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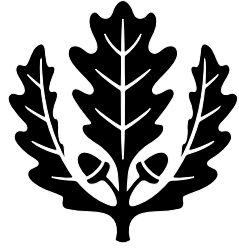
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Abstract

Some researchers, for example, Koop (1992), and Sims (1988), advocated for Bayesian alternatives to unit-root testing over the classical approach using the augmented Dickey-Fuller test (ADF). This paper studies what Koop (1992) called the Objective Bayesian approach to unit-root testing. We apply the objective Bayesian unit-root test to a study of long-run purchasing power parity (PPP) for the post-Bretton Woods era. While the classical approach using the ADF test cannot reject the unit-root hypothesis, the Bayesian approach, on the other hand, suggests that the unit-root hypothesis is not strongly supported by the sample data. Rather, the trend-stationary hypothesis receives the highest posterior probability in all cases except for the Japanese yen/German mark real exchange rate where the stationary hypothesis receives the highest posterior probability. In two Monte Carlo simulations, however, we find that the objective Bayesian test have relatively low power in distinguishing between plausible alternatives, making it difficult to draw any conclusions concerning long-run PPP. We conclude that, at least for the objective Bayesian test, the Bayesian approach is not necessary better than the classical ADF approach.

Journal of Economic Literature Classification: C22, F31

Is the Bayesian Approach Necessarily Better than the Classical Approach in Unit-Root Test?

1. Introduction

The question of how best to characterize the growth component of macroeconomic time series has been hotly debated since the publication of the study by Nelson and Plosser (1982). The most widely held view before 1982 was that most macroeconomic time series could be characterized as trend-stationary (TS) series, i.e., the series consists of a deterministic trend and stationary fluctuations around that trend. Nelson and Plosser's study called into question that widely held view by demonstrating that thirteen out of fourteen U.S. macroeconomic time series that they considered contained a unit root, and thus were difference-stationary (DS) series, i.e., they required differencing to induce stationarity. Although the debate is far from settled,¹ the focus of the debate has shifted to the appropriate statistical techniques to use in testing between TS and DS series. In particular, several economists have strongly advocated Bayesian alternatives to unit-root testing. We study one of the Bayesian alternatives in this paper by applying it to another controversial area in Economics, that of long run purchasing power parity (PPP) in the post-Bretton Woods era. Thus, we hope to shed some light on these two controversial areas of Economics. We present a general discussion of the Bayesian approach to unit-root testing in the next section. In section 3, we review some of the current literature on testing for long-run PPP. In section 4, we discuss our Bayesian unit-root test which has been called "objective" Bayesian test by Koop (1992). We present our empirical results in section 5. We study the properties of the "objective" Bayesian unit-root test using Monte Carlo simulations in section 6. Finally, our summary and conclusions are in section 7.

2. The Bayesian Approach to Unit-Root Testing

It should be noted at the onset that the classical (e.g., the regression approach) and the Bayesian approaches to econometrics are complementary rather than competing. There are, however, major differences between the two. We will start by reviewing some of the major differences in this section.

In the classical approach, the data are treated as random, and the parameters to be estimated as non-random. The Bayesian approach treats unknown quantities, such as the parameters in a model, as random variables and the data as non-random. In the classical approach, hypotheses are either rejected or failed to be rejected at a pre-chosen level of significance, say 5% or 10%. The Bayesian approach is based on Bayes' Theorem, which may be stated as:

$$g(\underline{\theta} | \underline{y}) = \frac{f(\underline{y} | \underline{\theta})g(\underline{\theta})}{f(\underline{y})}, \quad (1)$$

where $\underline{\theta}$ is a vector of parameters, \underline{y} is a vector of sample observations, $f(\underline{y})$ is the density function for \underline{y} , $f(\underline{y}|\underline{\theta})$ is the joint density function, it is algebraically identical to the likelihood function for $\underline{\theta}$, and contains all the sample information about $\underline{\theta}$. The function $g(\underline{\theta})$ is the prior density function for $\underline{\theta}$; it summarizes the non-sample information about $\underline{\theta}$. Finally, $g(\underline{\theta}|\underline{y})$ is the posterior density function for $\underline{\theta}$, it summarizes all the information about $\underline{\theta}$ after \underline{y} has been observed.

The modeling objective of the Bayesian approach is not to reject or fail to reject a hypothesis, but to determine how probable a hypothesis is relative to other competing hypotheses. There are several ways of comparing hypotheses using Bayesian methods. The most common method is to calculate posterior odds ratios for various competing hypotheses based on prior and sample information. This gives the researcher the odds in favor of one hypothesis relative to other competing hypotheses. For example, the posterior odds ratio for comparing the null hypothesis (H_1) to an alternative hypothesis (H_2) can be written as

$$K_{12} = \frac{P(H_1)P(H_1|\underline{y})}{P(H_2)P(H_2|\underline{y})}, \quad (2)$$

where $P(H_1)/P(H_2)$ is called the prior odds ratio, and $P(H_i|\underline{y}) = \int P(\theta_i|H_i)L(\theta_i|\underline{y},H_i)d\theta_i, i=1,2$, is the posterior probability that $H_i, i=1,2$, were true given the sample data \underline{y} , and $P(\theta_i|H_i)$ and $L(\theta_i|\underline{y},H_i)$ are the prior density and likelihood function, respectively, under each hypothesis.

