Is There a Peso Problem? Evidence from the Dollar/Pound Exchange Rate, 1976–1987

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One of the most puzzling aspects of the floating-exchange-rate regime since 1973 has been the apparent irrationality embedded in investors' exchange-rate expectations. This paper investigates whether exchange-rate forecasts, although biased, are still rational. The idea is that investors can be rational and yet make repeated mistakes if the true model of the exchange rate is evolving over time. My results support the hypothesis that the exchange rate has followed a switching-regime process. Moreover, the switching-regime model estimated can explain about 75 percent of the bias implied by the forward market and the survey data. (*JEL* 431)

One of the most puzzling characteristics of the floating-exchange-rate regime since the breakdown of the Bretton Woods system has been the apparent irrationality embedded in investors' exchange-rate expectations. The evidence on the systematic bias of dollar forecasts is by now overwhelming. For example, the forward rate consistently underpredicted the future value of the dollar in the early 1980's while it systematically overpredicted its value in the late 1970's and late 1980's. However, the forward-market bias may just reflect a time-varying risk premium. Even as the evidence from the forward market may not be conclusive, the finding of systematic expectational errors is fairly robust. Since 1976 three independent institutions (American Express Banking Corporation, *The Economist*, and Money Market Services, Inc.) have polled investors regarding their expectations of major exchange rates at different horizons into the future.[1] Similarly to the forward bias, the survey forecast errors are quite substantial. For example, for the 1981–1985 period the annual bias oscillates between 15 percent and 23 percent depending on the survey source.

This paper investigates whether exchange-rate forecasts, although biased, are still formed rationally. The idea is that investors can be rational and yet make repeated mistakes if the true model of the exchange rate is evolving over time. This proposition, also known in the international jargon as the "peso problem" hypothesis, has been gaining support. For example, Kaminsky and Rodrigo Peruga (1988) investigate whether the change in monetary regime in the United States in October 1979 from expansionary to contractionary led to systematic exchange-rate prediction errors while investors were learning about the switch in the money-supply process. Karen K. Lewis (1989) instead studies the effect on

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[1]For a detailed description of the survey data, see Jeffrey A. Frankel and Kenneth A. Froot (1987).

exchange-rate expectations of the shift in U.S. money demand starting approximately in 1981. In both studies the claim is that those changes in regimes took investors by surprise and led to systematic forecasting mistakes while the market was rationally learning about the change in the fundamentals.

However, in those papers the authors do not examine directly whether the process followed by the exchange rate did in fact switch as a result of those events. Instead, the proposition is tested indirectly by examining the link between the *ex post* forecast errors in the forward market and prediction errors of the market fundamentals. More recently, Charles Engel and James D. Hamilton (1990) examine whether in fact the exchange rate follows a switching-regime process. The empirical evidence in their paper strongly supports the hypothesis that the true model of the exchange rate is evolving over time. They show that, contrary to the hypothesis of a zero-drift random-walk model for the exchange rate supported by the previous literature (see e.g., Richard Messe and Kenneth Rogoff, 1983), a better representation of the exchange-rate depreciation is an uncorrelated shock around a drifting mean. Surprisingly, however, the forecasts implied by the switching-regime model—despite the potential peso-problem effect—could not reproduce forward-rate and survey forecasts. For example, during the January 1983–October 1984 period, well before the dollar depreciation started to materialize, the three-month forward rate was predicting on average an annual depreciation of the dollar/pound exchange rate of 0.37 percent, and Money Market Services three-month data were predicting 4.46-percent depreciation (see Frankel and Froot, 1987). In contrast, the rational forecasts from the Engel and Hamilton (1990) model predict an annual appreciation of 14 percent for the same period. Also surprisingly, their model does not very well predict turning points for the dollar rate. For example, the zero-drift random-walk model has a forecasting performance that significantly beats the switching-regime model when the post-sample includes a change in regime.

One explanation that could be suggested for the inability of the switching-regime model estimated by Engel and Hamilton (1990) to reproduce the forward-market and survey data and to forecast turning points is that it is assumed that investors use only past exchange-rate observations to make forecasts. This information set may not be enough to forecast changes in policies that will affect the future path of the exchange rate. Since nobody doubts that when investors are trying to forecast exchange rates they try to collect as much information as they can about present and future monetary policy, output growth rates, and trade deficits, as well as public announcements of government officials, it is important to extend the switching-regime model by including other variables in the information set of investors. In this paper, I have chosen to include also the announcements made by Federal Reserve officials about U.S. monetary policy. Sometimes these statements are vague.[2] Nevertheless, investors do care about these types of statements and act upon them.[3] This paper presents a model in which investors use these rather imprecise statements made by Federal Reserve officials to learn rationally about current and future monetary policy and hence about the exchange-rate regime. These announcements do not, in general, provide perfect regime classification. Hence, one has to develop an efficient estimation method which takes this imperfect information into account. As a by-product I also propose a method for evaluating the Fed's (or government's) reputation over time.

My results can be summarized as follows. Similarly to the findings in Engel and

[2]For example, in early 1985 the chairman of the Federal Reserve Board referred to an overvalued dollar and said that "attempts by the U.S. and other countries to check the dollar's rise should have been more forceful" (*Wall Street Journal*, February 27, 1985, p. 1); but in none of his comments does he mention the Fed's "target" value for the dollar.

[3]For example, according to the *Wall Street Journal* of March 8, 1984, there was a decline in the financial markets due to the fact that Paul Volcker had termed the economy very strong.

Hamilton (1990), my estimates indicate that the process followed by the exchange rate has been switching between a "depreciating" and an "appreciating" regime. However, in contrast to the results in Engel and Hamilton (1990), I find that investors using this new information set could have anticipated future policy changes and thus changes in regime of the process governing the exchange rate. More importantly, by comparing the expectations from the surveys and the forward market with those implied by the switching-regime model, I find evidence suggesting that forward-rate and survey expectations could have been in fact formed rationally.

The remainder of the paper is organized as follows. In Section I, I motivate the estimations by presenting a simple example of exchange-rate determination when the process followed by the market fundamentals evolves over time. In Section II, I briefly discuss the results of the model estimated by Engel and Hamilton (1990), to which I will refer from now on as "a switching-regime model without regime classification information," as a reference point for the switching-regime model that uses the Federal Reserve announcements as an indicator of the exchange-rate regime. This last model will be referred as "a switching-regime model with imperfect regime classification information" and is described and estimated in Section III. Finally, in Section IV, I present the conclusions.

I. Changing Regimes in Market Fundamentals and the Exchange Rate

The following simple example, based on the well-known Robert E. Lucas (1982) model, demonstrates how exchange-rate expectations may be systematically incorrect while the market rationally learns the stochastic process followed by the market fundamentals. The model represents a world economy with two countries (the United States and the United Kingdom), two goods (x and y), and two currencies (M and N). Consumers in the United States receive an endowment ξ_t of good x, while consumers in the United Kingdom receive an endowment η_t of good y. Agents in both countries demand dollars (M) and pounds (N), the demands being motivated by cash-in-advance constraints. Agents are assumed to maximize an intertemporal utility function of the form

$$(1)\quad V(x,y)=\sum_{t=0}^{\infty}\beta^t\left(x_t^{\alpha}y_t^{1-\alpha}\right)\qquad \beta<1$$

subject to a budget constraint and two cash-in-advance constraints.

As is well known, the equilibrium dollar/pound spot exchange rate (S) in this example is just a function of the ratio of the domestic (U.S.) and foreign (U.K.) stock of money:

$$(2)\qquad S_t=\left(\frac{1-\alpha}{\alpha}\right)\frac{M_t}{N_t}.$$

To motivate the behavior of the exchange-rate forecasts, suppose that the money supply in the domestic economy follows the simple process below:

$$(3)\quad m_t=\delta_i+m_{t-1}+\varepsilon_t\qquad \varepsilon_t\sim\mathcal{N}(0,\sigma^2)$$

where $m_t=\log(M_t)$, δ_i is the growth rate of money supply in regime i ($R_t=i$), and $i=0,1$. Arbitrarily I set $\delta_1>\delta_0$. Hence, regime 1 will reflect an expansionary monetary policy, while regime 0 will be identified by a contractionary monetary policy. I assume that the process R_t is a Markov chain with a stationary transition probability matrix:

(4)

	$R_{t-1}=1$	$R_{t-1}=0$
$R_t=1$	$1-\lambda$	λ
$R_t=0$	λ	$1-\lambda$

To economize in notation I assume, without loss of generality, that the money stock in the United Kingdom is constant over time and known with certainty. From equations (2) and (3) one obtains

$$(5)\quad s_t=\log([1-\alpha]/\alpha)+\delta_i+m_{t-1}-n+\varepsilon_t\qquad \text{if } R_t=i$$

$$(7'')\quad d_t - {}_{t-1}d_t = \begin{cases} (\delta_1-\delta_0)\lambda + [1-\mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})](1-2\lambda)(\delta_1-\delta_0)+\varepsilon_t & \text{if } R_{t-1}=1, R_t=1 \\ (\delta_0-\delta_1)(1-\lambda) + [1-\mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})](1-2\lambda)(\delta_0-\delta_1)+\varepsilon_t & \text{if } R_{t-1}=1, R_t=0 \\ (\delta_1-\delta_0)(1-\lambda) + \mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})(1-2\lambda)(\delta_1-\delta_0)+\varepsilon_t & \text{if } R_{t-1}=0, R_t=1 \\ (\delta_0-\delta_1)\lambda + \mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})(1-2\lambda)(\delta_0-\delta_1)+\varepsilon_t & \text{if } R_{t-1}=0, R_t=0 \end{cases}$$

where $s_t = \log(S_t)$ and $n = \log(N)$. The rate of exchange-rate depreciation, d_t, will be

$$(6)\quad d_t = s_t - s_{t-1} = \delta_i + \varepsilon_t \qquad \text{if } R_t = i$$
$$\varepsilon_t \sim \mathcal{N}(0,\sigma^2).$$

From (6) it is clear that changes in regime in the domestic money-supply process will generate changes in regime in the stochastic process followed by the exchange rate. Now, suppose for a moment that investors do observe the current regime directly and know exactly when the regime switch will take place. Then, taking conditional expectations in equation (6) gives white-noise, mean-zero forecast errors:

$$(7)\qquad d_t - {}_{t-1}d_t = \varepsilon_t$$

where ${}_{t-1}d_t$ is the expected exchange-rate depreciation in period t conditioned on the information set known in period $t-1$ ($\mathbf{I}_{t-1}$).

