Distribution Dynamics of Food Price Inflation Rates in EU: An Alternative Conditional Density Estimator Approach

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Paper prepared for presentation at the 113th EAAE Seminar "A resilient European food industry and food chain in a challenging world", Chania, Crete, Greece, date as in: September 3 - 6, 2009

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Abstract. This paper examines the existence of convergence and distribution dynamics of food price inflation rates within the European Union. Differences in such specific price index inflation rates and changes in their regional distributions reflect largely differences and developments in market conditions and structures. Traditional measures and approaches to β-convergence and σ-convergence, fail to capture sufficiently the evolving distributional dynamics. The latter includes possible mobility prospects within distributions and potential formation of clubs. To deal with these issues, the paper adopts developments in the literature of non parametric econometric methods and employs an alternative conditional density estimator as well. Implementation of this estimator is superior, not only to the restrictive discrete Markov chain approaches, but also to the usual estimation of conditional densities using stochastic kernels. The adopted estimator has smaller integrated mean square error than the conventional estimators. Panel data analysis of β-convergence is conducted too, using panel unit root tests. Data used are the harmonized consumer price indices of food and eleven specific food product groups for 15 European countries, older member states of the EU. Extracted evidence based on the estimates is presented, analyzed, and conclusions are discussed.

Keywords: Kernel density estimator, convergence, distribution dynamics, food price inflation.

1. Introduction

The issue of inflation convergence and dispersion has gained increasing attention in the economic literature during the last few years. Several studies investigate the inflation dynamics and its determinants. In the existing literature there are two different trends. On one hand, there are several studies of inflation convergence or divergence between different regions of a country. Thus, Cecchetti et al. (2002) and Rogers (2006) examine inflation convergence trends in USA., Dayanandan and Ralhan (2005)[3] investigate price index convergence among Canadian districts as well as cities. Fan and Wei (2006)[2] investigate inflation convergence among 36 Chinese cities, Busetti et al. (2006)[5] test for convergence among Italian regions and Yilmazkuday (2009)[4] tests inflation convergence among different regions in Turkey.

On the other hand, inflation convergence is investigated within a group of countries like the European Monetary Union (EMU) members or countries during transition to EU. In fact, it was the formation of the EMU that boosted the interest on inflation rates dispersion and convergence, with the work of Rogers (2001), Montuega-Gomez (2002), Sarno and Zazzaro (2003), Altissimo et al. (2005), Kutan and Yigit (2005), Weber and Beck (2005), Busetti et al. (2007), Boschi and Giraldi (2007), Faber and Stokman (2008), Lopez and Papell (2008), Sturm et al. (2009), Erber and Hagemann (forthcoming), Coricelli (forthcoming). Additionally, EU inflation rate convergence has been analyzed relative to a benchmark, most commonly USA. or Japan (e.g. Beck et al., 2006). Finally, some studies deal with the issue of global inflation rate dispersion and convergence (e.g. Lee and Wu, 2001 and Borio, 2007).

Many studies connect inflation differentials with the productivity catching-up process (eg. Canzoneri, 2003). Other studies focus on the role of monetary and fiscal policies in the formation of inflation differentials as Cecchetti et al., (2002) and Weber and Beck (2005) who try to identify whether the European Central Bank's 'one size for all' inflation rate target of 2% under covers the risk of deflation for some countries. A well founded monetarist view is that continued and even increasing inflation cannot be attributed to market structure, since that would imply that this structure deteriorates constantly and market concentration increases at an increasing rate, both of which are not usually confirmed. Hence, for other reasons too, the supply of money remains the significant factor. However, when we deal with inflation rate differentials among regions and countries or with price inflation rates for specific groups of products such as food, other factors play an important role on inflation dynamics and convergence. These factors are strongly related with market structure, the country specific trade policy, the food supply chain functioning and the degree of absorption of external shocks in different countries.

Dalsgaard (2008) recognizes the influence of competition and market structure issues, such as the degree of market concentration, mergers and acquisitions procedures and formation of cartels, in inflation rates. Also Fousekis P. (2008) points out the fragmentation of the European market and claims that the inflation rate differentials and dispersions are not efficiently confronted by horizontal EU measures but by changes in the market structures in the EU countries.

Additionally, Bukeviciute et al. (2009) associate the fluctuations of the food price inflation with differences in the food supply chain functioning. They also point out that an external shock (e.g. the rapid increase in agricultural commodities and in energy prices that have been lately observed) is differently absorbed in each country, and thus contributes to high inflation dispersions. This fragmentation, revealed by the different degree of absorption, is a possible consequence of the different market competition and regulatory framework. In this sense food price inflation differentials are a signal that the EU food market still remains fragmented.

The above effects are rather difficult to determined, when the examination of the inflation rates is restricted to the general inflation index. As our interesting is located in the food sector, we examine the existence of convergence in the ‘Food and non alcoholic beverages’ index as well as in its eleven product groups. Data is provided by Eurostat and consists on monthly HICP indices for the EU15 countries from 1997:01 to 2009:05.

The methodologies we used in this analysis come from the growth literature. This is also the case for the vast majority of the inflation convergence studies, where the notions of β-convergence[1] and σ-convergence are very popular. In the first case, what is examined is the ‘mean-reverting’ behaviour of the inflation rate. A negative and statistically significant β value indicates convergence. β-convergence can be estimated either by cross-section regressions, or by time-series and panel unit root tests. The rejection of the unit roots indicates convergence. In the case of σ-convergence analysis, the evolution of inflation rate dispersion along time is examined. Decreasing dispersion is an evidence of σ-convergence. Finally, Weber and Beck (2005) introduce another methodology commonly used in the growth literature, the distribution dynamics approach.

In our analysis, we used panel unit root tests, according to Levin, Lin and Chu (2002), σ-convergence, as described by Sala-i-Martin (1996), and the distribution dynamics approach, which was first introduced by Quah (1993). The latter approach is applied using the kernel density estimator, provided by Hyndman et al. (1996) and Hyndman and Yao (2002). This estimator has been introduced in the growth literature from Arbia et al. (2005), who examined the convergence of GDP per capita in the Italian regions. This new alternative approach has two advantages. First, it gives a density estimator with smaller integrated mean square error and additionally it provides more efficient visualization of the distribution dynamics evolution.

The rest of the paper is organized as follows. Section 1.1 provides a literature review on previous findings on food inflation rates dynamics and its determinants. In Chapter 2 we present the data used in this analysis and some descriptive statistics. In Chapter 3 we describe the methodologies we use as well as our findings. Specifically, Section 3.1 analyzes the notion of β-convergence, while Section 3.2 describes the notion of σ-convergence, its importance and the connection with β-convergence. Finally, in Section 3.3 we introduce the notion of distribution dynamics following a discussion on the several disadvantages of the aforementioned convergence measures. Thus the paper is organized so that each methodology is followed by the results it yields. Finally, our concluding remarks are presented in Chapter 4.

