

Explaining the Early Years of the Euro Exchange Rate: an episode of learning about a new central bank

Manuel Gómez,^a Michael Melvin,^b and Federico Nardari^c

February 2006

Abstract:

Many observers were surprised by the depreciation of the euro after its launch in 1999. Handicapped by a short sample, explanations tended to appeal to anecdotes and lessons learned from the experiences of other currencies. Now sample sizes are just becoming large enough to permit reasonable empirical analyses. The model of this paper provides empirical support for the euro exchange rate to be affected by learning. By focusing on euro-area inflation as the key fundamental, the model is structured toward the dynamics of learning about ECB policy with regard to inflation. While a stated target inflation rate of 2 percent existed, it may be that market participants had to be convinced that the ECB would, indeed, generate low and stable inflation. With a prior distribution drawn from the pre-euro EMS experience and updating based upon the realized experience each month following the introduction of the euro, the evidence suggests that it was not until December of 1999 that the market assessed a greater than 50 percent probability that the inflation process had changed to a new regime. From this point on, trend depreciation of the euro ends and further increases in the probability of the new inflation process are associated with euro appreciation versus the US dollar, the British pound and the Japanese yen.

^aUniversity of Guanajuato, Mexico

^bContact author: Department of Economics, Arizona State University, Tempe, AZ 85287 -3806; phone 480-965-6860; fax 480-965-0748; email: mmelvin@asu.edu

^cDepartment of Finance, Arizona State University

We thank seminar participants at the Econometric Society winter meetings, Arizona State University, and the universities of Bern, Frankfurt, and Tübingen for their comments on an earlier draft. In addition, helpful comments were received from Siddhartha Chib, two referees and the editor (Juergen von Hagen). We remain responsible for any remaining shortcomings.

JEL code: C1, C4, F31, F33

Keywords: euro, ECB, exchange rates, Bayesian learning, Markov Chain Monte Carlo, Bayes Factors.

1. Introduction

The launch of the euro on January 1, 1999 was the most important international financial event since the end of World War II. This new currency was expected by many to garner immediate acceptance and challenge the role of the dollar as a vehicle currency. Nevertheless, in its infancy its role in the foreign exchange market has been less than what was expected.

As shown by Hartmann (1998), the nations that comprise the European Monetary Union make an economic unit at least as large as the United States. European Union (EU) GDP exceeds US GDP, EU population exceeds US population, EU exports surpass US exports, and outstanding claims in total EU capital markets (bank assets, bonds and equities) are larger than those in the United States. All these indicators would lead us to think that the new currency would challenge the supremacy of the dollar as the most important currency in the world. Nevertheless, the triennial Bank for International Settlements (BIS) survey indicates that the dollar's share of foreign exchange market activity has risen while that of the euro compared to legacy European currencies has fallen. In 1998, the dollar entered on one side of 87 percent of foreign exchange transactions and the legacy euro currencies 53 percent¹. In 2001, the dollar share rose to 90 percent while the euro's share was but 38 percent. In 2004, the dollar share was 89 percent while the euro's share was 37 percent. Further evidence is provided in Hau, Killeen and Moore (2002) who show that the average daily dollar/euro volume in foreign

¹ Since there are two currencies involved in every foreign exchange (FX) transaction, the global sum of currencies' shares will equal 200 percent.

exchange trading is nine percent lower than the dollar/DM volume². Moreover, they show that the trade volume of the euro with the yen and the Swiss franc decreased by 44 and 25 percent respectively when compared with the mark. This decrease in volume is striking if we consider that the mark is only one of the legacy currencies in the monetary union.

Our focus is not on the volumes traded but on the prices. Most scholars and practitioners would consider a major issue to be an understanding of the determinants of the level of the exchange rate. Earlier explanations have included Sinn and Westermann (2001, 2003), who explain the early weakness of the euro by arguing that holders of black market currency were afraid to convert their old European coins and black market notes into the euro in 2002, so they either spent them on goods and services, whereby the lower demand for money is associated with euro depreciation, or else they exchanged them for dollars prior to the appearance of euro currency. Alquist and Chinn (2001) say that the appreciation of the dollar after 1999 can be explained by U.S.-Euro area productivity differentials; however, the euro was also depreciating against the yen, so that this explanation alone cannot do. Our explanation emphasizes the role of the new central bank and the effect of a lack of ECB credibility on the exchange rate when the market is learning about the ECB policymaking process and addresses the initial euro depreciation as well as later appreciation against the dollar and pound.

Credibility of the European Central Bank, or the lack of it, has likely played a very important role in the determination of the price of the euro in its infancy. The ECB is not the central bank of one country. It covers the geographical area of 12 different countries, each with its own history, culture and economic background. In addition, the

² They are comparing the average daily volume between the period January 1998 to December 1998 with the period January 1999 to August 1999.

lack of historical performance creates uncertainty about the capability of this new institution in achieving low levels of inflation. Such characteristics initially increased the difficulty of accomplishing the principal mission of this central bank, price stability.

The introduction of a new central bank changed the inflation process in the euro area. Initially, the market had limited information about how committed the ECB was to maintaining low inflation. Even though the ECB stated that its primary objective, as laid down in the Maastricht Treaty, is to maintain price stability,³ rational agents need more than mere announcements to be convinced that the ECB is going to devote all its efforts to accomplish that goal. They will use all available past and current information to evaluate whether or not the European Central Bank can achieve the target level of inflation.