Instead, suppose now that market participants do not know with certainty when the regime switch will take place but they do know the current regime (R_{t-1}). The conditional expectation of the future exchange-rate depreciation will be equal to

$$ {}_{t-1}d_t = R_{t-1}[\lambda\delta_0 + (1-\lambda)\delta_1] + [1-R_{t-1}][(1-\lambda)\delta_0 + \lambda\delta_1]$$

and forecast errors will be equal to

$$(7')\quad d_t - {}_{t-1}d_t = \begin{cases} (\delta_1-\delta_0)\lambda + \varepsilon_t & \text{if } R_{t-1}=1, R_t=1 \\ (\delta_0-\delta_1)(1-\lambda) + \varepsilon_t & \text{if } R_{t-1}=1, R_t=0 \\ (\delta_1-\delta_0)(1-\lambda) + \varepsilon_t & \text{if } R_{t-1}=0, R_t=1 \\ (\delta_0-\delta_1)\lambda + \varepsilon_t & \text{if } R_{t-1}=0, R_t=0. \end{cases}$$

Forecasts will look biased *ex post* if regime changes occur only sporadically. For example, if regime 0 persists for some time, the sample mean of the forecast errors conditioned on $R_t = 0$ will be negative even though forecasts are rational *ex ante*. This phenomenon is known in the international jargon as the "peso problem."[4]

If market participants do not observe the current regime directly, however, they will have to estimate the probabilities of being in the different regimes based on the available information ($\mathbf{I}_{t-1}$). In this case, the conditional expectation of the future exchange-rate depreciation is

$$ {}_{t-1}d_t = \mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})[\lambda\delta_0 + (1-\lambda)\delta_1] + [1-\mathrm{Prob}(R_{t-1}=1|\mathbf{I}_{t-1})] \times[(1-\lambda)\delta_0 + \lambda\delta_1]$$

and forecast errors are equal to those given in (7″), above.

As before, if regime changes occur only sporadically, forecasts will look biased *ex post* although *ex ante* they are rational. The forecasting bias under these new assumptions can be decomposed into two parts: the bias due to the peso problem (if the current regime were known) and the bias due to learning about the current regime. I will call this phenomenon (the effect of both biases) the "generalized peso problem."

[4] The conditional expectation of the forecast error with respect to time-($t-1$) information only is still zero, but an econometrician observing only a small sample of observations conditioned on regime 0 will reject the hypothesis of no bias using the standard methods of inference. See Maurice Obstfeld (1987) for a more detailed examination of the peso problem.

Naturally, changes in monetary regime in the foreign country will also affect the path of the exchange-rate depreciation. In what follows I will assume that the changing drift in the exchange rate (δ_i) incorporates the changing growth rate of the "market fundamentals," and I will focus the analysis on studying just the univariate process followed by the exchange rate without identifying the source of the switching regimes. The probabilities in (4) will from now on only be associated with "exchange-rate regimes." Also, from now on, I will refer to regime 1 as the "depreciating regime" and to regime 0 as the "appreciating regime."

II. A Switching-Regime Model without Regime Classification Information[5]

The model in equations (4) and (6) is estimated under the assumptions that investors do not know when the regime switch is going to occur, they do not observe the current exchange-rate regime, and they have to learn about it using Bayesian updating.[6] The information set of investors is assumed to consist *only* of past observations on the exchange rate (i.e., $\mathbf{I}_{t-1} = \{d_{t-1}, d_{t-2}, \ldots, d_1\}$). The data set consists of monthly observations of the dollar/pound exchange rate for the March 1976–December 1987 period. The results are reported in Table 1.[7] For the most part, the parameters are accurately estimated. When the economy is in regime 1, the dollar depreciates 1.07 percent per month on average. When in regime 0, the dollar appreciates 1.49 percent per month on average. Interestingly, the probability of switching regimes, λ, is insignificiantly different from zero. Since the estimated probability of leaving the regime once one is in it is so small, if investors used this model, their expectations conditioned on being in one regime would be unbiased (as will be seen later on). However, this contradicts the peso-problem hypothesis and the empirical evidence from the forward market and the survey data.

Figure 1 plots the dollar/pound exchange rate and the prior and smoothed probabilities of being in a depreciating regime, (that is,

$$\mathrm{Prior}(R_t = 1) = P(R_t = 1 | d_{t-1}, \ldots, d_1)$$

and

$$\mathrm{Smooth}(R_t = 1) = P(R_t = 1 | d_T, d_{T-1}, \ldots, d_1)$$

where T is the last period in the sample). Note again that the probability series are almost step functions either close to zero (when the dollar appreciates) or close to one (when the dollar depreciates), suggesting that the model cannot support the peso-problem hypothesis.

Although the true regime that generates the sample d_t each period is unknown, one can use the smoothed probabilities to classify the observations into underlying regimes for each period (see Hamilton, 1988). The classification criterion is that the observation in period t belongs to regime 1 if

$$P(R_t = 1 | d_T, d_{T-1}, \ldots, d_1) > 0.5$$

and regime 0 otherwise. The all-sample smoothers divide the sample into four subperiods: March 1976–October 1976, November 1976–October 1980, November 1980–February 1985, and March 1985–December 1987.[8] Interestingly, this regime classification captures exactly the four long swings in the exchange rate.

[5]The results in this section mostly reproduce the findings in Engel and Hamilton (1990) and Kaminsky (1988), and they are more extensively discussed in the working-paper version of this article (Kaminsky, 1991).

[6]See Hamilton (1988) or Kaminsky (1988) for a description of the estimation procedure.

[7]I also estimated models of the exchange-rate depreciation with a richer structure than the one presented in equations (4) and (6). In particular, I estimated models in which the probability of switching regimes and the variance of the errors in (6) were regime-dependent. Since the fit of the different models did not improve compared to the model specified in (4) and (6), I just report those results.

[8]The dates at which this criterion indicates that the process followed by the exchange rate has switched regimes are shown as vertical lines in Figure 1.

TABLE 1—SWITCHING-REGIME MODEL WITHOUT REGIME CLASSIFICATION INFORMATION: MAXIMUM-LIKELIHOOD ESTIMATES

Statistic	Variable λ	δ_0	δ_1	σ^2
Coefficient	0.0301	−0.0149	0.0107	0.0010
Standard error	0.0303	0.0056	0.0048	0.0001
t	0.9922	−2.6499	2.2240	8.4502
p value	0.3228	0.0090	0.0277	0.0000

Notes: Parameters are defined by equations (4) and (6) and were estimated solely on the basis of observations on the dollar/pound exchange rate for the March 1976–December 1987 period.

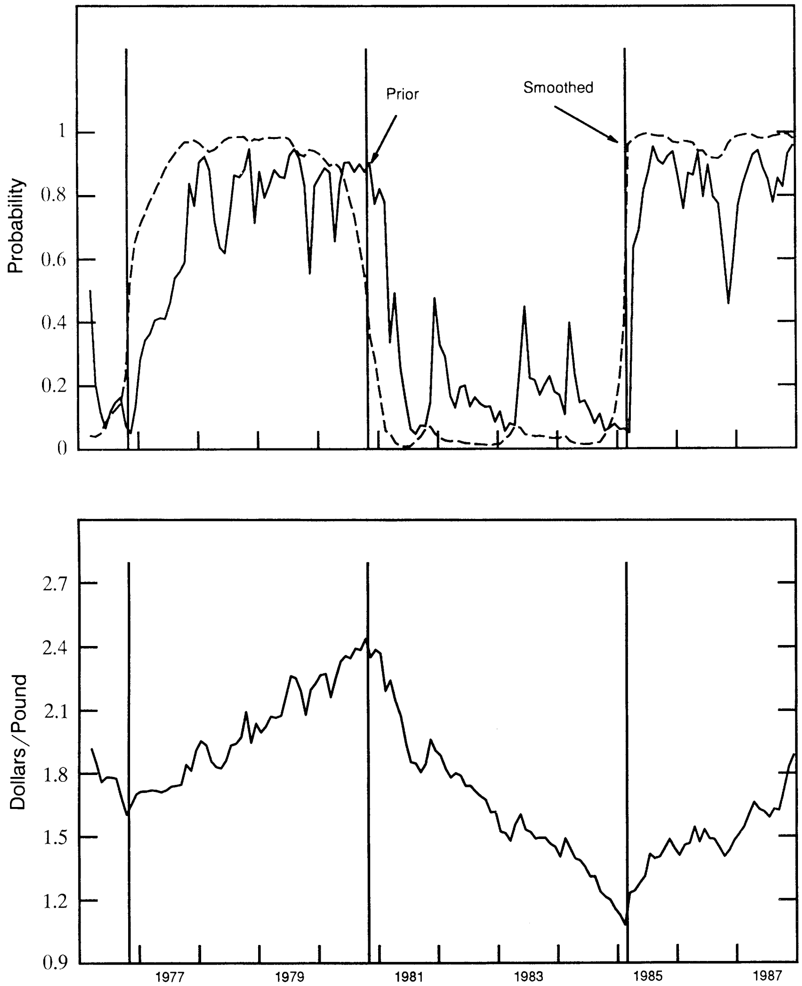

FIGURE 1. PROBABILITY OF A DEPRECIATING REGIME IMPLIED BY THE MODEL WITHOUT REGIME CLASSIFICATION INFORMATION (ABOVE) AND THE DOLLAR/POUND EXCHANGE RATE (BELOW)

