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Food Inflation in EU: Distribution Analysis and Spatial Effects

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In the European Union homogenous inflation forces are expected to prevail due to the increased economic integration, especially after the creation of the single currency area. This expectation is directly related to the issue of inflation convergence which has gained increasing attention by both academia and policy makers in Europe. While the examination of the core inflation is of great importance for macroeconomic policy, the prominent role of disaggregate inflation indices and especially food inflation has been also frequently emphasized in the literature. However, the issue of food inflation convergence has been largely ignored in empirical studies. This study explores the evolving distribution of the food inflation rates in the EU-25 member states, using the distribution dynamics analysis and covering the period from January 1997 to March 2011. This analysis rests on the assumption that each country represents an independent observation which provides unique information that can be used to estimate the transition dynamics of inflation. However, we show that inside EU-25, spatial autocorrelation prevails and therefore, the independency assumption is violated. To insure spatial independence, the Getis spatial filter is implemented prior to the distribution dynamics analysis. The results of the analysis confirm the existence of convergence trends which are even more clear after the spatial filtering procedure, indicating, on the one hand, the influence of spatial effects on food inflation and, on the other hand, the effectiveness of Getis spatial filtering.

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Introduction

The issue of inflation convergence has recently gained attention due to its importance in monetary unions, for the design of regional policies and for the assessment of the regional effects of trade and growth. In the case of the European Union, homogenous inflation is expected to prevail due to the increased economic integration, the formation of a single market and the formation of the single currency area.

In the long-run, inflation - as a monetary phenomenon - is determined by money supply changes. In the short-run, however, and until the full impact of such changes is felt, other forces may also play a role, especially for small range changes of the price index. Such forces can be used to explain, at least partially, longer term inflation rate differentials (Liontakis and Papadas, 2010).

The empirical studies on inflation convergence literature explore this issue among different regions of a country[1] or inside a cluster of countries as the members of the EMU and the new EU member states[2]. However, according to Lünnemann and Mathä (2004), even though the available international evidence focuses mainly on core inflation, the usage of more disaggregated inflation indices may prove a useful complement in identifying the key drivers of aggregate inflation persistence. A disaggregate analysis may uncover inflation persistence differences and allow their categorization according to sectors. Moreover, several authors provide evidence that core inflation persistence is predominantly driven by the most persistent disaggregate inflation components (e.g., Beck, Hubrich and Marcellino, 2009; Zaffaroni, 2004).

[1] e.g. Nagayasu, (2012); Yilmazkuday, (2009); Roberts, (2006); Cecchetti, Mark and Sonora (2002).
[2] e.g. Lopez and Papell, (2010); Busetti et al., (2007); Weber and Beck, (2005); Holmes, (2002); Kocanda and Papell, (1997).

In the above context, the examination of a disaggregated inflation index like the food inflation index is of great interest. Moreover, food inflation presents some special characteristics that make its examination even more important. As Walsh (2011) emphasizes, food inflation is in many cases more persistent than nonfood inflation, and food inflation shocks in many countries are propagated strongly into nonfood inflation. Under these conditions, and particularly given high global commodity price inflation in recent years, a policy focus on core inflation may be highly misleading and suffering by severe lags in policy responses.

The food price spike preceding the 2008 global financial crisis set off a number of studies on the role of food price inflation in the development of monetary policy. Catão and Chang (2010) point out the distinctive role of food in household utility and claim that the presence of high food price volatility may have important implications for the welfare effects of different monetary policy regimes. Moreover, as Anand and Prasad (2010) conclude, in an environment of credit-constrained consumers, a narrow policy that ignores food inflation can lead to suboptimal outcomes.

Several authors provide possible explanations for the food inflation differentials inside EU. Fousekis (2008) points out the fragmentation of the European market and claims that inflation rate differentials are not efficiently confronted by horizontal EU measures but by changes in countries' market structures. Altissimo, Benigno and Palenzuela (2011) emphasize the importance of different responses of EU countries to common, Euro-area shocks. Similarly, Bukeviciute, Dierx and Ilzkovi (2009) argued that food price inflation differentials are caused by the different ways and degrees in which the food supply chains of member states absorb external shocks such as the rapid increase of energy prices. This, in turn, occurs due to different food market structures and regulatory frameworks across EU. In this sense food price inflation differentials are a signal that the EU food market still remains fragmented. Finally, Dalsgaard (2008) and Beck, Hubrich and Marcellino (2009) emphasize the role of market concentration, mergers & acquisitions, and cartel formations on inflation rate differentials.

A common way to examine the hypothesis of a homogeneous inflation trend is the examination of inflation convergence. A large part of the empirical studies on this issue follows the introduction and development of quantitative methods in the area of economic growth and convergence (Liontakis, 2012; Liontakis and Papadas, 2010). Consequently, the concepts of stochastic convergence and σ-convergence have dominated the relevant literature (e.g. Lopez and Papell, 2010; Kutan and Yigit, 2005; Holmes, 2002; Kocenda and Papell, 1997).

Recently, another methodological tool, the distribution dynamics analysis, also borrowed from the economic growth literature, has been introduced in the analysis of inflation rates convergence (see Nath and Tochlov, 2012; Cavallero, 2011; Weber and Beck, 2005). Following these studies, we implement the distribution dynamics analysis on food price inflation rates of the member states of EU-25. However, in our study this analysis is highly differentiated as it takes under consideration the effect of spatial autocorrelation. According to Anselin (1988), the existence of spatial dependence may lead to important distortions as it can invalidate the inferential basis of traditional statistics and econometric methods since the assumption of observational independence no longer holds (Anselin, 1988). In the analysis of inflation convergence, this issue has not yet gained any attention[3]. In this study, we control spatial autocorrelation using the Getis filtering approach (see Getis 1995), which is based on the local spatial autocorrelation statistic G_i (see Getis and Ord 1992).

Data used consist of monthly observations of the absolute food inflation deviation from the mean (based on the Harmonized Indices of Consumer Prices - HICP - for the "food and non-alcoholic beverages" index) and covers the period from January 1997 to March 2011. The examination of the evolving distribution dynamics is conducted using a kernel density estimator that has been proposed by Hyndman, Bashtannyk and Grunwald (1996). This estimator was firstly introduced in the growth and income convergence literature by Arbia, Basile and Piras (2005) and thereafter, several empirical studies have been based on this estimator.

Studies on Food inflation convergence

Despite of its importance, the issue of food inflation convergence has been largely ignored in the relevant literature. In the few studies that examines this issue, the analysis is narrow and the results are just presented without any further interpretations. Weber and Beck (2005), examined the inflation convergence in two samples of European countries. For this purpose, they used Harmonized Indices of Consumer Prices of the total price index as well as for 12 sub-indices. Although β-convergence was found for the "food and non-alcoholic beverages" index, it was slower for the period after the introduction of the common currency, implying the existence of non-linearities in the convergence process.

