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Food Inflation in the European Union: Distribution Analysis and Spatial Effects

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In the European Union (EU), homogenous inflation forces are expected to prevail because of increased economic integration, especially after the creation of a single currency area. This expectation is directly related to the issue of inflation convergence, which has gained increasing attention by both academics and policy makers in Europe. Although the examination of core inflation is of great importance for macroeconomic policy, the role of disaggregate inflation indices, and especially food inflation, has also been emphasized in the literature. However, the issue of food inflation convergence has been largely ignored to date in empirical studies. This study explores the evolving distribution of food inflation rates in the EU-25 member states using distribution dynamics analysis and covering the period from January 1997 to March 2011. This analysis assumes that each country represents an independent observation, providing unique information that can be used to estimate the transition dynamics of inflation. We show that spatial autocorrelation prevails inside the EU-25, and, therefore, the independency assumption is violated. To ensure spatial independence, the Getis spatial filter is implemented prior to a distribution dynamics analysis. The results of this analysis confirm the existence of convergence trends, which are even clearer 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 the Getis spatial filtering technique.

Introduction

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

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may also play a role, especially for small changes in the economy's price index. Such forces can be used to explain, at least partially, longer term inflation rate differentials (Liontakis and Papadas 2010).

Empirical studies about inflation convergence explore this issue among different regions of a country[1] or inside a cluster of countries such as the members of the European Monetary Union (EMU) and the new EU member states.[2] However, according to Lünnemann and Mathä (2004), although available international evidence focuses on core inflation, the usage of more disaggregate 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 predominantly is driven by the most persistent disaggregate inflation components (e.g., Zaffaroni 2004; Beck, Hubrich, and Marcellino 2009).

In this context, the examination of a disaggregated inflation index like that for food is of great interest. Moreover, food inflation presents some special characteristics that make its examination even more important. As Walsh (2011) emphasizes, in many cases, food inflation is more persistent than nonfood inflation, and food inflation shocks in many countries often translate 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 deficient or misleading.

The food price spike preceding the 2008 global financial crisis motivated a number of studies about 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 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 food inflation differentials inside the EU. Fousekis (2008) points out the fragmentation of the European market and claims that inflation rate differentials are efficiently confronted by changes in countries' market structures rather than by horizontal EU measures. Altissimo, Benigno, and Palenzuela (2005) emphasize the importance of different responses of EU countries to common Euro-area shocks. Similarly, Bukeviciute, Dierx, and Ilzkovi (2009) argue that food price inflation differentials are caused by the various ways and degrees that the food supply chains of member states absorb such external shocks as a rapid increase in energy prices. This varied response, in turn, occurs because different food market structures and regulatory frameworks exist across the EU. In this sense, food price inflation differentials are a signal that the EU food market remains fragmented. Finally, Dalsgaard (2008) and Beck, Hubrich, and Marcellino (2009) emphasize the role of market concentration, mergers and acquisitions, and cartel formations on inflation rate differentials.

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

Recently, another methodological tool, distribution dynamics analysis, borrowed from the economic growth literature, has been introduced into the analysis of inflation rates convergence (see Weber and Beck 2005; Cavallero 2011; Nath and Tochkov 2012). Following these studies, we implement a distribution dynamics analysis of food price inflation rates for the member states of the EU-25.[3] Our analysis is distinct because it takes into consideration the effect of spatial autocorrelation. According to Anselin (1988), the existence of spatial dependence may lead to important distortions because it can invalidate the inferential basis of traditional statistics and econometric methods by causing the assumption of observational independence to no longer hold. In the analysis of inflation convergence, this issue has not yet gained much attention.[4] In this study, we control for spatial autocorrelation using the Getis filtering approach (Getis 1995), which is based on the local spatial autocorrelation statistic G_i (Getis and Ord 1992). Data used for the analysis summarized in this article consist of monthly observations of the absolute food inflation rate deviation from the mean (based on the Harmonized Indices of Consumer Prices[5]—HICP—for the "food and nonalcoholic beverages" index) and cover the period from January 1997 to March 2011.[6] An examination of the evolving distribution dynamics is conducted using a kernel density estimator proposed by Hyndman, Bashtannyk, and Grunwald (1996). This estimator was first introduced in the growth and income convergence literature by Arbia, Basile, and Piras (2005), and several empirical studies have been based on it.