We hypothesize that, beginning in 1999, the market was *learning* about ECB policymaking by observing the inflation rate in the euro area. Since then, agents are using this information to recognize how different the inflationary process is before and after the introduction of the ECB. We model this learning process using Bayesian updating to calculate the probability that the inflation process in the euro area has actually changed. The evolution of the probability of being in the new state, and consequently, the effects that learning has on the exchange rate, are the focus of the empirical work.

The paper is organized as follows: The next section presents a framework for modeling the exchange rate as a function of learning about the euro-area inflation process. Section 3 illustrates the empirical framework and the Bayesian estimation and inference methodology we adopt. Section 4 reports the empirical results from the

³ In order to bring about absolute clarity as regards the primary objective, the Governing Council decided to define price stability “as a year-on-year increase of the Harmonised Index of Consumer Prices (HICP) for the euro area of below 2%”.

estimation of the change point model. Then in section 5, the estimated probability of a new inflation process is used as a variable to explain the dollar/euro, pound/euro, and yen/euro exchange rates. Finally, section 6 offers a summary and conclusion.

2. A New Currency and Learning

2.a. Pre- and Post-Euro Exchange Rates

Before the introduction of the euro, the most important currency pair in the foreign exchange market was the mark/dollar. Denote the currencies as dollar (A) and mark (G). Here it is assumed that the market believes that exchange rates change because of the inflation differential between Europe and the U.S and additional fundamental determinants which include interest differentials. Prior to the euro, the U.S.-Europe inflation differential for EMS currencies was greatly influenced by German inflation. In the pre-euro era the dollar/DM exchange rate followed,

$$dP_{AG} = \mathbf{j}_o + \mathbf{k}_o + \mathbf{h}_G \quad (1)$$

where \mathbf{j}_o is the “old” inflation differential between Germany and the U.S., \mathbf{k}_o represents additional fundamentals, and \mathbf{h}_G is a stochastic shock which comes from the German central bank. In the post-euro era the dollar/euro exchange rate fluctuates according to:

$$dP_{AE} = \mathbf{j}_n + \mathbf{k}_n + \mathbf{h}_E \quad (2)$$

where \mathbf{j}_n is the “new” inflation differential between Europe and the U.S., \mathbf{k}_n represents other fundamentals, and \mathbf{h}_E is a stochastic shock which comes from the ECB.

2.b. Learning About the Inflation Process

The market considers that the inflation process in the euro area may have changed due to the creation of the ECB, so that the expected rates of inflation after January 1999 will be different from the ones observed before that date. We assume that the U.S. inflation process did not change over the sample period, so that the market focuses on the important institutional change in Europe.

The market assumes that EMS inflation is set in Germany and is generated by a stationary process given by,

$$\mathbf{j}_{o,t} = \mathbf{d}_o + \mathbf{x}_{o,t} \quad (3)$$

Where \mathbf{d}_o is a constant parameter, and $\mathbf{x}_{o,t}$ is an error term that is likely to exhibit autoregressive persistence.

Once the euro begins on January 1, 1999, the market considers that the process might have changed, and now follows,

$$\mathbf{j}_{n,t} = \mathbf{d}_n + \mathbf{x}_{n,t} \quad (4)$$

Where $\mathbf{d}_n < \mathbf{d}_o$, and $\mathbf{x}_{n,t}$ is an error term that is likely to exhibit autoregressive persistence.

Given the uncertainty about the true inflation process in Europe, the market assigns a probability $P_{n,t}$ to the event that \mathbf{d} switched from \mathbf{d}_o to \mathbf{d}_n , and $P_{o,t}$ represents the probability that the market assigns to the event that the inflation differential did not

change, and $P_{n,t} + P_{o,t} = 1 \quad \forall t$. Subsequently, the market updates these probabilities after observing the realized inflation rate every month according to Bayes' law:⁴

$$\left(\frac{P_{n,t}}{P_{o,t}} \right) = \frac{P_{n,t-k} f(\mathbf{j}_t, \dots, \mathbf{j}_{t-k} | \mathbf{d}_n)}{P_{o,t-k} f(\mathbf{j}_t, \dots, \mathbf{j}_{t-k} | \mathbf{d}_o)} \quad (5)$$

where $f(\mathbf{j}_t, \dots, \mathbf{j}_{t-k} | \mathbf{d}_i)$ is the likelihood function of \mathbf{j}_t given \mathbf{d}_i , and the $P_{i,t-k}$ are the prior probabilities at lag k .

These probabilities reflect the credibility that the ECB has in the market, in particular over its ability to maintain price stability. The evolution of these probabilities over time will depend upon future realizations of the stochastic variable \mathbf{j} . The posterior probability $P_{n,t}$ will converge to one, if in fact the process has changed, or to zero if there has not been a change.

The exchange rate will be a function of this learning process. If in fact inflation switched from \mathbf{d}_o to the lower \mathbf{d}_n we would expect appreciation of the euro against other currencies as the market begins to recognize the change.

