BRUEGEL WORKING PAPER 2013/04

INFLATION PERSISTENCE IN CENTRAL AND EASTERN EUROPEAN COUNTRIES

ZSOLT DARVAS AND BALÁZS VARGA

Highlights

- This paper studies inflation persistence with time-varying-coefficient autoregressions for twelve central European countries, in comparison with the United States and the euro area. Inflation persistence tends to be higher in times of high inflation. Since the oil price shocks, inflation persistence has declined both in the US and euro-area. In most central and eastern European countries, for which our study covers 1993-2012, inflation persistence has also declined, with the main exceptions of the Czech Republic, Slovakia and Slovenia, where persistence seems to be rather stable.

Keywords: flexible least squares, inflation persistence, Kalman-filter, time-varying coefficient models
JEL classifications: C22, E31

Zsolt Darvas (zsolt.darvas@bruegel.org) is Research Fellow at Bruegel, Research Fellow at the Hungarian Academy of Sciences Research Centre for Economic and Regional Studies, and Associate Professor at Corvinus University of Budapest Department of Mathematical Economics and Economic Analysis. **Balázs Varga** (balazs.varga@uni-corvinus.hu) is Quant Analyst at OTP Fund Management Ltd and PhD Candidate at the Corvinus University of Budapest. Financial support from OTKA grant (Hungarian Scientific Research Foundation) No. K76868 is gratefully acknowledged. We thank David I. Harvey for providing us his GAUSS code for the calculation of tests of Harvey, Leybourne and Taylor (2006).

JULY 2013

1 Introduction

Inflation is often exposed to numerous macroeconomic shocks that pull it away from its mean, which is generally identified by the central bank's inflation target. Shocks can be persistent or could have persistent effects on inflation because of, for example, nominal rigidities, leading to persistent deviations of inflation from its target. Knowing the persistence of these shocks and inflation deviations from target plays an essential role for the central bank whose primary aim is to achieve price stability. The adjustment of inflation towards its long-run level after a shock can be characterised by the speed with which it converges back to its mean. The greater this speed, the less complicated the central bank's task of maintaining price stability. Inflation persistence is a measure of this convergence speed, based on different kinds of properties of the impulse response function within the model built to describe inflation.

Inflation persistence has been studied by various models, ranging from simple autoregressions to well-structured dynamic general equilibrium models. In studying univariate autoregressive time-series models, many authors found very high persistence or even could not reject the hypothesis of a unit root for a 50-year long sample stretching from the post-second world war era, both in the United States and in the euro area. More recent studies have found that inflation series have several structural breaks[1] and most of these could be explained by corresponding historical events, for example, the oil crises of the 1970s. When studying the properties of the estimated autoregressive models for sub-periods identified by the break points, persistence turned out to be significantly smaller, particularly in the more recent periods. Hence, inflation persistence could be changing in time.

Naturally, a change in inflation persistence could be the result of (a) change in the type of underlying shocks, (b) change on the persistence of the underlying shocks, (c) change in the monetary policy reaction function, (d) change in the way the economy responds to shocks or monetary policy actions, or (e) the fact that a linear approximation of an otherwise non-linear underlying structure is poor. A univariate autoregressive model estimated on different samples cannot discriminate among these alternatives. Obviously, a time-varying coefficient autoregression also cannot discriminate among these alternatives, but allows to investigate changes in persistence more accurately and particularly, to highlight the dating and amplitude of breaks. Time-varying coefficient models were used for either or both the euro area and the US, for example, in Cogley and Sargent (2001, 2005), Dossche and Evaraert (2005) and Pivetta and Reis (2007).

[1] Pivetta and Reis (2007) challenge this view and claims that IP was reasonably stable in the post second world war US.

Although the analysis of inflation persistence in the euro area and the US has received much attention[2], there has been very limited research regarding the central and eastern European (CEE) countries. For example, Cuestas and Harrison (2010) use five different unit root tests for 12 CEE countries during 1994-2007, while Ackrill and Coleman (2012) use a variety of unit root tests and tests for fractional integration for a different set of 12 CEE countries for the sample period 1994-2011. Both papers argue that such tests have an implication for inflation persistence. However, while a unit root in the inflation series obviously indicates full persistence (that is, all shock have permanent effects), but a rejection of the unit root in itself is not informative about the nature of inflation persistence. Franta, Saxa and Smidkova (2007) adopt a more sensible approach, based on Dossche and Evaraert (2005). Among others, they measure the magnitude of inflation persistence by incorporating the possibility of time-varying means, for four CEE countries for the period 1993-2006.

Understanding inflation persistence in CEE countries is not just crucial for the central banks of these countries for the conduct of monetary policy, but it also has implications for their future membership of the euro area. Similar persistence to that of the euro area will be essential for the optimality of the common monetary policy. The European Central Bank's policy considers the euro-area average. Higher persistence in a country would imply that after an inflationary shock, inflation in this country will not be reduced parallel with the euro area's aggregate inflation, but remain higher after the ECB has reversed monetary tightening when euro-area average inflation is on track to reach the inflation target.

Time-varying coefficient analysis of inflation persistence in CEE countries seems inevitable[3]. These countries went through substantial structural changes when transformed their economies and institutions from a socialist to a market one. The transformation process was a gradual one and the economies of these countries probably still changing in a faster pace than mature economies. These arguments imply that it is rather difficult to set a date from which constancy of the parameters could be assumed on safe grounds.

In this paper we study inflation persistence in twelve CEE countries (Albania, Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia), in comparison with the euro area and the US, using time-varying coefficient autoregressions. We estimate the time-varying coefficient models two ways: one is based on the maximum likelihood estimation of a state-

[2] Eurosystem central banks even set up an Inflation Persistence Network (IPN) and directed substantial resources for the study of various aspects of IP; see Altissimo, Ehrmann and Smets (2006) for a summary of IPN. A debate whether IP has declined in the US has also received much attention in the academic literature; see, for example Pivetta and Reis (2007) for a summary of the debate.

[3] There is also a strong case for applying time-varying coefficient methods for studying euro-area data for the pre-1999 period. The euro area did not exist before 1999 and its data were constructed by aggregating country time series. It is rather likely that these constructed euro-area time series include structural breaks.

space model with the help of the Kalman-filter, while the other is a related but less-known methodology, the Flexible Least Squares (FLS) estimator introduced by Kalaba and Tesfatsion (1988).

In Darvas and Varga (2012) we assessed the ability of these two methodologies to uncover the parameters of various autoregressive data generating processes using Monte Carlo methods. We found that neither the FLS, nor the Kalman-filter can uncover sudden changes in parameters, but when parameter changes are smoother, such as linear, sinusoid or even random walk changes in the parameters, the FLS with a weight parameter 100 works reasonably well and typically outperforms even the Kalman-smoother, which in turn performed better than the Kalman-filter. We therefore use the FLS with a weighing parameter 100, but due to the arbitrariness of the selection of the smoothing parameter of the FLS, we also use Kalman-filtering.

The rest of the paper is organised as follows. Section 2 briefly introduces the time-varying coefficient autoregression and sketches Kalman-filtering and the FLS. In section 3 we describe the data we use. Section 4 presents the empirical results for the twelve central and eastern European countries, the euro area and the US. Finally, the main results are summarised in section 5.

2 Methodology

In this paper we use Kalman-filtering (Kalman, 1960) and the less frequently used Flexible Least Squares (FLS) introduced by Kalaba and Tesfatsion (1988) to estimate time-varying coefficient autoregressions.

2.1 Time-varying coefficient autoregression

There are different measures of inflation persistence (see, for example, Fuhrer, 2010) of which the most common is the parameter of a first-order autoregression, or the sum of the autoregressive parameters of a higher order autoregression. We also adopt a higher order autoregression and allow the parameters to change in time:

$$(1) \quad y_t = \rho_{0,t} + \rho_{1,t}\, y_{t-1} + \ldots + \rho_{p,t}\, y_{t-p} + u_t\,, \qquad t = 1,\ldots,T,$$

where y_t is an observed variable, $\rho_{i,t}$ denote the parameters which can change in time, and u_t is the error term. Since we use quarterly data, we allow for at most six lags in the autotergession and use the Box-Pierce and Ljung-Box statistics to determine the optimal length. Our measure of inflation persistence at time *t* is the sum of the autoregressive parameters:

(2) $\iota_t = \sum_{i=1}^{p} \rho_{i,t}$, t = 1, ...,T,

where ι_t is the time-varying measure of inflation persistence.

2.2 Time-varying coefficient methods

In Darvas and Varga (2012) we described Kalman-filtering and the FLS and also compared their ability in uncovering time-varying parameters using a Monte Carlo study, and therefore here we only briefly sketch these methods.

The FLS algorithm solves the time-varying linear regression problem with a minimal set of assumptions. Suppose y_t is the time t realisation of a time series for which a time-varying coefficient model is to be fitted,

(3) $y_t = x_t' \beta_t + u_t$, t = 1, ...,T,

where $x_t = (x_{0,t}, ..., x_{K-1,t})$ denotes a $K \times 1$ vector of known exogenous regressors (which can also contain the lagged values of y_t), $\beta_t = (\beta_{0,t}, ..., \beta_{K-1,t})$ denotes the $K \times 1$ vector of unknown coefficients to be estimated, which can change in time, and u_t is the approximation error.

The two main assumptions of the method:

(4) $y_t - x_t' \beta_t \approx 0$, t = 1, ...,T.

(5) $\beta_{t+1} - \beta_t \approx 0$, t = 1,...,T-1.

That is, the prior measurement specification states that the residual errors of the regression are small, and the prior dynamic specification declares that the vector of coefficients evolves slowly over time.

The idea of the FLS method is to assign two types of residual error to each possible coefficient sequence estimate. A quadratic cost function is assumed:

(6) $C(\beta, \mu, T) = \mu \cdot \sum_{t=1}^{T-1} (\beta_{t+1} - \beta_t)' (\beta_{t+1} - \beta_t) + \sum_{t=1}^{T} (y_t - x_t' \beta_t)^2$.

where μ is the weighting parameter. The minimisation of this cost function for β, given any μ>0, leads to a unique estimate for β. Consequently, there are a continuum number of FLS solutions for a given set of observations, depending on the weight parameter μ. The selection of the weighing parameter is a highly critical part of the FLS procedure, as the appropriate coefficient sequence lies somewhere between the most variable and the fully stable – OLS – solution.[4]

There is a close connection between the FLS and Kalman-filtering, as already described by Kalaba and Tesfatsion (1990). They emphasise that the two methods address conceptually distinct problems, but also prove that the Kalman-filter recurrence relations could be derived by means of simple intuitive cost considerations (similarly to FLS), without reliance on probabilistic arguments.

