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LEARNING DYNAMICS AND THE RATIONALITY OF INFLATION EXPECTATIONS IN CEE COUNTRIES

Abstract. *This paper investigates the empirical validity of two well-known approaches to modelling expectations in economic literature, i.e. rational expectations and adaptive learning. Survey data on consumers' inflation expectations for four emerging Central and Eastern European economies with an inflation targeting monetary policy regime, i.e. Romania, Czech Republic, Poland and Hungary, is used. The empirical evidence doesn't support the rationality hypothesis of inflation expectations. In case of adaptive learning approach, the results suggest that constant gain learning algorithm provides a better description of inflation expectations than the recursive least squares algorithm, a possible explanation being the fact that it allows economic agents to incorporate structural changes, frequent in emerging economies, faster. Also there is evidence that consumers from Romania and Hungary use simple models to forecast inflation, that includes only a constant and the lagged inflation as determinants, while in case of Poland and Czech Republic the best fit is obtained for models that also includes other explanatory variables.*

Key words**:** *inflation expectations, rationality, adaptive learning.*

JEL Classification: D84, E31, E37

1. Introduction

Expectations play a prominent role in economic theories due to their often substantial impact in the process of agents' decision making. For example, the permanent income hypothesis stresses the role of expected future incomes[1], the New Keynesian Phillips Curve relates the current inflation to real marginal cost and expected inflation[2], the uncovered interest rate parity condition states that the difference in interest rates between two countries is equal to the expected change in

[1] See Ţigănescu and Roman (2005) for a more recent discussion of the subject.
[2] See Muraraşu (2015) for a study on the impact of forward looking expectations in the context of a reduced form hybrid New Keynesian Phillips Curve. The econometric estimation is performed for the same countries as the ones considered in the current analysis.

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the exchange rate between the countries' currencies. Many other examples can be considered.

Since the seminal works of Lucas (1976) and Sargent and Wallace (1975), the standard methodology for modelling expectations in both microeconomics and macroeconomics has been to assume rational expectations. However, the empirical evidence usually does not give much support to this hypothesis, given the strong assumptions underlying it[3] (see, for example, Łyziak (2013a), Weber (2010)).

Therefore alternative ways for modelling expectations have been considered in the economic literature. One of the most promising is the adaptive learning approach in which agents are supposed to have a more limited degree of knowledge, i.e. bounded rationality, and to learn over time about the impact of different factors on the variables of interest. Evans and Honkapohja (2001) offer a comprehensive introduction to adaptive learning models.

There are several reasons why the study of adaptive learning dynamics may be important in practice. First of all, it provides a micro-foundation for the rational expectations hypothesis by offering insights regarding the way in which agents may acquire such expectations (e.g. Bray (1982)). Secondly, it can be used as a selection criterion among multiple rational expectations equilibria by considering only those ones that are stable under learning. Woodford (1990) demonstrates that it is possible for sunspot solutions to be learned by agents in the context of the overlapping generations' model of money. Furthermore, this form of bounded rationality can be used in explaining observed dynamics of macroeconomics and financial variables as shown, among others, by Slobodyan and Wouters (2012).

The objective of this paper is to test the empirical validity of rational expectations hypothesis and adaptive learning approach in explaining expectations of consumers from emerging economies of Central and Eastern Europe, these countries having received little attention in the adaptive learning literature. Given some specific features of emerging economies, namely frequent policy changes, less reliable data series, considering an adaptive learning methodology for modelling expectations may prove to be a more suitable approach than the rational expectations assumption. Data on consumers' inflation expectations for Romania, Czech Republic, Poland and Hungary is used. These four countries from Central and Eastern Europe are new European Union member states with an explicit inflation targeting monetary policy regime, so understating the formation of inflation expectations is of crucial importance for policymakers.

The remainder of the paper is organized as follows: in section 2 an overview of the data is provided; an assessment of the degree of rationality of inflation expectations is performed in section 3; the adaptive learning approach is described

[3] The rational expectations hypothesis implies that agents fully know the structure of the economy, the values of the structural parameters that govern the relationships between the economic variables, as well as the distribution of any exogenous shock. These assumptions allow them to use all available information in an optimal way, so deviations from perfect foresight are only random.

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in section 4, which also presents an analysis of the fit of simple learning rules with the data; finally, section 5 concludes.

