I(1) and jointly cointegrated. In this case the difference between the idiosyncatric (country) shocks and the common factors follows a common trend in the long-run.

Thus equation (4) is a simple way of looking at the "strong" form of PPP.[1] Basically it states that if the common factors and the country-specific shocks are non stationary and non cointegrated, PPP will not hold because the common shocks have different impacts on r_{ijt}, i.e. $\lambda_i \neq \lambda_j$, and/or country-specific shocks have different impacts on the real exchange rate, i.e $\varepsilon_{it} \neq \varepsilon_{jt}$. In synthesis, the nonstationarity of the real exchange rate have by two different causes. One is connected to the common (macroeconomic) effects and the other to the country specific effects. The main task is thus to find a method that allows one for to disentangle the effects of the common and idiosyncratic components in determining (or not determining) the convergence of food prices toward PPP.

The most common test for PPP is the univariate *ADF* test. This regresses the first difference of r_{ijt} on a deterministic component its lagged level and m_{ij} lagged first differences,

$$\Delta r_{ijt} = \mu_{ij} + \rho_{ij} r_{ij,t-1} + \sum_{k=1}^{m_{ij}} \gamma_{ijk} \Delta r_{ij,t-k} + u_{ijt}. \tag{5}$$

The null hypothesis of nonstationarity of the real exchange rate r_{ijt} is rejected in favor of level stationarity if $\rho_{ij} < 0$. Note that using (4) we are able to compute $N(N-1)/2$ real exchange

[1] The "weak" form of PPP is usually investigated using cointegration analysis. It requires that $\left(q_{it} - \beta q_{jt}\right)$ is an I(0) variable and, differently from the "strong" form, it allows for $\beta \neq 1$, (see for example Ardeni , 1989; Goodwin , 1992; and Zanias , 1993). It is interesting to note that our methodology can be easily enlarged to study the "weak" form of PPP, i.e. the stationary properties of residuals from the cointegrating regression $\left(q_{it} - \beta q_{jt}\right)$.

rates, i.e we end with $N(N-1)/2$ *ADF* test statistics. Thus, also for a moderate number of countries as 11 (the number *N* of countries that we include in the Euro-zone area), we will end up with 55 *ADF* test values.

One way of synthetizing the large number of *ADF* test statistics is to adopt the pairwise approach recently proposed in Pesaran (2007), which is basically a vote-counting method. To be more precise, the method proposes defining a dicotomic variable Z_{ij} that will be equal to 1 if $ADF_{ij}\left(m_{ij}\right) \leq c_{\alpha}$, where c_{α} is the critical value of size α for the $ADF_{ij}\left(m_{ij}\right)$ test with m_{ij} lagged first differences, and 0 if $ADF_{ij}\left(m_{ij}\right) > c_{\alpha}$. This allows one to compute the fraction of the total $N(N-1)/2$ pairs for which the null unit root hypothesis in (5) is rejected as

$$\bar{Z} = \left[\frac{2}{N(N-1)} \sum_{i=0}^{N-1} \sum_{j=i+1}^{N} Z_{ij} \right]. \tag{6}$$

The $\bar{Z}$ statistics shows the proportion of pairs for which PPP holds. Given that $\bar{Z}$ ranges in the interval $[0,1]$, equation (6) supplies a simple number that measures the strongness of PPP across the food price indexes.

As shown in Pesaran (2007), $\bar{Z}$ can be also treated as a test statistic. From (6) we can infer that under the null hypothesis H_0, i.e. r_{ijt} is nonstationary, $\bar{Z}$ goes to α, that is the probability to reject the null-hypothesis when the null-hypothesis is true, as $T \rightarrow \infty$, and the variance goes to zero as N grows large. Thus when H_0 holds everywhere, we would expect $\bar{Z}$ to be close to the size of the test (in our case we use the 10% and 5% critical size). Otherwise, if the alternative H_A holds, i.e. PPP is true, then we would expect $\bar{Z}$ to be large and converging to 1 for N and T which grow large.

To investigate (5) we use not only the standard Dickey-Fuller *ADF* test but also the *ADF-GLS* test of Elliot *et al.* (1996) and the *ADF-WS* test of Park and Fuller (1995) as these have been shown to have more power than the standard *ADF*. We also provide the results for the set of unit root tests proposed by Ng and Perron (2001). These have been proved to have an exact size close to the nominal size even in the presence of large negative moving-average component. All these tests have the null of a unit root, i.e. nonstationarity of the process.

