Structural Breaks in Inflation Dynamics within the European Monetary Union

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Abstract

To assess the effects of the EMU on inflation rate dynamics of its member states, the inflation rate series for 21 European countries are investigated for structural changes. To capture changes in mean, variance, and skewness of inflation rates, a generalized logistic model is adopted and complemented with structural break tests and breakpoint estimation techniques. These reveal considerable differences in the patterns of inflation dynamics and the structural changes therein. Overall, there is a convergence towards a lower mean inflation rate with reduced skewness, but it is accompanied by an increase in variance.

Keywords: inflation rate, structural break, EMU, generalized logistic distribution.

1. Introduction

Since the beginning of the European Union (EU), the topic of a common currency was a controversial issue. Although the Economic and Monetary Union (EMU) is now a fact, the discussion about the economic effects of the euro is far from being settled. The controversial topics range from the question of whether or not the eurozone is indeed an optimal currency area (as developed in Mundell 1961), all the way to the very survival of the euro in light of the budgetary problems of some of its member states. The effects of monetary unions on a number of macroeconomic indicators, with inflation being of increased importance, is at the center of an ongoing debate. This concerns the issue of short-run and steady-state inflation uncertainty – in relation to inflation expectations – as dealt with in Caporale and Kontonikas (2009), or the degree of similarity of short-run dynamic properties of the inflation rates in EU countries, which is the topic of the investigation by Palomba, Sarno, and Zazzaro (2009). Throughout the literature, there is still a considerable degree of uncertainty as to what extent the introduction of the euro, or monetary unions in general, affects the inflation rate.

As the way towards the EMU essentially consisted of three stages (I: 1990–1994, a phase of liberalization; II: 1995–1998, a phase of convergence; III: 1999–2001, a transition period ending with the replacement of the national currencies by the euro), it seems natural to ask whether this transition was accompanied by structural changes in the inflation dynamics in the different European countries. Furthermore, a possible fourth stage is the continuing integration of new member states, mostly former communist countries. Typically, changes in the mean level of the inflation rates attract the widest interest, but there are also reasons for investigating changes in higher moments, such as variance and skewness. Emerson, Gros, Italianer, Pisani-Ferry, and Reichenbach (1992) emphasize that a high inflation rate is usually

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also more variable and uncertain and thus causes more relative price variability, leading to a less efficient price mechanism. Furthermore, Jarociński (2010) finds a positive correlation between the level and the standard deviation of inflation.

Therefore, a thorough investigation of the evolution of the inflation dynamics within a country over time requires assessment not only of the mean level, but also of higher moments. Hence, we contribute to this field of research by developing a new method for testing for structural breaks based on a generalized logistic (GL) distribution. This provides flexible modeling of means, variances, and skewness, while also allowing for fat tails. Structural breaks are tested using score-based tests (Andrews 1993; Zeileis 2005) and breakpoints are estimated by extending the least squares approach of Bai and Perron (2003) to (quasi-)maximum likelihood estimation of GL distributions (similar in spirit to the Gaussian model employed by Zeileis, Shah, and Patnaik 2010).

The empirical results show that there are different patterns and timings of structural breaks in the inflation dynamics of different groups of countries. Inflation rates in the core euro area did not change significantly after completion of the first convergence stage, yielding low mean and variance. The Southern euro area member states (and Ireland), on the other hand, managed to decrease the mean level of inflation in the mid-1990s, but at the price of higher volatility. Finally, the Eastern European countries reduced both mean and variance on their way towards joining the EMU. Generally, the inflation rates converged from very different distributions at the beginning of the sample to rather similar patterns at the end of the 2000s. Skewness also plays an important role in this convergence: Some Southern and Eastern countries have clear breaks from right-skewed to roughly symmetric inflation rates, signaling a reduction of size and frequency of outlying high inflation rates.

The remainder of this paper is structured as follows: Section 2 briefly presents the data, Section 3 introduces the model and the estimation techniques used, Section 4 discusses the empirical results, and Section 5 concludes.

2. Data

All empirical analyses are based on seasonally adjusted monthly inflation rates (in percent) for 21 countries (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom) in the time period from the early or mid-1990s to the end of 2010. The original data source are seasonally unadjusted HICP series provided by the Organisation for Economic Cooperation and Development (2010) from January 1990 (if available) to December 2010, that were transformed to inflation rates using log-returns and subsequent seasonal adjustment via X-12-ARIMA (Findley, Monsell, Bell, Otto, and Chen 1998).

The countries in this sample can be divided into three different groups: (1) euro countries – Austria, Belgium, Estonia, France, Finland, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain; (2) EU members not participating in the ERM II – Czech Republic, Hungary, Poland, United Kingdom, Sweden; (3) Denmark which stands on its own as a member of the EU and the ERM II, but not yet of the EMU. Latvia, Lithuania, Bulgaria, Romania are excluded due to data scarcity. Cyprus, and Malta are not included since they are very small economies.

Seasonal adjustment is necessary due to the harmonization of the treatment of sales prices[1] in the HICP, resulting in changes of the seasonal inflation patterns over time within several countries and also between the countries. See Lünnemann and Mathä (2009) for a detailed discussion.

3. Model

The goal of the modeling strategy, that is subsequently introduced, is the following: detection of structural changes in the distributional properties of the inflation rates over time, e.g., as potentially caused by interventions. However, unlike many standard least squares approaches (such as Bai and Perron 2003), not only changes in the mean level should be addressed, but also changes in variance and potential skewness.