I also examine the out-of-sample accuracy of the switching-regime model relative to the zero-drift random-walk paradigm. Not surprisingly, the switching-regime model beats the zero-drift random-walk model when the post-sample does not include a change in regime (for example, when the post-sample is January 1983–December 1984 the improvement in forecasting oscillates between 6 percent and 41 percent depending on the forecasting horizon). On the contrary, when the post-sample includes changes in regimes, the zero-drift random-walk model outperforms the switching-regime model. Remember that the estimated probability of staying in the same regime $(1-\lambda)$ is very close to 1. This makes the model a bad predictor of the exchange rate when a change in regime takes place.

Finally, I examine whether the model rational forecasts can reproduce forward-rate and survey forecasts. This hypothesis is rejected at all conventional significance levels. For example, during the November 1980–February 1985 period the mean forward-market forecast error was 1.6 percent per month for a one-month contract with a t statistic equal to 4.0. On the other hand, the mean forecast error implied by the switching-regime model was 0.57 percent with a t statistic equal to 1.4. Similarly, during March 1985–December 1987 the average forward-rate forecast error for a one-month contract was -1.96 percent (and it was significantly different from zero), while the model forecast error was -1.06 percent and insignificantly different from zero. These results are robust across maturities and subperiods. Similarly, the model forecasts do not reproduce the bias of the surveys. For example, the six-month mean bias using *The Economist* survey data during June 1981–September 1984 was 8.69 percent per semester (with a t statistic equal to 4.0), while the model bias for the same sample was only 0.87 percent and not statistically different from zero.

III. A Switching-Regime Model with Imperfect Regime Classification Information

Although the model in Section II has served its purpose of showing that in fact the exchange-rate process has been evolving over time, its restrictive assumption about rational investors using only past exchange-rate observations to make forecasts makes it not fully appropriate for the study of rational learning and the peso-problem phenomenon. Casual observation suggests that market participants try to collect as much information as they can in order to make forecasts about future exchange rates. Public announcements of the monetary authority in the domestic and the foreign economy, statistics about growth rates and trade deficits, and other indicators are all used in conjunction with past values of the exchange rate to forecast the future path of this variable. One possible strategy that incorporates all of this information is to estimate the model in equations (4) and (6) jointly for the exchange rate and the market fundamentals. My goal is more modest though. In this section I introduce only the information provided by one of these variables. In particular, I assume that the information set of investors also includes announcements made by Federal Reserve officials about U.S. monetary policy. These are Fed statements that contain information about current and future monetary policy covered in the *Wall Street Journal* Index.[9] The choice of the Fed announcements as indicators is not arbitrary. There is empirical evidence that these announcements affect the behavior of investors in the foreign-exchange market. For example, Kathryn Dominguez (1986) matched the announcements made by the Fed from January 1977 to February 1981 to movements in the exchange rate to classify the sample into periods of high and low Fed reputation.

I classify the announcements into two groups: for example, if the Open Market Committee of the Federal Reserve System (FOMC) stated that it intended to "tighten credit conditions," I set the indicator equal to zero, since this would indicate an appreciating-dollar regime (regime 0 in the nota-

[9] These announcements are reported in the working-paper version of this article (Kaminsky, 1991) and are available from the author upon request.

tion in Section I). On the contrary, if a reduction in the discount rate is announced, I set the indicator equal to 1, since this is a signal of an expansionary monetary policy, and a possible depreciating-dollar regime (regime 1 in Section I). This dichotomous indicator, which I denote by ω_t, does not provide perfect sample separation. In fact, ω_t is a measure of R_t with an error. This error may arise for several reasons. First, the Fed may use the announcements to signal future monetary policy truthfully. But it may also use these announcements to manipulate market expectations in order to pursue exchange-rate targets or inflationary targets that are inconsistent with the actual monetary policy. Market participants know this and consequently do not always believe the central bank's announcements. In this case ω_t will not be a correct indicator of the monetary regime. Second, even if the central bank were always conveying correct information in its announcements about current and future monetary policy, the announcement may not signal correctly the exchange-rate regime because of the offsetting effects of other market fundamentals (not explicitly considered). For example, the dollar might appreciate even if monetary policy is expansionary due, for example, to an expansionary domestic fiscal policy. Finally, since the monetary authorities in general do not make precise statements about their policy objectives,[10] one has the errors derived from the interpretation of the announcements by investors and the econometrician.

In this new framework, rational investors are assumed not only to recognize the possibility of changes in regime, but also to incorporate the information provided by the Fed announcements into their forecasts. I further assume that investors know that the announcements indicate the regime with an error. Under these circumstances, investors assign a certain probability to the event that the announcement correctly classifies the exchange-rate regime. Hence, in this section I generalize the Hamilton model to take into account this extra information. The econometric model is based on the approach suggested by Lung-Fei Lee and Robert H. Porter (1984) and Stephen R. Cosslett and Lee (1985). In these papers, the authors study the pricing behavior in the rail-freight industry in cooperative and noncooperative pricing regimes. The classification indicator used in both papers is based on a monthly report published in the *Railway Review*. The authors suspect measurement errors in this index and propose an iterative algorithm for solving the likelihood equations. However, it is assumed that the measurement error was serially independent. In the present case, however, this assumption does not seem appropriate. For example, measurement errors due to offsetting fiscal policies will be serially correlated since periods of expansionary (contractionary) fiscal policy are themselves correlated. Also, the Fed-information strategy may be serially correlated, as the evidence in Dominguez (1986) seems to suggest. Hence, in this section I generalize those models to incorporate serial correlation in the measurement error. Furthermore, I provide a Bayesian approach for investors to learn rationally about the states with correct (incorrect) monetary announcements.[11]

I first discuss the estimation procedure and present the empirical results; then I analyze the out-of-sample forecasting accuracy of the model, and finally I discuss whether the model supports the peso-problem hypothesis.

A. *Empirical Implementation*

As in the previous section, I assume that investors allow for the possibility of changes in regimes in the process followed by the exchange rate. As before, they assume that the exchange rate follows the stochastic process described in equations (4) and (6). Now, however, investors are assumed to use

[10] The rationale behind this behavior has been examined by Jeremy Stein (1989).

[11] I will refer to those states in which the indicator conveys the correct exchange-rate regime classification as "correct information" states.

$$(11)\quad f(d_t,\omega_t|\mathbf{I}_{t-1})$$

$$=\{[f(d_t|R_t=1)\text{Prior}(C_t)-f(d_t|R_t=0)(1-\text{Prior}(C_t))]\text{Prior}(R_t=1)+f(d_t|R_t=0)(1-\text{Prior}(C_t))\}^{\omega_t}$$

$$\times\{[f(d_t|R_t=1)(1-\text{Prior}(C_t))-f(d_t|R_t=0)\text{Prior}(C_t)]\text{Prior}(R_t=1)+f(d_t|R_t=0)\text{Prior}(C_t)\}^{1-\omega_t}$$

$$(12)\qquad \text{Post}(R_t=1)=\frac{f(d_t|R_t=1)\text{Prior}(R_t=1)\text{Prior}(C_t)^{\omega_t}[1-\text{Prior}(C_t)]^{1-\omega_t}}{f(d_t,\omega_t|\mathbf{I}_{t-1})}$$

$$(13)\qquad \text{Post}(C_t)=\frac{\text{Prior}(C_t)[f(d_t|R_t=1)\text{Prior}(R_t=1)]^{\omega_t}[f(d_t|R_t=0)\text{Prior}(R_t=0)]^{1-\omega_t}}{f(d_t,\omega_t|\mathbf{I}_{t-1})}$$

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the information provided by the Fed announcements together with past observations of the exchange rate. Since investors know that the announcements may not provide the correct regime classification, they have to assign a certain probability to the event that the announcements give the correct information about the exchange-rate regime. I assume that the information states follow a Markov chain with a stationary transition probability matrix

(8)

	C_{t-1}	W_{t-1}
C_t	$1-q$	p
W_t	q	$1-p$

where C_t is the state characterized by the indicator providing the correct information about the exchange-rate regime (i.e., $C_t=\{\omega_t=i|R_t=i;\ i=0,1\}$). The state W_t is the state characterized by the indicator providing the wrong information (i.e., $W_t=\{\omega_t=i|R_t=j\neq i;\ i,j=0,1\}$).

