# Structural Breaks in Inflation Dynamics within the European Monetary Union

Thomas Windberger

Universität Innsbruck

Achim Zeileis

Universität Innsbruck

#### Abstract

text when everything else finished, present innovation of paper

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

# 1. Introduction

Ever 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 (OCA) (Z: include a citation for OCA or is this completely common knowledge?) 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 regards the question about short-run and steady-state inflation uncertainty (in context to inflation expectations) dealt with in Caporale and Kontonikas (2009), or the structural convergence of the inflation rates in EU countries, which is the topic of an investigation by Palomba, Sarno, and Zazzaro (2009).

The way towards the EMU basically consisted of three stages: 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. Any new state that wants to join the EMU is first obliged to fulfill the Maastricht criteria, which, besides setting rules for government debts and interest rates, also requires the participation in the ERM II (Exchange Rate Mechanism II) for two years, while the exchange rates towards the euro are not allowed to cross the nominal band.

Emerson, Gros, Italianer, Pisani-Ferry, and Reichenbach (1992) put emphasize on 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. Failing to stabilize inflation leads to severe economic problems. 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. The EMU requires a country to possibly alter a number of economic policies and institutions, which may demand for significant short term adjustments to take

FIXME

place.

Given that a country experienced quite volatile inflation rates, its efforts to meet the convergence criteria are likely to lead to an alteration at least in the mean (since this was one of the requirements) and possibly in the volatility of their respective inflation rates as well.

However, a deeper inquiry into this problem is in need of a method able to capture changes in inflation dynamics. We contribute to this debate by developing a new method for testing for structural breaks in the dynamics of the inflation rates and thereby upon the effect of the EMU on a number of European countries both within and outside the eurozone. The framework developed in this paper makes it possible to test for any significant changes of a countries inflation dynamics 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). The GL distribution is a suitable one due to its flexibility to capture nonsymmetry and because of its fatter tails. For this purpose, we develop a new estimation approach building on previous research by Zeileis and Hornik (2007).

FIXME

This (Jesus: sell method better, why this one and not another) framework allows us to assess the evolution of mean, variance and skewness over time. The skewness parameter turns out to be quite important to measure changes 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. Our estimation technique enables the simultaneous estimation of breaks in the mean (which is important in the context of the Maastricht criteria), the variance (which should be low for the price mechanism to be efficient) and the skewness (where a change in skewness is evidence of a shift of the distribution towards a new "center of gravity") of the inflation rates of interest. This than can be used to search for answers regarding the question about the effect of the EMU on the inflation dynamics of its member states or more general to investigate the effects of external shocks.

FIXME

The (Jesus: maybe comment on results here) 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<sup>1</sup> 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.

<sup>&</sup>lt;sup>1</sup>Inclusion of sales prices in the HICP was demanded by a Commission regulation (see European Commission 2010, 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  $y_i$   $(i=1,\ldots,n)$  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  $\theta_i$ , scale  $\sigma_i$ , and shape  $\delta_i$  at time i. Structural change techniques are then employed to check whether the parameter vector  $\phi_i$  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).<sup>2</sup>

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 inflation rates by Batchelor and Orr (1988). Its generalization – which additionally allows for asymmetries – has been applied to analyze risk (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 type I GL distribution (also known as skew-logistic distribution), as defined in Johnson et al. (1995), has the log-density function

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

with location  $\theta$ , 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

<sup>&</sup>lt;sup>2</sup>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 (2010); however, this is not pursued here.

