

Chapter 3

Real exchange rate dynamics: An alternative approach

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Abstract

This exercise presents a systematic study on the presence of Markov switching dynamics in three dollar-based real exchange rates. A Monte Carlo approach is adopted to circumvent the statistical inference problem inherent to the test of regime-switching behavior. Annual, quarterly and monthly data are considered. While annual and quarterly data yield inconclusive or weak evidence on the presence of Markov switching behavior, monthly data strongly indicate the presence of multiple regimes in real exchange rate data. The results suggest that data frequency can be crucial for determining the number of regimes.

3.1 Introduction

Real exchange rate dynamics have significant implications for both academia and policymakers. For instance, real exchange rate behavior bears some direct implications for the relevancy of purchasing power parity hypothesis, which is a key assumption in international economics. On the other hand, policymakers are interested in the nature of shocks to real exchange rates that affect trade balances.

Over time, the study of real exchange rate dynamics evolves from simply computing the correlation to sophisticated modeling of nonlinear temporal be-

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havior. The level of technical complexity in these empirical studies traces the development in (time-series) econometrics. Despite a plethora of empirical studies on real exchange rate behavior, there are still unsettled issues on, for example, the persistence of real exchange rates (Cheung and Lai (2000a, 2000b)), the sources of real exchange rate persistence (Cheung, Lai, and Bergman (2003), Engel and Morley (2001)), and the nonlinear real exchange rate dynamics (Obstfeld and Taylor (1997), Taylor, Peel, and Sarno (2001)). The recent empirical studies on real exchange rate dynamics are surveyed and evaluated in, for example, Rogoff (1996) and Sarno and Taylor (2002).

The purpose of the exercise is to investigate whether real exchange rates follow Markov switching dynamics. Engel and Hamilton (1990), for example, advocate the use of a Markov switching model to describe the behavior of nominal exchange rates. These authors found that a two-regime Markov switching model performs well in both in-sample and out-of-sample periods for three exchange rate series. It is well documented that real exchange rate variability is mainly driven by movements in nominal exchange rates. A Markov switching model for nominal exchange rates is, thus, suggestive of a Markov switching model for real exchange rates. The possibility that real exchange rates follow a Markov switching process is recently explored in Bergman and Hansson (2003).

The presence of regime-switching dynamics has important implications for theoretical models of real exchange rate dynamics. For instance, real exchange rate behavior can depend on how far the real exchange rate is from its equilibrium position (Dumas (1992)). Further, if a real exchange rate "inherits" the time-series property of the corresponding nominal exchange rate, then factors that generate regime-switching behavior in nominal data can also induce regime-switching behavior in real exchange rates. These factors include the "Peso problem", the changing importance of chartists and fundamentalists in the foreign exchange market, differences between domestic and foreign monetary and fiscal policies, and the presence of transaction costs and diversity of opinions (De Grauwe and Vansteenkiste (2001), Engel and Hamilton (1990), Vigfusson (1996)). The relevance of these factors depends critically on whether the observed real exchange rates are generated from multiple regimes. Thus, the research on Markov switching dynamics sheds some useful insight on modeling of real exchange rate behavior.

One main feature of the current exercise is the focus on the determination of the number of regimes in the empirical Markov switching model. Most existing empirical studies on Markov regime-switching dynamics either explicitly or implicitly assume that data are drawn from a specific multi-regime Markov switching process and estimate the model parameters accordingly. The absence of a formal test before estimation is probably due to the fact that the test for the number of regimes is a non-standard statistical inference problem. The commonly used test statistics, including the likelihood ratio statistic, do not have their usual asymptotic distributions. However, without formal evidence of the existence of multiple regimes, estimation of Markov switching models may lead to spurious results. For instance, data generated from a Markov switching model exhibit long swings. However, it is also known that realizations of

a random walk process resemble observations displaying long swings. Fitting a Markov switching model to a unit root process may generate spurious estimation results and mis-identify long swings due to unit root persistence as regime-switching behavior. Thus, a formal test for the number of regimes is essential for determining the presence of Markov switching dynamics.