To learn about the exchange-rate regime and about the information content of the monetary announcements, rational investors will follow a Bayesian strategy. Each period, they start with a prior about the exchange-rate regime and about the informational regime:

$$(9)\qquad \text{Prior}(R_t=1) = (1-2\lambda)\text{Post}(R_{t-1}=1)+\lambda \quad \text{if } t=1,\ \text{Prior}(R_1=1)=\pi_1$$

$$(10)\qquad \text{Prior}(C_t)=(1-q-p)\text{Post}(C_{t-1})+p \quad \text{if } t=1,\ \text{Prior}(C_1)=\gamma_1$$

where $\text{Post}(C_t)=\text{Prob}(C_t|\mathbf{I}_t)$,[12] $\text{Post}(R_t=1)=\text{Prob}(R_t=1|\mathbf{I}_t)$, and $\mathbf{I}_t=\{d_t,\ \omega_t,\dots,d_1,\ \omega_1\}$. Every period, investors obtain more information on exchange rates and on the monetary regime and estimate the joint density function (11) above, where

$$f(d_t|R_t=i)=((1/2)\pi\sigma^2)^{-1/2}\times\exp\left[(-1/2)(d_t-\delta_i)^2/\sigma^2\right].$$

This new information is used to update their priors, given as equations (12) and (13) above.

[12]Interestingly, in other examples, $P(C_t)$ could be used as an index of the monetary-authority credibility. For example, investors could estimate a joint model of money supply and monetary announcements similar to one in this section. If money supply is controlled by the monetary authority, the information content of the indicator will just reveal whether the monetary authority is conveying information about the monetary regime truthfully.

The above model, which is carefully derived in Appendix B, can be estimated as follows. One can start at $t=1$ with the unconditional probability of being in regime 1 ($\pi_1 = 0.5$), and the unconditional probability of being in regime C ($\gamma_1 = p/[p+q]$). Using (9)–(13), one can construct the sample log likelihood

$$(14)\quad \ln f(d_t, \omega_t, d_{t-1}, \omega_{t-1}, \dots, d_1, \omega_1) = \sum_{t=1}^{T} \ln f(d_t, \omega_t | d_{t-1}, \omega_{t-1}, \dots, d_1, \omega_1)$$

which can be maximized numerically with respect to the unknown parameters δ_1, δ_0, σ^2, λ, p, and q.

It is interesting to note that one can test very easily the null hypothesis that the indicator does not provide any information about the exchange-rate regime. First, note that if $p=(1-q)=0.5$, the indicator does not provide any (correct or incorrect) information on the exchange-rate regime. In this case the joint density function for d_t and ω_t will be just a function of the marginal density function $f(d_t|d_{t-1},\dots,d_1)$ estimated in Section II: $f(d_t, \omega_t|d_{t-1}, \omega_{t-1}, \dots, d_1, \omega_1) = 0.5 f(d_t|d_{t-1},\dots,d_1)$. Also, the probabilities of being in a depreciating (appreciating) regime will be just functions of the marginal density function of d_t. Second, I construct the likelihood-ratio test

$$(15)\quad \mathrm{LRT} = 2\{\ln f(d_t, \omega_t, \dots, d_1, \omega_1) - [\ln f(d_t, \dots, d_1) + \ln(n/2)]\}$$

where the first likelihood value is the one for the model with imperfect sample separation information derived in (14). The second likelihood value is the one for the model with no regime classification information estimated in Section II. The likelihood-ratio test statistic in (15) is asymptotically distributed as χ^2 with two degrees of freedom.

B. *Estimation Results*

The results from the estimation of the model with imperfect regime classification information [equations (4), (6), and (8)] are reported in Table 2 under the heading "no Fed chairman effect." One should first note that the estimates of δ_0 and δ_1 are not statistically different from the ones obtained in Table 1. This indicates that, at least for these parameters, the asymptotic efficiency gains in using the indicators, ω_t, in addition to the observations of the exchange-rate depreciation, d_t, are small. This occurs since the two means of d_t are far apart. However, there are some differences in the estimates of λ (the probability of switching from one exchange-rate regime to another) and the variance of the process in either regime. Both parameters are now more precisely estimated. The point estimate of λ increases from 0.03 to 0.17, and it is significantly different from zero. One now also finds that it is possible to reject the null hypothesis that the variability of the exchange-rate depreciation is equal across regimes. I find that the exchange rate was more volatile in regime 1. In Table 2, I also present the likelihood-ratio test (LRT1) for the null hypothesis that the indicator does not provide any information about the exchange-rate regime. This test was described in equation (15). It is apparent that the unconstrained version has a much better fit, even though the estimates of δ_0 and δ_1 are similar. Obviously, the constraint $p = 1-q = 0.5$ is rejected.

Although this model clearly outperforms the one without regime classification information, the probabilities in the transition matrix in (8) are estimated very imprecisely. These imprecise results might be the consequence of imposing a stationary Markov matrix, when in fact it may be changing over time. It is important to remember that monetary announcements may incorrectly predict the exchange-rate regime because the Federal Reserve chooses to send misleading signals; but also different administrations may choose to follow different information strategies. In this case the unconditional probabilities of being in a "correct information" state may be idiosyncratic to each Federal Reserve administration. To test this hypothesis I associated each Federal Reserve chairmanship with a different Markov matrix for the informational states. In par-

TABLE 2—SWITCHING-REGIME MODEL WITH IMPERFECT REGIME CLASSIFICATION INFORMATION: MAXIMUM-LIKELIHOOD ESTIMATES

	No Fed chairman effect				With Fed chairman effect			
Variable	Coefficient	Standard error	t	p value	Coefficient	Standard error	t	p value
δ_0	−0.0010	0.0030	−3.3463	0.0011	−0.0089	0.0033	−2.6973	0.0079
δ_1	0.0124	0.0049	2.5393	0.0122	0.0082	0.0051	1.6120	0.1093
λ	0.1747	0.0504	3.4700	0.0007	0.1338	0.0522	2.5645	0.0114
p	0.0431	0.0314	1.3749	0.1714				
q	0.0703	0.0362	1.9419	0.0542				
p_{BM}					0.0205	0.0369	0.5563	0.5790
q_{BM}					0.3051	0.2109	1.4465	0.1504
p_{VG}					0.1988	0.1185	1.6779	0.0957
q_{VG}					0.0589	0.0476	1.2376	0.2181
σ_0^2	0.0007	0.0001	5.8226	0.0000	0.0007	0.0001	5.2466	0.0000
σ_1^2	0.0014	0.0003	5.6551	0.0000	0.0015	0.0003	5.4698	0.0000

LRT1 = 21.427 (p value = 0.00002); LRT2 = 6.0090 (p value = 0.04956)

Notes: Parameters are defined by equations (4), (6), and (8) and were estimated using observations on the dollar/pound exchange rate and the announcements made by the Fed officials for the period March 1976–December 1987. LRT1 is a likelihood-ratio test of the null hypothesis that the indicator (ω) does not provide any regime classification information; LRT2 is a likelihood-ratio test that compares the models with and without the Fed chairman effect.

ticular, I allowed for four different p's and q's: p_B and q_B for the Burns period (January 31, 1970–March 7, 1977); p_M and q_M for the Miller period (March 8, 1977–August 5, 1979), p_V and q_V for the Volcker period (August 6, 1979–August 10, 1987), and p_G and q_G for the Greenspan period (August 11, 1987–end of sample). The estimation with four different transition matrices did not converge, possibly because there are only five observations for the Greenspan period. I then restricted $p_V = p_G = p_{VG}$, and $q_V = q_G = q_{VG}$. Also, since the transition matrices for the Burns and Miller administrations did not differ significantly (in preliminary estimations not reported), I just present the estimates of the model after having imposed the restriction $q_B = q_M = q_{BM}$, and $p_B = p_M = p_{BM}$. Furthermore, since at the start of each administration the public does not have access to a track record on the different officials and it is therefore difficult to judge how credible the announcements are, I assumed that $\text{Prior}(C_t) = 0.5$ at the moment when the administration changes.

The results of this estimation are also reported in Table 2 under the heading "with Fed chairman effect." Although the probabilities in the information transition matrix continue to be estimated imprecisely, the point estimates suggest that the "credibility" associated with the Volcker–Greenspan administrations is higher than that associated with the Burns–Miller administrations.[13] In particular, the unconditional probability of being in a "correct information" state $[\gamma_1 = p/(p+q)]$ is equal to 0.063 during the Burns–Miller administrations and equal to 0.772 during the Volcker–Greenspan administrations. One can also test whether the explanatory power of the model increases when one allows for a Fed chairman effect. In LRT2, I present the likelihood-ratio test for the null hypothesis $p_{BM} = p_{VG} = p$ and $q_{BM} = q_{VG} = q$. This statistic is asymptotically distributed as χ^2 with two degrees of

[13]Obviously, the unconditional probabilities of being in a "correct information" regime may also be evolving because of the changing behavior of other market fundamentals, such as fiscal policy, not explicitly incorporated in the model.