In unit-root testing, the frequently used classical approach is the augmented Dickey-Fuller (ADF, 1981) test, where a linear regression of the following type is typically estimated by ordinary least squares:

$$y_t = \delta_0 + \rho y_{t-1} + \sum_{i=1}^k \delta_i \Delta y_{t-i} + \varepsilon_t, \quad (3)$$

where δ_0 is a constant, Δ is the first difference operator, i.e., $\Delta y_t = y_t - y_{t-1}$, and ε_t is a serially uncorrelated error process. The null hypothesis is $H_0 : \hat{\rho} = 1$, against the alternative that $\hat{\rho} < 1$. Several studies, e.g., Hakkio (1986), and DeJong, Nankervis, Savin, and Whiteman (1992), have shown that the ADF test has low power against plausible alternatives, especially against trend-stationary alternative. Indeed, studies using Bayesian approaches to unit-root testing, e.g., DeJong and Whiteman (1991a, 1991b), and Koop (1992), have generally found much weaker evidence in favor of unit-root, and much stronger evidence in favor of trend-stationarity. This led researchers such

as Koop (1992), DeJong and Whiteman (1991), Sims (1988), and Sims and Uhlig (1991) to advocate forcefully for Bayesian alternatives over the more traditional classical approach such as the ADF tests in unit-root testing.² These researchers pointed out several advantages of the Bayesian approach over the classical approach. For example, DeJong et al. (1992), Koop (1994), and others have noted that given that classical unit-root tests have low power against trend-stationary alternative, a small finite data set generated from a unit-root model may be virtually indistinguishable from a small finite data set generated from a trend-stationary model with strong persistence. Faced with the trend-stationary model, classical testing procedures would fail to reject the null hypothesis of a unit root. The Bayesian approach, however, would reveal that both the unit root and the trend-stationary hypotheses receive similar posterior probabilities. Thus, the Bayesian approach provides a more reasonable summary of sample information than the classical approach.

Another problem with the classical unit-root tests is the discontinuity of the classical asymptotic theory at $\hat{\rho} = 1$ [see Sims (1988) especially for a good discussion of this point]. For example, the standard asymptotic theory applies when $|\hat{\rho}| < 1$, and does not apply when $\hat{\rho} = 1$, or $\hat{\rho} > 1$, and Monte Carlo studies are necessary to establish the appropriate asymptotic critical values. The Bayesian approach, on the other hand, since it is based on the likelihood function, which is continuous in ρ , does not have the same discontinuity problem. Koop (1994) also pointed out that, in the classical approach, frequently researchers have to rely on the asymptotic critical values, which could differ substantially from the small sample critical values. The Bayesian approach, on the other hand, since it is conditional on the observed sample, provides exact small sample results.

Despite the apparent advantages of the Bayesian approach over the classical approach in unit-root testing, only a relatively small but growing number of studies have appeared using the Bayesian approach. The reasons may be that the Bayesian approach requires a likelihood function and the use of prior information. The perception is that other than for the simplest cases, the Bayesian approach is computationally burdensome, and the use of prior information is by far the most controversial. Frequently in many applications, however, there is considerable agreement among researchers. For example, in unit-root testing, many researchers would agree that the alternative to $\rho = 1$ is that ρ is concentrated near one, as opposed to say ρ is near 2 or 0.1. Thus, a reasonable prior may be to allocate significant probability in the region near and including one. An alternative is to use noninformative (or flat) priors. The one serious drawback, however, is that they are frequently improper, i.e., they do not integrate to one. An improper prior poses problems for hypothesis testing but not for estimation and prediction, however. As

far as computational burden is concerned, both Sims (1988) and Koop (1992) have shown relatively simple methods to implement a Bayesian alternative to classical unit-root tests. In summary, there is no consensus on the merits of the classical vs. the Bayesian approach to unit-root testing. Bayesian researchers have put forth a strong case to at least consider the Bayesian alternative to unit-root testing. We suspect that all researchers would agree that the Bayesian approach provides a useful alternative empirical approach.³ We study what Koop (1992) called the “objective” Bayesian test in this paper and apply it to a study of long-run PPP using data from the post-Bretton Woods era. In the next section, we review briefly the controversies surrounding tests for long-run PPP.

3. Testing for Long-Run PPP

The theory of PPP has a long tradition in international economics. It is a central building block in the monetary models of exchange rate determination, e.g., Frenkel (1978) and Dornbusch (1976). In its simplest form, PPP can be expressed as a relationship between the nominal exchange rate, and relative prices, or, in natural logarithm form:

$$e_t = P_t - P_t^*, \quad (4)$$

where e_t is the natural logarithm of the nominal exchange rate, defined as the domestic currency price of one unit of foreign currency, P_t is the natural logarithm of an index of the domestic price level, and P_t^* is the natural logarithm of an index of the foreign price level. Recent empirical tests of PPP have mainly focused on the long run given that there are frequent large and persistence short-run deviations from PPP. Tests of long-run PPP based on equation (4) have mostly used the techniques of cointegration of Engle and Granger (1987), or Johansen (1988).⁴ A weak test of long-run PPP is to determine whether or not a cointegration vector exists. The existence of at least one cointegration vector would imply that an equilibrium long-run relationship exists between the nominal exchange rate and the relative prices, so that there is no permanent deviation from PPP. In addition to finding a cointegration vector, a stronger test of long-run PPP, however, would also require that the two properties implied by PPP -- (a) symmetry between domestic and foreign price levels, and (b) proportionality between the relative prices and the nominal exchange rate -- are also satisfied.

Another approach to testing long-run PPP is to rewrite equation (4) in its real exchange rate equivalent form by imposing both the symmetry and the proportionality properties. That is, in natural logarithm form:

$$q_t = e_t + P_t^* - P_t, \quad (5)$$

where q_t is the natural logarithm of the real exchange rate. If PPP holds continuously, $q_t = 0$ for all t . This is unrealistic, however, given that we observe frequent deviations from PPP. The question therefore is whether deviations from PPP are transitory or permanent. If deviations from PPP are transitory, the time series of q_t is a stationary series. On the other hand, if deviations from PPP are permanent, then the time series of q_t is non-stationary and contains a unit-root. Tests for unit-roots have mostly been carried out using the ADF test using a regression such as Equation (3). Long-run PPP requires that $\hat{\rho} < 1$. If $\hat{\rho} = 1$, there is a unit-root in the series q_t , shocks to the real exchange rate are permanent and long-run PPP does not hold.