In a recent paper Montana *et al* (2009) shed new light on the relation of FLS to Kalman-filtering by adding mild probabilistic assumptions to FLS and weakening the assumptions behind the Kalman-filter. Specifically, they assume that the errors to equations describing the observed variables and the time-varying coefficients have finite first and second moments. Formally speaking, the dynamic and measurement priors are expressed in the state and measurement equations of the model, respectively, as follows:

(7) $$\beta_{t+1} = \beta_t + \omega_t , \qquad t = 1,...,T\text{-}1,$$

(8) $$y_t = x_t{}' \beta_t + \varepsilon_t , \qquad t = 1,...,T.$$

In essence, the requirement that innovations ω_t and ε_t are mutually and individually uncorrelated and have finite expected values and covariance matrices is close in spirit to the assumptions of FLS. The key difference is the randomness of the unknown parameter vector: recall that the smoothness prior of FLS does not require β_t to be random walk – only the smooth change in time is postulated.

Montana *et al* (2009) first prove that the Kalman-filter recursions work perfectly well under this distribution free circumstance – in fact, the derivation is even simpler and does not require any matrix inversion which makes it easy to implement even in higher dimension spaces with long streams of observations. The authors also show that the recursive updating equations of the Kalman-filter are equivalent to those of FLS under the new assumptions and that maximising the likelihood function of the Kalman-filter is the same as minimising the quantity:

(9) $$\sum_{t=1}^{T}\left(y_t - x_t{}' \beta_t \right)^2 + V_\omega^{-1} \sum_{t=1}^{T-1} (\beta_{t+1} - \beta_t)' (\beta_{t+1} - \beta_t),$$

[4] The solutions lie between two extremes. First, if μ approaches zero, the incompatibility cost function places absolutely no weight on the smoothness prior. This means that while the dynamic cost stays relatively large, the measurement cost will be brought down close to zero, resulting in a rather erratic sequence of estimates. Second, as μ becomes arbitrarily large, the cost function assigns all importance to the dynamic specification. This case yields the ordinary least squares (OLS) solution, because the dynamic costs will be zero when parameters do not change and therefore the measurement cost is minimised as in the OLS.

where V_ω is the covariance matrix of the ω_t errors of the parameter vector. The proof thus sheds light on the role of the μ smoothing parameter of FLS: comparing (11) to the definition (6) of incompatibility cost we get:

(10) $V_\omega = \mu^{-1} I_K$,

where I_K is the $K \times K$ identity matrix. Not surprisingly, equation (10) underlines that the variance of the innovations of the estimated parameter vector of the FLS is inversely related to μ.

As mentioned earlier, we use FLS with μ = 100, considering the simulation results of Darvas and Varga (2012), and use Kalman-filtering as well. For both the FLS and the Kalman-filtering we report the both the filtered and the smoothed estimates. The filtered estimates consider data up to time *t*, while the smoothed estimates consider data till the end of the sample period. For comparison, we also show the OLS estimate both for the full sample (which corresponds to the smoothed estimate of FLS and Kalman-filter), but also for recursive samples (which corresponds to the filtered estimates of FLS and Kalman-filter).

3 Data

We use quarterly data and adjust seasonally the raw time series using Census X12. We define inflation as *Δln(seasonally adjusted consumer price level)x100*. We study inflation time series of twelve central and eastern European countries: Albania, Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. We also study the US and the euro area as benchmarks and for comparison with the literature. The sample period for the CEE countries is 1993Q1-2012Q4, but we start the effective sample in 1995Q1 for all of these countries, preserving the earlier data points for differencing and lags (note that we allow for at most six lags). The sample period for the euro area is 1970Q1-2012Q4 and 1957Q1-2012Q4 for the US, which are also shortened by two years in the effective sample. The main source is the IMF's International Financial Statistics (IFS) database. For the euro-area data in the IFS start in 1998Q1: earlier data is taken from Datastream and the IFS data is chained to it. The data are plotted on Figure 1.

4 Empirical results

4.1 Tests for break in persistence

To see whether there has been a significant change in the persistence of our inflation series, we employ several formal tests. Kim (2000), which was corrected in Kim, Belaire-Franch and Amador (2002), proposed tests for shifting from stationarity to nonstationarity, while Busetti and Taylor (2004) developed tests for shifting from nonstationarity to stationarity. Both tests have the null hypothesis of stationarity. However, Harvey, Leybourne and Taylor (2006) have shown that these tests have the highly undesirable property that they display a very strong tendency to spuriously reject the constant I(0) null hypothesis in favour of a change in persistence when the data are generated as a constant I(1) process. They also showed that this effect does not vanish asymptotically and proposed modified versions of these tests developed by Kim (2000), Kim, Belaire-Franch and Amador (2002) and Busetti and Taylor (2004). In our paper we use the modified versions of the tests by Harvey, Leybourne and Taylor (2006).

Tables 1 and 2 show the results. We cannot reject the null hypothesis of constant persistence stationarity against the alternative of a change from stationarity to nonstationarity, but we reject, for most time series, the null hypothesis against the alternative of a change from nonstationarity to stationarity, though for Latvia and Slovakia the rejection can be made at 10 percent significance level only.

4.2 Estimation results

We selected the lag length for our time-varying coefficient autoregression (equation 1) with the Box-Pierce and Ljung-Box statistics, allowing for at most six lags. The results are presented in Table 3. For eight CEE countries, the simple first order autoregression proved to be adequate, while two lags were needed for Estonia, three lags for the euro area and the USA, and five lags for Croatia and Lithuania. For Albania, the null hypothesis of no autocorrelation is rejected at five percent for all lags by the Ljung-Box statistics, while the Box-Pierce did not reject at five percent when the lag length is five. We therefore used five lags for Albania as well.

Estimation results are shown in Figures 2-15. We use the FLS with a weight parameter of 100, based on the results of Darvas and Varga (2012). For the FLS and the Kalman-filter we show both the filtered values (which, for time *t*, are based on data up to time *t*, though the estimation of parameters uses the full sample of data) and the smoothed values (which, for time *t*, are based on data up to the end of the sample). For the OLS we show two similar lines: the full sample OLS corresponds to the smoothed values, while the recursive OLS corresponds to some extent the filtered values. Naturally, at the last data point the recursive OLS equals the full sample OLS, and the filtered values of the FLS and Kalman-filter correspond to the smoothed values of the FLS and Kalman-filter, respectively. The findings of Darvas and Varga (2012) suggest that we should prefer the smoothed values relative to the filtered values.

It is evident for all countries that OLS persistence estimate is much larger than the time-average of the time-varying persistence estimations. To assess if the OLS persistence estimate is upward biased relative to the time-average of the time-varying ones, we perform a one-sided t-test. To carry this out, we need the variances of both the OLS persistence estimate and of the average time-varying persistence estimate. The former comes easily from the estimated covariance matrix of the OLS coefficients since the persistence is simply the sum of the non-constant terms (see equation 2). The latter – namely the variance of the time-average of the time-varying persistence estimates – is approximated by using the computed sample covariance matrix of the time-varying coefficient sequences. Since these two variances are clearly different, we use Welch's t-test which – besides the t-statistic – also gives an approximation for the degrees of freedom to be used with the test.

The upper panel of Table 4 shows the OLS point estimates and their standard errors. The lower panels of Table 4 show the time-average persistence of various time-varying methods with their standard errors, t-statistic values, degrees of freedom and finally the test p-values. The results clearly show that the OLS estimates are significantly higher than the average of the time-varying ones, the null hypothesis of equality cannot be accepted for any of the countries.

Since we concluded earlier that there was a change in persistence according to the tests of Harvey, Leybourne and Taylor (2006), we conclude that the OLS estimates are likely upward biased. This finding is in line with the simulation results of Darvas and Varga (2012), who found that the OLS estimator proved to be upward biased compared to the time-average of the parameters, when there were changes in the parameters of the data generating process.

Note that it is widely documented in the literature that the OLS estimate of the autoregressive coefficient (or the dominant autoregressive root) is *downward* biased when parameters are fixed. Hence, our findings complement this literature by showing that when there are changes in the parameters of an autoregression, the OLS is upward biased compared to the time-average of the parameters.

Turning to the country-specific results, in the US, our estimates suggests that there was a low, and even negative, inflation persistence in the late 1950ies and early 1960ies, which has increased close to one during the oil crises. Persistence started to decline in the early 1980ies, possible due to the aggressive monetary policy that was adopted that time. It gradually declined by the global financial and economic crisis, when there was a sudden further decline, leading to almost zero persistence estimate by the last observation of our sample period, 2012Q4.

The effective sample period for the euro area starts in 1972, ie around the time of the first oil shock, and similarly to the US, our results suggests relatively high inflation persistence at this time period. Persistence then declined, but stayed at a higher level than in the US, reaching the value of about 0.4 by the late 1990ies, ie, by the creation of the euro. Interestingly, our results suggests that inflation persistence remained rather stable since the creation of the euro and did not change much even during the global financial and economic crisis.

In a number of CEE countries, inflation persistence has declined since 1995, the start date of our sample period. Albania, Hungary, Poland, Romania clearly show this pattern. In three other countries, Estonia, Latvia and Lithuania, there was also a declining path of persistence, but there was also a temporary increase shortly before the global financial crisis. In these three countries inflation increased significantly before the crisis and inflation persistence tends to be higher when inflation is also higher. In Bulgaria there was a non-monotonous path of inflation persistence. As Figure 1 indices, there was a very high inflation in Bulgaria in the first part of our sample which may distort the results. For Croatia, our smoothed FLS persistence estimate is quite similar at the start and at the end of the sample period (around 0.2), with some variation between zero and 0.3 in the meantime, while the Kalman-smoother estimate suggest an almost continuous increasing trend from a highly negative value (-0.5), which does not sound too realistic. Finally, there are three countries, the Czech Republic, Slovakia and Slovenia, for which our estimates suggest broadly stable persistence estimate through the sample period. More precisely, the Kalman-smoother identified constant persistence for these three countries, while the FLS-smoother suggest some changes, in particular, some decline compared to 1995.

In order to foster a better comparison across countries, Table 5 shows persistence estimates (based on the FLS-smoother and the Kalman-smoother) for specific dates. For the twelve CEE countries, we also show the median and the interquartile range. The table confirms the broadly stable persistence in the euro area, the close to zero persistence in the US by the end of the sample period, and the gradual decline in persistence in most CEE countries.