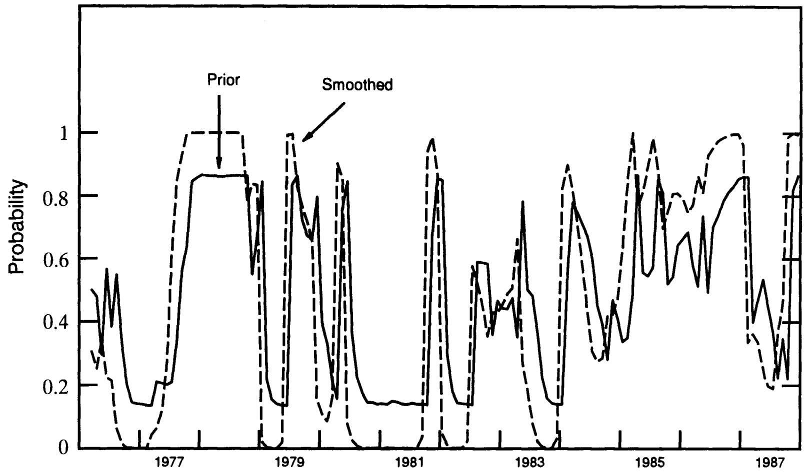

FIGURE 2. PROBABILITY OF A DEPRECIATING REGIME IMPLIED BY THE MODEL WITH IMPERFECT REGIME CLASSIFICATION INFORMATION

freedom. One can reject the null hypothesis at less than the 5-percent confidence level. In view of this result, in what follows I will just report the results of the different tests using the model "with Fed chairman effect."

Figure 2 presents the evolution of the probabilities (priors and all-sample smothers) of being in a depreciating regime. Interestingly, these probabilities seem to capture investors' beliefs at the time of some major policy changes. One well known episode is the change in monetary policy announced by the Federal Reserve in October 1979 to lower money growth and inflation. In retrospect, there is no doubt that Federal Reserve officials were seriously committed to following a noninflationary monetary policy, and eventually this shift in monetary policy led the dollar to appreciate. However, during 1980 the market did not yet have enough information to assess the reality of this change. As examined in Olivier Blanchard (1984), doubts were particularly acute in the summer of 1980 when the Fed chose partial accommodation to what it perceived to be autonomous velocity shifts, leading to large and erratic fluctuations in monetary aggregates. Only by the first half of 1981 does uncertainty seem to have disappeared, due in part to the Fed's policy of high interest rates. Blanchard's account of the events and of the change in beliefs of financial markets following October 1979 is captured by the probabilities in Figure 2. The prior probabilities of being in an inflationary monetary regime decrease after the announcement of an anti-inflationary monetary policy in October 1979, and then they increase substantially (from 0.157 in April 1980 to 0.846 in June 1980) when the Fed announces controls on interest rates and the money supply soars. Also, by the end of 1980 the probabilities of being in an inflationary regime decrease to an average 0.15.

Another major shift in policy took place in 1987 when the Fed started to tighten the credit reins. Also, in February 1987 the G-7 countries (with the exception of Italy) agreed to cooperate to support the dollar. This agreement included specific fiscal-policy commitments by each of the participant countries, such as a German tax cut and U.S. federal deficit-reduction measures (G-6 Communique; February 22, 1987). These announcements together with central-banks intervention in the foreign-exchange market seem to have tilted (at least temporarily) investors beliefs toward a more stable dollar, as suggested by comments of analysts

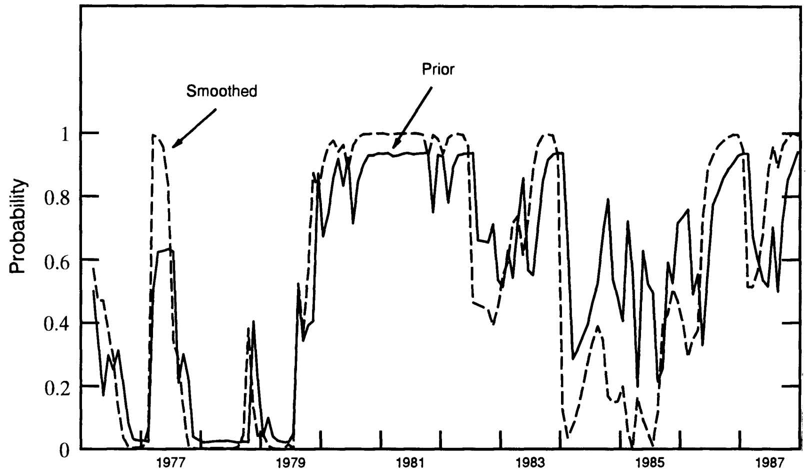

FIGURE 3. PROBABILITY OF A "CORRECT INFORMATION" REGIME

found in the *Wall Street Journal* after the accord.[14] Also, Dominguez (1989) finds that Fed intervention in the foreign-exchange market had a stabilizing effect on the dollar after the Louvre Agreement. The probabilities in Figure 2 capture these changes in beliefs (the priors of being in a depreciating regime decrease from 0.86 in February 1987 to an average of 0.38 during the March 1987–October 1987 period).

On the other hand, during 1983 there were several announcements that indicated that the Fed was going to ease its monetary policy. These announcements led investors to expect a depreciation of the dollar (for example, the three-month *Economist*-expected depreciation increased from 0.26 percent in January 1983 to 3.8 percent in June 1983). Reflecting this effect, the probabilities in Figure 2 increase to an average of 0.5 in the summer of 1983. As money growth declined in the second half of 1983 and monetary policy turned out to be expansionary only starting in 1985, investors mispredicted the future path of the exchange rate.

The behavior of the probabilities in Figure 2 is in sharp contrast with the one implied by the switching-regime model without regime classification information (Fig. 1). In that case the probabilities were either very close to 1 or 0 for long periods of time and did not reflect the change in investors' beliefs examined by, among others, Blanchard (1984), Dominguez (1986), and Frankel and Froot (1987). Finally, note that the all-sample smoothers in Figure 2 divide the sample into 18 subperiods instead of just capturing the long swings in the exchange-rate process as the model in Section II did.

In Figure 3, I report the probabilities (priors and all-samples smoothers) of being in a "correct information" state, Prob(C_t). I will briefly examine the evolution of these probabilities. While the story of the late 1970's is a story of inflationary monetary policy and a depreciating dollar, monetary announcements basically tell a story of monetary restraint (see appendix 2 in the working-paper version of this article [Kaminsky, 1991]). Not surprisingly then, the estimated probabilities of being in a "correct information" regime are close to zero. In contrast, the focus of the early 1980's was the fight against inflation. Announcements about the commitment of the Federal Reserve to lower

[14] For example, on March 9, 1987, it was reported that "although it's too early to say whether the accord has changed the psychology of the markets, the six appear to have spooked traders enough to make them leery about driving the dollar down too rapidly."

inflation abound, and they are backed by concrete policy actions. It is also in the early 1980's that the dollar starts to appreciate in response to this change in policy. Notably, the probabilities of being in a "correct information" state capture this policy turnaround, increasing to an average 0.9 during the November 1979–June 1982 period. By the end of 1982 and the beginning of 1983 monetary policy turns out to be more expansionary, and monetary announcements reflect this shift in policy. However, the dollar continues to appreciate, perhaps reflecting the effect of the expansionary fiscal policy. Monetary announcements lose their ability to predict correctly exchange-rate regimes, and probabilities of being in a "correct information" regime decrease.

During 1984, monetary policy was highly contractionary, and the dollar constantly appreciated, but some announcements indicated that the Federal Reserve had decided to ease its grip on monetary policy. Similarly, while in 1985 monetary policy turned out to be expansionary, bringing the dollar down, some announcements indicated that the FOMC was inclined to tighten its grip on credit. This created conflicting signals which are reflected by low probabilities of being in a "correct information" state. These conflicting signals disappear by June 1986, and the probabilities of being in a "correct information" regime increase to an average of 0.85.

C. *Forecast Accuracy*

In Table 3, I report for comparison purposes the mean-square forecast errors of the zero-drift random-walk model as well as the mean-square forecast errors of the switching-regime models with and without regime classification information for different horizons and for different out-of-sample projection periods. The first six rows present the root-mean-square forecast errors for projection periods ending in December 1984. Not surprisingly, in this case the switching-regime model without regime classification information outperforms both the zero-drift random-walk model and the model with the monetary announcements. The efficiency loss by using the model with imperfect regime classification instead of the Engel and Hamilton (1990) model oscillates between a minimum of 5.52 percent for the one-month horizon during the period January 1983–December 1984 to a maximum of 46.5 percent at a six-month horizon for the January 1984–December 1984 sample. This evidence does not provide strong support for the model with imperfect regime classification information. However, once the out-of-sample projection period is enlarged so as to include observations belonging to different "exchange-rate regimes," the model with the monetary announcements clearly outperforms the model estimated in Section II. The maximum efficiency gain by using the information contained in the monetary announcements occurs at a 12-month horizon for the January 1985–December 1985 sample (33 percent).

Still, when one compares the out-of-sample performance of both models with the zero-drift random walk for the whole period (December 1982–December 1987), the accuracy of the latter model is greater. The statistical rejection of the switching-regime model on this account may not have much economic significance. The model still explains most of the variation in the exchange rate even if it is outperformed in some of the samples by the zero-drift random-walk model. More importantly, the model presents a new approach toward learning the behavior of rational investors when the process followed by the market fundamentals changes. One also learns from the model how investors evaluate the announcements of the monetary authority about current and future monetary policy, update their beliefs, and try to make forecasts as well as they can under the circumstances.