Another interesting feature of the exercise is the attempt to find a level field to determine whether a random walk model or a Markov switching model provides a better description of real exchange rate dynamics. A typical procedure will test the null hypothesis of a random walk against a Markov switching alternative. Such a procedure demands strong evidence to overturn the null hypothesis and establish the alternative specification. It is known that the non-rejection of the null hypothesis does not necessarily mean that the null hypothesis is correct and the alternative is false. If a test procedure has low power, then it may not reject the null hypothesis even if it is false. To mitigate the problem, we consider the null hypothesis of a random walk process and, then, the null hypothesis of a Markov switching process. Thus, both a random walk and a Markov switching model have the same opportunity to be treated “favorably” under the null hypothesis. In addition, we tally the power of the test procedures and incorporate the information in making statistical inferences.

In this study, we adopt a Monte Carlo approach to test for the number of regimes in a Markov switching model (Rydén, Teräsvirta, and Asbrink (1998)). In particular, the data-specific empirical distribution of the likelihood ratio statistic is used to evaluate the probability of the presence of regime-switching behavior. While simulation may not offer general conclusions, it circumvents the issues of non-standard statistical inferences inflicting the standard approach to model regime switching and provides some useful sample-specific results. Further, the use of data-specific distributions helps mitigate finite sample biases.

The remainder of the paper is organized as follows. In Section 3.2 we state the random walk and Markov switching models examined in the exercise and conduct some preliminary analyses on the real exchange rate data. Section 3.3 describes the Monte Carlo based test for the number of regimes. Test results from the annual, quarterly, and monthly data set are also reported in this section. Some concluding remarks are offered in Section 3.4.

3.2 Preliminary analyses

The US dollar real exchange rates of Deutsche mark, British pound, and French franc are considered. The corresponding nominal exchange rates are examined by Engel and Hamilton (1990). The sample spans from 1973 to 1997 and contains data at the monthly, quarterly, and annual frequencies. All data are retrieved from the International Monetary Fund data CD.

It is conceived that the frequency of observations plays a role in revealing regime-switching behavior. Specifically, a higher sampling frequency can give better information on the dynamic property. Suppose a real exchange rate switches between two regimes. If the expected duration of the real exchange

rate to stay in one regime is less than a year, then the use of annual data to test for Markov switching dynamics is deemed to be fruitless. Even if the expected duration is a year or two, annual samples still may not offer enough observations within and across realized regimes for the test procedure to disentangle the regime-switching behavior from, say, the random walk behavior. Relatively speaking, monthly observations have a better chance to retain and capture regime-switching behavior. Thus, in this exercise, we explore whether sampling frequency offers some useful information about Markov switching dynamics.

In the following section, we determine whether a random walk (with drift) specification or a two-regime Markov switching model offers a better description of real exchange rate dynamics. These two models are given by

$$\Delta s_t = \mu + \varepsilon_t \quad (3.1)$$

and

$$\Delta s_t = \sum_{i=1,2} I(S_t = i) [\mu_i] + \varepsilon_t \quad (3.2)$$

where Δ is the first-difference operator, s_t is the log real exchange rate at time t , μ is the drift term, $\varepsilon_t \sim (0, \sigma^2)$ is an error term, $I(\cdot)$ is an indicator function, $\mu_1 \neq \mu_2$ are the drift terms across regimes 1 and 2, and S_t is the state (regime) variable. The state variable assumes the values of 1 or 2 and follows the transition probabilities P_{ij} , $i, j = 1, 2$, $\sum_{j=1,2} P_{ij} = 1$ for $i = 1, 2$, where P_{ij} is the probability of $S_t = j$ given $S_{t-1} = i$.

Equation (3.1) is the random walk specification. While there is no verdict on whether real exchange rates are stationary, it is difficult for high frequency real exchange rate data to reject the nonstationarity null hypothesis³. In this exercise, we take the random walk specification as a reasonable approximation of real exchange rate behavior. The Markov switching model is given by equation (3.2). In essence, the model allows the real exchange rate to behave differently across two regimes defined by the state variable S_t . See, for example, Hamilton (1989) for a discussion on the properties and estimation of a Markov regime-switching model. In this study, we employ a fully unconstrained maximum likelihood method to estimate the model⁴.

