Comenius University, Bratislava
Faculty of Mathemaics, Physics and Informatics

Department of Applied Mathematics and Statistics

Consistency of the Taylor rule with the CEEC data

Darina Polovková

9.1.9 Aplikovaná matematika
Economic and Financial Mathematics

Master thesis supervisor:
doc. Dr. Jarko Fidrmuc

Bratislava 2009

Consistency of the Taylor rule with the CEEC data

MASTER THESIS

Darina Polovková

COMENIUS UNIVERSITY, BRATISLAVA
FAKULTY OF MATHEMATICS, PHYSICS AND INFORMATICS
DEPARTMENT OF APPLIED MATHEMATICS AND STATISTICS

9.1.9 Economic and Financial Mathematics

doc. Dr. Jarko Fidrmuc

BRATISLAVA 2009

Platnosť Taylorovho pravidla v krajinách strednej a východnej Európy

DIPLOMOVÁ PRÁCA

Darina Polovková

UNIVERZITA KOMENSKÉHO V BRATISLAVE
FAKULTA MATEMATIKY, FYZIKY A INFORMATIKY
KATEDRA APLIKOVANEJ MATEMATIKY A ŠTATISTIKY

9.1.9 Ekonomická a finanančná matematika

doc. Dr. Jarko Fidrmuc

BRATISLAVA 2009

I declare this thesis was written on my own, with the only help provided by my supervisor and the reffered-to literature.

....

Darina Polovková

Acknowledgment

I would like to express special thanks to my supervisor doc. Dr. Jarko Fidrmuc for all support and guidance he offered throughout the elaboration of this thesis.

Abstract

Polovková, Darina: Consistency of the Taylor rule with the CEEC data [Master thesis], Comenius University, Bratislava, Faculty of Mathemaics, Physics and Informatics, Department of Applied Mathematics and Statistics. Supervisor: doc. Dr. Jarko Fidrmuc. Bratislava: FMFI UK, 2009. 59 pages.

We conduct an analysis of the validity of the Taylor rule for the five Central and Eastern European Countries and the Euro Area, using two different approaches. First, we treat our data as stationary and we estimate the simple and the dynamic form of the Taylor rule by GMM. Our results are not consistent with the Taylor rule requirements. Next, we test our input variables for stationarity and reveal the unit-root behavior of the inflation and interest rate. Thus, the results from GMM estimates are likely to be spurious, since we have violated the GMM stationarity assumptions. We therefore employ an alternative estimation method (VEC), which takes the non-stationarity of the variables into account. For the VEC to exist, the variables need to be cointegrated. The cointegration vector is a stationary long-run relationship among the variables and costitutes the Taylor rule. We are able to find a cointegration vector in all countries, but only in the case of the Slovak Republic, the Czech Republic, and the Euro Area this approach yields a stable reaction function.

Key words: Taylor rule, GMM, cointegration, VEC

Abstrakt

Polovková, Darina: Platnosť Taylorovho pravidla v krajinách strednej a východnej Európy [Diplomová práca], Univerzita Komenského v Bratislave, Fakulta matematiky, fyziky a informatiky, Katedra aplikovanej matematiky a štatistiky. Školiteľ: doc. Dr. Jarko Fidrmuc. Bratislava: FMFI UK, 2009. 59 s.

V tejto práci analyzujeme platnosť Taylorovho pravidla v piatich krajinách strednej a východnej Európy a v Eurozóne. Analýzu začneme predpokladom o stacionarite vstupných časových radov a pomocou GMM odhadneme jednoduché a dynamické Taylorovo pravidlo. Naše odhady nespĺňajú podmienky stabilných reakčných funkcií v žiadnej krajine. Ďalší krok spočíva v testovaní stacinarity časových radov. Výsledky štatistických testov potvrdzujú, že inflácia a úroková miera sú nestacionárne proscesy integrované rádu 1. V takom prípade sme nesplnili predpoklady GMM o stacionárnosti premenných a regresia môže byť zavádzajúca. Preto na odhad Taylorovho pravidla použijeme inú metódu - VEC, ktorá zohľadňuje nestacionaritu časových radov. Na existenciu VEC modelu je potrebné, aby naše premenné boli kointegrované. Kointegrácia je dlhodobý stacionárny vzťah medzi nestacionárnymi premennými, ktorý reprezentuje Taylorovo pravidlo. Kointengračný vektor nájdeme vo všetkých krajinách, no vlasnosti stabilnej reakčnej funkcie majú len pravidlá odhadnuté pre Slovenksú, Českú a Európsku centrálnu banku.

Kľúčové slová: Taylorovo pravidlo, GMM, kointegrácia, VEC

Contents

Introduction

Over the past several years, monetary policy reaction functions have considerably attracted the attention of macroeconomists. An important contribution to this field was made by Taylor [46], who introduced a simple linear rule that captures the dependence of the interest rate from the changes of the output and the inflation. Since its introduction the rule has reached widespread popularity and become employed in many empirical and theoretical studies[1]. However, no central bank so far has officially commited to a simple instrument rule - such rules should not be mechanically followed by policymakers. They are only found to track the real data surprisingly well and can only provide a good recommendation for the decision makers.

There is one serious point in estimating the validity of the Taylor rule and that is the fact that many of the previous studies ignore the time series properties of the variables included in the model. Phillips [42] showed that if variables have unit root, the regression in levels is likely to be spurious.

In this study we want to find out whether the simple Taylor rule can be supported by the data on the five central and eastern European countries and the Euro Area, considering the time series properties of the input variables.

This thesis is organised as follows. In Chapter 1 we present a brief discussion about the monetary policy rules. Next, we illustrate how an optimal policy rule can be derived and how it is related to the simple Taylor rule. We continue with the explanation of the Taylor rule rationale and we introduce various modifications of the rule often discussed in the literature.

Chapter 2 describes the econometric methodology we are using to estimate the Taylor rule in the Central and Eastern European Countries, namely the generalized method of moments (GMM), unit root (ADF) and stationarity (KPSS) tests, cointegration, and vector error-correction model (VEC). We also provide a brief overview of the Hodrick-Prescott filter, which is used to obtain a smoothed representation of time series.

In Chapter 3 we first estimate both the simple and the dynamic Taylor rule by GMM and present our results. Then we perform the tests to reveal the unit root behavior of our series and find out that we face the risk of spurious regression. We therefore use

[1]For empirical analyses see for instance Clarida *et al.* [6], Orphanides [37], or Gerlach and Schnabel [44]. For some theoretical work see for instance Levin *et al.* [28].

an alternative estimation method, which takes the non-stationarity into account, namely the vector error-correction model. The chapter concludes with the interpretation of our results, which are also compared to the results obtained by other authors.

Chapter 1

Monetary Policy Rules

Monetary policy is one of the tools that the monetary authority uses to influence the country's economy. Well designed monetary policy influences the overall level of economic activity in line with its political objectives and improves economic stability and welfare. Its main goal is macroeconomic stability - low unemployment, low inflation, economic growth etc. But how should the monetary authority formulate its policy? Due to the limited knowledge that economists have about the macroeconomy there is substantial disagreement about the design of stabilization policy.

One approach is that the monetary authority is free to act in accordance with its own judgement, without any specific policy guide. An advantage of this approach is that the authority can accommodate its judgment to present conditions period by period.

On the other hand, committing to follow a rule has several important advantages over such discretionary policy approach. Following a rule is particularly important for the policymakers because it may help them find the proper policy prescription. It also improves the credibility of future policy actions. Moreover, it is a useful approximation tool for the financial market participants who want to forecast the future course of monetary policy. Another benefit is for the general public - people can expect and understand better the central bank's objectives and its response.

To overview the debate on rules versus discretion in monetary policy see Gerald and Dwyer [14].

1.1 Money Supply Model versus Interest Rate Reaction Function

There has been a vast amount of various proposals for monetary policy rules, and an enormous literature devotes to examination of the advantages and caveats of the different approaches.

Some propose a rule in terms of the main goals of monetary policy, for example to maintain economic stability or a constant aggregate price level. However, there is a pragmatic difficulty with such proposals: the central bank cannot control these concepts, so the proposals are not very operational. To be useful in practice, policy rules must be simple to implement. This demands an apparent choice of what should serve as the policy instrument. There are two main different approaches to what the policy instrument should be: the first takes the money supply and the other the short-term interest rate.

Perhaps the simplest example of the first approach is the Milton Friedman's (Friedman [13]) proposal that the central bank should expand the money supply at a constant rate, equivalent to the rate of growth of real GDP. An advantage of a constant money growth rule is that very little information is required to implement it. In addition, the rule is remarkably stable across different models and robust to misspecification.

Later, simple modifications allowing for some automatic response of money growth to economic developments have been proposed, e.g. by McCallum [31]. He found out that if the rule he proposed was followed, it could have improved the performance of the U.S. economy.

However, according to Orphanides [38], a factor that complicates the use of the money stock as a policy instrument is the potential for instability in the demand for money either due to temporary disturbances or due to persistent changes resulting from financial innovation. In part for this reason, central banks typically prefer to adjust monetary policy using an interest rate instrument. This attitude greatly influenced monetary policy research.

An example of interest rate rules are Taylor rules. Taylor rules are simple reactive rules that adjust the interest rate policy instrument in response to developments in both inflation and economic activity.

In the next section we illustrate a derivation of the optimal interest rate rule, imposing several simplifications, and show how it relates to the classic form of the Taylor rule.

1.2 Deriving the Optimal Interest Rate Rule

In line with Carlin and Soskice [4] we derive the optimal interest rate rule for a central bank aiming to minimize the fluctuations of output and inflation from their targets. To do so, we need to know the central bank's loss (or utility) function, the policy instrument, and constraints. This entails the following steps:

1. Define the central bank's loss function. The purpose of the central bank is to minimize the cost to the economy created by various inflation and output shocks.

2. Define the central bank's constraints; these are represented by the Phillips curves. The Phillips curve is defined as a feasible set of inflation and output pairs for a given rate of inflation inertia.

3. Derive the central bank's monetary rule in terms of output and inflation. The rule is derived from the central bank's policy trade-off between output and inflation given the constraints it faces. According to the rule, the central bank sets the optimal output as a response to the current rate of inflation in the economy, determined by the Phillips curve. The policy instrument of the central bank to secure the appropriate level of output is the interest rate.

4. Define a function which shows the level of the interest rate which should be set in order to deliver the right level of output. This is the IS curve.

5. Derive the optimal interest rate rule, which prescribes how should the central bank adjust the interest rate in response to the inflation and output disturbances.

1.2.1 The Central Bank's Loss Function

Contemporary central banks tend to stabilize the economy around the inflation target and the equilibrium level of output. This effort appears logical since the constant rate of inflation is only implied by an equilibrium output. We also assume that the central bank is equally concerned about the positive and negative deviation from the target, i.e. it has the same tolerance for inflation (or output) that is slighthly below the target and inflation (or output) that is above the target[1]. Another assumption is that the further the inflation (or output) deviates from its target, the bigger importance attaches the monetary authority to stabilize it. This can be expressed by the following loss function:

$$L = (y_t - y_t^*)^2 + a(\pi_t - \pi^*)^2,$$

where y_t is the output level, y_t^* is the equilibrium output level, π_t is the inflation rate, π^* is the inflation target, and a is the relative weight attached to the loss from inflation. The higher a, the more inflation averse the central bank is; a central bank with $a > 1$ puts more weight on deviations in inflation than in output. An $a = 1$ characterizes a central bank concerned about the inflation and output deviations equally.

1.2.2 The Phillips Curve

The Phillips curve (PC) is a simple linear expression which shows how output affects inflation. The economic interpretation behind that is that nominal wages increase by lagged inflation plus the function of the percentage difference between current and equilibrium employment. Since wages increase by the same amount as prices, and employment and

[1]We assume that the equilibrium output level is known and that it is the target output, which central bank wants to stick to.

output are proportional, the Phillips curve can be expressed in the following form:

$$\pi_t = \pi_{t-1} + b(y_t - y_t^*),$$

where π_{t-1} is an inflation inertia and b is a positive constant. The inclusion of the lagged inflation in the expression results from the wage and price setting intertia; the wage setters factor the past inflation into their current wage setting in order to capture the change in the real wage.

It can be seen from the expression that the output above the equilibrium output will raise the inflation above the past inflation rate and vice versa. The lagged inflation rate defines the height of the Phillips curve on a vertical inflation line, e.g when the past inflation rate rises, the Phillips curve shifts up. The slope of the Phillips curve depends on the parameter b; the larger b, the more will the inflation react on the output gap.