1.1. Evidence on Food Inflation Rate Dynamics

While the vast majority of the existing literature examines the general inflation rate dynamics there are several studies which go beyond it. Weber and Beck (2005), examined the inflation convergence in two samples of European countries. For this purpose, they used HICPs of the total index as well as for 12 sub-

[1] In fact, there is a theoretical gap in the β-convergence notion, as we cannot derive it theoretically, as in the case of GDP per capita. Nevertheless, it is rational to expect that as a common union grows up, the common policy as well as the market integration processes will follow up by a common inflation rate in the long-run (ECB, 2003).

indices, including the 'Food and non alcoholic beverages' index. What they found is that there is convergence in the 'Food and non-alcoholic beverages' index, but they did not provide half-lives[2] as the solution of the nonlinear expression for β-convergence they used, produced complex number. Additionally they found that the estimated β's are greater in the total period rather than the period after the EMU, an evidence of slower β-convergence after the introduction of the common currency. This evidence indicates non-linearities in the convergence process i.e. the further the convergence has proceeded the slower the speed of the convergence. Additionally, they found evidence of overall dispersion decline but only in the first half of 90's. After the second half the dispersion is not further decreased and in the first years of 2000 the inflation dispersion has even increased. This is a somewhat paradox finding, as a period of strong β-convergence does not coincide with σ-convergence. In growth literature (see Sala-i-Marin, 1996) this phenomenon is called 'leapfrogging' and indicates that countries with relative low rank in inflation, not only converged but even overtake other countries with relative high rank in inflation rate, and vice-versa.

Dayanandan and Ralhan (2009) using panel unit roots test (according to Levine and Lin, 1992 and Im, Pesaran and Shen, 1997), found evidence of β-convergence for 'food' index in Canada with half life equals to 7.4 years. Sturm et al. (2009) estimate the coefficients of variation for several CPI's categories, and for different groups of European countries. They found significant β-convergence only for non-EMU countries and only for period 2001-2005. They also found significant evidence for σ-convergence both for EMU and non-EMU countries[3].

Exploring the 'Food and nonalcoholic beverages index', Faber and Stokman (2008) found evidence in favour of convergence from 1980 to 2003 in Europe. In the early 90s, there was a strong price level convergence for all 2nd-level indices (including 'Food and non alcoholic beverages'). Finally, Fan and Wei (2006), used panel unit roots test, according to Levin and Lin, (1992) and In, Perasan and Shen, 1997) for 'Food' index in China, based on monthly price indices across 36 major Chinese cities and over a seven year period. The two tests provided contradictory results, as convergence was only supported by the Im, Pesaran and Shen test, and only when the lag selection was based in the 'modified Schwartz information criterion'. In this case, the half-life was estimated to 4.6 months, which is substantially lower duration than those usually found in literature. Fan and Wei (2006), suggest that those results are stemming from the fact that they use high-frequency data which fit better with the time needed for price convergence in domestic markets and thus they claim that the results of the other studies are suffering from the 'aggregation bias' (the consequence of using aggregating data, see Taylor, 2001).

2. Data and descriptive statistics

To examine the food inflation dynamics in EU, we use monthly data of HICPs for 'Food and non alcoholic beverages' and for the eleven different products groups (Table 1). Inflation rates are computed as annual percentage changes of the price index as follows:

$$\pi_t = 100 * (\ln P_t - \ln P_{t-1}) = 100 * (p_t - p_{t-1}) \quad (1)$$

where π_t , denotes the inflation rate in period t, and P_t, represents the respective price index in period t. p_t and p_{t-1} are the natural logarithms of P_t and P_{t-1} . The results for the 'Food and non alcoholic beverages' index are summarized in Table 1. On average, Greece and Spain have the greatest inflation rate, while Sweden and Germany have the lowest. It is also worth mentioning that Ireland and UK have the greatest inflation rate deviations, while Luxemburg and Germany have the lowest.

2 The half-live is the time necessary to fill half of the transition between the initial level and the stationary value.

3 Also, the examination of more disaggregated data reveals a statistically significant β- and σ-convergence for two products groups.

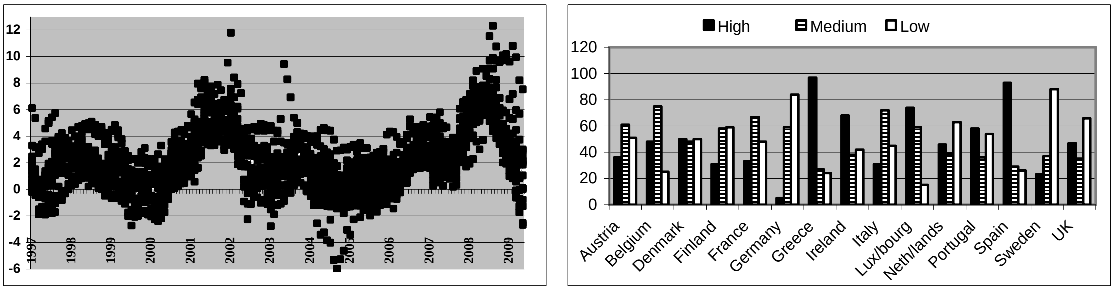


Figure 1. a) Food inflation rates for the EU15 countries **b)** Times that each country has been included in the 'high', 'medium' and 'low' food inflation rate category.

Figure 1a presents an illustration of the inflation rate dispersion in the 'Food and non-alcoholic beverages' index. Dispersion is spanning a band around 4-6% width with extreme minimum and maximum values equals to 2.6 and 10.8 respectively.

Table 1. Descriptive statistics for the general food inflation rates and for the eleven food product groups.

		Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Lux/bourg	Neth/lands	Portugal	Spain	Sweden	UK	AV/AGE	STD.DEV
1.Food and Non-alcoholic beverages	Mean	2.02	2.38	2.29	2.17	2.03	1.27	3.40	2.59	2.16	2.63	1.81	2.19	3.09	1.75	2.24	2.23	0.53
	St.dev.	1.97	1.96	2.32	2.59	1.87	2.26	2.29	2.41	1.73	1.43	2.89	2.08	2.00	2.23	3.09	2.16	
1.1.1.Bread and cereals	Mean	2.64	3.24	3.27	1.95	1.98	1.65	4.37	2.96	2.38	2.95	1.71	3.51	3.43	1.87	2.10	2.60	0.82
	St.dev.	2.44	2.50	2.91	2.27	1.51	2.11	3.05	3.04	2.48	1.77	2.14	2.62	2.31	2.88	3.43	2.39	
1.1.2.Meat	Mean	1.77	2.09	1.43	1.32	2.31	1.21	2.84	1.93	1.96	2.30	1.67	1.26	2.98	1.47	1.85	1.88	0.53
	St.dev.	2.28	1.83	3.04	3.62	2.29	2.84	1.86	3.24	1.85	1.76	2.94	3.60	3.07	2.78	4.15	2.71	
1.1.3.Fish and seafood	Mean	2.54	3.29	3.28	3.01	2.25	2.87	4.35	3.23	2.90	2.96	3.44	3.46	3.46	3.24	3.72	3.20	0.48
	St.dev.	3.38	3.57	3.32	2.66	1.73	1.74	3.75	3.56	1.60	3.28	3.78	5.31	2.12	3.22	4.25	3.06	
1.1.4.Milk, cheese and eggs	Mean	2.11	2.15	2.47	2.92	1.80	1.21	3.75	3.10	1.84	2.84	2.01	1.45	2.93	2.06	2.64	2.28	0.72
	St.dev.	3.98	3.80	3.95	4.47	2.83	5.16	1.85	4.57	2.01	2.99	4.89	3.36	4.02	2.80	4.51	3.54	
1.1.5.Oils and fats	Mean	2.21	2.16	2.92	2.82	2.34	1.05	1.37	3.43	1.73	2.46	2.17	0.17	-0.20	1.58	2.21	1.85	0.97
	St.dev.	3.67	3.75	4.98	4.03	2.73	5.85	8.71	3.96	3.96	2.81	4.63	8.13	16.64	2.88	5.80	5.43	
1.1.6.Fruit	Mean	3.84	2.88	1.80	3.55	2.44	1.35	4.04	2.21	2.41	3.53	2.56	2.67	4.45	3.22	2.01	2.82	0.87
	St.dev.	7.61	5.43	4.27	5.87	6.57	4.04	10.86	2.72	4.36	3.29	4.81	5.81	4.23	4.90	4.52	5.17	
1.1.7.Vegetables	Mean	1.53	2.14	1.00	2.34	2.14	0.70	3.06	2.72	2.61	3.21	3.11	3.51	4.27	1.98	2.55	2.43	0.91
	St.dev.	5.07	8.53	6.66	7.45	5.75	6.17	11.71	7.81	4.33	4.95	8.41	12.22	4.34	6.80	8.04	6.99	
1.1.8.Sugar,jam, honey, chocolate, confectionery	Mean	1.57	2.30	2.34	1.28	1.57	1.62	3.84	3.28	1.79	2.17	0.82	1.34	2.14	0.99	2.89	2.25	0.82
	St.dev.	2.07	1.63	1.42	1.72	1.74	1.73	1.34	2.69	0.90	1.63	2.64	1.21	1.34	1.79	1.99	1.88	
1.1.9.Food products n.e.c.	Mean	1.87	1.71	1.87	1.55	1.99	1.00	3.01	2.64	1.70	1.97	1.25	1.99	1.96	0.98	1.26	1.76	0.56
	St.dev.	1.59	2.96	2.14	2.14	1.76	1.12	2.31	1.88	1.29	1.36	2.91	3.02	2.34	1.70	2.79	2.69	
1.2.1.Coffee, tea and cocoa	Mean	0.52	1.72	0.68	-0.13	1.22	0.35	1.75	3.05	1.25	1.36	0.69	0.00	1.27	-0.07	1.23	1.07	0.83
	St.dev.	7.63	9.03	8.42	13.28	2.90	5.23	3.29	3.48	2.14	4.15	8.14	2.28	3.60	9.32	4.85	5.43	
1.2.2.Mineral water, soft drinks, fruit & veg/ble juices	Mean	1.11	1.13	3.85	3.23	1.36	1.09	3.28	2.14	1.34	1.90	0.99	0.13	2.06	0.91	1.31	1.66	1.01
	St.dev.	2.80	2.11	4.67	1.78	1.53	1.62	1.92	2.16	1.20	1.17	4.28	1.62	1.45	1.19	1.87	1.99	

Another interesting point revealed by the data, is that countries have possessed different ranks during the sample period. Figure 1b, shows how many times, each country has been included in the 'high', 'medium' and 'low' rank inflation rate group. The 'high' inflation group consists by the first 5 countries in the relative ranking, while the 'medium' and the 'low' inflation groups consist by the countries with relative rankings from 6 to 10 and from 11 to 15, respectively. It's obvious that even the countries with low average inflation rate, have been placed in the 'high' inflation groups at least for a few periods. This is an example of 'leapfrogging'.

Looking at the mean rate of the 'Food and non-alcoholic beverages' index (Table 1) we can see that the lowest average inflation rate is detected in Germany, followed by Sweden, Netherlands and Austria. However, a look at the disaggregated product groups provides a somewhat different picture. Whereas Germany has the lowest inflation rate in 'Food and non alcoholic beverages' this is not the case for 6 out of 9 product groups ('Fish and seafood', 'Oils and fats', 'Sugar, jam, honey, chocolate, confectionery', 'Food products n.e.c.', 'Coffee, tea and cocoa' and 'Mineral water, soft drinks, fruit and vegetable juices'). On the other side, Greece has the highest average inflation rate in 'Food and non-alcoholic beverages' as well as in five product groups ('Bread and Cereals', 'Fish and Seafood', 'Milk, Cheese and

‘Eggs’, ‘Sugar, Jam, Honey, Chocolate and Confectionary’). Ireland has the highest rate for ‘Oils and Fats’ and ‘Coffee, Tea and Cocoa’ but the lowest rate for ‘Food products n.e.c.’. On the other side, Spain has the lowest inflation rates in ‘Oils and Fats’ but the highest in three food product groups (‘Meat’, ‘Fruit’, ‘Vegetables’).

Finally, the dispersion of inflation rate for each product group provides us with some useful insights. Dispersion is lower for the ‘Food and non-alcoholic beverages’ and also for the ‘Fish and seafood’, ‘Meat’ and ‘Food products n.e.c.’ (0.48-0.56) while it is highest for ‘Mineral water, soft drinks, fruit and vegetable juices’, ‘Oils and Fats’ and ‘Vegetables’ (from 0.91 to 1.01).

These statistics clearly illustrate the complexity nature of our data. Whereas some countries possess high ranking in one product group they may possess low ranking in another product group. Additionally, these rankings are continuously changing during our sample period and thus the interpretation of the descriptive statistics should be very careful, as ‘criss-crossing’ and ‘leapfrogging’ effects are clearly present.

Moreover, it seems that the market in each product group has its own dynamics and structural characteristics. This is in accordance with our view that food inflation rates in Europe are not only affected by a common factor (like the fiscal and monetary policy). Country-specific factors as well as different market structures may contribute to the observed heterogeneity.

3. Methodology

3.1. β-convergence

According to Barro and Sala-i-Martin (1991), β-convergence is present when different cross-sectional time series show a mean reverting behavior[4]. Beck et al. (2006) estimate the average growth rate, as a function of the deviation from equilibrium at a given starting point, while Mentz and Sebastian (2003) analyze inflation convergence using Johansen cointegration test. But usually researchers use either time series or panel data unit roots tests for the examination of the mean–reverting behavior (e.g. Weber and Beck, 2005, Bussetti et al., 2006, Lopez et al., 2007, Fan and Wei, 2006, Cecchetti, 2002). One of the major problems faced by researchers regarding time-series unit root tests is their low power, especially in small samples. Recently, the use of panel unit root tests has alleviated this problem to a great extent by exploiting both cross and time series variation. Taking this under consideration, we implement the Levin Lin and Chu (2002) panel unit root test[5] (LLC).