first three moments are

$$E(y) = \theta + \sigma(\gamma(\delta) - \gamma(1)) \tag{2}$$

$$Var(y) = \sigma^2(\gamma'(\delta) + \gamma'(1))$$
(3)

$$Skew(y) = \frac{\gamma''(\delta) - \gamma''(1)}{(\gamma'(\delta) + \gamma'(1))^{3/2}}$$
(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

$$s(y \mid \phi) = \frac{\partial \ell(y \mid \phi)}{\partial \phi} = \begin{pmatrix} \frac{1}{\sigma} - \frac{(\delta + 1)\tilde{y}}{\sigma(1 + \tilde{y})} \\ \left\{ \frac{1}{\sigma} - \frac{(\delta + 1)\tilde{y}}{\sigma(1 + \tilde{y})} \right\} \cdot \frac{y - \theta}{\sigma} - \frac{1}{\sigma} \\ \frac{1}{\delta} - \log(1 + \tilde{y}) \end{pmatrix}$$
 (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, ..., 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):  $\hat{\phi} = \operatorname{argmax}_{\phi} \sum_{i=1}^{n} \ell(y_i | \phi)$ . 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

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

$$efp(t) = \hat{V}^{-1/2} n^{-1/2} \sum_{i=1}^{\lfloor nt \rfloor} s(y_i | \hat{\phi}) \quad (0 \le t \le 1),$$
 (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  $\sup LM$  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  $\tau_1, \ldots, \tau_B$  and the segment-specific GL parameters  $\phi^{(b)}$  ( $b = 1, \ldots, B+1$ ). 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 clearly 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.

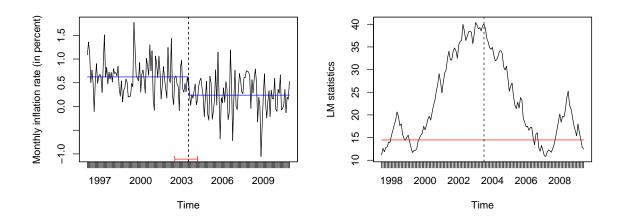


Figure 1: Inflation rate series for Slovenia with breakpoint estimate (Jul 2003), associated confidence interval, and fitted mean from generalized logistic distribution (left). Corresponding  $\sup LM$  test (right) with sequence of LM statistics, critical value at 5% level (horizontal red line line),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

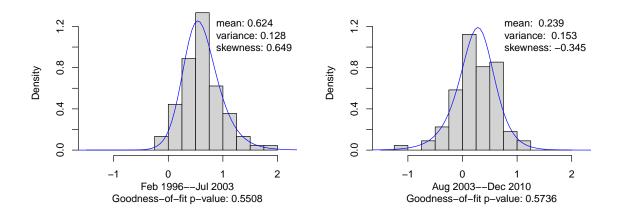


Figure 2: Histogramm of observed monthly inflation rates in Slovenia for Feb 1996–Jul 2003 (left) and Feb 1996–Jul 2003 (right), along with fitted generalized logistic probability density function, associated moments, and  $\chi^2$  goodness-of-fit test.

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, deposited 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  $\chi^2$  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

The modeling strategy 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 in Table 1 (and ordered alphabetically within each group).

If there is only a single segment, the  $\sup LM$  test was non-significant at 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).

#### 4.1. The countries in detail

(Z: I have reordered the groups in Table 1 which tries to be roughly in the order of joining EU/ERM/EMU. Probably the following interpretations should start with a very short overview of the groupings.)

g FIXME v

The first group that draws particular attention is a subgroup of the PIIGS countries (Portugal, Ireland, Italy, Greece, Spain) consisting of Ireland and Spain. Both show a break in the summer of 2008 following the financial crisis and the severe problems in both countries concerning the real estate situation. In both countries this had a strong deflationary impact, with Ireland actually showing negative inflation rates for 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. This deflationary trend, which for a time affected all countries, can be seen in Figure 3, which depicts a rolling mean estimation, where the mean is calculated using the first moment of a fitted GL distribution. There is evidence of a decline in mean inflation, which returns to its previous path roughly a year later.

The second 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 (Slovenia is an exception with an increase in variance after the break). Most of them experienced a break in 1997/1998, with Poland, Slovakia and Slovenia somewhat later. The break during the late 90s is a result of these countries efforts to curb in inflation by decreasing money supply and indicates the time when these countrie's actually overcame the biggest transitionally shocks on their way towards free market economies. Slovakia is very similar to Slovenia, as its inflation dynamics too changed roughly one year prior to its entry into ERM II.