The introduction of Euro in January 1999 has clearly influenced the real exchange rates of the European countries. Starting from that date, for the group of Euro-area countries the nominal exchange rate e_{0it} in (1) is simply a constant variable. Thus we include a known break in (5), i.e we introduce an intercept dummy in (5) for capturing the Euro break in the series.[2] The reason is also that it is well known that not accounting for a break when it is actually present may result in a false acceptance of the nonstationary hypothesis, see Perron (1989b).

Let us assume now that we have a method, which we will explain soon, for estimating the common components $\hat{F}_t$ and the factor loading $\hat{\lambda}_i$ in (2). Thus we can compute a new real exchange rate which is net from the impact of common components. Specifically, using (2) and for each $i = 1, 2, ..., N$, we can easily write the food prices as

$$q_{it}^{*} = \left(q_{it} - \hat{\lambda}_t^{'}\hat{F}_t\right) = d_i + \varepsilon_{it}, \tag{7}$$

and the "defactored" real exchange rate as

$$r_{ijt}^{*} = \left(q_{it}^{*} - q_{jt}^{*}\right) = \left(d_i - d_j\right) + \left(\varepsilon_{it} - \varepsilon_{jt}\right). \tag{8}$$

Note that unlike (4), here the possible nonstationary of r_{ijt}^{*} can be only attributed to the difference between the idiosyncratic, i.e country-specific, components of food prices. Now can compute the unit root tests and the $\overline{Z}$ statistic for the defactored real exchange rate r_{ijt}^{*}. Looking at these new results, we will be able to show whether the proportion of stationary real exchange rates rises or not after the impact of the common components have been removed from equation (4). In other words, comparing the values of the $\overline{Z}$ statistic computed for the real exchange rates and the defactored real exchange rates allow us to highlight the relative importance of the common and individual countries internal differences in determining relative food prices convergence or divergence.

Now, we must provide a methodology to estimate first the number of common components k in (2), second the common component $\hat{F}_t$, and finally the factor loadings $\hat{\lambda}_i$. Some methods have been proposed in recent years. Stock and Watson (2002) and Bai and Ng (2006) showed that the Principal Components consistently recover the space spanned by the factors when *N* is large and the number of principal components used is at least as large as the true number of factors. This procedure has the advantages of being simple to compute and easy to implement, and there are also few distributional assumptions. It also allows for some degree of cross-correlation in the idiosyncratic error term ε_{it}. There are alternative strategies for estimating factor models with a large set of indicators exist (see Forni *et al.*, 2000). The evidence suggests that they perform similarly in practice (see for example D'Agostino and Giannone, 2006).

In order to estimate the number of common components k, we use the information criteria

[2]We also include a dummy for the slope but the results, available upon request, do not show appreciable differences from those of the pure intercept break case.

suggested by Bai and Ng (2002). These criteria are similar in spirit to the common AIC and BIC criteria for time series. Bai and Ng (2002) propose twelve different criteria for estimating the true number of factors. In the paper we adopt their IC criteria.[3] Specifically the method minimizes the following function

$$IC(k) = \min_{k}\left[ln(\hat{\sigma}_{\varepsilon}^{2}(k)) + k\left(\frac{ln(min(N,T))}{min(N,T)}\right)\right], \tag{9}$$

where $\hat{\sigma}_{\varepsilon}^{2}(k)$ is just the sum of squared idiosyncratic components in (2) , i.e

$$\hat{\sigma}_{\varepsilon}^{2}(k) = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(q_{it} - \lambda_{i}^{k'}F_{t}^{k}\right)^{2}. \tag{10}$$

The estimated common factors $\hat{F}_t$ is T times the eigenvectors corresponding to the k largest eigenvalues of $\left(Q_t^{'}Q_t\right)$, where $Q_t = \left(q_{1t},\ldots,q_{lt}\right)$, with $l = 1,...,N\times M$ and M the number of observed price series for each of the N countries. In practice, each columns of the matrix Q contains now T observations for the single price index l. The matrix of factor loadings Λ is computed as $Q_t^{'}\hat{F}_t / T^2$. Clearly, this is the method of principal components used for example in Connor and Korajczyk (1986) for large N but fixed T, and Stock and Watson (2002) for large N and large T.[4]

