Structural Breaks in Inflation Dynamics within the European Monetary Union

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Abstract

In this paper, we test for structural breaks in the inflation dynamics of 21 European countries. To capture changes in the first three moments of the inflation rates, we assumed them to be distributed according to a generalized logistic distribution. We find breaks in all but 4 countries. Overall, there is a convergence towards a lower inflation rate, but with an increase in variance and a change towards negative skewness.

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

1. Introduction

(perhaps skip this paragraph?) The way towards the EMU basically consisted of three stages: README stage I (1990–1994) as a phase of liberalization, stage II (1995–1998) a phase of convergence, and stage III (1999–2001) the transition period, which ended with the introduction of the euro as legal tender. A possible fourth stage is the continuing integration of new member states, mostly former communist countries.

Since the beginning of the European Union, 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 the most important one in this context, is in the center of an ongoing debate. This concerns the issue of short–run and steady–state inflation uncertainty – in context to inflation expectations – 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 an 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, affect the inflation rate.

However, a deeper inquiry into the effects of monetary unions on the inflation rates of its member countries is in need of a method able to capture changes in inflation dynamics. We contribute to this field of research by developing a new method for testing for structural breaks in the dynamics of the inflation rates. The framework utilized in this paper allows testing for any possible alternations and thus helps interpreting the effects of the EMU. We focus on changes in the first three moments of these inflation rates, which we assume to be distributed according to a generalized logistic distribution (GL). For this purpose, we build on previous research by Zeileis and Hornik (2007).

FIXME This *(describe method)* framework allows us to assess the evolution of mean, variance, and skewness over time. Our estimation technique enables the simultaneous estimation of breaks in these moments. The skewness parameter turns out to be quite important to measure alterations in the long run inflation dynamics, as it changes considerably over the time of the analysis. This trend would be all but invisible using a normal distribution.

FIXME *(comment on results here)* Overall, we find four periods during which structural breaks happened. Two of them in the 90s (early and late), another one in the early 2000s, and the last period covers the financial crisis. There is also a tendency towards a lower mean inflation rate, combined with a decreasing difference between individual inflation rates.

The remainder of this paper is structured as follows: Section 2 presents the data, Section 3 presents the model and the estimation techniques used, Section 3.5 illustrates our approach using Slovenia as an example, Section 4 presents the results, and Section 5 concludes.

2. Data

All empirical analyses are based on seasonally adjusted 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 patters over time within several countries and also between the countries. See Lünnemann and Mathä (2009) for a detailed discussion.

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

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 assesed, 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.

The GL distribution in the parameterization employed here is also used in Shao (2002) and has the log-density function[3]

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

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

[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.

[3] Which is similar to the type 1 GL distribution as defined in Johnson *et al.* (1995).

first three moments are

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

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

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

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

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

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 (Zeileis and Hornik 2007) from the model fit under H_0. 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):

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

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 using 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, Shah, and Patnaik (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 successfull in realigning its economy and introduced a number of reforms leading to a stable growth in recent 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 parmaters (6) is not valid, as 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 kernal 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.