It is commonly conceived that long swings are found in realizations from a random walk process. Thus, before implementing the Monte Carlo test for the

³While there are recent studies indicate that real exchange rates are stationary (Cheung and Lai (2000a)), Engel (1999) argues that the stationarity results may be spurious.

⁴We reproduced the estimates reported in the Engel and Hamilton using their approach assuming a Bayesian Prior. These estimates are virtually the same as those from the fully unconstrained maximum likelihood method. Various randomized starting values are used in the optimization process to ensure that a global maximum likelihood, instead of a local one, is obtained. The fully unconstrained maximum likelihood method is discussed in, for example, Hamilton (1994).

number of regimes, we conducted a pilot simulation study to examine what one may observe when a Markov switching model is fitted to a random walk series. Specifically, we fit a two-regime Markov switching model to artificially generated random walk series. It was found that the average estimates of the transition probabilities P_{11} and P_{22} were indicative of the presence of regime-switching dynamics⁵. Obviously, the pilot study does not rule out the possibility of the existence of Markov switching dynamics in real exchange rate data. However, the result underlines the general conception that long swings in random walk data may lead to spurious evidence of regime-switching behavior and highlights the relevancy of a formal test for the number of regimes.

3.3 Testing for the presence of Markov switching dynamics

In general, the null and alternative hypotheses of the test for the presence of Markov switching can be stated as

- H_0 : the number of regimes in the data is N , and
- H_1 : the number of regimes in the data is $N + 1$.

For the current study, we mainly consider the $N = 0$ case. That is, the data are drawn from a single regime under the null hypothesis and from two distinct regimes under the alternative. Let θ_N and θ_{N+1} be the parameter vectors under the null and alternative hypotheses and $\hat{\theta}_N$ and $\hat{\theta}_{N+1}$ be the corresponding maximum likelihood estimators. The likelihood ratio statistic is

$$LR = 2 \left[L \left(\hat{\theta}_{N+1} \right) - L \left(\hat{\theta}_N \right) \right] \quad (3.3)$$

where $L \left(\hat{\theta}_{N+1} \right)$ and $L \left(\hat{\theta}_N \right)$ are the log likelihood functions evaluated at their respective maximum likelihood estimators $\hat{\theta}_{N+1}$ and $\hat{\theta}_N$.

In testing for Markov switching, the complexity arises because some parameters are not identified under the null. The presence of un-identified parameters invalidates the regularity conditions under which the likelihood ratio statistic can be shown to follow an asymptotic chi-square distribution. Several procedures have been suggested to test for the number of regimes; see, for example, Hansen (1992), Gong and Mariano (1997), and Garcia (1998). These procedures typically derive the asymptotic behavior of the test statistic under some pre-specific conditions and offer different finite-sample performance for different model configurations⁶.

⁵Specifically, the averages of the estimated transition probabilities obtained from the simulation exercise are 0.89.

⁶The Hansen (1992) test, for instance, involves a grid search over the parameter space and can be computationally complicated for a multi-regime dynamic model. The Garcia (1998)

Following the lead of Rydén, Teräsvirta, and Asbrink (1998), a Monte Carlo approach is adopted to derive the empirical distribution of the likelihood ratio statistic, which is then used to determine the significance of the statistic computed from the actual data. For a given real exchange rate series, the empirical distribution for testing H_0 against H_1 is constructed according to these steps: a) find the maximum likelihood estimator $\hat{\theta}_N$ that gives the best specification within the class of N -regime models, b) use $\hat{\theta}_N$ to generate a sample of the artificial data, c) compute the likelihood statistic (3.3) from the generated data, and d) repeat steps (b) and (c) M times and store the simulated likelihood ratio statistics. The M simulated likelihood ratio statistics are used to derive the empirical distribution to test the null. Specifically, the empirical p -value of the Markov switching test is given by $(m + 1)/(M + 1)$, where m is the number of simulated statistics that are larger than the likelihood ratio statistic computed from the actual data series.