Earlier empirical tests of long-run PPP using either equation (4) or (5), or variants of them, have produced mixed results, but largely unfavorable to long-run PPP, especially when data from the post-Bretton Woods floating period are used [see the survey by Rogoff (1996)]. Several explanations have been offered for this failure of long-run PPP in the post-Bretton Woods period. First, it is known that when German mark is used as the base currency, researchers tend to find more favorable results for long-run PPP than when the U.S. dollar is the base currency [see Papell (1997), and Papell and Theodoridis (1998) for recent examples]. This leads Lothian (1998) to conclude that the frequent failures to find evidence in favor of long-run PPP in the post-Bretton Woods floating exchange rate period is not a generic problem to this period. Rather, it is confined to using the U.S. dollar as the base currency and is restricted to the early to mid-1980s time period when first there was a substantial real appreciation of the U.S. dollar for 1980-1985, and an almost equal offsetting real depreciation of the U.S. dollar for 1985-1987. Second, since the empirical methodologies generally used to test equation (4) or (5) are known to have low power in small samples, it is not possible to distinguish whether the failure to find cointegration (using equation 4), or the failure to reject the unit-root hypothesis (using equation 5) is due to the low power of the tests employed or that long-run PPP does not hold in the post-Bretton Woods floating period.

One way to increase the power of the empirical tests is to use longer span of data. For example, Diebold, Husted, and Rush (1991),⁵ using data going back to the gold standard period, Lothian, and Taylor (1996), using data dating back to the 1790s and early 1800s, found evidence to support long-run PPP. On the other hand, Engel and Kim (1999), using monthly data dating back to 1885, found evidence of a permanent (i.e., a unit-root) component in the U.S./U.K. real exchange rate. In addition, Rogoff (1996) and others have noted that studies that used long spans of data typically mix fixed and floating exchange rates data, and the economic implications of mixing data from the two exchange rate regimes is unclear. Moreover, long spans of time series data may potentially contain serious

structural breaks. Engel (1996) also argued that these studies can have serious size biases, and may fail to reject a sizable unit root. Finally, these studies also do not shed much light on the question of whether or not PPP is a valid hypothesis in the post-Bretton Woods floating period.

Another way to increase the power of the cointegration and unit-root tests is to use panel data. Recent examples using data from the post-Bretton Woods floating exchange rate period include studies by Jorion and Sweeney (1996), Papell (1997), Papell and Theodoridis (1998), Koedijk, Schotman, and Van Dijk (1998), and Heimonen (1999). These studies all found evidence to support long-run PPP. On the other hand, O'Connell (1998) found little evidence to support long-run PPP after accounting for serial correlation. Papell (1997) found that evidence in favor of long-run PPP is dependent on the size of the panel and the countries included. Rogoff (1996) also noted that with panel studies, the evidence of long-run PPP tends to be much more favorable when high inflation countries are included. Finally, the interpretation of the panel studies' results is not always very obvious. For example, Karlsson and Löthgren (2000) using Monte Carlo simulations, found that for panels with long spans of data, the null hypothesis of unit roots can be erroneously rejected even when only a small proportion of the series is stationary. For panels with short spans of data, however, Karlsson and Löthgren found that the null hypothesis of unit roots is frequently not rejected even when a large fraction of the series is stationary. Thus, they concluded that the rejection or the non-rejection of the null hypothesis of unit roots in panel unit-root tests do not provide sufficient evidence to conclude that all the series in the panels are stationary or that they all have a unit root. An exception, however, is the panel study by Sarno and Taylor (1998). Using a special application of the Johansen (1988) Likelihood ratio, where the null hypothesis of a unit root is rejected only when all the series are stationary, Sarno and Taylor concluded that their four real exchange rates are jointly stationary series. Thus, panel unit root tests have produced encouraging but inclusive results.

Still other researchers, using different empirical methodologies, found mixed results with data from the post-Bretton Woods period. For example, Cheung and Lai (1998), using more efficient unit-root tests, found more encouraging results than when using the ADF tests. Culver and Papell (1999), using the tests proposed by Kwiatkowski, Phillips, Schmidt and Shin (1992) where stationarity is the null, rather than the alternative hypothesis, found favorable evidence to support long-run PPP. However, a recent study by Caner and Kilian (1999) shown that severe size distortion can result with the use of conventional asymptotic critical values for tests of the null hypothesis of stationarity if the model under the null hypothesis is highly persistent. On the other hand, using size-adjusted critical values can overcome the problem of size distortions, but result in low power of the tests for

economically plausible values of the first-order autoregressive (i.e., AR (1)) parameter. Finally, Baum, Barkoulas, and Caglayan (1999), allowing for fractional differencing or structural breaks, found no evidence to support long-run PPP.

Our brief review suggests that the recent empirical studies have tended to be more supportive of long-run PPP than the earlier studies. The results are not very robust, however. Moreover, even-though there is a growing body of literature that supports long-run PPP in the post-Bretton Woods period, consistent individual country time series evidence from the post-Bretton Woods period continues to be scarce.

4. Testing Long-Run PPP with the “objective” Bayesian Approach

We are aware of only three studies that have used the Bayesian approach to test for long-run PPP. Whitt (1992), using the Bayesian approach discussed in Sims (1988), found evidence to support long-run PPP using post-Bretton Woods monthly data for five real exchange rates, and post-World War II annual data for six real exchange rates. Schotman and van Dijk (1991) extended Sims’s (1988) results by introducing a constant term in the model and found mixed results using monthly data for eight real exchange rates from the post-Bretton Woods period. They concluded that for four of their eight real exchange rate series, the random-walk hypothesis received about equal posterior probabilities as the hypothesis that the series are stationary autoregressive processes of order one (i.e., AR(1) processes). Ahking (1995), using a Bayesian approach discussed in Koop (1992), and using both monthly and quarterly data from Canada’s floating exchange rate period in the 1950s, found mixed results, but generally not very supportive of long-run PPP.

In this paper, we also use the Bayesian approach discussed in Koop (1992) to study long-run PPP using data from the post-Bretton Woods era. Since we are using only univariate time series of the real exchange rates, we avoid the potential problems associated with using panel data. Furthermore, since our data are from the post-Bretton Woods period, we also avoid the criticisms of using long spans of data that mixed both fixed and floating exchange rates data.