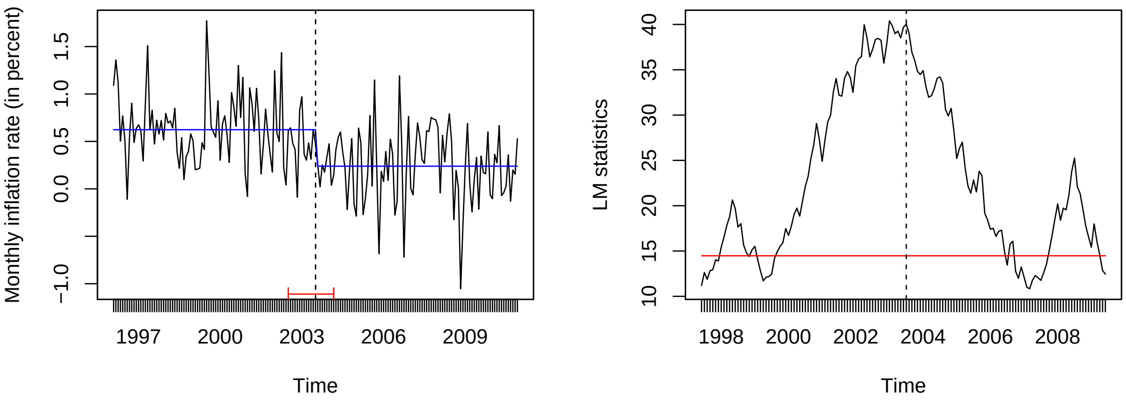

Figure 1: Inflation rate series for Slovenia with breakpoint estimate (Jul 2003), associated confidence interval, and fitted mean from generalized logistic distribution (left). Corresponding supLM test (right) with sequence of LM statistics, critical value at 5% level (horizontal red line line), and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

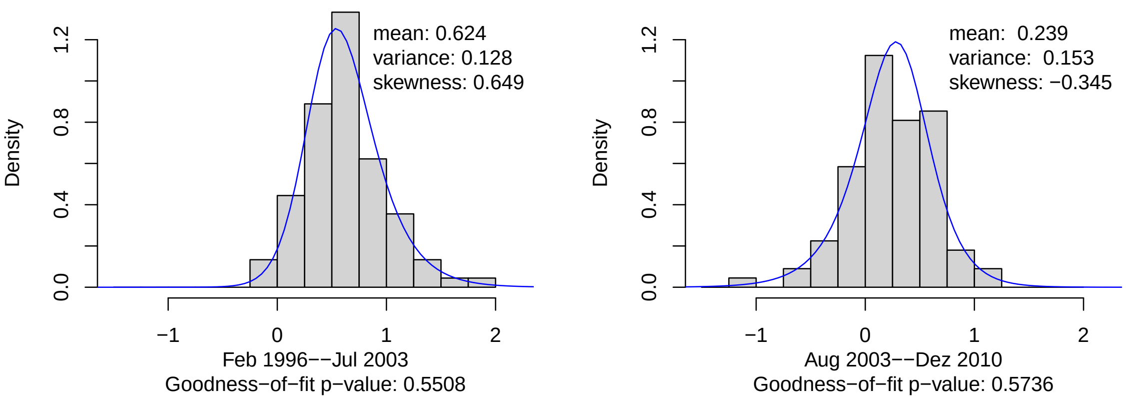

Figure 2: Histogramm of observed monthly inflation rates in Slovenia for Feb 1996–Jul 2003 (left) and Feb 1996–Jul 2003 (right), along with fitted generalized logistic probability density function, associated moments, and χ^2 goodness-of-fit test.

As there is evidence for at least one break, the LWZ criterion is employed for $B = 1, 2, \ldots$ breakpoints with a minimal segment size of two years per segment. It assumes its minimum for $B = 1$ associated with the breakpoint Jul 2003, depcited by a vertical dashed line in both panels of Figure 1. The resulting segmented fitted mean (horizontal blue lines in the left panel Figure 1) shows that in 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. These success of these actions ensured the Slovenian participation in the ERM II only a year later and the introduction of the euro two years later.

4. Results

(questions and challenges) The aim of this paper is to test for structural breaks in the dynamics of the inflation rates. Making use of the method developed in Section 3, the effect of the EMU upon national inflation rates can be investigated. Apart from the countries of the euro–zone, the inflation dynamics of the other European countries are also of interest. This issue is closely related with the question about the convergence of the national inflation rates of the EMU members towards some common mean. Many researchers, like Hofmann and Remsperger (2005) find a considerable amount of inflation differentials in parts of the sample. *(perhaps skip this one??)* Caporale and Kontonikas (2009) estimate short-run and steady-state inflation uncertainty in 12 EMU countries and find a considerable degree of heterogeneity in terms of average inflation and its degree of persistence. README README

(methods, approach) To explore these issues, we make use of three different approaches. First, in Section 4.1, the estimation technique proposed in Section 3 is applied to each of the countries included in the data set introduced in Section 2. 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. No HAC correction was employed as there was only negligible autocorrelation in the empirical scores after inclusion of the breakpoints (if any). README

Section 4.2 deals with the convergence issue. Table 2 gives an overview over the data aggregated into three different country groups: the core–euro countries (Austria, Belgium, Finland, France, Germany, Luxembourg, and Netherlands), the PIIGS countries (Portugal, Ireland, Italy, Greece, and Spain), and the other countries. This is done by showing mean, variance, and skewness over time and taking possible break points in the data into account.

