Heterogeneous Expectations, Learning and European Inflation Dynamics*

Anke Weber[†]
University of Cambridge

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Abstract

This paper provides a first attempt to investigate how different learning rules perform in explaining survey data on inflation expectations of households and professional forecasters in five core European economies (France, Germany, Italy, Netherlands and Spain). Overall it is found that adaptive learning algorithms with constant gain perform well in out-of-sample forecasting. It is also shown that households in high inflation countries are using higher best-fitting constant gain parameters than those in low inflation countries. They are hence able to pick up structural changes faster. Professional forecasters update their information sets more frequently than households. Furthermore, household expectations in the Euro Area have not converged to the inflation goal of the ECB, which is to keep inflation below but close to 2% in the medium term. This contrasts with the findings for experts, which seem to be more inclined to incorporate the implications of monetary union for the convergence in inflation rates into their expectations.

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[†]Address: Faculty of Economics, Sidgwick Avenue, Cambridge, CB3 9DD, E-mail: aw299@cam.ac.uk;

1 Introduction

Inflation expectations of economic agents are crucial for the conduct of monetary policy. Hence, central banks have a strong interest in monitoring expectations and in understanding the process by which they are formed. From the 1970s onwards the idea that expectations are rational has dominated much of the literature. Lately a new view on expectations has emerged, which views economic agents as econometricians when forecasting (for an overview of this literature see Evans and Honkapohja (2001)). This approach, referred to as adaptive learning, assumes that economic agents are boundedly rational but employ statistical forecasting techniques, which allow for the possibility of a rational expectations equilibrium to be learnt in the long run. One important insight from the adaptive learning literature is that policies, which may be optimal under rational expectations, are not when individuals use a learning process (Orphanides and Williams (2005)). Orphanides and Williams (2005) show that the optimal monetary policy under a learning process should respond more aggressively to inflation and become more narrowed to inflation stability than if expectations were rational. They conclude that policies emphasizing tight inflation control can facilitate learning and provide better guidance for the formation of inflation expectations. Given that the optimal policy of the central bank is sensitive to the expectations formation process of economic agents, it is hence of crucial importance to be aware of how these expectations are formed.

The contribution of this paper is twofold: First, it investigates whether learning by economic agents is a plausible assumption for the Euro Area and whether there is heterogeneity between countries and between households and professional forecasters. The second contribution of this paper is to analyse whether the learning process of economic agents converges towards equilibrium and specifically whether households and professional forecasters are able to learn the inflation goal of the European Central Bank (ECB), which is to maintain inflation close to but below 2% in the medium term.

In order to examine whether expectations result from a learning process, the paper assesses the performance of different forecasting models with time varying parameters in terms of their ability to fit actual data on inflation and inflation expectations. Data on household and expert expectations for five core countries participating in the single currency, namely Germany, Spain, France, Italy and the Netherlands, is used. The paper finds evidence that for these countries, inflation expectations result from a learning process and therefore are not rational. Furthermore professional forecasters use higher constant gain parameters than households. They hence update their information sets more frequently and are able to pick up structural changes faster. A possible explanation is that households find it more costly to update their information sets than professional forecasters. It is also shown, that in countries with higher inflation economic agents update their information sets more frequently. A possible explanation lies in Sims' theory of

'Rational Inattention'. Sims (2003, 2006) models economic agents as having a limited capacity to observe information. They therefore need to make the decision of how much to pay attention and which pieces of news to look at. Sims (2003, 2006) argues that when inflation is high, agents will pay more attention to new information as their opportunity cost of being inattentive is significantly higher during these periods.

In addition, it is crucial to investigate whether the learning process converges to equilibrium and whether expectations are anchored to the policy goal of the ECB. It has often been argued that economic agents should understand the implications of monetary union and hence conclude that inflation differentials cannot last in the medium to long run (see for example ECB (2003)). Empirical evidence typically finds large persistent inflation differentials between European countries (Rogers (2001), Berk and Swank (2002) and Ortega (2003)). Angeloni and Ehrmann (2007) show that after converging sharply in the 1990s, national inflation rates started to diverge again around 1999. They find that although recently the differentials have closed somewhat, inflation differentials in the Euro Area are larger and more persistent than, for example, in the United States. However, if actual inflation rates are influenced by inflation expectations of economic agents through wage and price setting behaviour, then convergence in inflation expectations should ultimately lead to convergence in inflation rates across countries. Thus, analysing the convergence of inflation expectations of households and professional forecasters gives us some indication on the likely convergence of future actual inflation rates. The results show that professional forecasters are more inclined to incorporate the implications of monetary union into their expectations than households.

The remainder of the paper is organised as follows: Section 2 gives an overview of the data. Section 3 discusses the general model. Section 4 analyses the fit of simple learning rules with Euro Area data. Section 5 tests for convergence of expectations to equilibrium. Section 6 concludes.

2 Data

2.1 Data sources

This paper uses data on household inflation expectations derived from the European Commission's Consumer Survey as well as expectations of professional forecasters extracted from Consensus Economics. Data for the following countries is used: Germany, France, Netherlands, Italy and Spain. The paper also uses Euro Area inflation and inflation expectations. This data is compiled by aggregating the individual country data using weights based on each country's share in total Euro Area private domestic consumption expenditure[1].

The EC Consumer Survey asks approximately 20000 consumers in the Euro Area for information regarding their expectations of future and past price developments. The survey is conducted on a monthly basis and consumers are asked about their expectations of inflation 12 months ahead. Questions and response categories of the survey are shown in Table 1[2]:

Q1: How do you think that consumer prices have developed over the last 12 months? They have...	**Q2: By comparison with the past twelve months, how do you expect consumer prices to develop over the next twelve months?They will...**
Fallen	Fall
Stayed about the same	Stay about the same
Risen slightly	Increase at a slower rate
Risen moderately	Increase at the same rate
Risen a lot	Increase more rapidly
Don't know	Don't know

Table 1: The EC Consumer Survey

The data derived from the EC Consumer Survey is hence qualitative in nature and needs to be quantified. This paper uses data, which has been quantified by Gerberding (2006). Gerberding (2006) follows the probability method of Carlson and Parkin (1975), which was extended to the five-category case by Batchelor and Orr (1988). Due to the wording of Question 2 (see above), the procedure requires the specification of a variable that captures the perception of respondents of the rate of inflation over the past 12 months. Gerberding (2006) follows Berk (1999) in estimating the perceived rate of inflation using the results from the question pertaining price developments in the past 12 months in the EC Consumer Survey (Question 1 in the above table). A detailed overview of the quantification method to quantify the qualitative data used in this paper, is provided by Gerberding (2001, 2006) and Nielsen (2003).

The data on experts' expectations is provided by Consensus Economics, a London based firm. More than 700 professional forecasters are recruited from major banks, economic research institutes and investment firms. Every quarter, Consensus economics asks these experts to provide quantitative forecasts on key macro variables, including consumer prices. These forecasts are available for each of the following one to six quarters. Simple arithmetic means of these quarterly forecasts are then published for each country. In order for expert expectations to be comparable to the inflation expectations of households derived from the EC Consumer Survey, this paper uses expectations of professional forecasters on consumer prices for four quarters

[1] The most recent weights that are assigned to each country are published by Eurostat with the release of the January data each year under HICP country weights (http://sdw.ecb.int/reports.do?currentNodeId=100000298)

[2] This table is adapted from Gerberding (2006).

ahead.

Further details on the data sources including those sources used to construct time series of actual inflation can be found in Table 18 in the Appendix.

It has to emphasised that there are limits to data compatibility in this paper. First, observations for households are monthly whilst the data on expectations of professional forecasters has a quarterly frequency. Second, household expectations have to be quantified whilst expert expectations are an average of quantitative forecasts. In addition, there are limitations to the probability method. These include the rather strict assumption of normality of the underlying aggregate distribution function. This assumption has been criticized by Carlson (1975) and Pesaran (1987) who find non-normal features of the aggregate distribution function. However, as noted by Nielsen (2003) and Berk (1999) alternatives to the normal distribution make little difference to the derived expectations series.

An advantage of the probability approach is that it does not impose unbiasedness as an a priori property of the measure of future expectations of inflation. This is important as in this paper, it is tested whether households are boundedly rational. Nevertheless, the limitations of the probability approach have to be taken into account when evaluating the results of this paper.

2.2 Preliminary look at data

Figure **??** in the Appendix shows data of actual inflation as well as household expectations from 1990-2006 for the different countries investigated in this paper[3]. Consensus forecasts and actual inflation are also plotted from 1990-2006. These series are shown in Figure 2.

The expectations series are dated back one year, that is twelve months for households and four quarters for experts. Hence, the vertical differences between the series in each figure measure the forecast errors of households and professional forecasters. From the graphs, it seems as if professional forecasters were on average better at forecasting inflation than households. This is confirmed by computing mean squared errors, which are larger for households than for professional forecasters. It is possible to test whether these differences in mean squared errors are significant for the period from 1990Q1 to 2006Q3[4]. Equal forecast accuracy can be tested using the method proposed by Diebold and Mariano (1995). The small sample correction for the Diebold/Mariano statistic as introduced by Harvey et al (1997) is used. It is found that with the exception of France and Spain, the differences between the mean squared errors of professional forecasters and households are significant at the 10% level.

[3]There were some missing observations in the quanitifed consumer expectations series, which reflects the fact that the quantification method breaks down when the share of respondents in one category is equal to zero (Berk, 1999). However, the consumer expectations series were interpolated using the cubic spline function in Matlab. This was needed for some of the computations conducted in this paper.

[4]In order to test for equal forecast accuracy, we had to transform household expectations, for which monthly data is available, into quarterly data. This was done by computing average expectations for each quarter.