Hence, a likelihood-based model is adopted that can also incorporate stylized facts for return data, such as heavy tails and skewness. Here, the seasonally adjusted returns y_i ($i = 1, \dots, n$) are assumed to come from a generalized logistic (GL) distribution (see Johnson, Kotz, and Balakrishnan 1995) with three-dimensional parameter $\phi_i = (\theta_i, \sigma_i, \delta_i)^\top$ for location θ_i, scale σ_i, and shape δ_i at time i. Structural change techniques are then employed to check whether the parameter vector ϕ_i remains constant over time and, if that is not the case, when and how the parameters change. This framework allows to trace breaks in the evolution of mean, variance, and skewness of the inflation series which may possibly be linked to underlying regime changes, e.g., in monetary policy.

For estimation of the parameters, a (quasi-)maximum likelihood framework is adopted and the observations are assumed to be (approximately) independent, i.e., potential autocorrelation is treated as a nuisance parameter and not explicitly incorporated in the model. The motivation for this is to focus on the shifts in mean, variance, and skewness – and it turns out to be a useful model for the data under investigation because only negligible amounts of residual autocorrelation remain after incorporation of the structural breaks. If the focus of the analysis were the dynamics in the autocorrelation, higher frequency data would be required, e.g., in order to apply techniques such as those expounded by Andreou and Ghysels (2002).[2]

In the following, details are provided about (1) the GL distribution and its properties, (2) how it can be estimated (under parameter stability), (3) how parameter stability can be assessed, and (4) how breakpoints can be estimated in the presence of parameter instability.

3.1. Generalized logistic distribution

The logistic distribution is often used in econometrics in the context of income and growth models due to its fatter tails compared to the normal distribution – it has also been applied to the modeling of expected inflation rates by Batchelor and Orr (1988). Its generalization – which additionally allows for asymmetries – has been applied to analyze extreme risks in the context of stock markets (e.g., by Tolikas, Koulakiotis, and Brown 2007) but has not yet been applied – to the best of our knowledge – to inflation rates. However, it will prove to be a rather simple model that fits HICP inflation rates quite well.

[1] Inclusion of sales prices in the HICP was demanded by a Commission regulation (see European Commission 2000, for details).

[2] For example, it would be conceivable to obtain high-frequency data for certain years from the Billion Prices Project of the Massachusetts Institute of Technology (2011); however, this is not pursued here.

The GL distribution employed here corresponds to the type 1 GL distribution from Johnson *et al.* (1995), using the parametrization and inference as in Shao (2002). It has the log-density function

$$\ell(y \mid \theta, \sigma, \delta) \;=\; \log(\delta) - \log(\sigma) - \frac{y-\theta}{\sigma} - (\delta+1)\cdot\log\left(1+\exp\left\{-\frac{y-\theta}{\sigma}\right\}\right) \tag{1}$$

with location θ, scale $\sigma > 0$, and shape $\delta > 0$. For $\delta = 1$ the distribution simplifies to the logistic distribution, for $\delta < 1$ or > 1 it is left- or right-skewed, respectively. The corresponding first three moments are

$$\mathrm{E}(y) \;=\; \theta + \sigma(\gamma(\delta) - \gamma(1)) \tag{2}$$
$$\mathrm{Var}(y) \;=\; \sigma^2(\gamma'(\delta) + \gamma'(1)) \tag{3}$$
$$\mathrm{Skew}(y) \;=\; \frac{\gamma''(\delta) - \gamma''(1)}{(\gamma'(\delta) + \gamma'(1))^{3/2}} \tag{4}$$

where $\gamma(\cdot)$, $\gamma'(\cdot)$, and $\gamma''(\cdot)$ are the digamma function and its first and second derivative, respectively.

The corresponding score function, i.e., the derivative of the log-density with respect to the parameter vector, is given by

$$s(y \mid \phi) \;=\; \frac{\partial \ell(y \mid \phi)}{\partial \phi} \;=\; \begin{pmatrix} \dfrac{1}{\sigma} - \dfrac{(\delta+1)\tilde{y}}{\sigma(1+\tilde{y})} \\ \left\{\dfrac{1}{\sigma} - \dfrac{(\delta+1)\tilde{y}}{\sigma(1+\tilde{y})}\right\} \cdot \dfrac{y-\theta}{\sigma} - \dfrac{1}{\sigma} \\ \dfrac{1}{\delta} - \log(1+\tilde{y}) \end{pmatrix} \tag{5}$$

where $\phi = (\theta, \sigma, \delta)^\top$ and $\tilde{y} = \exp\{-(y-\theta)/\sigma\}$.

3.2. Estimation

Under the assumption that $y_i \sim GL(\theta, \sigma, \delta)$ for $i = 1, \dots, n$ independently – i.e., are independent realizations from a GL distribution with parameter vector $\phi = (\theta, \sigma, \delta)^\top$ – the parameters can be estimated as usual by maximum likelihood (ML): $\hat{\phi} \;=\; \mathrm{argmax}_\phi \sum_{i=1}^n \ell(y_i|\phi)$. The corresponding first order condition is $\sum_{i=1}^n s(y_i|\hat{\phi}) = 0$.

To guard the inference against potential misspecification, e.g., autocorrelation or misspecification of higher moments of the distribution, one can treat $\hat{\phi}$ as the quasi-maximum-likelihood (QML) estimator and adjust the inference by using heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators (see e.g., Andrews 1991).

If the parameters are potentially varying over time – $y_i \sim GL(\theta_i, \sigma_i, \delta_i)$ – then $\hat{\phi}$ is the (Q)ML estimator under the null hypothesis of parameter stability

$$H_0: \;\phi_i \;=\; \phi_0 \quad (i = 1, \dots, n) \tag{6}$$

which should be tested against the alternative H_1 that at least one of the parameters changes over time.