Another interesting group consists – with the exception of Austria and Luxembourg – of the countries of the former DEM-zone. All these countries have a very low inflation rate in both mean and variance and their inflation dynamics did not change.

The next group consists of two countries that decided not to be part of any European Monetary System<sup>3</sup>, the United Kingdom and Sweden. Both show a clear break in the early 90s. They can be traced back to economic crisis, the currency crisis of the United Kingdom cumulating into the "Black Wednesday" in 1992 and the run on the Swedish currency in the same year.

<sup>&</sup>lt;sup>3</sup>If we ignore the short participating time of both countries in the EMS.

Country	Segment	Mean	Variance	Skewness	ERM	ERM II	Euro
	~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~ ~	1.10011	, 0.2.101100				
No change	P.1 1001 P. 2217	0.101		6 125	3.6		T
Belgium	Feb 1991–Dec 2010	0.161	0.071	-0.425	Mar 1979	- T 1005	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 conve	0						
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 199
	May 1993–Dec 2010	0.131	0.046	0.266			
France	Feb 1990–Mar 1992	0.257	0.056	0.214	Mar 1979	_	Jan 199
	Apr 1992–Dec 2010	0.140	0.028	0.055			
Phase 2 conve	ergence						
Greece	Feb 1995–Feb 1997	0.580	0.026	-0.337	Mar 1998	Jan 1999	Jan 200
	$Mar\ 1997\text{Dec}\ 2010$	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 199
	Jan 1998–Dec 2010	0.205	0.150	-0.702			
Portugal	Feb 1990–Jul 1992	0.850	0.072	1.140	Apr 1992	_	Jan 199
	Aug 1992–Mar 1995	0.408	0.024	1.139			
	Apr 1995–Dec 2010	0.200	0.054	-0.582			
Financial cris	sis						
Ireland	Feb 1995–Jun 2008	0.248	0.051	-0.041	Mar 1979		Jan 1999
	$\mathrm{Jul}\ 2008\mathrm{Dec}\ 2010$	-0.125	0.048	0.466			
Spain	Feb 1992–Aug 1994	0.398	0.013	1.062	Jun 1986	_	Jan 199
	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 count	tries						
Czech Rep.	Feb 1995–Mar 1998	0.736	0.186	0.304	_		_
czech resp.	Apr 1998–Dec 2010	0.197	0.087	0.363			
Estonia	Feb 1996–Mar 1998	0.854	0.262	0.507	_	Jun 2004	Jan 201
	Apr 1998–Dec 2010	0.335	0.147	0.104		3 33-1 - 2 3 3 -	
Hungary	Feb 1995–May 1998	1.569	0.245	1.139	_	_	_
O V	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 200
	Mar 2004–Dec 2010	0.199	0.064	-0.563			
						T 0004	Jan. 200
Slovenia	Feb 1996–Jul 2003	0.624	0.128	0.649	_	Jun 2004	Jan 200'

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. These are also the countries with the lowest inflation rates in both mean and variance after the adjustment.

The last group consists of three PHGS countries and Luxembourg. Greece and Portugal adjusted to the ERM shortly before or afterwards 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 14 with a strong shift in skewness towards the left.

## 4.2. Overview over the general trend

The disparity of the national inflation rates is still an issue. Many researchers, like Hofmann and Remsperger (2005) find a considerable amount of inflation differentials. Caporale and Kontonikas (2009) estimate short-run and steady-state inflation uncertainty in 12 EMU countries and find a considerable degree of heterogeneity across EMU countries in terms of average inflation and its degree of persistence. In a paper examining structural convergence of inflation rates in EU countries, Palomba et al. (2009) try to answer the question if during the 1990s the inflation rate dynamics of EU countries become more similar. They find that convergence over time of inflation dynamics was only partly observable. In a paper studying core inflation and using an aggregated euro area inflation rate, Morana (2000) finds three regimes (roughly 1980–1984, 1984–1993 and 1993–2000) governing the core inflation rate.