5 Summary

This paper studied inflation persistence with time-varying-coefficient autoregressions for twelve central European countries, in comparison to the US and the euro area. We used the well-known Kalman-filter and smoother and the less-known Flexible least Squares (FLS), in comparison with the simple OLS.

We found for most of the inflation series we studied that the parameters of the estimated time-varying coefficient autoregression has changed significantly, and hence there was a change in inflation persistence, a result confirmed by formal tests for change in persistence. Inflation persistence tends to be higher in times of high inflation. Since the oil shock, inflation persistence declined to historically low levels in the US and euro area, yet it remained higher in the euro area (where persistence was practically constant since the creation of the euro) than in the US. In most central and eastern European countries inflation persistence has declined since 1995, with the main exceptions of the Czech Republic, Slovakia and Slovenia, for which the Kalman-smoother suggested constant persistence, and the FLS-smoother a minor fall in persistence.

We argued that similar persistence is an important structural similarity in a currency union and progress on this front of the new EU members could contribute to the economic arguments in favour of their entry to the euro area.

We also concluded that the OLS estimate is likely *upward* biased when the parameters of an autoregression change. This finding complement the literature, which concluded that the OLS estimate of the autoregressive coefficient (or the dominant autoregressive root) is *downward* biased when parameters are fixed.

6 References

Ackrill, Rob and Simeon Coleman (2012) 'Inflation dynamics in central and eastern European countries', *Discussion Papers in Economics* 2012/01, Nottingham Business School, Economics Division

Altissimo, Filippo, Michael Ehrmann and Frank Smets (2006) 'Inflation Persistence and Price Setting Behaviour in the Euro Area – a Summary of the IPN Evidence', ECB *Occasional Paper* No. 46 (Jun 2006), ECB, Frankfurt am Main

Busettti, F., A. M. Robert Taylor (2004) 'Tests of Stationarity Against a Change in Persistence', *Journal of Econometrics*, 123, 33–66

Cogley, Timothy and Thomas J. Sargent (2001) 'Evolving Post-World War II U.S. Inflation Dynamics', *NBER Macroeconomics Annual* 2001, 331-372

Cogley, Timothy and Thomas J. Sargent (2005) 'Drifts and Volatilities: Monetary Policies and Outcomes in the Post World War U.S.', *Review of Economic Dynamics* 8(2), 262-302

Cuestas, Juan Carlos and Barry Harrison (2010) 'Inflation persistence and nonlinearities in Central and Eastern European countries', *Economics Letters* 106, 81-83

Dossche, Maarten and Gerdie Everaert (2005) 'Measuring Inflation Persistence – A Structural Time Series Approach', ECB *Working Paper* No. 495 (Jun 2005), ECB, Frankfurt am Main

Franta, Michal, Branislav Saxa and Katerina Smidkova (2007) 'Inflation persistence - euro area and new EU Member States', *Working Paper Series* 810, European Central Bank

Fuhrer, Jeffrey C. (2010) 'Inflation Persistence', in Benjamin M. Friedman & Michael Woodford (ed), *Handbook of Monetary Economics*, edition 1, volume 3, chapter 9, pages 423-486

Hansen, Bruce E. (2001) 'The New Econometrics of Structural Change: Dating Changes in U.S. Labor Productivity', *Journal of Economic Perspectives* 15, 117-128

Harvey, Dave I., Stephen J. Leybourne and A. M. Robert Taylor (2006) 'Modified Tests for a Change in Persistence', *Journal of Econometrics*, 134, 441-469

Kalaba, Robert and Leigh Tesfatsion (1988) 'The Flexible Least Squares Approach to Time-varying Linear Regression', *Journal of Economic Dynamics and Control*, Vol. 12, 43-48

Kalaba, Robert and Leigh Tesfatsion (1990) 'Flexible Least Squares for Approximately Linear Systems', *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 20, 978-989

Kalman, Rudolf Emil (1960) 'A New Approach to Linear Filtering and Prediction Problems, Transaction of the ASME', *Journal of Basic Engineering*, 35-45

Kim, Jae-Young (2000) 'Detection of Change in Persistence of a Linear Time Series', *Journal of Econometrics*, 95, 97-116

Kim, Jae-Young, Jorge Belaire-Franch and Rosa Badillo Amador (2002) Corrigendum to 'Detection of Change in Persistence of a Linear Time Series', *Journal of Econometrics*, 109, 389-392

Montana, Giovanni, Kostas Triantafyllopoulos, Theodoros Tsagaris (2009) 'Flexible Least Squares for Temporal Data Mining and Statistical Arbitrage', *Expert Systems with Applications* 36(2), 2819–2830.

Pivetta, Frederic and Ricardo Reis (2007) 'The persistence of inflation in the United States', *Journal of Economic Dynamics and Control* 31(4), 1326-1358.

Table 1: Test for the change in persistence for CEE countries

Series T = 79	MS_m (10%) MS_m (5%)	ME_m (10%) ME_m (5%)	MX_m (10%) MX_m (5%)	$MS^R{}_m$ (10%) $MS^R{}_m$ (5%)	$ME^R{}_m$ (10%) $ME^R{}_m$ (5%)	$MX^R{}_m$ (10%) $MX^R{}_m$ (5%)	$MS^M{}_m$ (10%) $MS^M{}_m$ (5%)	$ME^M{}_m$ (10%) $ME^M{}_m$ (5%)	$MX^M{}_m$ (10%) $MX^M{}_m$ (5%)
Albania	0.02	0.01	0.46	502.03 *	553.34 *	1137.98 *	484.50 *	528.65 *	1090.41 *
	0.01	0.00	0.25	484.40 **	528.60 **	1090.09 **	464.63 **	501.42 **	1036.72 **
Bulgaria	0.00	0.00	0.01	857.69 *	2907.37 *	6008.66 *	814.18 *	2719.34 *	5644.34 *
	0.00	0.00	0.01	813.94 **	2718.95 **	5641.91 **	765.74 **	2516.59 **	5241.91 **
Czech Republic	0.37	0.46	3.93	17.11 *	13.99 *	35.58 *	14.07 *	10.90 *	28.14 *
	0.31	0.36	3.10	13.90 **	10.73 **	27.72 **	11.08 **	8.06 **	21.10
Estonia	0.00	0.00	0.00	97.38 *	63.27 *	148.57 *	78.11 *	47.67 *	114.00 *
	0.00	0.00	0.00	78.02 **	47.65 **	113.80 **	60.25 **	34.34 **	83.36 **
Croatia	0.00	0.00	0.00	3696.58 *	3186.79 *	7261.66 *	2986.21 *	2422.93 *	5619.43 *
	0.00	0.00	0.00	2982.70 **	2421.50 **	5609.51 **	2322.47 **	1763.63 **	4149.76 **
Hungary	0.01	0.00	0.07	151.72 *	300.75 *	644.68 *	137.52 *	265.10 *	572.88 *
	0.00	0.00	0.01	137.44 **	265.02 **	572.41 **	122.48 **	229.02 **	498.23 **
Lithuania	0.00	0.00	0.00	119.72 *	204.31 *	558.75 *	72.06 *	106.45 *	303.61 *
	0.00	0.00	0.00	71.86 **	106.30 **	302.34 **	39.62 **	50.00 **	147.60 **
Latvia	0.00	0.00	0.00	6.52 *	6.71 *	20.88 *	3.72	3.26	10.63
	0.00	0.00	0.00	3.71	3.26	10.58	1.92	1.41	4.79
Poland	0.00	0.00	0.00	448.51 *	864.82 *	1960.54 *	366.47 *	667.22 *	1538.08 *
	0.00	0.00	0.00	366.07 **	666.85 **	1535.51 **	288.87 **	493.97 **	1154.36 **
Romania	0.01	0.00	0.03	435.91 *	628.24 *	1538.13 *	313.78 *	411.89 *	1036.26 *
	0.00	0.00	0.00	313.21 **	411.52 **	1033.44 **	213.03 **	252.52 **	649.58 **
Slovenia	0.01	0.00	0.02	18.02 *	30.70 *	79.23 *	12.72 *	19.62 *	52.13 *
	0.00	0.00	0.00	12.69 **	19.60 **	51.98 **	8.44 **	11.68 **	31.77 **
Slovakia	0.33	0.13	0.75	5.55 *	5.21 *	14.74 *	4.05	3.47	10.09
	0.24	0.08	0.49	4.04	3.47	10.06	2.79	2.17	6.44

Critical values

T= 100, *Mean case*	MS	ME	MX	MS^R	ME^R	MX^R	MS^M	ME^M	MX^M
10%	3.56	3.48	12.91	3.56	3.48	12.88	4.66	5.23	17.00
5%	4.67	5.31	17.24	4.64	5.25	17.00	5.91	7.38	21.72
1%	7.75	11.02	29.38	7.67	10.49	28.37	9.26	13.34	34.31

Note: The first three data columns show the test statistics on the basis of Kim (2000) and Kim, Belaire-Franch and Amador (2002), testing for a change from I(0) to I(1): MS=mean score, ME=mean exponential and MX=maximum score. The next three data columns show test statistics on the basis of Busetti and Taylor (2004) testing for a change from I(1) to I(0): MS^R=mean score / reciprocal, ME^R=mean exponential / reciprocal and MX^R= maximum score / reciprocal. The final three data columns are based on the test statistics of Busetti and Taylor (2004) for testing when the direction of change is unknown: MS^M=mean score / maximum = max(MS, MS^R), ME^M=mean exponential / maximum = max(ME, MER) and MX^M=maximum score / maximum = max(MX, MXR). *** shows rejection at the 1% level, ** at the 5% level, and * at the 10% level. There are two lines for each country: the first shows the modified tests at the 10% level and the second the modified tests at the 5% level, as in Harvey, Leybourne and Taylor (2006). As a consequence, the test outcome can only be analysed at the pre-set significance level.