Let i = (1, 2,….., N) denote the countries of our sample and t = (1, 2,….., T) represents the time index, the test for inflation convergence is based on the following equation:

$$\Delta\pi_{i,t} = \rho\pi_{i,t-1} + \theta_t + \sum_{j=1}^{k_i}\varphi_{i,j}\Delta\pi_{i,t-j} + \in_{i,t} \quad (2)$$

where Δ denotes the one-period (annual) change of $\pi_{i,t}$, θ_t, represents a common time effect and $\in_{i,t}$ is assumed to be a (possibly serially correlated) stationary idiosyncratic shock. The inclusion of lagged differences in the equation serves to control for serial correlation. LLC test allows for variation of the number of lagged differences, whereby their respective number is determined using the Akaike information criterion (AIC) and the Schwartz Information Criterion (SIC) methods. The inclusion of a common time effect is supposed to control for cross-sectional dependence caused by an external shock, e.g., by the upsurge of agricultural commodities and energy prices. To take control of this effect, we transform the data by subtracting the cross-sectional mean leading to

$$\Delta\tilde{\pi}_{i,t} = \rho_i\tilde{\pi}_{i,t-1} + \sum_{j=1}^{k_i}\varphi_{i,j}\Delta\tilde{\pi}_{i,t-j} + \in_{i,t} \quad (3)$$

where $\tilde{\pi}_{i,t}$ is computed as

[4] Using the example of a sport league, they present β-convergence in terms of how rapidly teams at the bottom of the ranking tend to rebound towards the middle, or equivalently, how quickly champions tends to revert to mediocrity.
[5] For a review on time series and panel data econometrics, see Durlauf et al. (2005).

$$\tilde{\pi}_{i,t} = \pi_{i,t} - \frac{1}{N}\sum_{j=1}^{N}\pi_{j,t} \tag{4}$$

Now, the examination of the mean reverting behaviour is implemented by testing the null hypothesis that all ρ_i are equal to zero against the alternative hypothesis that they are all smaller than zero. To test the Ho, we use the Newey-West (1994) bandwidth selection method with the Bartlett spectral kernel. The rejection of the null hypothesis (nonstationarity) implies that inflation rates exhibit mean reverting behaviour and thus any shock that causes deviations from equilibrium will eventually die out. The speed at which this occurs can be directly derived from the estimated value of ρ (denoted $\hat{\rho}$) using the formula: $t_{half} = \ln(0.5)/\ln(\hat{\rho})$. According to Nickell (1981), the estimates for β are biased downward for finite samples. So, following Cecchetti et al. (2002), we apply Nickell's formula[6] to correct for this downward bias. Additionally, to get a rough indication of non-linearities in the convergence process, we implement the LLC panel unit root tests in two different time periods. Rather than splitting data according to a specific event (e.g. the establishment of the EMU), we prefer to split the data in two almost equal parts, as anything else would lead to the creation of at least one very small sample. If we find different ρ-values in the second period, then as Goldberg (2005) and Berga (2009) report, we have an indication of non-linear convergence process meaning that as we are getting closer to the 'steady state' convergence speed is changing.

Results

For the whole period, β-convergence is present only in the 'Fruits' and 'Vegetables' product groups and only when the lag selection is based on the SIC method. Half-lives were estimated to 4 and 2.9 months respectively, based on the adjusted ρ values. As Weber and Beck (2005) claim, sometimes and especially when the sample size is rather small, Nickell's process might overstate about the necessary adjustment time. Adopting this argument, we consider the half-lives estimated by the unadjusted and adjusted ρ's, as the lower and the upper bound of the real half-live respectively. Our results are summarized in Table 2, where the half-lives are presented, only in those cases where the unit roots were rejected.

Getting to the first sub-period of our sample, the whole picture is completely different. Strong convergence evidences appear in 'Food and non alcoholic beverages' as well as in seven product groups. Also in three more product groups, LLC using AIC lag selection method gives statistical evidence for convergence and in one more product group the rejection of the null hypothesis is supported only when SIC method is adopted. Interestingly, the only product group where no convergence evidence was found, using both AIC and SIC methods, is the 'Sugar, jam, honey, chocolate and confectionery'.

Table 2. Panel unit root tests for food inflation rates and for the 11 product groups' inflation rates.

		TOTAL PERIOD					**1997M01 2002M12**					**2003M01-2009M05**				
Categories		**ρ**	**ρ-adj**	**t-stat**	**1/2 life**	**1/2 life adj.**	**P**	**ρ-adj**	**t-stat**	**1/2 life**	**adj. 1/2 life**	**ρ**	**ρ-adj**	**t-stat**	**1/2 life**	**adj. 1/2 life**
1	**S[a]**	0.92	0.94	0.72			0.87	0.90	-1.39*	**5.1**	**6.4**	0.92	0.95	0.755		
	A[b]	0.93	0.95	7.83			0.81	0.84	-2.58***	**3.4**	**4.0**	0.90	0.93	-0.08		
1.1.1	**S**	0.94	0.95	3.00			0.90	0.93	-0.80			0.92	0.94	1.006		
	A	0.94	0.95	6.70			0.88	0.90	-1.80**	**5.4**	**6.9**	0.86	0.88	-1.674		
1.1.2	**S**	0.91	0.92	0.56			0.88	0.91	-1.69**	**5.4**	**7.0**	0.93	0.95	0.592		
	A	0.91	0.93	8.80			0.86	0.89	-1.62**	**4.5**	**5.7**	0.91	0.93	-0.133		
1.1.3	**S**	0.90	0.91	0.30			0.89	0.91	-1.62**	**5.9**	**7.7**	0.88	0.91	-0.253		
	A	0.91	0.92	5.59			0.84	0.86	-4.31***	**4.0**	**4.8**	0.88	0.90	0.003		
1.1.4	**S**	0.94	0.95	6.48			0.90	0.92	-1.60**	**6.6**	**8.9**	0.92	0.94	-0.430		
	A	0.94	0.96	10.36			0.88	0.91	-2.31***	**5.6**	**7.5**	0.90	0.92	-0.379		
1.1.5	**S**	0.95	0.96	1.58			0.94	0.96	-3.10***	**10.7**	**17.6**	0.94	0.96	-0.52		
	A	0.94	0.96	7.45			0.95	0.98	-2.00**	**14.5**	**30.0**	0.93	0.95	-1.54*	**9.4**	**13.8**
1.1.6	**S**	0.83	0.84	-7.12***	**3.7**	**4.0**	0.82	0.85	-4.87***	**3.6**	**4.2**	0.84	0.86	-4.47***	**3.9**	**4.5**
	A	0.83	0.84	-0.53			0.81	0.83	-4.53***	**3.2**	**3.8**	0.84	0.87	-2.22***	**4.1**	**4.8**
1.1.7	**S**	0.78	0.79	-8.64***	**2.7**	**2.9**	0.75	0.77	-6.55***	**2.4**	**2.7**	0.73	0.75	-5.77***	**2.2**	**2.4**

---

[6] Nichell's formula for the estimation of the adjusted ρ is: $p\lim_{N\to\infty}(\hat{\rho}-\rho) = (A_T B_T)/C_T$, where $A_T = -(1+\rho)/(T-1)$, $B_T = 1-(1/T)(1-\rho^T)/(1-\rho)$ and $C_T = 1-2\rho(1-B_T)/[(1-\rho)(T-1)]$.