Concerning inflation differentials, Figure 3 depicts the inflation rates and a rolling mean estimation (with a window size of 12 months), where the mean is calculated using the first moment of a fitted GL distribution.<sup>4</sup> We do see that many of these countries follow a rather similar path. One event clearly visible is the financial crises and the short deflationary phase starting somewhere around the autumn of 2007 and lasting a few months. Over time, there are hints, that the inflation rates converged towards some common – albeit broad – mean level. For the inflation series of the whole EMU, as published by the Organisation for Economic Cooperation and Development (2010), we see an increase in mean from 0.114 (Feb 1996–Jun 1999) to 0.179 (Jul 1999–Aug 2007) with a strong decrease to 0.16 (Sep 2007–Dec 2010) following the financial crises. Whereas variance has increased over time from 0.01 over 0.014 to 0.055. Regarding skewness, we see a clear change towards a negative skewness from 0.253 over –0.311 to –0.397. (Z: interpretation needs to be adapted to modified analysis)

**FIXME** 

Regarding the general trend, Table 2 presents lower quartile, median, and upper quartile (25%, 50%, 75% quantiles) 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 (Austria, Belgium, Finland, France, Germany, Luxembourg and Netherlands), the PIIGS countries (Portugal, Italy, Ireland, Greece and Spain) and all the others. For this, we took account of possible breaks in the moments.

In the core-zone, we see a decrease in the lower quartile from 1994 to 2010, with no change in the median inflation rate, which is due to the fact, that there is no break after 1998 for these countries; however, the interquartile range decreased by almost 20%. The variance increased slightly (but with a 15% decrease in interquartile range), whereas skewness stayed symmetric

<sup>&</sup>lt;sup>4</sup>If more countries have the same inflation rate in a given month, the lines are overlapped and thus get darker. We wold see one black line if all countries would show the same month-on-month increase at any one time. The red lines depict the means.

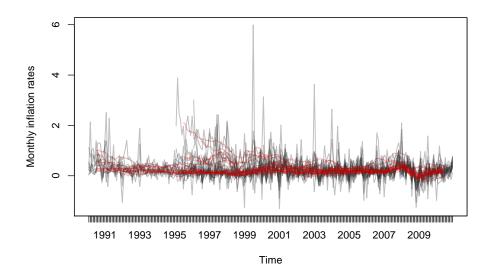


Figure 3: Observed monthly inflation rates (gray) and estimated means from rolling GL fits (red) over time for all countries.

in the median, with almost no change in the interquartile range.

The other countries were successfull in decreasing all three moments, but they are still higher than the euro-zone countries. Most importantly, the interquartile range for all moments decreased considerably showing a clear convergence towards the core-zone countries. The PIIGS countries decreased inflation rates as well with a strong change of skewness towards more negative values. The interquartile range of their inflation variance increased considerably, which is mostly due to Spain and Ireland and their strong reaction to the financial crisis.