Studies about food inflation convergence

Despite its importance, the issue of food inflation convergence has been largely ignored in the literature. In the few studies that examine this issue, the analysis is narrow and the results are presented without further interpretations. Weber and Beck (2005) examine inflation convergence in two samples of European countries. They use the HICP for the total price index as well as for 12 subindices. Although they reported β-convergence for the food and nonalcoholic beverages index, this convergence was slower for the period after the introduction of a common currency, implying the existence of nonlinearities in the convergence process.

Dayanandan and Ralhan (2005) find evidence of β-convergence for the food price index in Canada using panel unit root 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 in terms of the type of convergence explored (β-convergence or σ-convergence), the countries constituting the groups (EMU or non-EMU members), and the time period under investigation.

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

Liontakis and Papadas (2010) address the existence of inflation rate convergence in the EU-15[7] from 1997 to 2009 using stochastic convergence analysis and the distribution dynamics approach. Their study refers to the food and nonalcoholic beverages product group as well as to 11 food product subgroups. Parametric analysis indicates no stochastic convergence for the food and nonalcoholic beverages group or for almost all food product subgroups. In contrast to the parametric results, the general finding based on nonparametric distribution dynamics analysis is that food inflation tends to shrink to the mean. Similarly, Liontakis (2012) examines the mean reversion trend of food price inflation rates in the Euro-zone 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 on various aspects of convergence and highlights processes such as club formation and polarization.

Data, variables, and some descriptive statistics

Annualized inflation rates at time t (π_t) are estimated as annual percentage changes in the HICP at time t (P_t) as follows:

$$\pi_t = 100\left[\ln(P_t) - \ln(P_{t-12})\right] \tag{1}$$

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

$$x_t = \left|\pi_t - \bar{\pi}_t\right|, \tag{2}$$

where $\bar{\pi}_t$ represents the average inflation of the EU-25 countries. Table 1 reports the mean and standard deviation for x_t. Moreover, it provides the relative ranking of each country based on its

Table 1 Descriptive Statistics for the Food and Nonalcoholic 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
The 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
United Kingdom	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 Republic	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, *Harmonized Indices of Consumer Prices (HICP) Database* (available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/data/database), authors processing.

mean absolute food inflation deviation value throughout the period under investigation. Countries are presented in this table according to their relative rankings. On average, Hungary and Lithuania have the greatest absolute food inflation deviations from the mean during the study period, whereas Belgium, Austria, Denmark, and Luxemburg have the lowest. The large standard deviation values reflect the great volatility of x_t.

To get a clearer picture about the evolving distributions of x_t, we further investigate two subperiods: before and after the EU enlargement of 2004. Although the countries that possess the lower and higher relative rankings have a similar ranking position in both subperiods, this is not true in all cases. The most intense changes occur for two East European economies, namely Slovenia and Latvia; the former jumps 15 places back and the latter 17 places forward in the relative ranking. Other prominent ranking differences among the two subperiods are for France and Finland, ranking first and fifth, respectively, after the EU enlargement.

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

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 for each month. Groups L and H (low and high groups) include the first and last eight countries in the relative ranking, respectively, while group M (medium group) includes the remaining nine countries (9th to 17th position). The frequency of inclusion in each group shows that many East European countries, such as Hungary, Latvia, and Estonia, are usually placed in the high absolute inflation deviation group. In contrast, some core European countries, such as Austria, Belgium, and Luxemburg, are usually placed in the low absolute inflation deviation group. The preceding descriptive statistics reveal a high degree of complexity in the data. Beyond economic policies (common or less common), country- and product-specific factors may