1.2.3 The Monetary Rule

The monetary rule (MR) shows the level of output that the central bank needs to choose in order to minimize its loss at the given level of past rate of inflation. Geometrically, the monetary rule is a line that joins the points of tangency between the Phillips curves and the central bank's indifference curves. The monetary rule is derived from the central bank's loss function

$$L = (y_t - y_t^*)^2 + a(\pi_t - \pi^*)^2$$

and the Phillips curve

$$\pi_t = \pi_{t-1} + b(y_t - y_t^*).$$

To find the optimal value of y_t that minimizes L for each value of π_{t-1} we substitute the Phillips curve into L and derive it with respect to y_t:

$$L = (y_t - y_t^*)^2 + a[\pi_{t-1} + b(y_t - y_t^*) - \pi^*]^2$$
$$\frac{\partial L}{\partial y_t} = 2(y_t - y_t^*) + 2ab[\pi_{t-1} + b(y_t - y_t^*) - \pi^*] = 0$$

Since $\pi_t = \pi_{t-1} + b(y_t - y_t^*)$, we get

$$\frac{\partial L}{\partial y_t} = (y_t - y_t^*) + ab(\pi_t - \pi^*) = 0$$

$$\Rightarrow \pi_t - \pi^* = -\frac{1}{ab}(y_t - y_t^*).$$

This rule shows an inverse relation between inflation and output with the slope determined by two factors: the degree of the central bank's inflation aversion, captured by parameter a, and the responsiveness of inflation to output gap, captured by parameter b.

1.2.4 The IS Curve

The IS curve is a linear function which shows the level of the interest rate to be set in order to deliver the right level of output (we are talking about the real interest rate, since investments depend on the real interest rate):

$$y_t - y_t^* = -c(r_{t-1} - r^*),$$

where r is the real interest rate and r^* is the equilibrium real interest rate. The IS curve is downward sloping because a low interest rate generates high investment, which leads to high output.

1.2.5 Deriving the Optimal Interest Rate Rule

We now derive the optimal interest rate rule, which expresses the optimal change in the interest rate subject to current state of the economy. We want to derive the formula for the interest rate from the following three equations:

$$\pi_t = \pi_{t-1} + b(y_t - y_t^*) \tag{PC}$$
$$y_t - y_t^* = -c(r_{t-1} - r^*) \tag{IS}$$
$$\pi_t - \pi^* = -\frac{1}{ab}(y_t - y_t^*). \tag{MR}$$

However, to incorporate the real economy conditions we need to modify the timing of the variables. We continue to assume that the interest rate, r_{t-1}, affects only the next period output, y_t. We make a new assumption, which is supported by the empirical evidence, according to which it takes a year for output to have an effect on inflation. This makes a change to the Phillips curve, where y_t is replaced by y_{t-1}. Moreover, since the central bank's interest rate at time $t-1$ can only influence next period output, y_t, and two period later inflation, π_{t+1}, its loss function changes to:

$$L = (y_t - y_t^*)^2 + a(\pi_{t+1} - \pi^*)^2.$$

The monetary rule equation is modified, too, into the following form:

$$\pi_{t+1} - \pi^* = -\frac{1}{ab}(y_t - y_t^*).$$

Thus, our three-equation model changes to

$$\pi_t = \pi_{t-1} + b(y_{t-1} - y^*_{t-1}) \tag{PC}$$
$$y_t - y^*_t = -c(r_{t-1} - r^*) \tag{IS}$$
$$\pi_{t+1} - \pi^* = -\frac{1}{ab}(y_t - y^*_t). \tag{MR}$$

If we substitute the Phillips curve for the π_{t+1} in the monetary rule, we get

$$\pi_t + b(y_t - y^*_t) - \pi^* = -\frac{1}{ab}(y_t - y^*_t).$$

Now substitution for the output gap using the IS curve gives

$$\pi_t - \pi^* = c(\frac{1}{ab} + b)(r_{t-1} - r^*)$$

and using the Phillips curve again we get

$$r_t - r^* = \frac{1}{c(b + \frac{1}{ab})}[(\pi_t - \pi^*) + b(y_t - y^*_t)].$$

We have derived an optimal interest rate rule, which takes the form of the famous Taylor rule. With parameters $a = b = c = 1$ (i.e. the IS, PC, and MR curves all have a slope of 1 or -1) we obtain the following form of the rule:

$$r_t - r^* = 0.5(\pi_t - \pi^*) + 0.5(y_t - y^*_t),$$

which states that if output is 1% above equlibrium and inflation is at the target, the central bank should raise the interest rate by 0.5%, and analogically if inflation is 1% above the target and output is at equilibrium, the rule says to increase the real interest rate by 0.5%.

As shown by Taylor, these parameters describe the US economy between years 1987 and 1982 quite well. However, the Taylor's weights will be different from 0.5 if the central bank's inflation aversion, the supply-side structure reflected in the Phillips curve, or the interest sensitivity of aggregate demand are different.

1.3 The Taylor Rule

1.3.1 The Original Taylor Rule

Taylor's original formulation of a simple policy rule is as follows:

$$i_t = r^* + \pi_t + f_\pi(\pi_t - \pi^*) + f_y(y_t - y^*_t),$$

where i_t is the desired central bank nominal interest rate, r^* is the equilibrium real interest rate, π_t is the current inflation rate, π^* is the inflation target of the central bank, y_t^* is the potential output, and f_π and f_y are positive parameters.

Adding an error term and collecting constants, we can rewrite the equation as

$$i_t = \alpha + \beta_\pi \pi_t + \beta_x x_t + \epsilon_t \tag{1.1}$$

where $\alpha = r^* - (\beta_\pi - 1)\pi_t^*$, $\beta_\pi = f_\pi + 1$, $\beta_x = f_y$, and $x_t = y_t - y_t^*$.

The rationale for the Taylor rule is that it generates positive responses of the interest rate to changes in inflation and real output. When the output gap is positive, meaning that the actual output is higher than its potential level, the central bank increases the interest rate. Thus, the consumption and investitions, and consequently the GDP growth, slow down because more money is put on bank accounts because of higher interest rates, so the output is brougth back to its potential level.

Similarly, when inflation exceeds the target, the central bank rises the short-term interest rate in order to lower the consumption, GDP growth, and increase in prices. Moreover, the coefficient β_π should be larger that 1 in order for the rule to lead to stable inflation. The reason is that the central bank should increase the *nominal* interest rate by more than the increase in the inflation rate in order to increase the *real* interest rate, since an increase in the *real* interest rate brings back the inflation rate to its target.

Taylor proposed that the coefficients $r^* = 2, \pi^* = 2, f_\pi = f_y = 0.5$ captured the interest rate setting of the Federal Reserve Bank over the period 1987 to 1992 quite well. Assuming these suggestions we now get

$$i_t = 1 + 1.5\pi_t + 0.5x_t.$$

This form of the Taylor rule works well in the US conditions. However, it is very advisable to adjust the rule according to specific country conditions. Many different versions of this simple rule have been employed and tested in many empirical works.

1.3.2 Different Versions of the Taylor Rule

Extensive number of variants of the basic Taylor Rule have been employed in both theoretical and empirical works. For instance, there is a vast discussion regarding the timing of the variables - some (for example, McCallum and Nelson [32]) argue for the inclusion of lagged variables due to informational delays in central bank reaction; some, on the other hand, suggest to include forecasts of the regressors in order to capture the forward looking incentives of the central bank (employed for instance by Orphanides [37]). For a more thorough study of different approaches dealing with this issue, see Orphanides [37]. However, there is a risk of incorrect forecasting, especially in transition countries.

In our analysis we therefore decided to adhere to Taylor's original formulation and use contemporaneous data.

The Dynamic Taylor Rule

Another common modification of Taylor's Rule takes into account that the central bank wants to smooth the adjustments in the interest rate. This is made by adding lagged interest rate into the equation (1.1):

$$i_t = \gamma i_{t-1} + (1-\gamma)(\alpha + \beta_\pi \pi_t + \beta_x x_t) + \epsilon_t, \tag{1.2}$$

where $0 \leq \gamma < 1$ is a smoothing coefficient which indicates, how much is the central bank trying to preserve the stable interest rate. We will refer to this model as a dynamic version of the Taylor rule.

The coefficients β_π and β_x in the dynamic model should follow the simple-Taylor-rule rationale, i.e. the inflation coefficient should be larger than one and the output gap coefficient should be positive. Although the short-run impact of the increase in the right-hand side variables on the interest rate is multiplied by $(1-\gamma)$, the long-run effect is just given by the coefficients β_π and β_x. This can be seen from the following: if we infinitely recursively substitute for i_{t-1} in the equation 1.2 and add up coefficients on the inflation, we obtain an infinite sum of the geometric series $\sum_{k=0}^{\infty}(1-\gamma)\gamma^k\beta_\pi$, which is equal to $(1-\gamma)\frac{1}{(1-\gamma)}\beta_\pi = \beta_\pi$. Analogously we derive the long-run effect of the increase in the output gap, which is equal to β_x.

This dynamic specification was, for instance, employed by Levin *et al.* [28] or Gerlach and Schnabel [44]. Clarida *et al.* [6] estimated interest rate smoothing reaction functions for across different countries and found smoothing parameters with large and significant values. Gerlach and Schnabel [44] also found support for a dynamic Taylor rule in the EMU area between 1990 and 1998. However, Rudebusch [43] argues that the parameter on lagged interest rate probably reflects serially correlated errors. In other words, the tests may not be able to distinguish between interest rate smoothing and serially correlated disturbances in Taylor-type rules. Also Österholm and Welz [49] question the conclusions of Clarida *et al.* [6] that central banks gradually adjust the interest rate to its target value. They argue that the smoothing parameter value of 0.92 found by Clarida *et al.* indicates implausibly slow speed of adjustment process.

Despite doubts about the appropriateness of the Taylor rule, Nyberg [36] argues that the rule performes well even in an open economy with parameter uncertainty. Other empirical works also give support that the Taylor rule is a reasonable approximation to central bank behavior in a number of different macro models.

The Augmented Taylor Rule

Variable omission is a likely cause of misspecification in estimated reaction functions that only include the inflation and the output gap. The practical decission making depends on many economic indicators, which can be hardly approximated by just the inflation and the output gap. The relevant variable omission leads to biased and inconsistent coefficient estimates. For a deeper analysis of how the omission of various variables influence the remaining coefficiens in the Taylor rule, see Goodhart and Hofmann [15]. The likely candidates to augment the simple Taylor rule are monetary aggregates, the exchange rate, the growth rate of the exchange rate, the exhange rates' position in the band if the currency is pegged to an anchor currency, the foreign interest rate, foreign output gap (e.g. in the case of CEEC it would be reasonable to include the interest rate or the output gap of the ECB), financial market variables, measure of expected changes in the interest rate, balance of payments, evolution of export, index of real wages etc.

However, it is beyond the scope of this thesis to explore the relevant variables ommited from the reaction function. For an analysis of six different Taylor-type models in the four Visegrad countries, see Farrell [39]. For a study that explores whether the exchange rate matters in monetary policy rules in CEEC, see Frömmel, Garabedian, and Schobert [34].

Chapter 2

Econometric Methodology

The aim of this chapter is to introduce the main ideas behind the econometric methodology we are using in the empirical part. The following literature serves as a baseline for the elaboration of this chapter: Hamilton [18], Greene [17], Brooks [2], Enders [8], Johnston and DiNardo [23], Kennedy [25], and EVies Help among others.

2.1 The Hodrick-Prescott Filter

In this section we turn our attention to describing a method of decomposing a series into a trend and a stationary componet[1]. In 1997[2], Hodrick and Prescot [21] developed a two-sided linear filter that computes the smoothed series s of y by minimizing the variance of y around s, subject to a penalty that constrains the second difference of s. That is, the HP filter chooses s to minimize:

$$\frac{1}{T}\sum_{t=1}^{T}(y_t - s_t)^2 + \frac{\lambda}{T}\sum_{t=2}^{T-2}((s_{t+1} - s_t) - (s_t - s_{t-1}))^2,$$

where T is the number of observations and λ is a penalty parameter, which penalizes the fluctuations incorporated into the trend - the larger the λ, the smoother the series. As λ approaches infinity, s approaches a linear trend; when $\lambda = 0$, the sum of squares is minimized when the trend is equal to the series itself. For the monthly data it is suggested to use the value of $\lambda = 14400$.

2.2 The Generalized Method of Moments

This section covers a class of estimators called generalized method of moments (GMM). Since the Hansen's seminal paper [19], it has become one of the main statistical tools for

[1] We use this method to estimate the potential output y_t^*.

[2] Although the earlier version of the Hodrick and Prescott's seminal paper circulated already in the 1980s, the Journal of Money, Credit, and Banking published it only in 1997.

the analysis of economic data. There are two reasons for its current popularity. First, it does not require a specification of a likelihood function. The consistency depends only on correct specification of the residuals and the conditioning variables. Second, it provides a unifying framework for analysis of many familiar estimators such as OLS or IV. However, GMM is an estimator that achieves its desirable properties only in large samples.