We also compute for each real exchange rate r_{ijt} and defactored real exchange rate r_{ijt}^{*} the half-life of a shock, in order to investigate possible differences of the speed of adjustment toward PPP across relative food prices. The half-life is defined as the number of periods required to a unit shock to the series to dissipate by half. Thus the half-life is a measure of the speed of convergence toward PPP. The apparently very slow speed of adjustment of real exchange rates has been the source of considerable theoretical and empirical research in recent years. Rogoff (1996) noted in a survey that the consensus estimate of the half-life tends to fall into the three to five years range. Once an estimate for $\hat{\rho}_{ij}$ has been obtained, the half life can be easily computed from (5) as

$$HL_{ij} = ln(0.5)/ln\left(1+\hat{\rho}_{ij}\right). \tag{11}$$

Note that (11) can be computed both for the real exchange rates as measured in (4) as well as the “defactored” real exchange rates in (8). Thus computing (11), we provide a method that allow to show in which measure the common component and the idiosyncratic component influence the

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[3] The twelve criteria usually give the same results, with the exception of the BIC criteria which on average detect a smaller number of factors. However the BIC criteria do not satisfy the consistency property, Bai and Ng (2002).

[4] Actually, given the possible nonstatio-rity of the variables in (2), we follow Bai and Ng (2004) and we estimate the factors from the (log) differenced price series. The level values of the factors $\hat{F}_t$ are recovered by integrating the estimated differenced factors $\Delta\hat{F}_t$.

speed of adjustments of food prices toward PPP. Interestingly, we find that the estimates of the half-life for the European relative food prices are much lower than Rogoff (1996)'s consensus. These values will be reported in the next section.

However, using $\bar{Z}$ is not without problems. The main one is that the single Z_{ij} entries in (6) are not, in general, independents. The dependence occurs because two pairs of entries, for example Z_{ij} and Z_{kj} with $i \neq k$, share the same country j in this case. As a result, the statistical distribution of the $\bar{Z}$ test may be altered by the cross-section dependence between the Z_{ij} outcomes. One method to overcome this problem is to study the empirical distribution of the $\bar{Z}$ test using a bootstrap method.

Specifically, we study the $\bar{Z}$ test distribution using the sieve bootstrap method proposed in Chang (2004) for studying unit root tests with the possible presence of arbitrary cross-sectional dependence. The procedure consists of the following steps

Step 1: We estimate for each country $i = 1, 2, ..., N$, the parameters $\hat{\alpha}_{li}$ for $l = 1, 2, ..., m$, and the residuals $\hat{u}_{it}$, using the following OLS autoregression

$$\Delta q_{it} = \hat{\alpha}_{1i} \Delta q_{it-1} + ... + \hat{\alpha}_{mi} \Delta q_{it-m} + \hat{u}_{it} \tag{12}$$

where q_{it} has been previously defined in (1).

Step 2: We generate the N-dimensional vector $\hat{u}_t^{(r)} = \left(\hat{u}_{1t}^{(r)}, ..., \hat{u}_{Nt}^{(r)}\right)'$ using the residuals estimates in Step 1 and resample the centered residual $\hat{u}_t^{(r)}$, i.e. we resample the vector $\left(\hat{u}_t^{(r)} - T^{-1} \sum_{t=1}^{T} \hat{u}_t^{(r)}\right)$.

Step 3: We now generate recursively, using the estimates $\hat{\alpha}_{li}$ for $l = 1, 2, ..., m$, the variable $\Delta q_{it}^{(r)}$ as

$$\Delta q_{it}^{(r)} = \hat{\alpha}_{0i} + \hat{\alpha}_{1i} \Delta q_{it-1}^{(r)} + ... + \hat{\alpha}_{mi} \Delta q_{it-m}^{(r)} + \hat{u}_{it}^{(r)} \tag{13}$$

Step 4 We obtain $q_{it}^{(r)} = q_{i0}^{(r)} + \sum_{m=1}^{t} \Delta q_{imt}^{(r)}$ with some initial value for $q_{i0}^{(r)}$ that can be shown (see Chang, 2004) does not affect the asymptotics, as long as it is bounded.

Step 5 We finally define the bootstrapped real exchange rates $r_{ijt}^{(r)}$ using (4) and compute the fraction of the pairs for which the null hypothesis is rejected by the *ADF-WS* test, using for example the 10% critical values and repeat steps 2 to 5 $r = 1000$ times.

The final results will be the empirical distribution of $\bar{Z}$ from which we recover the exact 10% and 5% critical values of the test statistic.

A second possible criticism of our analysis may be the small span of the data. The question whether univariate unit root tests based on quarterly or monthly data are more powerful than those based on the corresponding yearly data have been investigated by Shiller and Perron (1985) and Perron (1989a), among others. They find, using Monte Carlo simulations, that the power of the *ADF* tests depends more on the span of the data rather than on the number of observations. By contrast Choi and Chung (1995) show that using data with high sampling frequency can significantly improve the finite sample power of unit root tests. However if a researcher adopts a longer span of data in order to rise the power of unit root tests, for example using a century of annual data, this may give rise to other problems such as, for example, possible breaks in the data process. Thus such breaks may alter the results of unit root tests.