Finally, Figure 3 in Section 4.3, depicts the inflation rates and a rolling mean estimation. This is another way of investigating into a possible convergence pattern of national inflation rates and is especially useful to depict the influence of the financial crisis.

4.1. Breakpoint estimation results

(changed to: 1) individual countries (table 1), 2) EU (table 1), 3) groups of countries (table 2), 4) crisis (fig.3)) For Table 1, we grouped the countries 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. README

The first group that draws particular attention consists – with the exception of Austria and Luxembourg – of the countries of the former DEM-zone. All these countries had and still have a very low inflation rate in terms of both mean and variance and their inflation dynamics did not change. This does make economic sense since the ECB is modeled after the Deutsche Bundesbank and the ECB did not – until recently – much diverge from the monetary policy of the former. Thus the EMU did have no effect since the policies in these countries were already much in line with Germany and thus the ECB.

Country	Segment	Mean	Variance	Skewness	ERM	ERM II	Euro
No change							
Belgium	Feb 1991–Dez 2010	0.161	0.071	−0.425	Mar 1979	–	Jan 1999
Denmark	Feb 1990–Dez 2010	0.162	0.034	0.149	Mar 1979	Jan 1999	–
Germany	Feb 1995–Dez 2010	0.120	0.042	−0.021	Mar 1979	–	Jan 1999
Netherlands	Feb 1990–Dez 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
	Okt 1994–Dez 2010	0.135	0.037	0.337			
Finland	Feb 1990–Apr 1993	0.328	0.062	1.059	Oct 1996	–	Jan 1999
	Mai 1993–Dez 2010	0.131	0.046	0.266			
France	Feb 1990–Mär 1992	0.257	0.056	0.214	Mar 1979	–	Jan 1999
	Apr 1992–Dez 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
	Mär 1997–Dez 2010	0.279	0.067	−0.089			
Italy	Feb 1990–Mai 1996	0.408	0.019	0.838	Mar 1979	–	Jan 1999
	Jun 1996–Dez 2010	0.179	0.024	−0.657			
Luxembourg	Feb 1995–Dez 1997	0.106	0.011	0.718	Mar 1979	–	Jan 1999
	Jän 1998–Dez 2010	0.205	0.150	−0.702			
Portugal	Feb 1990–Jul 1992	0.850	0.072	1.140	Apr 1992	–	Jan 1999
	Aug 1992–Mär 1995	0.408	0.024	1.139			
	Apr 1995–Dez 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–Dez 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–Dez 2010	0.085	0.084	−0.589			
Non-euro							
Sweden	Feb 1990–Jän 1993	0.478	0.376	0.734	–	–	–
	Feb 1993–Dez 2010	0.150	0.044	−0.251			
UK	Feb 1990–Jän 1992	0.547	0.088	1.139	–	–	–
	Feb 1992–Dez 2010	0.170	0.030	0.170			
Eastern countries							
Czech Rep.	Feb 1995–Mär 1998	0.736	0.186	0.304	–	–	–
	Apr 1998–Dez 2010	0.197	0.087	0.363			
Estonia	Feb 1996–Mär 1998	0.854	0.262	0.507	–	Jun 2004	Jan 2011
	Apr 1998–Dez 2010	0.335	0.147	0.104			
Hungary	Feb 1995–Mai 1998	1.569	0.245	1.139	–	–	–
	Jun 1998–Dez 2010	0.501	0.121	0.363			
Poland	Feb 1996–Jul 2000	0.939	0.227	1.125	–	–	–
	Aug 2000–Dez 2010	0.226	0.049	0.724			
Slovakia	Feb 1995–Feb 2004	0.581	0.196	1.140	–	Nov 2005	Jan 2009
	Mär 2004–Dez 2010	0.199	0.064	−0.563			
Slovenia	Feb 1996–Jul 2003	0.624	0.128	0.649	–	Jun 2004	Jan 2007
	Aug 2003–Dez 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–Dez 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.

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.