2.2.1 The Method of Moments

A useful starting point is the method of moments (MOM). We will define a *population* moment υ as the expectation of a function g of a random variable x: $\upsilon = E[g(x)]$. The most commonly discussed moment is the mean, where $g(.)$ is merely the identity function. A *sample* moment is the sample version of the population moment in a particular random sample: $\hat{\upsilon} = \frac{1}{n} \sum g(x)$. Then the method of moments is based on the following idea: To estimate a population moment we use the correponding sample moment.

This approach is straightforward if the number of moment conditions is equal to the nmber of parametes to be estimated. Whenever the number of moment conditions exceeds the number of parameters to be estimated, it is not possible to find such parameters for which all of the moment conditions would be satisfied. For example, if there are seven moment conditions and only three parameters, only three of these moment conditions can be satisfied. To deal with that, we can choose which three of the seven moment conditions should be satisfied. Such approach, however, is undesirable because it ignores information from the two abandoned moment conditions. The alternative is to choose the three parameters in order to minimize the total extent to which the six moment conditins are violated, even though this may mean that none of the seven conditions is exactly satisfied. This approach is called the generalized method of moments.

2.2.2 The Generalized Method of Moments

The basic idea underlying GMM is this: Theory yields a population moment condition (or orthogonality condition) that the true parameters θ_0 should satisfy. The conditions are of the form

$$E[g(w_t, \theta_0)] = 0,$$

where w_t is a vector of variables observed at time t. The method of moments estimator is defined by replacing the moment condition by its sample analog:

$$m(w, \theta) = (1/T) \sum_{t=1}^{T} g(w_t, \theta),$$

where T is the sample size. The GMM then minimizes the following with respect to the parameters θ in order to make the sample moment as close as possible to the population moment of zero:

$$\min_{\theta}(m(w,\theta)' W_T(m(w,\theta)),$$

where W_T is a weighting matrix that weights each moment condition and can be a function of the data. Regardless of the weighting matrix that is used, GMM is always consistent and assymptotically unbiased. When the correct weighting matrix is used, GMM is also asymptotically efficient in the class of estimators defined by the orthogonality conditions. It can be shown that a necessary (but not sufficient) condition to obtain an (asymptotically) efficient estimate of θ is to set W_T equal to the inverse of the covariance matrix of the sample moments $m(w,\theta)$. This follows intuitively, since we want to put less weight on the conditions that are more imprecise.

To sum up, the starting point of GMM estimation is a theoretical relation that the parameters should satisfy. The idea is to choose the parameter estimates so that the theoretical relation is satisfied as "closely" as possible. The theoretical relation is replaced by its sample analog and the estimates are chosen to minimize the weighted distance between the theoretical and actual values.

2.2.3 Instrumental Variables

To obtain GMM estimates, we must write the moment conditions as an orthogonality condition between the residuals of a regression equation and a set of instrumental variables (IV). Instrumental variables have to be strongly correlated with right-hand-side variables of the model and uncorreated with residuals. They need to be predetermined at the time of an interest rate decision, i.e. dated t-1 or earlier. The natural candidates for these are lagged variables of the inflation rate and the output gap, since they influence the behavior of the reggressors in the past and are uncorrelated with residuals.

Consider a linear model $y_t = x_t'\beta + u_t$, where x_t is a vector of explanatory variables. Let z_t be an $(r \times 1)$ vector of predetermined instrumental variables that are correlated with x_t but uncorrelated with u_t: $E(z_t u_t) = 0$. Then the true value β_0 is assumed to satisfy the r orthogonality conditions

$$E[z_t(y_t - x_t'\beta_0)] = 0.$$

This is a special case of GMM in which $w_t = (y_t, x_t', z_t')$, $\theta = \beta$, and

$$g(w_t,\theta) = z_t(y_t - x_t'\beta).$$

For instance, if the set of the instrumental variables contain a constant, z_1, and z_2, the orthogonality conditions in the case of the model (1.1) look as follows

$$\sum(i_t - \alpha - \beta_\pi \pi_t - \beta_x x_t) = 0,$$

$$\sum(i_t - \alpha - \beta_\pi \pi_t - \beta_x x_t) z_{1t} = 0,$$
$$\sum(i_t - \alpha - \beta_\pi \pi_t - \beta_x x_t) z_{2t} = 0.$$

2.2.4 GMM in EViews

To estimate by GMM in Eviews, we first need to specify the set of the instrumental variables. We have already discussed that above. Second, we need to select the weighting matrix W_T. If we select *Weighting Matrix: Time series (HAC)*, EViews will use the W_T equal to the inverse of the covariance matrix of the sample moments $m(w, \theta)$ and the GMM estimates will be robust to heteroskedasticity and autocorrelation of unknown form.

For the *HAC option*, we have to specify the kernel type, bandwidth and prewhitening. The *Kernel Options* determine the functional form of the kernel used to weight the autocovariances in computing the weighting matrix. The *Bandwidth Selection* option determines how the weights given by the kernel change with the lags of the autocovariances in the computation of the weighting matrix. The *Prewhitening* option runs a preliminary VAR(1) prior to estimation to 'soak up' the correlation in the moment conditions. For a description of these options in greater detail see the technical notes in Generalized Method of Moments (GMM) in EViews help.

EViews also reports J-statistics, the minimized value of the objective function. It tests the validity of overidentifying restrictions when we have more instruments than parameters to estimate.

2.3 Testing Stationarity

2.3.1 Stationary and Unit Root Time Series

A time series y_t with a finite mean and variance is *covariance stationary* if for all t and s

$$E(y_t) = E(y_{t-s}) = \mu$$

$$cov(y_t, y_{t-s}) = cov(y_{t-j}, y_{t-j-s}) = \gamma_s,$$

where μ and γ_s are all constants. In other words, the covariance stationary time series has a constant mean and all autocovariances are independent of time (note that $s = 0$ implies constant variance of y_t).

In literature, a covariance stationarity is also reffered to as a weak stationarity or simly - stationarity. In the following text the term stationarity also means covariance stationarity.

Box and Jenkins [1] claimed that most non-stationary economic time series data could be made stationary by differencing. If a non-stationary series y_t must be differenced d times before it becomes stationary, then it is said to be integrated of order d, denoted as $y_t \sim$I(d). An I(0) series is stationary, I(1) contains one unit root, I(2) contains two unit roots etc. The majority of economic time series contain a single unit root.

However, there are many different ways in which data can be nonstationary. For example, if the data is characterized by a cyclic movement, it might not be true that the mean does not change over time.

Stationary and nonstationary processes are very different in their properties, and they require different inference procedures.

Why is a Test for Non-Stationarity Necessary

The use of non-stationary data can lead to spurious regression (Granger and Newbold [16]). To offer an illustration, if we run regression on independent sets of stationary variables, we expect a very low value of R squared. However, if the variables have a trend although they are totally unrelated, the regression can produce a high R squared. So, the regression might look good, but it's valueless. The consequence of this is that it is very important to test for nonstationarity before preceeding with estimation. For a more thorough illustration of a spurious regression, see Hendry and Juselius [20].

2.3.2 Unit Root Test - ADF

It is not possible to use the ACF to determine unit root, since the ACF will usually decay away to zero (even though slowly) and thus the process might be mistaken for stationary. Therefore, Dickey and Fuller [7] established a test (DF) to examine the unit root null hypothesis.

Suppose a model $y_t = a_1 y_{t-1} + \epsilon_t$, in which we want to determine whether $a_1 = 1$, i.e. the series contains a unit root. By subtracting y_{t-1} we can rewrite the equation into

$$\Delta y_{t-1} = \gamma y_{t-1} + \epsilon_t,$$

where $\gamma = a_1 - 1$. Then testing the null hypothesis $a_1 = 1$ is equivalent to testing the hypothesis $\gamma = 0$. The regression forms depend on the presence of a constant and/or a trend.

The test statistic for the DF test, however, does not follow the usual t-distribution under the null-hypothesis. It follows a special distribution, which critical values are derived from Monte Carlo simulations and are tabulated. The appropriate statistic to use depends on whether the intercept or trend are included in the regression equation. These DF tests are also known as τ-tests: τ (without an intercept or trend), τ_μ (with only the intercept) and τ_τ (both trend and intercept). Later, MacKinnon [29] implemented a much larger set of simulations than those tabulated by Dickey and Fuller.

Nevertheless, not all time series can be well represented by the first order autoregressive process. Then Augmented Dickey – Fuller test is used, which augments the DF test using more lags of the dependent variable. Consider the p-th order autoregressive process

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \epsilon_t,$$

where y_t is a variable that we want to test for stationarity. This can be rewritten into the following form:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \epsilon_t,$$

where $\gamma = -(1 - \sum_{i=1}^{p} a_i)$ and $\beta_i = -\sum_{j=i}^{p} a_j$. Then we test the null hypothesis $\gamma = 0$, i.e. the series has a unit root.

In constructing the ADF test output we use the same critical values as in the case of DF, since the asymptotic distribution of the t-statistic is independent of the number of lagged first differences included in the ADF regression.

In performing the ADF test we face a problem whether to include a constant, a constant and a linear time trend, or neither in the test regression. We have to remember that including irrelevant regressors in the regression will reduce the power of the test to reject the null of a unit root. The standard recommendation is to choose a specification that is a plausible description of the data under both the null and alternative hypotheses. For a more detailed discussion on the choice of a plausible description of the data specification, see Hamilton [18].

2.3.3 Stationarity Test - KPSS

The ADF test has been argued that it has a low power if the process is nearly integrated. It is poor at deciding, whether the series contains unit root or just root close to unity. One way to cope with this problem is to complement the unit root test by stationarity test as well, which has stationarity as the null hypothesis. Thus, if there is, for example, little information, stationarity test cannot reject its null, i.e. the data will appear stationary unlike in the unit root test, where they appear to contain unit root. One such stationarity test is the KPSS (Kwiatkowski, Philips, Schmidt and Shin [27]).

The KPSS statistic is based on the the residuals e_t from the OLS regression of y_t on the exogenous variables. The test statistic is defined as

$$KPSS = T^{-2} \sum_{t=1}^{T} S_t^2 / \sigma_T(l),$$

where $S_t = \sum_{i=1}^{t} e_i$ is the partial sum of the residuals, T is the number of observations, and $\sigma_T(l)$ represents an estimate of the long run variance of the residuals. We reject the stationary null when KPSS is large, since that means the series deviate from its mean.

To specify the KPSS test in EViews, we must choose a method for estimating $\sigma_T(l)$. EViews supports two classes of estimators: kernel-based sum-of-covariances estimators, and autoregressive spectral density estimators. For details see EViews help.

For the conclusion to be robust, both tests should conclude the same, i.e. one test should reject its null hypothesis of unit root while the other shouldn't reject its null hypothesis of stationarity and vice versa.

2.3.4 Alternative Approaches for Testing Unit Root

Phillips and Perron [42] propose an alternative method of controlling for serial correlation when testing for a unit root. The test is similar to ADF test, but it incorporates a non-parametric correction to the DF procedure to allow for autocorrelated residuals. It usually gives the same conclusions as the ADF test. Although the PP test tends to be more powerful, it is also subject to more severe size distortions and is more sensitive to model misspecification. We do not report the results from this test in our empirical analysis.

Testing for Higher Order of Integration

If we reject the null of the ADF test, the conclusion is that the series does not contain a unit root. But if the null hypothesis is not rejected, it means that the series are integrated at least once. Then it is necessary to perform a test of second order of integration. The tests should continue for a further unit root until the null hypothesis is rejected. It has been argued, that the proper way of testing higher order of integration is to start by assuming the highest plausible order of integration. If that is rejected, than continue to test the next smaller order of integration etc. Nevertheless, in this study, this is a matter of less concern as the higher integration than of order one is very unlikely in economic data that we are using.

2.4 Cointegration and Vector Error Correction Model

If our variables are non-stationary, we face a real risk that the Taylor rule estimation by GMM is spurious and further inspection of the model is needed. The first task is to check for the existence of a cointegating relationship among the variables.

2.4.1 What is Cointegration

The Engel and Granger [10] definition of cointegration is as follows: Let w_t be a $(k \times 1)$ vector of variables, then the components of w_t are integrated of order (d, b) if:

- All components of w_t are I(d)
- There is at least one vector of coefficitents α such that

$$\alpha' w_t \sim I(d-b).$$

The vector α is called the cointegration vector. This vector is not uniquely identified - if it exists, then every nonzero multiple of it is also a cointegration vector. This property is often utilized in normalisation of the cointegration vector with respect to a particular variable by fixing its coeffitient at unity.