Besides testing for equal forecast accuracy, it is also possible to test for unbiasedness of expectations. Several studies have investigated whether expectations of households and professional forecasters are unbiased. For example, Forsells and Kenny (2004) using the same data set as in this paper, find that consumer expectations are a somewhat biased predictor of inflation twelve months ahead. Rationality is tested by running the following regression:

$$\pi_t = \alpha + \beta \pi_t^e + \varepsilon_t \tag{1}$$

where π_t denotes the actual inflation rate in period t and π_t^e denotes the expected inflation rate formed in $t-12$ by households and $t-4$ by professional forecasters where the data frequency is monthly and quarterly respectively. If the joint null hypothesis $H_0 : (\alpha, \beta) = (0, 1)$ cannot be rejected, then it follows that expectations are unbiased in a statistical sense. The above rationality test is conducted for both data on household and expert inflation expectations. It is found that for household expectations the null hypothesis that expectations are unbiased can be rejected at the 1% and 5% level for each country and the Euro Area as a whole. For expert expectations, it is found that the null hypothesis of unbiasedness can be rejected at the 1% and 5% levels for most countries and the Euro Area with the exception of Germany and the Netherlands. However, as Holden and Peel (1990) have shown, if the null hypothesis cannot be rejected this is sufficient for rationality but not necessary. Holden and Peel (1990) suggest to regress the forecast error on a constant instead and test whether the constant is significantly different from zero:

$$\pi_t - \pi_t^e = \alpha + \varepsilon_t \tag{2}$$

It can be shown that the condition $\alpha = 0$ is both necessary and sufficient for rationality. The test is conducted for household and expert expectations. For households, it is found that the null hypothesis of unbiasedness can be rejected at the 1% and 5% level for each country and the Euro Area with the exception of Italy. For experts, the null hypothesis of unbiasedness can be rejected for Italy, Spain and the Euro Area as a whole at the 1% and 5% level.

3 The model

This section follows Branch and Evans (2006) and Basdevant (2005) and outlines a general state space forecasting model that will be able to nest alternative models.

Let π_t denote inflation in period t. It is assumed that the reduced form that economic agents use in order to form expectations of inflation is given by

$$\pi_t = \mathbf{b}_t' \mathbf{x}_t + \varepsilon_t \tag{3}$$

where

$$\mathbf{b}_t = (b_{1t}, b_{2t}, b_{3t}, ..., b_{(n+1)t})' \text{ and } \mathbf{x}_t = (1, \mathbf{y}_{t-1})'$$

and

$$E(\varepsilon_t) = 0 \text{ and } E(\varepsilon_t \varepsilon_t') = H_t.$$

Let $\mathbf{y}_t$ with dimension nx1 denote variables of general interest. Thus n is the number of independent variables in our model. These could be lagged values of inflation, output growth or interest rate growth for example. It is hence assumed that economic agents view inflation in period t as a function of a constant and lagged variables of general interest. Furthermore economic agents are seen as forming their expectations for the value of inflation for the next period using the current values of variables of interest such as inflation and output growth.

Together with the assumption that

$$\mathbf{b}_t = \mathbf{b}_{t-1} + \boldsymbol{\eta}_t \tag{4}$$

where

$$E(\boldsymbol{\eta}_t) = 0 \text{ and } E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \mathbf{Q}_t$$

the above corresponds to a general state space model with $\mathbf{b}_t$ being the state.

Conditional forecasts of π_t are given by

$$\widehat{\pi}_{t|t-1} = \widehat{\mathbf{b}}_{t-1}' \mathbf{x}_t.$$

The parameter vector $\mathbf{b}_t$ can be estimated using the Kalman filter[5]. The recursion can be written as follows:

$$\widehat{\mathbf{b}}_t = \widehat{\mathbf{b}}_{t-1} + \mathbf{k}_t(\pi_t - \widehat{\mathbf{b}}_{t-1}' \mathbf{x}_t) \tag{5}$$

where the Kalman gain, $\mathbf{k}_t$, is given by

$$\mathbf{k}_t = \frac{(\mathbf{P}_{t-1} + \mathbf{Q}_t)\,\mathbf{x}_t}{H_t + \mathbf{x}_t'(\mathbf{P}_{t-1} + \mathbf{Q}_t)\mathbf{x}_t} \tag{6}$$

and

$$\mathbf{P}_t = \mathbf{P}_{t-1} - \frac{(\mathbf{P}_{t-1} + \mathbf{Q}_t)\,\mathbf{x}_t \mathbf{x}_t'\,(\mathbf{P}_{t-1} + \mathbf{Q}_t)}{H_t + \mathbf{x}_t'\,(\mathbf{P}_{t-1} + \mathbf{Q}_t)\,\mathbf{x}_t} + \mathbf{Q}_t \tag{7}$$

where

$$\mathbf{P}_t = E(\mathbf{b}_t - \widehat{\mathbf{b}}_t)(\mathbf{b}_t - \widehat{\mathbf{b}}_t)'.$$

[5] For an explanation of the basic Kalman filtering procedure, see for example Hamilton (1994).

As shown by Marcet and Sargent (1989a,b) the learning process converges only to equilibrium when the law of motion of parameters is time invariant[6]. In other words, convergence requires $\mathbf{Q}_t = 0$. Within the Kalman filter framework it is hence possible to test whether learning is perpetual or whether it converges to equilibrium by examining whether the variance of the state variables is significantly different from zero.

If $\mathbf{Q}_t = 0$ and $H_t = 1$, the Kalman filter recursions, (5)-(7), become equivalent to recursive least squares (RLS) as shown by Sargent (1999). The system can then be written as

$$\widehat{\mathbf{b}}_t = \widehat{\mathbf{b}}_{t-1} + \gamma_t \mathbf{R}_t^{-1} \mathbf{x}_t (\pi_t - \widehat{\mathbf{b}}'_{t-1} \mathbf{x}_t) \tag{8}$$

$$\mathbf{R}_t = \mathbf{R}_{t-1} + \gamma_t (\mathbf{x}_t \mathbf{x}'_t - \mathbf{R}_{t-1}) \tag{9}$$

where $\gamma_t = t^{-1}$ and $\mathbf{R}_t$ is the matrix of second moments of $\mathbf{x}_t$. As shown by Evans and Honkapohja (2001), recursive least squares is a recursive formulation of ordinary least squares. Furthermore, as shown by Evans and Honkapohja (2001), when economic agents use recursive least squares to update their parameter estimates, these estimates will eventually converge to their rational expectations values.

When

$$\mathbf{Q}_t = \frac{\gamma}{1-\gamma} \mathbf{P}_{t-1} \text{ and } H_t = 1 - \gamma$$

the system becomes equivalent to the constant gain version of recursive least squares (Sargent 1999), so that $\gamma_t = \gamma$ in equations (8) and (9). Using a constant gain algorithm implies that more weight is placed on recent observations. This algorithm is equivalent to applying weighted least squares where the weights decline geometrically with the distance in time between the observation being weighted and the most recent observation. Past observations are thus discounted at a geometric rate of $1 - \gamma$. Hence constant gain least squares learning (CGLS) is more robust to structural change than recursive least squares learning. Evans and Honkapohja (2001) provide a more detailed explanation of both learning algorithms.

4 Simple learning rules

This section compares the performance of alternative recursive forecasting models. It assesses the ability of different simple learning models to fit data on actual inflation and inflation expectations. It is thereby examined whether learning is a plausible description of household

[6] According to Basdevant (2005), the Kalman filter framework allows one to test whether expectations converge towards the rational expectations equilibrium. However, this assumes that agents use the correct model of the economy. If the model used for forecasting is incorrect, expectations may converge towards a so called 'restricted perceptions equilibrium' (Evans and Honkapohja (2001)).

and professional forecaster behaviour. It will also be investigated to what extent recursive least squares and constant gain least squares, which are the two most commonly used learning mechanisms described in the theoretical literature, provide a good description of forecaster behaviour. Estimates of the constant gain parameters are provided for each country and it is analysed whether there is country heterogeneity with respect to learning. Heterogeneity between households and professional forecasters is also examined. It will then be assessed to what extent the results are plausible and specifically whether they agree with other economic theories, such as Sims's theory of 'Rational Inattention'.

4.1 Estimation procedure

The paper follows Branch and Evans (2006) and divides the sample for each country in three parts: A pre-forecasting period in which prior beliefs are formed by estimating (3). An in-sample period in which optimal gain parameters are determined for the case of constant gain least squares. For recursive least squares learning the gain sequence continues to be updated as t^{-1}. Finally, there is an out-of-sample forecasting period.

For household expectations, a fairly long pre-forecasting period, 1981M1-1989M12 is chosen in order to avoid over-sensitivity of initial estimates. The in-sample period is 1990M1-1998M4. The out-of-sample period is hence 1998M5-2006M9[7]. Given the monthly frequency of the data, the independent variable vector $\mathbf{x}_t$ is defined as $(1, \mathbf{y}_{t-12})'$. The inflation expectation by households in period $t-12$ for period t is hence given by

$$\pi_{t|t-12} = \widehat{\mathbf{b}}'_{t-12}\mathbf{x}_t \tag{10}$$

When agents form expectations, the best estimate of the coefficients in period $t-12$ is used. As new data becomes available agents update their estimates according to either constant gain least squares learning or recursive least squares learning. The formulae for this updating process are given by equations (8) and (9).

To calculate the optimal in-sample constant gain parameters, the in-sample mean square forecast error

$$MSE_{IN}(\pi) = \frac{1}{T}\sum_{t=t_0}^{T}(\pi_t - \widehat{\pi}_t)^2$$

is minimised by searching over all $\gamma \in (0,1)$ with t_0 =1990M1 and T =1998M4. The distances between grids are set as 0.0001. $\widehat{\pi}_t$ denotes the forecast made in period $t-12$ for t. This forecast is generated by starting the recursions, which are given by equations (8) and

[7] This sample period was chosen so that the in- and out-of-sample periods correspond to the period for which household expectations are available. The period from 1990M1-2006M9 was then split in half to generate the in- and out-of-sample periods.