3.3. Test for structural change

The null hypothesis of parameter stability (6) can be assessed using the empirical scores $s(y_i|\hat{\phi})$ as measures of model deviation from the model fit under H_0 (as in Zeileis and Hornik 2007). Systematic deviations over time from the full sample estimates $\hat{\phi}$ can then be captured by cumulative sums of the empirical scores in an empirical fluctuation process $efp(t)$:

$$efp(t) \;=\; \hat{V}^{-1/2} n^{-1/2} \sum_{i=1}^{\lfloor nt \rfloor} s(y_i \mid \hat{\phi}) \quad (0 \leq t \leq 1), \tag{7}$$

where $\hat{V}$ is some consistent estimator of the variance of the scores. Below, we use the outer product of gradients $s(y_i|\hat{\phi})$ to estimate $\hat{V}$. Alternatively, HAC estimators could be used leading to the same qualitative results for the data under investigation.

As usual in structural change analysis, a functional central limit theorem holds for $efp(\cdot)$, which converges to a 3-dimensional Brownian bridge: $efp(\cdot) \xrightarrow{d} W^0(\cdot)$. Based on this, various types of test statistics can be computed (see Zeileis 2005 for details). In the following, the supLM test of Andrews (1993) is employed, which performs particularly well for single shift alternatives and if several of the three distribution parameters change simultaneously. The test statistic with 10% trimming is given by

$$\sup_{t \in [0.1, 0.9]} \frac{\| efp(t) \|_2^2}{t(1-t)}$$

and the appropriate p values can be computed from the corresponding limiting distribution – with $efp(t)$ replaced by $W^0(t)$.

3.4. Breakpoint estimation

If the null hypothesis of parameter stability (6) is rejected, a natural strategy is to assume that there are B breakpoints with stable parameters within each of the resulting segments. Bai and Perron (2003) have established a rigorous inference framework in this situation for least squares estimation which has been extended by Zeileis *et al.* (2010) to (Q)ML estimation. Here, we follow the same ideas and maximize the full segmented log-likelihood

$$\sum_{b=1}^{B+1} \sum_{i=\tau_b+1}^{\tau_b} \ell(y_i \mid \phi^{(b)})$$

for joint estimation of the breakpoints $\tau_1, \dots, \tau_B$ and the segment-specific GL parameters $\phi^{(b)}$ $(b = 1, \dots, B+1)$. Following the recommendations of Bai and Perron (2003), a modified Bayes information criterion (LWZ, proposed by Liu, Wu, and Zidek 1997) is employed selecting the number of breakpoints B.

3.5. An example: Slovenia

To illustrate the proposed strategy, the case of Slovenia is considered. After a period of relative instability following the independence from Yugoslavia, Slovenia was successful in realigning its economy and introduced a number of reforms leading to stable growth in recent

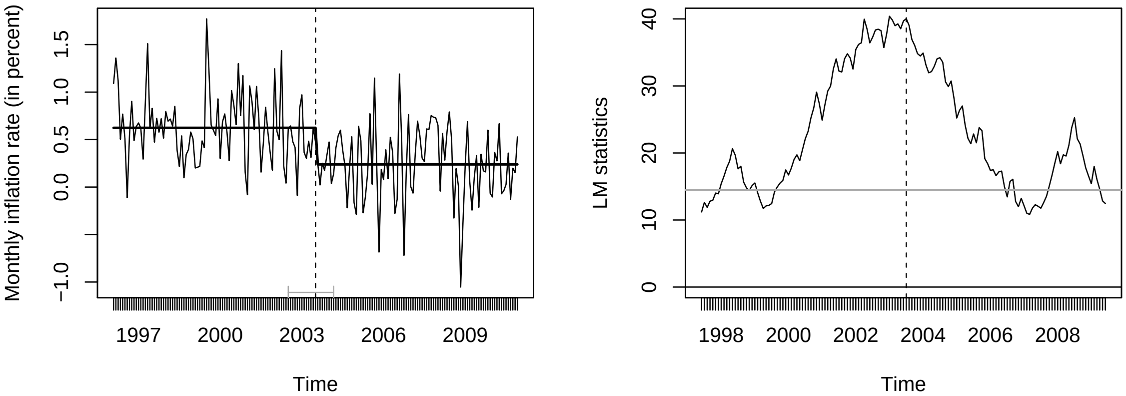

Figure 1: Inflation rate series for Slovenia with breakpoint estimate (Jul 2003) and associated sequence of LM statistics Left: Inflation rate series with breakpoint estimate (vertical dashed line), associated confidence interval (gray, at the bottom), and fitted mean from generalized logistic distribution (bold horizontal lines). Right: Corresponding supLM test with sequence of LM statistics, critical value at 5% level (horizontal gray line), and estimated breakpoint (vertical dashed line).

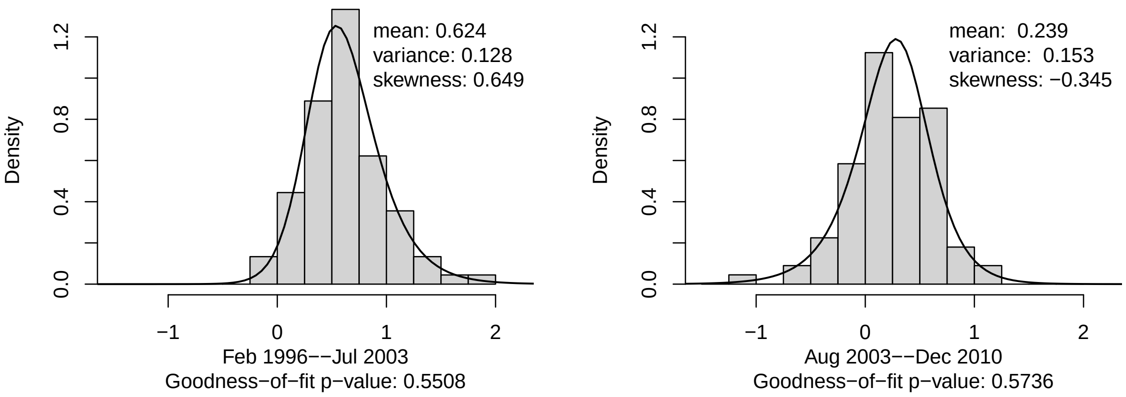

Figure 2: Histogram of observed monthly inflation rates in Slovenia for Feb 1996–Jul 2003 (left) and Aug 2003–Dec 2010 (right), along with fitted generalized logistic probability density function, associated moments, and χ^2 goodness-of-fit test.