Since our input variables are I(1), we will restrict to the case $d = b = 1$. Then the variables are cointegrated if a linear combination of them is stationary.

A cointegrating relationship may be seen as a long-run or equibrium relationship. There can exist $k-1$ linearly independent cointegrating vectors, which define the cointegrating rank of the system.

2.4.2 Vector Error Correction Model (VEC)

A vector error correction (VEC) model is a restricted VAR[3] designed for use with non-stationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that the short-term dynamics of the variables are influenced by the previous period's deviation from long-run equilibrium. The cointegration term is known as the error correction term since it reflects the current error in achieving long-run equilibrium.

Consider a VAR of order p:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \epsilon_t,$$

where y_t is a vector of k variables, the A_i are $(k \times k)$ matrices of coefficients and the error terms ϵ_t are assumed to be iid $\mathcal{N}(0, \Omega)$. The VAR can also be expressed in vector error correction notation as[4]

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \epsilon_t, \tag{2.1}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$.

[3]The vector autoregression (VAR) is an econometric model used to capture the interdependencies between multiple time series. It is a generalization of the univariate AR models. In the VAR approach, all the variables are treated symetrically - each variable is expressed as a linear combination of lagged values of itself and lagged values of all other variables in the system.

[4]If the variables tend to increase or decrease, i.e. we want to allow for the possiblility of a linear time trend in the data, we would include the inctercept term Π_0 in the equation.

The matrix Π represents the parameters of the error correction term of the model. Granger's representation theorem says that if the coefficient matrix Π has reduced rank $r < k$, then there exist $k \times r$ matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is stationary. r is the number of cointegrating relations (the cointegrating rank) and each column of β' is the cointegrating vector. The elements of α have the interpretation of speed of adjustment parameteres, which give the weights of the cointegrating relations entering into each equation of the VAR. The larger the adjustment parameters, the greater the response of the previous period's deviation from long-run equilibrium. Conversely, very small values imply unresponsiveness of the variable to last period's equilibrium error. Of course, at least one of the speed of adjustment terms must be nonzero, otherwise the long-run relationship does not appear and the model does not have an error correction representation.

The relationship between an error-correcting model and cointegration is that an error correction representation necessarily implies cointegration. We can see it from the following: the differenced terms on the left-hand side of (2.1) are by assumption stationary. For (2.1) to be sensible, the right-hand side must also be stationary. Since all terms involving Δy_{t-i} on the right-hand side are by assumption stationary and the ϵ_t are stationary as well, it follows that the Πy_{t-1} must also be stationary. Since Π contains only constants, each row of Π is a cointegrating vector of y_t. Hence, the variables in y_t must be cointegrated.

2.4.3 Testing for Cointegration

Several methods have been proposed in the literature to estimate cointegrating vectors, see for instance Engle and Yoo [11]. The most frequently used approach is that of Engle-Granger [10]. The first step is to estimate the long run relationship and regress one variable on the others by OLS. In the second step we take the residuals from the estimated equation and test by the ADF test whether they are stationary. If this is the case, then we found a stationary linear combination of the itegrated variables, i.e. they are cointegrated. This approach, however, does not distinguish between the existence of one or more cointegrating vectors and the OLS parameter estimates of the cointegrating vector depend on the normalization that we implicitly chose by selecting the dependent variable. This is a very undesirable feature of the procedure because the test for cointegration should be invariant to the choice of the variable selected for normalization. As a consequence, the Engle-Granger approach is well suited only for the case with two variables in which we can have at most one cointegration relationship. Moreover, the Engle-Granger procedure generates the resudual series in the first step and in the second steep it uses these generated errors to estimate another regression. Hence, any error introduced in the first step is carried into the second one.

Fortunately, there have been methods developed to avoid these problems. We adopt the Johansen [45] methodology.

Johansen Methodology

The Johansen procedure is in fact a multivariate generalization of the Dickey-Fuller test - the system to be estimated is

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \epsilon_t.$$

The Johansen methodology uses the fact that the number of distinct cointegrating vectors is equal to the rank of the matrix Π, which is equal to the number of its nonzero eigenvalues. In practice, we have only estimates of Π and its eigenvalues. There are two test statistics that test for the number of eigenvalues insignificantly different from unity, which are formulated as

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} ln(1 - \hat{\lambda}_i)$$

and

$$\lambda_{max}(r, r+1) = -T ln(1 - \hat{\lambda}_{r+1}),$$

where r is the number of cointegrating vectors under the null hypothesis, $\hat{\lambda}_i$ is the estimated value for the ith eigenvalue from the matrix Π, and T is the number of observations. λ_{trace} is a joint test where the null is that the number of cointegrating vectors is less than or equal to r against an alternantive that there are more than r. The statistic equals zero when all $\lambda_i = 0$ and the further the estimated eigenvalues are from zero, the more negative is $\ln(1 - \hat{\lambda}_i)$ and the larger is the statistic. The second statistic, λ_{max}, conducts separate tests on each eigenvalue and has as its null that the number of cointegrating vectors is r against an alternative of $r + 1$. Similarly, if the estimated value of the eigenvalue is close to zero, the statistic will be small.

If the two statistics yield conflicting results, we base our choice on the interpretability of the estimated cointegrating vectors.

Note that the asymptotic distribution of the test statistic for cointegration does not have the usual distribution, so the critical values depend on the trend assumptions and may not be appropriate for models that contain other deterministic regressors.

In some cases, the individual unit root tests will show that some of the series are integrated, but the cointegration test will indicate that the matrix Π has full rank (meaning that the series are stationary). This apparent contradiction may be the result of low power of the cointegration tests or might be an indication of specification error.

2.4.4 Estimation of VEC

The procedure of estimating a VEC consists of the following steps:

- First, information criteria like AIC or SBC are used to choose a lag length for the unrestricted VAR model. To specify the number of lags of the first difference terms we use the Akaike information criterion[5].
- We determine the cointegrating rank, that is, we run the Johansen cointegration test and determine the number of cointegrating relations, using the proper trend specification.
- We estimate the matrix of cointegrating vectors, β, and the asssociated weighting matrix α. Incorporating these cointegrating relations, we estimate VAR.
- We analyze the normalized cointegrating vectors and speed of adjustment coefficients and determine whether the estimated model appears to be reasonable.

[5]In EViews, the number of lags is specified as the number of lags of the first differenced terms used in the regression, not the levels. For example, if we specify 2 lags, then Δy_t is regressed on Δy_{t-1} and Δy_{t-2} (and possibly any other exogenous variables), while in terms of the level series the number of lags is 3.

Chapter 3

Estimation Results

In this chapter we employ two different methods of estimating the monetary policy rule followed by the CEEC's central banks and the ECB. The estimation methods differ in the underlying assumption about the stationary properties of the time series.

As usually done in literature, we first treat the data as stationary and estimate the coefficients in the optimal monetary policy rule. According to the derivation in Chapter 1, the optimal monetary policy rule takes the form of the standard Taylor rule (1.1), the benchmark coefficients being $\alpha = 1$, $\beta_\pi = 1.5$, and $\beta_x = 0.5$. In line with the chapter 1 we also estimate other modification - the dynamic Taylor rule.

However, such economic data as enter the Taylor rule equation usually perform unit root behavior and our stationarity asumption might not be reasonable. Thus, we perform stationarity and unit root tests in order to reveal the unit root behavior of the data. Then we test for a cointegration relationship among the variables and estimate the Taylor rule equation by vector error correction model.

3.1 Data Description

We examine the validity of the Taylor rule in the Euro Area and Central and Eastern European Countries (CEEC), namely the Slovak Republic, the Czech Republic, Poland, Hungary, and Romania, using monthly data on inflation, output gap and short-term interest rate. Data is supplied by Eurostat database, OECD, IMF, and European Central Bank and is based to the average of the year 2000. The period covered is 1993:1 - 2008:12 for all countries except Romania, where the sample period is shorther due to availability of the data, 1994:1 - 2006:12. Since the estimation period starts before the monetary union, for this time period an artificial Euro area is analyzed. This is not uncommon in the literature (see Gerlach and Schnabel [44]). For a descriptive statistics of the data, see the Figure 3.3.

Inflation

Inflation is measured by the annual percentage change in the seasonally-adjusted[1] Harmonised Consumer Price Index (HCPI).

Judd and Rudebusch [24] base their inflation rates on different price indices and come to the conclusion that the estimation is not very sensitive to different measures of inflation. Kozicki [26] comes to the opposite conclusion that the recommendations given by the Taylor rule are not robust to the inflation measures. We will base our estimates on the choice of only one index, HICP.

Output gap

The output is measured by the seasonally-adjusted Industrial Production Index (IPI). Generally, the way of calculation of the potential output is a difficult task and affects the results. However, if we assume the original series to exhibit a deterministic trend, which is the basis of the classical Taylor rule analysis, it is appropriate to use a filter. We measure the potential output by the Hodrick-Prescott filter (smoothing parameter 14400) of the IPI. The output gap is then computed as the percent deviation of the IPI from its HP trend.

Interest rate

There has been some discussion about what is the correct short-term interest rate. For the Euro area, the interest rate is usually measured by the Euro Overnight Index Average (EONIA) lending rate on the money market as it is the European equivalent of the Federal Funds rate for the US. Nevertheless, Perez-Quiros and Siciliae [41] raise objections to this approach because of the relatively high volatility when looking at a daily frequency due to short-term liquidity needs. For other studies (e.g. Ullrich [48]) this does not appear to be relevant, as the monthly averages smooth out such movements. Some studies find the conclusions unaffected when they replace the overnight rate with the 3-month EURIBOR (e.g. Carstensen and Colavecchio [5]).

According to Neupaerova [35], a comparatively strong correlation between 3-month base rate BRIBOR (the interest rate on Slovak inter-bank deposit market) and two-week REPO interest rate can be observed in Slovakia, especially during the last years. Consequently, it is possible to interchange the two rates in the reaction function of the central bank.

Since the different measures of interest rates are often found to be highly correlated, we consider the choice of the interest rate measure robust to our estimates and base our choice on the availability of the data. Thus, our short-term interest rate is measured by

[1] To remove cyclical seasonal movements from the series and extract the underlying trend component, we use the Census X12 seasonal adjustment program.

the three month interbank offer rate attached to loans given and taken amongst banks for any excess or shortage of liquidity over several months. The data is averages of the daily figures.

3.2 Treating Data as Stationary

In this section we provide an example of a typical finding in the empirical literature - we present the results from GMM regression of two versions of the Taylor rule: the simple TR (1.1) as an optimal policy rule and the dynamic TR (1.2) as an interest-rate smoothing policy rule.

3.2.1 Estimation of the Simple Taylor Rule by GMM

To run the GMM estimation of the Taylor rule (1.1), we first need to choose a set of instruments from the set of variables within the central bank's information set. Therefore, our instrumental variable set contains the constant, three lagged values of inflation and three lagged values of output gap.

We perform the GMM test robust to heteroskedasticity and autocorrelation of unknown form with Bartlett kernel where the bandwidth parameter is selected using the Newey and West's fixed bandwidth selection criterion. All tests for the validity of overidentifying restrictions (we have 4 more instruments than estimated parameters) couldn't reject the null hypothesis that the overidentifying restrictions are satisfied. From the evolution of the interest rate on the figure 3.2 in the Czech Republic we can detect a rapid increase in interest rates in 1997M4-1997M7, which was the result of the currency crisis in May 1997. Therefore we include four dummy variables which equal unity in one of the months in question and zero for every other month. This way we capture the negative effect of the instability. We also build in extra dummy variables in the case of Romania for the turbulent period in 1997-1998, which can catch the period of high inflation rate.

The parameter estimates based on the equation (1.1) are displayed in the table 3.2. In the Euro Area, as well as in all other countries, the point estimates of the inflation parameter are higly significant, but lower than one, which is not in line with an inflation-stabilizing policy. Turning to the output gap, the parameter estimates are significant at 5% significance level only in Hungary and Romania, but with the negative sign. So, the output gap either does not appear in the reaction function or enters the equation with the opposite sign, which is, again, not consistent with the main Taylor rule idea. The constant parameter is highly significant in all countries, but substantially larger than the benchmark coefficient 1.

Another problem with this estimation method is the presence of serial correlation, indicated by the very low Durbin-Watson statistic. If there is no serial correlation, the

DW statistic will be around 2; a DW statistic below about 1.5 is a strong indication of positive first order serial correlation, and in the worst case, it will be near zero. Our DW statistics for all counties lie within the range $(0.024, 0.196)$, which is an evident indication of the presence of serial correllation and thus may hint at a spurious regression.

Figure 3.1 provides a visual inspection of the real interest rate compared to the interest rate implied by the GMM estimates and the benchmark TR.