2. Data

The paper uses data on consumers' inflation expectations derived from the European Commission's (EC) Consumer Survey. Question number 5 and 6 from the survey, which deal with the perceived and the expected inflation rate, are of interest for the analysis conducted here. Table 1 shows the exact wording of both questions and the possible answers for the respondents:

Table 1. Questions 5 and 6 from the European Commission's Consumer Survey

Q5: How do you think that consumer prices have developed over the last 12 months? They have…	Q6: By comparison with the past 12 months, how do you expect consumer prices to develop over the next 12 months? They will…
Risen a lot Risen moderately Risen slightly Stayed about the same Fallen Don't know	Rise a lot Rise moderately Rise slightly Stay about the same Fall Don't know

Source: EC consumer survey

For comparability reasons, the sample under analysis for each country includes only the inflation targeting monetary policy regime[4]. Taking into account data availability[5], the time span is May 2005 - October 2016 for Romania, January 2001 - October 2016 for Czech Republic, May 2001 - October 2016 for Poland and June 2001 - October 2016 for Hungary, respectively.

Figure 1 shows monthly data for annual CPI inflation rate, as well as the balance statistics of consumers' opinions on perceived (BS^p) and expected (BS^e) inflation rate, determined by the EC as the difference between the percentages of respondents giving positive and negative replies:

$$BS^{p/e} = \left(PP^{p/e} + 0.5 \cdot P^{p/e}\right) - \left(0.5 \cdot M^{p/e} + MM^{p/e}\right) \quad (1)$$

[4] From the four countries analysed, the Romania was the last one to adopt the inflation targeting (IT) monetary policy regime in August 2005. The Czech Republic adopted it in January 1998, Poland in January 1999 and Hungary in June 2001.

[5] Although for Hungary the survey data is available since February 1993, for Czech Republic the survey has been conducted, on a regular basis, since January 2001, while in case of Romania and Poland only since May 2001.

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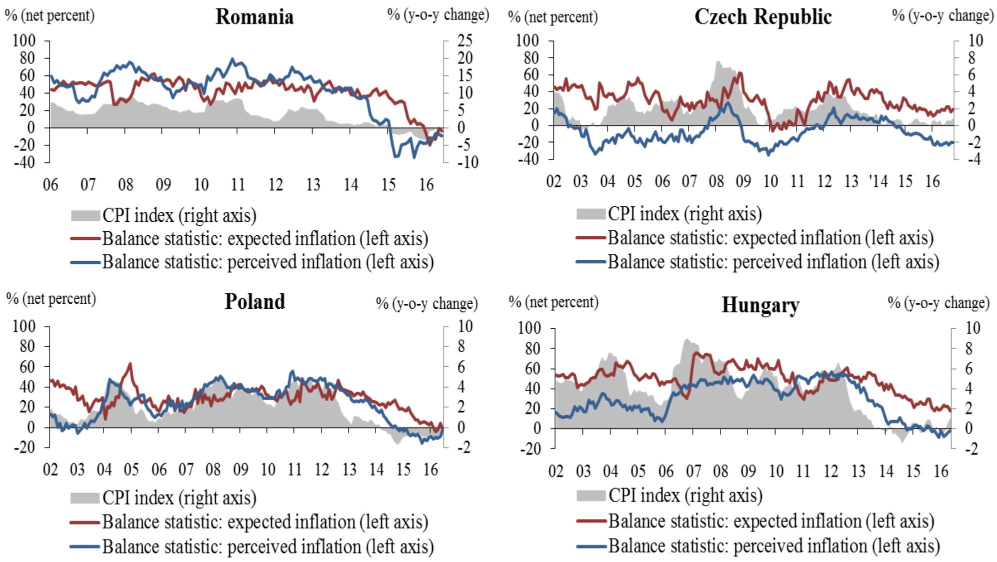
where $PP^{p/e}$ represents the fraction of respondents perceiving/expecting a high inflation, $P^{p/e}$ the fraction of respondents perceiving/expecting a moderate increase in prices, $M^{p/e}$ the fraction of respondents not perceiving/expecting a movement in prices, while $MM^{p/e}$ represents the fraction of respondents perceiving/expecting a decrease in prices.