3. Empirical Model and Methodology

We model the inflation process in Europe as a change point model. Specifically, to account for the predictable persistence in inflation rates we rewrite the model in equations (3) and (4) as

⁴ Lewis (1989) is an early example of Bayesian updating as a model of learning related to exchange rates.

$$\mathbf{j}_t = \mathbf{a}_t + \mathbf{b}\mathbf{j}_{t-1} + \mathbf{x}_t \quad (6)$$

where ξ_t is independently and identically distributed as a normal random variable with mean zero and variance σ^2 and where the parameters $\theta_t \equiv (\alpha_t, \beta_t)$ with $t=1, \dots, n$, are such that

$$\mathbf{q}_t = \begin{cases} \mathbf{q}_1 & \text{if } t \leq t_1 \\ \mathbf{q}_2 & \text{if } t_1 < t \leq t_2 \\ \dots & \dots \\ \mathbf{q}_{m+1} & \text{if } t_m < t \leq n \end{cases} \quad (7)$$

where n is the sample size. This nonlinear time series structure assumes that one or more of the parameters governing the evolution of the observed series are subject to discrete shifts at unknown points in time, (τ_1, \dots, τ_m) . Equivalently, the observation φ_t is drawn from one of $m+1$ populations given by the conditional density

$$\mathbf{j}_t | Y_{t-1}, \mathbf{y}_k \sim f(\mathbf{j}_t | Y_{t-1}, \mathbf{y}_k) \quad k=1, \dots, m+1 \quad (8)$$

where $Y_{t-1} = (f_1, \dots, f_{t-1})$ and \mathbf{y}_k denotes the parameter vector of the k -th population, $\mathbf{y}_k \equiv (\mathbf{q}_k, \mathbf{s}^2)$. The inferential problem includes the estimation of the parameter vector, the identification of the change points and the comparison of models with different numbers of change points. Such a problem is not amenable to straightforward maximum likelihood estimation as the likelihood function implied by (8) is not available in tractable form (see Chib (1998) and the discussion therein).

3.A Bayesian Analysis

We employ Bayesian Markov chain Monte Carlo (MCMC) methods to estimate the model. Unlike frequentist methods, Bayesian methods treat the parameters as random variables given a likelihood function and fixed data. Bayesian estimation requires three elements: the data, a likelihood function dictated by the model, and prior densities for the model's parameters. Bayesian inference is accomplished by analyzing the joint posterior density of the model's parameters, and of other functions of interest.

An additional appealing feature of the Bayesian approach is that it delivers exact small sample (as opposed to asymptotic) results. This is potentially of non-trivial importance in our analysis as we are naturally forced to deal with relatively short time series.

For the change point model in equations (6) and (7), we closely mimic the approach suggested by Chib (1998). In what follows we illustrate only the essentials of the estimation and inference procedure. Please refer to Chib (1998) for a more detailed treatment. First, redefine the model by introducing a discrete random variable, s_t , (the "state" of the system at time t), taking integer values between 1 and $m+1$ and, thus, denoting the regime from which observation ϕ_t is drawn. The variable s_t follows a discrete-time discrete-state Markov chain. The probabilities in the transition matrix of the chain are specified so that s_t can either stay at the value s_{t-1} or can jump to the next regime (but can't skip a regime and can't go back to a previous regime). So, for instance, for a two change-point (i.e., three regimes) model the transition matrix is

$$P = \begin{pmatrix} p_{11} & p_{12} & 0 \\ 0 & p_{22} & p_{23} \\ 0 & 0 & 1 \end{pmatrix}$$

where $p_j = \text{Prob}(s_t=j \mid s_{t-1} = i)$ is the probability that the process will move to state j at time t given that it was in state i at time $t-1$. Given that the elements of each row of P must sum to one, there is only one element to be estimated per row.

Notice that the transition probabilities are not our main quantity of interest. Instead, we focus on the probability that, at any given time t , the inflation process is in one of two (or, more) states given the available information up to time t . Namely, we are interested in estimating $p(s_t = k \mid Y_t, \psi, P)$, for $k=1, \dots, m+1$ and for $t=1, \dots, n$. These time-varying probabilities reflect the assessment the market makes of being in a given inflation regime. As such, they are the empirical equivalent of the “learning probabilities” in Section 2.b. Estimating these probabilities will tell us if and when the market has switched its beliefs about the ECB credibility.

3.B Prior Distributions

To conduct the MCMC analysis one needs to specify prior distributions for the parameters $a_k, \beta_k, k=1, \dots, m+1$, for s^2 and for the transition probabilities $p_{ij}, i=1, \dots, m$. We assume that the priors on the individual parameters are independent. For a_k and β_k we assume normally distributed priors although we impose stationarity within regimes on the AR(1) process in equation (6) by truncating the prior for β_k to the stationary region $(-1, 1)$ for each k . For s^2 we choose a standard inverse gamma prior. Formally:

$$\begin{aligned}
\mathbf{a}_k &\sim N(\mathbf{a}_{k0}, A_{k0}) & k = 1, \dots, m+1 \\
\mathbf{b}_k &\sim N(\mathbf{b}_{k0}, B_{k0}) & k = 1, \dots, m+1 \\
\mathbf{s}^2 &\sim IG(\mathbf{n}_0/2, \mathbf{g}_0/2)
\end{aligned}$$

where N denotes the Normal distribution and IG denotes the inverse gamma distribution. Finally, for p_{ii} we assume a prior Beta distribution independent of p_{jj} , for $j \neq i$.

$$p_{ii} \sim \text{Beta}(a, b), \quad i=1, \dots, m$$

The parameters of this Beta distribution imply beliefs about the average duration of each regime. In particular, the prior mean duration is approximately equal to $(a+b) / b$. The specific values assigned to the prior parameters (or, hyperparameters) will be discussed in the empirical section below.