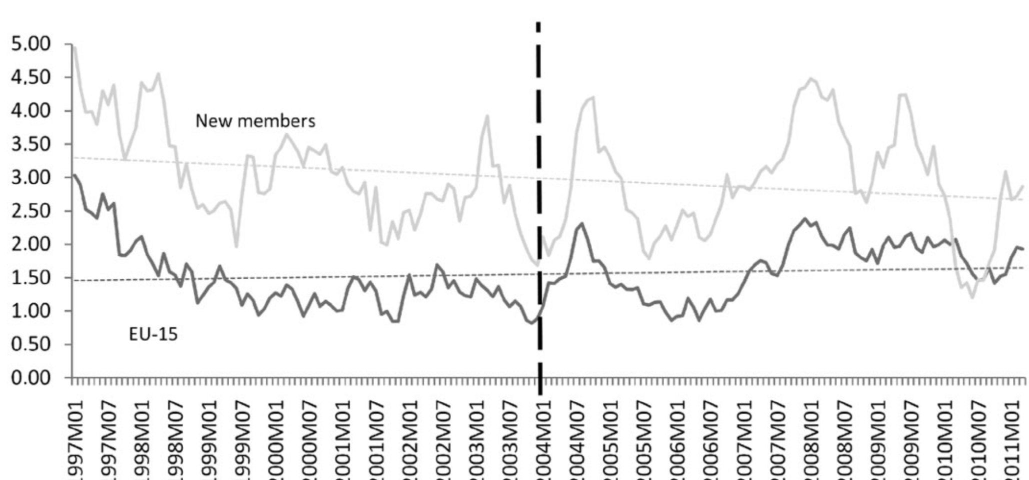
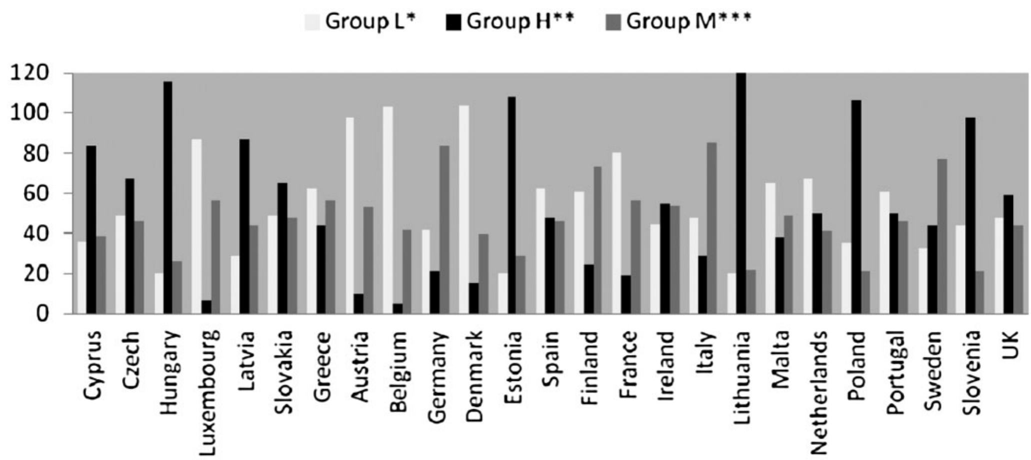


Figure 1. Evolution of absolute food inflation deviation from the mean.



* Group L includes the first eight countries in the relative ranking of absolute food inflation deviation.
** Group H includes the last eight countries in the relative ranking of absolute food inflation deviation.
*** Group M includes the countries that are placed between the 9th and the 17th ranking position in the relative ranking of absolute food inflation deviation.

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

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 stem from the descriptive statistics can be further explored using the Getis local $G_i(d)$ index, the spatial autocorrelation statistic of Getis and Ord (1992), which is defined as

$$G_i(d) = \sum_{j=1}^{n} w_{ij}(d) x_j \Bigg/ \sum_{j=1}^{n} x_j \text{ for } j \neq I, \tag{3}$$

where n is the number of observations, and $w_{ij}(d)$ are the binary elements of the spatial weight matrix W that takes a value of 1 for all features being within distance d of a given feature i and 0 otherwise. The numerator in equation (3) is the sum of all features' x values 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 values.

Therefore, this statistic shows whether features with either high or low values cluster spatially within a radius of length d from point i (a hot/cold 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 from the expected local sum[8] and this difference is too large to be the result of random chance, the result is a statistically significant z-score.[9]

In our study, spatial dependence may arise from a variety of measurement problems and from interactions such as trade or externalities across countries. These factors can contribute to 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. Hence, the original variable, x, is partitioned into two parts: a filtered spatial variable ($\tilde{x}$) and a spatial residual that captures spatial autocorrelation (Getis 1995; Getis and Griffith 2002). The Getis filter is commonly used to separate spatial effects from a variable's total effects. By ensuring spatial independence, this filter allows us to use the stochastic kernel to estimate properly 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 $G_i(d)$ for all i observations of the variable x. This single value is chosen because it represents the distance beyond which no further spatial association effects increase the probability that the observed value differs from the expected values (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 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 $E[G_i(\delta)] = W/n - 1$, which represents the realization, $\tilde{x}$, of the variable x at feature i when no spatial autocorrelation occurs. If no autocorrelation exists among the feature i and its neighbors, then the observed and expected values, x_i and $\tilde{x}_i$, are equal.