3.3.1 Annual data

Random walk against Markov switching

Let us consider the case in which (3.1) specifies the null hypothesis and (3.2) is the Markov switching model under the alternative. The sample likelihood ratio statistics are given in the second column ("Sample LR") of Panel A in table 3.1. The Deutsche mark and French franc series give similar sample likelihood ratio test statistics, which are smaller than the one computed from the and British pound data.

For each exchange rate series, the sample-specific empirical distribution of the likelihood ratio statistic is generated according to the procedure outlined above. Due to the computational complexity of the simulation experiment, the number of replications M is set to 250⁷. Some descriptive statistics of these empirical distributions and the associated p -values are given in table 3.1. All the empirical distributions have their means larger than the medians. Further, these are positively skewed distributions; that is, they have a long tail to the right. The ranges of these simulated statistics vary across real exchange rates. In general, these descriptive statistics indicate that the empirical distributions are series-specific.

and Gong and Mariano (1997) procedures are easier to implement but not much is known about their small sample performance. It should be noted that these procedures focus on testing between one or two regimes and become quite complicated when a higher dimension model is considered. On the other hand, the Monte Carlo approach adopted in this exercise can be readily modified to handle higher order Markov switching dynamics.

⁷Rydén, Teräsvirta, and Asbrink (1998), for example, set $M = 50$. For 250 replications and a 10% test used in the subsequent simulation, the 95% confidence interval of the rejection frequency is $10\% \pm 3.7\%$ under the null hypothesis. Thus, even after taking sampling uncertainties into consideration, the inferences presented in the text are not affected.

Table 3.1: Random walk or Markov switching. Annual data

| | Sample LR | P-Value | Mean | Median | Std Error | Skew. | Max. | Emp. power |
|---|--------------|---------|--------|--------|--------------|-------|--------|---------------|
| Panel A: Random Walk against Markov Switching | | | | | | | | |
| DEM | 2.418 | 0.891 | 5.619 | 5.153 | 2.727 | 0.755 | 13.010 | 0.100 |
| GBP | 8.263 | 0.187 | 5.678 | 5.152 | 3.027 | 0.832 | 15.710 | 0.564 |
| FFR | 3.996 | 0.661 | 5.660 | 4.848 | 3.251 | 0.848 | 19.671 | 0.152 |
| Panel B: Markov Switching against Random Walk | | | | | | | | |
| DEM | 2.418 | 0.030 | 5.736 | 5.426 | 3.105 | 0.581 | 15.629 | 0.170 |
| GBP | 8.263 | 0.291 | 11.817 | 11.422 | 6.087 | 0.536 | 32.003 | 0.288 |
| FFR | 3.996 | 0.299 | 6.319 | 5.654 | 3.391 | 1.302 | 24.217 | 0.136 |

The likelihood ratio statistics computed from the annual real exchange rate data (DEM = Deutsche mark, GBP = British pound, FFR = French franc) are reported under the column labeled "Sample LR". The p-values of these sample statistics derived from the empirical distributions are listed under "P-Value". Descriptive statistics of the empirical distributions are provided under "Mean", "Median", "Std Error", "Skew." (skewness) and "Maximum".

For Panel A, the empirical distributions of the likelihood ratio statistic are generated from random walk models estimated from the data. The column "Emp. Power" (empirical power) reports the frequency of rejections when these empirical distributions are used to evaluate the significance (at the 10% level) of the likelihood ratio statistics calculated from data generated from Markov switching processes estimated from real exchange rate data.

For Panel B, the empirical distributions of the likelihood ratio statistic are generated from Markov switching models estimated from the data. The column "Empirical Power" reports the frequency of rejections when these empirical distributions are used to evaluate the significance (at the 10% level) of the likelihood ratio statistics calculated from data generated from random walk processes estimated from real exchange rate data. In all cases, the number of replications is 250. The sample period is 1973 to 1997.