Figure 1. CPI inflation rate and survey data on consumers' perceived and expected inflation rate



Source: EC, NBR, CNB, NBP and MNB data

Note: The balance statistic of consumers' opinions on expected inflation rate has been shifted forward 12 months, i.e. the actual inflation rate and the balance statistic of consumers' opinions on perceived inflation rate, respectively, are compared with the expectation for the current period that has been formed 12 months before. Due to the shifting the plotted time period changes to May 2006 - October 2016 for Romania, January 2002 - October 2016 for Czech Republic, May 2002 - October 2016 for Poland and June 2002 - October 2016 for Hungary, respectively.

The data from the survey is qualitative in nature, providing a direction of change and not an exact value for the expected inflation rate, and needs to be quantified for further analysis. In this respect, the paper follows the method of Carlson and Parkin (1975), proposed for survey questions with three response categories, also known as the probability method, which was extended to the five-

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category case by Batchelor and Orr (1988)[6]. A detailed overview of this method is provided, among others, by Nielsen (2003) and Pop (2016). When applying this procedure one has to specify a certain distribution function for the future inflation rate, as well as a parameter to scale the expected inflation rate.

There is no consensus in the literature regarding the actual distribution of expectations, a number of alternatives to normal distribution, used by Carlson and Parkin (1975) in their seminal paper, being considered: the uniform distribution, the logistic distribution, the central and non-central t distributions and the triangular distribution[7]. However, without access to individual responses to the survey, it is not possible to check the accuracy of the different possible distribution assumptions. Moreover, there is evidence in the literature that the chosen distribution makes little difference to the derived expectations data series (e.g. Nielsen (2003), Batchelor (2006)). In this context, the assumption of normality of the underlying aggregate distribution function is chosen, more easily to handle.

As far as the scaling parameter is concerned, there are primary two proxies used in the literature: the most recent official inflation rate available to survey participants and the measure derived on the basis of the survey question concerning past prices, i.e. the agents' perceived inflation rate. The first proxy implies the rather strict assumption that the respondents perceive correctly the officially published inflation rate, so the second method is preferred. The Carlson-Parkin methodology is applied to question number 5, the role of the scaling parameter being replaced by a measure of the moderate rate of inflation[8] determined by applying the Hodrick-Prescott filter to the annual inflation rate. For the periods when the scaling factor is non-positive, the adjustment in the probability method proposed by Łyziak (2013b) is used[9].

The series of expected inflation rate, determined by applying the probability method, and the actual CPI inflation rate are represented in Figure 2. The expected

[6] The methods proposed in the economic literature for converting qualitative survey data into quantitative measures of agents' expectations are essentially three: the balance statistic, the probability method and the regression approach. While the balance statistic method does not directly measure the expectations, the regression approach does not offer an unique solution for the expectations data series as the re-estimation of regression models (for example in order to incorporate new data) leads to different values for the estimated coefficients and, implicitly, for the historical expectations data series. Nardo (2003) and Łyziak (2010) present a critical review of the different quantification methods, including an assessment of their strengths and weaknesses.

[7] See, for example, Łyziak (2003) and Nielsen (2003).

[8] The moderate rate of inflation is defined by Batchelor and Orr (1988) as the agents' best guess of the permanent or trend rate of inflation.

[9] The use of the Carlson-Parkin approach during episodes of non-positive inflation, as Romania, Poland and Hungary experienced recently, is constrained by the underlying assumption of a positive scaling factor. Łyziak (2013b) proposes an adjustment that allows the quantification of survey data in such circumstances.