We can conclude that the simple Taylor rule (1.1) describes the central bank setting of the interest rate quite poorly in each country under consideration, including the EA. Moreover, the model suffers from serial correlation in the residuals. This can be dealt with by including lagged variables into the estimated equation. This is done in the dynamic version of the TR, which follows.

3.2.2 Estimation of the Dynamic Taylor Rule by GMM

We now proceed to the estimation of the dynamic version of the Taylor rule (1.2). We perform the test with the same set of instrumental variables and HAC options as in the estimation of the simple Taylor rule in the previous section. The J-statistic again does not reject that the overidentifying restrictions are satisfied. As indicated in the case of the simple TR, we include four dummy regressors in the case of the Czech Republic and 13 dummy regressors in Romania.

The estimated dynamic Taylor rule seems to fit the data better with the R-squared markedly higher and the standard error of the regression substantially lower in all countries. This is not a suprising result since the inclusion of the lagged dependent variable into the model helps eliminate serial correlation in the residuals. However, there is not a significant improvement in the coefficient estimates related to the simple Taylor rule estimates. The inflation parameters remain either smaller than one or insignifficant; the output gap parameters are of the wrong sign or insignificant. The γ parameters are significant ewerywhere except for the Slovak and Czech Repbulic and lie in the interval $(0.82, 0.97)$. But the implications of this parameters to the adjustment mechanisms seem rather questionable. Let's take, for instance, an example of Hungary. The estimated value of $\gamma = 0.948$ implies that it took almost thirteen months for only *half* of the intended adjustments to take place (to reach this conclusion we calculate the sum $\sum_{k=0}^{14}(1-\gamma)\gamma^k \doteq 0.5$). In the case of Poland, Romania, and the Euro Area, the lengths of the periods needed to cover half of the gap between the actual and intended interest rate are 4, 8, and 26 months, respectively. Although we agree that aggressive movements in interest-rate setting can bring instability to financial markets and central bank try to avoid them, these gradual adjustments, especially in Romania and the Euro Area, appear to be implausibly slow. This issue, in addition to the poor coefficient estimates, casts doubt on the appropriateness of the dynamic Taylor rule specified in 1.2.

3.2.3 Conclusion

Comparing the benchmark TR to the real data, it is hard to conclude that the central banks follow the benchmark monetary policy rule. When we replace the benchmark coefficients by our estimates, we find that such equation does not correspond with the Taylor rule requirements. Moreover, it appears to suffer from serially correlated residuals. Although the statistical properties of the dynamic version of the TR have improved, we still come to unsatisfactory results, since the coefficient estimates do not comply with the theoretical expectations.

A lot of researchers finish at this stage with conclusion based on the GMM estimates (e.g. Dolores [30]). As already mentioned, there are several problems using GMM, since GMM requires all the variables in the estimation to be stationary. If this is not the case, then the estimations do not have the usual properties and should be interpreted with some caution. Therefore, let us proceed to the examination of the time series properties of the variables included in the models and see whether the regression should not be considered rather spurious.

3.3 Tests for Stationarity

In this section we perform tests for stationarity and unit roots on the input time series. Firstly, we plot the series in order to visually inspect its behavior. From the preview 3.2 we can assume unit root behavior of the inflation and the interest rate in all countries, though the output gap seems to behave stationary.

To support the claim, we run the Augmented Dickey-Fuller and KPSS tests. The results are summarized in Table 3.3 and Table 3.4.

In the tests we include the intercept term. However, the results are found to be robust to the choice of deterministic components, since they do not change whether we include the constant and trend or not (not reported here). The lag length used in ADF is determined by Akaike Information Criterion.

The KPSS test here is performed with Bartlett kernel with the bandwith parameter selected by Newey and West's automatic bandwith selection.

Both KPSS and ADF tests confirm unit root behaviour of the interest rate at any conventional significance level in all countries.

Regarding the inflation rate, both ADF and KPSS test reach the same conclusion of inflation being I(1) at any significance level in the Slovak Republic and Hungary. At 1% significance both tests suggest difference stationary inflation also in the Czech Republic and Poland. However, the two tests develop conflicting results in the case of Romania - both ADF and KPSS reject their null at 1% siginficance level. The ADF test might have reduced power due to insufficient length of time series, or due to several structural breaks. We therefore consider inflation in Romania as I(1) as well. In the case of the Euro Area, the conclusions are conflicting again, just the other way round - neither of the tests can at 5% significance level reject it's null hypothesis, meaning there is not a conclusive evidence of stationarity. Therefore we are inclined to treat inflation in EA as I(1) as well.

Turning to the output gap, the KPSS cannot reject its null hypothesis of stationarity at any conventional significance level in any of the countries. The ADF agrees by rejecting its null hypothesis in all countries. This is a natural conclusion, which implies from the construction of the output gap series using the Hodrick-Prescott filter[2].

Summing up, we will proceed with the assumption that the inflation and interest rate are I(1), the output gap I(0), and that this assumption is valid for all the countries.

3.4 Treating Data as Non-Stationary

We next present an approach to the Taylor rule which takes the non-stationarity[3] of the data into account and which captures the dynamics of the interest rate, inflation, and output gap better.

According to Johansen and Juselius [22] a stationary variable can be used in a test for cointegration. A stationary covariate might enhance the power of the cointegration test and it controls for some of the deviations from the long-run replationship. Therefore we incorporate our stationary output gap into the following analysis.

3.4.1 Estimation of the Taylor Rule by VEC

To estimate the simple Taylor rule (1.1) by VEC, we first need to choose the number of lags for the unrestricted VAR model. We use a lag length determined by the Akaike information criterion. Next we use the Johansen procedure to determine the number of cointegrating vectors for the interest rate, inflation rate, and the output gap. The running of the Johansen tests necessitates the decision upon the inclusion of the deterministic trends. Since we expect our level data to exhibit linear trends, we include intercepts in the VAR. We also include intercepts in the cointegration vectors. In the case of the Czech Republic and Romania we build in dummies as exogenous variables into the model in order to capture the sudden instabilities in the variables (the periods for which we include dummies are 1997:05 - 1997:08 and 1997:02 - 1998:02 in the Czech Republic and Romania, respectively).

The results from the Johansen tests are displayed in the Table 3.5. We will study the results for the individual countries later.

[2]Although the output gap does not appear to contain unit root, it might still be non-stationary. The use of the Hodrick-Prescott filter might create artificial business cycles in the output gap variable, if the underlying industrial production series is non-stationary. As already mentioned, a cyclical variable does not need to have a mean constant over time.

[3]By non-stationarity we mean I(1) series.

The next step in our analysis is to estimate the vector error-correction model. This system consists of three equations, each describing the reaction of Δi_t, $\Delta \pi_t$, and Δx_t to deviations from the cointegrating relationship:

$$\begin{aligned}
\Delta i_t &= a_1(i_{t-1} - \alpha - \beta_\pi \pi_{t-1} - \beta_x x_{t-1}) + \sum_{k=1}^{p}(b_{1k}\Delta i_{t-k} + c_{1k}\Delta \pi_{t-k} + d_{1k}\Delta x_{t-k}) + e_1 \\
\Delta \pi_t &= a_2(i_{t-1} - \alpha - \beta_\pi \pi_{t-1} - \beta_x x_{t-1}) + \sum_{k=1}^{p}(b_{2k}\Delta i_{t-k} + c_{2k}\Delta \pi_{t-k} + d_{2k}\Delta x_{t-k}) + e_2 \\
\Delta x_t &= a_3(i_{t-1} - \alpha - \beta_\pi \pi_{t-1} - \beta_x x_{t-1}) + \sum_{k=1}^{p}(b_{3k}\Delta i_{t-k} + c_{3k}\Delta \pi_{t-k} + d_{3k}\Delta x_{t-k}) + e_3,
\end{aligned}$$

where p is the appropriate number of lags determined in the previous step. The cointegration relationship takes the form

$$i_t = \alpha + \beta_\pi \pi_t + \beta_x x_t,$$

where the normalization is chosen with respect to the interest rate (in the Czech Republic and Romania the equations are extended with the dummy variables and their coefficients).

The estimates of the cointegration vectors and the adjustmnent coefficients are summarized in the Table 3.7. For brevity, we only present the estimates of the cointegration vectors and the adjustment coefficients and do not include the estimations of the stationary dynamics parameters.

Now the analysis of the VEC estimation results for the individual countries follows.

3.4.2 The Slovak Republic

Results from the Johansen tests in the table 3.5 show that λ_{trace} rejects the null hypothesis of no cointegration vector at the 5% significance level, but could not reject its null of at most one cointegration vector at any conventional level. Thus, the λ_{trace} indicates 1 cointegrating relationship. According to λ_{max}, the null hypothesis of no cointegration could not be rejected at any conventional sigificance level, thus the cointegration relationship does not seem to be present. Since the two statistics yield conflicting results, we will assume that there exists one cointegrating vector and look at the interpretability of the estimated long-run relationship and the adjustment coefficients.

According to the results presented in the table 3.7 the estimated cointegration vector for the Slovak Republic is

$$i_t = -11.441 + 2.725\pi_t + 8.179x_t.$$

The estimated coefficients for the inflation and the output gap are both significant and of expected sign. The inflation coefficient is higher than one, which tallies with the spirit of the Taylor rule. The output coefficient is markedly higher than the Taylor's proposed value of 0.5. Such high value implies that the Slovak National Bank is more concerned about the output gap than the inflation. The constant represents the equilibrium real interest rate and is supposed to take the value around 2%. Thus, the value of -11.441 is too small.

Now consider the speed-of-adjustment coefficient estimates of the error-correcting model, which looks as follows:

$$\begin{aligned}
\Delta i_t &= 0.001(i_{t-1} + 11.441 - 2.725\pi_t - 8.179x_t) + \text{stationary dynamics} \\
\Delta \pi_t &= 0.009(i_{t-1} + 11.441 - 2.725\pi_t - 8.179x_t) + \text{stationary dynamics} \\
\Delta x_t &= 0.031(i_{t-1} + 11.441 - 2.725\pi_t - 8.179x_t) + \text{stationary dynamics}
\end{aligned}$$

We can see that while the inflation and the output gap adjust to last period's equilibrium error in the correct direction, the interest rate adjustment coefficient has the opposite sign. To shed more light on it, if the interest rate is 1 percentage point *higher* than that suggested by the long-run relationship, the estimate says that the interest rate *increases* even more by 0.001 of a percentage point, which means that the deviations from the long-run relationship is not corrected. On the other hand, the inflation and the output gap respond in the correct direction to restore the long-run equilibrium: if the inflation (output gap) is one pecentage point *higher* than that suggested by the lon-run relationship, the estimated coefficient 0.009 (0.031) suggests that the inflation (output gap) *decreases* by 2.725×0.009 (8.179×0.031) percentage points.

Nevertheless, we still have not considered the significance of the parameters. While the inflation and the output gap adjustment coefficiets are both significant at 5% level, the interest rate adjustment coefficient is very small and insignificant. The insignificance implies that the short-term interest rate is unresponsive to disequilibrium in the long-run relationship (i.e. the interest rate is weakly exogenous).

Broadly speaking, since most of the estimated cointegrating and adjustment parameters have the expected sign and meaningful values and those that do not are insignificant, we can conclude that Slovakia satisfies the traditional Taylor rule principle. Still, it puts too high a weight on the output gap relative to the inflation.

3.4.3 The Czech Republic

In the Czech Republic, the trace test rejects the null hypothesis of no cointegration and cannot reject the hypothesis of at most 1 cointegration vector, whereas the maximum eigenvalue test finds no cointegration at 5% significance level. Thus we conclude there might be a cointegration relationship among the variables and investigate its interpretability.

The estimated long-run relationship for the Czech Republic is

$$i_t = -0.532 + 1.235\pi_t + 3.818x_t.$$

The parameter fitted for the inflation is significant and close to the coefficient of 1.5 proposed by Taylor. The output gap coefficient is significant and positive, which corresponds with the nature of the TR, although the value is markedly larger than the proposed 0.5. The constant term is of the wrong sign, but insignificant.

Now let us study the adjustment coefficients. The deviations of the interest rate from the steady state have a wrong, but insignificant effect on the interest rate. The deviations of the inflation rate affects the inflation rate correctly, but is significant only at 10% significance level. Thus, most of the adjustment process is performed by the deviations in the output gap - the parameter 0.078 is higly significant and of correct sign.

The Czech Republic also appears to follow an optimal policy rule.

3.4.4 Poland

At 5% significance level, the trace statistic supports two cointegrating vectors, whereas the maximum eigenvalue supports the existence of only one. The two test statistics disagree with one another, therefore we examine the estimated cointegrating vector

$$i_t = 4.963 + 0.611\pi_t + 3.145x_t.$$

All the coefficients have the expected sign. However, the inflation coefficient violates the stability condition by being less than one.

