Monetary Transmission in the New EU Member States: Evidence from Time-Varying Coefficient Vector Autoregression

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This paper studies the transmission of monetary policy in selected new EU Member States with structural time-varying coefficient vector autoregressions in comparison with that in the euro area. In line with the Lucas Critique, reduced-form models, like standard vector autoregressions (VARs), are not invariant to changes in policy regimes. Many of the new members of the EU have experienced changes in monetary policy regimes, which calls for the use of a time-varying parameter analysis. Our results indicate that some parameters change significantly, altering the shape of the impulse response functions. Monetary policy is most powerful in Poland and comparable in strength to that in the euro area and is least powerful in Hungary, while the strength of monetary policy in the Czech Republic lies in between. We explain these results by the credibility of monetary policy and openness.

1 Introduction

An important aspect of monetary integration is the similarity of the transmission mechanism of monetary policy across member states of a currency area. Ideally, monetary policy should have the same effect on all member states, causing them to equally share the burden of adjustment after a monetary contraction or the advantages of a monetary easing. Therefore, the analysis of similarities in the transmission mechanism in a common currency area is a pivotal concern. The Monetary Transmission Network of the European System of Central Banks (ESCB) analyzed in detail the transmission mechanism in the current euro area member countries (Angeloni et al., 2003). A large amount of research has also been conducted for the new Member States (NMS) of the EU; see Coricelli, Égert and MacDonald (2006) for an extensive survey.

Studying the NMS with standard techniques raises an elementary problem that is related to changes in monetary regimes. Both common sense and the Lucas Critique suggest that changes in monetary regimes are likely to affect the transmission of monetary policy. A number of NMS, namely the Czech Republic, Hungary and Poland, have made their exchange rate regimes more flexible and have changed the way monetary policy has been conducted during the last decade. Regime changes call into question the usefulness of studying the available sample period of these countries with fixed parameter models. Only a few years have passed since the last change in regime, and the period since the last change does not provide a sufficient number of observations for estimation. Moreover, even since the last major regime change, some less pronounced, although important changes may have taken place, like the band shift of the Hungarian forint in 2003. These minor or subregime changes

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further complicate the selection of sample periods for which one can safely assume a stable monetary policy regime and hence constant parameters.

Despite the above-mentioned obvious drawback, to our knowledge our paper is the first one that adopts time-varying coefficient (TVC) techniques to study the transmission mechanism of the NMS.[2] Still, possible time variation in the transmission mechanism or time variation in the variance of shocks hitting the economy is certainly not only an NMS issue. There is a heavy debate about the monetary policy of the U.S.A.; see, for instance, Canova and Gambetti (2006), Cogley and Sargent (2005), Sims and Zha (2004) and references therein. Canova and Gambetti (2006) e.g. question whether U.S. monetary policy is the result of "bad luck or bad policy," that is, whether the bad inflation outcome of the early 1980s and the good inflation outcome since the late 1980s are due to "luck" (the decline in the variance of the shocks) or to "policy" (changes in the way monetary policy is conducted). Canova and Gambetti (2006) found more evidence in favor of the bad luck hypothesis, while Cogley and Sargent (2005) support the bad policy view. For the euro area, Ciccarelli and Rebucci (2004) used a TVC technique to study changes in the monetary transmission mechanism.

In this paper we study the transmission mechanism in three NMS, namely the Czech Republic, Hungary and Poland, using TVC vector autoregressions (TVC-VAR). The VAR methodology is perhaps the most common econometric tool for the study of the transmission mechanism (see Christiano, Eichenbaum and Evans, 1999). However, since VARs are reduced-form models, their parameters are not invariant to policy changes, so that time-varying analysis is required when policies change in the sample period. More generally, since a standard VAR is a linear model (like most of the models used in empirical research), its parameters can change even if the underlying structural model has constant parameters, provided that the underlying structural model is nonlinear.

We also study the transmission mechanism of the euro area (using aggregates since 1991) to compare the transmission mechanism in the three NMS with that of the euro area as a whole. Our first results indicate that monetary transmission changed in the three countries, as it did in the euro area. We find that monetary policy is most powerful in Poland and comparable in strength to that of the euro area and is least powerful in Hungary. We explain these differences with the accumulated credibility of monetary policy in the three countries and with openness.

The rest of the paper is organized as follows. Section 2 briefly describes monetary regimes in the NMS. Section 3 surveys the TVC-VARs used in the literature and describes the model we use. Section 4 details the data and discusses important issues relating to seasonality and trends. The results of our TVC-VAR analysis are presented in section 5. Section 6 concludes, section 7 contains references and section 8 presents charts.

[2] *The survey presented in Coricelli, Égert and MacDonald (2006) identifies this paper as the only one adopting time-varying coefficient methods for the study of the monetary transmission mechanism in the NMS, in addition to a related paper of Darvas (2001), which studied the exchange rate pass-through using a TVC error-correction model.*

2 Monetary Regimes in the NMS

Charts 1, 2 and 3 show nominal exchange rate developments in the Czech Republic, Hungary and Poland, respectively. The Czech Republic had a narrow exchange rate band regime until 1996,[3] when the band was widened to ±7.5%. Not much later, in May 1997, the band was swept away by a speculative attack, and the koruna was floated with occasional central bank interventions.