(9) with the initial values calculated from the pre-sample period and then using these recursive equations to calculate $\widehat{\mathbf{b}}_t$. The fact that $\widehat{\pi}_t = \widehat{\mathbf{b}}'_{t-12}\mathbf{x}_t$ is then used to generate values for $\widehat{\pi}_t$. The grid search is conducted by systematically searching for the value of $\gamma \in (0,1)$ that minimises the in-sample mean square forecast error. When using recursive least squares to update estimates of $\widehat{\mathbf{b}}_t$, there is no need to compute an optimal gain parameter as $\gamma = t^{-1}$. However, the mean square errors can be computed by updating the sequence for $\widehat{\mathbf{b}}_t$ with t^{-1} and then using the fact that $\widehat{\pi}_t = \widehat{\mathbf{b}}'_{t-12}\mathbf{x}_t$ to generate values for $\widehat{\pi}_t$. These values can then be used as before in order to calculate in-sample mean square errors.

Having determined the optimal in-sample values of the constant gain, out of sample MSE's can be computed for each country as

$$MSE_{OUT}(\pi) = \frac{1}{T}\sum_{t=1}^{T}(\pi_t - \widehat{\pi}_t)^2$$

where t ranges from 1998M5 to 2006M9.

It is also possible to find best fitting constant gain parameters for households. These are computed by minimising the in-sample mean square comparison error

$$MSCE_{IN}(\pi) = \frac{1}{T}\sum_{t=t_0}^{T}(\pi_t^F - \widehat{\pi}_t)^2$$

by searching over all $\gamma \in (0,1)$ with t_0 =1990M1 and T =1998M4. π_t^F denote household expectations for period t. The distances between grids are set as 0.0001. Best fitting constant gain parameters are computed to determine whether the best fitting gains that are needed to fit household expectations are equivalent to the optimal gains needed to fit actual data on inflation in the in-sample period. This is important to investigate as Branch and Evans (2006) find that for explaining the forecasts of professional forecasters in the US, the best fitting gain is substantially below the optimal gain for fitting data on actual inflation. Similarly as before, using the best fitting gains for household expectations, the out-of-sample mean square comparison forecast error is determined. This is given by

$$MSCE_{OUT}(\pi) = \frac{1}{T}\sum_{t=1}^{T}(\pi_t^F - \widehat{\pi}_t)^2$$

where t ranges from 1998M5 to 2006M9.

For RLS learning, the in-sample and out-of sample MSCEs are calculated as above. The recursive equations (8) and (9) are updated with t^{-1}.

In addition to absolute mean square comparison errors, the paper also computes relative MSCEs for each country for the model that yields the smallest mean square comparison forecast error. This follows Forni et al (2003) and Schumacher (2007). Relative MSCEs are computed out-of-sample relative to the variance of the series that the paper is trying to predict, i.e. household inflation expectations. Computing relative MSCEs is related to the concept of predictability of a series (see for example Diebold and Kilian (2001)). It could be the case that household expectations are more predictable in some countries, which results in lower MSCEs for those countries. Computing the variances of these series gives us some indication about how predictable the different series are.

For professional forecasters the method is identical to the one described above with the exception that the data now has a quarterly frequency. The paper uses quarterly data on inflation from 1961Q1-2006Q3. Forecasts of experts for four quarters ahead are used in order to make results comparable between households and professional forecasters[8]. The sample is divided as follows: Data on inflation from 1961Q1-1975Q4 is used as the pre-sample period. The in-sample period consists of data from 1976Q1-1990Q3. The out-of-sample period was chosen so that it corresponds to the sample of professional forecasters: 1990Q4-2006Q3. Given the quarterly frequency of the data, the independent variable vector $\mathbf{x}_t$ is now defined as $(1, \mathbf{y}_{t-4})'$. The inflation expectation by professional forecasters in period $t-4$ for period t is hence given by

$$\pi_{t|t-4} = \widehat{\mathbf{b}}'_{t-4}\mathbf{x}_t \tag{11}$$

It should be noted that because of relatively few observations for expert expectations, it is only possible to determine in-sample best fitting gains and in-sample mean square comparison errors for quarterly data.

Four different models are estimated. Model 1 is a simple AR(1) model where the independent variables are a constant and the lagged value of inflation. Model 2 is a simple AR(2) model with a constant and lagged values of inflation[9]. Model 3 includes a constant, lagged inflation and lagged output growth, which is approximated by growth in industrial production[10]. Model 4 in addition to the variables in Model 3 includes changes in interest rates. Models 1-4 for households can thus be written as follows:

$$\pi_{t+12|t} = b_{1t} + b_{2t}\pi_t + \varepsilon_t \tag{Model 1}$$

$$\pi_{t+12|t} = b_{1t} + b_{2t}\pi_t + b_{3t}\pi_{t-1} + \varepsilon_t \tag{Model 2}$$

[8] Household expectations are averaged so that rather than having monthly data we get quarterly data for household expectations as well. Results for households are derived using the same methods as for experts. They are provided together with the results for professional forecasters for direct comparison purposes.

[9] Results for higher order AR models were also computed but it was found that the AR(1) and AR(2) models outperformed higher order models.

[10] This paper follows Branch and Evans (2006) in using output growth as one of the explanatory variables. Conventional New Keynesian Phillips curve estimations typically use the output gap instead. Results using the output gap (defined as $y = \ln(Y) - \ln(Y^*)$ where Y is GDP seasonally adjusted and Y^* is potential output estimated as the HP filtered Y) instead of output growth were also computed and found to be very similar.

$$\pi_{t+12|t} = b_{1t} + b_{2t}\pi_t + b_{3t}z_t + \varepsilon_t \quad \text{(Model 3)}$$

$$\pi_{t+12|t} = b_{1t} + b_{2t}\pi_t + b_{3t}z_t + b_{4t}w_t + \varepsilon_t \quad \text{(Model 4)}$$

where z_t denotes industrial production growth and w_t denotes changes in interest rates. For quarterly data, models 1-4 are identical except for the fact that the dependent variable is now denoted as $\pi_{t+4|t}$. In addition, for quarterly data, data on GDP is available and hence it is not necessary to approximate output growth by industrial production.

4.2 Results

4.2.1 'Households: Learning matters'

This section examines the ability of simple linear recursive forecasting rules to explain actual data on inflation and inflation expectations. It is also examined whether there exists heterogeneity between households in different countries.

In order to assess whether it is possible to fit actual inflation with a learning model, the optimal constant gains that minimise the MSE for the in-sample period are first computed for different countries. These are shown in Table 2.

1990M1-1998M4	γ			
	Model 1	Model 2	Model 3	Model 4
Germany	0.1400	0.0960	0.1740	0.1300
France	0.1870	0.1280	0.1700	0.1360
Netherlands	0.2410	0.1580	0.1420	0.1150
Italy	0.1790	0.1490	0.0950	0.0670
Spain	0.1750	0.1480	0.1752	0.1090

Table 2: Optimal constant gain parameters, monthly data

These optimal constant gain parameters are significantly higher than those typically found for the US (For the US, Orphanides and Williams (2007b) suggest estimates of around 0.01-0.04, Branch and Evans (2006) find values of the gain of around 0.06 and Milani (2007) finds values between 0.02-0.12 using quarterly data and depending on the time period used). This could reflect the fact that inflation in the Euro Area has been subject to more structural breaks and thus it is optimal to use fewer observations of past data to predict inflation implying a higher optimal constant gain.

The ability of different specifications of the model to fit actual inflation is also assessed and it is thereby examined whether RLS or CGLS generates better predictions of actual inflation. Table 3 shows out-of-sample mean square forecast errors using both constant gain as well as recursive least squares learning.

Out-of-Sample Period: 1998M5-2006M9								
	RLS				Constant Gain			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Germany	0.4929	0.4859	0.4864	0.5350	**0.0720**	0.0879	0.1220	0.4129
France	0.3269	0.3200	0.3217	0.3520	0.0457	0.0613	0.1648	**0.0430**
Netherlands	0.7602	0.4580	0.7584	0.4349	**0.0440**	0.0784	0.0806	0.0670
Italy	0.2153	0.2243	0.2147	0.2170	**0.0198**	0.0260	0.0535	0.0346
Spain	0.7727	0.7680	0.7631	0.8599	0.0664	**0.0611**	0.1397	0.0688

Table 3: Mean square forecast errors, monthly data

It can be seen that constant gain clearly dominates RLS in terms of forecast accuracy[11]. No single model seems to fit best for all countries though. However, it can be seen that the simple model with constant gain learning and just lagged inflation and a constant as the independent variables does well for all countries. Figure 3 shows actual inflation together with forecasts generated using the optimal gain and model for the different economies. Figure 3 highlights the fact, that constant gain recursive least squares performs well in fitting actual inflation.

It is also important to analyse, which model can best explain data on inflation expectations. Best fitting gains are computed by minimising the in-sample mean square comparison errors. Hence, it is possible to assess whether there is heterogeneity regarding the best fitting constant gain parameters between countries. The best fitting constant gains for each country and model are shown in Table 4.

1990M1-1998M4	γ			
	Model 1	Model 2	Model 3	Model 4
Germany	0.0010	0.0020	0.0010	0.0010
France	0.0002	0.0082	0.0001	0.0051
Netherlands	0.0010	0.0010	0.0210	0.0010
Italy	0.0270	0.0280	0.0260	0.0240
Spain	0.0530	0.0510	0.0640	0.0460

Table 4: Best fitting constant gain parameters, households, monthly data

From Table 4, it can be seen that best fitting gains are much smaller than the optimal constant gains and that households in so-called high inflation countries such as Spain and Italy are using higher constant gain parameters than households in 'low inflation' countries such as Germany and the Netherlands. Mean square comparison forecast errors are then computed for household

[11] We performed modified Diebold/Mariano tests with the null of equal forecast accuracy to test whether the differences in MSEs between RLS and CGLS are significant. We test whether the difference between the largest MSE under CGLS and the smallest MSE under RLS is significant. It is found that the null hypothesis of equal forecast accuarcy can be rejected at the 5% level of signifiance for each country. P-values and modified Diebold/Mariano statistics can be provided by the author upon request.

expectations using both data generated with the RLS algorithm as well as data generated using the CGLS algorithm with the best fitting constant gains. Hence, it is possible to examine whether learning matters for inflation expectation formation of households and which dependent variables households use when predicting inflation. But the paper also assesses whether recursive least squares or constant gain learning provides a better description of household behaviour and whether there is country heterogeneity with respect to learning. The results are found in Table 5.