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 successfull in reducing its inflation rate, whereas Luxembourg experienced a doubling of its former – very low – inflation rate with the variance rising by a factor of almost 14 with a strong shift in skewness towards the left. Apart from Luxembourg, the countries that had a structural break during the second phase of convergence were also successfull in reducing mean inflation rates. In this group, as well as in the previous, the EMU adjustment led to a lower mean inflation rate.

The forth subgroup consists of two of the PIIGS countries, namely Ireland and Spain. There is a break in both countries in the summer of 2008 following the financial crisis and the severe problems concerning the real estate situation. In Ireland as well as in Spain, 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 in such a degree.

The next group consists of two countries that, after a very short participation in the ERM, decided not to be part of it and in that way also not to participate in the EMU, i.e. the United Kingdom and Sweden. Both show a clear break in the early 90s. These can be traced back to economic crisis, the currency crisis of the United Kingdom cumulating into the "Black Wednesday" in 1992 and the banking crisis in Sweden during the early 90s.

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 later part of the 90s. Czech Republic, Estonia and Hungary experienced a break in 1997/1998. This is a result of these countries efforts to curb in inflation by decreasing the growth of the money supply and indicates the time when they actually overcame the biggest transitionally shocks on their way towards free market economies. In Poland, this took two more years. Slovakia and Slovenia are special cases: for once, they started with lower mean inflation values and on the other hand, their inflation dynamics both changed roughly one year prior to their entry into the ERM II.

In the case of the inflation rate of the euro–area, we witness three different regimes. One until 1999 with both a low mean and variance, the next shortly after the beginning of the third and final stage of monetary integration, accompanied with a significant increase in the mean. The overheating of the economy that culminated in the financial crisis shows itself in a big increase in variance and a lower mean inflation, reflecting the negative inflation rates is some euro–area 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 2: Aggregation of estimated moments from Table 1 across countries in January 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.

4.2. Convergence on an aggregate level

Table 2 presents lower quartile, median, and upper quartile (25%, 50%, 75% percentiles) of the first three moments of the inflation series in January 1994, 1998, 2007 and 2010. The countries are grouped into the "core" of the eurozone, the PIIGS countries and all the others. For this, we took account of possible breaks in the moments.

The time periods are chosen according to four fundamental change periods. Namely, the early 90s, with breaks in Austria, Finland, France, Sweden, and UK. The late 90s, with breaks in

Greece, Italy, Luxembourg, Portugal, Czech Republic, Estonia, and Hungary. And also the period after the second phase of convergence, with breaks in the early 2000s (Poland, Slovakia, and Slovenia) and the two countries with the most visible effect of the financial crisis (Ireland and Spain).

In the core-zone, there is a decrease in the lower quartile from 1994 to 1998. However, the interquartile range decreased by almost 20%. The variance increased slightly, but also with a 15% decrease in interquartile range. The skewness stayed symmetric in the median, with almost an 8% increase in the interquartile range.

The PIIGS countries significantly decreased the median inflation rates from 1994 to 2010. Whereas the interquartile range was very tight in 1994, it increased in 1998 and again in 2010. However, the median values are much smaller. The variance increased from 1994 to 1998 but did not change much in 2010. The interquartile range did not change much too. Median skewness changed considerable from highly positive to negative values. This is mostly due to the changes associated with the financial crisis, that was responsible for deflationary shocks. The interquartile range of skewness decreased considerably.

The other countries were successfull in decreasing all three moments from 1994 to 2007. Still, their median inflation rate is higher than those of the core countries. Also, the interquartile range of the mean decreased considerably. Contrary to the euro–zone and the PIIGS countries, variance decreased also, both in terms of the median value and the interquartile range. The skewness decreased as well, as did the interquartile range of the skewness parameter.

In context of the convergence issue, we find that, with the interquartile range of the mean of all the aggregated zones declining and getting tighter, there is evidence of a convergence towards some common mean inflation rate in the countries of our sample, both within the subgroups and the three groups put together. This is also visible in the median values, that diverge much less than at the beginning in 1994.