years. The good economic performance made it possible for Slovenia to enter the ERM II in June 2004 and later on to introduce the euro in January 2007. The seasonally adjusted inflation series for Slovenia encompasses the time from Feb 1996 to Dec 2010 and is depicted in the left panel of Figure 1.

Assuming a single stable set of parameters as in (6) is not valid, since the sequence of

LM statistics (see right panel of Figure 1) clearly exceeds its 5% critical value (red horizontal line), leading to a highly significant p-value < 0.001. If a quadratic spectral kernel HAC estimator (Andrews 1991) would have been used to adjust (7), the resulting p-value would be somewhat larger with 0.0046 but still clearly significant.

As there is evidence for at least one break, the LWZ criterion is employed for $B = 1, 2, \dots$ breakpoints with a minimal segment size of two years per segment. It assumes its minimum for $B = 1$ associated with the breakpoint Jul 2003, depicted by a vertical dashed line in both panels of Figure 1. The resulting segmented fitted mean (horizontal bold lines in the left panel of Figure 1) shows that before the break, Slovenia experienced very high inflation rates but was successful in reducing inflation to a much lower level afterwards.

This decrease in inflation is also conveyed by Figure 2 that shows the observed histograms of inflation rates before and after the breakpoint along with the fitted GL distribution. This highlights that along with the decrease in mean level, the variance increases somewhat and – probably more interestingly – the distribution changes from being right-skewed to slightly left-skewed. This confirms that very high inflation rates that occurred in several months before the breakpoint could be avoided afterwards. Furthermore, Figure 2 shows that the GL distribution fits the observed data very well, both before and after the breakpoint, with p values from χ^2 goodness-of-fit tests of 0.551 and 0.574, respectively.

The estimated breakpoint can be matched very well with the timing of financial reforms in Slovenia that severely decreased the annual growth in the M3 monetary aggregate. The success of these actions ensured the Slovenian participation in the ERM II only a year later and the introduction of the euro two years afterwards.

4. Results

To investigate the effects of the EMU on national inflation rates, the techniques expounded in Section 3 are employed to uncover changes in the dynamics of European inflation rates. The inflation dynamics within countries from the euro-zone (but also other European countries) is closely related with the question about the convergence of the national inflation rates of the EMU members towards some common mean. Many researchers provide evidence against convergence among European countries, e.g., Hofmann and Remsperger (2005) find considerable amounts of inflation differentials and Caporale and Kontonikas (2009) describe rather strong heterogeneity among 12 EMU countries, both in terms of average inflation and its degree of persistence.

To explore the question of convergence, we proceed in two steps: First, in Section 4.1, the estimation technique proposed in Section 3 is applied to each of the countries included in the data set (see Section 2). Second, Section 4.2 aggregates the results from each individual country to reveal different potential convergence patterns over time within three groups of countries: core-euro (Austria, Belgium, Finland, France, Germany, Luxembourg, Netherlands), PIIGS (Portugal, Ireland, Italy, Greece, Spain), and the other countries (Czech Republic, Denmark, Estonia, Hungary, Poland, Slovakia, Slovenia, Sweden, UK).

Finally, Section 4.3 focuses on the question of changes in the inflation dynamics during the 2008/2009 financial crisis.