Out-of-Sample Period: 1998M5-2006M9								
	RLS				Constant Gain			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Germany	0.5589	0.5508	0.5609	0.6502	**0.5349**	0.5631	0.5360	0.6858
France	0.3226	0.3096	0.3229	0.3549	0.4491	0.3532	0.3812	**0.2958**
Netherlands	0.5278	0.3320	0.5325	0.3657	0.4500	0.5753	0.6906	**0.2774**
Italy	0.3781	0.3785	0.3805	0.3229	0.3095	0.2991	0.3082	**0.2402**
Spain	1.7622	**1.7565**	1.7661	1.9075	1.9083	1.9885	2.0407	2.1847

Table 5: Mean square comparison errors, households, monthly data

Table 5 shows that expectations in France, the Netherlands and Italy can be fitted better with our simple models than expectations in Germany and Spain. Specifically Model 4 seems to perform well in those countries, which suggests that agents use more complicated models than those simply including lagged inflation. In the case of Spain, given the large forecast errors, there is little evidence that agents are using any of the simple linear forecasting models employed by this paper.

The relative MSCE for the model that yields the smallest mean square comparison error are also computed for each country. Relative MSCEs for the optimal model for each country are shown in Table 6.

Out-of-Sample Period: 1998M5-2006M9	
	Relative MSCE
Germany	0.7865
France	0.5096
Netherlands	0.5660
Italy	0.0619
Spain	0.9494

Table 6: Relative mean square comparison forecast errors, households, monthly data

Table 6 shows that the relative MSCE is still smallest for Italy, meaning that the model is able to fit expectations in Italy best. The difference between the relative MSCE for the best fitting model for Italy and the relative MSCE corresponding to the best fitting models for France and Netherlands is now larger than was the case with absolute MSCEs. There is hence evidence, that our simple learning model does significantly better in predicting household expectations in Italy than in predicting expectations in other countries.

Figure 4 shows actual household inflation expectations and the generated series for expectations of inflation using the optimal model and best fitting constant gain for each country. It can be seen that whilst the direction of inflation expectations can be predicted well (even for Spain), expectations are somewhat more volatile than our generated series. A possible explanation may be that whilst households use simple linear forecasting models, there are certain stochastic shocks and events to which households react and which also influence their expectations.

4.2.2 'Professional forecasters use higher constant gain parameters than households'

This section assesses the extent to which simple learning rules can explain survey data on inflation expectations by professional forecasters. It is also investigated whether there exists heterogeneity between experts and households.

First, it is assessed whether a simple learning model can fit actual data on inflation. Optimal gains for each model are shown in Table 7. Results are only shown for three countries. The reason is that there are data constraints for the Netherlands and Spain[12].

1976Q1-1990Q3	γ			
	Model 1	Model 2	Model 3	Model 4
Germany	0.1380	0.1120	0.1780	0.1110
France	0.2160	0.1050	0.1230	0.1020
Italy	0.3000	0.2000	0.1570	N/A

Table 7: Optimal constant gain parameters, quarterly data

As was the case in the previous section, optimal constant gains are again higher than those found by empirical studies for the US.

The out of sample forecast errors for actual data on inflation are shown in Table 8. It can be seen that constant gain least squares learning again dominates recursive least squares learning in terms of out-of-sample performance and that the simplest model does well in explaining actual inflation[13]. This is also shown in Figure 5, which shows actual inflation and predicted inflation

[12] Data on expert expectations for the Netherlands and Spain is available from 1994Q4-2006Q3. Data on output growth is available from 1977Q2 for the Netherlands and from 1970Q2 for Spain. Data on interest rate growth is available from 1986Q2 for the Netherlands and 1977Q2 for Spain. These series would have been too short for our purposes.

[13] Modified Diebold/Mariano tests are computed to test the hypothesis of equal forecast accuracy between the model yielding the largest MSE under CGLS and the model yielding the smallest MSE under RLS. The hypothsis of equal forecast accuracy can be rejected at the 5% level of significance for each country. Test statistics and

using the optimal model and optimal gain parameter for each country.

Out-of-Sample Period: 1990Q4-2006Q3								
	RLS				Constant Gain			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Germany	0.9801	1.0137	0.8508	0.8734	0.2356	0.3864	**0.2142**	0.3888
France	0.2986	0.3226	0.3043	0.4526	**0.0721**	0.1203	0.1742	0.2296
Italy	1.1611	1.3113	0.9977	N/A	**0.0658**	0.1011	0.2647	N/A

Table 8: Mean square forecast errors, quarterly data

Table 9 shows best fitting constant gains, which can be used to examine whether there is heterogeneity between professional forecasters and households. As indicated before, data on household expectations which has monthly frequency is averaged to convert it into quarterly data and then the same estimations are performed with household expectations as with expert expectations in order to have a direct comparison between expectations of households and professional forecasters.

In-Sample Period: 1990Q4-2006Q3								
	γ							
	Model 1		Model 2		Model 3		Model 4	
	Experts	HH	Experts	HH	Experts	HH	Experts	HH
Germany	0.1380	0.0018	0.1000	0.0010	0.1080	0.0010	0.0460	0.0012
France	0.0200	0.0080	0.0240	0.0142	0.0130	0.0060	0.0410	0.0070
Italy	0.1780	0.0720	0.1380	0.0720	0.1370	0.0930	N/A	N/A

Table 9: Best fitting constant gain parameters, households and experts, quarterly data

Experts seem to update their information sets more frequently than households. This could be due to the fact that households find it more costly to update their information sets than professional forecasters.

Tables 10 and 11 show mean square comparison errors for households and experts. It can be seen that there does not seem to be one model, which fits best across all three countries. There is some evidence that households are more inclined to use simpler models with just lagged values of inflation compared to professional forecasters who use a larger variety of variables to predict inflation. However, this does not correspond to the findings for monthly data. This apparent contradiction between the results for household expectations for monthly and quarterly data could due to the fact that by averaging data important information on household expectations is lost.

P-values are available from the author upon request.

In-Sample Period: 1990Q4-2006Q3								
	RLS				Constant Gain			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Germany	0.3419	0.4805	0.2930	0.3704	0.4068	0.2268	**0.2046**	0.2664
France	0.2752	0.2910	0.2765	0.4613	0.2780	0.2439	0.2707	**0.2194**
Italy	0.8475	1.0138	0.8242	N/A	**0.4300**	0.4865	0.4926	N/A

Table 10: Mean square comparison errors, experts, quarterly data

In-Sample Period: 1990Q4-2006Q3								
	RLS				Constant Gain			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Germany	0.7816	0.9610	0.7913	0.9064	0.7197	**0.6912**	0.7113	0.9762
France	0.7233	0.7918	0.7439	0.9859	**0.3897**	0.6250	0.5403	0.4757
Italy	0.8662	0.9625	0.9711	N/A	0.6062	**0.5811**	0.8091	N/A

Table 11: Mean square comparison errors, households, quarterly data

Again, it is possible in line with the previous literature on forecasting to compute relative mean square forecast comparison errors. The best fitting model is used for each country. Relative MSCEs for households and experts are shown in Table 12.

In-Sample Period: 1990Q4-2006Q3	Relative MSCEs	
	HH	Experts
Germany	1.0710	0.2794
France	0.6938	0.4705
Italy	0.1510	0.1679

Table 12: Relative mean square forecast comparison errors, households and experts, quarterly data

From Table 12 it can be seen that according to the relative MSCEs the simple recursive forecasting model is able to fit expectations in Italy best. This is different to the conclusions made from Tables 10 and 11. It highlights the fact that expectations in Germany and France may be somewhat more predictable than in Italy.

It seems to be the case that our simple forecasting models fit expectations of professional forecasters somewhat better than household expectations. It can be tested whether the differences in mean squared comparison errors are significant using a modified Diebold/Mariano (1995) test with the small sample correction proposed by Harvey et al (1997). It is possible to compare the mean square comparison errors of the optimal model for each country, i.e the model that yields the smallest absolute MSCE. For example, for Germany, Model 3 is used for experts and Model 2 for households. The results of the modified Diebold/Mariano tests are shown in

Table 13.

	mod. DM statistic	P-value
Germany	2.0921	0.0487
France	1.3768	0.1906
Italy	1.1567	0.2706

Table 13: Modified Diebold/Mariano tests for equal forecast accuracy of households and experts, quarterly data

It can be seen that with the exception of Germany, the null hypothesis of equal forecast accuracy cannot be rejected at the 1% and 5% level. There is hence evidence that for France and Italy the model is able to predict expectations of households and experts equally well. Figure 6 shows expert expectations and our generated series for inflation forecasts. It can be seen that the general direction of expectations can be predicted well with our model. This is also the case for fitting household expectations, which Figure 7 illustrates.

4.3 Discussion

Overall, there is hence evidence that constant gain least squares learning outperforms recursive least squares in fitting data on inflation and inflation expectations. This supports the results by Branch and Evans (2006) for the US economy. The optimal constant gain parameters needed to fit actual data on inflation in the Euro Area are somewhat higher than those found for the US. This is true for both, quarterly and monthly data and different time periods. It is shown that the optimal gain parameters for the European economies in our sample range from 0.07-0.30. For the US, Orphanides and Williams (2007b) suggest estimates of around 0.01-0.04, Branch and Evans (2006) find values of the gain of around 0.06 and Milani (2007) finds values between 0.02-0.12 using quarterly data and depending on the time period used[14]. A higher gain coefficient for the Euro area than in the US implies that agents should optimally use fewer years of data to form a prediction of inflation. A possible explanation for this might be that inflation in European countries is subject to more structural breaks. Constant gain least squares learning discounts past observations geometrically and hence if there are more structural breaks, fewer years of data should optimally be used to generate forecasts.