Koop’s (1992) Bayesian unit-root test is based on the work of Zellner and Siow (1980).⁶ There are several features of this approach that make it attractive for economists looking for an alternative to the classical unit-root tests. First, it is computationally simple. It does not require complicated numerical integration, and hence advanced programming skills are not necessary. Second, it requires informative priors, thus avoiding the problems associated with using non-informative priors. Third, it does not require significant subjective prior information, only that all the competing hypothesis have equal prior probability, leading Koop (1992) to call this an “objective” Bayesian test.

As we will argue below (see footnote 7), however, even-though we assign equal prior probability to all the competing hypotheses, there is a bias in favor of the unit-root hypothesis.

The objective of the analysis is to find the linear model that would best describe the time series of the real exchange rate, $\underline{q} = (q_1, q_2, \dots, q_T)'$. We consider three hypotheses:

$$H_1: \quad q_t = \alpha_0 + \sum_{i=1}^k \alpha_i q_{t-i} + \alpha_{k+1} t + \xi_{1t}, \quad (6)$$

$$H_2: \quad q_t = \alpha_0 + \sum_{i=1}^k \alpha_i q_{t-i} + \xi_{2t}, \quad (\alpha_{k+1} = 0) \quad (7)$$

$$H_3: \quad \Delta q_t = \alpha_0 - \left(\sum_{i=2}^k \alpha_i \right) \Delta q_{t-1} - \left(\sum_{i=3}^k \alpha_i \right) \Delta q_{t-2} - \dots - \alpha_k \Delta q_{t-(k-1)} + \xi_{3t}, \quad (8)$$

$$\left(\sum_{i=1}^k \alpha_i = 1, \alpha_{k+1} = 0 \right)$$

where t = a linear deterministic time trend; and ξ_{jt} , $j = 1, 2, 3$ is a serially uncorrelated error process with zero-mean and constant variance.

Hypothesis 1 (H_1) is the null model. It hypothesizes that the real exchange rate is a trend-stationary AR(k) process. H_2 hypothesizes a stationary AR(k) process for the real exchange rate, while H_3 hypothesizes an AR(k) process with a unit root. Note that both H_2 and H_3 are special cases of H_1 with linear restrictions (given in parentheses next to the respective equations), imposed on the null model. The trend-stationary hypothesis is included because several researchers have found that the stochastic processes of some of the real exchange rates cannot be adequately modeled without the inclusion of a linear deterministic time trend [see Cheung and Lai (1998), and Koedijk, Schotman, and Van Dijk (1998) for recent examples]. Since the time series of the real exchange rates typically show evidence of a trend, the trend-stationary hypothesis offers an alternative to the unit-root hypothesis as the source of the trend in the data. The linear deterministic time trend in the real exchange rate is generally interpreted as representing systematic differences in productivity growth between tradable and non-tradable goods in the two countries [see also Cheung and Lai (1998) for a recent discussion]. Thus, the presence of a linear deterministic time trend in the real exchange rate time series is generally not interpreted as a violation of long-run PPP.⁷

We compare the three hypotheses, based on both prior and sample information, by calculating the posterior odds ratios:

$$K_{1j} = \frac{P(H_1)P(H_1|\underline{q})}{P(H_j)P(H_j|\underline{q})}, j = 2, 3. \quad (9)$$

On the assumption that all three hypotheses have equal prior probability, i.e., $P(H_1) = P(H_2) = P(H_3)$, equation (9) reduces to⁸

$$K_{1j} = \frac{P(H_1|\underline{q})}{P(H_j|\underline{q})}, j = 2, 3. \quad (10)$$

That is, the posterior odds ratio gives the ratio of the probabilities of the two hypotheses holding given the sample data. Following Koop (1992), we calculate the posterior odds ratio for testing a set of exact linear restrictions with a formula suggested by Zellner and Siow (1980). The Zellner-Siow posterior odds ratio is calculated approximately as

$$K_{1j} \cong \frac{(\pi^{0.5} / \Gamma[(r+1)/2])(v/2)^{r/2}}{(1+rF/v)^{(v-1)/2}}, j = 2, 3, \quad (11)$$

where $\Gamma[\cdot]$ = the Gamma function, $v = T - n$, T = the total number of observations, n = the number of regressors in the null model, r = the number of linear restrictions tested, and F = the usual F-statistics for testing the set of linear restrictions. After we obtained the posterior odds ratios, we can then calculate the posterior probability for each of the three hypotheses using Equation (10). We discuss our data set and present our empirical results in the next section.

5. Empirical Results

The source of our data is the OECD G-7 countries, supplied on a diskette. Our data consist of monthly observations from April 1973 to February 1999 for the G-7 countries, and are not seasonally adjusted. The G-7 countries are the U.S., the U.K., Canada, Germany, Italy, France, and Japan. In all cases, we use the consumer price index as our measure of the average price level. The only bilateral nominal exchange rate available on the diskette uses the U.S. dollar as the base currency, i.e., foreign currency per U.S. dollar. We are, however, also interested in whether the use of non-U.S. dollar based real exchange rates may produce different results, as other studies have found. We therefore also computed real exchange rates based on the pound sterling, the Canadian dollar, the

German mark, the Italian lira, the France franc, and the Japanese yen. These non-U.S. dollar based exchange rates are computed as cross-rates.⁹

We start our empirical tests by first presenting in Table 1 our test for unit-root using the ADF test. This is motivated by two factors. First, our results provide an update on previous research through the beginning of 1999, and it is interesting to find out whether an addition of several more years of data would have made a difference in the ADF tests for unit root. Second, the ADF unit-root test results will provide a comparison to our Bayesian approach to unit-root testing. Note also that we provide unit-root test results for forty-two real exchange rates (six real exchange rates for each of the seven currencies). Of course, there are only twenty one different real exchange rates since the real exchange rate of country A's currency per unit of country B's currency is simply the inverse of the real exchange rate of country B's currency per unit of country A's currency. This is done so that we can examine how the real exchange rates based on non-U.S. dollar would behave compared to the U.S. dollar based real exchange rate.