Dayanandan and Ralhan (2005), find evidence of β-convergence for the food price index in

[3] According to our knowledge, the role of space has been acknowledged in two studies. Vaona and Ascari (2010) explore the regional patterns of inflation persistence in Italy showing that inflation persistence at the national level does not present any geographical aggregation bias. Additionally, Ailenei and Cristescu (2010), show how the food prices in Romania are spatially associated.

Canada, using panel unit roots tests. Sturm et al. (2009) estimate σ-convergence and β-convergence for the consumer price indices of several commodity groups - including food commodities - and for different groups of European countries. Their results vary considerably on the type of convergence explored (β-convergence or σ-convergence), on the countries that consist of the groups (EMU members or non-EMU members) and on the time period under investigation.

In the study of Fan and Wei (2006), panel unit root tests are used to study convergence of the food price inflation rates across 36 major Chinese cities and over a seven-year period. The authors find contradictory results on β- convergence, depending on the panel unit root test implemented and the time lag selection model.

Liontakis and Papadas (2010) investigated the existence of inflation rate convergence in the EU-15 from 1997 to 2009, using the stochastic convergence analysis and the distribution dynamics approach. Their study refers to the “food and non-alcoholic beverages” product group as well as to eleven food product subgroups. Parametric analysis indicates no stochastic convergence for the “food and non-alcoholic beverages” group and for almost all food product subgroups. Opposed to the parametric results, the general finding of the nonparametric distribution dynamics analysis is that food inflation tends to move backwards to the mean. Similarly, Liontakis (2012) examines the mean reversion attitude of food price inflation rates in the Eurozone, using distribution dynamics analysis and panel unit root tests. Mean reversion shows up in different time periods and in different food groups. Moreover, the analysis of distribution dynamics sheds light to different aspects of convergence and highlights processes like club formation and polarization.

Data, Variables, and Some Descriptive Statistics

Annualized inflation rates at time t (π_t) are estimated as annual percentage changes of the harmonized consumer price index at time t (P_t) as follows:

$$\pi_t = 100(\ln P_t - \ln P_{t-12}) \qquad (1)$$

Absolute food inflation deviation from the mean (x_t) is estimated as:

$$x_t = | \pi_t - \overline{\pi}_t | \qquad (2)$$

where $\overline{\pi}_t$ represents the average inflation of the EU-25 countries. Table 1 provides the mean and standard deviation for x_t. Moreover, it provides the relative ranking of each country based on its mean absolute food inflation deviation value throughout the period under investigation. Countries are presented in this table according to their relative ranking. On average, Hungary and Lithuania have the greatest absolute food inflation deviations from the mean during the period under investigation, while Belgium, Austria, Denmark and Luxemburg have the lowest. The high standard deviation values reflect the great volatility of x_t.

To get a clearer picture on the evolving distributions of x_t, we further investigate two sub-periods; before and after the EU enlargement. While the countries that possess the lower and higher relative rankings have a similar ranking position in both sub-periods, this is not true in all cases. The most intense changes occurred in two east European economies, namely Slovenia and Latvia that jumped 15 places back and 17 places forth in the relative ranking, respectively. Other prominent ranking differences among the two subperiods are France and Finland that rank 1st and 5th after the EU enlargement, respectively.

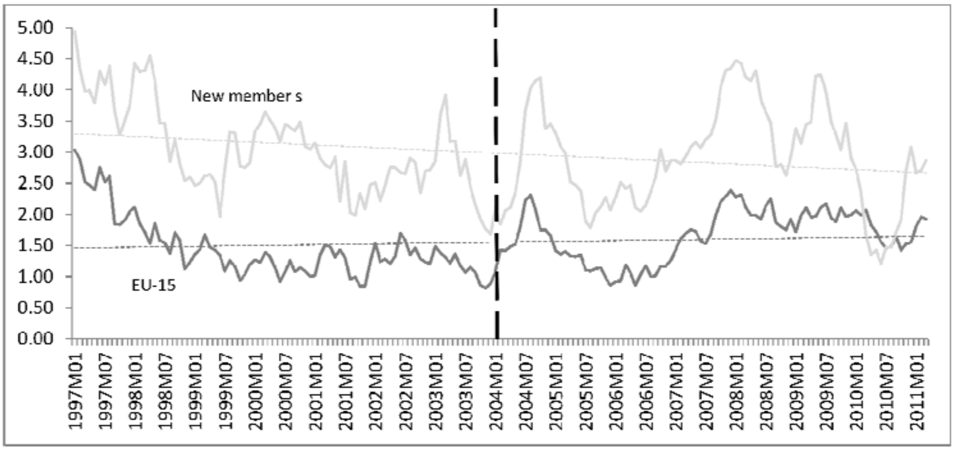

Figure 1. Evolution of absolute food inflation deviation from the mean

Additionally, Fig. 1 presents the evolution of x_t for the EU-15 and the new member states and gives an idea of possible spatial effects in EU-25 countries regarding this variable. Until 2004, there was a clear trend of reduction of the absolute deviation from the mean, especially for the new member states, mainly due to their efforts to fulfill the EU entrance criteria. After that, peaks and troughs appear in the evolution of absolute deviation, which ends up in a higher level at 2011.

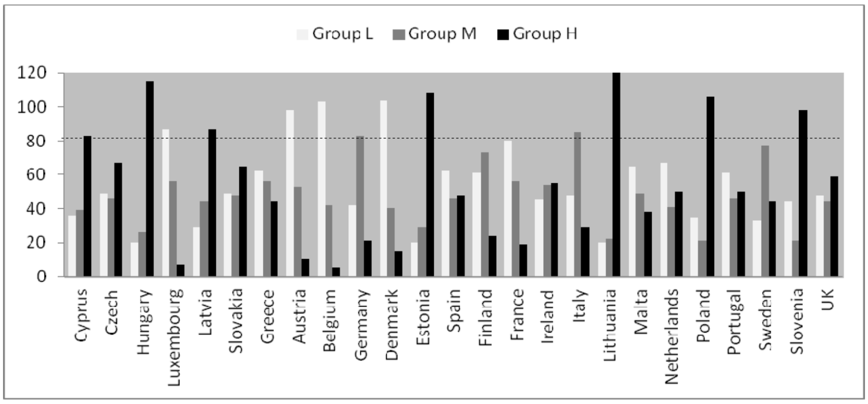

Figure 2. Frequency of inclusion in the L, M and H food inflation groups.

The volatile nature of absolute food inflation deviation is also revealed in Fig. 2. Three groups of absolute food inflation deviation were constructed according to the relative ranking of each country at each month. Groups L and H (low and high group) include the first and last 8 countries in the relative ranking, respectively, while group M (medium group) includes the rest 9 countries (9^{th} to 17^{th} position). The frequency of inclusion in each group shows that many East-European countries like Hungary, Latvia and Estonia are usually placed in the high absolute inflation deviation group. On the other hand, some core European countries like Austria, Belgium and Luxemburg are usually placed in the low absolute inflation deviation group.