In Hungary, a preannounced crawling band regime was introduced in 1995 after a long period with an adjustable peg. The adopted band was narrow at ±2.25%. However, as chart 2 shows, the market rate eventually evolved like in a crawling peg, since it was almost continuously at the strong edge of the band (with the exception of the period of the Russian and Brazilian crises in late 1998 and early 1999). The band was widened substantially in May 2001 to ±15%, and the rate of crawl was reduced to zero in October 2001. In June 2003, the band was devalued by 2%.

The Polish authorities made their exchange rate regime flexible gradually. As chart 3 indicates, Poland also adopted a preannounced crawling band for most of the 1990s, but the band was widened to ±15% in several steps. There were heavy central bank interventions until 1997, which is also reflected in the relatively stable rate within the band, but since early 1998, the rate was allowed to move freely within the wide band. In April 2000, the band was abolished and the zloty was allowed to float freely. For more information on the exchange rate systems of these countries, see Darvas and Szapáry (2000).

Hence, all three countries moved from an exchange rate targeting regime to an inflation targeting system (which is still combined with a wide exchange rate band in Hungary). These changes in monetary regimes definitely had an impact on the monetary transmission mechanism. Estimation for a sample consisting of both the exchange rate targeting and the inflation targeting regimes does not make sense with a fixed parameter model. The longest homogeneous sample is available for the Czech Republic starting in late 1997. In the cases of Poland and Hungary, the latest major regime change occurred in 2000 and 2001, respectively, but the band shift of the Hungarian forint in 2003 marked a minor or subregime change.[4] Therefore, the sample periods since the last regime changes are too short for reliable fixed parameter analyses, even if it is assumed that the linear approximation was correct.

3 Time-Varying Coefficient VARs

Three important issues for our model are described in this section – the most recent TVC-VAR methods, the sign restriction identification method and impulse response analysis.

[3] Chart 1 shows data starting in 1995; up to 1995 the width of the band was similarly narrow.

[4] The tiny 2% devaluation compared to the ±15% width of the band indicated that monetary authorities had changed their preferences. Up to 2003, the exchange rate had been allowed to reach the strong edge of the band fueled by high interest rates and revaluation expectations. The devaluation signaled that the authorities did not want to allow a strong nominal exchange rate anymore.

3.1 Specification

Three main types of TVC-VAR models have been proposed recent years:

1. Parameters treated as latent variables that follow random walks; the Kalman filter is used for estimation. This technique was used e.g. in Canova and Gambetti (2006), Ciccarelli and Rebucci (2004), and Cogley and Sargent (2005).
2. Parameters that switch between regimes (back and forth) driven by a latent state variable which follows a Markov switching process. This technique was used in Sims and Zha (2004).
3. Parameters that change from one regime to another smoothly (and permanently) in time; the specification is the multivariate extension of the STAR (smooth transition threshold autoregression) model. This technique was developed in He, Teräsvirta and González (2005).

In this paper we follow the three papers indicated in the first group by assuming that reduced-form VAR parameters follow random walks and use the Kalman filter for estimation and inference. The reason for our choice is the following: The random walk specification is a flexible model which can capture various time paths of the parameters. In contrast, the STAR-type time specification assumes a particular path and a smooth transition between the beginning and the end regime, which could be too restrictive. The Markov switching specification, on the other hand, assumes that there are several regimes and that the parameters switch back and forth between these regimes. However, regime changes in the countries under study can be regarded as permanent, at least until the end of the sample period. The countries under study are expected to enter ERM II and later the euro area, hence, the probability of returning to the initial monetary regimes of the early 1990s is almost zero. For these reasons we selected the random walk specification from among the three options indicated above.

3.2 Identification

The second important issue is identification. Traditional identification, which usually takes the form of some contemporaneous and/or long-run restrictions, has been severely criticized, e.g. in Faust and Leeper (1997), Cooley and Dwyer (1998), and Faust et al. (2004). A possible solution to this problem could be the recent sign restriction identification method popularized by e.g. Uhlig (1999), Canova and De Nicoló (2002), and Peersman (2005). Canova and Gambetti (2006) adopt this technique in a TVC-VAR framework. In the current version of the paper we use standard contemporaneous restrictions, but we will augment the paper with the results of the sign restriction methodology later.

3.3 Impulse Response Analysis

The third important issue is impulse response analysis. Since the model is nonlinear due to changing parameters, no unique impulse response function is available, but we can attach an impulse response function to each observation of the sample. Still, there are two possible ways to proceed. One could use the parameter set of time t to calculate the impulse response function for t, t+1, t+2, … or use the parameter set of time t, t+1, t+2, … that is, take into account future parameter changes.

The first option answers the question "*What did the monetary authorities think that the transmission would be?"*[5] while the second one answers *"How is the shock transmitted to the economy?"* Obviously, at the last observation of the sample only the first option can be used, at the last but one observation the second option can be used only for one observation, and so on. We used the first option in the whole sample period. In practice, we calculated the impulse responses as the difference between two simulations, of which in the first one there is a shock that hits the economy at time t Furthermore, we normalized the impulse response functions to show the effects of a 100 basis point monetary policy shock.

4 Data

Our data set includes quarterly data in the period from 1993 to 2004. VARs used for monetary transmission usually include four endogenous variables: measures for output, price, the interest rate, and the real exchange rate. Our raw data are plotted on charts 4 and 5. Chart 4, which shows log levels of GDP and consumer prices, indicates the two important features of our time series: seasonality and trends.