The empirical distributions of the likelihood ratio statistic cast doubts on the presence of Markov switching dynamics. According to the p -values, there is no strong evidence to reject the random walk null in favor of the Markov switching model. The p -values for the Deutsche mark and French franc data are 66% or higher. The one for British pound series is below 20%, which is a rather weak evidence against the random walk hypothesis. Thus far, the evidence is in favor of the random walk null hypothesis.

Are the non-rejection results driven by the low power of the testing procedure? To address the question on power, we generate artificial data series from two-regime Markov switching models estimated from individual real exchange rate series and calculate the likelihood ratio statistic. A 10% test (with the critical value from the corresponding simulated null distribution) is used to determine the proportion of rejection, which is defined as the empirical power. The empirical power is reported in the last column of table 3.1. The power of the test against the Deutsche mark and French franc Markov switching specifications is quite low — 10% for the Deutsche mark case and 15% for the French franc case. Nonetheless, more than 56% of the simulated British pound Markov switching series are rejected at the 10% level. While power can be an explanation of the non-rejection result for the Deutsche mark and French franc cases, it seems not relevant for the British pound result.

Markov switching against random walk

One potential criticism of the results reported in the previous subsection is that the inferences are made with the random walk specification as the null hypothesis. The setting gives the random walk specification the benefit of the doubt. Specifically, the random walk specification is rejected only if there is strong evidence against it. In this subsection, we consider a heuristic approach to account for this asymmetric treatment.

A natural question to ask is “What is the behavior of the likelihood ratio statistic if the data are in fact generated from a Markov switching model?” If the Markov switching model gives the true data generating process, we expect there is substantial gain in the likelihood value between $L(\hat{\theta}_{N+1})$ and $L(\hat{\theta}_N)$ and, hence, the likelihood ratio statistic to be large. Alternatively, if a random walk model generates the data, the likelihood value will tend to be small. Heuristically speaking, when the likelihood ratio statistic computed from the actual data is small compared with the values of the likelihood ratio statistic generated from simulated Markov switching data, it can be regarded as evidence against the Markov switching model and in favor of the random walk specification. Thus, we simulate the data under a Markov switching specification and tally the likelihood ratio statistics from these artificial data series. Then, we look at whether the likelihood ratio statistic computed from exchange rate data is “significantly” smaller than the simulated likelihood ratios. The notion of the presence of Markov switching dynamics is rejected only if there is strong evidence against it — that is, the Markov switching model is rejected if there is only a very small portion of the simulated statistics is less than the likelihood ratio statistic from the actual data. In doing so, we reverse the asymmetric treatment built into the procedure considered in the previous subsection.

Panel B of table 3.1 reports the results of testing for Markov switching dynamics against random walk alternatives. Artificial annual data series are generated according to Markov switching models fitted to the three real exchange rate series. The likelihood ratio statistic (3.3) is constructed from each replication and tabulated to derive the empirical distribution to determine the significance of the sample likelihood ratio statistic. The “ p -value” is calculated as $m/(M + 1)$, where m is the number of simulated statistics that are smaller than the likelihood ratio statistic computed from actual data. Compared with Panel A, the descriptive statistics in Panel B are consistent with the prior belief that the likelihood ratio statistic under the Markov switching model tends to be large. Again, these empirical distributions are positively skewed and data-specific.

For the British pound and French franc series, the results show that the sample likelihood ratio statistics are not too small compared with the simulated values. In these two cases, the sample likelihood ratio statistics are larger than at least 29% of the statistics generated from simulated Markov switching data. The results do not support the notion that the sample statistics are substantially less than what would be expected if data were generated via the Markov switching channel. Alternatively, we can say that, for these two real exchange rate series,

there is no strong evidence to reject the Markov switching model in favor of the random walk model.

On the other hand, the simulation result indicates the rejection of the Markov switching model for the Deutsche mark series. The sample likelihood statistic computed from the Deutsche mark data is less than 97% of the statistic simulated from a Markov switching specification. The power of the test, which is listed in the last column of Panel B, is in the range of 14% to 29%. That is, if the data are simulated with the random walk specifications, then 14% to 29% of the simulated series give a likelihood ratio statistic that is smaller than the 10th percentile of the empirical distributions based on the Markov switching models. Given the low power of the procedure, it is not sure whether the rejection in the Deutsche mark case is a statistical artifice or is a genuine piece of evidence that the Deutsche mark real exchange rate follows a random walk.