A possible way of raising the power of unit root tests with a short data span is to use panel unit root tests, (see for a recent survey Gutierrez, 2006). However if one uses panel unit root tests to investigate PPP one encounters the following problems. First, if a panel of data is used all real exchange rates must be measured in the same currency and thus the results will in general depend on the numerary currency used. Second, the null hypothesis of panel unit root tests is that all the series are nonstationary, and the alternative is that some of the series are stationary, i.e. for these series PPP holds. Thus, panel unit root tests do not provide information on how many series are stationary and how many are nonstationary. Using the $\bar{Z}$ statistic we are able to address this question.

Data statistics and empirical results

The availability and cross-countries comparability of the data meant that we had to to work with Eurostat consumer price data, which are a measure of the cost of goods and services as purchased by final consumers. These prices also include the margins charged by retailers and wholesalers at the various steps of the distribution process. This means that the consumer prices may not capture price dynamics at the production level properly. Unfortunately there are not farm prices databases that span a large number of products and countries as the consumer prices database supplied by the Eurostat does. However if shocks from farm prices are fully transmitted vertically to retail prices, i.e the margins are stable, then results on the relative convergence, or divergence, of consumer prices can be enlarged to include farm prices. Some studies have shown that in the long-run price transmission is perfect, and only in the short-run price adjustments between the farm and the retail levels are asymmetric (see v. Cramon-Taubadel, 1998; and Meyer and v. Cramon-Taubadel, 2004). Thus, if food margins are stationary, as it seems from the previous studies, our results may also be valid for farm prices.

To be precise we analyze real exchange rates obtained from the Eurostat dataset. We focus on the Harmonized Indices of Consumer Prices (HICP) for food products observed during the period

1996.1 - 2008.12. The HICP is based on national HICPs, which follow the same methodology in the whole European Economic Area. The present HICP index has a common index reference period set at 2005 = 100. [5] The list of products used in the analysis are printed in the following tables. The set of countries is: Belgium, Germany, Ireland, Spain, France, Italy, Luxembourg, Netherlands, Portugal, Finland, Austria, Latvia, Lithuania, Denmark, Poland, United Kingdom, Iceland, Sweden, Norway. We split this set of countries into two groups. The first group of eleven countries covers those that adopted the Euro currency in January 1999. The other is the group of non-Euro-zone countries.[6]

We start by showing the results of the proportion of pairs of real exchange rates for which the null hypothesis of nonstationarity can be rejected , i.e the $\bar{Z}$ statistical test values computed using (4). These are shown in Table 1. Due tolack of space, we only present the $\bar{Z}$ statistics for the *ADF-OLS*, *ADF-GLS* and *ADF-WS* tests. Similar values are obtained using the Ng and Perron (1997) tests. The lag orders p_{ij} in (5) are determined by the Schwarz Bayesian Criterion, and siimilar results are obtained using the Akaike Information Criterion.We set the nominal size of the tests at 10%.[7] Due the importance of the critical value in discriminating between non-stationary and stationary real exchange rates, for all tests the exact critical values for $T = 156$ have been computed using a Monte Carlo experiment with 100,000 rounds.[8] These values are available upon request.

Table 1 about here

Looking at Table 1, some interesting results emerge. We first note that the *ADF-OLS* $\bar{Z}$ statistics shows values that are always higher than 10% for the Euro-area countries. This means that PPP seems to hold for all consumer price indexes. The same results are obtained when using the *ADF-GLS* test, with the exception of the Bread and Cereals index that shows a value of 9.1%, i.e in this case we cannot reject the null hypothesis of non convergence toward PPP. The *ADF-WS* is more restrictive with respect to the evidence of convergence toward PPP. The test statistics show

[5] For a deeper analysis on HICP indexes see Diewert (2002).
[6] In the paper we provide the test results for the seasonally unadjusted series. Similar results are obtained when focusing on seasonal adjusted price series.
[7] The following results do not depend on the nominal size of tests. Using the 5% nominal size, we find that set of products for which we have relative food prices convergence toward PPP is the same. These results are available upon request.
[8] The data process in Monte Carlo analysis has been generated from $y_t = (1-\rho)\mu + \rho y_{t-1} + \sum_{i=1}^{p} \Delta y_{t-i} + \nu_t$, with ν_t i.i.d. $N(0,1)$ and for each $p = 1,...,12$, $t = -51,-50,...,T$. The random numbers ν_t are generated using the GAUSS routine. The size (under the null $\rho = 1$) of the tests are computed at the 5% and 10% nominal level.