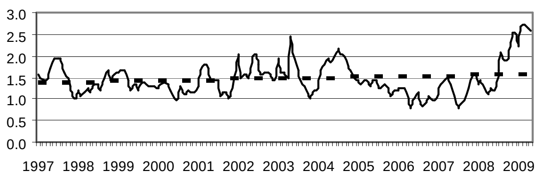
	A	0.76	0.77	4.79	0.72	0.74	-0.97			0.69	0.71	-3.01***	**1.9**	**2.1**
1.1.8	S	0.93	0.94	3.85	0.89	0.91	-1.10			0.92	0.94	0.218		
	A	0.94	0.96	9.98	0.88	0.91	-0.08			0.89	0.91	-1.053		
1.1.9	S	0.97	0.98	3.21	0.91	0.93	-0.68			0.94	0.96	0.296		
	A	0.97	0.98	5.46	0.87	0.90	-2.20**	**5.0**	**6.4**	0.93	0.95	0.193		
1.2.1	S	0.92	0.93	2.00	0.93	0.95	-4.20***	**8.9**	**14.1**	0.93	0.95	0.500		
	A	0.90	0.91	9.44	0.86	0.89	-5.92***	**4.7**	**5.9**	0.91	0.93	-0.460		
1.2.2	S	0.92	0.93	1.53	0.89	0.91	-0.79			0.92	0.94	-0.240		
	A	0.93	0.94	6.02	0.86	0.89	-1.46*	**4.7**	**5.8**	0.90	0.92	-1.27*	**6.6**	**8.6**

a) S, stands for the Schwartz Information Criterion for the selection of the lags number
b) A, stands for the Akaike Information Criterion for the selection of the lags number
* 10% level of significance, ** 5%level of significance, *** 1% level of significance

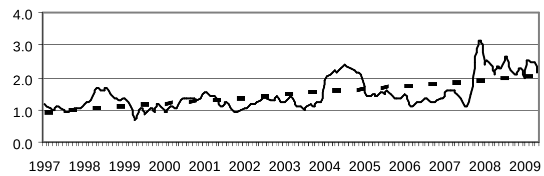
In the second subperiod, convergence is appeared only in four product groups (‘Fruits’, ‘Mineral water, soft drinks, fruit and vegetable juices’, ‘Vegetables’ and ‘Oils and fats’). The speed of convergence appeared to be slower in the first two cases, but in the third and fourth case, the speed of convergence has been increased. However, we have to carefully interpret the above results. The evidences of slowing down convergence, are supported by both SIC and AIC lag selection methods. On the other side, the evidences of convergence speed-up are only supported when the AIC method of lag selection is implemented and even in this case, unit roots are rejected with marginal level of statistical significance.

3.2. σ-convergence

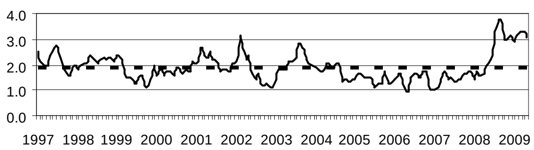
(a) 1. Food and non alcoholic beverages



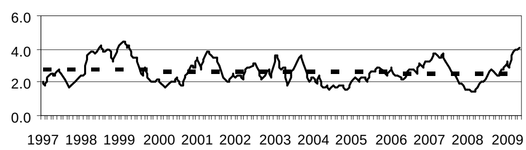
(b) 1.1.1. Bread and Cereals



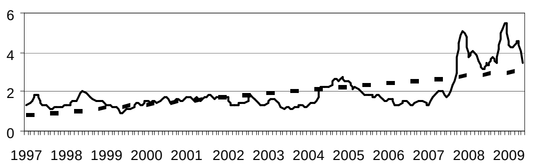
(c) 1.1.2. Meat



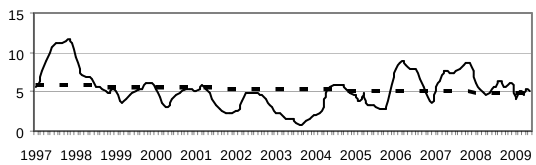
(d) 1.1.3. Fish and seafood



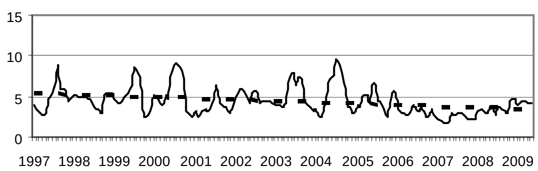
(e) 1.1.4. Milk, cheese and eggs



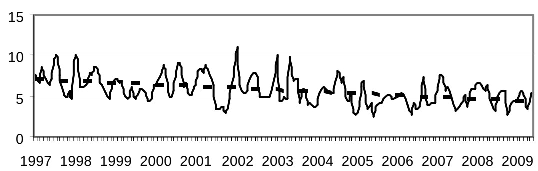
(f) 1.1.5. Oils and fats



(g) 1.1.6. Fruit

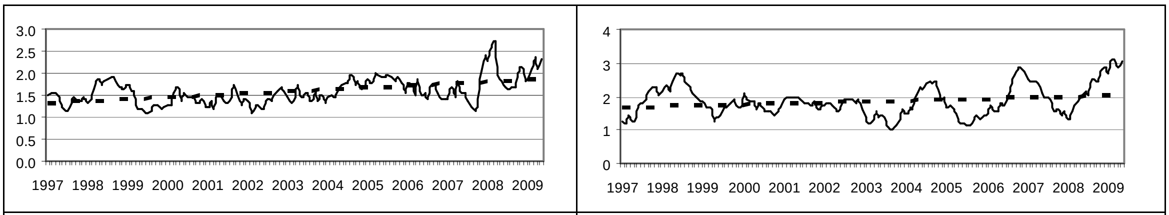


(h) 1.1.7. Vegetables



(i)1.1.8. Sugar, jam, honey, chocolate and confectionery

(j) 1.1.9. Food products n.e.c.



(k) 1.2.1. Coffee, tea and cocoa	(l) 1.2.2. Mineral water, soft drink, fruit and vegetable juice

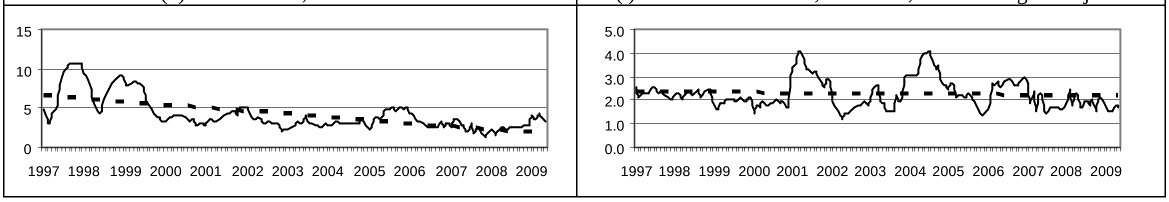


Figure 3. Inflation dispersion in food inflation rates and in the eleven food product groups

In addition to the question of whether regions with high inflation rates tend to have persistently higher inflation rates or not (β-convergence), another important aspect of convergence concerns the evolution of the overall cross-regional dispersion of inflation rates. According to Barro and Sala-i-Martin (1991) this issue is answered by exploring the existence of σ-convergence i.e. the evolution of dispersion in a data set over a given period of time. As Sala-i-Martin (1996) illustrates, in the presence of σ-convergence, some steady-state value for cross-sectional dispersion would finally be reached. Also, as Barro and Sala-i Martin (1992) mention, 'β-convergence is a necessary but not sufficient condition for σ-convergence'. This will be the case when 'leapfrogging' occurs to a large extent. As we have already illustrated in Figure 2, inflation rates for 'Food and non-alcoholic beverages' indeed exhibit this pattern.

In our case, σ-convergence is investigated through the examination of whether cross-regional dispersion of European inflation rates has stayed constant over time, has diminished or has increased in 'Food and non-alcoholic' index as well in the eleven product groups.

Results

Figure 3 presents the cross-section inflation rate dispersion from 1997:01 to 2009:05. What we can generally see, is that for most of these categories, there is an upward trend in the last year (or more, in some cases). This is probably the outcome of the rapid increase in agricultural commodity prices and energy prices beginning from the second half of 2007. Thus the overall dispersion time trend is affected, and in four product groups the results indicate an increasing dispersion time trend, while in four categories the dispersion trend seems to be stable (including the general 'Food and nonalcoholic beverages' index). Finally in the rest four product groups, the dispersion is more or less diminishing. Apart from the general time trend, we can see that each product group has its own characteristics. Average values, range of dispersion and the number and form of peaks are not similar.