Country	Segment	Mean	Variance	Skewness	ERM	ERM II	Euro
No change							
Belgium	Feb 1991–Dec 2010	0.161	0.071	−0.425	Mar 1979	–	Jan 1999
Denmark	Feb 1990–Dec 2010	0.162	0.034	0.149	Mar 1979	Jan 1999	–
Germany	Feb 1995–Dec 2010	0.120	0.042	−0.021	Mar 1979	–	Jan 1999
Netherlands	Feb 1990–Dec 2010	0.172	0.043	−0.186	Mar 1979	–	Jan 1999
Phase 1 convergence							
Austria	Feb 1990–Sep 1994	0.255	0.015	0.389	Jan 1995	–	Jan 1999
	Oct 1994–Dec 2010	0.135	0.037	0.337			
Finland	Feb 1990–Apr 1993	0.328	0.062	1.059	Oct 1996	–	Jan 1999
	May 1993–Dec 2010	0.131	0.046	0.266			
France	Feb 1990–Mar 1992	0.257	0.056	0.214	Mar 1979	–	Jan 1999
	Apr 1992–Dec 2010	0.140	0.028	0.055			
Phase 2 convergence							
Greece	Feb 1995–Feb 1997	0.580	0.026	−0.337	Mar 1998	Jan 1999	Jan 2001
	Mar 1997–Dec 2010	0.279	0.067	−0.089			
Italy	Feb 1990–May 1996	0.408	0.019	0.838	Mar 1979	–	Jan 1999
	Jun 1996–Dec 2010	0.179	0.024	−0.657			
Luxembourg	Feb 1995–Dec 1997	0.106	0.011	0.718	Mar 1979	–	Jan 1999
	Jan 1998–Dec 2010	0.205	0.150	−0.702			
Portugal	Feb 1990–Jul 1992	0.850	0.072	1.140	Apr 1992	–	Jan 1999
	Aug 1992–Mar 1995	0.408	0.024	1.139			
	Apr 1995–Dec 2010	0.200	0.054	−0.582			
Financial crisis							
Ireland	Feb 1995–Jun 2008	0.248	0.051	−0.041	Mar 1979	–	Jan 1999
	Jul 2008–Dec 2010	−0.125	0.048	0.466			
Spain	Feb 1992–Aug 1994	0.398	0.013	1.062	Jun 1986	–	Jan 1999
	Sep 1994–Jul 2008	0.259	0.040	0.327			
	Aug 2008–Dec 2010	0.085	0.084	−0.589			
Non-euro							
Sweden	Feb 1990–Jan 1993	0.478	0.376	0.734	–	–	–
	Feb 1993–Dec 2010	0.150	0.044	−0.251			
UK	Feb 1990–Jan 1992	0.547	0.088	1.139	–	–	–
	Feb 1992–Dec 2010	0.170	0.030	0.170			
Eastern countries							
Czech Rep.	Feb 1995–Mar 1998	0.736	0.186	0.304	–	–	–
	Apr 1998–Dec 2010	0.197	0.087	0.363			
Estonia	Feb 1996–Mar 1998	0.854	0.262	0.507	–	Jun 2004	Jan 2011
	Apr 1998–Dec 2010	0.335	0.147	0.104			
Hungary	Feb 1995–May 1998	1.569	0.245	1.139	–	–	–
	Jun 1998–Dec 2010	0.501	0.121	0.363			
Poland	Feb 1996–Jul 2000	0.939	0.227	1.125	–	–	–
	Aug 2000–Dec 2010	0.226	0.049	0.724			
Slovakia	Feb 1995–Feb 2004	0.581	0.196	1.140	–	Nov 2005	Jan 2009
	Mar 2004–Dec 2010	0.199	0.064	−0.563			
Slovenia	Feb 1996–Jul 2003	0.624	0.128	0.649	–	Jun 2004	Jan 2007
	Aug 2003–Dec 2010	0.239	0.153	−0.345			
Euro area							
EU	Feb 1996–Jun 1999	0.114	0.010	0.253	–	–	–
	Jul 1999–Aug 2007	0.179	0.014	−0.311			
	Sep 2007–Dec 2010	0.160	0.055	−0.397			

Table 1: Estimated breakpoints, fitted moments of generalized logistic distribution per segment, and ERM information for all countries under investigation.

Country	supLM (standard/HAC)	Segment	χ^2 GOF	AR(1)	Ljung-Box
No change					
Belgium	0.063	Feb 1991–Dec 2010	0.123	−0.044	0.497
	0.354				
Denmark	0.183	Feb 1990–Dec 2010	0.991	0.084	0.183
	0.285				
Germany	0.057	Feb 1995–Dec 2010	0.339	−0.106	0.140
	0.118				
Netherlands	0.146	Feb 1990–Dec 2010	0.680	0.049	0.438
	0.220				
Phase 1 convergence					
Austria	< 0.001	Feb 1990–Sep 1994	0.045	−0.033	0.799
	< 0.001	Oct 1994–Dec 2010	0.091	−0.059	0.407
Finland	0.001	Feb 1990–Apr 1993	0.379	−0.161	0.297
	0.006	May 1993–Dec 2010	0.298	0.018	0.793
France	0.044	Feb 1990–Mar 1992	0.312	−0.038	0.839
	0.110	Apr 1992–Dec 2010	0.268	0.157	0.018
Phase 2 convergence					
Greece	< 0.001	Feb 1995–Feb 1997	0.859	0.174	0.356
	0.002	Mar 1997–Dec 2010	0.621	−0.016	0.838
Italy	< 0.001	Feb 1990–May 1996	0.698	0.267	0.018
	< 0.001	Jun 1996–Dec 2010	0.970	0.030	0.690
Luxembourg	< 0.001	Feb 1995–Dec 1997	0.993	0.083	0.607
	0.001	Jan 1998–Dec 2010	0.770	−0.058	0.467
Portugal	< 0.001	Feb 1990–Jul 1992	0.255	0.350	0.044
	< 0.001	Aug 1992–Mar 1995	0.549	0.107	0.526
		Apr 1995–Dec 2010	0.969	0.166	0.021
Financial crisis					
Ireland	< 0.001	Feb 1995–Jun 2008	0.713	0.155	0.047
	< 0.001	Jul 2008–Dec 2010	0.910	−0.159	0.362
Spain	< 0.001	Feb 1992–Aug 1994	0.779	0.031	0.858
	0.043	Sep 1994–Jul 2008	0.215	0.315	< 0.001
		Aug 2008–Dec 2010	0.761	0.325	0.065
Non-euro					
Sweden	< 0.001	Feb 1990–Jan 1993	0.273	0.217	0.175
	< 0.001	Feb 1993–Dec 2010	0.465	0.163	0.016
UK	< 0.001	Feb 1990–Jan 1992	0.954	−0.123	0.522
	< 0.001	Feb 1992–Dec 2010	0.210	0.167	0.011
Eastern countries					
Czech Rep.	< 0.001	Feb 1995–Mar 1998	0.578	0.198	0.204
	0.002	Apr 1998–Dec 2010	0.652	0.268	< 0.001
Estonia	< 0.001	Feb 1996–Mar 1998	0.038	0.351	0.058
	0.176	Apr 1998–Dec 2010	0.911	0.412	< 0.001
Hungary	< 0.001	Feb 1995–May 1998	0.996	0.392	0.010
	0.028	Jun 1998–Dec 2010	0.989	0.376	< 0.001
Poland	< 0.001	Feb 1996–Jul 2000	0.587	0.473	< 0.001
	< 0.001	Aug 2000–Dec 2010	0.734	0.464	< 0.001
Slovakia	< 0.001	Feb 1995–Feb 2004	0.001	0.068	0.470
	0.041	Mar 2004–Dec 2010	0.360	0.203	0.061
Slovenia	< 0.001	Feb 1996–Jul 2003	0.551	0.162	0.118
	0.007	Aug 2003–Dec 2010	0.574	0.144	0.167
Euro area					
EU	0.001	Feb 1996–Jun 1999	0.449	0.065	0.667
	0.027	Jul 1999–Aug 2007	0.841	0.032	0.745
		Sep 2007–Dec 2010	0.616	0.284	0.062