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Moment	Quartile	1994	1998	2007	2010
Wedian         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             PHGS           Mean         Lower         0.398         0.200         0.08           Median         0.408         0.248         0.17           Upper         0.408         0.259         0.20           Variance         Lower         0.019         0.040         0.04           Median         0.024         0.051          0.05           Skewness         Lower         -0.041         -0.582         -0.58           Median         0.838         -0.089         -0.58           Wedian         0.624         0.199         0.08	Core euro					
Variance         Upper Lower D.022 D.039 Median D.042 D.043 D.059 D.059         D.025 D.039 D.059           Skewness         Lower D.045 D.059 D.050 D.059 D.059 D.050 D.059 D.050 D.051 D.050 D.050 D.051 D.050 D.051 D.050 D.051 D.050 D.050 D.051 D.050 D.0	Mean	Lower	0.126	0.133		
Variance         Lower Median 0.042 0.043 0.043 0.059         Median 0.045 0.059           Skewness         Lower −0.104 −0.305 Median 0.055 −0.021 Upper 0.328 0.161         −0.104 −0.305 Median 0.055 −0.021 Upper 0.328 0.161           PHIGS         Mean Lower 0.398 0.200 Median 0.408 0.248 0.17 Upper 0.408 0.259 0.20         0.08 Median 0.408 0.259 0.20           Variance Lower 0.019 0.040 Median 0.024 0.051 0.054 0.06         0.054 0.054 0.06           Skewness Lower −0.041 −0.582 −0.58 Median 0.838 −0.089 −0.58 Median 0.838 −0.089 −0.58 Upper 1.062 −0.041 −0.08         −0.08           Other         Median 0.624 0.199 Upper 0.854 0.239         0.239           Variance Lower 0.044 Median 0.186 0.044 0.044 Median 0.186 0.0064 0.00		Median	0.140	0.140		
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              Mean         Lower         0.398         0.200         0.08            Median         0.408         0.248         0.17         0.17           Upper         0.408         0.259         0.20         0.04           Variance         Lower         0.019         0.040         0.04         0.04           Median         0.024         0.051          0.05           Skewness         Lower         -0.041         -0.582         -0.58           Median         0.838         -0.089         -0.58           Webran         Lower         0.170         0.170           Median         0.624         0.199           Upper         0.854         0.239           Variance         Lower         0.		Upper	0.167	0.167		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variance	Lower	0.022	0.039		
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Median	0.042	0.043		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Upper	0.045	0.059		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Skewness	Lower	-0.104	-0.305		
PIIGS           Mean         Lower         0.398         0.200         0.08           Median         0.408         0.248         0.17           Upper         0.408         0.259         0.20           Variance         Lower         0.019         0.040         0.04           Median         0.024         0.051          0.05           Upper         0.026         0.054         0.06           Skewness         Lower         -0.041         -0.582         -0.58           Median         0.838         -0.089         -0.58           Upper         1.062         -0.041         -0.08           Other           Mean         Lower         0.170         0.170           Median         0.624         0.199         0.239           Variance         Lower         0.044         0.044         0.044           Median         0.186          0.064            Upper         0.227         0.121         0.121           Skewness         Lower         0.170         -0.251         0.121		Median	0.055	-0.021		
Mean         Lower Median Median 0.408 0.248 0.248 0.17         0.17           Upper 0.408 0.259 0.20         0.20           Variance Lower 0.019 0.040 Median 0.024 0.051 0.06         0.05           Upper 0.026 0.054 0.054 0.06         0.06           Skewness Lower −0.041 −0.582 −0.58         −0.58           Median 0.838 −0.089 −0.58         −0.58           Upper 1.062 −0.041 −0.08         −0.08           Other           Mean Lower 0.170 Median 0.624 0.199 Upper 0.854 0.239           Variance Lower 0.044 Median 0.186 0.044 Median 0.186 0.0044 0.0		Upper	0.328	0.161		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	PIIGS					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Mean	Lower	0.398	0.200		0.085
Variance         Lower Median Median 0.024 0.051 0.05         0.040 0.05           Skewness         Lower 0.026 0.054 0.06         0.06           Skewness         Lower 0.041 0.0582 0.058         0.089 0.058           Median 0.838 0.089 0.089 0.058         0.088           Upper 1.062 0.041 0.088         0.088           Other         Median 0.624 0.199 0.199 0.854 0.239           Variance         Lower 0.044 0.04		Median	0.408	0.248		0.179
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Upper	0.408	0.259		0.200
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Variance	Lower	0.019	0.040		0.048
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Median	0.024	0.051		0.054
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Upper	0.026	0.054		0.067
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Skewness	Lower	-0.041	-0.582		-0.589
Other         Mean       Lower Median       0.170 0.170 0.170 0.199         Upper       0.854 0.239 0.239         Variance       Lower 0.044 0.		Median	0.838	-0.089		-0.582
Mean         Lower Median         0.170 0.170 0.170           Wedian         0.624 0.199 0.239           Upper 0.854 0.239         0.239 0.044 0.044 0.044 0.044           Median 0.186 0.186 0.0664 0.064 0.09         0.0227 0.121 0.121           Skewness Lower 0.170 0.170         -0.251		Upper	1.062	-0.041		-0.089
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Other					
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Mean	Lower	0.170		0.170	
Variance       Lower       0.044       0.044         Median       0.186        0.064          Upper       0.227       0.121         Skewness       Lower       0.170       -0.251		Median	0.624		0.199	
		Upper	0.854		0.239	
$\begin{array}{cccc} & {\rm Upper} & 0.227 & 0.121 \\ {\rm Skewness} & {\rm Lower} & 0.170 & -0.251 \end{array}$	Variance	Lower	0.044		0.044	
Skewness Lower $0.170$ $-0.251$		Median	0.186		0.064	
		Upper	0.227		0.121	
Median $0.507$ $0.149$	Skewness	Lower	0.170		-0.251	
		Median	0.507		0.149	
Upper $1.125$ $0.363$		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.