that well 8 out of 11 indexes have a value lower than 10%. Thus this test clearly does not reject the null hypothesis of non-convergence toward PPP for the analyzed food prices. Looking at the full set of indexes, Fruit and Vegetables prices have the highest values of the $\bar{Z}$ statistics values, at well above 40% for all tests. Looking at the same $\bar{Z}$ values for the non-Euro area countries, we first note that there is a lower rate of convergence toward PPP than the Euro-zone countries. A higher $\bar{Z}$ statistic value is noted only for a limited number of non-Euro food indexes. In synthesis, we find that on average food prices in the Euro-zone seem to be more closer than food prices in the non-Euro-zone countries. Are these findings related, for example, to the common currency adopted by the group of Euro-zone countries and the common monetary policies adopted by the European Central Bank? At the moment, we can only speculate on this. Some further insights may be obtained by estimating the common and idosyncratic components of food prices.

As previously seen, these components are computed using the Principal Component method to a set of consumer price indexes that includes both food as well non-food prices series. The set is composed by 119 HICP indexes. The common component is computed for both for the Euro-zone and the non-Euro-zone countries. In detail, the factor components for the group of Euro-zone countries are extracted from a panel of 1309 single price series (109 indexes for 11 countries), while for the group of non-Euro countries the panel consists of 952 indexes (109 indexes for 8 countries). The number of factors were chosen using the criteria (9) and allowing for a maximum number of 5 factors. For both group of countries Bai and Ng's (2002) *IC* criteria propose 3 factors for both group of countries.

The importance of the common component in explaining food price dynamics is highlighted in Table 2, where we present the R^2 statistic which measures the fraction of the variance of food prices explained by the common component $\hat{\lambda}_i'\hat{F}_t$. We note that this component accounts on average for 86% of variance of food prices in the Euro-area. This suggests that only 14% of the monthly disaggregated food prices fluctuations are attributable to country-specific disturbances. By contrast the common component exerts a minor role and the idiosyncratic component a higher effect in the non-Euro-area. In this case the common component accounts on average for 78% of the variance of food prices and the idiosyncratic component accounts for the remaining 22%.

Table 2 about here

To investigate the degree of persistence, i.e. nonstationarity, of each component we fit, for each price series q_{it} and each of its components, $\hat{\lambda}_i'\hat{F}_t$ and $\hat{\varepsilon}_{it}$, an autoregressive process with 12 lags of the form,

$$x_t = \rho(L)x_{t-1} + \nu_t, \tag{14}$$

and we compute as measure of persistence the sum of the coefficients on all lags, i.e $\rho(1)$. [9]As expected price persistence is high, with a coefficient near 1 for all the food price series. Looking at the two components, on average the common factors $\hat{\lambda}_i'\hat{F}_t$ ae more persistent than the idiosyncratic component $\hat{\varepsilon}_{it}$, that is the main determinant of the nonstationarity of food prices comes from the common component while the idiosyncratic component plays a minor role.

Thus it is useful to analyze what happens if we remove the common component $\hat{\lambda}_i'\hat{F}_t$ from each food priceseries and compute the $\bar{Z}$ test statics for the "defactored" real exchange rate r_{ijt}^* presented in (8). The results are shown in Table 3. Observing the average value for the Euro-zone countries of the *ADF-WS* $\bar{Z}$ statistic, we note that the value rises from 16.6%, when food prices are non corrected for the common component, to 46.0% when the food prices are corrected for the common component. In the case of non-Euro countries, these values are respectively 10.5% and 60%. It is interesting to see that now all the $\bar{Z}$ statics are well above the nominal 10% critical value. As we have seen, given the general nonstationarity of the common factor components, this means that the common components $\hat{F}_t$ have different impacts on r_{ijt} across countries, i.e. from decomposition (4) we have that $\lambda_i \neq \lambda_j$, and this induces nonstationarity of real exchange rates or, in other words, non convergence of relative food prices. Thus, if we substract this component from food prices, leaving only the country-specific shocks, the probability that PPP holds increases enormously.