3.C Posterior Inference

Combining the likelihood function and the priors via Bayes rule, one obtains the joint posterior density of the model's parameters given the data. Given the form of the likelihood functions implied by equation (8) and given any of the priors described above, the joint posterior cannot be estimated (i.e., sampled) directly. Fortunately, the Gibbs sampling method bypasses the computation of the likelihood function and computation of the joint posterior density. Rather, the Gibbs sampler algorithm generates draws from the conditional distribution of each block of parameters (i.e., the distribution of each block given the data, the prior and the other blocks of parameters). The draws from these conditional densities eventually converge to draws from the joint posterior density. Inference is based on summary statistics (e.g., mean, standard deviation, etc.) describing the distribution of the sample draws of the model's parameters, and of functions thereof.

The crucial point in the simulation scheme for the change point model is recognizing that if ξ is known for $t=1, \dots, n$, then all observations with $\xi=k$ can be grouped together, the likelihood function can be easily computed in the k -th regime and, thus, standard results for computing posterior distributions in the AR(1) model could be used. The process can then be repeated for $k=1, \dots, m+1$. The latent state variables need, therefore, to be treated as parameters (a device called data augmentation in the literature) and estimated from the data. The sampling method works recursively. First, the parameters $\alpha_k, \beta_k, k=1, \dots, m+1, \sigma^2$ and $\rho_i, i=1, \dots, m$, are generated conditioning on the data and on the states. Second, the vector of state variables, $S_n = (s_1, \dots, s_n)$, is generated from its posterior distribution, conditioning on the data and the other parameters in the model. Formally, to generate samples from the joint posterior distributions of all parameters and state variables one cycles through the following conditional distributions (only the relevant conditioning variables are indicated for each block):

1. $\mathbf{p}(P | S_n)$
2. $\mathbf{p}(\mathbf{q}_1, \dots, \mathbf{q}_{m+1} | P, S_n, Y_n, \sigma^2)$
3. $\mathbf{p}(\sigma^2 | Y_n, \mathbf{q}_1, \dots, \mathbf{q}_{m+1})$
4. $\mathbf{p}(S_n | P, Y_n, \mathbf{q}_1, \dots, \mathbf{q}_{m+1}, \sigma^2)$

using in each step the most recent sampled values of the conditioning variables. The sampling from 1. and 4. follow the algorithm in Chib (1998). The posteriors in 2. and 3. follow from standard Bayesian updates in linear regression models. After a first set of

25,000 burn-in iterations, 30,000 draws from the Gibbs sampler above are collected for inferential purposes⁵.

3.D Model Comparison

As the number of change points in the data is not known, it is important to compare models with a different number of change points (including the case of no change points) in order to establish what specification best describes the data at hand. A formal model comparison through likelihood ratio tests is problematic since models with different numbers of change points are non-nested. However, Bayesian model comparison is viable as it does not require the models to be nested. In such a framework one needs to compute the marginal likelihood (defined as the integral of the likelihood function with respect to the prior density of the parameters) for each model specification. Formally, the marginal likelihood for model i (M_i) is

$$m(Y_n | M_i) = \int f(Y_n | M_i, \mathbf{y}, P) \mathbf{p}(\mathbf{y}, P | M_i) d\mathbf{y} \quad (9)$$

The Bayes factor comparing model i to model j is defined as the ratio of the respective marginal likelihoods:

$$BF_{ij} = \frac{m(Y_n | M_i)}{m(Y_n | M_j)}$$

⁵ We assess the convergence of the Gibbs sampler by well established diagnostics such as the autocorrelation functions of the draws and their Inefficiency Factors (the inverse of the numerical efficiency measure in Geweke (1992)): all diagnostics indicate a properly mixing Markov Chain.

Large values of BF_{ij} indicate support in favor of model i vs. model j . Assuming equal prior probabilities for each model, the Bayes factor coincides with the posterior-odds ratio. Thus, BF_{ij} can be interpreted as the posterior probability in favor of model M_i over model M_j . According to the Jeffreys' scale⁶, $10 > BF_{ij} > 3$ indicates moderate evidence for M_i vs. M_j , $100 > BF_{ij} > 10$ indicates strong evidence in favor of M_i whereas $BF_{ij} > 100$ indicates decisive evidence. Bayes factors provide a unified way to assess the relative support that the data provide for competing model specifications. Bayes factors also have the appealing property of implicitly penalizing models for additional parameters⁷. We employ Bayes factors to compare alternative models for the inflation process. The marginal likelihoods are computed by the method of Chib (1995) applied to change point models as described in Chib (1998). Additional details are provided in the Appendix⁸.

4 Empirical Results

We estimate the change point model in Section 3 using monthly inflation data for the euro area. From Datastream International we collect the monthly series of percentage year-to-year changes in the Harmonized mean of Consumer Price Indices. The series runs from December 1998 through May 2005 for a total of 78 observations.

4.b. Choice of prior parameters

⁶ See, for instance, Kass and Raftery (1995)

⁷ See Kass and Raftery (1995) for a comprehensive illustration of model comparison via Bayes factors. See O'Hagan (1994), Chapter 7, for a textbook treatment..

In general, we don't want the prior choices to have a decisive impact on the posterior inference. At the same time, we wish to incorporate at least some reasonable prior information. We then analyze the robustness of our inferences to sensible perturbations in the priors.