Table 2: Test for the change in persistence for the euro area and the United States

Series	MS_m (10%) MS_m (5%)	ME_m (10%) ME_m (5%)	MX_m (10%) MX_m (5%)	$MS^R{}_m$ (10%) $MS^R{}_m$ (5%)	$ME^R{}_m$ (10%) $ME^R{}_m$ (5%)	$MX^R{}_m$ (10%) $MX^R{}_m$ (5%)	$MS^M{}_m$ (10%) $MS^M{}_m$ (5%)	$ME^M{}_m$ (10%) $ME^M{}_m$ (5%)	$MX^M{}_m$ (10%) $MX^M{}_m$ (5%)
Euro Area	0.03	0.01	0.09	213.56 *	355.89 *	775.19 *	188.35 *	302.86 *	666.58 *
T = 171	0.01	0.00	0.01	188.22 **	302.76 **	665.88 **	162.44 **	251.21 **	557.60 **
United States	0.56	1.85	7.50	26.97 *	44.53 *	99.46 *	25.67 *	41.79 *	93.72 *
T = 223	0.29	0.75	3.20	25.67 **	41.79 **	93.69 **	24.22 **	38.83 **	87.37 **

Critical values

T= 200, *Mean case*	MS	ME	MX	MS^R	ME^R	MX^R	MS^M	ME^M	MX^M
10%	3.51	3.36	13.14	3.54	3.47	13.37	4.62	5.11	17.31
5%	4.58	5.06	17.18	4.68	5.27	17.65	5.85	7.24	22.06
1%	7.56	10.21	28.58	7.82	10.69	29.64	9.21	13.20	34.82

Note: see notes to Table 1.

Table 3: Box-Pierce and Ljung-Box tests for serial correlation of the residuals of the estimated autoregressions

Lags	Albania $T = 79$		Bulgaria $T = 79$		Czech Republic $T = 79$		Croatia $T = 79$		Estonia $T = 79$		Hungary $T = 79$		Latvia $T = 79$	
	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB
1	0.001	0.001	**0.193**	**0.168**	**0.101**	**0.076**	0.012	0.008	0.080	0.055	**0.219**	**0.184**	**0.187**	**0.153**
2	0.001	0.000	0.962	0.957	0.069	0.049	0.075	0.053	**0.128**	**0.096**	0.688	0.652	0.133	0.106
3	0.026	0.015	0.990	0.988	0.259	0.212	0.042	0.028	0.159	0.122	0.651	0.613	0.658	0.618
4	0.005	0.002	0.014	0.009	0.993	0.992	0.076	0.053	0.120	0.091	0.362	0.317	0.947	0.935
5	**0.055**	**0.039**	0.012	0.007	0.991	0.989	**0.146**	**0.112**	0.593	0.550	0.049	0.035	0.340	0.283
6	0.001	0.001	0.006	0.004	0.653	0.615	0.188	0.148	0.888	0.870	0.050	0.035	0.842	0.812

Lags	Lithuania $T = 79$		Poland $T = 79$		Romania $T = 79$		Slovakia $T = 79$		Slovenia $T = 79$		Euro-area $T = 171$		USA $T = 223$	
	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB	BP	LB
1	0.040	0.025	**0.854**	**0.836**	**0.492**	**0.461**	**0.119**	**0.097**	**0.653**	**0.623**	0.012	0.010	0.001	0.001
2	0.024	0.015	0.891	0.873	0.031	0.022	0.118	0.092	0.498	0.462	0.018	0.015	0.002	0.002
3	0.000	0.000	0.856	0.833	0.054	0.042	0.053	0.039	0.650	0.617	**0.156**	**0.140**	**0.145**	**0.133**
4	0.001	0.000	0.783	0.754	0.079	0.063	0.056	0.042	0.225	0.192	0.019	0.016	0.851	0.843
5	**0.265**	**0.217**	0.110	0.081	0.281	0.246	0.085	0.067	0.261	0.222	0.003	0.003	0.893	0.887
6	0.377	0.324	0.180	0.135	0.135	0.110	0.287	0.254	0.055	0.040	0.013	0.011	0.913	0.908

Note: the p-values are indicated. BP=Box-Pierce, LB=Ljung-Box. Bold numbers indicate our selection.

Table 4: Tests for the equality of the OLS estimate and the mean of the time-varying parameter estimates

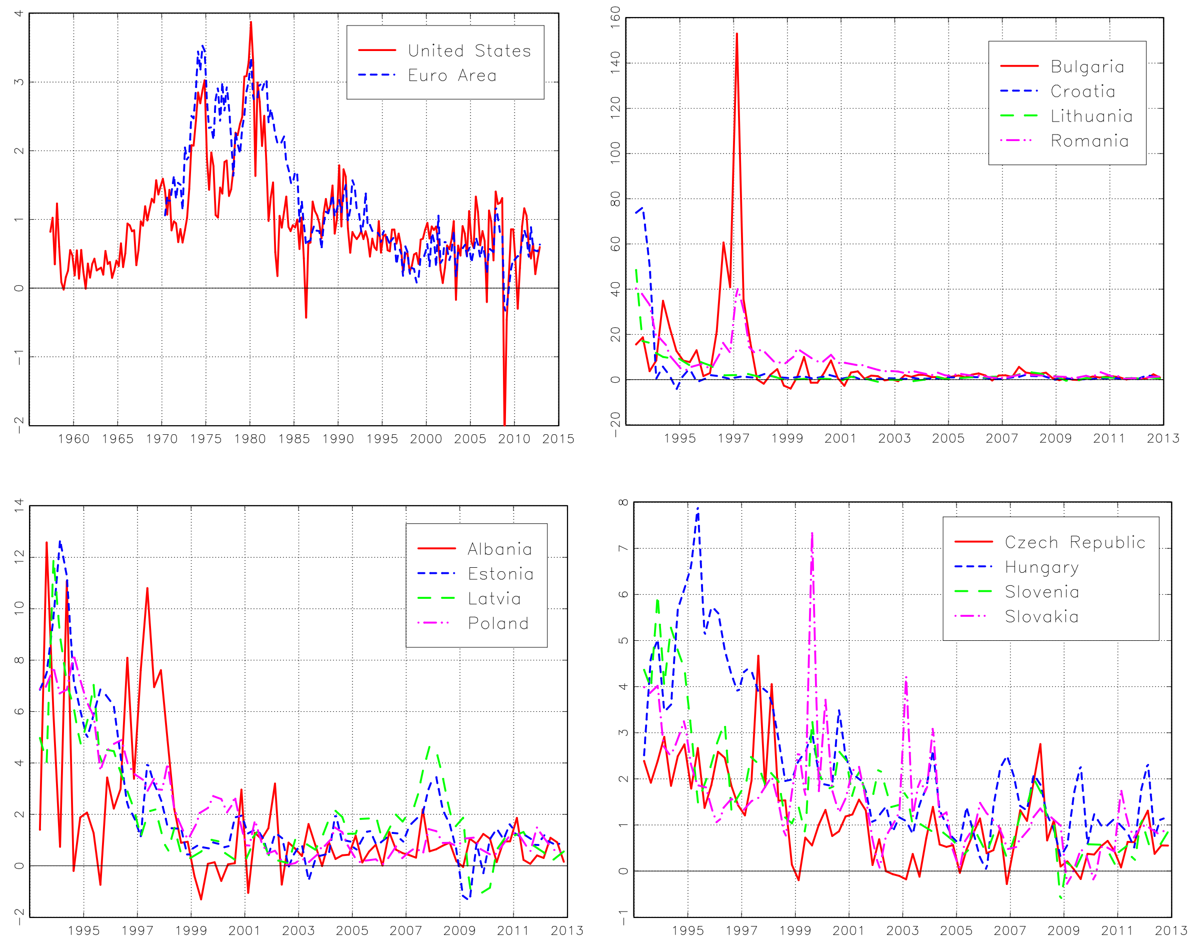
Method		Albania	Bulgaria	Czech Republic	Croatia	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Slovakia	Slovenia	Euro-area	USA
OLS	Estimate	0.705	0.477	0.579	0.235	0.811	0.877	0.826	0.774	0.847	0.725	0.330	0.692	0.966	0.864
	Standard Error	0.085	0.102	0.093	0.179	0.054	0.049	0.054	0.048	0.037	0.080	0.109	0.070	0.025	0.044
FLS Filtered	Mean of Estimate	0.008	0.056	0.260	-0.003	0.454	0.501	0.622	0.564	0.561	-0.754	0.141	0.305	0.538	0.307
	Standard Error	0.352	0.541	0.107	0.172	0.200	0.156	0.129	0.260	0.101	0.837	0.279	0.119	0.143	0.349
	T-stat Value	16.441	6.522	19.145	8.192	14.700	19.644	12.497	6.789	22.800	15.032	5.374	23.949	37.918	23.333
	T-stat DoF (est)	80	77	141	144	82	86	97	77	91	73	93	116	174	223
	T-stat P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FLS Smoothed	Mean of Estimate	0.008	0.208	0.349	0.111	0.513	0.473	0.693	0.542	0.565	-0.137	0.132	0.380	0.571	0.338
	Standard Error	0.468	0.529	0.051	0.116	0.134	0.165	0.094	0.177	0.110	0.481	0.039	0.073	0.155	0.278
	T-stat Value	12.505	4.268	18.520	4.965	17.647	20.109	10.479	10.818	20.788	15.126	14.616	26.478	32.340	27.581
	T-stat DoF (est)	77	77	111	124	94	85	115	82	88	76	90	144	173	227
	T-stat P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kalman Filter	Mean of Estimate	-0.046	0.033	0.292	-0.205	0.525	0.615	0.505	0.561	0.689	-0.485	0.184	0.459	0.522	0.306
	Standard Error	0.376	1.059	0.065	0.315	0.186	0.138	0.289	0.303	0.048	0.822	0.177	0.043	0.209	0.420
	T-stat Value	16.643	3.566	21.507	10.366	12.644	15.233	9.322	5.944	22.315	12.519	6.014	24.347	27.100	19.501
	T-stat DoF (est)	79	73	129	114	84	90	77	76	135	73	120	120	169	221
	T-stat P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kalman Smoother	Mean of Estimate	-0.058	0.266	0.334	-0.020	0.540	0.552	0.619	0.539	0.680	-0.156	0.131	0.456	0.609	0.289
	Standard Error	0.497	0.993	0.000	0.269	0.124	0.148	0.212	0.221	0.063	0.518	0.000	0.000	0.204	0.363
	T-stat Value	12.916	1.808	22.451	6.740	17.130	17.790	8.098	8.894	19.548	14.365	15.619	28.894	22.323	23.204
	T-stat DoF (est)	76	74	72	125	98	88	81	79	116	75	72	72	169	222
	T-stat P-value	0.000	0.037	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: see the description of the test in the main text.