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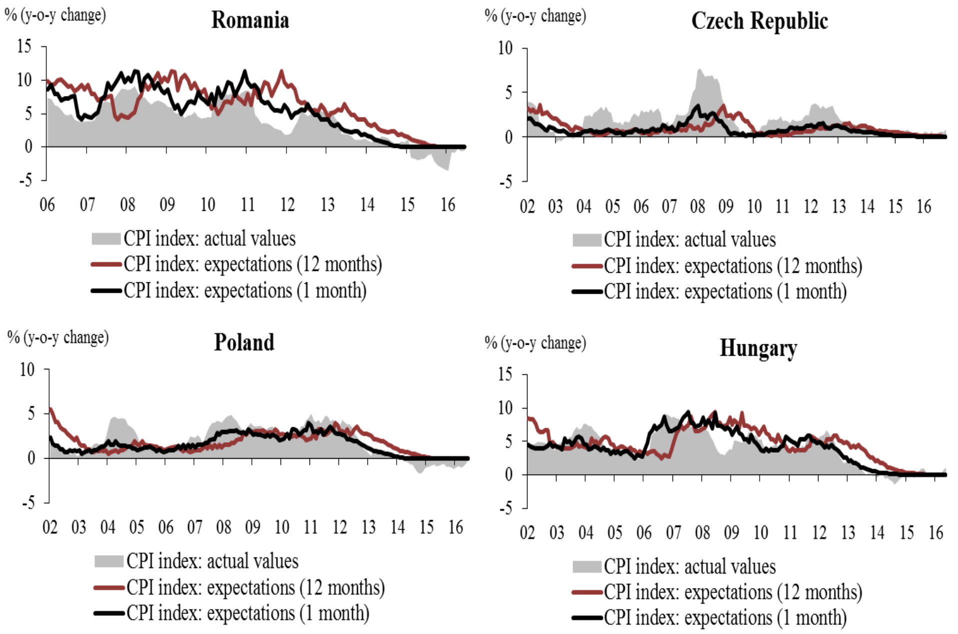
inflation rate lags behind the actual inflation rate, which, according to Nielsen (2003), may have two possible explanations: the expectations are formed in an adaptive manner or the survey participants consider a shorter time span than the twelve months period when answering the questionnaire. To examine this further, the predictive power of the expectations data series for different time horizons is determined. The result is shown in Table 2. The expectations data series comes closer to the actual CPI inflation rate as the time horizon decreases. So the second interpretation seems to be more suitable for the countries included in the analysis, as the lagging feature should persist in the context of adaptive expectations.

Figure 2. CPI inflation rate and the expected rate of inflation derived using the probability method



Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data

Note: As the data series of expected inflation rate concerns the next 12 months, the actual inflation rate is compared with the expectations that have been formed 12 months ago. Also, in order to investigate a possible deviation of the participants from a given time horizon of 12 months, the expected inflation rate, shifte forward 1 month is also plotted. Due to the shifting the plotted time period changes t August 2006 – October 2016 for Romania, January 2002 - October 2016 for Czech Republic, May 2002 - October 2016 for Poland and June 2002 - October 2016 for Hungary, respectively.

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Table 2. Root mean square error for different time horizons

Country	Time horizon		
	12 months	6 months	1 month
Romania	3.49	2.64	1.99
Czech Republic	1.95	1.68	1.62
Poland	1.57	1.16	1.05
Hungary	2.22	1.57	1.38

Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data

3. Testing rationality of inflation expectations

Since the seminal works of Lucas (1976) and Sargent and Wallace (1975), the standard methodology for modelling expectations in both microeconomics and macroeconomics has been to assume rational expectations. According to the rational expectations hypothesis, agents form their expectations based on the best available information and learn from past trends.

The fact that the consumers from Romania, Czech Republic, Poland and Hungary, respectively, consider a shorter time span than the twelve months period when answering the questionnaire, as emphasized in Section 2, is inconsistent with rationality because it implies that agents don't use the available information in an optimal way. Further examination of rationality is done by considering two testable characteristics of consumers' expectations, unbiasedness and efficiency with respect to available information, which represent the principal conditions for rationality required in the economic literature. On one hand, expectations are considered to be unbiased if they are equal to actual inflation on average, i.e. economic agents don't make systematic errors in their prediction. On the other hand, the macroeconomic efficiency requirement is associated with the orthogonality property and refers to the lack of correlation between the forecast error and the variables included in the available information set at the time predictions were made.

For testing the unbiasedness property of inflation expectations, the following equation is estimated:

$$\pi_t - \pi^e_{t/t-12} = \alpha + \varepsilon_t \tag{2}$$

where π_t stands for actual CPI inflation rate, while $\pi^e_{t/t-12}$ represents the expected inflation rate at time *t* formed 12 months before. According to Holden and Peel (1990), $\alpha = 0$ (equivalent to inflation forecast being on overage equal to the realized inflation) represents a necessary and sufficient condition for

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unbiasedness if ε_t is a sequence of independent and identically distributed random variables.