After ensuring spatial independence, the analysis of distribution dynamics can be safely applied. The distribution dynamics analysis was first introduced in the convergence literature (see Quah 1993) to provide insight into the dynamics of an entire cross-sectional distribution. The main idea is to find a law of motion that describes the evolution of a 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 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 its average at month t, and Y refers to the absolute deviation of a country's food inflation from its average at month $t + 12$ (a transition period equal to 12 months). Thus, the conditional density function describes the probability that a country moves to a certain level of absolute inflation deviation from the cross-sectional mean at time $t + 12$ given its current inflation rate deviation (at time t).

The traditional stochastic kernel estimator is defined as

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

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, where α and β are bandwidth parameters controlling the smoothness of fit, $\|\cdot\|_x$ and $\|\cdot\|_y$ are Euclidean distance metrics on spaces X and Y, respectively, and $K(\cdot)$ 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

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

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 $\{w_i(x)\}$ 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) comment that when the conditional mean function has an exacerbated curvature and when the points utilized in an estimation are not regularly spaced, equation (11) is biased. To correct for this bias, they propose an alternative estimator with better bias properties and a smaller integrated mean square error (IMSE).

The Bashtannyk and Hyndman (2001) algorithm involves 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). This rule is based on the assumption that the underlying marginal density is normal and that the conditional density has a constant variance. Then, the choice of bandwidth is based on minimization of the IMSE. According to Bashtannyk and Hyndman (2001), this rule is surprisingly robust and gives reasonable results, even for densities that are quite nonnormal.

The second step includes the estimation of α using the regression-based method of Fan, Yao, and Tong (1996). These three authors comment that the conditional density estimator given 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 $v_i(y) = c^{-1}K(|Y_i - y|/c)$ 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 $v_i(y)$ on X. Fan, Yao, and Tong (1996) use this property 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 (1991)[10] to derive an alternative method from the first step for selecting the bandwidth α given the bandwidth β.

The third step includes the reestimation 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 third steps may need to be repeated several times to extract robust α and β estimates. According to Bashtannyk and Hyndman (2001), this strategy provides a relatively fast and accurate procedure to find optimal bandwidths.[11]

In addition to the reduced bias estimator, Hyndman, Bashtannyk, and Grunwald (1996) propose 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 direct visualization of the conditional densities, which are considered as a sequence of univariate densities. Thus, it provides better understanding than the conventional three-dimensional perspective plots. A concentration of the mass of the distributions parallel to the x-axis line at the zero point indicates that any existing deviation in time t almost disappears at time $t + \tau$ (convergence or the mean reversion). In contrast, if the mass of the distributions is located on the 45° line (when the t and $t + \tau$ axes are similarly scaled), the existing deviations at time t still exist at time $t + \tau$ (persistence).

The HDR plot consists of consecutive HDRs. An HDR is the smallest region of a 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 HDRs are exactly the usual probabilities around the mean value. However, in the case of multimodal distributions, the HDR plot displays multimodal densities as disjoint subsets.

When examining the HDR plots, we observe whether the 25% or the 50% HDRs are crossed by the 45° diagonal (again, the t and $t + \tau$ axes must be similarly scaled), or if they are crossed by the horizontal line that intersects the vertical axis at the 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, there is again a sign of persistence; however, it is less intense, and, therefore, intradistribution mobility is present.

If the majority of the 25% or 50% HDRs are crossed by the horizontal line that intersects the vertical axis at a point close to zero, a strong convergence trend exists, whereas if the majority of the 75% HDRs are crossed by this line, weak convergence prevails. Finally, if only some of the 25% or 50% HDRs are crossed by this horizontal line, then evidence of club convergence or polarization exists.