The above descriptive statistics reveal the high degree of complexity of the data. Beyond economic policies (common or less common), country-specific and product-specific factors may contribute to the observed food inflation "heterogeneity" among countries. Moreover, strong indications of spatial associations are identified, especially for the groups of East European and core European member states.

Methodology

The indications of spatial association that stems from the descriptive statistics can be further explored using the Getis local $G_i(d)$ index. $G_i(d)$ is the spatial autocorrelation statistic of Getis and Ord (1992), which is defined as:

$$G_i(d) = \sum_{j=1}^{n} w_{ij}(d)x_j \Big/ \sum_{j=1}^{n} x_j \quad \text{for } j \neq i \tag{3}$$

where $w_{ij}(d)$ are the binary elements of the spatial weight matrix that takes value one for all features being within distance *d* of a given feature *i*, and zero otherwise. The numerator in (3), is the sum of all features' x that are located inside a radius *d* from feature *i* (except *i* itself). The denominator in equation (3) is the sum of all features' x.

Therefore, this statistic shows whether features with either high or low values cluster spatially, within a radius of length d from point i (spot). A feature with a high/low value that is also surrounded by other features with high/low values is called a hot/cold spot. When the local sum is much different than the expected local sum[4] and the difference is too large to be the result of random chance, a statistically significant Z score comes up[5].

In our study, spatial dependence may arise from a variety of measurement problems, as well as interactions or externalities across countries such as trade. These factors could be a major source of violation of the independence assumption (Fischer and Stumpner, 2010). Apart from any specific reasons, a violation of the independence assumption may result in misguided inferences and interpretations (Anselin, 1988).

A spatial filter can be used to transform a spatially autocorrelated variable into an independent variable by removing the spatial dependence embedded in it. The original variable, x, is hence partitioned into two parts, a filtered non-spatial variable ($\tilde{x}$) and a residual (Getis, 1995). A commonly used spatial filter is the Getis filter which is used to separate spatial effects from the variable's total effects. By insuring spatial independence, it allows us to use the stochastic kernel to properly estimate the underlying food inflation distribution and to analyze its evolution over time.

The value of d should represent the distance within which spatial dependence is maximized The approach to identify the appropriate distance d is based on finding the value of d that corresponds to the maximum absolute sum of the normal standard variate of the statistic $G_i(d)$ for all i observations of the variable x. This single value is chosen since it represents

[4] The value of G_i when the variable is randomly distributed over space.
[5] According to Getis and Ord (1992), under certain conditions, G_i distribution approaches normality and thus the z-score can be used to assess the statistical significance of G_i value.

the distance beyond which no further spatial association effects increase the probability that the observed value is different than the expected one (Getis, 1995).

The filtered observation ($\tilde{x}_i$) is given as:

$$\tilde{x}_i = x_i \left(\frac{1}{n-1} W_i \right) \Big/ G_i(\delta) \tag{4}$$

where n is the number of observation and W_i is a spatial weight matrix, defined as:

$$W_i = \sum_{j=1}^{n} w_{ij}(\delta) \text{ for } j \neq i \tag{5}$$

Equation (4) compares the observed value of $G_i(\delta)$ with its expected value $W/n-1$. $E[G_i(\delta)]$, represents the realisation, $\tilde{x}$, of the variable x at feature i when no spatial autocorrelation occurs. If there is no autocorrelation among the feature i and its neighbors then the observed and expected values, x_i and $\tilde{x}_i$, will be equals.

After insuring spatial independence, the analysis of distribution dynamics can be safely applied. The distribution dynamics analysis was firstly introduced in the convergence literature (see Quah, 1993) in order to provide an insight on the dynamics of the whole cross-sectional distribution. The main idea is to find a law of motion that describes the evolution of distribution over time. One of the techniques most commonly used involves the calculation of stochastic kernels (see Durlauf and Quah, 1999). This approach is based on the estimation of the conditional density of a variable y given a variable x. In our study, x, refers to the absolute deviation of a country's food inflation from the average at month t, and y, refers to the absolute deviation of a country's food inflation from the average at month t+12 (transition period equal to 12 months). Thus, the conditional density function describes the probability that a country will move to a certain level of absolute inflation deviation from the cross-sectional mean at time t+12 given its current inflation rate deviation (time t).

The traditional stochastic kernel estimator is defined as:

$$\hat{f}_\tau(y|x) = \hat{g}_\tau(x,y) / \hat{h}_\tau(x) \tag{6}$$

where

$$\hat{g}_\tau(x,y) = \frac{1}{na\beta}\sum_{i=1}^{n} K\left(\frac{\|x - X_i\|_x}{a}\right)\left(\frac{\|y - Y_i\|_y}{\beta}\right) \tag{7}$$

is the estimated joint density of (X, Y) and

$$\hat{h}_\tau(x) = \frac{1}{na}\sum_{i=1}^{n} K\left(\frac{\|x - X_i\|_x}{a}\right) \tag{8}$$

is the estimated marginal density. In the above equations, α, β, are bandwidth parameters controlling the smoothness of fit, $\|.\|_x$ and $\|.\|_y$ are Euclidean distance metrics on spaces X and Y respectively and K(.) is the Epanechnikov kernel function. The conditional density estimator can be rewritten as:

$$\hat{f}_\tau(y|x) = \frac{1}{\beta}\sum_{i=1}^{n} w_i(x) K\left(\frac{\|y - Y_i\|_y}{\beta}\right) \tag{9}$$

where

$$w_i(x) = K\left(\frac{\|x - X_i\|_x}{a}\right) \Bigg/ \sum_{j=1}^{n} K\left(\frac{\|x - X_j\|_x}{a}\right) \tag{10}$$

This estimator is the well-known Nadaraya-Watson kernel regression estimator. Equation (9) shows that the conditional density estimate at x can be obtained by the sum of n kernel functions in Y-space weighted by the $\{w_i(x)\}$ in X space. Using $w_i(x)$, the estimator of the conditional mean is given as:

$$\hat{m}(x) = \int y\hat{f}_\tau(y|x)dy = \sum_{i=1}^{n} w_i(x)Y_i \tag{11}$$

Hyndman, Bashtannyk and Grunwald (1996) noticed that when the conditional mean function has an exacerbate curvature and when the points utilized in the estimation are not regularly spaced, the above estimator is biased. In order to correct for this bias, they propose an alternative estimator with better bias properties and a smaller integrated mean square error.