Table 3. Unbiasedness of inflation expectations – Estimation results for coefficient α (equation 2)

Country	α	DW
Romania	-2.22*	0.20
Czech Republic	0.92*	0.09
Poland	0.21**	0.09
Hungary	-0.59*	0.14

Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data
Notes: (1) * (**) denotes statistical significance at a 5 (10) percent level. (2) DW denotes the Durbin-Watson statistic.

The estimation results, presented in Table 3, don't support the unbiasedness property of inflation expectations. Positive values of α suggest an underestimation of the actual inflation (Czech Republic, by 0.9 percentage points on average and Poland, by 0.2 percentage points on average), while the negative ones suggest an overestimation (Romania, by 2.2 percentage points on average and Hungary, by 0.6 percentage points on average). Moreover, the Durbin-Watson statistic shows evidence of autocorrelation in the residuals for all the four countries considered in the analysis which is inconsistent with rationality.

Another test for rationality deals with the efficiency of inflation expectations with respect to available information. The following equation is estimated:

$$\pi_t - \pi^e_{t/t-12} = \alpha_0 + \alpha_1 \cdot \Omega_t + \varepsilon_t \tag{3}$$

where Ω_t represents the available information set at time *t-12* of variables affecting inflation.

If expectations are rational, coefficient α_1 must be statistically insignificant, i.e. consumers take correctly into account all available information when forming their expectations. Different categories of macroeconomic indicators are considered for explaining the forecast errors: the 3-month interbank rate, the Euro/national currency exchange rate, demand variables (industrial production, unemployment rate) and cost variables (oil price, CPI inflation rate), respectively. For avoiding possible multi-collinearity issues, the statistical significance of each of the explanatory variables is tested in a univariate context. Publication lags are taken into account. A statistical significant value for the coefficient α_1 is interpreted as agents' failure to take account in an optimal way of the selected information variable, which is inconsistent with rationality.

Table 4 presents the results for macroeconomic efficiency. Although the degree of macroeconomic efficiency differs between the countries, the condition with

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respect to the variables considered is not fulfilled by neither one of the consumers' groups.

Table 4. Macroeconomic efficiency of inflation expectations – Estimation results of coefficient α_1 (equation 3)

Country	Information available					
	3-month interbank rate	Euro/national currency exchange rate	Industrial production in manufacturing	Unemployment	Oil price	CPI inflation
Romania	-0.06	-0.02	0.01	1.22*	-0.02	-0.52*
Czech Republic	0.13	0.05	0.06**	0.13	0.00	-0.42*
Poland	0.08	0.02	0.12*	0.03	0.01*	-0.23
Hungary	-0.23*	0.01	0.09*	-0.23**	0.00	-0.30*

Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data
Notes: (1) * (**) denotes statistical significance at a 5 (10) percent level. (2) The equations are estimated by ordinary least squares method using the covariance matrix correction proposed by Newey and West (1987) in order to correct for the autocorrelation in the error term.

In conclusion, the empirical evidence doesn't support the rationality hypothesis of inflation expectations. The next section investigates the learning approach as a possible alternative to rational expectations hypothesis.

4. Adaptive learning approach

4.1. Methodology

According to the rational expectations hypothesis, economic agents have complete knowledge about the economy, more exactly they fully know the structure of the economy, the values of the structural parameters that govern the

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relationships between the economic variables, as well as the distribution of any exogenous shock. These assumptions are rather strong. In practice, regardless of the type of model used in economic analysis, the parameters' values are not known and need to be estimated. The adaptive learning approach reduces the information requirements of rational expectations hypothesis by assuming that agents act as statisticians or econometricians and, in order to be able to form expectations about the future state of the economy, they estimate econometrically the parameters' values using the available information. Moreover, they update these estimates every period as new data becomes available.

Following Branch and Evans (2006) and Weber (2010), a general recursive forecasting model is defined. The competing forecasting models considered further in the analysis are special cases of this general model:

$$\pi_t = \beta_t' \cdot x_t + \varepsilon_t \tag{4}$$
$$\beta_t = \beta_{t-1} + \eta_t \tag{5}$$

where π_t represents the annual CPI inflation rate, β_t is the $(N\ x\ 1)$ parameter vector, modelled as a random walk process and x_t is the $(N\ x\ 1)$ vector of explanatory variables which are known by the agents when forming their expectations. N represents the number of explanatory variables. The observation error (ε_t) and the state equation error (η_t) are assumed to be Gaussian:

$$\mathrm{E}(\varepsilon_t \cdot \varepsilon_T') = \begin{cases} H_t, for\ t = T \\ 0, otherwise \end{cases}$$
$$\mathrm{E}(\eta_t \cdot \eta_T') = \begin{cases} Q_t, for\ t = T \\ 0, otherwise \end{cases}$$

and uncorrelated at all lags:

$E(\varepsilon_t \cdot \eta_T') = 0)$ for all t and T.