The results have shown that best fitting gains to fit household expectations are much smaller than optimal gains needed to fit actual data of inflation. Best fitting gain for the European economies in our sample range from 0.0001 to 0.064. These results roughly correspond with results found for the US (Pfajfar and Santoro (2006) find best fitting constant gains between

[14] If the gain is denoted by γ, then this gain implies that agents use $(1/\gamma)/f$ years of data, where f denotes the data frequency: $f = 1$ for yearly data, $f = 4$ for quarterly data and $f = 12$ for monthly data.

0.0008-0.001 for monthly data). The fact that best fitting constant gains are well below optimal constant gains might imply that households are possibly unaware of some of the structural breaks in the data and use a larger number of past observations to form an expectation of inflation than would be optimal.

It is interesting to note that households in 'high inflation' countries such as Spain and Italy use higher constant gains than those in 'low inflation' countries and are hence picking up structural changes faster. A possible explanation for the fact that households in the so-called high inflation countries are 'learning faster' is provided by Sims (2003, 2006). Sims (2003, 2006) argues that when inflation is high, economic agents will pay more attention to new information coming available as their opportunity cost of being inattentive is significantly higher during these periods. It is also found that higher constant gains are needed to explain the data on inflation expectations of professional forecasters than for households. This could be caused by a greater awareness of the presence of structural breaks by professional forecasters but it could also be the case that professional forecasters are more willing to incur the costs of updating their information sets than households, which update their information sets less frequently (Carroll (2003 a,b), Döpke (2005))[15]. Theories of sticky information also emphasise that households update their information sets infrequently because of the substantial costs incurred in this updating process (Mankiw and Reis, 2007).

5 Testing for convergence

5.1 Estimation procedure

This section investigates whether expectations converge to equilibrium. It is also investigated whether agents are able to learn the inflation goal of the ECB, which is to maintain inflation close to but below 2% in the medium term. As explained above this can be tested within a Kalman filtering framework by investigating whether the variance of the hyper-parameters is significantly different from 0. Time-varying parameters are estimated using the model outlined in equations (3)-(7). Given that the simplest model of inflation performs quite well for all countries, it is assumed that inflation expectations are derived from the following rule:

$$\pi_{t+12|t} = b_{1t} + b_{2t}\pi_t + \varepsilon_t \tag{12}$$

for households and

$$\pi_{t+4|t} = b_{1t} + b_{2t}\pi_t + \varepsilon_t \tag{13}$$

[15]Papers by Carroll (2003a,b) and Doepke (2005) are based on a model in which households only update their information sets sporadically by reading newspapers and thus learn from professional forecasters. Unfortunately, the data sample is too short to test for such behaviour in this paper.

for professional forecasters.

Furthermore the following assumptions are made:

$$b_{i,t} = b_{i,t-1} + \eta_{i,t} \tag{14}$$

and

$$\varepsilon_t \sim N(0, \sigma^2) \text{ and } \eta_{i,t} \sim N(0, (Q_t^i)^2).$$

It is hence assumed that the variance on the measurement equation is constant while the variance of the hyper-parameters may be time dependent. The variance of the measurement equation is assumed to be constant in order to restrict the number of free parameters that have to be estimated within the Kalman filter. To test for convergence, it is investigated whether the variance of the state decreases over time, which would imply that the learning process is converging towards least squares estimates. Following Basdevant (2005) who uses the methods discussed in Hall et al (1997) to test for convergence, Q_t is modelled as follows

$$Q_{i,t} = \lambda^2 Q_{i,t-1} \tag{15}$$

for $i = 1, 2$.

As shown by Hall et al (1997) and Hall and St. Aubyn (1995), if $0 \leq \lambda < 1$ convergence in expectations holds. The null hypothesis $H_0 : \lambda = 1$ is tested against the alternative $H_1 : \lambda < 1$. In order to obtain the distribution of some function of λ under the null, this paper follows Basdevant (2005) in constructing the test statistic proposed by Hall and St. Aubyn (1995) and St. Aubyn (1999). This is given by

$$HSA = \frac{\widehat{\lambda} - 1}{\widehat{\sigma}(\widehat{\lambda})}.$$

It should be noted that $\widehat{\sigma}(\widehat{\lambda})$ is the estimated standard error of the parameter λ. Hall and St. Aubyn (1995) and St. Aubyn (1999) calculate critical values for the HSA statistic. These are -3.479 at the 1% level, -2.479 at the 5% level and -1.970 at the 10% level.

In order to test for convergence in practice, EViews is used in order to set up a state space model. As EViews cannot estimate equation (15) in its present form, the equation is rewritten as $Q_{i,t} = \lambda^{2t} Q_{i,0}$ where t is a time trend. In order to impose values for $Q_{i,0}$, equations (12) and (13) are estimated using OLS and the squared standard deviations of the coefficients are used as estimates of the initial variances. For household expectations, initial values of the variances are determined using data from 1981M1-1989M12 and for experts initial values are determined using data from 1961Q1-1990Q3.

5.2 Results

5.2.1 Household expectations

This section investigates whether the learning process of households moves towards equilibrium. Data from 1990M1-2006M9 is used. The null hypothesis that $H_0 : \lambda = 1$ is tested against the alternative hypothesis that $H_1 : \lambda < 1$. The results are shown in Tables 14 and 15.

	λ	**Std. Error**	**HSA**
Germany	0.996640	0.000387	-8.6820***
France	0.998199	0.000525	-3.4302**
Italy	0.995096	0.000667	-7.3522***
Netherlands	0.998652	0.000579	-2.3274*
Spain	0.998010	0.000505	-3.9406***
Euro Area	0.991442	0.000543	-15.7510***
* "No convergence" rejected at 10% confidence level			
** "No convergence" rejected at 5% confidence level			
*** "No convergence" rejected at 1% confidence level			

Table 14: Households: Testing for convergence

		Final State	**Root MSE**	**P-value**
Germany	$\widehat{b}_1$	1.4536	0.3550	0.0000
	$\widehat{b}_2$	-0.0584	0.2934	0.8422
France	$\widehat{b}_1$	2.3013	0.4103	0.0000
	$\widehat{b}_2$	0.2106	0.1934	0.2759
Italy	$\widehat{b}_1$	3.0022	0.734328	0.0000
	$\widehat{b}_2$	-0.7352	0.3493	0.0353
Netherlands	$\widehat{b}_1$	1.1782	0.4746	0.0131
	$\widehat{b}_2$	0.1214	0.1172	0.3002
Spain	$\widehat{b}_1$	4.4108	1.2780	0.0006
	$\widehat{b}_2$	-0.1406	0.2512	0.5755
Euro Area	$\widehat{b}_1$	1.7892	0.3176	0.0000
	$\widehat{b}_2$	0.2662	0.1455	0.0673

Table 15: Households: Testing for convergence: Final state estimates

It can be seen that there is evidence of convergence to equilibrium for all countries. However, the values found for λ are extremely close to 1 and hence the convergence process occurs very slowly. It can also be seen that the respective weights on lagged inflation converge to zero. This suggests that inflation expectations are becoming more anchored to a constant. However, coefficients on the constant do not converge to something just below 2, which would imply that economic agents have learned the inflation goal of the ECB correctly. Instead, households in

Spain and Italy consistently over-estimate the inflation goal and households in Germany and the Netherlands consistently under-estimate the inflation goal. For the European Union as a whole it can be seen that inflation has converged to a constant, which is in line with the goal of the ECB. Figure 8 shows smoothed state estimates. It can be seen that the estimates for the constant in equation (12) rise substantially around the year of 2002 and then fall again in Germany and the Netherlands but stay at elevated levels in Italy and Spain. In 2002 there was the introduction of the European single currency and this had a large effect on the perceived inflation rate of households. Berk and Hebbink (2006) also conclude that the introduction of the common currency had significant effects on perceived inflation. They argue that this effect is due to a relative price increase of the most visible expenditure items in the period before the Euro introduction. The fact that household expectations are affected by the introduction of the European single currency so substantially means that one has to be cautious in interpreting the results in Tables 14 and 15. Even though the final state estimates for the constant in Table 15 are highly significant, it could be the case that as a result of the developments in 2002 our estimates for the coefficients are somewhat affected and may not have converged to their final values. A longer data period after the introduction of the European single currency would enable us to be more confident in the conclusions drawn from Tables 14 and 15.

5.2.2 Expectations of professional forecasters

It is also investigated whether the expectations of professional forecasters converge towards equilibrium. Tables 16 and 17 show the results of convergence tests for expectations of professional forecasters from 1990Q4-2006Q3.