## 5. Conclusion

**FIXME** 

(Jesus: this belongs to the intro section) An interesting approach to this question – using a theoretical framework – is taken by Holtemöller (2007). What he finds out via simulations of different interest rate rules is that the standard deviation of the home CPI inflation rate can be substantially reduced by joining a monetary union. The effects of joining a monetary union on inflation variability in his framework depend on structural parameters like risk aversion, price flexibility, export demand elasticity, openness and shock correlations. However, due to the fact that not all of these parameters are known and that their interaction as well has to be estimated, the whole model is very dependent on a variety of assumptions.

Any new country willing to join must first participate in the second exchange rate mechanism (ERM II) with their currencies floating in a rather narrow band against the euro, which basically requires the same synchronization tools. For the countries in the core of the eurozone, the most disturbing trend seems to be the rise in inflation volatility in almost half of the euro countries. A very volatile inflation rate will likely contribute to greater macroeconomic instability. Although Grier and Perry (2000) find no evidence that higher inflation uncertainty raises the average inflation rate – at least in the case of the USA – Jarocinski (2010) finds a positive correlation between the level and the standard deviation of inflation. This finding might be still more problematic if we take into account that on average the skewness parameter has decreased substantially in most of the euro-zone countries, and especially the PIIGS, indicating that in future higher inflation rates are more likely. This will put pressure on the ECB to achieve its inflation target of 2%.

# Computational details

Our results were obtained using R 2.13.0 (R Development Core Team 2011) with the packages glogis 0.0-6, 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).

# References

- Andreou E, Ghysels A (2002). "Detecting Multiple Breaks in Financial Markets Volatility Dynamics." *Journal of Applied Econometrics*, **17**, 579–600.
- Andrews DWK (1991). "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." *Econometrica*, **59**, 817–858.
- Andrews DWK (1993). "Tests for Parameter Instability and Structural Change with Unknown Change Point." *Econometrica*, **61**, 821–856.
- Bai J, Perron P (2003). "Computation and Analysis of Multiple Structural Change Models." Journal of Applied Econometrics, 18, 1–22.
- Batchelor RA, Orr AB (1988). "Inflation Expectations Revisited." *Economica*, **55**(219), 317–331.
- Caporale GM, Kontonikas A (2009). "The Euro and Inflation Uncertainty in the European Monetary Union." *Journal of International Money and Finance*, **28**(6), 954–971.
- Cottrell A, Lucchetti R (2011). gretl User's Guide Gnu Regression, Econometrics and Time-Series Library. Version 1.9.5, URL http://gretl.sourceforge.net/.
- Emerson M, Gros D, Italianer A, Pisani-Ferry J, Reichenbach H (1992). One Market, One Money, An Evaluation of the Potential Benefits and Costs of Forming an Economic and Monetary Union. Oxford University Press.
- European Commission (2010). "Commission Regulation (EC) No. 2602/2000." http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2000:300:0016: 0017:EN:PDF. Online, accessed 2010-11-17.
- European Consumer Centres (2010). "Shopping in Europe." http://www.konsumenteuropa.se/en/Shopping-in-Europe. Online, accessed 2010-11-17.