Economic agents form their expectation regarding the future inflation rate according to equation (4):

$$\pi_{t/t-1}^e = \hat{\beta}_{t-1}' \cdot x_t \tag{6}$$

where $\pi_{t/t-1}^e$ represents the expected inflation rate for time *t*, conditional on information available at time *t-1*.

The sequence $\{\hat{\beta}_t\}$ is updated by agents periodically, as new data becomes available, and it can be constructed by using the Kalman Filter recursion[10]:

$$\hat{\beta}_t = \hat{\beta}_{t-1} + k_t \cdot (\pi_t - \hat{\beta}_{t-1}' \cdot x_t) \tag{7}$$
$$k_t = \frac{P_{t-1} \cdot x_t}{H_t + x_t' \cdot P_{t-1} \cdot x_t} \tag{8}$$

[10] Under the conditions considered here (linear system, Gaussian and uncorrelated errors), the Kalman filter produces the optimal estimate. For an explanation of the procedure, see Hamilton (1994).

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$$P_t = P_{t-1} - \frac{P_{t-1} \cdot x_t \cdot x_t' \cdot P_t}{H_t + x_t' \cdot P_{t-1} \cdot x_t} + Q_t \tag{9}$$

where $P_t = E(\beta_t - \hat{\beta}_t) \cdot (\beta_t - \hat{\beta}_t)'$ is the covariance matrix of $\hat{\beta}_t$.

The two widely used econometric forecasting rules in the learning literature, which are also employed in the present paper, recursive least squares learning (RLS) and constant gain learning (CG-RLS), are special cases of the above model, as shown by Sargent (1999). If $Q_t = 0$ and $H_t = 1$ the system of equations (4)-(5) is equivalent to RLS, which is simply a recursive formulation of ordinary least squares[11]:

$$\hat{\beta}_t = \hat{\beta}_{t-1} + g_t \cdot R_t^{-1} x_t \cdot (\pi_t - \hat{\beta}_{t-1}' \cdot x_t) \tag{10}$$

$$R_t = R_{t-1} + \gamma_t \cdot (x_t \cdot x_t' - R_{t-1}) \tag{11}$$

where R_t is the second moment matrix of the variables included in x_t and $g_t = t^{-1}$. The restrictions $Q_t = \frac{g}{1-g} \cdot P_{t-1}$ and $H_t = 1 - g$ lead to the constant gain version of RLS, in which the gain g_t from the system of equations (10)-(11) is replaced by a constant g. In the first case (RLS), as time passes every new forecast error, i.e. the term in the brackets in equation (10), has a smaller weight, t^{-1}, in the latest estimation. In the second case (CG-RLS), the previous period error has the same weight g as the past one, implying a geometric discounting of old observations at a rate $1 - g$; this is equivalent to an ordinary least squares estimation on a rolling window of data of size $1/g$ and is a more appropriate approach in environments characterized by policy changes or any structural shift in general as these imply a drift in the value of the estimated parameters[12].

Four different simple learning models are estimated and their performance on fitting data on actual inflation and consumers' inflation expectations is assessed[13]. The first model defines a random walk process for inflation, while the following ones consider also some standard explanatory variables of inflation for small open economies with an inflation targeting regime, i.e. the output growth, approximated by the growth in industrial production, changes in the exchange rate and changes in the interest rate. The models employed are specific cases of equation (4):

$$\pi^e_{t/t-12} = \beta_{1t} + \beta_{2t} \cdot \pi_{t-14} + \varepsilon_t \qquad \textit{(Model 1)}$$

$$\pi^e_{t/t-12} = \beta_{1t} + \beta_{2t} \cdot \pi_{t-14} + \beta_{3t} \cdot ip_{t-14} + \varepsilon_t \qquad \textit{(Model 2)}$$

[11] The derivation of the recursive version of the ordinary least squares method can be found, for example, in Fernandez Telleria (2013).