Table 3 about here

As stated in the methodology section, the results may be affected by the possible cross-section dependence of the test outcomes. Because of this we study the empirical distribution of the $\bar{Z}$ test using a bootstrap method. For convenience in the first column of Table 4, we report the previously presented values of the *ADF-WS* $\bar{Z}$ statistics computed for the Euro-area countries. In the second

[9] A value of $\rho(1)$ closes to the unity means that the variable is nonstationary.

column, we report the 10% quantile of the test distribution computed using the sieve bootstrap method.[10] We first note that the empirical 10% rejection rate is usually higher, with an average value of 15%. This means that an higher rejection rate is required to reject the null hypothesis of nonstationarity. Using the bootstrapped critical values only four products, specifically Fruits, Vegetables, Coffee, Tea and Cocoa and Wine have a value of the $\bar{Z}$ statistics well above the critical values. In case of Meat the $\bar{Z}$ test statistic is equal to the critical value. The previous procedure has been also applied to the "defactored" r_{ijt}^{*}. The 10% bootstrapped critical values is quite similar to the previous critical values, with an average of 14%. Note that in this case all the $\bar{Z}$ statistics are well above both the nominal as well as the bootstrapped critical values and this reinforce the conclusion that the main determinant of the nonstationarity of the relative prices comes from the different impact exerted by the common component on food prices.

Table 4 about here

In table 5, we finally show the median half-life for each food item using (11). We present the values computed using the $ADF-WS\left(\hat{\rho}_{ijt}\right)$ estimates. Similar values were obtained using the $ADF-OLS$, and $ADF-GLS$ estimates. We present both the median half-life values computed from the full of set of pairs r_{ijt} and for the set of pairs r_{ijt} for which we reject the null hypothesis of unit roots, i.e. the PPP holds. The results show that adjustment after a shock is rapid. If we use all the pairs r_{ijt}, on average the median half-life is around one year and half for the Euro-area countries and only one year for the non-Euro-area countries. These values decrease to six/seven months if we only consider the stationary pairs. Thus aggregate shocks, i.e. macroeconomic shocks, have a long lasting effects on food prices convergence toward PPP. Country-specific shocks are recovered in a minor number of months. However, the median half-life estimates are lower than those reported in Rogoff (1996) who found that the consensus estimate of the half-life tended to fall into the three to five years range. Thus food prices adjustment is more rapid than previously expected.

Table 5 about here

[10] We also compute the bootstrapped critical values for the set of non-Euro countries. The results are similar to those presented and they are available upon request.

Conclusion

In this paper, we analyze the behaviour of relative food prices in 19 European countries observed during the period 1996.1 - 2008.12. We split the countries into two subgroups. The first is the group of 11 countries that adopted the Euro in January 1999. The second group is made-up of non-Euro countries. Some interesting results seem to emerge from the analysis. First, we find that relative consumer food prices convergence varies across products and European countries. Euro-zone countries have a higher rate of convergence than non-Euro-zone countries. Second, we find evidence that consumer prices are mainly characterized by a common component, which accounts for a large share of their variance. The importance of the common component is more pronounced for the set of countries included in the Euro-area. Third, both the common and the idiosyncratic components explain relative food price convergence across countries and products, but it seems that the different impacts of the common component are the main reasons for the lack of PPP. Finally we find that the half-live of a shock on relative food prices varies between products, and the adjustment is generally faster than that usually reported in literature.

From the previous analysis we may arrive at the following picture. During the last thirteen years the Euro-zone countries have shown a higher rate of convergence of food prices toward PPP than non-Euro-zone countries. Moreover our analysis suggests that this is mainly related to the effects of an unobserved and nonstationary common component. Interestingly, if we remove the effect of the common component from food prices, i.e we focus only on country-specific effects, we end up with a similar picture in the Euro and non-Euro area, i.e. the relative food price convergence is quite similar for both the group of countries.

In synthesis, our results highlight that the common component, which may be connected to macroeconomic shocks, is much more important than the idiosyncratic component, i.e. the country-specific shocks, in determining PPP and the speed of convergence toward PPP. Whether or not the common component is driven by policies such as the Single Market Program and/or the common monetary policy of the European Central Bank is an open question. Our next research will be into whether the above-mentioned or other macroeconomic variables are the underlying common component. Bai (2004) has proposed some interesting inferential theory on this. The present paper may be considered a first step in this direction.

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Table 1 Fraction of pairs of real exchange rates for which the null hypothesis of unit root is rejected at 10% significance level
1996.1-2008.12