Another interesting point is that while the first period panel unit root tests indicate mean-reverting behaviour in most cases, an analogous decline in dispersion is not so obvious. With the exception of the 'Oils and fats' and 'Vegetables' product groups, there is no evidence of σ-convergence in our data. In most cases, it seems that the dispersion is more or less stable in the first subperiod. So, it seems that the β-convergence is more or less not coinciding with σ-convergence and thus the common evidence of 'leapfrogging' appears in our data.

In the latter period, there is an obvious upward trend, which in most cases inevitably arises from the great dispersion of the last two years. This is not the case for 'Vegetables', 'Fruits', 'Coffee, tea and cocoa' and 'Mineral water, soft drink, fruit and vegetable juice' product groups where the dispersion seems to be decreasing. So, the absence of β-convergence in the second period coincides with the absence of σ-convergence in the latter period, with the exception of the 'Oils and fats' product group (leapfrogging).

3.3. Distribution dynamics

While the two previous analyses provide us with important information about the inflation rate convergence, they have serious limitations. As far as it concerns β-convergence, it sheds light on the transition towards to a steady state, but it provides no insight on the dynamics of the whole cross-sectional distribution. More specific, a negative β can be associated with rising, declining or stationary cross-section inflation deviation. Clearly, a method that cannot differentiate between convergence, divergence and stationarity is of limited use (Arbia et al., 2005).

Additionally, the combination of β-convergence and σ-convergence approach is also no effective solution: analyzing the change of cross-sectional inflation deviation does not provide any information on the intra-distribution dynamics. A constant standard deviation of the inflation rate could coexists with very different dynamics of the distribution ranging from criss-crossing and leap-fogging to persistent inequality. The distribution dynamics approach overcomes the above limitations as it examines directly how the whole distribution changes over time.

Thus, in this section we are interesting in revealing the composition of inflation deviation distribution or as Weber and Beck (2005) question:

"*…do regions with relatively low/high inflation rates stay in this position for a prolonged period of time, or is the composition changing rapidly, i.e. do regions with relatively low/high inflation rates move away from the tail into the middle of the distribution relatively fast?*"

Based on our previous results, one could suggest that as far as β-convergence and σ-convergence give different results for a specific time period, then there should be intra-distribution dynamics. In order to make it clear, we will use the method of distribution dynamics, which was first introduced by Quah (1993). Whereas this methodology has been mostly applied in the economic growth literature[7], it has been already spread in several other economic areas, like environmental economics (e.g. Aldy, 2006).

The idea behind distribution dynamics is to find a law of motion that describes the evolution of the entire distribution over time. Initially, Quah suggested the development of a probability model to describe how a given economy observed in a given class of the income distribution at time t moves to another class of the income distribution at the time t+τ. To do this, he used a Markov process. The dynamics of the probability measure of the distribution can be modelled as a first order autoregressive process:

$$F_{t+\tau} = M'(F_t) \tag{5}$$

where M'(.) denotes the operator mapping period's t distribution into period's t+τ distribution. Quah uses M'(.) as a transition probability of Markov process. Adjusted to our case, each element of M'(.) describes the probability that a country with inflation rate belonging to the class i at time t, will move to the class j at time t+τ. Then, the distributions of $F_{t+\tau}$'s reveal the undercover dynamics of the distribution of the inflation rate deviation. More specifically, if one finds that there is a tendency towards a single point mass then he can conclude in favour of convergence towards equality. On the other hand, if $F_{t+\tau}$'s display a tendency towards a two points mass or more, this is a clear evidence of polarization or stratification.

Whereas this approach is very simple and easy to implement, it is not generally suggested in the literature, as it has disadvantages stimulated by the discretization process which is more or less arbitrary and could yields different results when different discretization processes are applied (Reichlin, 1999). Markov property assumes that in each moment of time the temporal process depends only on the previous time period[8]. For this reason, Bickenbach and Bode (2003) pointed out that Markov chain theory imposes restrictions on the data-generating process.

Quah (1996) recognizing the problems arising by the discretization process, suggested the substitution of the discrete transition matrices with a stochastic kernel of a continuous state-space Markov process to reflect the probabilities of transition between a hypothetically infinite number of classes. In this case, equation (5) transform to

$$F_{t+\tau} = \int_A P(x, A) F_t(dy) \tag{6}$$

where, A is any subset of the underlying state space for X_t and P(x, A) is a conditional density function that describes the probability of a country to be in A in t + τ given that it is currently (time t) in state x, i.e.

$$P(x, A) = P(X_{t+\tau} \in A \mid X_t = x) \tag{7}$$

[7] For a recent survey in distribution dynamics, see Magrini (2007) and Durlauf and Quah (1999).

[8] a process is said to be a Markov chain if the random variable at time t+τ depends exclusively on the information set at time t and not on any other previous period in time

In our analysis, we define, X_t, as the deviation of a country's inflation rate from the cross-regional mean and so the underlying state space is the real line R. In addition, we look for the reaction of the countries in one year period i.e. τ=1. Thus, the conditional density function describes the probability that a country will move to a certain level of inflation deviation from the cross-sectional mean after one year, given its current inflation rate deviation (time t).

The conditional density function can be estimated using a nonparametric estimation, first proposed by Rosenblatt (1969). Hyndman et al. (1996) further developed this estimator, and also introduced very convenient tools for better visualization of the kernel density. They define this estimator as:

$$\hat{f}_\tau(y \mid x) = \hat{g}_\tau(x, y) / \hat{h}_\tau(\chi) \tag{8}$$

where

$$\hat{g}_\tau(x, y) = \frac{1}{nab} \sum_{i=1}^{n} K\left(\frac{\|x - X_i\|_x}{a}\right)\left(\frac{\|y - Y_i\|_y}{b}\right) \tag{9}$$

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

$$\hat{h}_\tau(x) = \frac{1}{na} \sum_{i=1}^{n} K\left(\frac{\|x - X_i\|_x}{a}\right) \tag{10}$$

is the estimated marginal density. In the above equations, a, b, are bandwidth parameter controlling the smoothness of the fit, $\|.\|_x$ and $\|.\|_y$ are Euclidean distance metrics on the spaces of X and Y respectively and K(.) is a symmetric density function, knowing as the kernel function. Whereas there are many different kernels functions, the most usual choices are the Gaussian and the Epanechnikov. In any case the selection of the kernel function is not as important, as the bandwidth selection (Silverman, 1986).