	λ	**Std. Error**	**HSA**
Germany	0.998366	0.000199	-8.2094***
France	0.998787	0.000341	-3.5580***
Italy	0.994084	0.000368	-16.0773***
Netherlands	0.996944	0.000314	-9.7319***
Spain	0.998939	0.000394	-2.6927**
Euro Area	0.992691	0.000515	-14.1916***
* "No convergence" rejected at 10% confidence level			
** "No convergence" rejected at 5% confidence level			
*** "No convergence" rejected at 1% confidence level			

Table 16: Experts: Testing for convergence

It can be seen that the null hypothesis of 'no convergence' can be rejected at the 5% level of significance for all countries in our sample. However, λ is very close to 1, which implies that convergence takes a long time. It is again interesting to note that with the exception of Spain and Germany the weight on lagged inflation converges to zero and expectations become anchored

		Final State	**Root MSE**	**P-value**
Germany	$\widehat{b}_1$	1.6322	0.2622	0.0000
	$\widehat{b}_2$	0.3248	0.1644	0.0482
France	$\widehat{b}_1$	1.7068	0.1753	0.0000
	$\widehat{b}_2$	-0.0021	0.0510	0.9716
Italy	$\widehat{b}_1$	1.6705	0.1825	0.0000
	$\widehat{b}_2$	0.0591	0.0872	0.4980
Netherlands	$\widehat{b}_1$	1.7160	0.1622	0.0000
	$\widehat{b}_2$	-0.0050	0.0534	0.9260
Spain	$\widehat{b}_1$	2.9048	0.3512	0.0000
	$\widehat{b}_2$	0.1007	0.0455	0.0270
Euro Area	$\widehat{b}_1$	1.7463	0.2636	0.0000
	$\widehat{b}_2$	0.1548	0.1156	0.1806

Table 17: Experts: Testing for convergence: Final state estimates

to a constant. The coefficients on this constant seem to be more in line with the goal of the ECB. This contrasts the findings for the inflation expectations of households. Only professional forecasters' expectations for Spain now somewhat overestimate inflation. Hence, professional forecasters' expectations of inflation seem to be more anchored to the inflation goal of the ECB than it is the case for the inflation expectations of households. Figure 9 shows smoothed state estimates for the constant and lagged inflation. It can be seen that expectations have not been affected by the introduction of the Euro currency. The graphs give further evidence that coefficients have converged to the values given in Tables 16 and 17.

5.3 Discussion

It is found that household expectations in European economies do not seem to have converged to the inflation goal of the ECB. If there is a link between actual inflation and expected subjective rates of inflation, via a New Keynesian Phillips curve relationship for example, this implies that it is not likely that there will be convergence in inflation rates in the Euro Area in the near future. Instead it is likely that there will remain persistent differences in inflation rates between Euro Area countries even though the average Euro Area inflation rate will be on target.

In an integrated market such as the Euro Area, inflation differentials across countries arise as an integral part of catching up and adjustment mechanisms to shocks. However, if the inflation differentials between countries are more than just temporary deviations from the Eurozone average, they could be harmful in a monetary union. As Angeloni and Ehrmann (2007) argue in a monetary union all countries share the same nominal interest rates and thus a high-inflation country tends to have a lower real interest rate, assuming the relevant inflationary expectations are, at least partly, country-specific. A lower real interest rate discourages saving and stimulates consumption and investment, thereby amplifying the inflation differentials. This effect may be further amplified by wealth effects, as low real interest rates may inflate share and real estate prices. Whilst a high inflation country tends to lose price competitiveness within the currency area, something that dampens demand and output at home and thus inflation, this effect is likely to operate only at a slow pace (Arnold and Lemmen, 2006).

The results in this paper suggest that professional forecasters are more inclined to incorporate the implications of monetary union for convergence in inflation rates into their expectations than ordinary consumers. However, this is not true for all countries as expectations in Spain are still more linked to local inflation rates than the inflation goal of the ECB. Unfortunately, given that the EC Consumer Survey only asks households for expectations of inflation 12 months ahead, it is not possible to test whether our results hold for longer expectation horizons (for instance expectations 2 years ahead). It should be noted that our findings correspond to those by Arnold and Lemmen (2006) who use a growth theory type of model to test for convergence and also find that Consensus data on the inflation expectations of professional forecasters demonstrates more convergence than exists among the public.

6 Conclusion

Recently, there has been a growing number of theoretical papers modelling economic agents as econometricians when forecasting. Against this background this paper provides the first attempt to assess whether adaptive learning behaviour of economic agents is a reasonable assumption for the Euro Area. This is analysed using survey data on inflation expectations by households and professional forecasters and by assessing the ability of different linear forecasting rules to explain this data.

Overall, the paper provides further support for constant gain algorithms as a description of actual forecaster behaviour. Heterogeneity in expectations is found between different Euro Area economies and between households and professional forecasters. Households in so-called 'high inflation' countries use higher constant gain parameters and hence update their information sets more frequently than households in 'low inflation' countries. A possible explanation for this behaviour is Sims' theory of 'Rational Inattention'. According to this theory, consumers will pay more attention to new information in periods when their opportunity cost of being inattentive is significantly higher. It is also shown that professional forecasters are updating their information sets more frequently than households. This can be explained by theories of sticky information, in which households face substantial costs when updating their information sets.

In the second part of the analysis the paper turns to the question of whether an equilibrium can be learnt by economic agents. The paper also investigates whether households and professional forecasters incorporate the goal of the ECB, which is to keep inflation close to but below 2% in the medium term, into their expectations. It is found that the inflation expectations by households and experts converge to equilibrium but at a very slow rate. Furthermore the results show that household expectations do not seem to have converged to the inflation goal of the ECB. Professional forecasters are more inclined to incorporate the implications of monetary union into their expectations. However, even for professional forecasters this is not true for every country. If expected inflation rates have a direct influence on actual inflation via price and wage setting by economic agents as proposed by New Keynesian theories, this finding may hence provide a partial explanation for the fact that convergence in inflation rates across countries in the Euro Area has not yet been observed.

Some useful directions for further research should be noted. First of all, it would be interesting to evaluate more complicated forecasting models. Data on expectations of output is available for professional forecasters and with this data it would be possible to use vector autoregressive forecasting models in order to predict inflation-output vectors. Furthermore, it would be worthwhile to include more countries in our sample. The UK would be an interesting example, as it is not part of the monetary union and has had an independent central bank since 1997 with an explicit inflation target. One could for example investigate whether different institutional setups of central banks affect the learning behaviour of agents. Once longer data sets on expectations are available it would be possible to test whether optimal gains stay constant over time. One could then analyse whether learning is faster in periods of high inflation than in periods of low inflation, a finding, which would give further support to theories of rational inattention. Additionally, with longer data sets, it would be possible to test whether agents exhibit switching behaviour as outlined by Marcet and Nicolini (2003) in which they switch between constant gain least squares and recursive least squares learning. It would be interesting to investigate whether recursive least squares learning outperforms constant gain least squares learning in periods with very stable inflation, such as have been observed during the past decade. These questions are left to be explored in future research.

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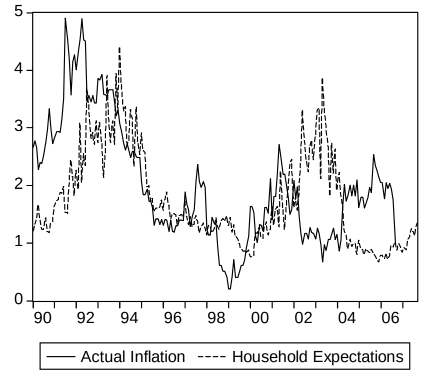
8 Appendix

9 Tables and Figures

Variable	**Source**	**Frequency**	**Data period**
Household Expectations for Inflation in $t+12$	European Commission Consumer survey (DG ECFIN)	Monthly	1990M1-2006M9
Professional Experts Expectations for Inflation in $t+4$	Consensus Economics	Quarterly	1990Q1-2006Q3
Consumer Price Index (HICP)	Eurostat-Indices of Consumer Prices	Monthly	1981M1-2006M9
Consumer Price Index-All Items	OECD-Main Economic Indicators	Quarterly	1961Q1-2006Q3
Industrial Production-All Items, Seasonally adjusted	Bank of International Settlements (BIS)	Monthly	1981M1-2006M9
GPP in real terms, Seasonally adjusted	BIS	Quarterly	1961Q1-2006Q3
3-month interest rate	BIS and ECB	Monthly	1981M1-2006M9
3-month interest rate	BIS and ECB	Quarterly	1961Q1-2006Q3

Table 18: Data sources



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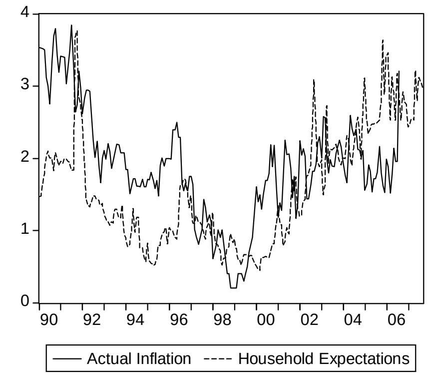

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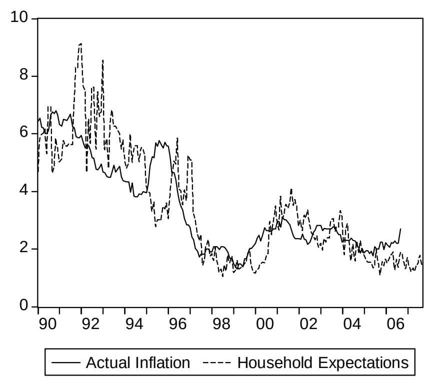

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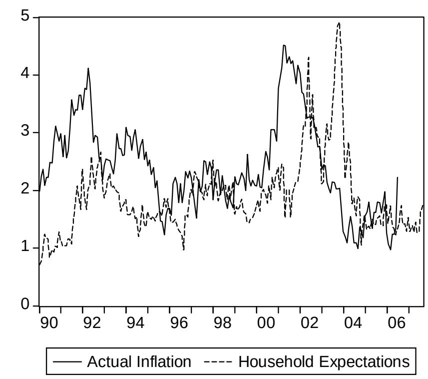

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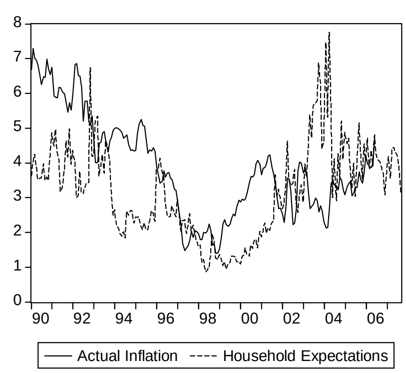

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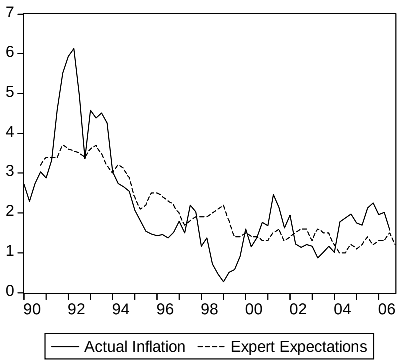
Figure 1: Actual inflation and household expected inflation from t-12 for t.