Table 2: Diagnostics for model fits in each country. Two supLM test p values of the full-sample model with and without HAC correction and segment-specific assessments of the model fit: χ^2 goodness-of-fit (GOF) p value; autocorrelation at lag 1; Ljung-Box p value.

4.1. Inflation dynamics on a national level

As a first step towards the investigation of inflation convergence, the structural breaks in the inflation dynamics within each country are investigated using the methods introduced in Section 3. Table 1 reports the estimated breakpoints along with the segment-specific moments (mean, variance, skewness) implied by the corresponding parameter estimates. Furthermore, entry dates for ERM/ERM II and the euro are included as additional information. For ease of interpretation, countries with similar patterns of change are grouped together and ordered alphabetically within each group. If there is only a single segment, the supLM test was non-significant at the 5% level. In significant cases, the number of breakpoints was selected via the LWZ criterion and subsequently all parameters (breakpoints and segment-specific GL parameters) were estimated by ML. The p values from the supLM test with and without HAC correction are reported in Table 2 along with further diagnostics for each of the fitted segments concerning goodness of fit and autocorrelation. As autocorrelation was very low in most of the segments (typically below 0.4 and non-significant, with a few exceptions), we focus on the results from the analysis without HAC correction but point out if there are noteworthy deviations. In both Table 1 and 2 the countries are grouped according to either a similar timing of the changes in inflation dynamics or according to economic similarities, as in the case of the former communist countries in Eastern Europe.

The first group that draws particular attention consists of the former DEM (Deutsche Mark) zone countries, with the exception of Austria and Luxembourg. All these countries had and still have a very low inflation rate, both in terms of mean and variance, and their inflation dynamics did not change significantly. This is plausible from an economic point of view since the European central bank (ECB) is modeled after the Deutsche Bundesbank and the ECB did not – until recently – diverge much from the monetary policy of the former. Thus, the EMU did have no effect on inflation dynamics since the policies in these countries were already much in line with Germany and hence the ECB. Table 2 does not suggest any problems in this group of countries.

The second group of countries, Austria, Finland, and France, adjusted to the requirements of the EMU during the first phase of convergence. In these countries, the result of the adjustment process was a lower inflation rate and an overall decrease in the variance. Additionally, if a HAC correction is used, the change for France would be nonsignificant, suggesting that France may also belong to the group of countries which did not change at all.

The next group consists of three of the PIIGS countries and Luxembourg. Greece and Portugal adjusted to the ERM shortly before or after its introduction. Italy was successful in reducing its inflation rate, whereas Luxembourg experienced a strong increase in its formerly very low inflation rate, both in terms of mean and variance, also associated with a shift in skewness towards the left. Apart from Luxembourg, the countries that had a structural break during the second phase of convergence were also successful in reducing mean inflation rates. After the changes in this group, all countries have rather similar mean inflation rates, which are closer to the levels of the previous two groups. The diagnostics from Table 2 indicate good model fits with low autocorrelations.

The fourth subgroup consists of two of the PIIGS countries, namely Ireland and Spain. There is a break in both countries in the summer of 2008 that captures the effects of the financial crisis and the severe problems concerning the real estate situation. In both countries, this had a strong deflationary impact, with deflation in Ireland over an extended period of time.

In Spain, which was affected by a housing bubble of roughly the same size as Ireland, the housing prices did not adjust so abruptly and so strongly. The model fit diagnostics appear to be reasonable except for the middle segment of Spain, where the Ljung-Box test shows that not all of the autocorrelation has been captured.

The fifth group consists of two countries that, after a very short participation in the ERM, decided not to be part of it and hence also not to participate in the EMU: the United Kingdom and Sweden. Both show clear breaks in the early 1990s which can be traced back to economic crises: the currency crisis of the United Kingdom cumulating in "Black Wednesday" in 1992 and the banking crisis in Sweden during the early 1990s. With regard to the last segment for both countries, the Ljung-Box test suggests that the autocorrelation, albeit low around 0.16, is significant. However, both the standard and the HAC-corrected supLM lead to highly significant evidence for structural breaks.

The last group consists of the Eastern European countries: Czech Republic, Estonia, Hungary, Poland, Slovakia, and Slovenia. In almost all of these countries, the mean and the variance of their inflation rates declined in the late 1990s or early 2000s. Czech Republic, Estonia, and Hungary experienced a break in 1997/1998 resulting from efforts to curb in inflation by decreasing the growth of the money supply. The timing of the break thus indicates the date when the the biggest transitionally shocks on the way towards free market economies have been overcome. In Poland, this transition took two more years. Slovakia and Slovenia are somewhat different: On the one hand, they started with lower mean inflation rates and on the other hand, their inflation dynamics both changed roughly one year prior to their entry into the ERM II. Thus, compared to other inflation rates, these series show the most dynamic behaviour. However, the models also do not fit as well as for the previous groups of countries. There is the highest occurrence of non-captured autocorrelation and for Estonia and Slovakia the χ^2 goodness-of-fit test suggests that the generalized logistic distribution might not fit sufficiently well in the first segments.