Harmonized indices of consumer prices (HICP)		Euro countries			Non-Euro countries		
		ADF OLS	ADF GLS	ADF WS	ADF OLS	ADF GLS	ADF WS
CP0111	Bread and cereals	10.9	9.1	5.5	7.1	7.1	0.0
CP0112	Meat	18.2	16.4	14.6	14.3	32.1	14.3
CP0113	Fish and seafood	27.3	40.0	27.3	3.6	17.9	3.6
CP0114	Milk, chease and eggs	10.9	16.4	5.5	10.7	14.3	3.6
CP0115	Oil and fats	18.2	18.2	9.1	3.6	7.1	0.0
CP0116	Fruit	47.3	54.6	45.5	28.6	25.0	25.0
CP0117	Vegetables	54.6	52.7	52.7	35.7	46.4	42.9
CP0118	Sugar, jam, honey, chocolate and confectionery	12.7	18.2	5.5	10.7	14.3	3.6
CP0119	Food products n.e.c.	14.6	16.4	9.1	7.1	17.9	10.7
CP0121	Coffee, tea and cocoa	18.2	20.0	27.3	14.3	10.7	14.3
CP0122	Mineral waters, soft drinks, fruit and vegetable juices	23.6	25.5	9.1	3.6	7.1	0.0
CP0211	Spirits	12.7	12.7	0.0	7.1	14.3	7.1
CP0212	Wine	16.4	27.3	18.2	21.4	17.9	17.9
CP0213	Beer	18.2	18.2	3.6	10.7	10.7	3.6
	Max Z values	54.6	54.6	52.7	35.7	46.4	42.9
	Min Z values	10.9	9.1	0.0	3.6	7.1	0.0
	Mean Z values	21.7	24.7	16.6	12.8	17.3	10.5
	Std. Deviation Z values	13.3	14.3	16.1	9.7	10.9	12.0

Data Source: Eurostat

Table 2 Persistence (*) of log food prices - 1996.1 – 2008.12

Harmonized indices of consumer prices (HICP)		Euro countries				Non-Euro countries			
		R^2(**)	Persistence			R^2(**)	Persistence		
			Food Price	Common Component	Country Specific		Food Price	Common Component	Country Specific
CP0111	Bread and cereals	0.97	1.00	1.00	0.86	0.84	0.96	1.00	0.80
CP0112	Meat	0.90	1.00	1.00	0.85	0.77	0.95	0.99	0.79
CP0113	Fish and seafood	0.95	0.99	1.00	0.85	0.93	0.98	0.99	0.83
CP0114	Milk, chease and eggs	0.88	1.00	1.00	0.86	0.85	0.98	1.00	0.82
CP0115	Oil and fats	0.79	1.00	1.00	0.90	0.77	0.97	1.01	0.82
CP0116	Fruit	0.82	0.98	1.00	0.81	0.79	0.97	1.00	0.68
CP0117	Vegetables	0.67	0.97	1.00	0.69	0.58	0.95	1.01	0.71
CP0118	Sugar, jam, honey, chocolate and confectionery	0.95	1.00	1.00	0.84	0.82	0.96	1.00	0.83
CP0119	Food products n.e.c.	0.95	1.00	1.00	0.86	0.81	0.96	1.00	0.78
CP0121	Coffee, tea and cocoa	0.71	0.97	0.99	0.82	0.59	0.95	1.00	0.89
CP0122	Mineral waters, soft drinks, fruit and vegetable juices	0.84	0.99	1.00	0.85	0.83	0.98	1.02	0.80
CP0211	Spirits	0.90	1.00	1.00	0.87	0.75	0.95	0.98	0.80
CP0212	Wine	0.79	0.98	1.00	0.87	0.83	0.97	1.00	0.81
CP0213	Beer	0.92	1.01	1.00	0.79	0.77	0.97	1.00	0.78
	Mean	0.86	0.99	1.00	0.84	0.78	0.96	1.00	0.80
	Std. Deviation	0.09	0.01	0.00	0.05	0.09	0.01	0.01	0.05

(*) Persistence is based on estimated AR processes with 13 lags.

(**) R^2 statistics measure the fraction of the variance of food prices explained by ($\lambda_i F_t$).

Data Source: Eurostat

Table 3 Fraction of pairs of defactored real exchange rates for which the null hypothesis of unit root is rejected at 10% significance level - 1996.1-2008.12