Arbia, Basile, and Piras (2005) emphasize the importance of analyzing central points like modes; that is, the values of y where the density function takes its maximum values. This focus is particularly important when a distribution function is multimodal. In this case, the mean and the median are only compromise values among the multiple peaks. The highest modes for each conditional density are superimposed as bullets on the HDR plots (see Figs. 6, 7A, 7B discussed later).

Results

The implementation of the local Getis $G_i(d)$[12] index confirms the indications of spatial association provided by the descriptive statistics and reveals the existence of significant spatial autocorrelation.[13] As Fig. 3 indicates, significant cold and hot spots are present in almost all monthly observations of absolute food inflation deviation from the mean.

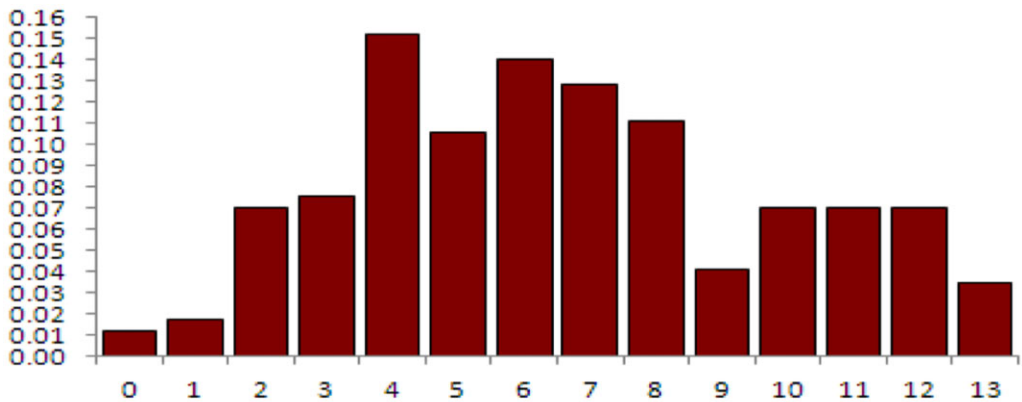
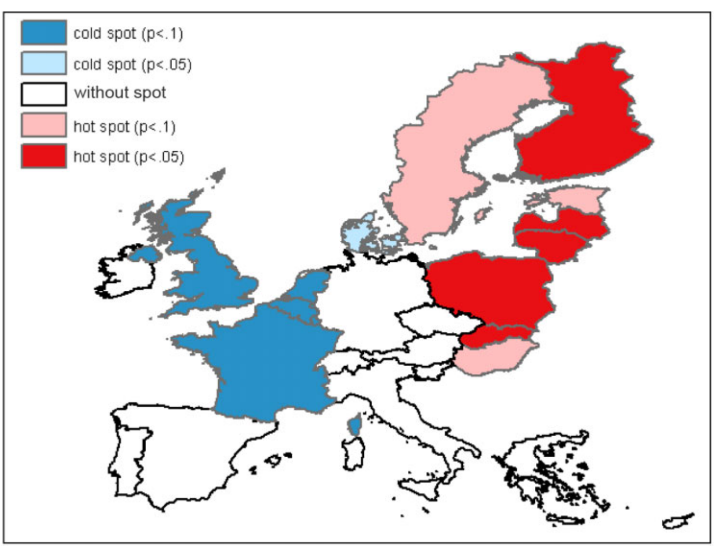


Figure 3. Frequency of hot and cold spots in EU-25 countries for the absolute food inflation deviation from the mean.



	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 for the absolute food inflation deviation from the mean.

Fig. 4 portrays the geographic distribution of the significant hot and cold spots, resulting from an examination of the median absolute food inflation deviations for each country. The actual G_i values and the associated z-scores are presented next to the map.[14]

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

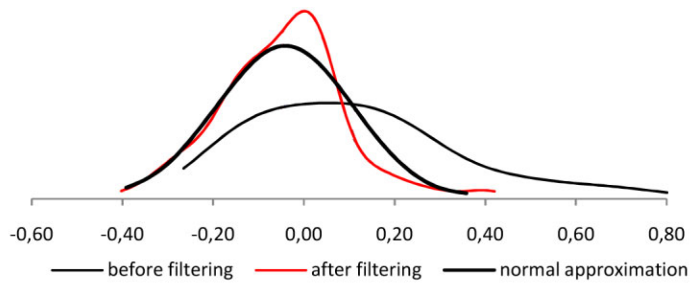


Figure 5. Empirical distribution of the global Moran's *I* statistic using the filtered and the unfiltered observations for absolute food inflation deviation.