Table 5: Summary of time-varying measures of persistence at specific dates

	FLS-smoothed					**Kalman-smoothed**				
Country	**1995Q1**	**1999Q1**	**2003Q1**	**2007Q1**	**2012Q4**	**1995Q1**	**1999Q1**	**2003Q1**	**2007Q1**	**2012Q4**
Euro Area	0.51	0.41	0.42	0.42	0.43	0.53	0.36	0.43	0.43	0.45
United States	0.28	0.21	0.14	0.11	-0.04	0.24	0.14	0.05	0.32	-0.01
Albania	0.61	0.22	-0.17	-0.33	-0.45	0.39	0.16	-0.14	-0.40	-0.59
Bulgaria	0.40	0.05	-0.11	0.21	0.07	0.55	1.23	-0.39	0.19	-0.14
Croatia	0.18	0.20	-0.10	0.13	0.20	-0.49	-0.26	-0.08	0.20	0.37
Czech Republic	0.44	0.31	0.29	0.36	0.34	0.33	0.33	0.33	0.33	0.33
Estonia	0.79	0.44	0.33	0.65	0.47	0.84	0.53	0.40	0.61	0.45
Hungary	0.82	0.61	0.42	0.43	0.25	0.86	0.68	0.51	0.48	0.37
Latvia	0.84	0.57	0.67	0.88	0.65	1.01	0.35	0.57	0.98	0.47
Lithuania	0.76	0.38	0.52	0.84	0.34	0.76	0.42	0.65	0.64	0.24
Poland	0.77	0.67	0.51	0.48	0.46	0.80	0.74	0.66	0.63	0.62
Romania	0.01	0.39	-0.16	-0.65	-0.55	-0.47	-0.09	-0.34	-0.53	-0.17
Slovakia	0.27	0.18	0.16	0.10	0.13	0.13	0.13	0.13	0.13	0.13
Slovenia	0.49	0.41	0.39	0.37	0.27	0.46	0.46	0.46	0.46	0.46
75% percentile of CEE	0.77	0.47	0.44	0.52	0.37	0.81	0.57	0.53	0.62	0.45
Median of CEE	0.55	0.39	0.31	0.36	0.26	0.50	0.39	0.36	0.40	0.35
25% percentile of CEE	0.37	0.22	-0.10	0.12	0.12	0.28	0.15	-0.10	0.18	0.06

Figure 1: Seasonally adjusted quarterly inflation rates (percent)



Note: The central and eastern European countries are grouped according to the highest level of inflation during the sample period.