[12] For a complete discussion of these algorithms, including the stability of the rational expectations solution under a learning rule, see Evans and Honkapohja (2001).

[13] Although the true data generating process of inflation is probably of a more complex form, it is more realistic to assume that survey respondents don't have a solid background in advanced macroeconomics and use simple models when assessing the future evolution of prices.

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$$\pi^e_{t/t-12} = \beta_{1t} + \beta_{2t} \cdot \pi_{t-14} + \beta_{3t} \cdot ip_{t-14} + \beta_{4t} \cdot z_{t-13} + \varepsilon_t \qquad \textit{(Model 3)}$$

$$\pi^e_{t/t-12} = \beta_{1t} + \beta_{2t} \cdot \pi_{t-14} + \beta_{3t} \cdot ip_{t-14} + \beta_{4t} \cdot z_{t-13} + \beta_{5t} \cdot i_{t-13} + \varepsilon_t \qquad \textit{(Model 4)}$$

where ip, z and i denote annual changes in industrial production, Euro/national currency exchange rate and the 3-month interbank rate, respectively. Publication lags are taken into account.

In performing the estimations, the sample for each country is divided in three parts, each of them having the same number of observations[14]: a pre-forecasting period, in which prior beliefs are formed (β_0 and R_0) by estimating equation (4), an in-sample period in which the value of the optimal gain parameter g is estimated for the case of CG-RLS algorithm (for RLS algorithm the gain sequence continues to be updated) using the system of equations (10)-(11) and an out-of-sample forecasting period for models' evaluation. The measure employed for determining the out-of-sample performance is the root mean square forecast error indicator. The length of the data sample for Czech Republic, Poland and Hungary is approximately the same, while for Romania the data sample is relatively small, starting only in August 2005, aspect that may distortion the interpretation of results in terms of heterogeneity with respect to learning for this country as compared to the other three.

4.2. Results

Table 5 reports the estimates of the constant gain parameter. The estimates are usually higher for the actual CPI inflation rate than those obtained for US (e.g. Branch and Evans (2006)), but are comparable with the values reported for euro area countries (e.g. Weber (2010)).

Table 5. Estimates for the optimal constant gain parameter (g)

Measure	Country	Model 1	Model 2	Model 3	Model 4
Actual CPI inflation rate	Romania	0.141	0.135	0.098	0.082
	Czech Republic	0.174	0.167	0.121	0.062
	Poland	0.240	0.144	0.192	0.080
	Hungary	0.223	0.190	0.141	0.059
Expected inflation rate	Romania	0.165	0.075	0.041	0.045
	Czech Republic	0.202	0.100	0.084	0.078
	Poland	0.203	0.152	0.112	0.115
	Hungary	0.217	0.197	0.136	0.065

Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data
Note: The gain coefficient was estimated by minimizing the in-sample mean square forecast error indicator over the parameter space $g \in (0,1)$.

[14] Results with different sub-samples of data were also computed and found to be very similar with the ones reported here. They are available from the author upon request.

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A higher value for the gain coefficient implies fewer years of data used in an optimal way in inflation prediction and is directly related with the frequency of structural breaks in the data as, when structural breaks are present, a lower number of observations should be used to generate optimal forecasts, i.e. relatively more weight should be put on more recent observations. The gain estimates for the series of inflation expectations are in general close to the values obtained for the series of actual inflation which implies that consumers are aware of the structural breaks in the data. The reported results correspond to a period between 4 months and 2 year of data taken into consideration by the consumers for assessing the expected inflation rate[15], being usually higher for more complex models.

Table 6 reports the values of the root mean square forecast error indicator for the out-of-sample forecasts computed for consumers' inflation expectations. As is usually found in the literature, constant gain learning algorithm clearly provides a better description of consumers' inflation expectations than the recursive least squares one. The root mean square forecast error statistic is the smallest for Czech Republic, implying that the forecasting models considered are able to fit the Czech consumers' inflation expectations best.