The ADF regression actually estimated is

$$\Delta q_t = \beta_0 + \phi q_{t-1} + \sum_{i=1}^l \beta_i \Delta q_{t-i} + \beta_{l+1} t + v_t, \quad (12)$$

where t = a linear deterministic time trend, and v_t is a serially uncorrelated error process with zero mean and constant variance. The lag length for the lagged first-differences is determined by the shortest lag length that produces serially uncorrelated residuals at the 10% significance level using the Ljung-Box Q-statistic computed over the first thirty-six lags of the residuals. The lag lengths determined by this procedure are shown in column 2 of Table 1.¹⁰ In column 3, we show the t-statistic for the hypothesis $H_0 : \phi = 0$. As can be seen, with the exception of the Japanese yen/German mark real exchange rate, the null hypothesis of a unit root cannot be rejected at the 5% and the 10% significance levels using either the critical values from Fuller (1976) or the lag-adjusted critical values for exact sample size from Cheung and Lai (1995). For the Japanese yen/German mark real exchange rate, the null hypothesis of a unit root can be rejected at the 10% level using either Fuller's or Cheung and Lai's critical values. This is consistent with the results of Cheung and Lai (1998), but they also found that the French franc/German mark real exchange rate could be characterized as a stationary process, a result that we do not obtain. Thus, the addition of a few more years of monthly data appears to have no impact on the power of the ADF unit-root test. What is more surprising, however, is the finding that this is true regardless of the base currency used, contrary to some earlier results. The German mark-based real exchange rate produces marginally better result, with the rejection of the unit-

root hypothesis at the 10% significance level for the Japanese yen/German mark real exchange rate. This is a very marginal improvement over the U.S. dollar-based real exchange rates, however. Moreover, using Pound sterling-based or Italian lira-based real exchange rates produce equally dismal results as using U.S. dollar-based real exchange rates. Thus, our ADF results provide no support to Lothian's (1998) assertion that the frequent failures to find favorable evidence of long-run PPP in earlier studies for the post-Bretton Woods period is confined to using U.S. dollar as the base currency.

Column 4 shows the χ^2 test statistic for the joint null hypothesis of a unit root and the absence of a linear deterministic time trend, i.e., $H_0 : \phi = \beta_{l+1} = 0$. Not surprisingly, this hypothesis is not rejected in all cases except for the Japanese yen/German mark real exchange rate, which can be rejected at the 10% significance level using the critical values from Dickey and Fuller (1981). Once again, this is true for all base currencies considered. Thus, based on the ADF unit-root test results presented in Table 1, the evidence against long-run PPP appears to be quite overwhelming.

We next turn to our Bayesian test results presented in Table 2. In column 2 of Table 2 we show the autoregressive lag length, determined using the same method as in the ADF tests.¹¹ The next three columns of Table 2 give the posterior probabilities of the three hypotheses. What we find striking is that, of the three hypotheses, the trend-stationary hypothesis receives the highest posterior probability in all cases except for the Japanese yen/German mark real exchange rate.¹² In that case, the stationary hypothesis receives the highest posterior probability. The French franc/German mark real exchange rate also deserves mention because it is the only case where the trend-stationary and the stationary hypotheses receive approximately the same posterior probabilities. Interestingly, these are the same two real exchange rates that Cheung and Lai (1998) have found to be well characterized by stationary or trend-stationary processes using the conventional ADF tests. The unit root hypothesis, on the other hand, receives no significant posterior probability. In sum, the Bayesian results strongly support the hypothesis that the real exchange rate series are trend-stationary AR processes. Or, put differently, the restrictions on the null model are not strongly supported by the data. Finally, we wish to also note two other points. First, as with the ADF results, we find no compelling evidence to suggest that non-U.S. dollar based real exchange rates produce more favorable evidence in support of long-run PPP than U.S. dollar based real exchange rates. In our Bayesian results, we see that the French franc/German mark and the Japanese yen/German mark real exchange rates receive relatively high posterior probability for the stationary hypothesis. In this respect, the use of the German mark as the base currency produces different results. Second, the real exchange rates of the four European countries

only (that is, the real exchange rate expressed as the currency of European country A per unit of European country B's currency), do not behave differently from those that are based on the non-European currencies. Since the four European countries in our sample all participated in the European Currency Unit (ECU), membership in the ECU does not appear to contribute to the behavior of the real exchange rate.

6. The power of the “objective” Bayesian unit-root test

In this section, we perform two Monte Carlo experiments to study the power of the “objective” Bayesian unit-root test. This will allow us to assess the reliability of our results in Section 5, and also investigate whether the “objective” Bayesian approach is better than the classical ADF approach in unit-root tests.

In the first experiment, we use a data generating model of the following form:

$$y_t = 0.059317 + \rho y_{t-1} - 0.0000201t + u_t,$$

where $u_t \sim iid N(0, 0.000564)$, and ρ varies from 0.95 to 0.99, in increment of 0.01. Thus, the data generating process is a trend-stationary AR(1) model. The constant, the time-trend coefficient, and the variance of the error process are averages from estimating the null model (Equation 6) with data from the twenty-one real exchange rate series. Thus, they represent economically plausible parameters. The values of ρ that we choose are also based on what we consider to be plausible alternatives for monthly series. For example, Sims (1988) argued that for monthly data, it is reasonable to concentrate the prior odds on the interval (0.98, 1) as opposed to, say (0.5, 1). Second, there appears to be a consensus among economists that found favorable evidence for long-run PPP in the post-Bretton Woods era that deviations from long-run PPP have a half-life of about three to five years [see e.g., Abuaf and Jorion (1990), Rogoff (1996)].¹³ According to Caner and Kilian (1999), this corresponds to a ρ value of 0.98 and 0.99, respectively, for three and five years, using monthly data. In sum, we believe that the parameter values that we choose for our Monte Carlo experiment are economically plausible.