Harmonized indices of consumer prices (HICP)	Euro countries			Non-Euro countries		
	ADF OLS	ADF GLS	ADF WS	ADF OLS	ADF GLS	ADF WS
CP0111 Bread and cereals	60.0	74.6	50.9	85.7	78.6	75.0
CP0112 Meat	61.8	74.6	58.2	71.4	85.7	60.7
CP0113 Fish and seafood	60.0	69.1	54.6	71.4	92.9	57.1
CP0114 Milk, chease and eggs	65.5	76.4	36.4	64.3	85.7	60.7
CP0115 Oil and fats	41.8	47.3	29.1	82.1	85.7	71.4
CP0116 Fruit	85.5	85.5	81.8	82.1	89.3	78.6
CP0117 Vegetables	67.3	85.5	63.6	78.6	89.3	78.6
CP0118 Sugar, jam, honey, chocolate and confectionery	41.8	65.5	34.6	71.4	82.1	53.6
CP0119 Food products n.e.c.	52.7	58.2	40.0	82.1	85.7	71.4
CP0121 Coffee, tea and cocoa	87.3	92.7	69.1	82.1	85.7	64.3
CP0122 Mineral waters, soft drinks, fruit and vegetable juices	45.5	58.2	36.4	85.7	92.9	46.4
CP0211 Spirits	41.8	58.2	27.3	71.4	78.6	39.3
CP0212 Wine	38.2	56.4	25.5	50.0	78.6	32.1
CP0213 Beer	49.1	67.3	36.4	67.9	75.0	50.0
Max Z values	87.3	92.7	81.8	85.7	92.9	78.6
Min Z values	38.2	47.3	25.5	50.0	75.0	32.1
Mean Z values	57.0	69.2	46.0	74.7	84.7	59.9
Std. Deviation Z values	15.7	13.1	17.3	9.9	5.5	14.5

Data Source: Eurostat

Table 4 Bootstrapped fraction of rejections Euro-area countries - ADF-WS test
1996.1-2008.12

Harmonized indices of consumer prices (HICP)		Non Defactored		Defactored	
		Point Estimate	Bootstrapped 10%	Point Estimate	Bootstrapped 10%
CP0111	Bread and cereals	5.5	16.4	50.9	14.6
CP0112	Meat	14.6	14.6	58.2	14.6
CP0113	Fish and seafood	27.3	14.6	54.6	16.4
CP0114	Milk, chease and eggs	5.5	16.4	36.4	10.9
CP0115	Oil and fats	9.1	16.4	29.1	12.7
CP0116	Fruit	45.5	14.6	81.8	16.4
CP0117	Vegetables	52.7	16.4	63.6	14.6
CP0118	Sugar, jam, honey, chocolate and confectionery	5.5	12.7	34.6	16.4
CP0119	Food products n.e.c.	9.1	16.4	40.0	12.7
CP0121	Coffee, tea and cocoa	27.3	14.6	69.1	14.6
CP0122	Mineral waters, soft drinks, fruit and vegetable juices	9.1	18.2	36.4	12.7
CP0211	Spirits	0.0	16.4	27.3	12.7
CP0212	Wine	18.2	12.7	25.5	12.7
CP0213	Beer	3.6	16.4	36.4	14.6

Data Source: Eurostat

Table 5 Median half-life values (months) - ADF WS test - 1996.1 - 2008.12

Harmonized indices of consumer prices (HICP)	Non Defactored				Defactored			
	Euro-Area countries		Non-Euro-Area countries		Euro-Area countries		Non-Euro-Area countries	
	(*)	(**)	(*)	(**)	(*)	(**)	(*)	(**)
CP0111 Bread and cereals	33.0	5.0	-	-	6	3	10	4
CP0112 Meat	22.0	6.0	9	4.5	8	4	7	4
CP0113 Fish and seafood	9.0	5.0	12	5	6	3	6	4
CP0114 Milk, chease and eggs	25.0	4.0	13	7	6	3	6	4
CP0115 Oil and fats	20.5	5.0	-	-	12	3	5.5	4
CP0116 Fruit	9.5	3.0	18	4	6	2	2.5	2
CP0117 Vegetables	6.0	3.0	8.5	3	2	1	3.5	2
CP0118 Sugar, jam, honey, chocolate and confectionery	23.5	6.0	15	4	6	3	7	4
CP0119 Food products n.e.c.	17.5	9.0	10	10	7	3	7.5	4
CP0121 Coffee, tea and cocoa	12.5	9.0	11.5	4.5	7	3	6.5	3
CP0122 Mineral waters, soft drinks, fruit and vegetable juices	20.0	6.0	-	-	8	4	6	4
CP0211 Spirits	-	-	15.5	8.5	7.5	3	7	4
CP0212 Wine	16.0	6.0	12	8	9	4.5	7	4
CP0213 Beer	22.0	8.0	10	6	5	3	6	3
Max Z values	33.0	9.0	18.0	10.0	12.0	4.5	10.0	4.0
Min Z values	6.0	3.0	8.5	3.0	2.0	1.0	2.5	2.0
Mean Z values	18.2	5.8	12.2	5.9	6.8	3.0	6.3	3.6
Std. Deviation Z values	7.5	2.0	3.0	2.2	2.2	0.8	1.8	0.8

(*) Median half-life values for the full set of pairs.

(**) Median half-life values for the set of pairs for which the test is able to reject the null of a unit root.

Data Source: Eurostat