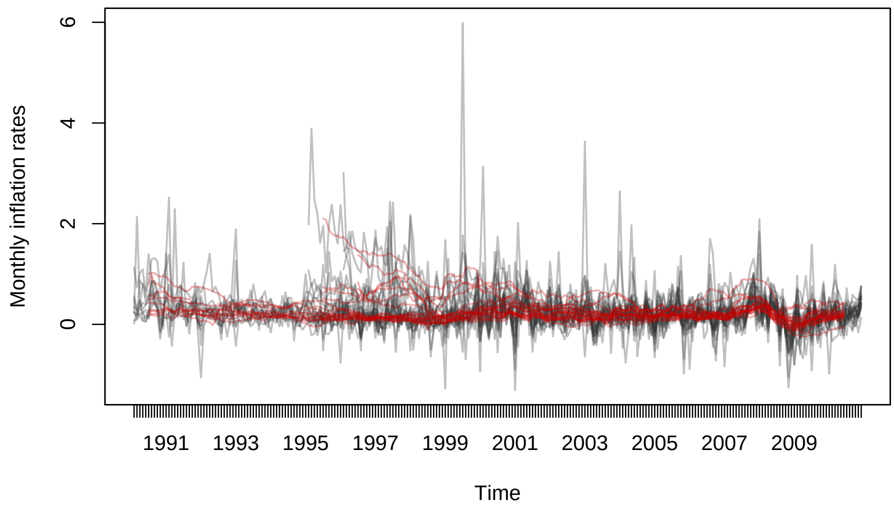

Figure 3: Observed monthly inflation rates (gray) and estimated means from rolling GL fits (red) over time for all countries, with a window size of 12 months

4.3. The influence of the financial crisis

Another way to address the convergence behavior of the inflation rates and the influence of the financial crisis is a graphical representation, as in Figure 3. It depicts the inflation rates and a rolling mean estimation, where the mean is calculated using the first moment of a fitted GL distribution. The financial crises and the short deflationary phase starting around the autumn of 2007 and lasting a few months is clearly visible. It is outlined by a strong increase in mean inflation during the boom years of 2007/2008 accompanied by an equally strong deflation following the bust. However, the level of mean inflation did not change much, as the inflation rates seem to have returned to their prior path. The inflation series of the euro–area conveys the same message. With regard to the financial crisis, this shows that for low frequency data, like inflation, rapid changes that persist only for a very short period of time are not captured well. Specifically, short-lasting changes in the mean may simply be attributed to increased variance. For example, the mean inflation of the euro–area 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. The general trend also suggests that the inflation rates converged towards some common – albeit broad – mean level. There is still some visible difference in the inflation rates, but the mean estimates are moving closer, albeit 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

(start with 1) short recap of what we did, 2) conclusions) README

To assess changes in the dynamics of the inflation rates of a number of European countries both within and without the EMU, we developed a new method for estimating structural breaks resting on the assumption that the inflation rates are GL distributed.

The results suggest that a GL distribution is appropriate for the modeling of the seasonally adjusted inflation rate series and that failing to account for a change in the skewness of the distribution might lead to wrong conclusions concerning the dynamics.

The results of Holtemöller (2007), whose simulations indicated that the standard deviation of the home CPI inflation rate can be substantially reduced by joining a monetary union, can not be empirically validated.

For the countries in the core of the eurozone, one clearly visible trend is the rise in inflation volatility in almost half of the euro countries. Emerson, Gros, Italianer, Pisani-Ferry, and Reichenbach (1992) emphasize the fact that a high inflation rate is also more variable and uncertain and thus causes more relative price variability, leading to a less efficient price mechanism. From an economic point of view, a very volatile inflation rate will likely contribute to greater macroeconomic instability. In the literature, there is no consensus about the effects of higher inflation volatility on the inflation rate. Grier and Perry (2000) find no evidence that higher inflation uncertainty raises the average inflation rate – at least in the case of the USA. However, Jarociński (2010) finds a positive correlation between the level and the standard deviation of inflation. Naturally, an efficient price mechanism will benefit from inflation rates that do not diverge too much from the expectations.