D. *Does the Model Support the Peso-Problem Hypothesis?*

The results presented in Subsection III-B at least informally seem to support the empirical evidence from the forward market and from the surveys on exchange-rate expectations. In this section I subject this hypothesis to more formal testing. In Table 4 I compare the forecasts of the

TABLE 3—OUT-OF-SAMPLE FORECASTING ACCURACY: ROOT-MEAN-SQUARE ERROR

Out-of-sample projection period	Model	Forecasting horizon			
		1 month	3 months	6 months	12 months
January 1983–December 1984	RW	0.0318	0.0553	0.0875	0.1455
	NI	0.0300	0.0479	0.0660	0.0939
	II	0.0316	0.0554	0.0855	0.1297
January 1984–December 1984	RW	0.0338	0.0650	0.1276	0.2252
	NI	0.0301	0.0426	0.0854	0.1329
	II	0.0325	0.0624	0.1251	0.1861
January 1984–December 1985	RW	0.0427	0.0794	0.1415	0.1746
	NI	0.0423	0.0778	0.1501	0.2135
	II	0.0429	0.0811	0.1482	0.1869
January 1985–December 1985	RW	0.0501	0.0895	0.1704	0.2208
	NI	0.0518	0.1046	0.2138	0.3609
	II	0.0511	0.0964	0.1894	0.2718
January 1985–December 1986	RW	0.0418	0.0678	0.1099	0.1568
	NI	0.0434	0.0791	0.1368	0.2184
	II	0.0428	0.0724	0.1218	0.1856
January 1983–December 1987	RW	0.0363	0.0666	0.0997	0.1505
	NI	0.0358	0.0669	0.1042	0.1694
	II	0.0367	0.0688	0.1039	0.1601

Notes: RW denotes the zero-drift random-walk model; NI denotes the switching-regime model without regime classification information; and II denotes the switching regression model with imperfect regime classification information and with the Fed chairman effect.

switching-regime model using the announcements with the forecasts of the forward market. Since the peso problem arises when market forecasts reflect the possibility of changes in regime that are infrequent in small samples, in order to test the hypothesis that *ex ante* rational expectations may appear biased *ex post* in small samples, I divide the sample into four subperiods, following the regime classification provided by the probabilities (all-samples smoothers) in Figure 1.[15] Columns 4 and 5 report the mean of the forward-rate forecast errors $[f_t(j)-s_{t+j}]$ and corresponding t statistics for the different forecasting horizons ($j=1,3,6$, or 12 months). These columns show that, as it is well known in the literature, the forward market underpredicted the value of the dollar in the early 1980's and consistently overpredicted its value in the late 1970's and late 1980's. In the next two columns, for comparison, I present the mean and corresponding t statistics of the forecasting errors of the switching-regime model without regime classification information $[{}_ts^{\mathrm{NI}}_{t+j}-s_{t+j}]$, where ${}_ts^{\mathrm{NI}}_{t+j}$ is formed using past and current observations on the exchange rate. It is clear from the results in these columns that the model cannot replicate the evidence in the forward market, since for all the different subsamples and horizons the mean bias is not significantly different from zero.

The next two columns report the mean forecasting bias of the switching-regime model with imperfect regime classification information $[{}_ts^{\mathrm{II}}_{t+j}-s_{t+j}]$ and the corresponding t statistics. Now the probabilities of switching regimes are significantly different from zero, and investors anticipate possible changes in the stochastic process followed by the market fundamentals. Furthermore, announced policy changes that

[15]The results are robust to using other subsamples. See the working-paper version of this article (Kaminsky, 1991) for comparisons using other periods.

TABLE 4—ARE FORWARD RATES RATIONAL FORECASTS OF FUTURE SPOT EXCHANGE RATES?

					Model error							
					Model without regime classification information,		Model with imperfect regime classification information					
Dates	Forecast horizon (months)	N	Forward-rate error, $f_t(j)-s_{t+j}$ Mean	t	${}_ts^{\mathrm{NI}}_{t+j}-s_{t+j}$ Mean	t	${}_ts^{\mathrm{II}}_{t+j}-s_{t+j}$ Mean	t	${}_Ts^{\mathrm{II}}_{t+j}-s_{t+j}$ Mean	t	Test of rationality, $f_t(j)-{}_ts^{\mathrm{II}}_{t+j}$ Mean	t
March 1976–October 1976	1	7	1.90	1.97	1.37	1.40	2.32	2.58	2.12	2.28	−0.43	−5.25
	3	5	3.62	1.22	1.91	0.60	4.92	1.62	4.43	1.51	−1.30	−2.99
November 1976–October 1980	1	47	−1.10	−2.65	−0.44	−1.03	−0.83	−2.01	−0.83	−2.00	−0.26	−3.67
	3	45	−3.06	−2.97	−1.35	−1.15	−2.33	−2.08	−2.31	−2.09	−0.74	−2.72
	6	42	−5.89	−3.88	−3.16	−1.64	−4.75	−2.84	−4.69	−2.83	−1.14	−2.02
	12	36	−11.91	−5.02	−7.69	−2.18	−9.65	−4.48	−9.51	−4.37	−2.26	−2.24
November 1980–February 1985	1	52	1.60	3.98	0.57	1.39	1.27	3.22	1.24	3.19	0.33	4.74
	3	50	4.88	4.14	1.90	1.47	3.98	3.37	3.88	3.34	0.90	3.00
	6	47	9.33	3.92	3.83	1.34	7.81	3.33	7.66	3.32	1.52	2.32
	12	41	15.96	10.24	6.57	4.08	13.49	8.94	13.37	9.01	2.48	9.15
March 1985–December 1987	1	34	−1.96	−3.20	−1.06	−1.64	−1.46	−2.32	−1.35	−2.21	−0.50	−8.01
	3	32	−4.89	−2.70	−2.47	−1.22	−3.66	−1.98	−3.41	−1.89	−1.24	−4.59
	6	29	−8.05	−2.40	−3.73	−0.89	−5.77	−1.72	−5.47	−1.63	−2.27	−4.33
	12	23	−13.76	−4.86	−7.33	−2.40	−10.11	−3.48	−9.53	−3.36	−3.64	20.72
March 1976–December 1987	1	141	−0.17	−0.60	−0.13	−0.46	−0.06	−0.21	−0.05	−0.19	−0.11	−2.35
	3	139	−0.44	−0.46	−0.44	−0.51	−0.17	−0.19	−0.16	−0.18	−0.27	−1.29
	6	136	−0.56	−0.27	−0.80	−0.44	−0.07	−0.04	−0.07	−0.04	−0.49	−1.04
	12	130	−0.84	−0.18	−2.05	−0.48	−0.06	−0.01	−0.02	−0.01	−0.78	−0.77

Notes: The mean bias is reported as a percentage. Degrees of freedom used to estimate the t statistic for the different mean errors in the table are the numbers of nonoverlapping observations in each sample. N = number of observations.

take time to be implemented lead to *ex post* biased expectations in small samples. This is at the foundation of the peso problem. In fact, I obtained the result that expectations, although unbiased in large samples, show a statistically significant bias in small samples. For example, during 1984 the Fed announced an easier monetary policy that was not implemented until 1985, leading investors to believe in a dollar depreciation. Since this policy was not implemented until 1985, the dollar continued to appreciate, and market expectations appeared to be biased *ex post*. This bias is captured in Table 4: although the dollar appreciated at a 1.52-percent monthly rate during November 1980–February 1985, investors anticipated only a monthly appreciation of 0.25 percent, generating an *ex post* monthly bias of 1.27 percent. The model mean error in this period is different from zero at all conventional significance levels ($t = 3.22$), and it can explain approximately 79 percent of the forward market bias. Similarly, during the first half of 1987 there were several announcements of the Fed suggesting tightening of monetary policy to support the dollar. For example, the *Wall Street Journal* reported in its edition of February 27, 1987, that "Volcker declined to rule out tightening credit policy if the dollar resumes a sharp drop." These announcements (given the high credibility of the Fed at that time) led investors to attach a small probability to the depreciating regime. Since the dollar continued to depreciate, forecasting biases became larger. This effect is reflected in the model forecasting bias during March 1985–December 1987. In this subsample, the one-month model bias is -1.46 with a t statistic of -2.32, and it is approximately 75 percent of the forward market bias.

The model bias reported in column 8 $[{}_t s^{\mathrm{II}}_{t+j} - s_{t+j}]$ is composed of the bias due to the uncertainty about the time of the regime switch (the peso problem) plus the bias due to uncertainty about the current exchange-rate regime. I have denoted the bias due to both effects as the "generalized peso problem." In column 10, I report the bias of the model due to the peso problem $[{}_T s^{\mathrm{II}}_{t+i} - s_{t+i}]$.[16] Most of the model bias can be accounted for by the pure peso-problem effect (uncertainty about the time of the regime switch). This result is not surprising since the probability of switching regimes implied by the switching-regime model with imperfect regime classification information is quite large.[17]

More formal tests of the peso-problem hypothesis are reported in the last two columns of Table 4. In these columns I report the mean and the corresponding t statistics for the difference between the forward rate and the model forecast $[f_t(j) - {}_t s^{\mathrm{II}}_{t+j}]$. If investors used the model in this section to forecast future exchange rates, then the mean error should not be significantly different from zero. Unfortunately in most cases, although the model represents significant progress in explaining the bias in the forward market data, it cannot explain fully the anomalies in the foreign-exchange market. Interestingly, the model can explain the bias in the forward exchange market during 1984. During this period (although not reported in Table 4) the one-month forward bias was on average 1.83 percent while the model bias was 1.80 percent. The mean difference between the two forecasts is not significantly different from zero, indicating that in fact investors may have expected a depreciation of the dollar well before this depreciation started in March 1985.