Table 6. Out-of-sample mean square forecast errors

	RLS				CG-RLS			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Romania	2.1566	2.1556	2.0787	2.0429	**0.9203**	1.4542	1.6177	1.4928
Czech Republic	0.2138	0.2546	0.2555	0.2522	0.1559	0.1868	0.1865	**0.1513**
Poland	0.5108	0.5083	0.4909	0.4925	0.3719	**0.3672**	0.3716	0.3784
Hungary	1.3067	1.3938	1.1990	1.1807	**0.5904**	1.0295	0.6009	0.7109

Source: Author's calculation based on EC, NBR, CNB, NBP and MNB data

Notes: (1) For CG-RLS algorithm, the estimated gain parameter reported in Table 4 was used to generate the forecasts for each model. (2) Bold entries mark the smallest value for the root mean square forecast error indicator.

The worst fit is obtained in case of Romanian data and it is most probably associated with the successive VAT rate changes that this country experienced in the last years, which had a significant impact on the headline CPI inflation rate[16].

[15] The number of years used for assessing future inflation is equal to $(1/g)/f$, where f denotes the data frequency: $f = 1$ for yearly data, $f = 4$ for quarterly data and $f = 12$ for monthly data.

[16] VAT rate changes in Romania during the analyzed period (in brackets the first round effect on headline inflation rate as estimated by the National Bank of Romania, source: *NBR Inflation Reports*): an increase in the standard VAT rate from 19 percent to 24 percent as from 1 July 2010 (2.4 percentage points), a cut in the VAT rate applied to flour and

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Furthermore, expectations in Romania and Hungary can be better fitted with the simplest model (Model 1), which includes only a constant and the lagged inflation as the independent variables. In the case of Poland and Czech Republic, the best fit is obtained for the models that also includes other explanatory variables besides the lagged inflation. For the best-fitting model there is a surprisingly homogeneity in the frequency with which the consumers from Romania, Poland and Hungary update their information sets (5 to 6 months), while for Czech Republic the period is higher (12 months).

5. Conclusions

In the last decades, numerous emerging economies have adopted the monetary policy regime of inflation targeting. For a successful anchoring of agents' expectations to inflation target, it is of crucial importance for central banks to understand how inflation expectations are formed.

In testing different expectation formation schemes data from surveys are often used. However, these data are usually qualitative in nature and need to be quantified for further analysis. This study implements the probability method in order to estimate consumers' inflation perceptions and predictions using data from European Commission's Consumer Survey in several Central and Eastern European countries with an inflation targeting monetary policy regime, i.e. Romania, Czech Republic, Poland and Hungary. As the tests performed don't support the rationality hypothesis in either one of the countries considered in the analysis, the paper further assesses whether the adaptive learning approach is a more reasonable assumption for these economies. Two widely used econometric forecasting rules in the learning literature, recursive least squares learning and constant gain learning, respectively, are tested in a Kalman filter framework. The results suggest that constant gain learning algorithm provides a better description of inflation expectations than the recursive least squares algorithm, a possible explication being the fact that it allows economic agents to incorporate structural changes, frequent in emerging economies, faster. Also there is evidence that consumers from Romania and Hungary use simple models to forecast inflation, that includes only a constant and the lagged inflation as determinants, while in case of Poland and Czech Republic the best fit is obtained for the models that also includes other explanatory variables (industrial production in case of Poland, industrial production, the exchange rate between Czech koruna and EUR and the interest rate in case of Czech Republic). Romania, Hungary and Poland present

bread to 9 percent as of 1 September 2013 (-0.7 percentage points), a lowering of the VAT rate to 9 percent for all food items, non-alcoholic beverages and public food services as of 1 June 2015 (-2.8 percentage points) and a cut in the standard VAT rate from 24 percent to 20 percent as from 1 January 2016 (-1.0 percentage points). The information set available to the consumers when forming expectations regarding the price developments over the next 12 months did not include these measures, as they were not known 12 months before their entry into force.

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similarities regarding the frequency with which the consumers update their information sets (5 to 6 months for the best fitting model).

In conclusion, this paper provides support for the constant gain algorithm as an alternative to rational expectations hypothesis for modelling inflation expectations in CEE emerging economies. The implications of considering this approach instead of the rational expectations hypothesis in more complex models (for example, DSGE models) in terms of policy recommendations may represent a direction for future research.

The results presented in the paper support previous findings, but should be interpreted with caution because of data constraints. The study of learning behaviour requires the use of a large number of observations as this is a process that takes place in time and, moreover, it is very sensitive to the prior beliefs used to start the recursions. Furthermore, the results are also affected by the uncertainty surrounding the quantification technique used to obtain proxies for consumers' inflation perceptions and predictions.

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