Finally, the inflation rates for the whole euro area[3] are considered and three different regimes are found: (1) until 1999 with both a low mean and variance, (2) the third and final stage of monetary integration, accompanied by a significant increase in the mean, (3) a period encompassing the overheating of the economy and its culmination in the financial crisis, showing a large increase in variance and a lower mean inflation.

4.2. Convergence on an aggregate level

Given the results above for the individual countries, a natural question is whether there is convergence on an aggregate level and, if so, which pattern it follows. Hence, we aggregate the results from Table 1 for the individual countries into three groups and at four time points to reflect the general dynamics of European inflation rates during the time period of interest. The groups have been selected based on prior expectations (i.e., not based on the breakpoints estimation results) as the "core" of the euro zone, the PIIGS countries, and the rest. Similarly, the time points have been chosen as to fall "between" times where transitions in one or more groups of countries could be expected: Jan 1994 during stage I on the way towards the EMU, Jan 1998 during stage II, Jan 2007 after transition into the EMU but before the financial crisis,

[3]This is the EU17 series as provided by the Organisation for Economic Cooperation and Development (2010), starting in Jan 1996. It is calculated as a weighted average of the HICPs of the then seventeen euro countries.

Moment	Quartile	1994	1998	2007	2010
Core euro					
Mean	Lower	0.126	0.133		
	Median	0.140	0.140		
	Upper	0.167	0.167		
Variance	Lower	0.022	0.039		
	Median	0.042	0.043	...	...
	Upper	0.045	0.059		
Skewness	Lower	−0.104	−0.305		
	Median	0.055	−0.021		
	Upper	0.328	0.161		
PIIGS					
Mean	Lower	0.398	0.200		0.085
	Median	0.408	0.248		0.179
	Upper	0.408	0.259		0.200
Variance	Lower	0.019	0.040		0.048
	Median	0.024	0.051	...	0.054
	Upper	0.026	0.054		0.067
Skewness	Lower	−0.041	−0.582		−0.589
	Median	0.838	−0.089		−0.582
	Upper	1.062	−0.041		−0.089
Other					
Mean	Lower	0.170		0.170	
	Median	0.624		0.199	
	Upper	0.854		0.239	
Variance	Lower	0.044		0.044	
	Median	0.186	...	0.064	...
	Upper	0.227		0.121	
Skewness	Lower	0.170		−0.251	
	Median	0.507		0.149	
	Upper	1.125		0.363	

Table 3: Aggregation of estimated moments from Table 1 across countries in Jan 1994, 1998, 2007, and 2010. Dots signal that the moments have not changed from the previous time point, i.e., that no breakpoint was estimated in the corresponding time period.

and Jan 2010 after the crisis. The result of these considerations is presented in Table 3 which extracts the three moments for each country from Table 1 at the indicated time points and aggregates them within the group. Lower quartile, median, and upper quartile (25%, 50%, 75% percentiles) are provided to assess both changes in location and spread across countries.

For the core euro countries, there are only changes from stage I to stage II because after 1998 no breaks have been detected. The changes in this first phase did not affect mean inflation much, while variance increased slightly (in both quartiles) and skewness decreased somewhat (from slightly right- to slightly left-skewed). The heterogeneity (assessed by the interquartile range) declined for all three moments of the inflation rates. This reflects that the monetary policies of the corresponding countries were already closely connected prior to stage I and now even moved somewhat closer together.

For the PIIGS countries, changes occurred from 1994 to 1998 and then again during the crisis, before 2010. In the first phase, mean inflation was almost halved, accompanied by a doubling of variance and a change from clearly right-skewed to approximately symmetric. The latter reflects that the occurrence of shocks with high inflation rates have been successfully reduced. Moreover, the changes in the PIIGS countries between 2007 and 2010 lead to a further decrease in mean inflation and associated skewness which are both caused by several extremely low inflation rates during the time following the crisis.

The other countries do not exhibit any significant breakpoints during the mid-1990s, but many changes occur in the transition period from 1998 to 2007, encompassing both the completion of the transformation from planned to free market economies and the intended entry into the EMU. During this time, the countries were successful in decreasing all three moments of their inflation distributions while simultaneously decreasing the heterogeneity (as captured by the corresponding interquartile ranges) across countries. Before the transition, all three moments were extremely large compared to the other two groups, while afterwards all moments are much closer to those of the other groups. In Jan 2007, mean inflation is in between the levels for the core euro and PIIGS countries, variance is still slightly higher, and skewness is not too far away from symmetry.

In context of the convergence issue, we find that up to 2007 the inflation dynamics of all three groups of countries become much more similar, both within and across groups. The interquartile ranges of the means decline and become tighter for all groups and there appears to be convergence towards some common mean inflation rate in the countries of our sample. Variances also move more closely together, corresponding to an increase for the core euro and PIIGS countries but a clear decrease for the others. Right-skewness (and thus large outlying inflation rates) has been reduced for all three groups of countries but to a different extent. Thus, while ending in similar inflation dynamics, the timing and patterns of changes in this convergence process are rather different across the three groups, depending on the different starting situations of the countries.

4.3. The influence of the financial crisis

The results from the previous sections convey that the financial crisis of 2008/2009 did not have a significant effect on the inflation dynamics in most of the European countries (except Ireland and Spain). This may be somewhat surprising and is not entirely correct. In fact, there is a rather clear effect, but as it is very short-lived and not persistent, it is not picked up by the structural break techniques.