The good news is that mean inflation declined considerably, most notably in the Eastern European countries that 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 2.13.0 (R Development Core Team 2011) with the packages **glogis** 0.0-5, **strucchange** 1.4-4 (Zeileis, Leisch, Hornik, and Kleiber 2002), and **fxregime** 1.0-1 (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 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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A. Data and sales periods

In addition to Germany, Portugal, Belgium, Italy, Luxembourg, and Spain, there are a number of other countries where the sales periods are regulated by law. In France the sale periods time span is regulated by each department. In Greece there are also two set sales-periods in winter and summer. In Italy the sales periods are fixed each year by the Chambers of Commerce. Portugal has two set sales periods as well, but for two month (January and February as well as Mid-July to Mid-September). The source for this information is European Consumer Centres (2011). According to Lünnemann and Mathä (2009), the official dates of the inclusion of these sales periods are: January 1998 for Germany and Portugal, January 1999 for Luxembourg and Ireland and January 2000 for Belgium, while Italy and Spain introduced them in January 2001.

B. Graphs

Figures 4–9 depict the data underlying the results in Section 4 along with the GL-based means from Table 1.

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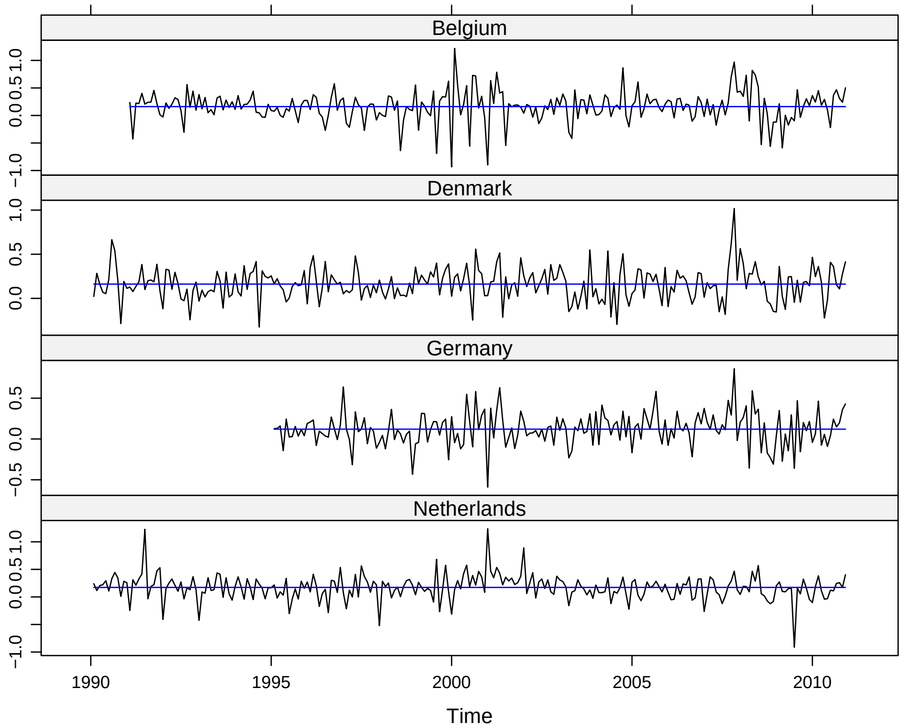

Figure 4: No change.

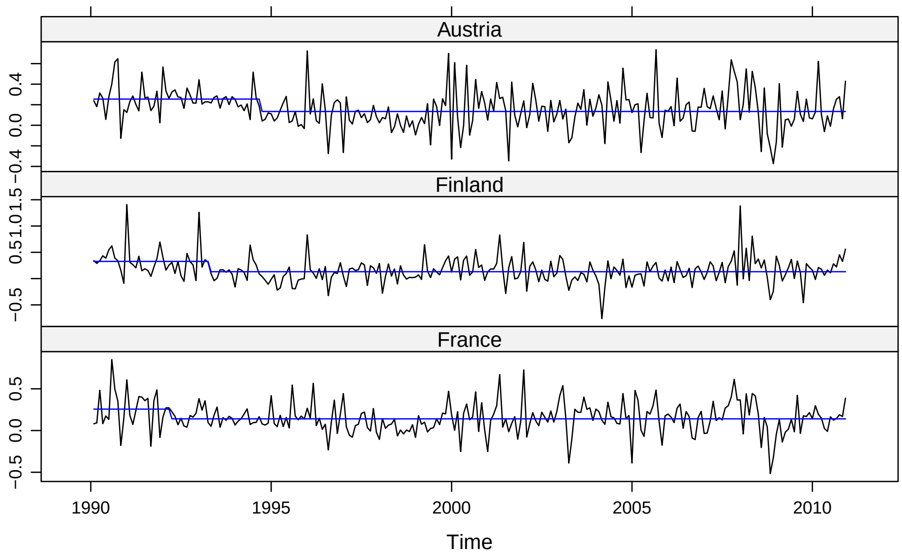

Figure 5: Phase 1 convergence.