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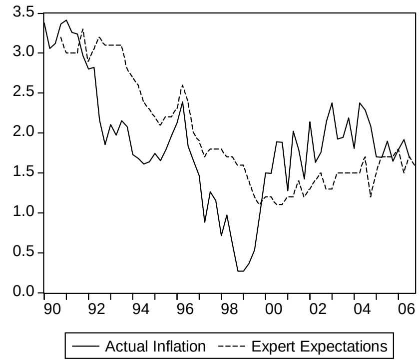

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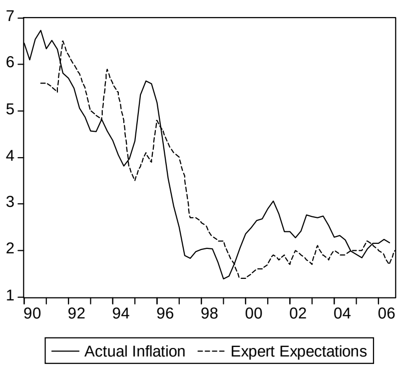

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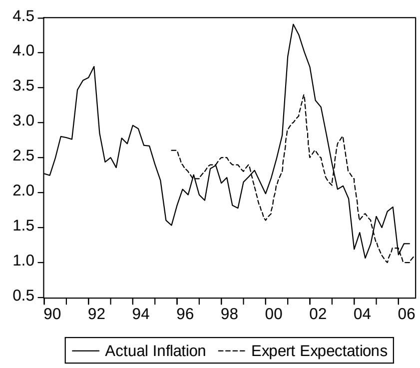

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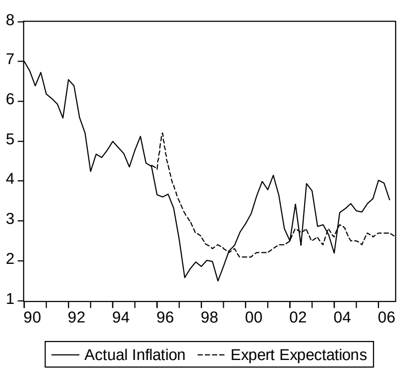

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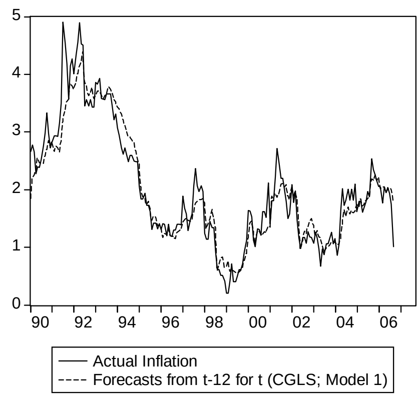
Figure 2: Actual inflation and consensus forecasts from t-4 for t



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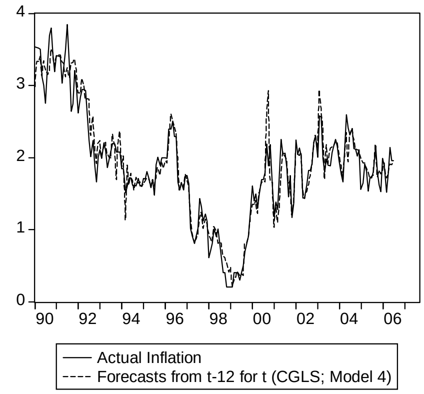

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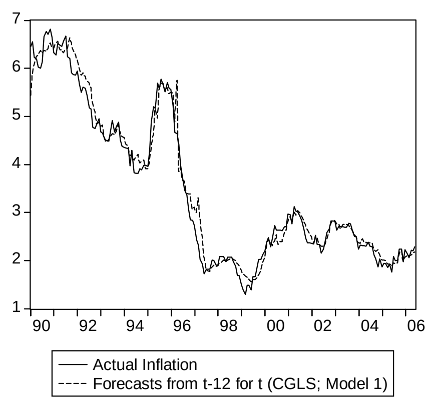

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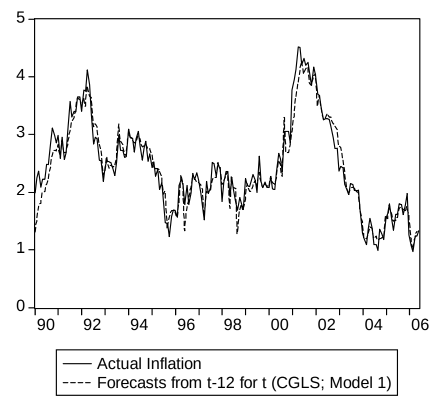

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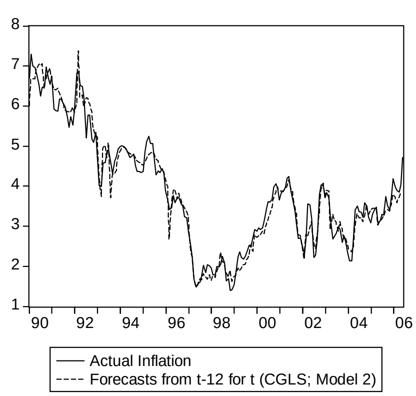

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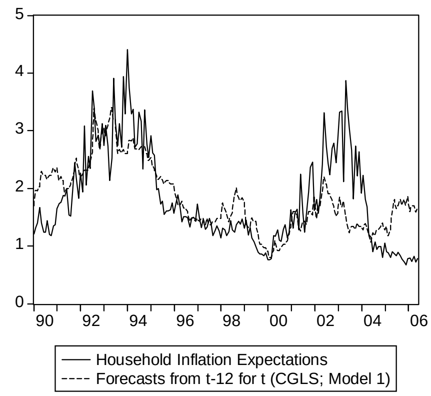
Figure 3: Actual inflation and generated forecasts from t-12 for t using the optimal constant gain and model



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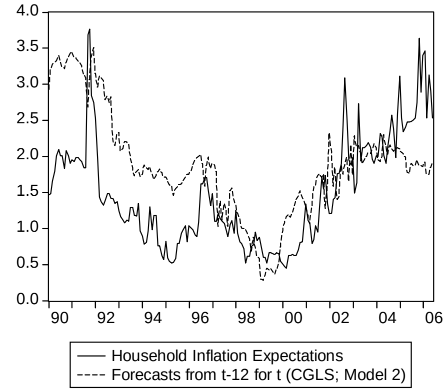

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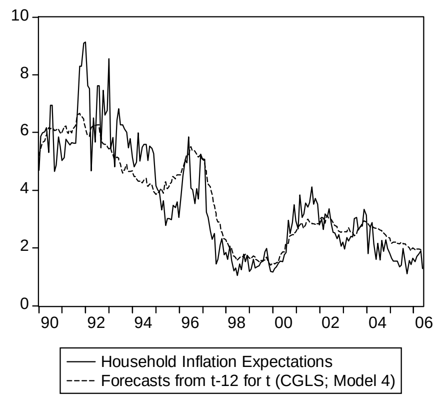

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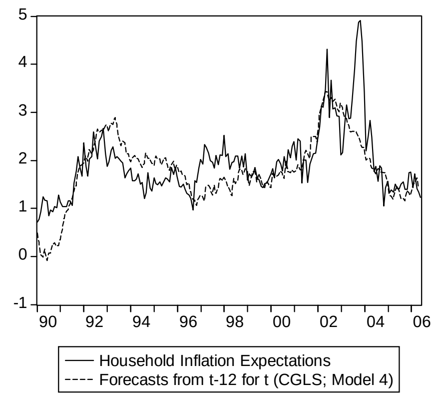

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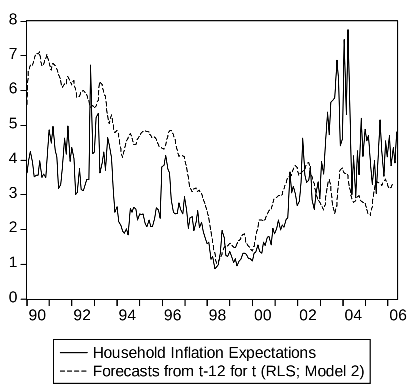

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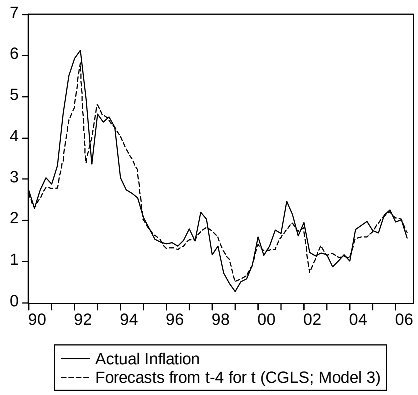
Figure 4: Household expectations from t-12 for t and generated forecasts using the best-fitting constant gain and model



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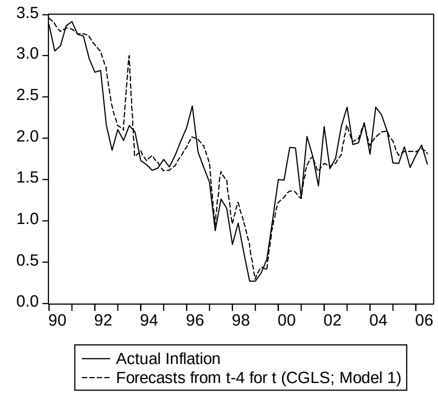