Figure 2: US – Estimated inflation persistence

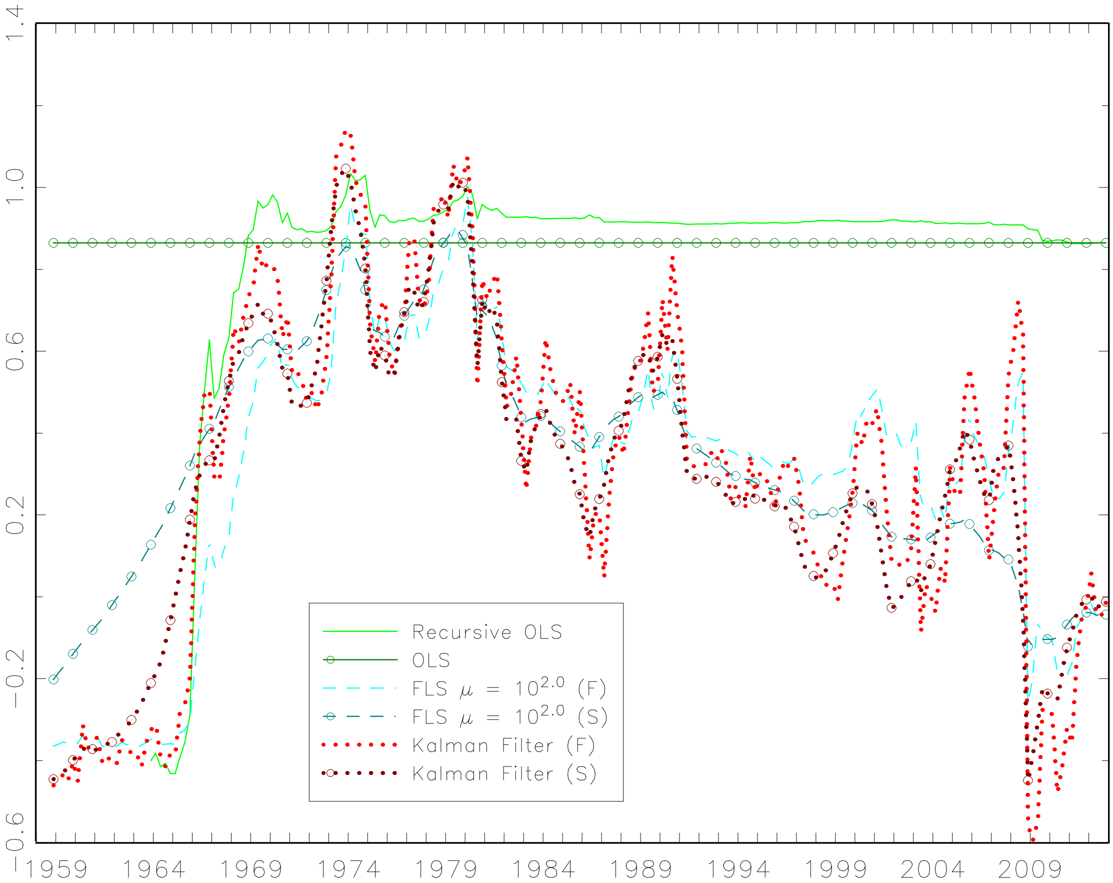


Figure 3: Euro-area – Estimated inflation persistence

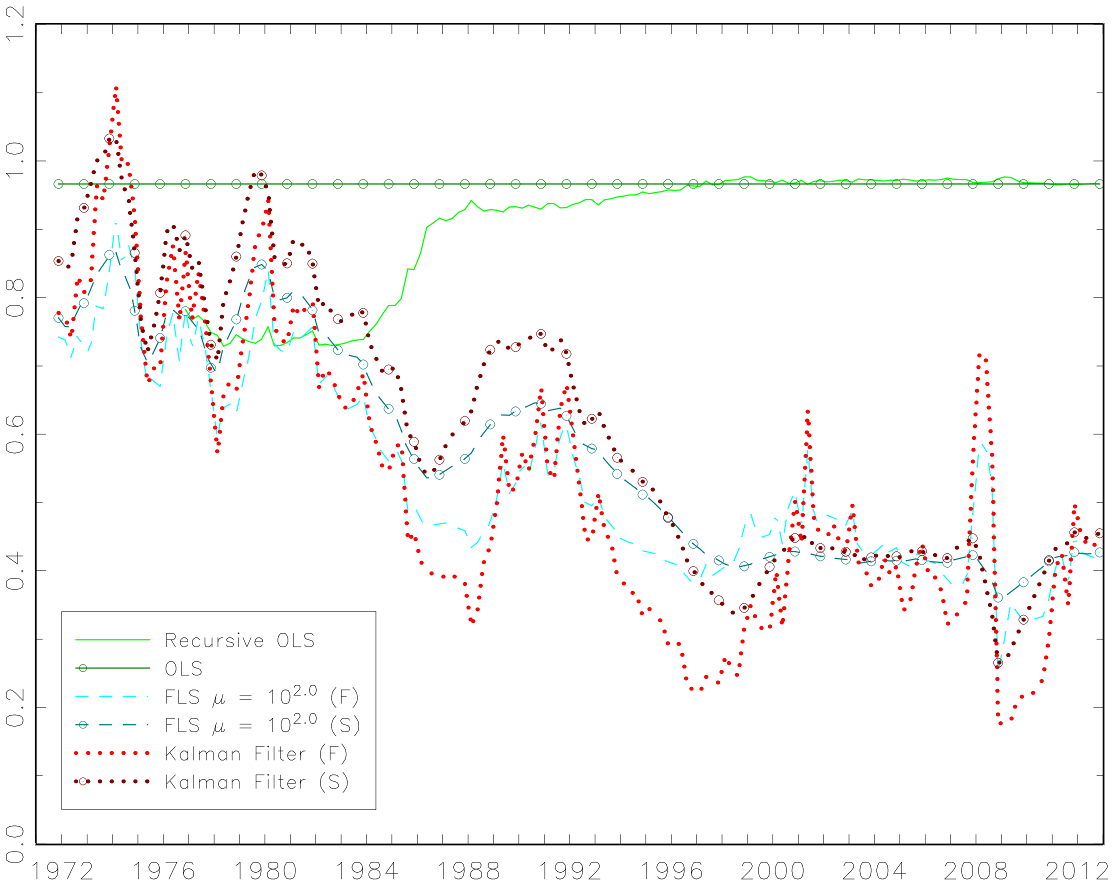


Figure 4: Albania – Estimated inflation persistence

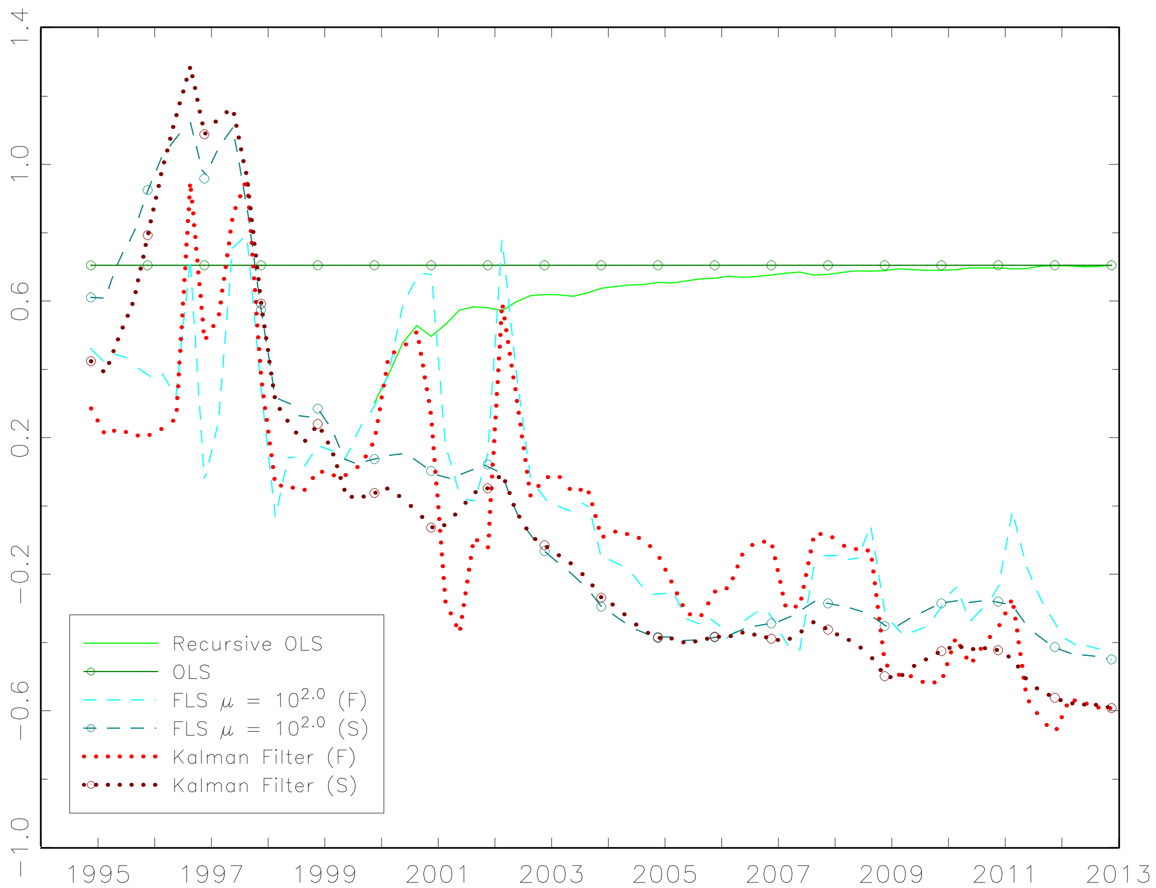


Figure 5: Bulgaria– Estimated inflation persistence

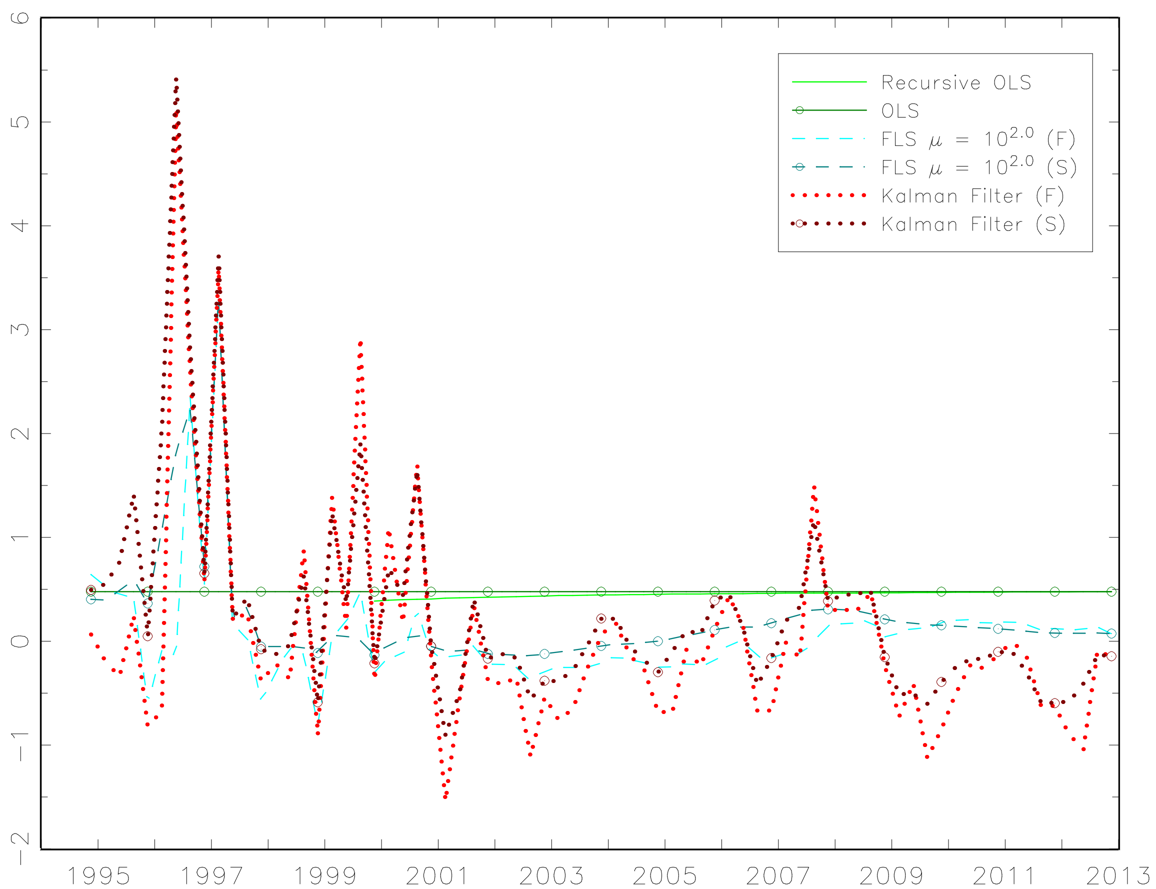


Figure 6: Czech Republic – Estimated inflation persistence