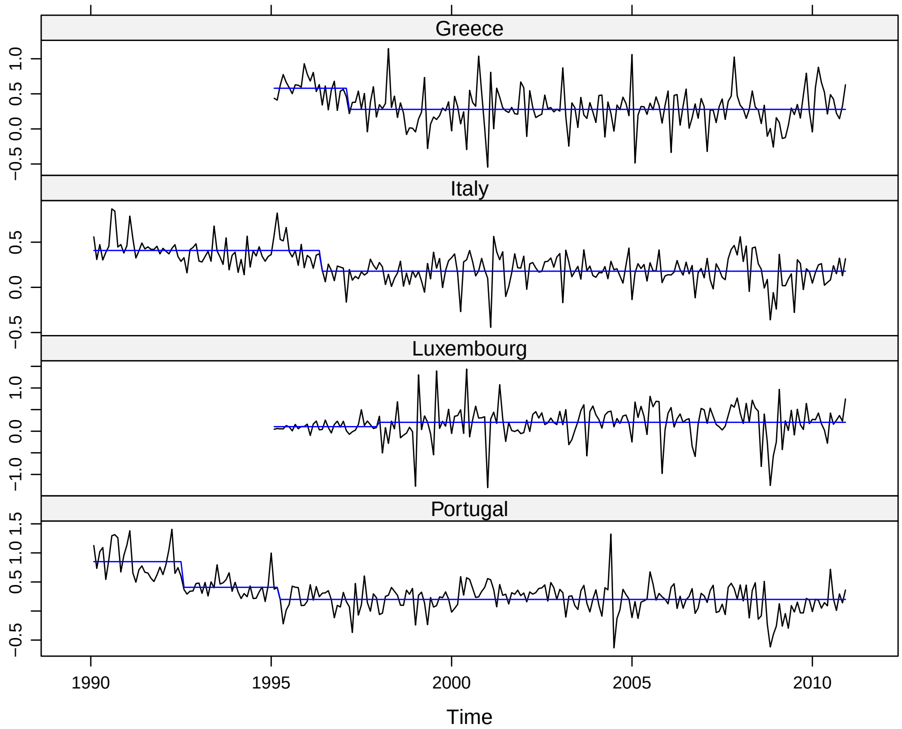

Figure 6: Phase 2 convergence.

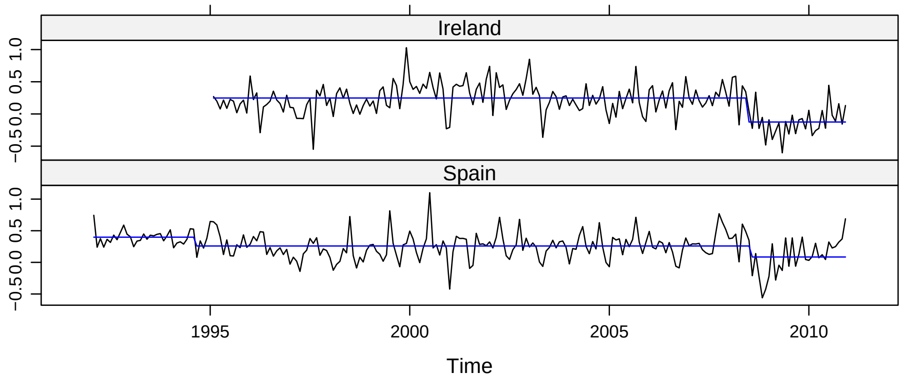

Figure 7: Financial crisis.