Seasonality is a salient feature of GDP levels, but consumer prices also exhibit seasonality.[6] The standard approach used in empirical VARs is to eliminate seasonality by using a seasonal adjustment method. However, it has been argued in the literature that standard seasonal adjustment procedures introduce artificial features into the data. To increase the robustness of our results, we used and compared two seasonal adjustment techniques: the standard X12 method and the so-called basic structural model (BSM) of Harvey (1989), which is described in the following section.

The second main feature of the data is the presence of trends. However, standard differencing, which is usually done before estimating VARs, is not suitable in the case of the NMS. Chart 4b shows log CPI levels, and there is clear ocular evidence of a marked slowdown in inflation in the slope of the CPI level. This is also reflected in chart 5a, which shows nominal interest rate developments: there is a downward moving trend in the nominal interest rate that is consistent with falling inflation. Therefore, simple differencing is not suitable for detrending. Finally, chart 5b shows the log levels of real effective exchange rates, which show upward moving trends. Scores of papers study the real exchange rate behavior of the NMS, giving good reasons to expect an equilibrium real exchange rate appreciation; see, for instance, Égert, Halpern and MacDonald (2004). Consequently, an upward movement in the real exchange rate in a given quarter does not necessarily imply a contraction, only if it exceeds the rate of equilibrium real appreciation.

Apart from differencing, which could be inadequate, as we have argued above, we can handle the issue of trends by using other detrending methods or

5 *Since parameters are assumed to follow driftless random walks, their forecasts are equal to their current values.*

6 *Moreover, the relative price level used to calculate the real exchange rate also exhibits seasonality if the seasonality in prices of the countries does not cancel out perfectly. In the empirical section we found that the relative price levels do have seasonal components.*

by estimating the VAR for levels (which is also a standard practice). We adopted the pragmatic approach to estimating the models for levels, first differences, and for detrended series using four additional methods: the linear trend, the quadratic trend, the Hodrick-Prescott filter, and a high-pass filter (not band-pass[7]).

4.1 Seasonal Adjustment

We used and compared the results of the X12 method and the BSM model for seasonal adjustment.[8] The BSM model is an unobserved components model which allows a smooth I(2) trend and changing seasonal components. The I(2)-ness is an important feature for the time series to be modeled, since, for instance, there were marked but gradual changes in the inflation process of these countries, and the I(1) assumption for the price level is inadequate, as we have argued before. The possibility of changing seasonal patterns is also important, which is supported by the analysis.

In this section we also suggest a new initialization of the BSM model.

The BSM model consists of the following equations:

$$y_t = \mu_t + \gamma_t + \varepsilon_t \qquad (1)$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad (2)$$

$$\beta_t = \beta_{t-1} + \zeta_t \qquad (3)$$

$$\sum_{i=0}^{3} \gamma_{t-i} = \omega_t \qquad (4)$$

where equation (1) is the measurement equation relating the observed series y_t to its unobserved seasonally adjusted component μ_t and its unobserved seasonal component y_t; state equation (2) defines the I(2) process of μ_t with an unobserved time-varying drift β_{t-1}, which follows a random walk according to state equation (3), while equation (4) defines the seasonal components. The error terms ε_t, η_t, ζ_t, and ω_t are assumed to be mutually uncorrelated and normally distributed with variances $\sigma_{(\varepsilon)}$, $\sigma_{(\eta)}$, $\sigma_{(\zeta)}$ and $\sigma_{(\omega)}$ respectively. Given the initial conditions, the Kalman filter can be used to evaluate the likelihood function of the process; this function can then be used to calculate maximum likelihood estimates of the four variances.

Initial conditions should be set for the mean and the variance-covariance matrix of the unobserved vector consisting of the level of the seasonally

[7] *In business cycle research, a band-pass filter is frequently adopted to recover the component of the series corresponding to cycles between 1.5 and 8 years, that is, the component without "short-run" noise and without long-run trends. However, monetary policy does have an effect in the first 1.5 years; therefore, we eliminated only long-run trends via a high-pass filter in the manner of Christiano and Fitzgerald (2003), which is the latest among the three mostly commonly adopted band-pass filter approximations in the literature.*

[8] *We also carried out a small simulation exercise to compare the two methods. That is, we assumed an either constant or changing seasonal pattern, added a trend and some noise, simulated this artificial data-generating process, and used the two seasonal adjustment techniques on the simulated data. The BSM method was slightly better than the X12 method, in the sense that the squared deviation of the estimated seasonal factor from the true one was smaller than that of the X12's seasonal factor. However, both methods created artificial autocorrelation in the data which was not present in the data generating process.*

adjusted series (μ_0), its growth rate (β_0), and three seasonal factors (γ_0, γ_{-1}, γ_{-2}) The initial conditions for seasonal factors are usually set equal to zero. However, when we adopted this assumption, a simple graph of the estimated seasonal factors indicated that the seasonal patterns were usually smaller in the first years than in later years. This phenomenon could partly reflect the change in seasonality over time, but could also simply reflect the zero initial conditions of the seasonal factors. Therefore, we adopted an iterative procedure of setting initial conditions and estimation. Specifically, to get a first estimate of the unobserved components, we adopted the following initial conditions:

$$a_0^{(1)} = \begin{bmatrix} y_1 - (y_5 - y_1)/4 \\ (y_5 - y_1)/4 \\ 0 \\ 0 \\ 0 \end{bmatrix}, P_0^{(1)} = \mathrm{diag}\begin{pmatrix} \sigma_0^2 \\ \sigma_0^2 \\ \sigma_0^2 \\ \sigma_0^2 \\ \sigma_0^2 \end{pmatrix} \tag{5}$$

where e.g. y_1 indicates the first observation in the sample (e.g. of the logarithm of output). The initial condition for the growth rate is set equal to one fourth of the four-quarter growth in the first year of the series and is subtracted from the first observation to get an initial condition for the seasonally adjusted level of the series, and $\sigma_0=0.01$. Estimation of the BSM model in equations (1) to (4) using the initial conditions in (5) allows for the calculation of both filtered and smoothed estimates for the unobserved components. We used the smoothed estimates to define a new vector for the initial conditions:

$$a_0^{(2)} = \begin{bmatrix} \widehat{\mu}_{1,T}^{(1)} - (\widehat{\mu}_{5,T}^{(1)} - \widehat{\mu}_{1,T}^{(1)})/4 \\ (\widehat{\mu}_{5,T}^{(1)} - \widehat{\mu}_{1,T}^{(1)})/4 \\ \widehat{\gamma}_{4,T}^{(1)} \\ \widehat{\gamma}_{3,T}^{(1)} \\ \widehat{\gamma}_{2,T}^{(1)} \end{bmatrix}, P_0^{(2)} = \widehat{P}_{1,T}^{(1)} \tag{6}$$

where e.g. $\widehat{\mu}_{1,T}^{(1)}$ indicates the first observation of the smoothed estimate of the seasonally adjusted level of the series and $\widehat{P}_{1,T}^{(1)}$ indicates the smoothed estimate of the variance-covariance matrix of the unobserved components in the first observation; superscript (1) indicates that initialization is based on the first set of initial conditions. Estimation of the BSM model using the second set of initial conditions allows for the calculation of new estimates for the unobserved components and their covariance matrices, which can be used to define a third set of initial conditions, and so on. We continued this iterative procedure until the state estimates converged, which was defined as

$$d^{(i,i-1)} \equiv \sum_{t=1}^{T} \left| \widehat{\mu}_{t,T}^{(i)} - \widehat{\mu}_{t,T}^{(i-1)} \right| < \upsilon \tag{7}$$

where we have set $\upsilon = 10^{-5}$.

5 Results

5.1 Seasonal Adjustment

GDP and the price level of various countries are usually highly seasonal. Consequently, the real exchange rate is also seasonal unless the seasonality of prices at home and abroad cancel each other out exactly, which is unlikely. This effect is neglected in most of the studies using monthly or quarterly data on real exchange rates. Nominal exchange rates (and also nominal interest rates), though, are not seasonal. Therefore, we adjusted GDP, the domestic price level and the relative price level, and calculated the seasonally adjusted real exchange rate by using the seasonally adjusted relative price level and the raw nominal exchange rate series.[9]

The number of iterations required by the criterion in (7) averaged 24 in the range of [13–41] for all three series of three countries (the Czech Republic, Hungary and Poland). However, the Slovene data required many more iterations: 111 for the price level, 118 for the relative price level and 169 for GDP.

There were, in some cases, important differences between the first-state estimates (based on the initial conditions indicated in (5)) and the result of our iterative procedure. For GDP, the difference was around 1% in most cases in the first year of the sample, but in the case of Poland, it even reached 3.3%. By contrast, the difference for prices was generally tiny.

5.2 VAR Estimates

In the current version of the paper we estimated first-order VARs, i.e. VARs using only one lag of all series. Since we have four TVCs per equation and 4 series, in a VAR(1) without a constant, 16 TVCs need to be estimated. This implies 16 parameters; they are the standard errors of the innovations driving the parameters in the state equations. There are 4 additional parameters in the measurement equations as well; they are the standard errors of the innovations of the measurement equations. Hence, in a VAR(1) without a constant, 20 parameters need to be estimated. This is difficult to compute, although all of our estimations converged to a unique maximum. However, a VAR(1) is not satisfactory: innovations in some (not all) equations are autocorrelated. There are two possible solutions: (1) we can increase the order without any constraint, which explodes the number of parameters to be estimated, or (2) we can adopt some restrictions. For example, Stock and Watson (2005), who estimate fixed parameter VARs for the G-7, allow more lags only for the left-hand side variable and restrict the number of lags of all other variables to one.

[9] *Nominal exchange rates do not include seasonal patterns, but are very volatile, which could complicate seasonal adjustment. Our calculations also reflected this. For comparison, we also seasonally adjusted the real exchange rate itself (using the BSM method with our iterative procedure), which required iterations between 51 and 123 for 4 of our countries, while the seasonal adjustment of relative prices converged faster, with the number of iterations in the range of [17–35].*

We are currently experimenting with such extensions; hence, the results presented in this version of the paper are preliminary.

Our first goal was to compare different treatments of the data. To this end, we estimated six possible specifications for all countries: levels,[10] differences, deviation from the linear trend, deviation from the quadratic trend, deviation from the Hodrick-Prescott trend, and high-pass filtered series. The 95% confidence bands of time-varying parameters indicate that some, but not all parameters change significantly.