For the intercept, slope and variance of the residuals, we select the prior distributions by considering the period prior to the establishment of the European Monetary Institute (EMI) in 1994 and use data averaged across the countries that joined the euro. The EMI was the precursor to the ECB and began the process of instituting a single central bank for the euro area. We compute the parameters of the "old" inflation process using monthly inflation from the pre-EMI period of January 1990 to December 1993. We, thus, take an empirical Bayesian approach and estimate a simple AR(1) model for this period in order to choose the hyperparameters for the later period. We omit the period from January 1994 to December 1998, assuming that inflation in these years does not reflect the latent inflationary tendencies of the whole euro area before the introduction of the new central bank, given that in this period countries were under great pressure to converge to the requirements of the Maastricht Treaty and monetary policy coordination was being discussed in the framework of the EMI. We take the point estimate over the early period as our prior means and 2 times their standard errors as the prior standard deviations. This yields the following priors:

$$\begin{aligned} \mathbf{a}_k &\sim N(0.25, 0.2) & k = 1, \dots, m+1 \\ \mathbf{b}_k &\sim N(0.8, 0.2) & k = 1, \dots, m+1 \\ \mathbf{s}^2 &\sim IG(4.32, 0.093) \end{aligned}$$

As the distributions are the same across regimes, they actually reflect a prior view that there is going to be no change in the inflation process after the introduction of the euro.

We repeat the analysis by setting the parameters so that the prior standard deviations are four times as big and find essentially no change in the results

For the transition probabilities, p_{ii} , we set a relatively short prior duration for the first inflation regime in the one change point case. By setting $a=3$ and $b=1$ the prior mean duration is 4 months. This choice reflects the view that the ECB would quickly achieve its target of lower inflation. However, as we realistically have very little prior information about the length of the regimes, we re-estimate the posterior distributions by allowing for very different prior average durations. Namely, we vary a between 6 and 40, keeping $b=1$. The good news is that, even across these very different priors, the posterior estimates for the state probabilities, and thus, for the times of occurrence of the change points change very little, if at all.

4.c. Model Comparisons and Posterior Inference

We first want to assess whether the inflation process does display change points, as opposed to following a simpler, one-regime, AR(1) process. If so, we need to establish how many change points occur and when they occur in our sample period. Therefore, we sequentially estimate models with no change point, one change point and two change points and compare through Bayes factors the support they receive from the data. In all comparisons we assume that the models are equally likely a priori. Therefore, in our application the Bayes factors coincide with the posterior odds ratios. The results are shown in Table 1. The Bayes factor for one change point versus no change point is 63.34, indicating strong evidence in support of one change point. When comparing one vs. two change points, the Bayes factor is 109.28, decisively supporting the one change

point specification. Interestingly the Bayes factor for two change points vs. no change point suggests that there is not enough evidence in the data to support either one of these specifications. Allowing for two breaks seems, therefore, to run the risk of overfitting. Given these findings, we conclude that the AR(1) model with one change point is an adequate characterization of the inflation process in the euro area for our sample period and we will only discuss this specification in detail in what follows.

Table 2 reports posterior summaries for the model parameters and Table 3 for the state probabilities. All parameters appear to be precisely estimated, with posterior standard deviations significantly smaller than their respective means. The most relevant result in Table 2 is the shift in the distribution of expected inflation (computed as $a_k / (1 - \beta_k)$) across regimes: the mean decreases from 3.336% in annualized terms before the change point to 2.158% after the break. This is a first robust indication that the inflationary regime did change towards lower levels following the introduction of the euro. Noticeable is also the decrease in persistence for the inflation process as indicated by the posterior mean of the AR(1) coefficient going from about 0.80 to about 0.72 after the change point. Detecting a break is clearly relevant to our analysis as it shows the success of the ECB in achieving its inflationary target. However, what is most important is establishing when the market assessed a sufficiently high probability that a switch had occurred. The state probabilities in Table 3 address the point: it is only by the end of 1999 that the probability of being in a lower inflation state becomes higher than 50%: in January of 2000 the probability is 61.5% and rises smoothly to over 99% by May of 2005. The probabilities are graphically shown in Figure 1. The intersection of the two lines locates the change point in December of 1999. The small initial probabilities during

the first months of 1999, support the hypothesis that much uncertainty existed regarding the ability of the ECB to achieve a low level of inflation. This skepticism started to disappear to a considerable degree by early 2000.

5 Learning Effects on the Euro Exchange Rate

To test the hypothesis that learning about the inflation process affected the euro exchange rate, we model the monthly change in the logarithm of the exchange rate ($DLog(E)$) as the dependent variable, and the probability that euro-area inflation follows a new process ($Prob$) along with a constant term as the independent variables. We estimate the effect of learning about the ECB inflation process on the dollar/euro, pound/euro, and yen/euro exchange rates.⁹ Since the three exchange rates each have the same explanatory variable, efficiency was enhanced by using seemingly-unrelated-regression.