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

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

Results indicate that, prior to the spatial filtering, global Moran's I values are significant in 26.9% of the monthly observations ($P < 0.05$). Spatial autocorrelation is more apparent in the period after 2004 (42.53% of cases). This outcome is an indication that the higher level of economic integration in the EU results in the creation of more intense spatial linkages that, in turn, lead to higher levels of spatial autocorrelation with regard to 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% ($P < 0.05$).

Fig. 5 also emphasizes the effect of spatial filtering on reducing the spatial autocorrelation by presenting the empirical distribution of the global Moran's I before and after spatial filtering.[15] Prior to spatial filtering, significant spatial autocorrelation exists, which is reflected in the values of the global Moran's I. However, after the application of the Getis filter, spatial autocorrelation no longer exists.

Fig. 6 presents the conditional density of the filtered observations given the original ones. The 25%, 50%, and 75% HDRs are shown, beginning with the darker shaded region and moving to the lighter, respectively. In the absence of spatial effects, one would expect the masses of the distributions to concentrate along the 45° line, indicating that the original observations are equal to the filtered ones. According to the HDR 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 at lower levels of spatially filtered inflation 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 a level of inflation differential greater than eight units show a tendency toward cohesion when the spatial effects are filtered out. Therefore, we conclude that spatial effects account for a large part of inflation distribution dynamics in the EU-25.

Fig. 7A and 7B presents the results from the implementation of the distribution dynamics analysis. As in Fig. 6, the 25%, 50%, and 75% HDRs are shown, beginning with the darker

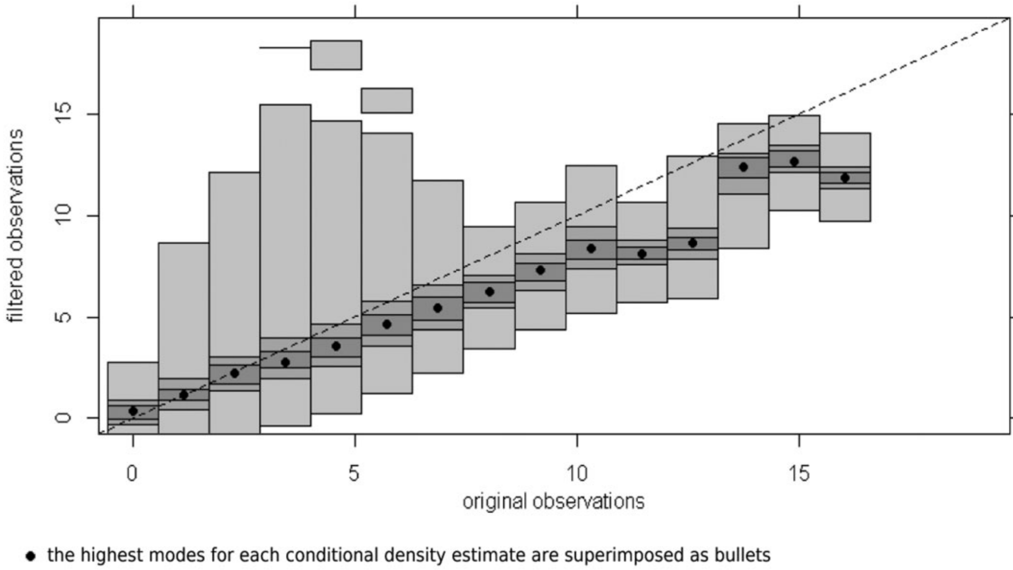


Figure 6. HDR plot of the conditional density of filtered observations, given the original observations for the absolute food inflation deviation from the mean.

shaded region and moving to the lighter, respectively. This analysis is applied not only to the filtered values but also to the unfiltered values for comparison purposes. 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 important convergence trends exist for the food inflation rates in the EU-25. The absolute food inflation deviation tends to diminish after the transition period, as indicated by the 25% HDR and the 50% HDR being located close to the zero point (crossed by a horizontal line that intersects at a point near zero). These results generally are in line with those of Weber and 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 six units. After this level, the convergence trends weaken, and the HDR plot becomes more complex. However, even at higher levels of deviations, a weaker convergence trend continues to prevail, as the HDRs always are to the right of the 45° line, which indicates food inflation persistence.