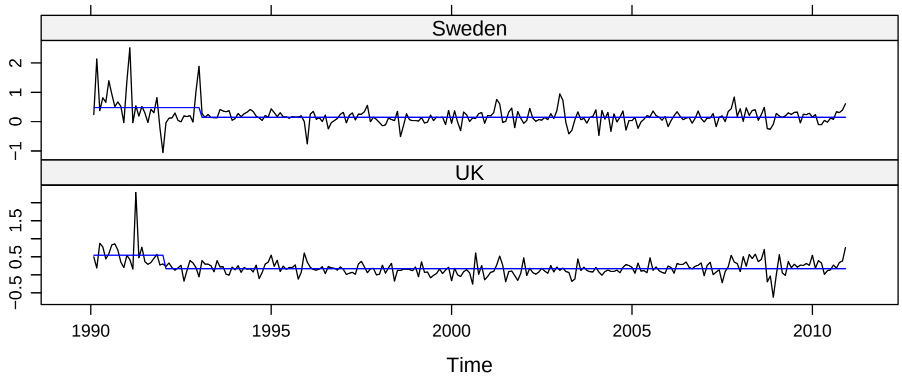

Figure 8: Non-euro.

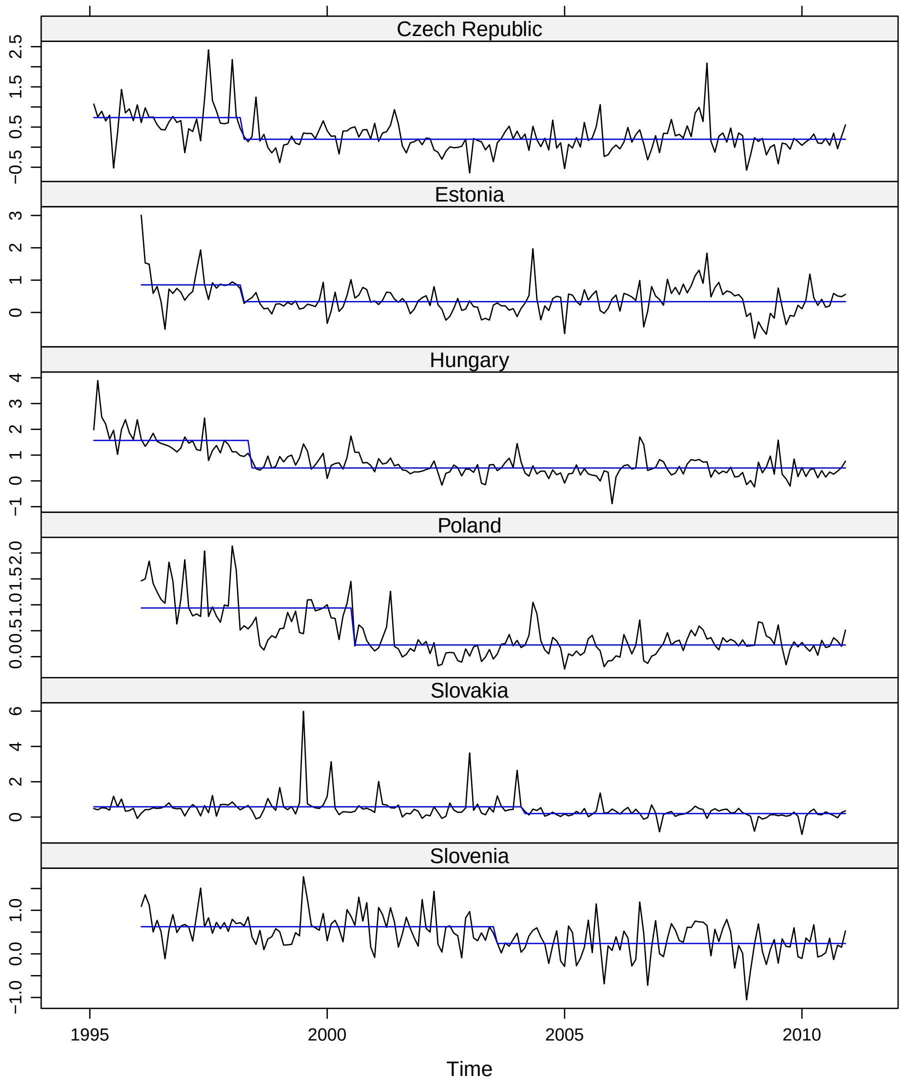

Figure 9: Eastern countries.