As far as the bandwidth selection is concerned, the Bashtannyk and Hyndman (2001) algorithm is applied. These authors proposed a three-step strategy for bandwidth selection. The first step includes the estimation of β using a rule of thumb, like the one proposed by Silverman (1986). The authors provide a rule which is based on the assumption that the underlying marginal density is normal and the conditional density has a constant variance. Then, the choice of bandwidth is based on the minimization of the Integrated Mean Square Error (IMSE). According to Bashtannyk and Hyndman (2001), this rule is surprisingly robust and gives reasonable results even for densities which are quite non-normal.

The second step includes the estimation of α, using the regression-based method of Fan, Yao and Tong (1996). These authors noticed that the conditional density estimator obtained by equation (9) for given values of x and y is the value of b that minimizes the weighted least-squares function: $\sum w_i(x)\{\upsilon_i(y) - b^2\}$, where $\upsilon_i(y) = c^{-1}K(|Y_i - y|/c$ is a kernel function. For a given bandwidth c and a given value y, finding $\hat{f}_\tau(y|x)$ is a standard nonparametric problem of regressing $\upsilon_i(y)$ on X. Fan, Yao and Tong (1996) use the above fact to define local polynomial estimators of conditional densities. Bashtannyk and Hyndman (2001) further exploit this idea by modifying the bandwidth selection method proposed by Hardle (2001)[6] to derive an alternative method for selecting the bandwidth α given the bandwidth β, from the first step.

The third step includes the re-estimation of β, given α from the second step, using the bootstrap method of Hall, Wolff and Yao (1999) for bandwidth selection in local polynomial estimators, that has been modified by Bashtannyk and Hyndman (2001) to cover the estimation of conditional density functions. The second and the third steps may be repeated several times until the extraction of robust α and β estimates. According to Bashtannyk and Hyndman (2001), this strategy provides a relatively fast and accurate approach to find optimal bandwidths[7].

In addition to the reduced bias estimator, Hyndman, Bashtannyk and Grunwald (1996) proposed two new ways to visualize the conditional densities, namely, the "stack conditional density" (SCD) and the "high density region" (HDR) plots. The former was introduced for the direct visualization of the conditional densities, which is considered as a sequence of univariate densities. Thus, it provides better understanding than the conventional three-dimensional perspective plots. If the mass of the distribution concentrates parallell to x-axis line at zero point, it is an indication that any existing deviation in time t almost disappears at time t + τ (convergence or mean reversion). On the

[6] Hardle (1991) describes selecting the bandwidth for regression by minimizing the so-called: "*penalized average square prediction error*".

[7] Throughout the literature, several procedures have been proposed for the estimation of the optimal bandwidth. In this study we choose the strategy proposed by Bashtannyk and Hyndman (2001) as it has several advantages and it has also been widely used in distribution dynamics analysis (e.g. Peron and Rey, 2012; Maza, Hierro and Villaverde, 2012; Fischer and Stumpner, 2010; Arbia, Basile and Piras, 2005).

other hand, if the mass of the distributions is located on the 45^o degree line (when t and t + τ axes are similarly scaled), the existing deviations at time t still exist at time t + τ (persistence).

The HDR plot consists of consecutive high density regions. A high density region is defined as the smallest region of the sample space containing a given probability. These regions allow a visual summary of the characteristics of a probability density function. In the case of unimodal distributions, the HDR are exactly the usual probabilities around the mean value. However, in the case of multi-modal distributions, the HDR plot displays multimodal densities as disjoint subsets.

When examining the "high density region" plots, we observe whether the 25% or the 50% HDRs are crossed by the 45^o diagonal (again, t and t + τ axes should be similarly scaled) or if they are crossed by the horizontal line that crosses the vertical axis at zero point. When the majority of the 25% or 50% HDRs are crossed by the diagonal, strong persistence is present. This means that most observations of the variable remain at almost the same position after the transition period. If the diagonal only crosses the 75% HDRs, we can conclude in favor of law persistence and more intra-distribution mobility.

On the other hand, if the majority of the 25% or 50% HDRs are crossed by the horizontal line that crosses the vertical axis at a point close to zero, there is a strong convergence trend, while if the majority of the 75% HDRs are crossed by this line, weak convergence prevails. Finally, if some of the 25% or 50% HDRs are crossed by this horizontal line, there are evidence of club convergence or polarization.

The 25%, 50% and 75% HDRs are shown, beginning with the darker shaded region and moving to the lighter respectively. Arbia, Basle and Piras (2005) emphasized also the importance of analyzing central points like modes, i.e. the values of y where the density function takes its maximum values. This is particularly important when the distribution function is multimodal. In this case, the mean and median are only "compromise" values among the multiple peaks. The highest modes for each conditional density are superimposed as bullets on the HDR plots.

Results

The implementation of the local Getis $G_i(d)$[8] index confirms the indications of spatial association provided by the descriptive statistics and reveals the existence of significance spatial autocorrelation[9][10,11]. As Fig. 3 indicates, in almost all monthly observations of absolute food inflation deviation from the mean, there are significant "cold" and "hot" spots.

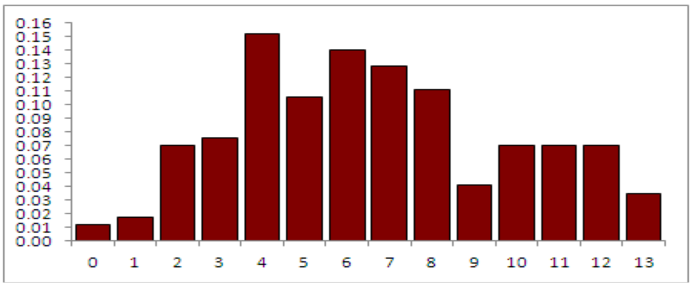

Figure 3. Frequency of Spots ("Hot" and "Cold") in EU-25 countries, regarding the absolute food inflation deviation from the mean in each month observations.

Fig. 4 maps the significant "hot" and "cold" spots, resulting by the examination of the median absolute food inflation deviations for each country. The actual G_i values and the

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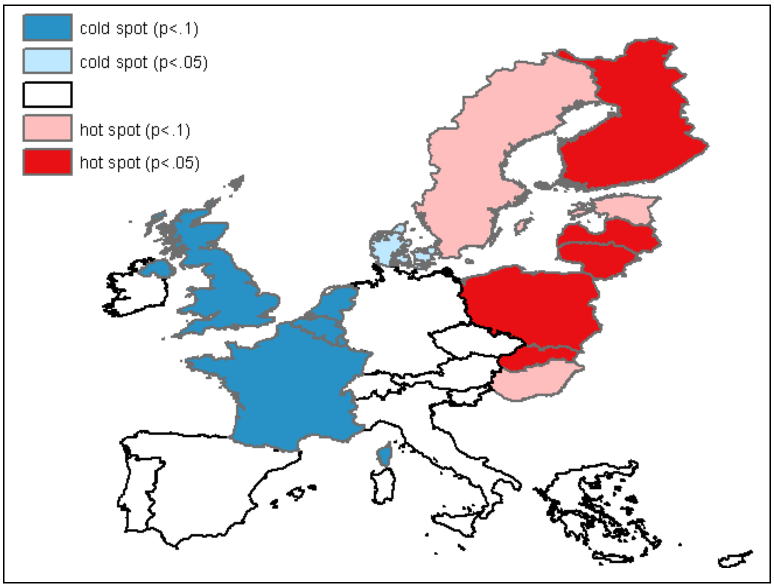
[8] Source of geographical data: Centroids of EU-25 countries from Eurostat's GISCO NUTS dataset (available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/gisco_Geographical_information_maps/popups/references/administrative_units_statistical_units_1).