At very low initial levels of food inflation differentials (less than 1), the corresponding deviation after the transition period tends to be slightly higher. Finally, initial food inflation deviations close to 1 produce a conditional density with a mode equal to 1, indicating food inflation persistence. Moreover, the corresponding values after the transition period do not display excessive spread, with the length of the 75% HDRs being relatively small. This outcome is an indication that countries with low food inflation tend to retain this low food inflation rate, forming a low food inflation group.

The preceding results can also be identified by exploring the SCD plot. The masses of the conditional densities produced at low initial values of absolute food inflation deviation concentrate 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 a transition period, concentrate at a low food inflation level. However, as the initial level of food inflation increases,

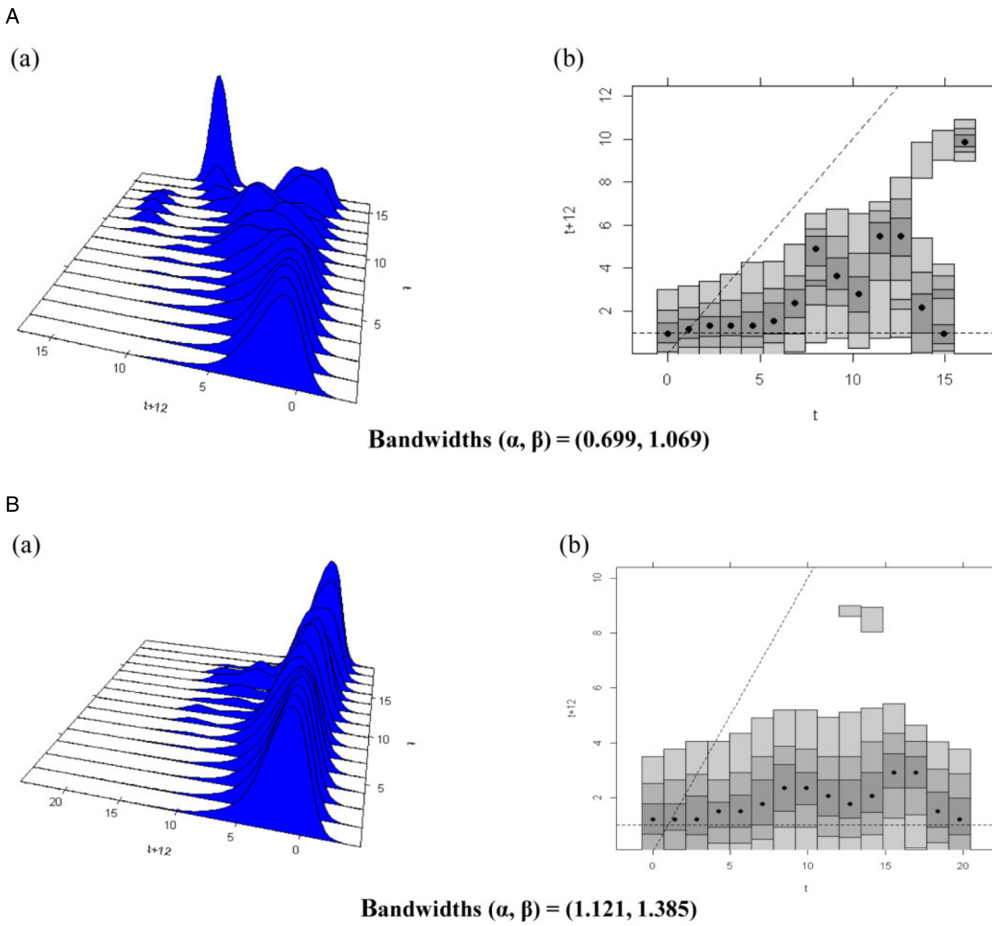


Figure 7. (A) Intradistribution dynamics of annualized unfiltered inflation rate transitions. (a) Stacked density plot and (b) HDR plot. (B) Intradistribution dynamics of annualized filtered inflation rate transitions. (a) Stacked density plot and (b) HDR plot.

the mass of the corresponding conditional density moves to the left, indicating weaker convergence trends.