Looking at the adjustment coefficients on the inflation and the output gap: since they are both insignificant, the short-term interest rate and the inflation does not respond to a deviation from the cointegrationg relationship. However, the output gap is estimated to adjust with a higly significant coefficient of the correct sign.

The estimated Taylor rule for Poland suffers from destabilizing small inflation coefficient.

3.4.5 Hungary

For Hungarian data, the two test statistics from the Johansen procedure agree on one cointegration relationship.

All three coefficients in the estimated cointegration relationship

$$i_t = 3.163 + 1.041\pi_t - 1.317x_t$$

are significant, but the ouptup gap coefficient is negative, contrary to theoretical predictions. However, the Hungarian Central Bank appears to react to the inflation in line with theory with the coefficient near unity, and the equilibrium interest rate also reaches an acceptable value.

Since a negative response to the output gap is inconsistent with a standard model of the Taylor rule, we do not believe that the reported equation is meaningful.

3.4.6 Romania

In Romania, both test statistics for the number of cointegration vectors conclude that there is one cointegration relationship

$$i_t = 5.884 + 0.693\pi_t + 2.256x_t$$

with highly significant inflation and output gap parameter estimations. The inflation coefficient is found to be smaller than unity which does not correspond with the nature of the Taylor rule. Moreover, the deviations of the inflation from the steady state have although small, but significant effect with a cointerintuitive sign. This provides an evidence that the inflation responds to a discrepancy from the equilibrium by moving in the wrong direction.

The estimate of the cointegrating vector is not supportive of the Taylor rule as a reasonable description of the Romanian economy due to small value of the inflation coefficient.

3.4.7 The Euro Area

The null of no cointegration can be rejected in favor of the alternative for both test statistics. There is no evidence of a second cointegrating vector.

The estimated cointegrating vector

$$i_t = 0.091 + 1.798\pi_t + 1.604x_t$$

yields significant positive coefficients for both inflation and output gap, and the inflation coefficient is above unity in line with a stabilizing policy rule. Interestingly, the coefficient estimate on the inflation rate is with 1.798 close to the value of 1.5 originally suggested by Taylor. Still, the equilibrium interest rate reaches a small value.

Turning to the adjustment coefficients, the interest rate and the output gap both respond to deviations from the equilibrium in the right direction, whereas the inflation appears to be weakly exogenous.

The estimated rule in the Euro Area appears to be consistent with the spirit of the original Taylor rule.

It is noteworthy that according to our estimates, the ECB appears to put less weight on the output gap compared to the CEE countries (except for Hungary where there is a destabilizing output gap coefficient). This implies that the CEE countries focused more on the output gap stability than the EA and performed more conservative policy strategy. On the other hand, the inflation coefficient in the EA is the second highest (after the Slovak Republic), which means that the ECB is more concerned about the inflation stability than most of the CEEC. This result is rather surprising, since one would expect that preparation for membership to the EU would imply stronger focus on inflation stability of the CEEC's central banks.

3.4.8 Estimation of the subperiods

We now estimate the monetary policy rules in the same set of countries, but for different time periods. This way we can explore whether our results are robust to the choice of different data span. The Visegrad countries (the Slovak Republic, the Czech Republic, Hungary, and Poland) were first focused on exchange rate targeting, but then gradually made their exchange rates more flexible and finally introduced inflation targeting. Such unstable and dynamic situation may have negatively influenced the estimation results. For the starting date of the subperiods we choose the year when the countries changed their monetary policy strategies and adopted inflation targeting, i.e. 1998 for the Czech Republic, Poland, and Slovakia and 2002 for Hungary. Romania never officially introduced inflation targeting, therefore we analyze the period beginnig with year 1998, which is the end of the turbulencies in Romanian inflation rate. For the starting year in the Euro Area we take the year of the euro introduction (1999).

We first perform unit-root (ADF) and stationarity tests (KPSS) on such shortened time series (not reported here). The results are found to be robust to the choice of the data range and we can continue with the assumption that the inflation and interest rate are I(1) and the output gap I(0). We then repeat the procedure of finding cointegration vector and finally estimate the VEC model. The results are shown in the Table 3.7.

Indeed, the inflation coefficient for the Slovak Republic increased and reached relatively high value, which indicates strong incentives for stable inflation. However, the counterintuitive sign for the output gap and implausibly high equilibrium interest rate hint at misspecified rule. The constant term is too high in the majority of the countries. While preparing for the membership to the EU, these transition countries had to manage to disinflation. One would therefore expect the decline in the subperiod equilibrium real interest rates compared to those estimated for the whole period. This is, however, true only in the case of Hungary and Romania; in other countries we can record substantial increase. With regard to the output gap, the estimates deteriorated in Hungary, Poland, and the Euro Area due to destabilizing coefficient. Both Romanian and Czech central banks react, according to the estimated rule, to the inflation and the output gap in the right direction, however, their inflation coefficients do not fulfill the above-unity requirement.

Due to unsatisfactory results for any of the countries we abandon the subperiod estimates and return to our original results. We compare our findings to those of other authors working with CEEC data.

3.5 Comparison of the results with the existing literature

There are only few papers on monetary policy rules in CEEC. This might be caused by the availability of only relatively short data or by unstable economic situation with several regime shifts. However, there are still some papers dealing with this issue. For example, Maria-Dolores [30] attempts to describe the monetary policy in the four Visegrad countries and the Euro Area in the period shorter than ours, from 1998 to 2003. She estimates three versions of the Taylor-type models by GMM: contemporaneous dynamic TR and its forward- and backward-looking versions. She finds the bacward-looking version to predict the best. Contrary to our GMM estimates she finds support for the Taylor rule in the Czech Republic, Poland, Hungary, and the Euro Area with both the inflation and the output gap coefficients close to those of the benchmark TR. On the other hand, Slovakia does not seem to move the short-term interest rate as suggested by Taylor.

The same set of countries is analyzed by Paez-Farell [40], but for different time periods. This paper specifies six different models and uses GMM to determine if any of the models provide a good description of interest rate setting behaviour in the Visegrad countries. The paper finds that exchange rates play an important role in three of the four countries' policy and that Poland and Hungary are the most aggressive in responding to inflation, with a coefficient (ignoring exchange rate effects) on the inflation rate of 1.4 and 1.2, respectively.

However, these papers do not test the time series properties and thus run a risk of spurious results.

Another study by Frömmel, Garabedian, and Schobert [34] analyzes the Taylor rule's validity in the five CEEC, applying the cointegration methodology. They cover the period similar to ours, 1994:1 - 2008:8, and estimate the simple Taylor rule augmented with the exchange rate. For this period we have estimated the Taylor rule to work well in both the Slovak and Czech Republic, with relatively strong focus on the output gap. The authors in [34] find inflation coefficient estimates above unity only in the Czech Republic, with the output gap coefficients insignificant in all countries. In the second part of the paper they estimate the Taylor rule for the periods characterized by inflation targeting, which is consistent with our choice of the subperiods. While we found the above-unity inflation coefficient only in the Slovak Republic, their results changed remarkably with the Czech, Polish, and Romanian inflation coefficient above unity. This is in line with the inflation oriented policy in this subperiod. However, their output gap remains insignificant, meaning that it is of low importance over this period.

Conclusion

Most of the literature on the estimation of Taylor-type reaction functions does not pay much attention to the properties of the time series. Stationarity of the series is rather assumed than tested. In this thesis we first follow this assumption and estimate the simple Taylor rule using GMM. We find it difficult to track the behavior of any of the countries' central banks with a simple Taylor rule reaction function. Moreover, such simple rule specification suffers from econometric shortcomings. Although this can be dealt with by incorporating the dynamic version of the Taylor rule, the interpretability of the coefficient estimates remains poor.

If we test the time series we come to the conclusion that some of our variables should be treated as unit root. Therefore the TR estimation is carried out with the alternative approach, which provides a natural framework for the analysis of both long- and short-run behaviour. We use an approach called Vector error correction model. For this model to be specified, a cointegration relationship (which represents the TR) must exist.

Compared to the GMM estimates, we see that the cointegration approach is more in line with theory - in the Slovak Republic, the Czech Republic, and the Euro Area we have found a meaningful estimation of the Taylor rule, with a strong commitment to output gap stabilisation. In Hungary the estimations seem to perform rather poorly and do not comply with the theory. The remaining two countries suffer from destabilizing inflation coefficients.

We also perform an analysis on the subperiods characterized by the official commitments to inflation targeting. We expect the inflation coefficients to increase, but these expectations do not correspond with the data and we are not able to find a convincing description of the interest rate setting over this periods. Since there are not much literature working with CEEC data, it is hard to conclude whether our findings are in line with those of other authors.

Bibliography

[1] Box, G. E. P., and Jekins, G. M. Time series analysis: Forecasting and control. *San Francisco: Holden Day* (1970).

[2] Brooks, C. *Introductory Econometrics for Finance*. Cambridge University Press, 2002.

[3] Bunzel, H., and Enders, W. Is the Taylor rule missing? A statistical investigation. Staff General Research Papers 12301, Iowa State University, Department of Economics, 2005.

[4] Carlin, W., and Soskice, D. *Macroeconomics: imperfections, institutions and policies*. Oxford University Press, 2005.

[5] Carstensen, K., and Colavecchio, R. Did the revision of the ecb monetary policy strategy affect the reaction function? Kiel Working Papers 1221, Kiel Institute for the World Economy, 2004.

[6] Clarida, R., Gali, J., and Gertler, M. Monetary policy rules in practice: Some international evidence. NBER Working Papers 6254, National Bureau of Economic Research, Inc, 1997.

[7] Dickey, D., and Fuller, W. A. Distribution of the estimates for autoregressive time series with a unit root. *Journal of the American Statistical Association 74* (1979), 427–31.

[8] Enders, W. *Applied econometric time series*. Wiley, 2003.

[9] Enders, W., Lee, J., and Strazicich, M. Threshold cointegration tests of the taylor rule without the nuisance parameters. - (2007).

[10] Engle, R. F., and Granger, C. W. J. Co-integration and error correction: Representation, estimation, and testing. *Econometrica 55*, 2 (1987), 251–76.

[11] Engle, R. F., and Yoo, B. S. Forecasting and testing in co-integrated systems. *Journal of Econometrics 35*, 1 (1987), 143–159.

[12] Florens, C., and Jondeau, E., and Bihan, H. L. Assessing gmm estimates of the federal reserve reaction function. Econometrics 0111003, EconWPA, 2001.

[13] Friedman, M. A program for monetary stability. *New York* (1960).

[14] Gerald P. Dwyer, J. Rules and discretion in monetary policy. *Review* (1993), 3–13.

[15] Goodhart, C., and Hofmann, B. Asset prices and the conduct of monetary policy. Royal Economic Society Annual Conference 2002 88, Royal Economic Society, 2002.

[16] Granger, C. W. J., and Newbold, P. Spurious regressions in econometrics. *Journal of Econometrics 2*, 2 (1974), 111–120.

[17] Greene, W. *Econometric analysis.* Prentice Hall Upper Saddle River, NJ, 2003.

[18] Hamilton, J. *Time series analysis.* Princeton university press, 1994.

[19] Hansen, L. P. Large sample properties of generalized method of moments estimators. *Econometrica 50*, 4 (1982), 1029–54.

[20] Hendry, D., and Juselius, K. Explaining cointegration analysis: Part I. *Institute of Economics, University of Copenhagen* (1999).

[21] Hodrick, R., and Prescott, E. Postwar business cycles. *Journal of Money, Credit, and Banking 29* (1997), 1–16.

[22] Johansen, S., and JUselius, K. Testing structural hypothesis in a multivariate cointegration analysis of the PPP and the UIP for UK. *Journal of Econometrics 53* (1992).

[23] Johnston, J., and DiNardo, J. *Econometric methods.* 1984., 1972.

[24] Judd, J., and Rudebusch, G. Taylor's Rule and the Fed: 1970-1997. *Economic Review-Federal Reserve Bank of San Francisco* (1998), 3–16.

[25] Kennedy, P. *A guide to econometrics.* MIT press, 2003.

[26] Kozicki, S. How useful are Taylor rules for monetary policy? *Economic Review-Federal Reserve Bank of Kansas City 84* (1999), 5–34.

[27] Kwiatkowski, D., Phillips, P., and Schmidt, P. Testing the null hypothesis of stationarity against the alternative of unit root: How sure are we that economic time series have a unit root? Papers 8905, Michigan State - Econometrics and Economic Theory, 1990.