- Findley DF, Monsell BC, Bell WR, Otto MC, Chen BC (1998). "New Capabilities and Methods of the **X-12-ARIMA** Seasonal Adjustment Program." *Journal of Business and Economic Statistics*, **16**, 127–177.
- Grier KB, Perry MJ (2000). "The Effects of Real and Nominal Uncertainty on Inflation and Ouptut Growth." *Journal of Applied Econometrics*, **15**, 48–58.
- Hofmann B, Remsperger H (2005). "Inflation Differentials among the Euro Area Countries: Potential Causes and Consequences." *Journal of Asian Economics*, **16**(3), 403–419.
- Holtemöller O (2007). "The Effects of Joining a Monetary Union on Output and Inflation Variability in Accession Countries." *Technical report*, RWTH Aachen University.
- Jarocinski M (2010). "Responses to Monetary Policy Shocks in the East and the West of Europe: A Comparison." *Journal of Applied Econometrics*, **25**, 833–868.
- Johnson NL, Kotz S, Balakrishnan N (1995). Continuous Univariate Distributions, Volume 2. 2nd edition. John Wiley & Sons, Hoboken, New Jersey.
- Liu J, Wu S, Zidek J (1997). "On Segmented Multivariate Regression." Statistica Sinica, 7, 497–525.
- Lünnemann P, Mathä TY (2009). "Mean Reversion and Sales." Applied Economic Letteres, **16**, 1271–1275.
- Massachusetts Institute of Technology (2010). "The Billion Prices Project." http://bpp.mit.edu/. Online, accessed 2010-11-17.
- Morana C (2000). "Measuring Core Inflation in the Euro Area." *Technical report*, European Central Bank.
- Organisation for Economic Cooperation and Development (2010). "OECD.Stat." http://www.oecd-ilibrary.org/content/data/data-00285-en. Online, accessed 2010-11-17.
- Palomba G, Sarno E, Zazzaro A (2009). "Testing Similarities of Short-Run Inflation Dynamics among EU-25 Countries after the Euro." *Empirical Economics*, **37**(2), 231–270.
- R Development Core Team (2011). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.
- Smith RJ, Mixon JW (2006). "Teaching Undergraduate Econometrics with gretl." *Journal of Applied Econometrics*, **21**(7), 1103–1107.
- Tolikas K, Koulakiotis A, Brown RA (2007). "Extreme Risk and Value-at-Risk in the German Stock Market." The European Journal of Finance, 13(4), 373–395.
- US Census Bureau (2009). **X-12-ARIMA** Reference Manual, Version 0.3. Time Series Staff, Statistical Research Division, Washington, DC. ISBN 3-900051-07-0, URL http://www.census.gov/srd/www/x12a/.
- Zeileis A (2005). "A Unified Approach to Structural Change Tests Based on ML Scores, F Statistics, and OLS Residuals." Econometric Reviews, 24(4), 445–466.

- Zeileis A, Hornik K (2007). "Generalized M-Fluctuation Tests for Parameter Instability." Statistica Neerlandica, **61**(4), 488–508.
- Zeileis A, Leisch F, Hornik K, Kleiber C (2002). "strucchange: An R Package for Testing for Structural Change in Linear Regression Models." *Journal of Statistical Software*, **7**(2), 1–38. URL http://www.jstatsoft.org/v07/i02/.
- Zeileis A, Shah A, Patnaik I (2010). "Testing, Monitoring, and Dating Structural Changes in Exchange Rate Regimes." Computational Statistics & Data Analysis, 54(6), 1696–1706.

# 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. France has an individual time span regulated by each department. This should pose no problem, since there is no global state level solution. 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 (2010). According to Lünnemann and Mathä (2009), the official dates of the inclusion of these sales periods are: January 1998 for Germany and Portugal, January 2000 for Belgium and January 1999 for Luxembourg and Ireland, 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.