Since the nonzero bias in the forward market could also be explained by the existence of a risk premium, I also test the peso-problem hypothesis using survey data. The survey data set is exactly the one used by Frankel and Froot (1987).[18] Table 5 reports the forecasting errors implied by the model with imperfect regime classification information $[{}_t s^{\mathrm{II}}_{t+j} - s_{t+j}]$ and by survey expectations $[{}_t s^{s}_{t+j} - s_{t+j}]$. Also, for comparison I report the forecasting bias of the Engel and Hamilton model $[{}_t s^{\mathrm{NI}}_{t+j} - s_{t+j}]$. I first report forecasting errors as implied by the survey data for different samples.[19] Note that well before the dollar started to depreciate in March 1985, survey expectations indicate that market participants expected

[16]While in Table 4 the "peso problem" effect is obtained using the all-sample smoothed probabilities, it could also be estimated under the assumption that investors know the current regime with certainty. The results do not change substantially. For example, if investors know the current exchange-rate regime with certainty, the peso-problem effect for the sample November 1976–October 1980 is equal to -0.83, -1.31, -3.03, and -7.61 percent for the 1-, 3-, 6-, and 12-month forecasting horizons, respectively, while the corresponding biases using the all-sample smoothers are -0.83, -2.31, -4.69, and -9.51 percent.

[17]On the contrary, in the Engel and Hamilton (1990) model, the pure peso-problem effect constitutes only a small part of the model forecasting bias.

[18]The American Express Banking Corporation (AMEX) data consist of observations on expectations 6 and 12 months into the future for the period 1976–1984. *The Economist* data consist of observations on expectations 3, 6, and 12 months into the future for the period June 1981–May 1986, while the Money Market Services (MMS) data consist of expectations 1 month into the future for the period January 1983–September 1984 and expectations 3 months into the future for the same period. In each survey, it is the median response that is reported.

[19]Since I want to compare survey expectations with the monthly expectations implied by the switching-regime model, I use only end-of-month survey data.

TABLE 5—ARE SURVEY EXPECTATIONS RATIONAL?

						Model error					
				Survey error, ${}_t s^s_{t+j} - s_{t+j}$		Model without regime classification information, ${}_t s^{NI}_{t+j} - s_{t+j}$		Model with imperfect regime classification information, ${}_t s^{II}_{t+j} - s_{t+j}$		Test of rationality ${}_t s^s_{t+j} - {}_t s^{II}_{t+j}$	
Forecast horizon (months)	Survey	Dates	N	Mean	t	Mean	t	Mean	t	Mean	t
1	MMS	October 1984–June 1986	13	−1.37	−1.09	−0.86	−0.73	−0.97	−0.84	−0.40	−0.84
3	MMS	January 1983–September 1984	19	4.09	2.28	0.08	0.05	2.86	1.69	1.22	2.12
	Econ.	June 1981–May 1986	17	0.85	0.47	−1.59	−1.14	0.04	0.03	0.81	1.18
	Econ.	June 1981–September 1984	12	4.24	3.11	0.05	0.04	2.61	2.07	1.64	3.22
	Econ.	February 1985–May 1986	5	−7.29	−2.47	−5.54	−1.68	−6.11	−2.33	−1.18	−0.66
6	Econ.	June 1981–May 1986	17	3.83	1.27	−1.34	−0.47	1.82	0.63	2.01	2.92
	Econ.	June 1981–September 1984	12	8.69	4.02	0.87	0.38	5.79	2.60	2.90	4.75
	Econ.	February 1985–May 1986	5	−7.84	−1.62	−6.64	−0.88	−7.73	−1.39	−0.11	−0.07
	AMEX	July 1976–June 1985	11	1.47	0.49	−2.27	−1.21	0.29	0.12	1.18	1.10
	AMEX	July 1976–November 1978	6	−4.62	−2.01	−4.84	−2.53	−3.91	−1.65	−0.71	−0.72
	AMEX	June 1981–June 1985	5	10.61	3.92	1.59	0.53	6.59	1.92	4.02	2.97
12	Econ.	June 1981–May 1986	17	7.79	1.23	−1.70	−0.28	4.08	0.67	3.72	3.49
	Econ.	June 1981–September 1984	12	15.39	2.83	1.47	0.23	10.38	1.82	5.01	5.12
	Econ.	February 1985–May 1986	5	−10.44	−2.08	−9.32	−0.74	−11.06	−1.34	0.62	0.26
	AMEX	July 1976–June 1985	11	−0.61	−0.11	−6.72	−2.54	−1.97	−0.50	1.36	0.81
	AMEX	July 1976–November 1978	6	−11.16	−2.86	−10.67	−3.58	−8.91	−2.35	−2.25	−1.60
	AMEX	June 1981–June 1985	5	15.22	7.58	−0.79	−0.32	8.44	4.79	6.78	20.25

Notes: Surveys: MMS = Money Market Services, Inc.; Econ. = *The Economist*; AMEX = American Express Banking Corporation. Degrees of freedom used to estimate the t statistic for the different mean errors in the table are the number of nonoverlapping observations for each data set. N = number of observations.

the dollar to depreciate. For example, the MMS three-month expectation data available for the period January 1983–September 1984 show a positive bias that is statistically significant at all conventional significance levels. After the depreciation started in March 1985, the different surveys indicate that market participants consistently overestimated the value of the dollar. For example, both the MMS data and *The Economist* data show a negative bias after February 1985. Similarly, AMEX data show a negative bias in the period 1976–1978 (when the dollar was depreciating) and a positive bias in the 1979–1984 period (when the dollar was appreciating) but do not show unconditional bias when all the information is taken together.

As may be seen by glancing at Table 5, the forecasts of the Engel and Hamilton (1990) model are at odds with the survey data, while the rational forecasts of the model with monetary announcements seem to replicate survey expectations. For example, the mean error for the model in Section II for January 1983–September 1984 (to match with the MMS three-month forecast data) is only 0.08 percent. Instead, the mean error implied by the model in this section is 2.86 percent. The error obtained from the model in this section corresponds more precisely to the survey data: in that period the MMS three-month expectations mean error was 4.09 percent. Similarly, for the sample that matches *The Economist* data (first sample: June 1981–September 1984), the six-month mean error implied by the model in Section II is 0.87 percent while the one from the model in Section III is 5.79 percent. Since the mean error using *The Economist* data is 8.69 percent, one must conclude that expectations obtained with the imperfect-regime-classification model seem to replicate the *Economist* data more closely. The above results are robust to using different subperiods and survey sources: the order of magnitude of the errors of the model in Section III is close to that of the errors in the surveys. On the contrary, the errors from the model in Section II are several times smaller. However, as the t statistics in the last column of Table 5 indicate, in some cases one continues to reject the null hypothesis that $E({}_ts^{\mathrm{s}}_{t+i} - {}_ts^{\mathrm{II}}_{t+i}) = 0$. I found that sometimes investors overpredicted the value of the dollar, while at other times they underpredicted the strength of the dollar relative to the model. Naturally these results, together with those in Table 4, do not necessarily imply the rejection of the hypothesis of rational learning by investors. My model, even when I incorporate monetary announcements, is still very restrictive. What is clear from the above discussion is that rational learning may in fact be the key to explaining the apparently inefficient predictive performance of forward rates and the systematic biases observed in survey data. Although the model presented in this section has made the above point clear, it is just an initial step into the investigation of expectations formation.

IV. Conclusions

In this paper I have provided some support for the peso-problem hypothesis using the spot dollar/pound exchange rate. This paper supplements previous research in this area by Eduardo Borensztein (1987), Kaminsky and Peruga (1988), and Lewis (1989). First, I have confirmed the results in Engel and Hamilton (1990) that the exchange-rate process has been evolving over time, perhaps capturing the changing regimes in the market fundamentals. Second, I have tested whether the exchange-rate expectations implied by the model could explain the forward-market and survey forecasts. Although the model expectations cannot replicate completely the forward-market and survey forecasts, the sign and the magnitude of the model forecasting bias suggest that forward market and survey forecasts could have been in fact rational.

Despite the apparent strengths of the model, a few caveats are in order. Although I have shown that monetary announcements help to predict the future path of the exchange rate, I have assumed that the path of the exchange rate conditioned on R_t is independent of these announcements. This is not necessarily true since Fed officials' announcements, by providing information about future monetary policy, will affect investors' behavior and thus may affect the exchange-rate path. Naturally, investors' behavior and, hence, the exchange-rate path will be affected differently depending on whether the announcement is believed. Hence, one should model the stochastic process followed by the exchange rate using a four-state Markov matrix. This estimation will be the subject of future research.

Whatever the simplifications of the model, I think that it helps explain the behavior of investors in the foreign-exchange market and helps build a bridge between a full-information rational-expectations model and a model in which investors do not exactly know the stochastic process followed by the market fundamentals at each moment.

However, this study does not allow identification of the source of the drifting mean of the exchange-rate depreciation. One fruitful area of research will be the joint estimation of the changing regimes in the market fundamentals and the nominal exchange rate.

Finally, the methodology proposed in Section III can provide some light on issues that have been at the center of the debate in macroeconomics. For example, economists have speculated for years about why many stabilizations succeed while others fail. Sargent's (1982) analysis of the end of four big inflations associated the failure of the stabilizations with the lack of credibility. Since then, credibility has become one of the most studied topics in macroeconomics. However, the credibility literature has not provided a methodology for empirically evaluating the evolution of government reputation. This paper provides the first step in that direction.