The non-rejection of Markov switching result is enlightening. It underscores a fundamental issue in hypothesis testing — the non-rejection of the null hypothesis does not necessarily mean the null hypothesis is correct. In fact, what the results in table 3.1 indicate that, for the British pound and French franc real exchange rates and the parametric information retrieved from the data, we reject neither the random walk nor the Markov switching specification. In the following, we will examine the robustness of the Deutsche mark random walk result.

As attested by the simulation results, the Monte Carlo based tests may not offer a definite evaluation on whether there is Markov switching dynamics in the annual data. The inference depends on which specification is being considered as the null hypothesis. Seemingly, annual data may not contain sufficient information to discriminate between the two alternatives.

3.3.2 Quarterly and monthly data

To explore the implication of data frequency, we examine quarterly and monthly data of the same three real exchange rates. The results derived from quarterly and monthly data are summarized in table 3.2 and table 3.3, respectively. Again, for both data frequencies, we a) test the null hypothesis of a random walk against the alternative of a Markov switching model and report the results in Panel A of the tables, and b) test the Markov switching null against the random walk alternative and report the results in Panel B of the tables. Artificial data generated according to random walk and Markov switching specifications estimated from real exchange rates are used to compute data-specific size and power estimates. For both quarterly and monthly data, the empirical distributions constructed under a random walk model and a Markov switching model are sample-specific, and, thus, reinforce the importance of using data-specific information to evaluate the relative performance of the competing models.

Compared with annual data, the quarterly data offer stronger evidence of Markov switching behavior (table 3.2). The random walk model is strongly rejected with a p -value of 0.4% in the French franc case, rejected with a p -value of 2.8% in the Deutsche mark case, and not rejected in the British pound case.

The empirical power of the test is higher than that reported for the annual data. Indeed, the empirical power in Panel A of table 3.2 ranges from 53% to 94%. Very likely, the power improvement attributes to the rejection results associated with the quarterly data.

Table 3.2: Random walk or Markov switching. Quarterly data

| | Sample LR | P-Value | Mean | Median | Std Error | Skew. | Max. | Emp. power |
|---|--------------|---------|--------|--------|--------------|-------|--------|---------------|
| Panel A: Random Walk against Markov Switching | | | | | | | | |
| DEM | 14.560 | 0.028 | 7.123 | 6.326 | 2.799 | 1.414 | 19.077 | 0.724 |
| GBP | 9.344 | 0.211 | 7.286 | 6.637 | 2.972 | 1.350 | 20.582 | 0.532 |
| FFR | 17.887 | 0.004 | 6.571 | 5.866 | 2.499 | 1.377 | 17.218 | 0.936 |
| Panel B: Markov Switching against Random Walk | | | | | | | | |
| DEM | 14.560 | 0.502 | 15.685 | 14.525 | 6.217 | 0.661 | 34.641 | 0.772 |
| GBP | 9.344 | 0.299 | 12.035 | 11.119 | 4.440 | 0.901 | 25.716 | 0.580 |
| FFR | 17.887 | 0.514 | 19.069 | 17.699 | 7.327 | 1.305 | 60.667 | 0.940 |

The likelihood ratio statistics computed from the quarterly real exchange rate data (DEM = Deutsche mark, GBP = British pound, FFR = French franc) are reported under the column labeled "Sample LR". The sample period is 1973:I to 1997:IV. See the note to table 3.1.