[9] The null hypothesis of normality is rejected only in the 1.75% cases of monthly observations, using the D'Agostino test.

[10] Distances are measured in terms of geodesic distances between the countries centroids.

[11] The local Getis index (and the associated optimum distance band) was estimated in R. The routine is available upon request.

associated z-scores are presented next to the map[12].



	G_i	$E(G_i)$	z
CY	0.033	0.042	-0.452
CZ	0.610	0.583	0.599
HU	**0.524**	**0.458**	**1.661***
LU	**0.318**	**0.417**	**-2.297****
LV	**0.457**	**0.333**	**2.959****
SK	**0.577**	**0.458**	**2.601****
EL	0.265	0.208	1.166
AT	0.479	0.500	-0.484
BE	**0.319**	**0.417**	**-2.282****
DE	0.499	0.542	-0.946
DK	**0.386**	**0.458**	**-1.676***
EE	**0.321**	**0.250**	**1.814***
ES	0.061	0.083	-0.887
FI	**0.203**	**0.125**	**2.624****
FR	**0.306**	**0.417**	**-2.538****
IE	0.065	0.083	-0.745
IT	0.478	0.500	-0.690
LT	**0.457**	**0.333**	**2.957****
MT	0.226	0.208	0.479
NL	**0.309**	**0.417**	**-2.408****
PL	**0.589**	**0.500**	**1.968****
PT	0.059	0.083	-0.951
SE	**0.369**	**0.292**	**1.867***
SI	0.495	0.542	-1.016
UK	**0.163**	**0.250**	**-2.213****

* p<.1 **p<.05

Figure 4. Mapping of the "hot" and "cold" spots in the EU-25 member states regarding the absolute food inflation deviation from the mean.

The next step in the analysis includes the applications of the spatial filtering to rule out spatial autocorrelation. To illustrate the effect of spatial filtering, we follow Getis (1995) by estimating global Moran's I statistic to see whether spatial autocorrelation remains after the spatial filtering. This statistic is estimated in each point in time (every month in our study) and it is expressed as follows (Anselin, 1988):

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{12}$$

where $\overline{x}$ is the mean of the x variable and w_{ij} are the binary elements of the weight matrix, which is estimated using the inverse squared distance (see Getis, 1995).

Results indicates that, prior to the spatial filtering, global Moran's I values were significant in the 26.9% of the monthly observations (p<.05). It is also important to mention that

[12] D'Agostino Test for Normality shows that the median values are normally distributed (K^2 statistic =2.1539, p-value: 0.34).

spatial autocorrelation was more apparent in the period after 2004 (42.53% of cases). This is an indication that the higher level of economic integration in EU, results in the creation of more intense spatial linkages that, in turn, lead to higher levels of spatial autocorrelation, regarding the absolute food inflation deviation. After the application of spatial filtering, the percentage of significant global Moran's I values falls dramatically to 4.68% ($p<.05$).

Fig. 5 also emphasizes the effect of spatial filtering in reducing the spatial autocorrelation by presenting the empirical distribution of global Moran's I prior and after spatial filtering[13]. It is obvious that prior to spatial filtering, there was significant spatial autocorrelation, reflected in the values of global Moran's I. However, after the application of the Getis filter, spatial autocorrelation no longer exists.

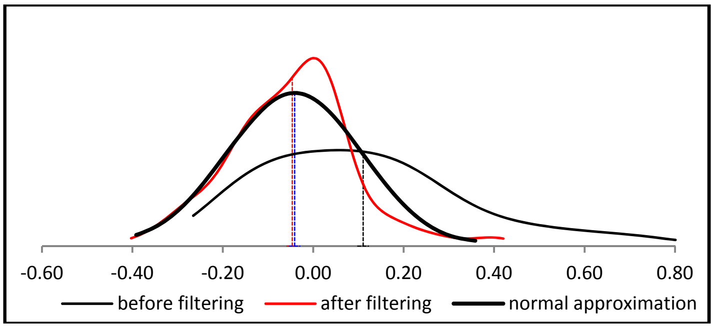


Figure 5. Empirical distribution of global Moran's I statistic using the filtered and the unfiltered observations of absolute food inflation deviation.

Fig. 6 presents the conditional density of the filtered observations given the original ones. In the absence of spatial effects, one would expect the masses of the distribution to concentrate in the 45^{o} line, indicating that the original observations are equal to the filtered ones. According to the high density region plot depicted in Fig. 6, this is the case when the inflation differentials are low. However, as the level of inflation differentials increases, the masses of the distributions concentrate to lower levels of - spatially filtered - inflation

[13] Empirical distributions constructed using the Gaussian kernel type and the Silverman rule for bandwidth selection (Silverman, 1986).

differentials. Therefore, the observations that correspond to these conditional distributions tend to have lower filtered than unfiltered (original) values. This is a sign of greater spatial effects at higher levels of inflation differentials. Specifically, the countries with level of inflation differential greater than 8 units, show a tendency towards cohesion, when the spatial effects are filtered out. Therefore, we conclude that spatial effects account for a large part of inflation distribution dynamics in EU-25.