The conditional density estimator can be rewritten as:

$$\hat{f}_\tau(y \mid x) = \frac{1}{b} \sum_{i=1}^{n} w_i(x) K\left(\frac{\|y - Y_i\|_y}{b}\right) \tag{11}$$

where

$$w_i(x) = K\left(\frac{\|x - X_i\|_x}{a}\right) \Big/ \sum_{j=1}^{n} K\left(\frac{\|x - X_j\|_x}{a}\right) \tag{12}$$

This estimator is in fact the Nadaraya-Watson kernel regression estimator. Equation (11) shows that a conditional density 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:

$$\hat{m}(x) = \int y \hat{f}_\tau(y|x) dy = \sum_{i=1}^{n} w_i(x) Y_i \tag{13}$$

Hyndman et al. (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 given by:

$$\hat{f}^*_\tau(y \mid x) = \frac{1}{b} \sum_{i=1}^{n} w_i(x) K\left(\frac{\|y - Y_i^*\|_y}{b}\right) \tag{14}$$

where $\hat{f}_\tau^*(x) = e_i + \hat{r}(x) - \hat{l}(x)$, $\hat{r}(x)$ is the estimator of the conditional means r(x)=E(Y|X=x), $e_i = y_i - \hat{r}(x)$ and $\hat{l}(x)$ is the mean function of $\hat{f}_\tau^*(e \mid x)$. Instead of estimating $\hat{r}(x)$ by the Nadaraya-Watson smoother, we can apply many different smoothers with better properties. In this way, we can obtain an estimator of the conditional density with lower mean-bias properties. Moreover, as Hyndman et al. (1996) show, the modified estimator has a smaller integrated mean square error than the standard kernel estimator[9]. Lately, Hyndman and Yao (2002) proposed an alternative estimation method, called the local parametric estimation which is defined as:

$$R(\beta_0, \beta; x, y) = \sum_{i=1}^{n} \left\{ K\left(\frac{\|y - Y_i\|_y}{b} \right) - \exp(\beta_0 - \beta_1 (X_i - x)) \right\}^2 K\left(\frac{\|x - X_i\|_x}{a} \right) \tag{15}$$

This local linear density estimator can be combined with the mean-bias-correction method of Hyndman et al. (1996) in order to force the density function to have a mean equal to any pre-specified smoother (see Basile, 2006). In our estimations we will use this procedure. As far as the bandwidth selection is concerned, we follow Hyndman and Yao (2002) algorithm (for a review of the existing methods for bandwidth selection, see Li and Racine, 2007)

In addition to the reduced bias estimator, Hyndman et al. (1996), propose two new ways to visualize the conditional densities, namely the ‘stack conditional density’ and the ‘high density region’ (HDR) plots. The former was introduced to direct visualization of the conditional density which is considered as a sequence of univariate densities and thus provides better understanding than the conventional three-dimensional perspective plots. 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 distribution 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 displays multimodal densities as disjoint subsets in plane.

In the ‘stacked conditional density’ plots, we observe how the series of the univariate conditional densities are located relative to the x-axis. If the mass of the distribution concentrates in a parallel to x-axis line at zero point, it is an indication that any existing deviation in time t, almost disappears in time t+τ. On the other hand, if the mass of the distributions is located in a 45^o degree line (when t and t+τ axes are similar scaled), then the existing deviations in time t, are more or less the same in time t+τ.

Additionally, we are interested in the existence of multiple modes in the conditional densities. It is what Quah (1997) report as ‘polarization’ or ‘stratification’ effects. If in a univariate conditional density, there are more that one peaks, it means that from a certain inflation rate deviation in time t, countries tends to end up in two (ore more) different point mass of inflation deviation.

In the case of ‘high density region’ plots, we observe whether the 25% or the 50% HDRs cross the 45-degree diagonal (again t and t+τ axes should be similar scaled), or are parallel to the horizontal axes. Arbia et al. (2005) also emphasize the importance of analyzing central points like modes, the values of y where the density function takes on its maximum values. Indeed, especially when the distribution function is bimodal, the mean and the median are not very useful, since they will provide only a “compromise” value between the two peaks. Highest modes for each conditional density estimate are superimposed as bullets on the HDR plots.

Results

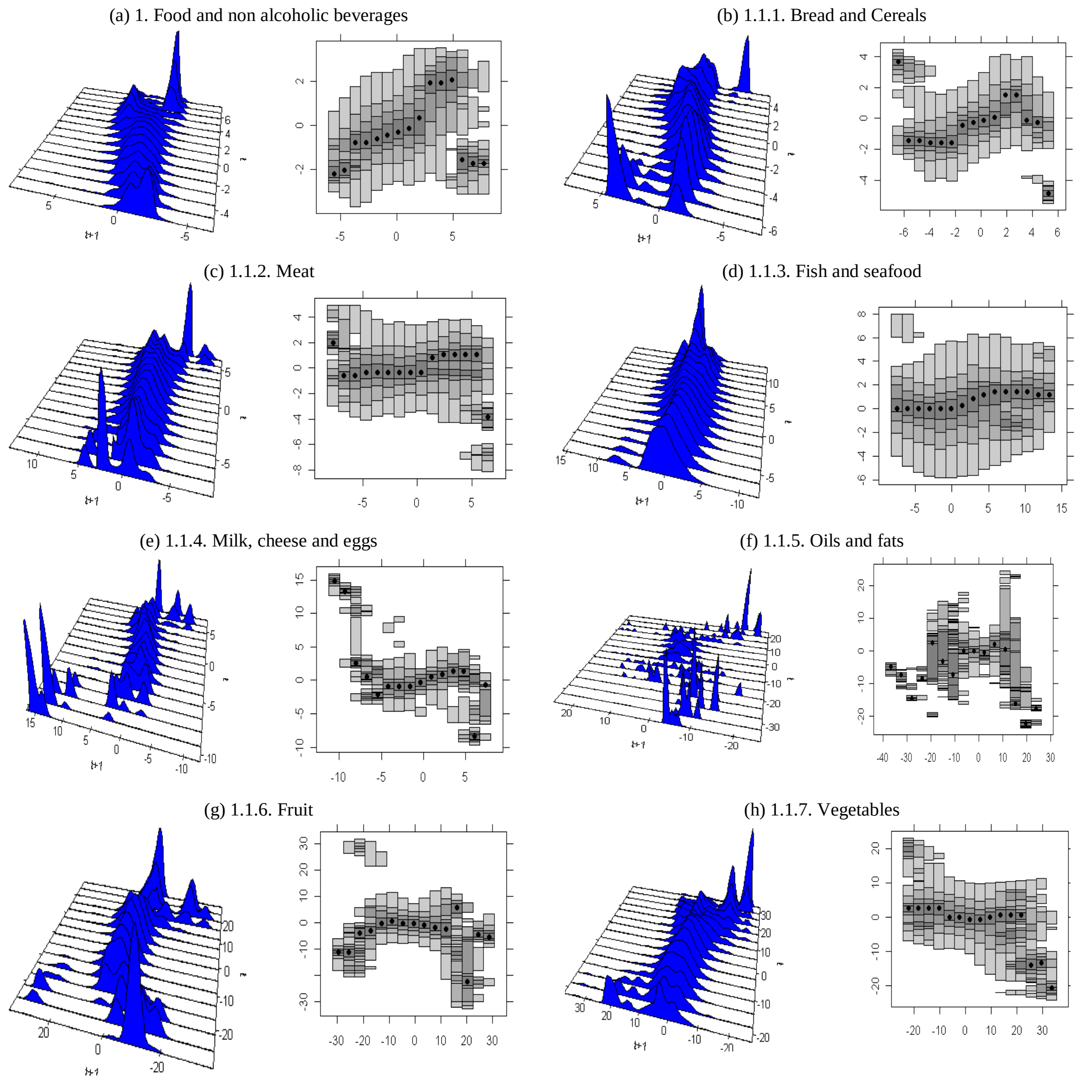
Our results are briefly indicated below in Figure 4. As we can see, there are many product groups where the mass of the distributions concentrate in an almost parallel to x-axis line close to zero point i.e. the existing deviation in time t, almost disappear in time t+1. This is not so apparent for the ‘Food and non alcoholic beverages’ index but it is well obvious for the most of the food product groups. Exceptions from this trend are ‘Oils and fats’, ‘Coffee, tea and cocoa’ and ‘Sugar, jam, honey, chocolate and confectionery’ groups. In the first two cases the univariate conditional distributions do not follow an obvious trend. Both plots are so confusing, that we can conclude for no common trend or law of motion