## **Affiliation:**

Thomas Windberger, Achim Zeileis Department of Statistics Universität Innsbruck Universitätsstraße 15 A-6020 Innsbruck, Austria

 $E-mail: \verb|Thomas.Windberger@student.uibk.ac.at|, \verb|Achim.Zeileis@R-project.org| \\$ 

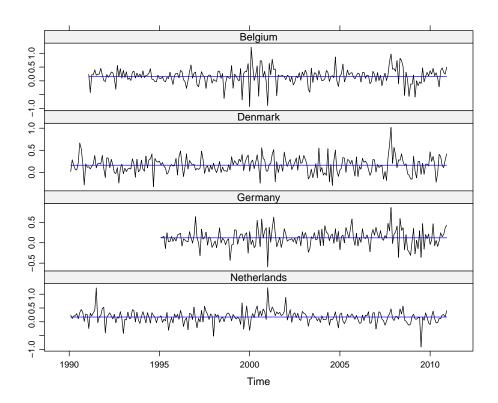


Figure 4: No change.

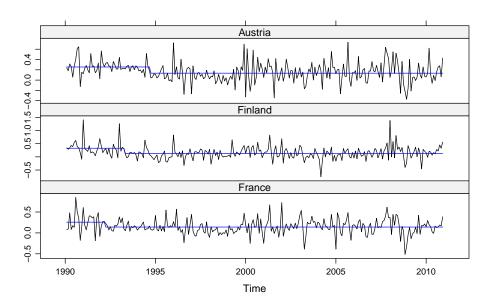


Figure 5: Phase 1 convergence.

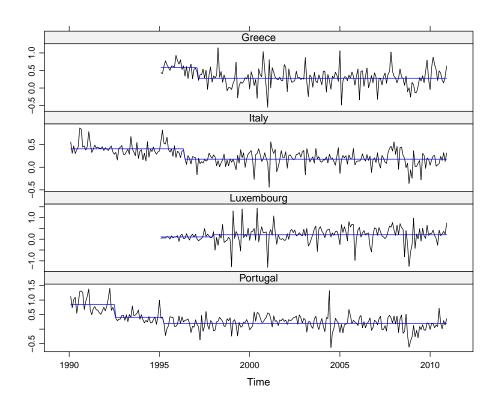
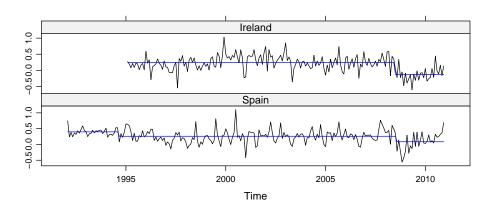


Figure 6: Phase 2 convergence.



 $\ \, \text{Figure 7:} \ \, \text{Financial crisis.}$ 

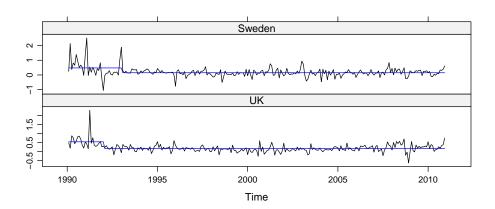


Figure 8: Non-euro.

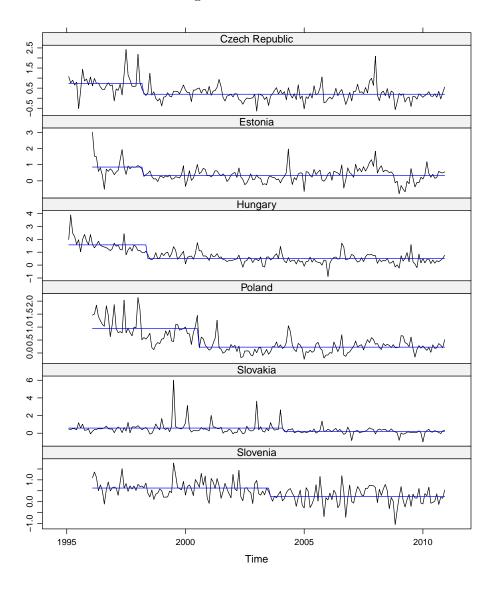


Figure 9: Eastern countries.