Estimation results are reported in Table 4A. The coefficient estimates and p-values in the first three rows indicate strong support for the learning effect on the exchange rate in the case of all three currencies, with $Prob$ coefficients of 0.016 for the pound, 0.027 for the dollar and 0.030 for the yen; the p-values are 0.021, 0.022 and 0.037, respectively. As the exchange rate levels are all expressed in units of foreign currency per euro, the positive coefficients show an appreciation of the euro associated with an increased probability of being in the lower inflationary state. The estimated coefficients imply that if we evaluate the exchange rates at sample means, a 10 percentage point increase in $Prob$

⁹ The exchange rate data were retrieved from DataStream.

is associated with a 32 basis point depreciation of the dollar against the euro (from a mean of 1.0523); a 46 basis point depreciation of the pound against the euro (from a mean of 0.6519); and a 3600 basis point depreciation of the yen against the euro (from a mean of 120.13). Finally, the R -squares are non trivial by time-series exchange rate standards, especially for a short monthly sample like ours, and the Q statistics indicate that the residuals are white noise.

As a robustness exercise, we re-estimated the exchange rate models including the interest differential between each currency and the euro and the lagged exchange rate return on the RHS. Specifically, one-month LIBOR rates at the beginning of each month were retrieved from the British Bankers Association and the dollar-euro, pound-euro, and yen-euro interest differentials were then created. The interest differential at the start of the month should serve as a market predictor of the expected change in the exchange rate over the month. Adding the interest differentials to the models may serve as a summary regarding additional fundamentals relevant to exchange rate determination.

The augmented exchange rate models were estimated via seemingly-unrelated-regressions and the results are reported in Table 4B. It turns out that the interest rate differential between the dollar and the euro is highly collinear with the state probabilities: we, therefore, choose not to include it in the estimation as the coefficients of both variables are estimated imprecisely if both variables are included together in the dollar/euro equation. The qualitative results regarding the effect of the probability of a change in the inflation regime are unchanged from part A of the table. All three major currencies display significant depreciations associated with an increase in the probability of a change in the inflation regime and the coefficients on the probabilities are not

appreciably altered by the inclusion of additional variables. The interest differentials are seen to have a positive coefficient on the pound/euro rate and a negative coefficient on the yen/euro rate. However, the coefficients are seen not to be statistically significant for either currency. The key for our analysis is that even with the incorporation of the interest differentials, the effect of changes in the probability of a new inflation process remain significant as determinants of the foreign exchange value of the euro.

An additional robustness check was performed by re-estimating both models with an alternative prior distribution for the computation of the probabilities of a new euro-area inflation process. The results so far were based upon a prior distribution for euro-area inflation drawn from the pre-EMI period of January, 1990 to December, 1993. As an alternative, we calculated a prior from the pre-Maastricht-Treaty period of January, 1988 to January, 1992. The Bayesian updating computations were then redone with the alternative prior distribution and used to re-estimate the exchange rate models. The estimated coefficients on the change in the probability of a new euro-area inflation process are very similar to those reported in Table 4, the statistical significance and associated explanatory power are as before. The dollar/euro, pound/euro and yen/euro exchange rates are all significantly affected by the evolution of the state probabilities. So our results are not being driven by the choice of sample period used to determine the prior distribution. Finally, we estimated the exchange rate models using filtered probabilities as an alternative to the smoothed probabilities used for the estimation results reported in Table 4. The estimation results were qualitatively the same as those reported in the table and coefficient estimates were quite similar. The battery of robustness checks employed serve to enhance our confidence in the inferences drawn from the results.

6. Summary and Conclusion

To understand the behavior of the foreign exchange value of the euro in its infancy, we suggest that the market was learning about the ECB ability to maintain low inflation in Europe. We model this learning using Bayesian estimation and calculate probabilities that reflect the market's beliefs about the ECB's low inflation commitment. The calculated probabilities indicate that it was not until December of 1999 that the market assessed a greater than 50 percent probability that the inflation process changed. Exchange rate models were estimated for the dollar/euro, pound/euro, and yen/euro as a function of the change in the probability that the inflation process has changed. Regression results reveal that increases in the probability of the new inflation process are associated with significant euro appreciation versus all three major currencies. The evidence suggests that learning about ECB policymaking was an important fundamental determining the foreign exchange value of the infant euro against the dollar and pound.

The framework presented here is not intended to serve as a general model of exchange rate determination. As the title states, learning about a new ECB and the associated new euro currency should be viewed as an episode in monetary and exchange rate history. Once the ECB established some threshold of credibility regarding its inflation commitment, the trend depreciation of the euro ended and further increases in the probability of a new inflation process for the euro area resulted in euro appreciation.

Our results indicate that by December 1999, the probability of a new inflation process for the euro area surpassed 50 percent and never fell below this threshold again.

Appendix: Calculation of Marginal Likelihoods for Change Point Model

We briefly outline the steps followed to compute the marginal likelihood in equation (9). The marginal likelihoods are computed by the method of Chib (1995). The starting point of the Chib method is the basic marginal likelihood identity under which the log of the marginal likelihood can be written as

$$\log m(Y | M_i) = \log \mathbf{p}(\mathbf{y}_i^*, P^* | M_i) + \log p(Y | M_i, \mathbf{y}_i^*, P^*) - \log \mathbf{p}(\mathbf{y}_i^*, P^* | M_i, Y) \quad (10)$$