Figure 7: Croatia – Estimated inflation persistence

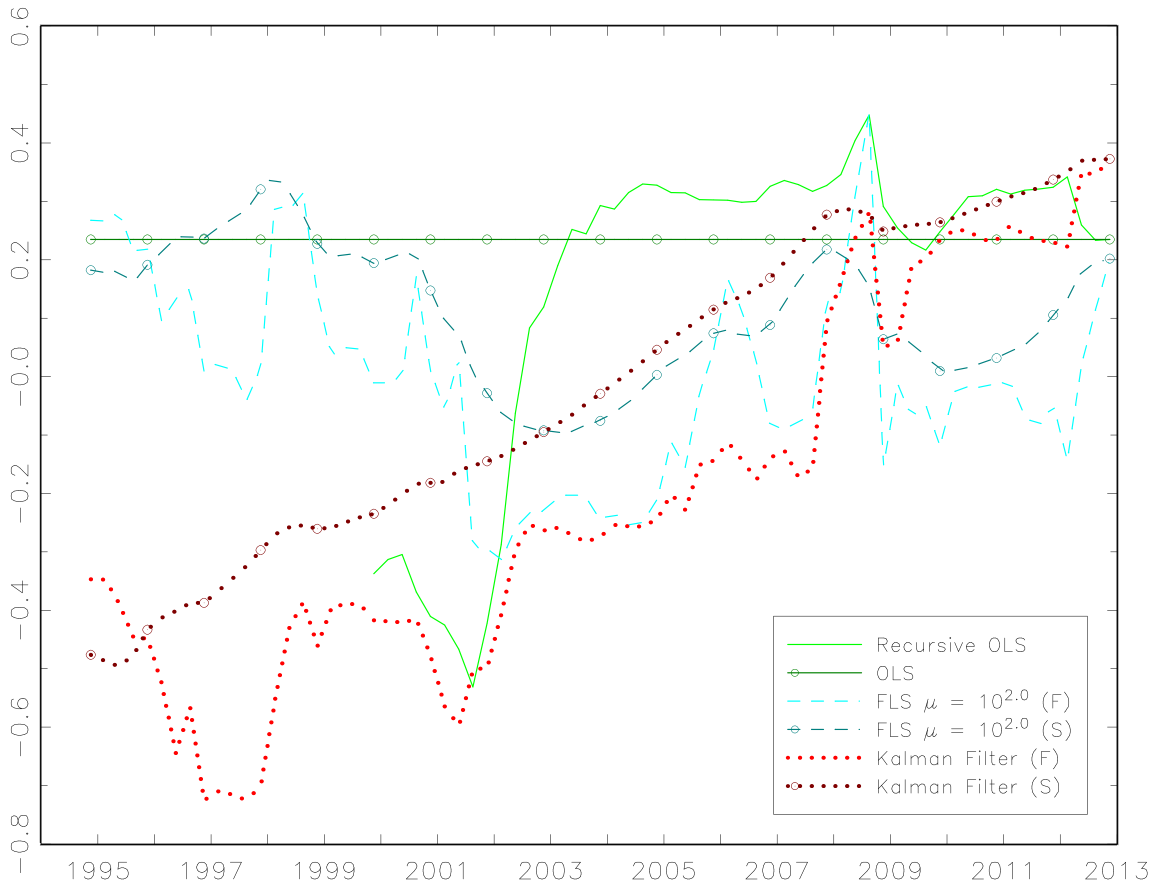


Figure 8: Estonia – Estimated inflation persistence

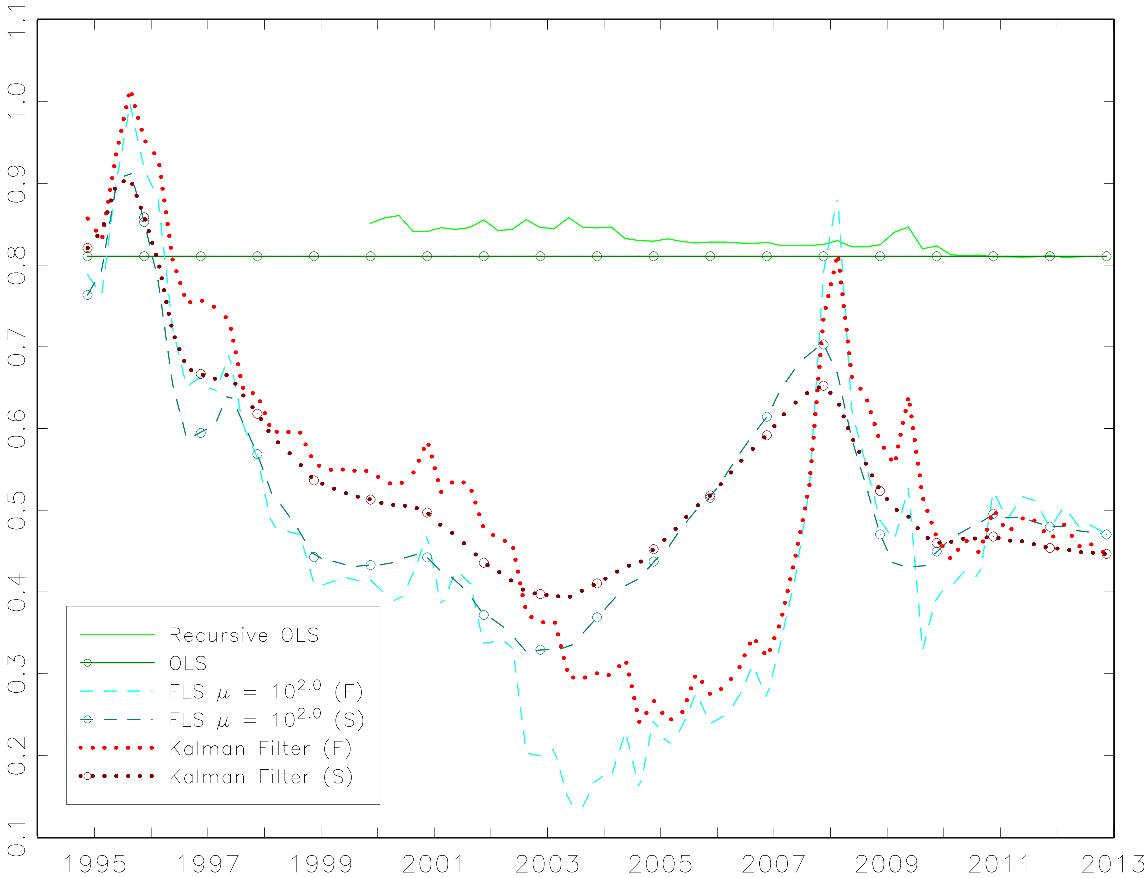


Figure 9: Hungary – Estimated inflation persistence

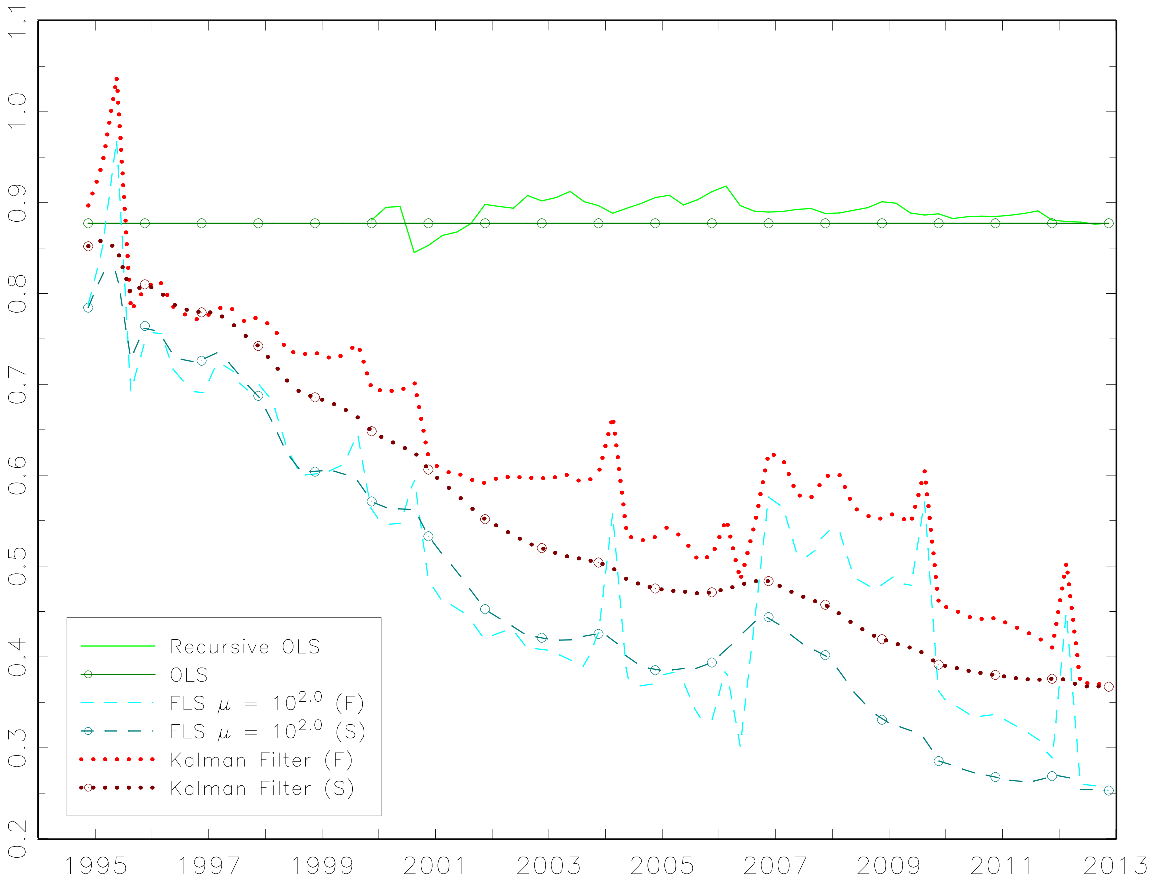


Figure 10: Latvia – Estimated inflation persistence

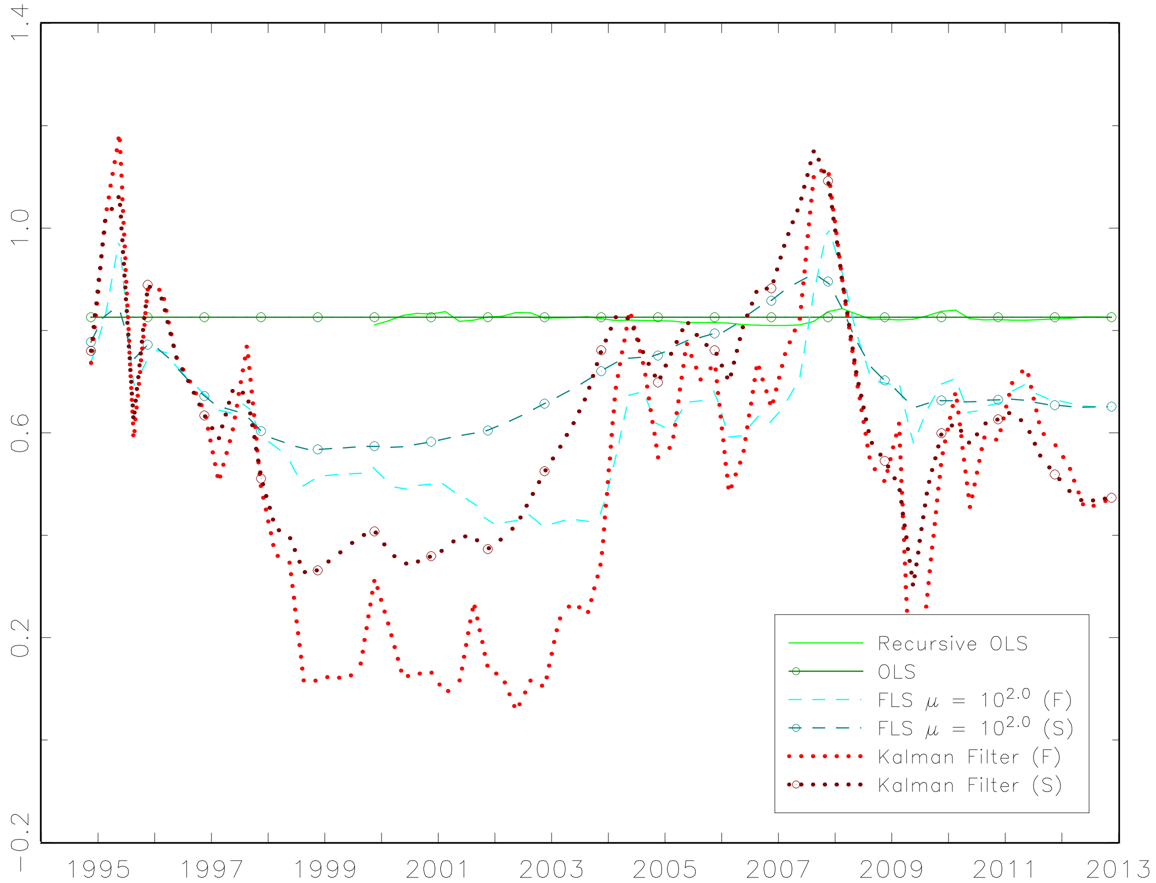