[28] Levin, A., Wieland, V., and Williams, J. C. Robustness of simple monetary policy rules under model uncertainty. NBER Working Papers 6570, National Bureau of Economic Research, Inc, 1998.

[29] MacKinnon, J. G. Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics 11*, 6 (1996), 601–18.

[30] Maria-Dolores, R. Monetary policy rules in accession countries to eu: Is the taylor rule a pattern? *Economics Bulletin 5*, 7 (2005), 1–16.

[31] McCallum, B. T. Robustness properties of a rule for monetary policy. *Carnegie-Rochester Conference Series on Public Policy 29*, 1 (1988), 173–203.

[32] McCallum, B. T., and Nelson, E. Nominal income targeting in an open-economy optimizing model. Seminar Papers 644, Stockholm University, Institute for International Economic Studies, Aug. 1998.

[33] Mesároš, M. *Menová politika nových členských krajín EU.* Diplomová práca FMFI UK, 2006.

[34] Michael, F., Franziska, S., and Garo, G. Monetary policy rules in central and eastern europe. Diskussionspapiere der Wirtschaftswissenschaftlichen Fakultät der Universität Hannover dp-341, Universität Hannover, Wirtschaftswissenschaftliche Fakultät, 2006.

[35] Neupauerova, M. The optimal monetary rule for the Slovak republic. Working Papers 200616, Faculty of Economics, Department of Economics, 2006.

[36] Nyberg, D. Should exchange rates be ignored in the setting of monetary policy? Research Papers in Economics 2002:8, Stockholm University, Department of Economics, 2002.

[37] Orphanides, A. Monetary policy rules based on real-time data. *American Economic Review 91*, 4 (2001), 964–985.

[38] Orphanides, A. Taylor rules. *Federal Reserve Board Finance and Economics Discussion Series*, 2007-18 (2007).

[39] Paez-Farrell, J. Understanding monetary policy in central european countries using taylor-type rules: the case of the visegrad four. *Economics Bulletin 5*, 3 (2007), 1–11.

[40] Paez-Farrell, J. Understanding monetary policy in central european countries using taylor-type rules: the case of the visegrad four. *Economics Bulletin 5*, 3 (2007), 1–11.

[41] Perez-Quiroz, G., and Sicilia, J. Is the European central bank (and the United States Federal Reserve) predictable? *ECB Working Paper Series No. 192* (2002).

[42] Phillips, P., and Perron, P. Testing for a unit root in time series regression. *Biometrika 75* (1988), 335–346.

[43] Rudebusch, G. D. Term structure evidence on interest rate smoothing and monetary policy inertia. Working Papers in Applied Economic Theory 2001-02, Federal Reserve Bank of San Francisco, 2001.

[44] Schnabel, G., and Gerlach, S. The Taylor rule and interest rates in the EMU area: a note. BIS Working Papers 73, Bank for International Settlements, 1999.

[45] Soren, J. Statistical analysis of cointegration vectors. *Journal of Economics dynamics and control 12* (1988), 231–54.

[46] Taylor, J. B. Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy 39*, 1 (1993), 195–214.

[47] Taylor, J. B. *Monetary Policy Rules*. The University of Chicago press, 1999.

[48] Ullrich, K. A comparison between the Fed and the ECB: Taylor rules. ZEW Discussion Papers 03-19, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research, 2003.

[49] Welz, P., and Österholm, P. Interest rate smoothing versus serially correlated errors in taylor rules: Testing the tests. Working Paper Series 2005:14, Uppsala University, Department of Economics, 2005.

Appendix

Table 3.1: The GMM estimates of the simple TR (1.1)

	SK	CZ	HU	PL	RO	EA
α	5.875*** (1.184) [0.000]	2.297*** (0.619) [0.000]	3.304*** (0.434) [0.000]	6.095*** (0.637) [0.000]	22.159*** (1.504) [0.000]	2.398*** (0.591) [0.000]
β_π	0.223** (0.107) [0.038]	0.741*** (0.124) [0.000]	0.955*** (0.048) [0.000]	0.826*** (0.036) [0.000]	0.301*** (0.029) [0.000]	0.683** (0.300) [0.024]
β_x	-0.181 (0.424) [0.669]	0.060 (0.213) [0.776]	-0.330** (0.130) [0.012]	0.116 (0.206) [0.574]	-0.254** (0.117) [0.032]	0.178 (0.209) [0.395]
R-squared	0.077	0.556	0.652	0.678	0.104	0.170
S.E. of regression	4.104	3.264	3.025	3.413	11.067	1.472
DW statistic	0.048	0.174	0.196	0.081	0.076	0.024
J-statistic	0.004	0.018	0.015	0.030	0.089	0.059
p-J	0.94	0.90	0.57	0.94	0.77	0.24

Notes:

Standard errors are reported in parentheses below the coefficients' estimates; p-values are reported in brackets.

DW statistic is the Durbin-Watson statistic, which tests for serial correlation.

J-statistic is the minimized value of the objective function; p-J is the p-value of the test statistic with the null hypothesis that the overidentifying restrictions are satisfied.

*, **, and *** denote the rejection of the null hypothesis at the 10 %, 5%, and 1% significance level, respectively.

The estimated period is 1993:3-2008:10 with number of observations 188 everywhere except in Romania, where the estimation period is 1995:7 - 2006:12 with 138 observations.

Table 3.2: The GMM estimates of the dynamic TR (1.2)

	SK	CZ	HU	PL	RO	EA
α	5.719***	2.379***	4.247**	5.408***	18.29***	2.692
	(1.204)	(0.672)	(2.075)	(0.881)	(5.334)	(2.216)
	[0.000]	[0.000]	[0.042]	[0.000]	[0.002]	[0.2262]
β_π	0.205*	0.725***	0.645***	0.833***	0.184***	0.463
	(0.116)	(0.134)	(0.194)	(0.039)	(0.061)	(1.089)
	[0.079]	[0.000]	[0.001]	[0.000]	[0.005]	[0.6701]
β_x	-0.369	0.078	0.941	0.440*	-0.173	1.400
	(0.695)	(0.268)	(0.770)	(0.264)	(0.322)	(1.589)
	[0.595]	[0.7713]	[0.223]	[0.097]	[0.591]	[0.379]
γ	0.657	0.316	0.948***	0.828***	0.912***	0.973***
	(0.585)	(0.298)	(0.019)	(0.086)	(0.098)	(0.030)
	[0.262]	[0.290]	[0.000]	[0.000]	[0.000]	[0.000]
R-squared	0.867	0.773	0.986	0.993	0.972	0.990
S.E. of regression	1.562	2.355	0.888	0.788	1.936	0.158
J-statistic	0.007	0.013	0.022	0.021	0.014	0.007
p-J	0.84	0.96	0.67	0.55	0.99	0.82

Notes:

Standard errors are reported in parentheses below the coefficients' estimates; p-values are reported in brackets.

J-statistic is the minimized value of the objective function; p-J is the p-value of the test statistic with the null hypothesis that the overidentifying restrictions are satisfied.

*, **, and *** denote the rejection of the null hypothesis at the 10 %, 5%, and 1% significance level, respectively.

The estimated period is 1993:3-2008:10 with number of observations 188 everywhere except in Romania, where the estimation period is 1995:7 - 2006:12 with 138 observations.

Figure 3.1: Comparison of the interest rates implied by the GMM estimates of the simple TR 1.1, the benchmark rule and the real data