Appendix A: Data Definition and Sources

The dollar/pound exchange rate (both spot and forward) used in the estimations is the rate on the last day of the month (excluding holidays and weekends) and is the average of the bid and the ask rates. They were taken from DRI and Reuters, respectively. The spot rate is reported in Table A1. The survey data set is identical to the one used in Frankel and Froot (1987). The data used in this paper were kindly provided by Phillipe Bachetta, Susan Collins, and Kenneth Froot. Monetary announcements are taken from *The Wall Street Journal* and Dominguez (1986).

Table A1—Dollar/Pound Monthly Rate of Depreciation

Year	Month	d_t
1976	March	−0.0572
	April	−0.0376
	May	−0.0469
	June	0.0124
	July	0.0000
	August	−0.0036
	September	−0.0536
	October	−0.0477
	November	0.0293
	December	0.0302
1977	January	0.0068
	February	0.0000
	March	0.0034
	April	−0.0017
	May	−0.0034
	June	0.0052
	July	0.0104
	August	0.0017
	September	0.0035
	October	0.0520
	November	−0.0146
	December	0.0502
1978	January	0.0232
	February	−0.0097
	March	−0.0398
	April	−0.0148
	May	−0.0037
	June	0.0203
	July	0.0380
	August	0.0039
	September	0.0157
	October	0.0589
	November	−0.0726
	December	0.0458
1979	January	−0.0202
	February	0.0141
	March	0.0225
	April	−0.0021
	May	0.0041
	June	0.0445
	July	0.0421
	August	−0.0045
	September	−0.0267
	October	−0.0534
	November	0.0556
	December	0.0133
1980	January	0.0180
	February	0.0023
	March	−0.0488
	April	0.0397
	May	0.0344
	June	0.0117
	July	−0.0047
	August	0.0190
	September	−0.0024
	October	0.0217
	November	−0.0359
	December	0.0142
1981	January	−0.0071
	February	−0.0775
	March	0.0222
	April	−0.0439
	May	−0.0338
	June	−0.0643
	July	−0.0475
	August	−0.0037
	September	−0.0219
	October	0.0201
	November	0.0609
	December	−0.0271
1982	January	−0.0114
	February	−0.0352
	March	−0.0216
	April	0.0108
	May	−0.0054
	June	−0.0283
	July	0.0000
	August	−0.0156
	September	−0.0136
	October	−0.0101
	November	−0.0362
	December	0.0016
1983	January	−0.0597
	February	−0.0046
	March	−0.0240
	April	0.0517
	May	0.0285
	June	−0.0455
	July	−0.0076
	August	−0.0196
	September	0.0015
	October	0.0000

TABLE A1—*Continued.*

Year	Month	d_t	Year	Month	d_t	Year	Month	d_t
	November	−0.0192		March	0.1317		August	−0.0030
	December	−0.0102		April	0.0087		September	−0.0279
				May	0.0291		October	−0.0285
1984	January	−0.0328		June	0.0233		November	0.0212
	February	0.0608		July	0.0777		December	0.0318
	March	−0.0338		August	−0.0141			
	April	−0.0327		September	0.0042	1987	January	0.0201
	May	−0.0070		October	0.0285		February	0.0225
	June	−0.0219		November	0.0293		March	0.0380
	July	−0.0347		December	−0.0293		April	0.0330
	August	0.0000					May	−0.0194
	September	−0.0561	1986	January	−0.0229		June	−0.0075
	October	−0.0184		February	0.0345		July	−0.0160
	November	−0.0121		March	0.0044		August	0.0245
	December	−0.0366		April	0.0512		September	−0.0034
				May	−0.0468		October	0.0586
1985	January	−0.0252		June	0.0391		November	0.0606
	February	−0.0431		July	−0.0272		December	0.0301

APPENDIX B: DERIVATION OF EQUATIONS (11), (12), AND (13)

Under the assumptions made in (4), (6), and (8), the joint density function for d_t and ω_t is

$$(A1)\quad f(d_t,\omega_t|\mathbf{I}_{t-1}) = f(d_t,\omega_t|\mathbf{I}_{t-1},R_t=1)\text{Prior}(R_t=1) + f(d_t,\omega_t|\mathbf{I}_{t-1},R_t=0)\text{Prior}(R_t=0)$$

where $\mathbf{I}_{t-1}=\{d_{t-1},\omega_{t-1},\dots,d_1,\omega_1\}$. However, conditional on R_t, d_t and ω_t are independent by assumption. Hence,

$$(A2)\quad f(d_t,\omega_t|\mathbf{I}_{t-1},R_t=i) = f(d_t|R_t=i)\text{Prob}(\omega_t|R_t=i,\mathbf{I}_{t-1}).$$

On account of the discrete nature of ω_t one can write

$$(A3)\quad \text{Prob}(\omega_t|R_t=1,\mathbf{I}_{t-1}) = \omega_t\,\text{Prob}(\omega_t=1|R_t=1,\mathbf{I}_{t-1}) + (1-\omega_t)\text{Prob}(\omega_t=0|R_t=1,\mathbf{I}_{t-1}) = \omega_t\,\text{Prior}(C_t)+(1-\omega_t)[1-\text{Prior}(C_t)]$$

$$(A4)\quad \text{Prob}(\omega_t|R_t=0,\mathbf{I}_{t-1}) = \omega_i\,\text{Prob}(\omega_t=1|R_t=0,\mathbf{I}_{t-1}) + (1-\omega_t)\text{Prob}(\omega_t=0|R_t=0,\mathbf{I}_{t-1}) = \omega_t[1-\text{Prior}(C_t)]+(1-\omega_t)\text{Prior}(C_t).$$

Using (A2), (A3), and (A4), (A1) can be rewritten as equation (A1′), below. From (A1′) one can obtain (11). To obtain (12)

$$(A1')\quad f(d_t,\omega_t|\mathbf{I}_{t-1}) = f(d_t|R_t=1)[\omega_t\,\text{Prior}(C_t)+(1-\omega_t)(1-\text{Prior}(C_t))]\text{Prior}(R_t=1) + f(d_t|R_t=0)[\omega_t(1-\text{Prior}(C_t))+(1-\omega_t)\text{Prior}(C_t)]\text{Prior}(R_t=0).$$

note that

$$\text{(A5)}\quad \text{Post}(R_t=1) = \text{Prob}(R_t=1\,|\,d_t,\omega_t,\dots,d_1,\omega_1) = \frac{\text{Prob}(R_t=1,d_t,\omega_t\,|\,d_{t-1},\omega_{t-1},\dots,d_1,\omega_1)}{f(d_t,\omega_t\,|\,d_{t-1},\omega_{t-1},\dots,d_1,\omega_1)}.$$

$\text{Prob}(R_t = 1, d_t, \omega_t | d_{t-1}, \omega_{t-1}, \dots, d_1, \omega_1)$ can be written as follows:

$$\text{(A6)}\quad \text{Prob}(R_t=1,d_t,\omega_t|\mathbf{I}_{t-1}) = f(d_t,\omega_t|R_t=1,\mathbf{I}_{t-1})\text{Prior}(R_t=1).$$

Then, using (A2), (A3), and (A4), and after some manipulation, one can obtain (12). To obtain (13) note that $\text{Post}(C_t)$ can be written as follows:

$$\text{(A7)}\quad \text{Post}(C_t) = \frac{f(d_t,\omega_t,C_t|\mathbf{I}_{t-1})}{f(d_t,\omega_t|\mathbf{I}_{t-1})} = \frac{f(d_t|\omega_t,C_t,\mathbf{I}_{t-1})\text{Prob}(\omega_t,C_t|\mathbf{I}_{t-1})}{f(d_t,\omega_t|\mathbf{I}_{t-1})}.$$

On account of the discrete nature of ω_t one can write

$$\begin{aligned}\text{(A8)}\quad \text{Prob}(\omega_t,C_t|\mathbf{I}_{t-1}) &= \omega_t\,\text{Prob}(\omega_t=1,C_t|\mathbf{I}_{t-1}) + (1-\omega_t)\text{Prob}(\omega_t=0,C_t|\mathbf{I}_{t-1})\\ &= \omega_t\,\text{Prob}(\omega_t=1,R_t=1|\mathbf{I}_{t-1}) + (1-\omega_t)\text{Prob}(\omega_t=0,R_t=0|\mathbf{I}_{t-1}).\end{aligned}$$

$\text{Prob}(\omega_t=i,R_t=i|\mathbf{I}_{t-1})$ can be written as

$$\begin{aligned}\text{(A9)}\quad P(\omega_t=i,R_t=i|\mathbf{I}_{t-1}) &= P(\omega_t=i|R_t=i,\mathbf{I}_{t-1})\text{Prior}(R_t=i)\\ &= \text{Prior}(C_t)\text{Prior}(R_t=i).\end{aligned}$$

Also note that

$$\begin{aligned}\text{(A10)}\quad f(d_t|\omega_t,C_t,\mathbf{I}_{t-1}) &= \omega_t f(d_t|\omega_t=1,C_t,\mathbf{I}_{t-1}) + (1-\omega_t)f(d_t|\omega_t=0,C_t,\mathbf{I}_{t-1})\\ &= \omega_t f(d_t|\omega_t=1,R_t=1,\mathbf{I}_{t-1}) + (1-\omega_t)f(d_t|\omega_t=0,R_t=0,\mathbf{I}_{t-1})\\ &= \omega_t f(d_t|R_t=1) + (1-\omega_t)f(d_t|R_t=0).\end{aligned}$$

Now, using (A8)–(A10) in (A7), one can obtain equation (13).

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