In VARs it is difficult to interpret the parameters. Therefore, chart 6 compares the effect of a 100 basis point monetary shock on the level of output using the six possible treatments of the trends.[11] Chart 6 indicates that responses are similar for the level, the Hodrick-Prescott (HP) filtered and the high-pass filtered series, reaching the largest effect of about 0.5% to 0.7% of GDP three or four quarters after the shock, although in the case of the high-pass filtered series the effect is more persistent than in the other two cases. By construction, the shock does not have a permanent effect using these treatments of the data.[12] For the differenced specification, the shock does not have a long-run effect on the growth rate, but the accumulated effect on the growth rate could be different from zero, implying a permanent effect on the level of the series. As chart 6 indicates, the response of output up to four to six quarters is similar for differenced data for these three methods, but there is no reversal toward zero afterwards. Finally, using data as a deviation from both the linear and quadratic trends yields a highly cyclical response which is implausible. Since responses based on estimates for the level, HP-filtered and high-pass filtered series were reasonably similar, we show results for HP-filtered series only in chart 7.

Chart 7 shows responses of the euro area at different dates – 1994, 1998, and 2005. The point estimates indicate a decline in output responses.

Plotting time-varying coefficients for the Czech Republic, Hungary and Poland indicates, again, that some, but not all parameters have changed: Changes in the parameters of the exchange rate and the interest rate equations are significant in most cases, indicating time-varying structures in accordance with our expectations. It is also remarkable that we can observe "substantial" parameter changes at the time of monetary regime changes: around 1996 to 1997 in the case of the Czech Republic, in 1995 and in 2001 in Hungary, and around 1998 to 2000 in Poland.

Chart 8 compares output responses[13] in each of the three NMS with that of the euro area, normalized, again, to a 1 percentage point monetary shock. In the three NMS, monetary policy is least effective in Hungary and most effective in Poland, while its effect in the Czech Republic is in between. The strength of the Polish response is comparable to that of the euro area. We sug-

[10] *We allowed a time-varying intercept for the specification using levels, which adds four additional parameters to be estimated.*

[11] *We show responses to output only. For prices we have the so called price-puzzle result, that is, prices increase after a monetary contraction. We are currently working on extending the VAR with exogenous variables, such as commodity prices, a method that is frequently found to be useful in removing the price puzzle.*

[12] *This is also true, of course, for linearly and quadratically detrended data.*

[13] *We have also received the "price-puzzle" result for Hungary and the Czech Republic in most of the sample, although in the case of Hungary, it had disappeared by the end of the sample.*

gest two possible explanations for these results: the credibility of monetary policy on the one hand, and openness on the other. Hungarian monetary policy was rather accommodative during the crawling peg period from 1995 to 2001. The approach of the central bank was to tightly manage the exchange rate in order to gradually decrease inflation without risking large trade imbalances. Moreover, the tiny devaluation of the wide band in 2003 also indicated that the preferences of the monetary authorities did change, and can change. These factors could have contributed to the low credibility of central bank policy; hence, market participants might not react forcefully to monetary actions. Poland, on the other hand, adopted a very tight monetary policy even in an economic downturn. This could have contributed to the high credibility of monetary actions: market participants learned that policy was strict and concentrated only on inflation in the past, hence, they might react forcefully to monetary policy actions, because if they did not, they could expect further consistent steps from the Polish central bank. Openness could also explain the differences: Hungary is rather open, while Poland is fairly closed.

6 Conclusions

The similarity of the transmission mechanism of monetary policy across the member states of a monetary union is an important aspect of monetary integration. This paper studies the transmission of monetary policy in three new Members States of the EU with structural time-varying coefficient VARs in comparison with that in the euro area. In line with the Lucas Critique, reduced-form models, like standard VARs, are not invariant to changes in policy regimes. Many of the new Member States have experienced changes in monetary policy regimes, which calls for the use of a time-varying parameter analysis. Our preliminary results indicate that some parameters change significantly, altering the shape of the impulse response functions. Among the three countries studied, monetary policy is most powerful in Poland and comparable in strength to that in the euro area and is least powerful in Hungary, while the strength of monetary policy in the Czech Republic lies in between. We explained these differences by the credibility of monetary policy and openness.

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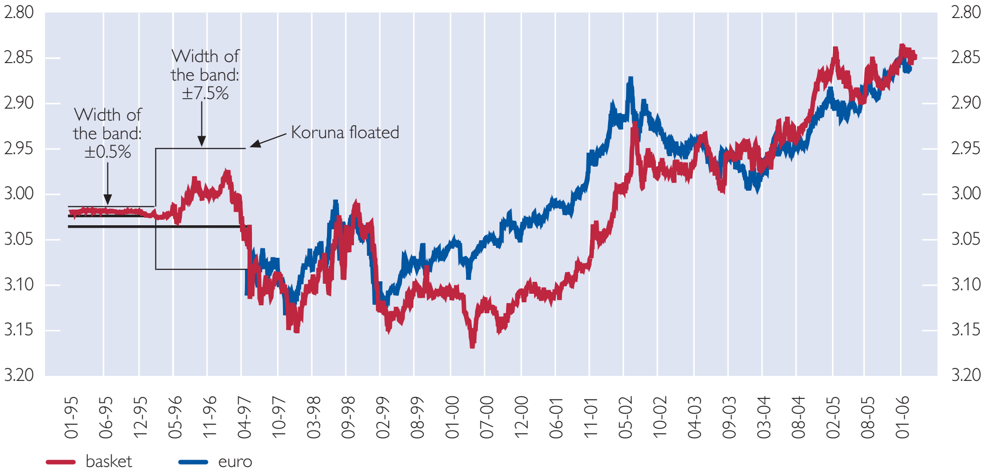
8 Charts

Chart 1

Nominal Exchange Rate of the Czech Koruna

January 1, 1995, to March 31, 2006

logarithm of koruna per basket (inverted scale)



Source: Updated from Darvas and Szapáry (2000).