The power of the “objective” Bayesian unit-root test in this experiment is defined as the proportion of times that the hypothesis that corresponds to the data generating model receives the highest posterior probability in repeated samples. Some Bayesian researchers may object to this definition of power. It means, for example, that if the trend-stationary hypothesis receives 40% of the posterior probability and the unit-root hypothesis receives 41% of the posterior probability, all the credit will be given to the unit-root hypothesis and none to the trend-stationary hypothesis, while Bayesian researchers would view the two hypotheses as equally likely. We believe, however, that if in fact it is not possible to distinguish between a trend-stationary series from a unit-root series, then in repeated

samples, the “objective” Bayesian unit-root test should allocate roughly the same proportion of times that the trend-stationary hypothesis and the unit-root hypothesis receive the highest posterior probability.

We generate 411 observations, and discard the first 100 observations to avoid the initialization problem. The remaining 311 observations correspond to the sample size of our real exchange rates. The experiment is replicated 5,000 times for each ρ value. The results are reported in the upper panel of Table 3. The results reveal a surprising pattern. For $0.95 < \rho < 0.98$, the trend-stationary hypothesis receives the highest posterior probability the largest proportion of the times. The power of the test increases from $\rho = 0.95$ and peaks at $\rho = 0.97$. At $\rho = 0.99$, however, the unit-root hypothesis receives the highest posterior probability the largest proportion of the times, suggesting an extremely low power of the “objective” Bayesian test at this value of ρ . Before drawing any conclusion, we turn next to our second experiment.

In our second experiment, we use a data generating model of the following form:

$$y_t = 0.059317 + \rho y_{t-1} + u_t,$$

where u_t has the same properties as the first experiment. In this experiment, however, we vary ρ from 0.95 to 1.00, in increment of 0.01. Thus, the data generating model is a stationary AR(1) model and a random-walk with drift model. We use the same procedure to generate the data and the experiment is also replicated 5,000 times for each ρ value. The results are reported in the lower panel of Table 3. Interestingly, for $0.95 < \rho < 0.99$, the results mirror the results reported in the upper panel of Table 3. This, perhaps, is not surprising since the effect of the time trend is extremely small, thus making the two data generating models almost the same. At $\rho = 1.00$, the trend-stationary hypothesis receives the highest posterior probability the largest proportion of the times, followed by the stationary hypothesis, while the unit-root hypothesis receives the highest posterior probability less than 1% of the time.

The results in Table 3 are not very encouraging to the “objective” Bayesian unit-root test. First, for $0.95 < \rho < 0.98$, it cannot distinguish between a highly persistent trend-stationary model from a highly persistent stationary AR model. There appears to be a bias in favor of the trend-stationary model. At $\rho = 0.99$ the unit-root hypothesis is favored regardless of the data generating model used. When the data generating model is a random-walk with drift model, the “objective” Bayesian unit-root is biased in favor of the trend-stationary model. Thus, just as the classical ADF test is criticized frequently for its bias in favor of finding a unit-root, it appears that the

“objective” Bayesian unit-root test can also be criticized for its bias in favoring trend-stationarity. In practice then, at least for the “objective” Bayesian unit-root test, there is no evidence that it is a better statistical approach than the classical ADF test in unit-root testing.

Given the Monte Carlo results, it is impossible to draw any conclusions regarding long-run PPP.

According to Table 3, the data generating processes of the real exchange rates can come from a trend-stationary model, a stationary AR model, or a random-walk with drift model.

7. Summary and Conclusions

Researchers generally agree that the Bayesian approach offers an alternative and useful way to the classical approach to empirical modeling. In unit-root testing, Sims (1988), Sims and Uhlig (1991), and Koop (1994) have presented a strong case for favoring the Bayesian approach over the classical ADF tests. Thus, it is surprising that only a relatively small number of studies have appeared that utilize the Bayesian approach. In this paper, we use the Bayesian approach to unit-root testing discussed in Koop (1992) to test for long-run PPP. Our results indicate that when the ADF test is used for unit-root testing, the hypothesis of a unit-root is not rejected except for the Japanese yen/German mark real exchange rate. This is also true for the joint null hypothesis of a unit root and the absence of a linear deterministic time trend. Thus, the evidence against long-run PPP appears to be overwhelming. Our Bayesian results, on the other hand, provide a stark contrast to the ADF results. In all cases, the hypothesis of a unit root does not receive significant posterior probability. Rather, sample information appear to strongly support the hypothesis of trend-stationarity for all cases except the Japanese yen/German mark real exchange rate where the sample information suggest a stationary time series. The French franc/German mark real exchange rate is the other case where the stationary hypothesis receives significant posterior probability.

Next, we study the power of the “objective” Bayesian test using two Monte Carlo simulations. The results are not very encouraging. In particular, using economically plausible parameters for monthly data of the real exchange rates for our data generating models, we find that the “objective” Bayesian test cannot distinguish between a trend-stationary AR model from a stationary AR model when the time trend effect is relatively small, and the time series is highly persistence. The bias is in favor of finding a trend-stationary model. When $\rho = 0.99$, the “objective” Bayesian test is biased in favor of a unit-root. On the other hand, when the data generating model is a random-walk with drift model, the test is biased in favor of the trend-stationary hypothesis. We find this to be rather disappointing since the “objective” Bayesian test has several desirable features that make it an attractive alternative to the ADF test in unit-root testing.

The Monte Carlo results suggest that the “objective” Bayesian test is not necessarily better than the classical ADF test in unit-root testing. Based on the Monte Carlo results, we cannot draw any conclusions regarding long-run PPP. It should be emphasized, however, that our conclusions apply only to the “objective” Bayesian test and do not apply to Bayesian tests in general. Moreover, since our Monte Carlo simulations are carried out using parameter values which are relevant only to our real exchange rates series used in this study, Monte Carlo study of the “objective” Bayesian test may very well come to different conclusions when different parameter values are used. Nevertheless, we believe that the claim that the Bayesian approach to unit-root testing is better than the classical approach must be established on a case by case basis.

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Footnotes

¹ For a recent contribution to the debate, see Murray and Nelson (2000).