Another point of interest in the conditional density plots is the presence of several multimodalities when the level of initial food inflation differentials is very high. In these cases, more than one mass exists 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 implication emerges from the multimodal univariate conditional densities in the stacked density plot and from the disjoint HDRs in the HDR 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 reflect the situation in countries with high food inflation.

When examining the conditional density plots that are produced by the filtered observations, the presence of mean reversion is even more apparent. The main difference is present 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 decreases after a 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. In contrast, results that refer to low initial food inflation levels still remain. Furthermore, the multimodality cases almost disappear after application of the spatial filtering.

The preceding evidence with regard to filtered observations strongly supports the conclusion that our previous results for unfiltered observations are biased due to spatial autocorrelation that contaminates the observations. Adjusting for the spatial component gives a clearer picture of the mean reversion trends in the EU-25 and provides a possible explanation for the existing deviations of food inflation from the cross-sectional mean.

Conclusions

This article summarizes a study that applies 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, which can invalidate the inferential basis of traditional statistics and econometric methods into consideration.

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

Distribution dynamics analysis reveals existing convergence trends in the food inflation rates. Countries with relatively higher or lower absolute food inflation deviation are expected to move back toward the mean after a 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 a low food inflation group. Moreover, at higher food inflation rates, the tendency for 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 distribution dynamics of food inflation. After 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 finding, in turn, indicates that in the absence of spatial autocorrelation, the hypothesis of homogenous food inflation seems more rational.

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Notes

1 For example, Cecchetti, Mark, and Sonora (2002), Roberts (2006), Yilmazkuday (2009), and Nagayasu (2012).
2 For example, Kočenda and Papell (1997), Holmes (2002), Weber and Beck (2005), Busetti et al. (2007), and Lopez and Papell (2010).
3 EU-25 is an economic and political union of 25 member states that are located primarily in Europe; it includes Belgium, Austria, Denmark, Luxembourg, France, Italy, Finland, Germany, Greece, Malta, Spain, the Netherlands, Sweden, Portugal, United Kingdom, Slovakia, Ireland, Czech Republic, Cyprus, Slovenia, Estonia, Poland, Latvia, Lithuania, and Hungary.
4 According to our knowledge, the role of space has been acknowledged in three studies. Weissbrod (1976) studies the diffusion of relative wages in southeastern Pennsylvania. Vaona and Ascari (2010) explore regional patterns of inflation persistence in Italy, showing that inflation persistence at the national level does not present any geographical aggregation bias. Finally, Ailenei and Cristescu (2010) show how food prices in Romania are spatially associated.
5 The HICP is an indicator of inflation and price stability for the European Central Bank (ECB). It is a consumer price index compiled according to a methodology that has been harmonized across EU countries.
6 Data are available at http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/data/database.
7 The term EU-15 refers to the 15 member states of the EU as of December 31, 2003, before more states joined. The 15 member states are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.
8 The value of G_i when the variable is randomly distributed over sampling space.
9 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.
10 Hardle (1991) describes selecting the bandwidth for regression by minimizing the "penalized average square prediction error."
11 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 has also been widely used in distribution dynamics analysis (e.g., Arbia, Basile, and Piras 2005; Fischer and Stumpner 2010; Maza, Hierro, and Villaverde 2012; Peron and Rey 2012).
12 Geographical data source: centroids of EU-25 countries from the Eurostat's GISCO (Geographical Information Systems at the Commission) NUTS data set (available at: http://epp.eurostat.ec.europa.eu/portal/page/portal/gisco_Geographical_information_maps/popups/references/administrative_units_statistical_units_1).
13 The null hypothesis of normality is rejected only in the 1.75% of the cases of monthly observations using the D'Agostino test. Distances are measured in terms of geodesic distances between the country's centroids. The local Getis index (and the associated optimum distance band) was estimated in *R*. The routine is available upon request.
14 The D'Agostino test for normality shows that the median values are normally distributed (K^2 statistic = 2.1539, P-value = 0.34).
15 Empirical distributions constructed using the Gaussian kernel type and the Silverman rule for bandwidth selection (Silverman 1986).

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