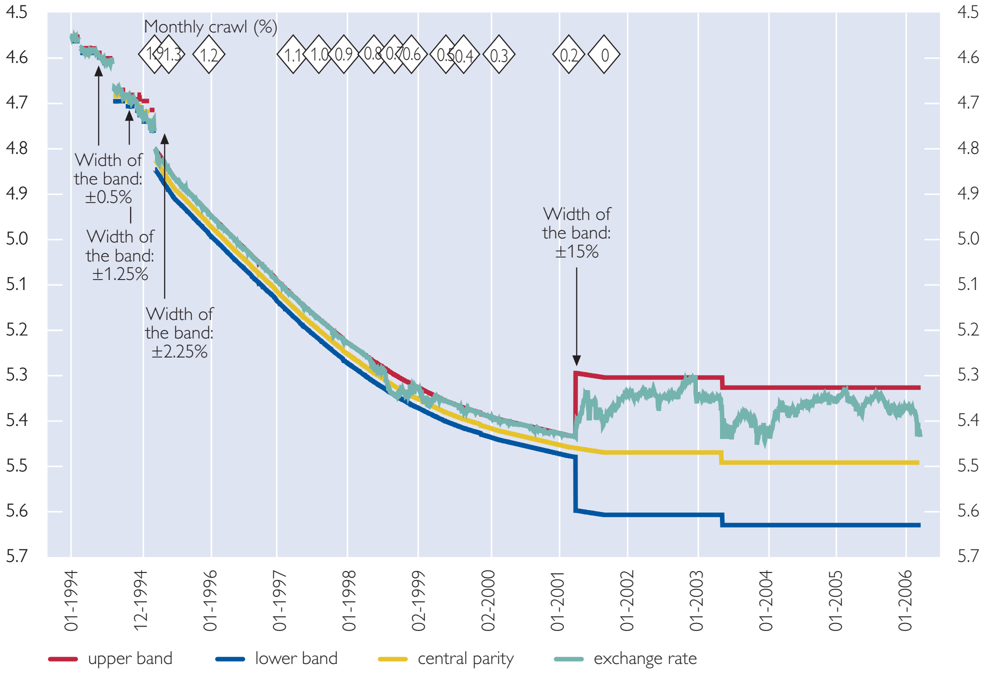
Notes: Basket used prior to May 1997: 65% Deutsche mark – 35% U. S. dollar. For better comparison, we use both the composition of the basket and the euro for the floating period.

Chart 2

Nominal Exchange Rate of the Hungarian Forint

January 1, 1994, to March 31, 2006

logarithm of forint per basket (inverted scale)



Source: Updated from Darvas and Szapáry (2000).

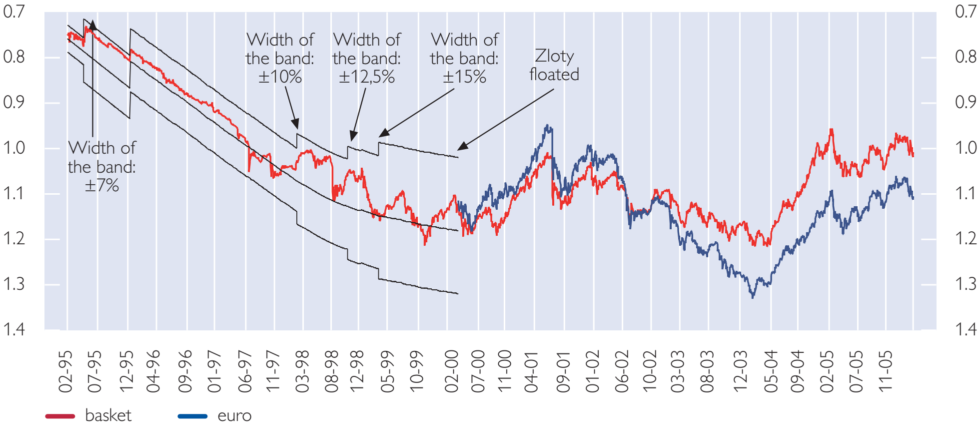
Notes: Composition of the basket: 50% Deutsche mark – 50% U.S. dollar from August 1993 to May 1994, 70% ECU – 30% U.S. dollar from May 1994 to December 1996, 70% Deutsche mark – 30% U.S. dollar from January 1997 to December 1998, 70% euro – 30% U.S dollar from January to December 1999, 100% euro since 2000.