² In addition to the authors cited, Hamilton (1994), pp. 532-534 also contains a good discussion of the advantages and disadvantages of using the classical approach vs. the Bayesian approach in unit-root testing.

³ See the lively debate on the classical vs. the Bayesian methods of unit-root testing in the October-December 1991 issue of the *Journal of Applied Econometrics*.

⁴ This assumes that the nominal exchange rate and the relative prices are integrated of the same order, i.e., the time series of the nominal exchange rate and the relative prices contain the same number of unit roots. Previous empirical studies have found that, generally, they contain one unit root each.

⁵ It should be noted that in addition to using long span of data, Diebold, Husted and Rush (1991) also used fractional differencing in their model. Thus, it is not possible to distinguish whether their finding of favorable evidence of long-run PPP is due to the long span of data or to the use of autoregressive fractionally integrated moving-average process (ARFIMA).

⁶ We prefer Koop's Bayesian approach over Sims's approach because Sims's approach is limited to a rather restrictive AR(1) process without a constant term. Schotman and van Dijk (1991) have shown that the inclusion of a constant term increases the computational burden tremendously. Koop's approach, however, allows us to use a more flexible AR process that is not only a higher order AR process, but also allows for the inclusion of a constant and a linear deterministic time trend. Furthermore, Koop also performed Monte Carlo simulations and concluded that his test has reasonable size and power for plausible values. The size and power of Sims's Bayesian test are unknown.

⁷ Other researchers, Papell (1997), and Culver and Papell (1999), for example, argued that the presence of a linear deterministic time trend is inconsistent with long-run PPP, however.

⁸ One could argue that even-though the three competing hypotheses have equal prior probability, the unit-root hypothesis is the most favored, and the trend-stationary hypothesis is the least favored. For example, in equation (3), the prior probability for the unit-root hypothesis, i.e., $\rho = 1$ is 33.33 percent, while the stationary interval ($0 < \rho < 1$) also receives 33.33 percent prior probability, distributed uniformly in that interval, resulting in each point in that interval receiving extremely low prior probability. For the trend-stationary hypothesis, however, the 33.33 percent prior probability, in addition to being distributed on the stationary interval, must also be distributed on the infinite interval of values that the time-trend coefficient may take.

⁹ This assumes cross-rate equality except for transaction costs. This is probably a valid assumption for the G-7 countries. Alternatively, as long as the measurement error is a stationary process, our tests for unit-root will not be affected.

¹⁰ We have also tried other methods of lag-length determination, e.g., Akaike's Information Criteria. While the lag lengths determined are different, they do not produce significantly different results than those reported in Table 1, however.

¹¹ Rather than using the same Bayesian approach to determine the lag lengths, we used a non-Bayesian method. This reduces the number of alternative hypotheses we need to consider and allow us to allocate the entire prior probability to the three hypotheses in question which are what we are most interested in. To check the robustness of our Bayesian results, we have also used a uniform four lags for all the real exchange rate series. The results are not very different from those reported in the paper. The additional Bayesian results are available as Appendix A from the author.

¹² Note also that it is the Japanese yen/German mark real exchange rate that provides the lone exception to the uniformly unfavorable long-run PPP results in Table 1.

¹³ A recent paper by Murray and Papell (2002) has shown that the half-life estimates are extremely unreliable, however.

Table 1: Univariate ADF Test Results

	l	$t(\phi)$	χ^2
Base Currency: U.S. Dollar			
Canada	2	-1.128	0.936
U.K.	1	-2.695	3.632
Germany	0	-1.717	1.505
Italy	1	-2.301	2.655
Japan	1	-2.264	2.638
France	1	-2.052	2.113
Base Currency: Canadian Dollar			
U.S.A.	1	-1.087	0.960
U.K.	1	-2.546	3.280
Germany	1	-2.219	2.469
Italy	1	-3.050	4.665
Japan	1	-2.496	3.123
France	1	-2.258	2.563
Base Currency: Pound Sterling			
U.S.A.	1	-2.695	3.632
Canada	1	-2.546	3.280
Germany	1	-2.404	2.910
Italy	1	-2.654	3.535
Japan	4	-2.722	3.734
France	1	-2.630	3.469
Base Currency: German Mark			
U.S.A.	0	-1.717	1.505
Canada	1	-2.219	2.469
U.K.	1	-2.404	2.910
Italy	1	-2.292	2.628
Japan	1	-3.310**	5.514**
France	0	-2.617	3.429
Base Currency: Italian Lira			
U.S.A.	1	-2.301	2.655
Canada	1	-3.050	4.665
U.K.	1	-2.654	3.535
Germany	1	-2.292	2.629
Japan	1	-3.007	4.560
France	1	-2.055	2.112
Base Currency: Japanese Yen			
U.S.A.	1	-2.264	2.638
Canada	1	-2.496	3.123
U.K.	3	-2.557	3.330
Germany	1	-3.310**	5.514**
Italy	1	-3.007	4.560
France	1	-3.013	4.588
Base Currency: French Franc			
U.S.A.	1	-2.052	2.112
Canada	1	-2.258	2.563
U.K.	1	-2.630	3.470
Germany	0	-2.617	3.429
Italy	1	-2.055	2.112
Japan	1	-3.013	4.588

Note: ** denote the rejection of the null hypothesis at the 10% significance levels.