[9] Mean square error is the sum of the variance and the square of the bias. Because it is a point-wise property, we are interesting in minimizing integrated mean square error (Li and Racine, 2007)

that can adequately describes the evolution of the inflation rate deviation. Another possible explanation for this phenomenon could the under-smoothing, which is the consequence of a wrong kernel bandwidth. This requires further investigation and can be the object of future research. In the case of the 'Sugar, jam, honey, chocolate and confectionery' group, we can conclude that the distribution is in the middle of the two extremes cases (the parallel to horizontal-axis and the 45^{o} degree line). But apart from those product groups, we can conclude that countries with low (high) relative inflation rates are expected to move back towards the mean in one-year period. These results are demonstrating the convergence hypothesis, something that was not so apparent, regarding our previous analysis.

A very interesting outcome of this analysis is the existence of thresholds points in our sample. A closer look at the plots indicates that after a certain point of inflation deviation (either negative or positive) the mass of the conditional distribution is not anymore located close to the zero point but near to the opposite of this point. For example, in the 'Bread and cereals' group, when inflation deviation is greater than 5 or lower than -6, the next year inflation deviation is around -5 and 4 respectively. This is also the case for the 'Milk, cheese and eggs' and 'Meat' product groups. Most of other categories also appear to have threshold points, but only in the one side (either negative or positive value). Those threshold points are in fact 'leapfrogging' cases and reveals that this phenomenon is mainly occurs in extreme points.

Finally, there are several cases of multimodalities, especially at the edges (e.g. 'Meat' and 'Bread and cereals'). These cases are observed more clearly in the HDRs plots. This is an indication that in some cases, a low or a high inflation rate deviation is not leading to a common point mass in the next year, but to two point masses.



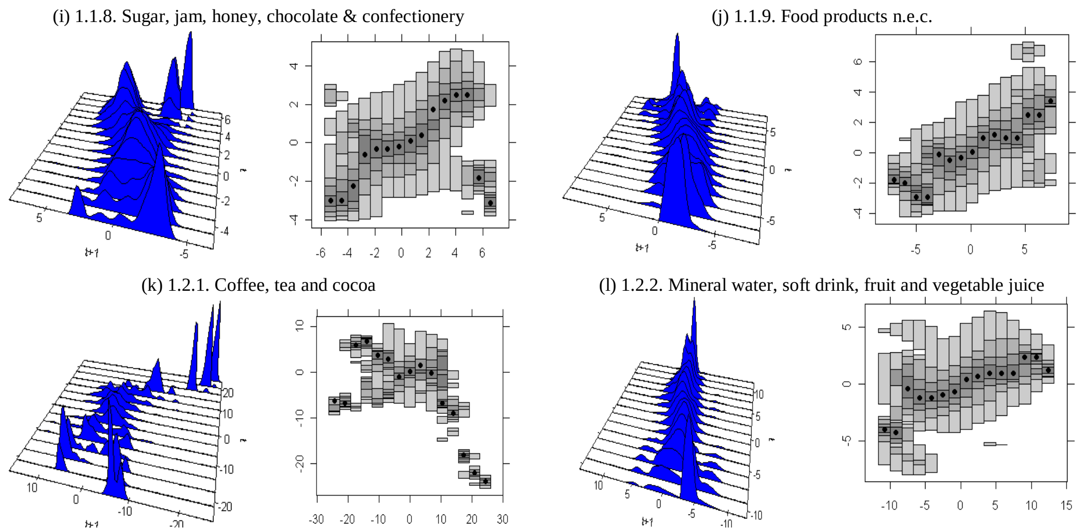


Figure 4. Intra-Distribution Dynamics of annualized inflation rate transitions. Stacked density plot (left hand side panel) and HDR plot (right hand side panel).

10. Conclusions

Several factors affect the inflation rates in European countries. Some of them contribute to a comovent of the inflation rates or in a diminishing cross-sectional deviation, while others, usually country-specific factors, create distortions and deviations from the cross-sectional mean. Many researchers have tried to investigate such factors usually from a less-market oriented point of view. However, inflation rates could reveal different market structures among the EU countries as well as European market fragmentations. Market concentration, mergers and acquisitions, formation of cartels, differences in the food supply chain functioning as well as different degree of absorption of external shocks and horizontal EU measures could be important factors for the inflation rate dynamics. Thus, the examination of inflation rate convergence could also be an issue of interest for the market researches. In this sense, we are interested in food inflation rates persistent, convergence or divergence trends in the countries of EU15.

The data we used in this analysis consist of monthly HICPs for each EU15 country from 1997:01 to 2009:05. HICPs concern the ‘Food and nonalcoholic beverages’ index, as well as eleven food product groups. The analysis of these indices can provide us with very strong insight of the dynamics of each specialized market.

The methodological tools we implement were initially developed in the growth literature and provide different aspects of the notion of convergence. Thus, β-convergence and σ-convergence are initially developed and then the distribution dynamics approach is implemented. For this purpose, we apply recently developed panel unit root tests and innovative kernel densities estimation methods and new graphical tools, (namely ‘stacked density’ plot and ‘high density regions’ plot).

Our results indicate that the general food inflation rate dynamics are inefficient to capture the different dynamics in each product group. Additionally, the examined period is characterized by dual behaviour. In the first half period, β-convergence appears in most groups, as well as in the general food inflation rate. On the contrary, in the second half time period, only 4 product groups appear evidences for β-convergence. Moreover, the second half time period is characterized in the most cases by increasing dispersion (σ-diconvergence).

Distribution dynamics approach was implemented only for the whole time period. In several cases, this approach indicates that there is a trend of reversion of inflation rates to the cross sectional mean. Of course, this was not the case for all product groups, while the degree of the mean-reversion is also quite different. Additionally, this analysis indicates that the ‘leapfrogging’ and criss-crossing’ phenomena are very usual in our data and are mostly appears in extreme points i.e. in cases of great negative or positive inflation rate deviations.

To conclude, this analysis reveals the heterogeneity of Europe food market and shows clearly that the market of each product group has its own dynamics. Thus the consideration of the general food index is not adequate to present a clear view of each group. The differences across groups can be due to market and country specific reasons, as has been already mentioned. The specific examination of each product group could reveal more detailed and more robust results.

Certainly, further research is needed to get a clear view of the food market in Europe. In this direction, the implementation of recently developed pair-wise convergence tests, as described in Pesaran et al. (2009), which are more robust in small sample sizes, are suggested. Additionally, different approaches for the estimation of the conditional density function (see Li and Racine, 2007), could be used and evaluate. Also, a possible expansion of our data, by inclusion of regions rather than countries (as in Weber and Beck, 2005), additional countries (as in Lopez, 2009) or greater time period, can further serve the objectives of our study. Unfortunately, both expansions are difficult to implement as, to our knowledge, there is no available data for such disaggregated indices. Finally, a joint inflation and price convergence strategy as described in Busetti et al. (2006) could also offer valuable information.

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