Figure 11: Lithuania – Estimated inflation persistence

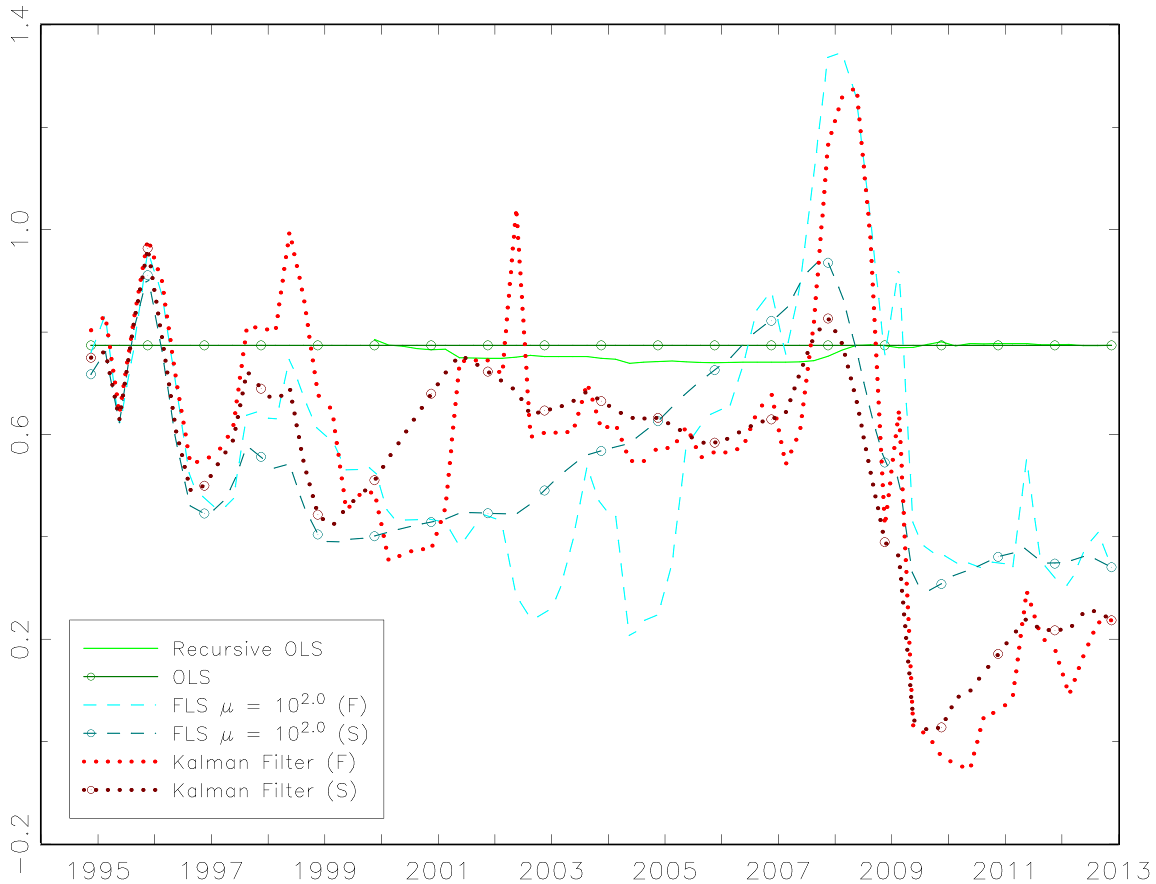


Figure 12: Poland – Estimated inflation persistence

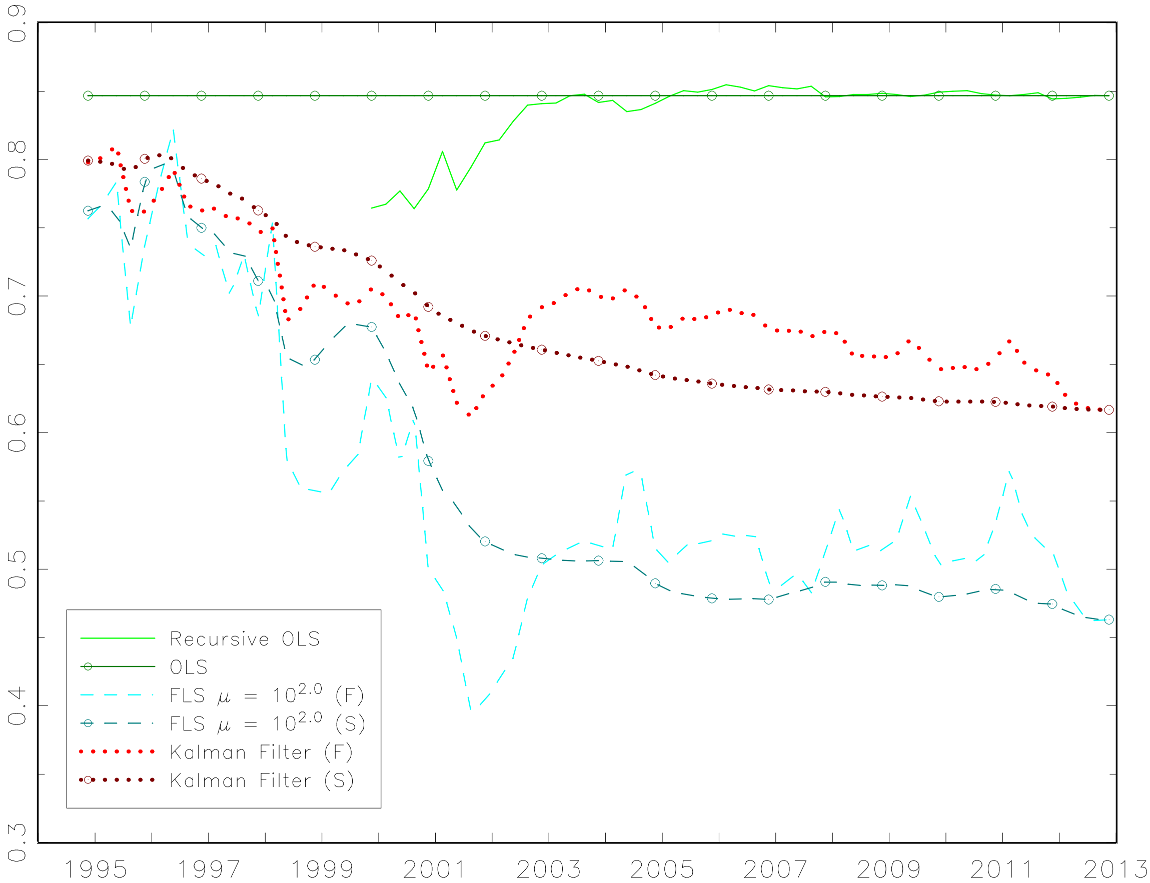


Figure 13: Romania – Estimated inflation persistence

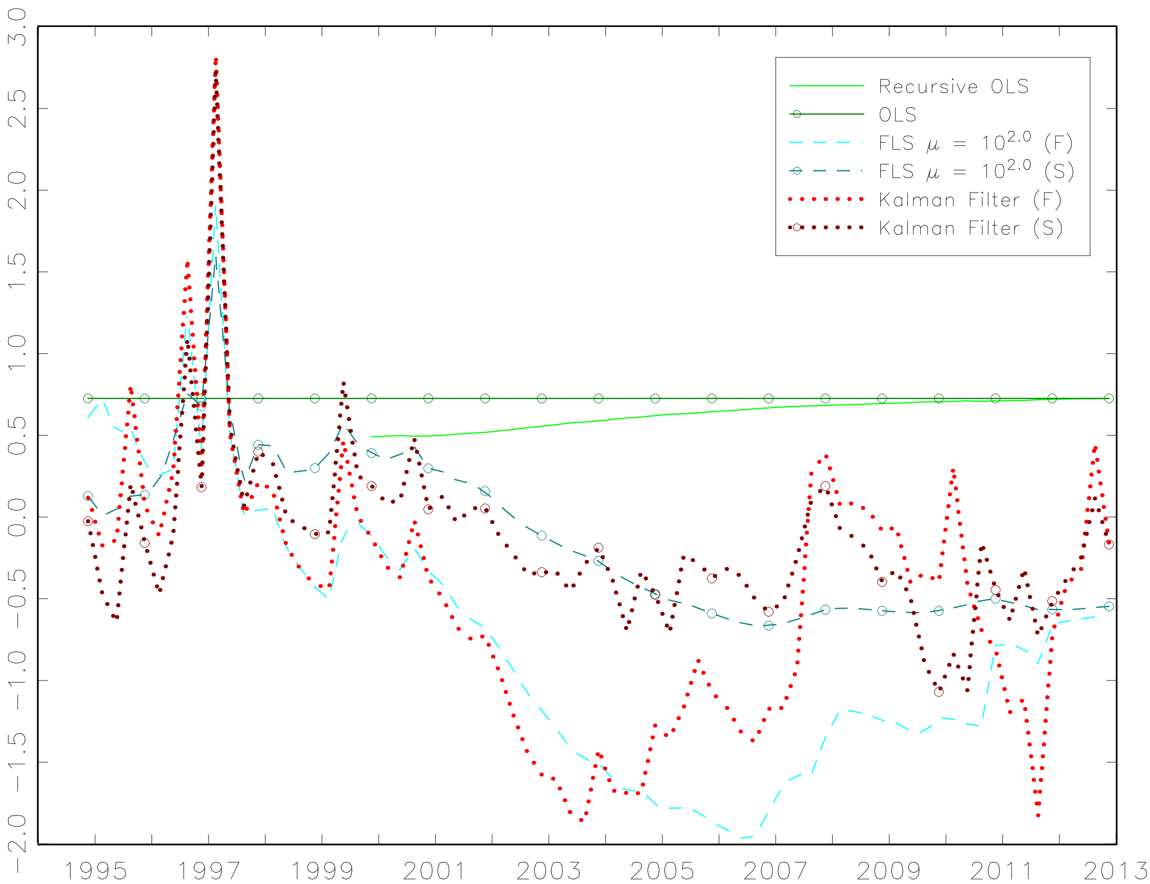


Figure 14: Slovakia – Estimated inflation persistence

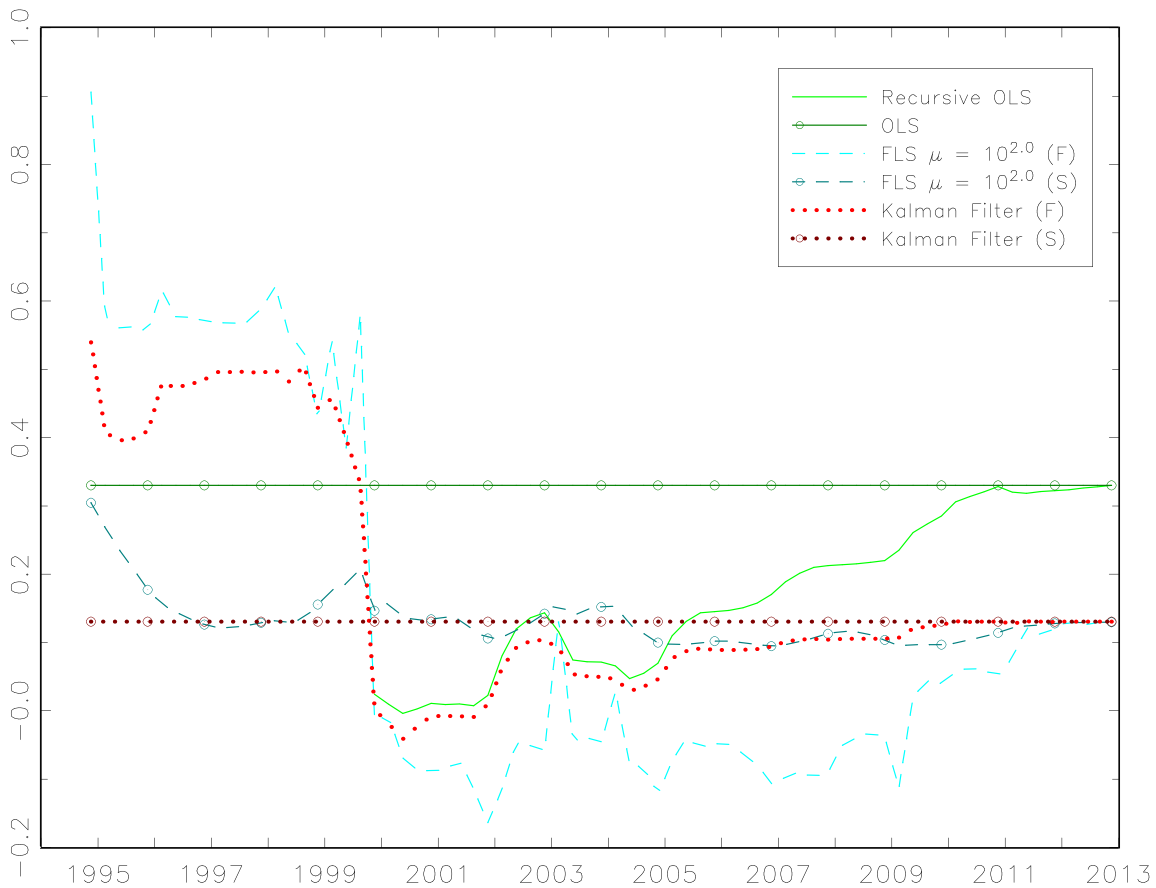


Figure 15: Slovenia – Estimated inflation persistence