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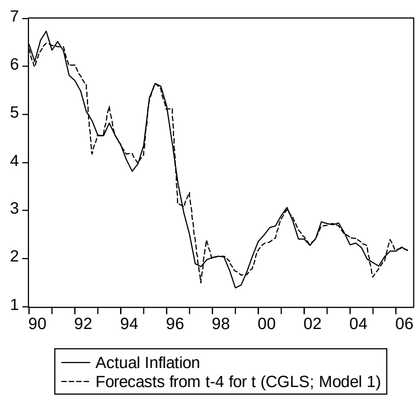

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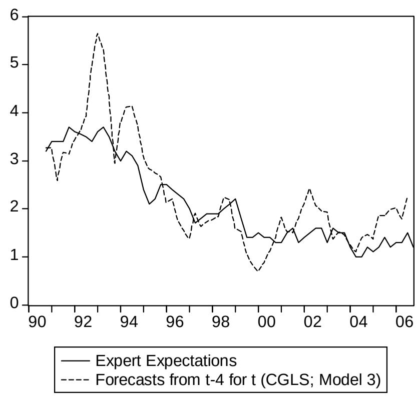
Figure 5: Actual inflation and generated forecasts using the optimal constant gain and model from t-4 for t



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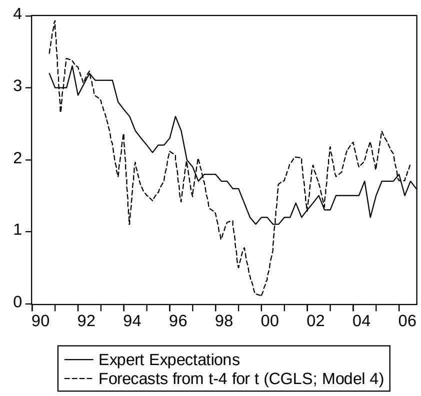

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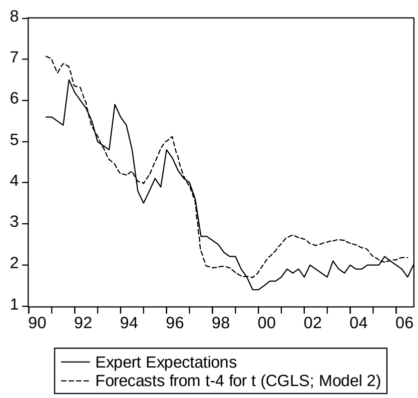

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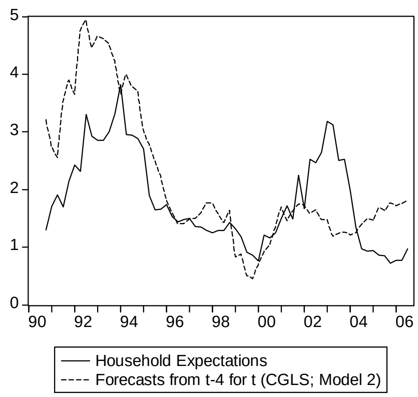
Figure 6: Consensus forecasts from t-4 for t and generated forecasts using the best-fitting constant gain and model



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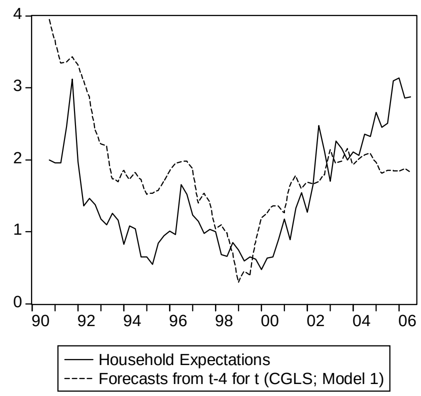

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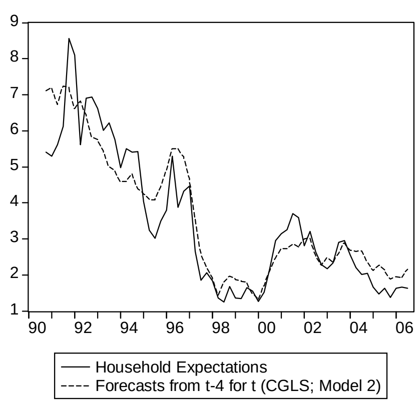

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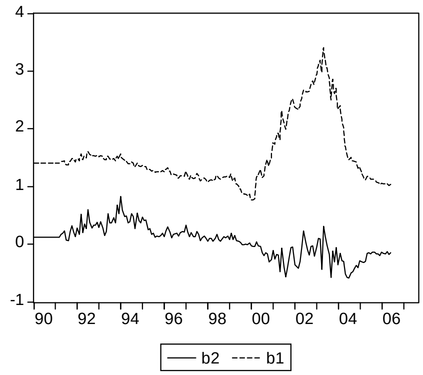
Figure 7: Household expectations from t-4 for t and generated forecasts using the best-fitting constant gain and model



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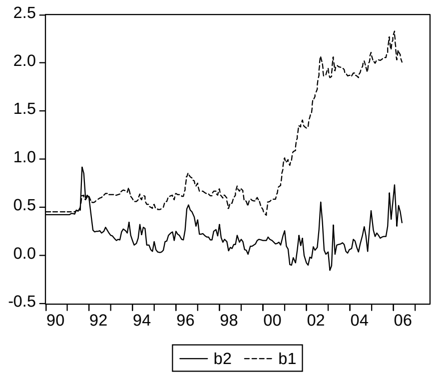

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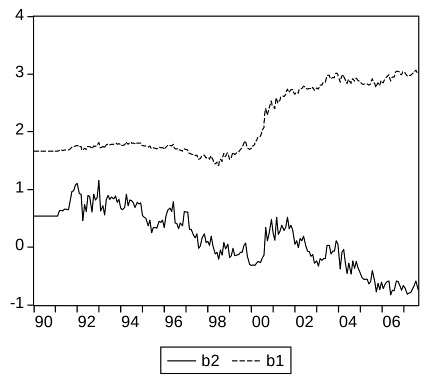

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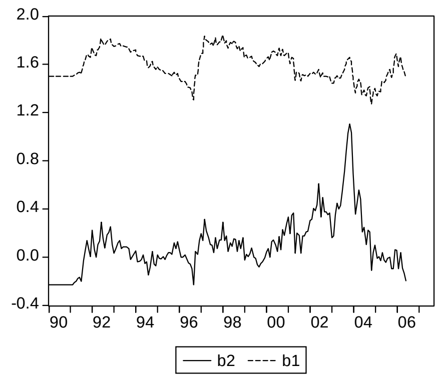

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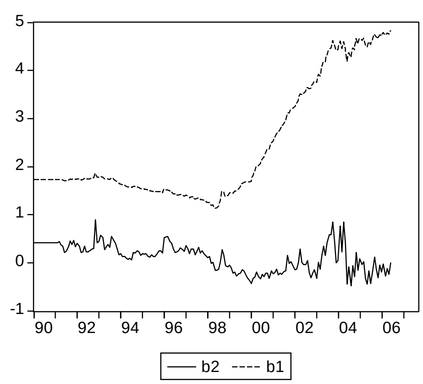

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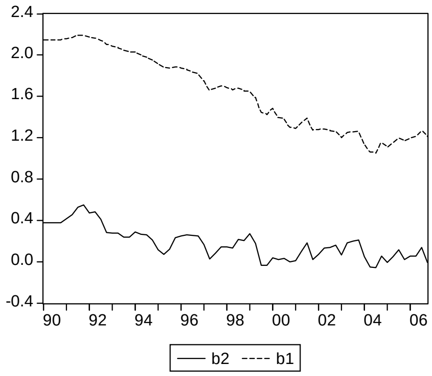
Figure 8: Smoothed state estimates, Household expectations



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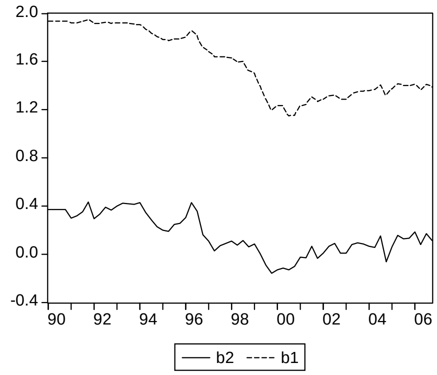

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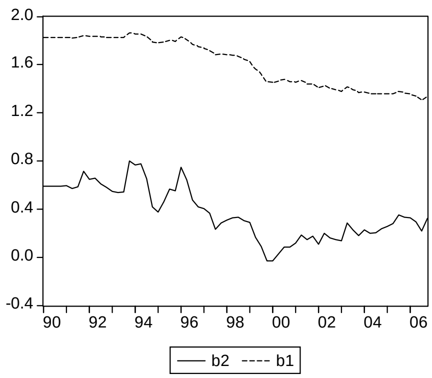

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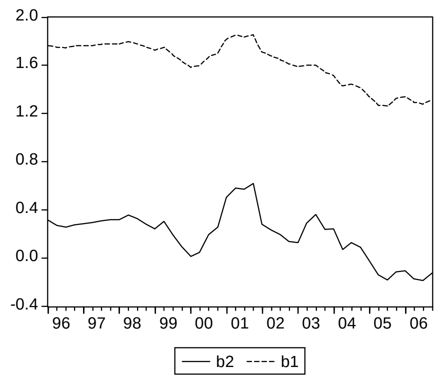

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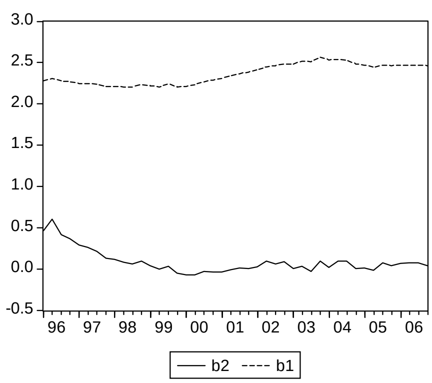

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Figure 9: Smoothed State Estimates, Consensus forecasts