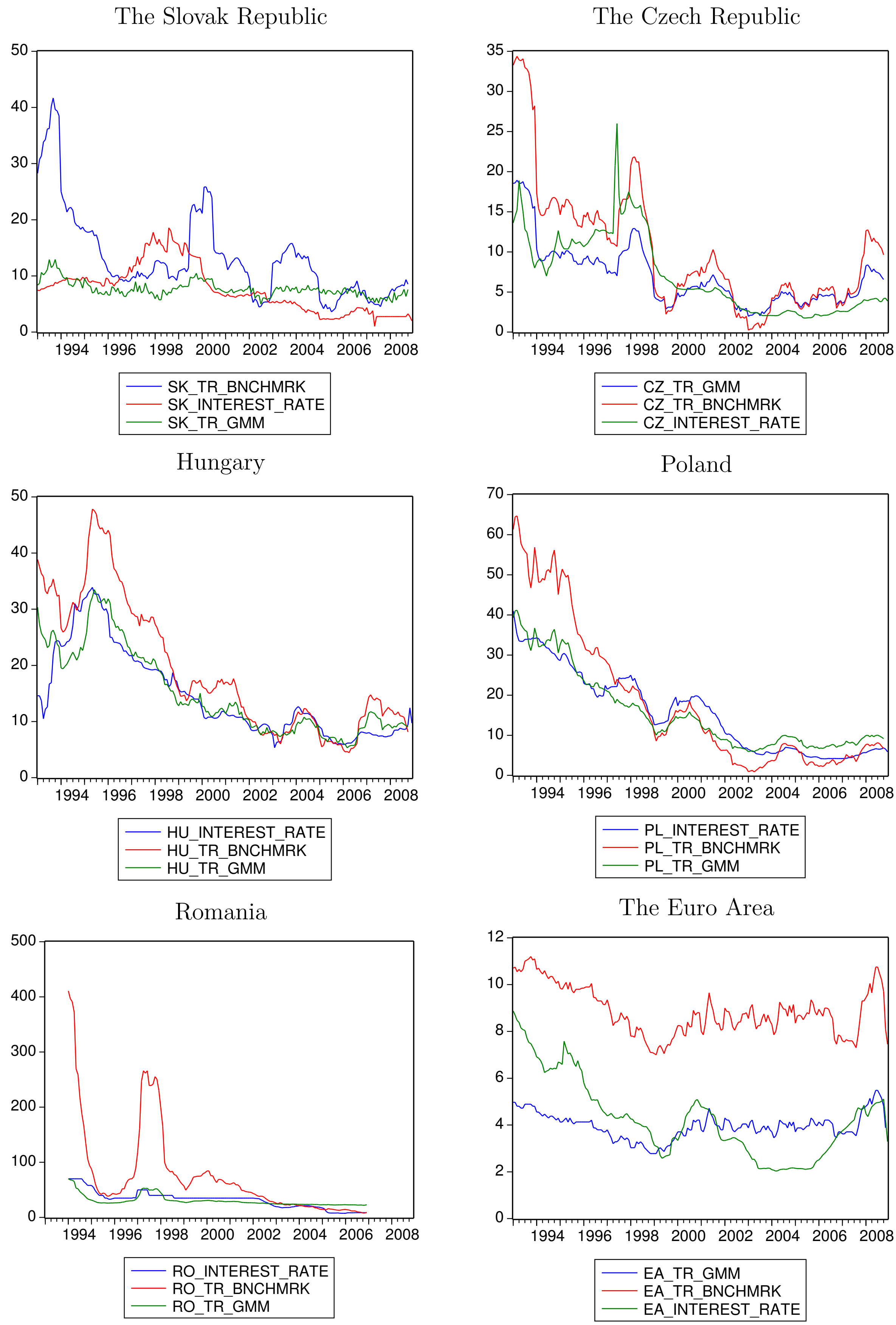

Figure 3.2: Prewiew of the input time series for all countries

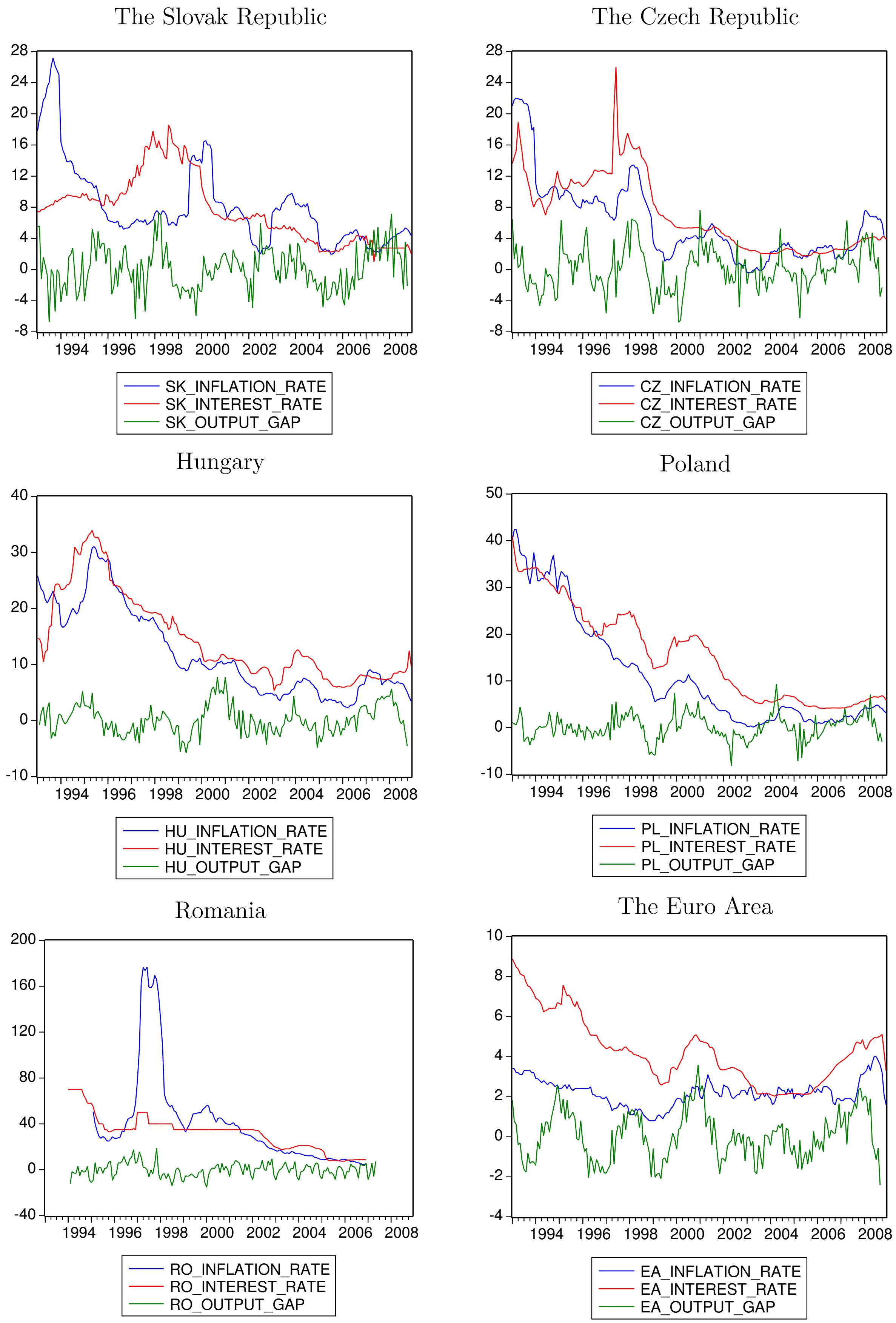

Figure 3.3: Descriptive Statistics of the Data

The Slovak Republic

	π	i	x
Mean	8.103	7.684	0.123
Median	6.722	7.060	0.0714
Maximum	27.161	18.570	7.227
Minimum	1.958	1.023	-6.732
Std. Dev.	5.316	4.218	2.795
Observ.	190	190	190

The Czech Republic

	π	i	x
Mean	6.100	7.067	0.097
Median	4.200	5.340	0.033
Maximum	22.01	25.990	7.599
Minimum	-0.374	1.750	-6.792
St.Dev.	5.174	4.925	2.738
Observ.	190	190	190

Hungary

	π	i	x
Mean	12.072	14.637	0.152
Median	9.395	11.220	0.035
Maximum	31.034	33.900	7.775
Minimum	2.361	5.350	-5.768
Std. Dev.	7.742	7.787	2.605
Observ.	189	189	189

Poland

	π	i	x
Mean	11.556	15.671	0.078
Median	6.287	14.850	0.149
Maximum	42.453	41.000	9.329
Minimum	0.092	4.130	-8.180
Std. Dev.	11.785	10.070	2.656
Observ.	190	190	190

Romania

	π	i	x
Mean	39.944	29.014	0.212
Median	29.030	35.000	0.518
Maximum	176.610	55.000	18.993
Minimum	4.650	7.500	-15.386
Std. Dev.	40.225	11.881	5.996
Observ.	143	143	143

The Euro Area

	π	i	x
Mean	2.197	4.275	0.026
Median	2.200	4.130	-0.019
Maximum	4.000	8.875	3.585
Minimum	0.800	2.030	-3.980
Std. Dev.	0.656	1.692	1.240
Observ.	190	190	190

Notes:
π – inflation rate
i – interest rate
x – output gap

Table 3.3: ADF test results

ADF		interest rate	inflation rate	output gap
SK	no of lags	0	1	2
	test statistics	-0.776	-2.465	-3.851***
CZ	no of lags	4	1	1
	test statistics	-1.783	-3.246**	-4.890***
HU	no of lags	1	1	1
	test statistics	-0.925	-1.264	-4.160 ***
PL	no of lags	3	3	1
	test statistics	-1.258	-3.373**	-4.209 ***
RO	no of lags	0	1	0
	test statistics	-2.020	-4.172***	-4.654 ***
EA	no of lags	1	3	1
	test statistics	-2.522	-2.868 *	-0.600 ***

Notes:

Test statistic is the sample value of the t-statistic for the null hypothesis $\gamma = 0$.

The number of observations is 188 in all countries except for Romania, where the observation number is 138.

With given number of observations, the DF critical values at the 1%, 5%, and 10% significance levels are -3.456, -2.877, -2.575 except in Romania, where the critical values are -3.473, -2.88, -2.577, respectively.

The superscripts *, **, and *** denote the rejection of the null hypothesis of unit root at the 10 %, 5%, and 1% significance level, respectively.

Table 3.4: KPSS test results

KPSS		interest rate	inflation rate	output gap
SK	no of lags	11	10	9
	test statistics	1.042***	0.888***	0.080
CZ	no of lags	11	10	9
	test statistics	1.269***	1.176***	0.058
HU	no of lags	11	11	10
	test statistics	1.263***	1.3924***	0.077
PL	no of lags	11	11	9
	test statistics	1.572***	1.405***	0.048
RO	no of lags	10	9	9
	test statistics	1.277***	0.883***	0.070
EA	no of lags	11	10	10
	test statistics	1.016***	0.265	0.033

Notes:

The number of observations is 188 in all countries except for Romania, where the observation number is 138.

The KPSS critical values at the 1%, 5%, and 10% significance levels are 0.739, 0.463, 0.347.

The superscripts *, **, and *** denote the rejection of the null hypothesis of unit root at the 10 %, 5%, and 1% significance level, respectively.

Table 3.5: Johansen tests for the number of cointegrating vectors

	Lags	H_0	λ_{trace}	p-value	CE_{trace}	λ_{max}	p-value	CE_{max}
		$n = 0$	30.313**	0.043		18.796	0.102	
SK	3	$n \leq 1$	11.517	0.181	1	11.038	0.15	0
		$n \leq 2$	0.4793	0.488		0.479	0.488	
		$n = 0$	38.223**	0.022		21.033*	0.074	
CZ	4	$n \leq 1$	17.189	0.125	1	14.802*	0.073	0
		$n \leq 2$	2.386	0.700		2.386	0.700	
		$n = 0$	43.112***	0.001		28.411***	0.004	
HU	1	$n \leq 1$	14.700*	0.065	1	13.914*	0.056	1
		$n \leq 2$	0.790	0.373		0.790	0.373	
		$n = 0$	48.001***	0.001		26.286**	0.013	
PL	3	$n \leq 1$	21.715**	0.031	2	13.662	0.108	1
		$n \leq 2$	8.052*	0.081		8.052*	0.081	
		$n = 0$	34.573**	0.013		22.670**	0.030	
RO	4	$n \leq 1$	11.903	0.161	1	11.308	0.139	1
		$n \leq 2$	0.595	0.440		0.595	0.440	
		$n = 0$	36.983***	0.006		22.692**	0.029	
EA	2	$n \leq 1$	14.291*	0.075	1	9.431	0.252	1
		$n \leq 2$	4.859	0.027		4.859	0.027	

Notes:
'Lags' reffer to number of lags in first differences.
'H_0' denotes the null hypothesis of the test statistics λ_{trace} and λ_{max}, where n is the number of cointegrating vectors.
'CE_{trace}' and 'CE_{max}' denote the number of cointegrating equations indicated by the trace and max. eigenvalue statistics at the 5% significance level.
*, **, and *** denote the rejection of the null hypothesis at the 10%, 5%, and 1% significance level, respectively.
The 0.05 critical values for λ_{trace} and λ_{max} for the null hypotheses stated in the table are 29.797, 15.494, 3.841, and 21.131, 14.264, 3.841, respectively.
The estimated period is 1993:3-2008:10 with number of observations 188 everywhere except in Romania, where the estimation period is 1995:7 - 2006:12 with 138 observations.

Table 3.6: Estimations of the cointegrating vectors and the adjustment coefficients for the whole periods

	Lags	α	β_π	β_x	a_1	a_2	a_3
		-11.441	2.725**	8.179***	0.001	0.009**	0.031***
SK	3	(8.577)	(0.909)	(2.179)	(0.002)	(0.004)	(0.008)
		[-1.333]	[2.997]	[3.753]	[0.625]	[2.269]	[3.698]
		-0.532	1.235**	3.818***	0.004	0.013*	0.078***
CZ	4	(2.854)	(0.416)	(0.938)	(0.003)	(0.006)	(0.018)
		[-0.186]	[2.965]	[4.070]	[1.227]	[2.075]	[4.348]
		3.163**	1.041***	-1.317***	-0.017	0.053***	-0.083**
HU	1	(1.316)	(0.093)	(0.313)	(0.016)	(0.012)	(0.034)
		[2.402]	[11.104]	[-4.203]	[-1.089]	[4.327]	[-2.422]
		4.963**	0.611***	3.145***	-0.012*	-0.012	0.090***
PL	3	(1.913)	(0.127)	(0.667)	(0.006)	(0.008)	(0.021)
		[2.594]	[4.804]	[4.710]	[-1.885]	[-1.492]	[4.171]
		5.884	0.693***	2.256***	-0.047***	-0.002**	0.093
RO	4	(4.257)	(0.122)	(0.650)	(0.013)	(0.000)	(0.041)
		[1.382]	[5.639]	[3.468]	[-3.433]	[-2.335]	[2.250]
		0.091	1.798**	1.604***	-0.016**	-0.002	0.076**
EA	2	(1.518)	(0.686)	(0.397)	(0.005)	(0.007)	(0.026)
		[0.060]	[2.621]	[4.031]	[-2.876]	[-0.294]	[2.857]

Notes:

Standard errors are in ( ), t-statistics in [ ].

'Lags' reffer to number of lags in first differences.

*, **, and *** denote parameter significance at the 10%, 5%, and 1% significance level, respectively.

The estimated period is 1993:3-2008:10 with number of observations 188 everywhere except in Romania, where the estimation period is 1995:7 - 2006:12 with 138 observations.

Table 3.7: Estimations of the cointegrating vectors and the adjustment coefficients for the subperiods

	Lags	α	β_π	β_x	a_1	a_2	a_3
SK	2	27.087**	7.420***	-5.703**	0.009***	0.010**	-0.018**
		(11.405)	(1.776)	(2.397)	(0.002)	(0.004)	(0.008)
		[2.374]	[4.176]	[-2.378]	[3.543]	[2.568]	[-2.223]
CZ	2	1.377**	0.569***	0.236	-0.064***	0.044***	0.004
		(0.528)	(0.138)	(0.176)	(0.009)	(0.020)	(0.084)
		[2.604]	[4.123]	[1.332]	[-7.061]	[2.125]	[0.057]
HU	1	-1.159	-1.601***	1.751***	0.003	0.072***	-0.238***
		(1.899)	(0.335)	(0.283)	(0.023)	(0.021)	(0.068)
		[-0.610]	[5.226]	[-5.566]	[0.139]	[3.338]	[-3.459]
PL	1	14.627	-2.930	13.547***	-0.000	-0.003**	0.017**
		(11.03)	(1.977)	(3.037)	(0.001)	(0.001)	(0.006)
		[1.325]	[-1.481]	[4.459]	[-0.293]	[-2.500]	[2.960]
RO	1	4.936**	0.835***	1.333***	-0.004	0.201***	0.125**
		(2.234)	(0.065)	(0.298)	(0.006)	(0.028)	(0.042)
		[2.209]	[12.77]	[4.467]	[-0.723]	[7.129]	[2.962]
EA	3	24.094***	-9.8633***	0.775	-0.000	-0.008**	-0.051***
		(4.288)	(1.950)	(1.051)	(0.002)	(0.003)	(0.011)
		[5.617]	[-5.055]	[0.737]	[-0.354]	[-2.295]	[-4.512]

Notes:

Standard errors are in ( ), t-statistics in [ ].

'Lags' reffer to number of lags in first differences.

*, **, and *** denote parameter significance at the 10%, 5%, and 1% significance level, respectively.

The estimated period is 1998:1-2008:10 with number of observations 130 in the Slovak Republic, Czech Republic, and Poland; in Romania 1998:1-2006:10 with 108 observations; in Hungary 2002:1 - 2008:12 with 82 observations; in the EA 1999:1-2006:10 with 118 observations.