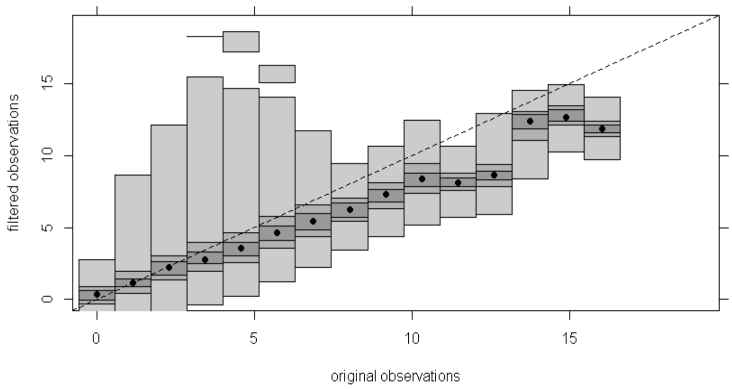
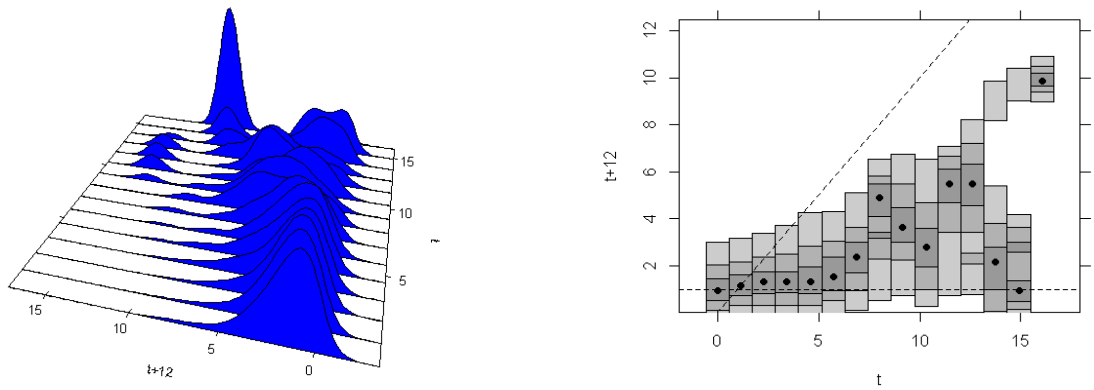


Figure 6. High density region plot of the conditional density of filtered observations, given the original observations of absolute food inflation deviation from the mean.

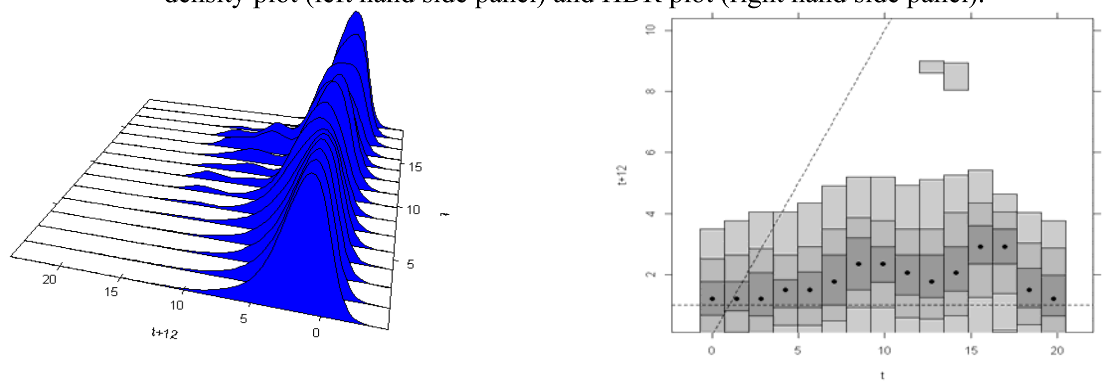
Fig. 7A and 7B present the results from the implementation of the distribution dynamics analysis. This analysis is not only applied to the filtered values but also to the unfiltered for reasons of comparisons. We begin with the interpretations of the conditional density plots derived using the original (unfiltered) observations of the absolute food inflation deviation from the cross-sectional mean (Fig. 7A). The conditional density plots indicate that there are important convergence trends of the food inflation rates in the EU-25. The absolute food inflation deviation tends to diminish after the transition period as the 25% HDR and the 50% HDR are located close to the zero point (crossed by a horizontal line that crosses at a point near zero. These results are generally in line with Weber Beck (2005), Liontakis and Papadas (2010) and Liontakis (2012).

This obvious trend of food inflation convergence is not present when food inflation differentials are greater than 6 units. After this level, the convergence trends weaken and the high density region plot becomes more complex. However, even in higher levels of deviations, a weaker convergence trend continues to prevail, as the HDRs are always lying on the right of the 45^{o} line, which indicates food inflation persistence.



bandwidths (α, β)=(0.699, 1.069)

Figure 7A. Intra-Distribution Dynamics of annualized unfiltered inflation rate transitions. Stacked density plot (left hand side panel) and HDR plot (right hand side panel).



bandwidths (α, β) = (1.121,1.385)

Figure 7B. Intra-Distribution Dynamics of annualized filtered inflation rate transitions. Stacked density plot (left hand side panel) and HDR plot (right hand side panel).

It is also important to mention that in very low initial levels of food inflation differentials (less than one), the corresponding deviation after the transition period tends to be slightly higher. Finally, when initial food inflation deviations are close to one, they produce a conditional density with a mode equal to one, indicating food inflation persistence.

Moreover, the corresponding values after the transition period are not excessively spread, as the length of the 75% HDRs is relatively small. This is an indication that countries with low food inflation, tends to retain this low food inflation rate, forming in this way a low food inflation group.

The above results can also be identified, by exploring the stack conditional density plot. The masses of the conditional densities, produced at low initial values of absolute food inflation deviation concentrated close to the zero point of the t+12 axis. This is an indication that when initial food inflation deviations are low, the vast majority of food inflation differentials, after the transition period, concentrated on a low food inflation level. However, as the initial level of food inflation increases, the mass of the corresponding conditional density moves to the left, indicating weaker convergence trends.

Another point of interest in the conditional densities plots is the presence of several multimodalities when the level of initial food inflation differentials is very high. In these cases, there are more than one mass in the corresponding conditional densities. This means that at high food inflation levels, the food inflation deviation after the transition period concentrates in two distinct areas; an area of low values (indicating strong convergence) and an area of higher values (indicating very weak convergence). This is emerging from the multimodal univariate conditional densities in the stack density plot and from the disjoint HDRs in the high density region plot. This phenomenon indicates that the existence of a very high level of food inflation, can be either a random effect or a short-term shock which can be corrected relatively quickly (after the transition period) or a phenomenon with more permanent characteristics, which may reflects the situation in countries with high food inflation.

When examining the conditional density plots that are produced by the filtered observations, the signs of mean reversion are even more apparent. The main difference is presented in the conditional densities that correspond to higher levels of initial inflation differentials. At these levels of food inflation, the absolute deviation from the mean decreased after the transition period, indicating strong inflation convergence trends. Actually, this result is in line with Fig. 6, where we show that the spatial effects mainly appear in the observations with high food inflation differentials.

On the other hand, the results that refer to the low initial food inflation levels still remain. Also, the multimodalities cases almost disappear after the implementation of the spatial filtering.

The above facts provide strong evidence that our previous results are biased due to the spatial autocorrelation that contaminates the observations. Ruling out the spatial component, gives a clearer image of the mean reversion trends in EU-25 and provide a possible explanation for the existing deviations of food inflation from the cross-sectional mean.

Conclusions

This study applies the distribution dynamics analysis to explore the evolution of food inflation in the EU-25, covering the period from January 1997 to March 2011. Unlike most studies in the field, it takes the effect of spatial dependence into consideration which can invalidate the inferential basis of traditional statistics and econometric methods.