where $p(Y | M_i, \mathbf{y}_i^*, P^*)$ is the likelihood function under M_i , $\mathbf{p}(\mathbf{y}_i^*, P^* | M_i)$ and $\mathbf{p}(\mathbf{y}_i^*, P^* | M_i, Y)$ are the corresponding prior and posterior densities, evaluated at any specified point \mathbf{y}_i^* . Although (10) is an identity, computational reasons suggest that \mathbf{y}_i^* should be a high-density point in order to avoid numerical overflows and underflow. In our implementation we set \mathbf{y}_i^* to the posterior means from the Gibbs sampler. The first two terms on the LHS of (10) are computed, respectively, following Chib (1998) and from the prior densities in section 3.B. The only remaining issue is the estimation of the posterior ordinate, $\log \mathbf{p}(\mathbf{y}_i^*, P^* | M_i, Y)$. This is done through a marginal/conditional decomposition of the posterior density and using the output from the original and subsequent reduced MCMC runs. In a reduced run some of the parameters are held fixed at their posterior means computed from the full Gibbs run described earlier and only the remaining parameters are simulated from their conditional densities. Let

$$\begin{aligned} \mathbf{p}(\mathbf{y}^*, P^* | M_i, Y) &= \mathbf{p}(\mathbf{y}^* | M_i, Y) \mathbf{p}(P^* | M_i, Y, \mathbf{y}^*) \\ &= \mathbf{p}(\mathbf{s}^{2*} | Y) \mathbf{p}(\mathbf{q}_1^*, \dots, \mathbf{q}_{m+1}^* | M_i, Y, \mathbf{s}^{2*}) \mathbf{p}(P^* | M_i, Y, \mathbf{q}^*, \mathbf{s}^{2*}) \end{aligned}$$

The first term on the RHS in the last line can be estimated directly from the full Gibbs draws by averaging the posterior inverse gamma densities evaluated at s^{2*} across G draws. Conditioning on the states, the term $\mathbf{p}(\mathbf{q}_1^*, \dots, \mathbf{q}_{m+1}^* | M_i, Y, \mathbf{s}^{2*})$ can be factored into the product of $m+1$ independent densities. The typical term of the product cannot be evaluated directly from the MCMC output as the draws for \mathbf{q}_k^* are made conditioning on Y and s^2 not Y and s^{2*} . However, the required ordinate can be estimated by fixing s^2 at s^{2*} and continuing the Gibbs sampler for G^* reduced iterations. The ordinate for the typical term is then estimated as

$$\mathbf{p}(\mathbf{q}_k^* | M_i, Y, \mathbf{s}^{2*}) \approx \frac{1}{G^*} \sum_{g=1}^{G^*} \mathbf{p}(\mathbf{q}_k^{(g)} | M_i, Y, \mathbf{s}^{2*})$$

i.e., by averaging the Gaussian density of \mathbf{q}_k evaluated at \mathbf{q}_k^* over the additional MCMC draws. A similar strategy based on an additional reduced run, with μ and s^2 fixed at μ^* and s^{2*} , is utilized to estimate $\mathbf{p}(P^* | M_i, Y, \mathbf{q}^*, \mathbf{s}^{2*})$. Here, beta densities evaluated at P^* are averaged over the additional G^* draws. This completes the computation of the marginal likelihood. In all the examples below, the MCMC algorithm is augmented with reduced runs of $G^*=10000$ iterations each for the purpose of estimating the posterior ordinate¹⁰.

¹⁰ The complete procedure is very fast: on a standard 3.2Mhz PC running Linux, our C code needs less than 12 seconds for the full Gibbs sampler and for the marginal likelihood calculation.

References

- Alquist, Ron and Menzie D. Chinn, 2001. "The Euro and the Productivity Puzzle: An Alternative Interpretation." *Working Paper, University of California, Santa Cruz and IMF*.
- Chib, S., 1995, "Marginal Likelihood from the Gibbs Output", *Journal of the American Statistical Association*, 90, 1313-1321.
- Chib, S., 1996, "Calculating posterior distributions and modal estimates in Markov mixture models", *Journal of Econometrics* 75, 79-97.
- Chib, S., 1998, "Estimation and comparison of multiple change-point models", *Journal of Econometrics* 86, 221-241.
- Geweke, J. (1992). Efficient simulation from the multivariate Normal and Student-t distributions subject to linear constraints. *Computing Science and Statistics: Proceedings of the Twentythird Symposium*, 571-578.
- Hartmann, P., 1998. *Currency Competition and the Foreign Exchange Markets: The Dollar, The Yen and the Euro*. Cambridge University Press.
- Hau, Harald, William P. Killeen and Michael Moore, 2002. "The Euro as an International Currency: Explaining Puzzling First Evidence from the Foreign Exchange Markets." *Journal of International Money and Finance*, 21: 351-384.
- Kass, R. A. and Raftery, A. E. (1995), "Bayes factor", *J. American Statistical Association*, 90, 773-795.
- Lewis, Karen K., 1989. "Changing Beliefs and Systematic Rational Forecast Errors with Evidence from Foreign Exchange." *American Economic Review*, Sept. 1989, 79, 621-636.
- O'Hagan, A., 1994, Bayesian Inference. Vol. 2B of Kendall's Advanced Theory of Statistics, (Edward Arnold: London)
- Sinn, Hans-Werner, and Frank Westermann, May 2001. "Why has the Euro been falling?" *CESifo Working Paper No. 493*.
- _____, February 2003, "The Currency Hypothesis of ExchangeRate Determination," *CESifo Working Paper*.

Table 1: Bayes Factors

This table presents Bayes factors (BF_{ij}) comparing models with different number of change points. Each cell compares the model identified with the column (M_i) to the model identified with the row (M_j). Only non-redundant cells are filled.