More specifically, the mean inflation of the euro area from a GL fit in the year before the crisis (Aug 2007–Jul 2008) was 0.334 and after the crisis (Aug 2008–Jul 2009) it dropped to -0.049 before rising again in the following year (Aug 2009–Jul 2010): 0.145. One way to bring out this pattern graphically is Figure 3. It depicts the inflation rates (in gray) and a 12-month rolling mean (in red), calculated again as the first moment of a fitted GL distribution. The strong increase in mean inflation during the boom years of 2007/2008 accompanied by an equally strong deflation following the burst of the bubble is clearly visible for most countries. However, the level of mean inflation did not change persistently, as the inflation rates seem to have returned to their prior path, conveying the same message as the inflation series of the

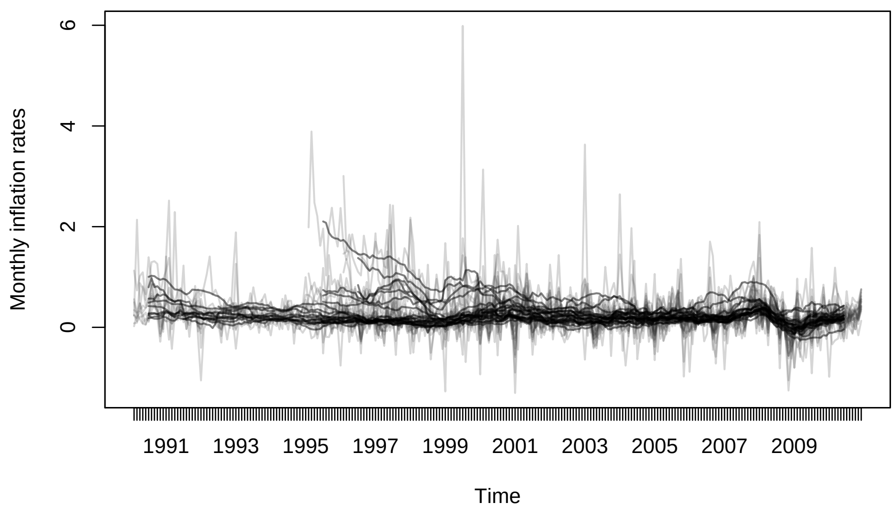

Figure 3: Observed monthly inflation rates (light gray) and estimated means from 12-month rolling GL fits (dark red) over time for all countries.

euro area.

As for the structural break methods adopted in the previous sections, this means that such rapid and non-persistent effects in the mean level are not picked up from low frequency data, like inflation rates. Instead, they may simply be attributed to increased variance.

Apart from bringing out more details about the short-term crisis effects, Figure 3 also provides an alternative view on the long-range convergence behavior of the inflation rates studied in the previous sections. Over the 1990s and early 2000s, there is a clear general trend towards some common – albeit broad – mean level. There is still some visible difference in the inflation rates, but the mean estimates are moving closer in a rather broad band. So contrary to Palomba *et al.* (2009), who find that the degree of similarity in short-run inflation dynamics is still weak, we find evidence of convergence within the countries in the sample.

5. Conclusion

To assess changes in the dynamics of the inflation rates of a number of European countries – both within and outside the EMU – a new method for estimating structural breaks in inflation rates is proposed. The method allows to test for changes in mean, variance, and skewness of inflation rate series by adopting a (quasi-)likelihood model based on the generalized logistic (GL) distribution. Thus, unlike normally distributed models, this approach can deal with fat tails and (potentially changing) skewness.

The empirical results suggest that a GL distribution is appropriate for modeling seasonally adjusted inflation rate series and is able to uncover important changes in all three moments. Towards the end of the 2000s, before the financial crisis, our results broadly confirm convergence hypotheses, since the first three moments from all countries in our sample move closer together. Especially the changes in skewness – caused by a reduction of size and frequency of outlying high inflation rates in some countries – might have gone unnoticed with traditional structural change techniques, leading to potentially misleading conclusions concerning the dynamics.

At the beginning of the sample, many PIIGS and Eastern countries did have very high inflation rates, while for the core euro countries, convergence was already achieved in the mid-1990s. The PIIGS countries lowered their inflation rates considerably in preparation to the adoption of the euro. The Eastern European countries lowered their high initial inflation level in the late 1990s or early 2000s, prior to the entry into the ERM II. They clearly benefited from the monetary discipline that is demanded for those countries who want to join the EMU.

Computational details

Our results were obtained using R 3.0.0 (R Development Core Team 2011) with the packages **glogis** 0.1-0, **strucchange** 1.4-7 (Zeileis, Leisch, Hornik, and Kleiber 2002), and **fxregime** 1.0-2 (Zeileis *et al.* 2010), all of which are available under the General Public License (GPL) from the Comprehensive R Archive Network (`http://CRAN.R-project.org/`). Package **strucchange** provides various techniques for inference in structural-change settings which are complemented with additional maximum-likelihood-based methods by **fxregime**. Inference for the generalized logistic model (that can be combined with **strucchange**/**fxregime**) is implemented in the new package **glogis** that also contains the data used, both the raw monthly price indexes (as provided by the Organisation for Economic Cooperation and Development 2010) and the seasonally adjusted monthly inflation rates. The seasonal adjustment was performed in **X-12-ARIMA** 0.3 (U.S. Census Bureau 2009, see also Findley *et al.* 1998) through the interface provided by gretl 1.9.5 (Cottrell and Lucchetti 2011, see also Smith and Mixon 2006 for a review).

Replication scripts for all analyses are provided within the **glogis** package: An overview is provided in `demo(package = "glogis")` and the scripts can be launched easily, e.g., via `demo("Austria", package = "glogis")` etc.

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