Chart 3

Nominal Exchange Rate of the Polish Zloty

February 1, 1995, to March 31, 2006

logarithm of zloty per basket (inverted scale)



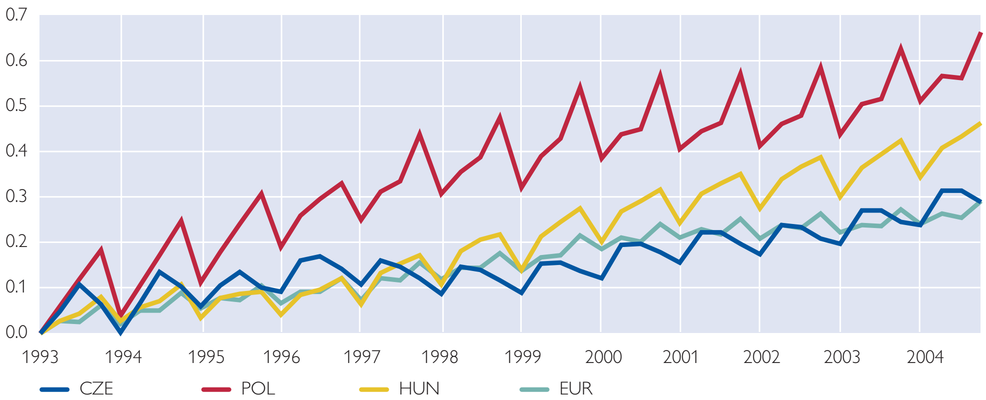
Source: Updated from Darvas and Szapáry (2000).

Notes: Composition of the basket prior to 1999: 45% U.S. dollar, 35% Deutsche mark, 10% pound sterling, 5% French franc, 5% Swiss franc; since 1999: 55% euro , 45% U.S. dollar. The zloty was floated in April 2000. For better comparison we use both the composition of the last basket and the euro for the floating period.

Chart 4a

Log Levels of Unadjusted Output

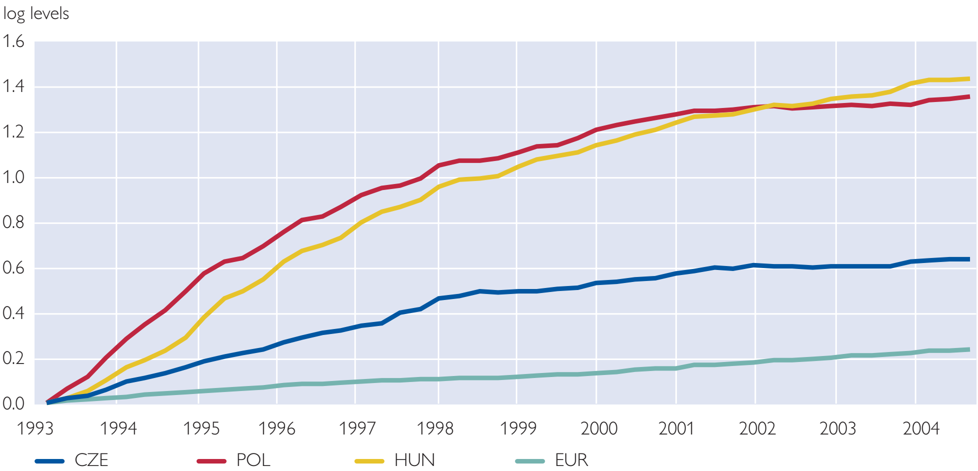
Index (December 2000 = 100)



Quelle: Author.

Chart 4b

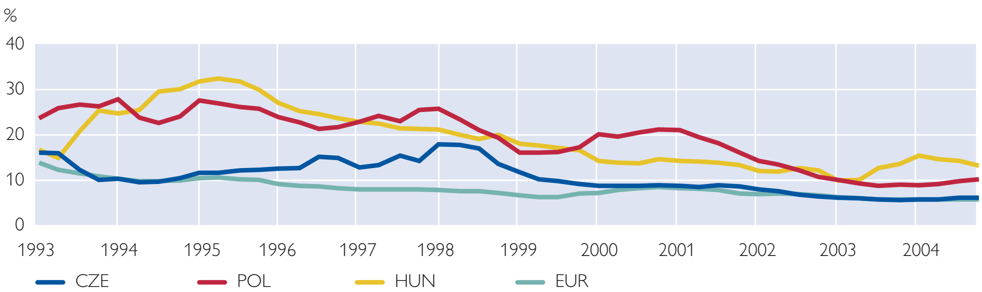
Log Levels of Consumer Prices



Quelle: Author.

Chart 5a

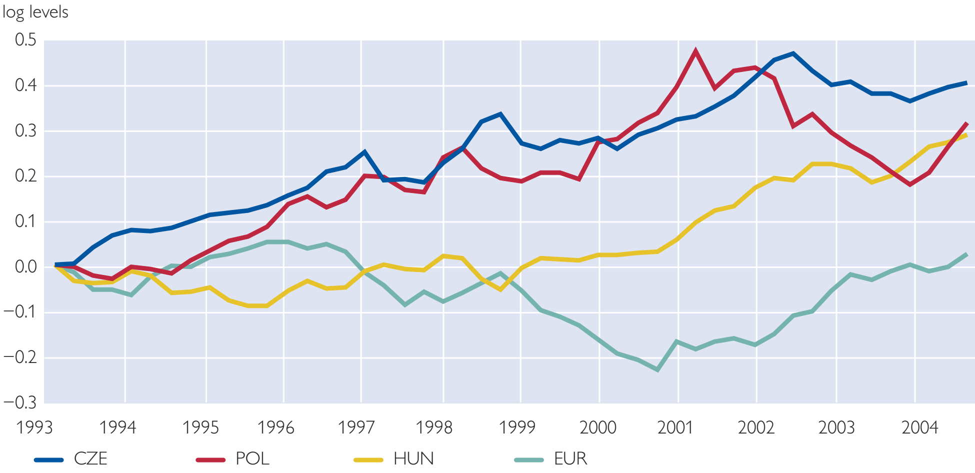
Short-Term Nominal Interest Rates



Quelle: Author.