Table 3.3: Random walk or Markov switching. Monthly data

| | Sample LR | P-Value | Mean | Median | Std Error | Skew. | Max. | Emp. power |
|---|--------------|---------|--------|--------|--------------|-------|--------|---------------|
| Panel A: Random Walk against Markov Switching | | | | | | | | |
| DEM | 26.191 | 0.004 | 6.402 | 5.551 | 2.882 | 1.467 | 17.324 | 0.968 |
| GBP | 16.308 | 0.004 | 6.296 | 5.714 | 2.588 | 1.049 | 15.910 | 0.928 |
| FFR | 26.708 | 0.004 | 6.200 | 5.492 | 2.795 | 1.592 | 18.653 | 0.968 |
| Panel B: Markov Switching against Random Walk | | | | | | | | |
| DEM | 26.191 | 0.681 | 23.510 | 22.610 | 8.932 | 0.947 | 56.961 | 0.960 |
| GBP | 16.308 | 0.426 | 19.047 | 17.691 | 7.760 | 0.861 | 48.448 | 0.920 |
| FFR | 26.708 | 0.634 | 24.303 | 23.450 | 9.221 | 0.571 | 49.170 | 0.972 |

The likelihood ratio statistics computed from the monthly real exchange rate data (DEM = Deutsche mark, GBP = British pound, FFR = French franc) are reported under the column labeled "Sample LR". The sample period is 1973:1 to 1997:12. See the note to table 3.1.

The results in Panel B of table 3.2 do not represent any significant evidence against the Markov switching model. The lack of power does not appear to be a relevant explanation of the non-rejection results. The ability of the procedure to reject a random walk model is pretty high. The simulated empirical power is in the range of 58% to 94%, which is comparable to the power figures in Panel A. One interesting observation is that the annual and quarterly Deutsche mark real exchange rate series give different results from the test of the Markov switching model against the random walk model — the former series rejects the Markov switching specification while the latter does not. Comparing the empirical power in tables 3.1 and 3.2, we can rule out the possibility that the quarterly data non-rejection result is due to the power of the test. Thus, it is

possible that the annual frequency result is a statistical artifice because the null hypothesis, even though it is correct, can be rejected by chances. We will get back to this point again in analyzing monthly data.

Table 3.3 reports the results obtained from monthly data. Contrary to annual and quarterly data, the monthly data yield a much sharper inference on real exchange rate dynamics. For all the three monthly real exchange rate series, the Monte Carlo based test rejects the random walk null hypothesis with a p -value 0.004. When Markov switching is assumed to be the data generating process, the sample likelihood ratio statistics are larger than 43% to 68% of the simulated statistics — indicating that the sample statistics are not likely to come from a random walk process. Further, the procedures have very good power against their respective alternatives. In all cases, the simulated power is larger than 90%. Regarding the Deutsche mark case, the result from the monthly data is similar to the one from quarterly data but different from annual data. Taking all the evidence into consideration, it is reasonable to infer that the Deutsche mark data have switching dynamics and the annual data result is likely to be spurious. Overall, there is strong evidence of monthly real exchange rates following Markov switching dynamics.

One observation comes out pretty clearly in the annual, quarterly and monthly results. An increase in sampling frequency has an appreciable effect on the test performance. Specifically, high frequency data allow the observations to display switching behavior that may have duration too short to be observed in low frequency data. Further, an increase in sampling frequency, for a given sample time span, increases the number of observations and boosts the power of the test procedure. These two factors together offer a better chance to detect Markov switching dynamics in data.

3.4 Concluding remarks

The study presents a systematic empirical examination on the presence of Markov switching dynamics in three dollar-based real exchange rate series. Annual, quarterly, and monthly data from 1973 to 1997 are considered. A Monte Carlo approach is adopted to circumvent the statistical inference problem inherent to the modeling of regime switching. To address the asymmetry of having the random walk as the null hypothesis, we also examine the empirical behavior of the likelihood ratio statistic under the sample-specific Markov switching models. Because the behavior of the statistic is found to be contingent on the sample-specific dynamics, sample-specific empirical distributions of the likelihood statistic are used to infer the relative performance of the random walk and Markov switching models.

The ability to discriminate between random walk and Markov switching depends on the power of the test and the information content of the data. The current exercise illustrates that the Monte Carlo based test can be a promising procedure to detect Markov switching dynamics. The results obtained from three data frequencies are consistent with the informational interpretation. Bet-

ter information about Markov switching dynamics can be obtained by increasing the sampling frequency. Our results buttress the importance of using high frequency data to extricate Markov switching dynamics.

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