Table 2: Posterior Probabilities

	k	Trend Stationary	Stationary	Unit Root
Base Currency: U.S. Dollar				
Canada	11	0.83	0.14	0.03
U.K.	2	0.84	0.06	0.10
Germany	2	0.91	0.06	0.03
Italy	2	0.91	0.05	0.04
Japan	2	0.85	0.11	0.04
France	2	0.93	0.04	0.02
Base Currency: Canadian Dollar				
U.S.A.	11	0.83	0.14	0.03
U.K.	2	0.74	0.20	0.06
Germany	2	0.92	0.04	0.03
Italy	2	0.53	0.29	0.17
Japan	2	0.70	0.25	0.05
France	2	0.89	0.07	0.04
Base Currency: Pound Sterling				
U.S.A.	2	0.84	0.06	0.10
Canada	2	0.74	0.20	0.06
Germany	2	0.80	0.15	0.05
Italy	2	0.87	0.04	0.09
Japan	3	0.89	0.07	0.04
France	2	0.83	0.09	0.08
Base Currency: German Mark				
U.S.A.	2	0.91	0.06	0.03
Canada	2	0.92	0.04	0.03
U.K.	2	0.80	0.15	0.05
Italy	2	0.83	0.14	0.04
Japan	2	0.21	0.65	0.15
France	2	0.39	0.36	0.25
Base Currency: Italian Lira				
U.S.A.	2	0.91	0.05	0.04
Canada	2	0.53	0.29	0.17
U.K.	2	0.87	0.04	0.09
Germany	2	0.83	0.14	0.04
Japan	2	0.63	0.18	0.18
France	2	0.91	0.07	0.02
Base Currency: Japanese Yen				
U.S.A.	2	0.85	0.11	0.04
Canada	2	0.70	0.25	0.05
U.K.	3	0.89	0.07	0.04
Germany	2	0.21	0.65	0.15
Italy	2	0.63	0.18	0.18
France	3	0.65	0.24	0.11
Base Currency: French Franc				
U.S.A.	2	0.93	0.04	0.02
Canada	2	0.89	0.07	0.04
U.K.	2	0.83	0.09	0.08
Germany	2	0.39	0.36	0.25
Italy	2	0.91	0.07	0.02
Japan	3	0.65	0.24	0.11

Note: The posterior probabilities may not sum to one because of rounding.

Table 3: The Power of the “Objective” Bayesian Unit-Root Test

(a) Data Generating Model: $y_t = 0.059317 + \rho y_{t-1} - 0.0000201t + u_t$,

Proportion of times that a hypothesis receives the largest posterior probability:

ρ	Trend Stationary	Stationary	Unit Root
0.99	3.64	0.02	96.34
0.98	68.18	16.36	15.46
0.97	73.00	14.80	12.20
0.96	66.76	10.30	22.94
0.95	55.44	6.16	38.40

(b) Data Generating Model: $y_t = 0.059317 + \rho y_{t-1} + u_t$,

Proportion of times that a hypothesis receives the largest posterior probability:

ρ	Trend Stationary	Stationary	Unit Root
1.00	67.22	32.32	0.46
0.99	5.08	0.10	94.82
0.98	75.26	3.84	20.90
0.97	79.76	2.16	18.08
0.96	69.60	1.36	29.04
0.95	56.34	0.52	43.13

Is the Bayesian Approach Necessarily Better than the Classical Approach in Unit-Root Test?

Appendix A

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Is the Bayesian Approach Necessary Better than the Classical Approach in Unit-Root Test?

This appendix contains Table A.1 which contains the results of using a uniform four lags for the null model for all the real exchange rates. The results are consistent with those reported in Table 2 in the paper. First, the trend stationary hypothesis receives the greatest posterior probabilities in all cases except for the Japanese yen/German mark real exchange rate. Second, the stationary hypothesis receives the highest posterior probabilities for the Japanese yen/German mark real exchange rate. Third, for the France franc/German mark real exchange rate, the sample data now decisively favor the trend stationary hypothesis, but now the unit-root hypothesis receives the second highest posterior probabilities. This is also true for the Japanese yen/Italian lira real exchange rate. We obtain a slightly different result for the Japanese yen/French franc real exchange rate here than from Table 2. For this real exchange rate, the trend stationary hypothesis receives the greatest posterior probabilities, but the stationary and the unit-root hypotheses receive roughly the same posterior probabilities. Overall, the results in this appendix are consistent with those reported in Table 2 of the paper.

Table A.1: Posterior Probabilities

	k	Trend Stationary	Stationary	Unit Root
Base Currency: U.S. Dollar				
Canada	4	0.90	0.09	0.01
U.K.	4	0.86	0.06	0.07
Germany	4	0.92	0.04	0.04
Italy	4	0.91	0.05	0.04
Japan	4	0.85	0.11	0.04
France	4	0.92	0.04	0.04
Base Currency: Canadian Dollar				
U.S.A.	4	0.90	0.09	0.01
U.K.	4	0.76	0.18	0.06
Germany	4	0.89	0.06	0.05
Italy	4	0.53	0.31	0.16
Japan	4	0.70	0.25	0.05
France	4	0.83	0.10	0.07
Base Currency: Pound Sterling				
U.S.A.	4	0.86	0.06	0.07
Canada	4	0.76	0.18	0.06
Germany	4	0.83	0.09	0.09
Italy	4	0.88	0.04	0.08
Japan	4	0.83	0.09	0.07
France	4	0.83	0.06	0.10
Base Currency: German Mark				
U.S.A.	4	0.92	0.04	0.04
Canada	4	0.89	0.06	0.05
U.K.	4	0.83	0.09	0.09
Italy	4	0.92	0.06	0.02
Japan	4	0.30	0.43	0.27
France	4	0.49	0.20	0.31
Base Currency: Italian Lira				
U.S.A.	4	0.91	0.05	0.04
Canada	4	0.53	0.31	0.16
U.K.	4	0.88	0.04	0.08
Germany	4	0.92	0.06	0.02
Japan	4	0.59	0.18	0.23
France	4	0.93	0.05	0.02
Base Currency: Japanese Yen				
U.S.A.	4	0.85	0.11	0.04
Canada	4	0.70	0.25	0.05
U.K.	4	0.83	0.09	0.07
Germany	4	0.30	0.43	0.27
Italy	4	0.59	0.18	0.23
France	4	0.38	0.33	0.29
Base Currency: French Franc				
U.S.A.	4	0.92	0.04	0.04
Canada	4	0.83	0.10	0.07
U.K.	4	0.83	0.06	0.10
Germany	4	0.49	0.20	0.31
Italy	4	0.93	0.05	0.02
Japan	4	0.38	0.33	0.29

Note: The posterior probabilities may not sum to one because of rounding.