Chart 5b

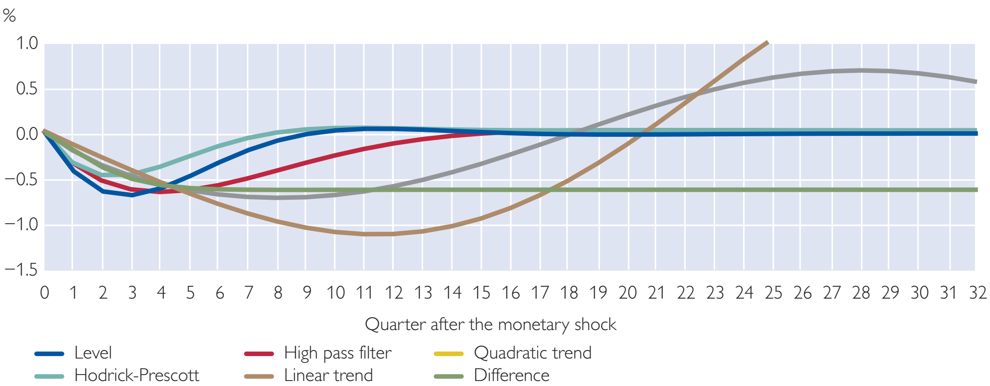
Log Levels of Unadjusted Real Exchange Rates



Quelle: Author.

Chart 6

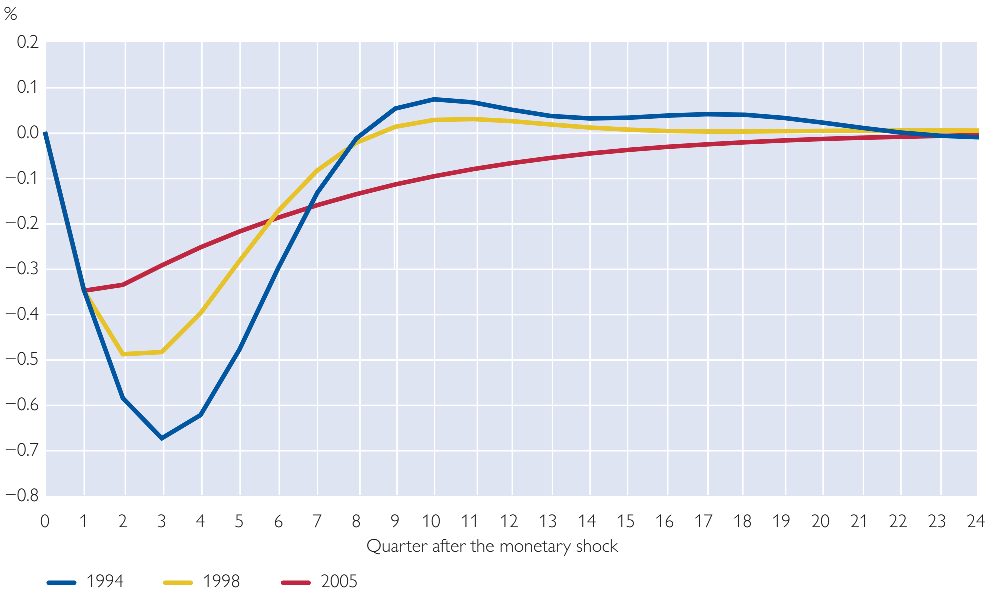
Comparison of Euro Area GDP Responses, Different Treatments of the Trend Q4 98



Quelle: Author.

Chart 7

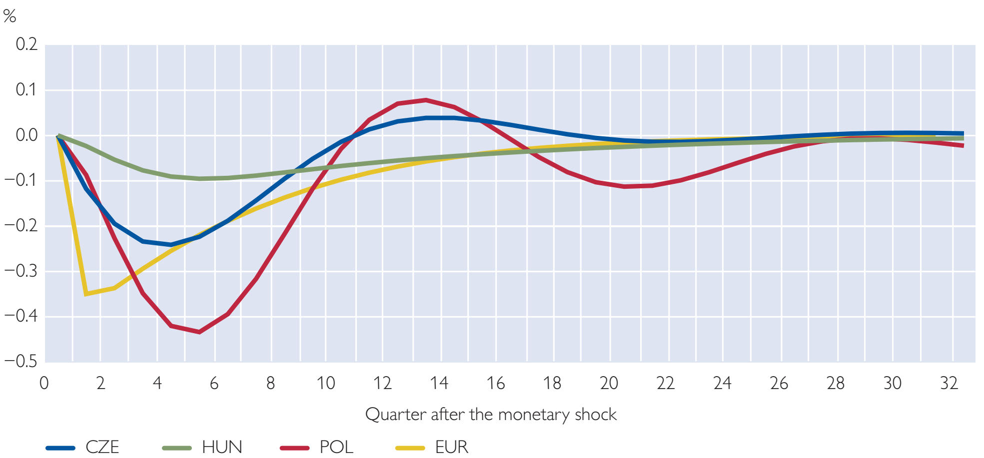
Comparison of Euro Area GDP Responses Using HIP-Filtered Data



Quelle: Author.

Chart 8

Output Response to a 1 Percentage Point Monetary Shock of End-2004



Quelle: Author.