The presence of spatial autocorrelation was confirmed using the local Getis $G_i(d)$ index. The spatial effects was isolated using the Getis spatial filter to isolate the spatial component in the absolute food inflation deviation observations. As Fischer and Stumpner (2010) emphasize, this is essential, as the properties of the kernel estimators, under spatial autocorrelation, are unknown and therefore, the implementation of the distribution dynamics analysis may lead to false interpretations. However, as the authors also claim, the lack of an appropriate inferential theory restricts the study mainly to a descriptive analysis.

The distribution dynamics analysis reveals the existing convergence trends in the food inflation rates. Countries with relatively higher or lower absolute food inflation deviation are expected to move back towards the mean after the transition period. While the food inflation convergence trends are more obvious in relatively low initial food inflation differentials, even in higher levels of deviation, a weaker convergence trend continues to prevail. The analysis also indicates that countries with low food inflation, tend to retain this low inflation level, forming in this way a low food inflation group. Moreover, at higher food inflation rates, the trend of convergence diminishes, the conditional densities get a more complex structure and several cases of multimodality appear.

The application of this analysis to both original and filtered observations reveals the presence of significant spatial effects that, to some extent, shape the evolving distributions dynamics of food inflation. After the spatial filtering, the mean reversion trend is more obvious and not limited to relatively low food inflation differentials. Moreover, the complexities of the conditional densities and the cases of multimodality in very high inflation differentials almost disappear. This, in turn, indicates that in the absence of spatial autocorrelation, the hypothesis of homogenous food inflation seems more rational.

References

Ailenei, D. and Cristescu, A. (2010). "Regional distribution of inflationary pressures in Romania." *Romanian Journal of Economic Forecasting* 4, 32-43.

Altissimo, F., Benigno, P. and D.R. Palenzuela (2005). "Long-run Determinants of Inflation Differentials in a Monetary Union." CEPR Discussion Paper no. 5149.

Anand, R. and Prasad E.S. (2010). "Optimal Price Indices for Targeting Inflation Under Incomplete Markets." NBER Working Paper Series, w16290.

Anselin, L. (1988). *Spatial econometrics: methods and models*, Kluwer, Dordrecht.

Arbia G., Basile, R. and G. Piras (2005). "Analyzing Intra-Distribution Dynamics. A reappraisal." REAL Discussion Papers 05-T-11, Regional Economics Applications Laboratory. University of Illinois.

Bashtannyk D. M, Hyndman R. J (2001). "Bandwidth selection for kernel conditional density estimation." *Computational Statistics & Data Analysis* 36, 279–298

Beck, G., Hubrich, K. and M. Marcellino (2009). "Regional Inflation Dynamics Within and Across Euro Area Countries and a Comparison with the United States." *Economic Policy*, 24, 141-184.

Bukeviciute L., Dierx, L. and F. Ilzkovi (2009). "The functioning of the food supply chain and its effect on food prices in the European Union." European Commission Occasional Papers 47.

Busetti, F., Forni, L., Harvey, A. and F. Venditti (2007). "Inflation Convergence and Divergence within the European Monetary Union." *International Journal of Central Banking* 3, 95-121.

Catão, L.A.V. and R. Chang (2010). "World Food Prices and Monetary Policy." IMF Working Paper 10/161.

Cavallero, A. (2011). "The convergence of inflation rates in the EU-12: A distribution dynamics approach." *Journal of Macroeconomics* 33, 341-357.

Cecchetti, S. G., Mark, N. C., and R. J. Sonora (2002). "Price index convergence among united states cities." *International Economic Review* 43, 1081-1099.

Dalsgaard, T. (2008). "Product market competition in Slovenia: Stylised facts and policy challenges." Paper presented at the Bank of Slovenia Research Seminar on Contemporary Macroeconomic Issues: Challenges and Policies. Ljubljana.

Dayanandan, A. and M. Ralhan (2005). "Price Index Convergence among Provinces and Cities across Canada: 1978–2001." Working Paper No 0504, Econometrics Working Paper, University of Victoria, Canada.

Durlauf, S. N. and Quah, D. T. (1999). "The new empirics of economic growth." In: Taylor J. B., Woodford M. (eds) Handbook of macroeconomics, vol. 1. Elsevier, Amsterdam, pp. 235–308.

Faber, R.P. and C.J. Stokman (2009). "A Short History of Price Level Convergence in Europe." *Journal of Money, Credit, and Banking*, 41, 461-477.

Fan, J., Yao, Q. and H. Tong (1996). "Estimation of conditional densities and sensitivity measures in nonlinear dynamical systems." *Biometrika* 83(1), 189–206

Fan, S.C. and X. Wei (2006). "Price Index Convergence in China." Paper presented in the APEA Conference, University of Washington, Seattle, USA.

Fischer, M. M. and Stumpner, P. (2010). "Income distribution dynamics and cross-region convergence in Europe." In Fischer M.M. and Getis A. (eds.): Handbook of Applied Spatial Analysis, pp. 599-628. Springer, Berlin, Heidelberg and New York, [=reprint, Journal of Geographical Systems 10(2), 109-140].

Fousekis, P. (2008). "Price Convergence in the EU Poultry and Eggs Market." *Economics Bulletin* 3, 1-11.

Getis, A. (1990). "Screening for spatial dependence in regression analysis." Papers of the regional science association 69, 69–81.

Getis, A. (1995). "Spatial filtering in a regression framework". In: Anselin L, Florax R (eds) *New directions in spatial econometrics*, pp 172-185. Springer, Heidelberg Berlin New York.

Getis, A. and Ord, J. K. (1992). "The analysis of spatial association by use of distance statistics." *Geographical Analysis* 24(3), 189–206.

Hall, P., Wolff, R. C. and Q. Yao (1999). "Methods for estimating a conditional distribution function." *Journal of the American Statistical Association* 94(445), 154-163.

Hardle, W., 1991. Smoothing Techniques with Implementation in S. Springer, New York.

Holmes, M. (2002). "Panel data evidence on inflation convergence in the European Union." *Applied Economics Letters*, 9, 155-58.

Hyndman, R. J., Bashtannyk, D. M. and G. K. Grunwald, (1996). "Estimating and Visualizing Conditional Densities." *Journal of Computational and Graphical Statistics*. 5, 315-336.

Kočenda, E. and D. Papell (1997). "Inflation convergence within the European Union: A panel data analysis." *International Journal of Finance and Economics*, 2, 189-98.

Kutan, A. M. and Yigit, T. M. (2005). "Real and Nominal Stochastic Convergence: Are the New EU members Ready to Join the Euro Zone?" *Journal of Comparative Economics* 33, 387-400.

Laurent, T., Ruiz-Gazen, A. and C. Thomas-Agnan (2009). "GeoXP: an R package for exploratory spatial data analysis." *Journal of Statistical Software* 47(2), 1-23.