	No Change-Points	1 Change-Point	2 Change-Points
No Change-Points		1	63.343
1 Change-Point			1
2 Change-Points	1.725	109.268	1

Table 2: Posterior Summaries for Model Parameters

This table reports summary statistics describing the Bayesian posterior densities of parameters for the one-change point model in equation (6) and (7). The data are monthly inflation rates (year-to-year) for the period 1998:12 to 2005:05 (78 monthly observations). $E(\text{inflation})$ denotes the implied expected inflation from the AR(1) in each regime. The model was estimated using Markov chain Monte Carlo (MCMC) techniques. The posterior mean, standard deviation, and 5th and 95th percentile critical values for each parameter are based on 30,000 Gibbs sampler iterations from a suitably constructed Markov chain.

	Mean	Standard Deviation	5 th Percentile	95 th Percentile
a_1	0.256	0.157	0.046	0.553
a_2	0.600	0.204	0.274	0.941
β_1	0.797	0.168	0.457	0.983
β_2	0.721	0.093	0.566	0.870
$E(\text{Inflation})_1$	3.336	0.882	0.580	5.088
$E(\text{Inflation})_2$	2.158	0.767	1.956	2.350
s^2	0.045	0.008	0.034	0.059
P_{11}	0.917	0.061	0.799	0.986

Table 3: Posterior State Probabilities

The tables reports the posterior probability of $s_t=2$, where s_t is the state variable for the change point model in equation (6) and (7) and 2 indicate the low inflation regime. The probabilities are computed by averaging across 30,000 draws from the posterior distribution obtained using a suitably constructed Gibbs sampler.

Month	P_{22}	Month	P_{22}
December 98	0.000000	March 02	0.956374
January 99	0.012773	April 02	0.959490
February 99	0.028206	May 02	0.961735
March 99	0.048327	June 02	0.963423
April 99	0.061728	July 02	0.964974
May 99	0.073863	August 02	0.966323
June 99	0.096955	September 02	0.967658
July 99	0.170774	October 02	0.969095
August 99	0.227994	November 02	0.970680
September 99	0.291357	December 02	0.972048
October 99	0.417958	January 03	0.973332
November 99	0.497671	February 03	0.974613
December 99	0.573078	March 03	0.976129
January 00	0.615031	April 03	0.977793
February 00	0.647945	May 03	0.978944
March 00	0.676493	June 03	0.979587
April 00	0.700640	July 03	0.980262
May 00	0.742139	August 03	0.981195
June 00	0.793690	September 03	0.981915
July 00	0.810285	October 03	0.982808
August 00	0.828095	November 03	0.983500
September 00	0.844990	December 03	0.984069
October 00	0.854390	January 04	0.984435
November 00	0.863442	February 04	0.984764
December 00	0.872415	March 04	0.985805
January 01	0.882504	April 04	0.986939
February 01	0.886297	May 04	0.987632
March 01	0.890960	June 04	0.988006
April 01	0.894213	July 04	0.988710
May 01	0.896978	August 04	0.989139
June 01	0.920884	September 04	0.990003
July 01	0.931274	October 04	0.990641
August 01	0.935878	November 04	0.991164
September 01	0.939985	December 04	0.991941
October 01	0.943570	January 05	0.993193
November 01	0.946315	February 05	0.993879
December 01	0.949042	March 05	0.994727
January 02	0.951169	April 05	0.995606
February 02	0.953445	May 05	0.981527

Table 4**The Effect of Inflation Learning on the Exchange Rate**

The estimation results reported here are for a model with $DLog(E)$ as the dependent variable, where the exchange rate includes the dollar/euro, pound/euro, and yen/euro. In part A, the independent variable is $Prob$, the probability that the market assigns to euro-area inflation following a new process under the ECB. Part B reports results with the addition of the lagged exchange rate return, $AR(1)$, and of the 1-month LIBOR interest differential at the beginning of each month for each currency versus the euro. The sample period is January 1999 to May 2005. $Q(20)$ is the Ljung-Box statistics for testing autocorrelation in the residuals up to lag 20. P-values are in parentheses.

Panel A				
Exchange Rate	Constant	$Prob$	R^2	$Q(20)$
\$/€	-0.0215 (0.037)	0.0274 (0.021)	0.0535	21.24 (0.383)
£/€	-0.0137 (0.025)	0.0160 (0.022)	0.0524	23.42 (0.269)
¥/€	-0.0245 (0.050)	0.0300 (0.037)	0.0419	21.94 (0.343)

Panel B						
Exchange Rate	Constant	$AR(1)$	$Prob$	$Interest Diff.$	R^2	$Q(20)$
\$/€	-0.0197 (0.082)	0.014 (0.876)	0.0253 (0.051)		0.0415	20.34 (0.441)
£/€	-0.0134 (0.130)	-0.235 (0.016)	0.0178 (0.028)	1.354 (0.597)	0.0414	25.66 (0.143)
¥/€	-0.0430 (0.013)	-0.192 (0.045)	0.0370 (0.015)	-5.0628 (0.237)	0.0698	17.64 (0.611)

Figure 1: Posterior Means of State Probabilities

The figure shows the posterior probability of $s_t=1$ (solid line) and the associated posterior probability that $s_t=2$ (dotted line), where s_t is the state variable for the change point model in equation (6) and (7), 1 and 2 indicate, respectively, the high and the low inflation regime. The plotted probabilities are computed by averaging across 30,000 draws of a suitably constructed Gibbs sampler.