Liontakis, A. and Papadas, C.T. (2010). "Stochastic Convergence and Distribution Dynamics of Food Price Inflation Rates in EU." AUA Working Paper Series No2010-6.

Liontakis, A. (2012). "Food price inflation rates in the Euro-zone: Distribution dynamics and convergence analysis." *Economics Research International*, Special Issue: Economics of Agricultural and Food Markets.

Lopez, C. and D.H. Papell (2010). "Testing for Group-Wise Convergence with an Application to Euro Area Inflation." MPRA Paper No. 20585.

Lünnemann, P. and T. Mathä (2004). "How Persistent in Disaggregate Inflation? An Analysis Across EU15 Countries and HICP Sub-indices." European Central Bank Working Paper, No. 466.

Maza, A, Hierro, M and J. Villaverde (2012). "Income distribution dynamics across European regions: Re-examining the role of space." *Economic Modelling* 29(6), 2632-2640.

Nagayasu, J. (2012). "Regional inflation and industrial structure in monetary union." MPRA Paper No. 3731.

Nath, H.K. and K. Tochkov (2012) "Relative inflation dynamics in the new EU member countries of Central and Eastern Europe." *Empirical Economics*, forthcoming.

Quah, D.T. (1993). "Empirical Cross-section Dynamics in Economic Growth." *European Economic Review* 37, 426-434.

Peron, O. and Rey S.J (2012). "Trade and convergence of per capita income in the Indian Ocean Zone, 1950–2008." *The Annals of Regional Science* 49(3), 657-683.

Rey, S. J. and Janikas, M. V. (2005). "Regional convergence, inequality and space." *Journal of Economic Geography* 5(2), 155–176.

Roberts, J.M. (2006). "Monetary Policy and Inflation Dynamics." *International Journal of Central Banking*, 2,193-230.

Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall.

Sturm, J.E., Fritche, U. Graff, M., Lamla, M., Lein, S., Nitch, V. Liechti, D. and D. Triet (2009). "The euro and prices: changeover-related inflation and price convergence in the euro area." European Commission Economic papers 381|June, European Commission Directorate-General for Economic and Financial Affairs, Brusells:ECOP.

Vaona, A. and Ascari, G. (2010). "Regional Inflation Persistence: Evidence from Italy." *Regional Studies*, First published on: 09 October 2010 (iFirst).

Walsh, J.P. (2011). "Reconsidering the Role of Food Prices in Inflation." IMF Working Paper, Asia and Pacific Department, WP/11/71.

Weber, A. A. and Beck, G. W. (2005). "Price stability, inflation convergence and diversity in EMU: Does one size fit all?" Manuscript, Goethe University, Frankfurt.

Yilmazkuday, H. (2009). "Inflation Targeting and Inflation Convergence within Turkey." MPRA Paper No. 16770.

Zaffaroni, P. (2004). "Contemporaneous Aggregation of Linear Dynamic Models in Large Economies." *Journal of Econometrics*, 120, 75-102.

Table 1 Descriptive statistics for the "Food and non-alcoholic beverages" inflation rates

	FROM 1997 TO 2011			AFTER 2004			BEFORE 2004		
	Mean	(SD)	Relative Ranking	Mean	(SD)	Relative ranking	Mean	(SD)	Relative ranking
Belgium	1	(0.75)	1	1.01	(0.76)	2	1	(0.74)	2
Austria	1.03	(0.78)	2	0.79	(0.6)	1	1.28	(0.86)	6
Denmark	1.06	(0.81)	3	1.03	(0.88)	3	1.09	(0.73)	3
Luxembourg	1.11	(0.82)	4	1.13	(0.76)	4	1.1	(0.89)	4
France	1.3	(1.02)	5	1.81	(1)	10	0.77	(0.72)	1
Italy	1.58	(1)	6	1.49	(0.74)	6	1.68	(1.22)	13
Finland	1.66	(1.36)	7	2.11	(1.61)	17	1.19	(0.82)	5
Germany	1.68	(0.83)	8	1.53	(0.84)	7	1.83	(0.79)	14
Greece	1.69	(1.34)	9	1.49	(1.1)	5	1.89	(1.52)	16
Malta	1.72	(1.54)	10	1.96	(1.93)	13	1.46	(0.95)	9
Spain	1.75	(1.23)	11	1.62	(0.81)	9	1.88	(1.54)	15
Netherlands	1.76	(1.52)	12	2.2	(1.81)	18	1.29	(0.93)	7
Sweden	1.79	(0.87)	13	1.96	(0.77)	12	1.61	(0.94)	11
Portugal	1.84	(1.46)	14	2.06	(1.66)	16	1.61	(1.19)	12
UK	1.99	(1.45)	15	1.97	(1.64)	15	2.01	(1.23)	17
Slovakia	2	(1.43)	16	1.97	(1.49)	14	2.04	(1.37)	18
Ireland	2.08	(1.42)	17	2.6	(1.62)	21	1.54	(0.91)	10
Czech	2.43	(1.91)	18	1.93	(1.42)	11	2.95	(2.2)	21
Cyprus	2.59	(1.63)	19	2.45	(1.42)	20	2.73	(1.82)	20
Slovenia	2.69	(1.75)	20	1.58	(1.36)	8	3.85	(1.32)	23
Estonia	3.14	(1.98)	21	3.73	(2.27)	24	2.53	(1.4)	19
Poland	3.3	(2.52)	22	2.41	(1.84)	19	4.22	(2.8)	24
Latvia	3.66	(3.11)	23	5.82	(2.94)	25	1.42	(0.93)	8
Lithuania	3.67	(2.17)	24	3.61	(2.25)	23	3.74	(2.09)	22
Hungary	4.63	(3.81)	25	3.55	(2.29)	22	5.75	(4.68)	25

Source: Eurostat

Figure 1. Evolution of absolute food inflation deviation from the mean

Figure 2. Frequency of inclusion in the L, M and H food inflation groups.

Figure 3. Frequency of Spots ("Hot" and "Cold") in EU-25 countries, regarding the absolute food inflation deviation from the mean.

Figure 4. Mapping of the "hot" and "cold" spots in the EU-25 member states regarding the absolute food inflation deviation from the mean.

Figure 5. Empirical distribution of global Moran's I statistic using the filtered and the unfiltered observations of absolute food inflation deviation.

Figure 6. High density region plot of the conditional density of filtered observations, given the original observations of absolute food inflation deviation from the mean.

Figure 7A. Intra-Distribution Dynamics of annualized unfiltered inflation rate transitions. Stacked density plot (left hand side panel) and HDR plot (right hand side panel).

Figure 7B. Intra-Distribution Dynamics of annualized filtered inflation rate transitions. Stacked density plot (left hand side panel) and HDR plot (right hand side panel).