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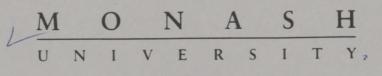
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#### UNIT ROOT TESTS AND MEAN SHIFTS

Graham J. Edmonds, R.J. O'Brien and Jan M. Podivinsky

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DEPARTMENT OF ECONOMETRICS, FACULTY OF ECONOMICS COMMERCE & MANAGEMENT

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# UNIT ROOT TESTS AND MEAN SHIFTS

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September 1992

#### Abstract

A mean shift can cause tests for a unit root to erroneously fail to reject the null hypothesis of the existence of a unit root. Perron (1990) and Hendry and Neale (1991) provide simulation evidence of this for (augmented) Dickey-Fuller This paper extends these analyses by tests in models without a time trend. considering a wider range of test statistics (including statistics proposed by Bhargava (1986)) applied to models (possibly including a time trend) subject at least for show that, simulation results a shift in mean. Our to appropriate Bhargava test close to the unit root, either an alternatives statistic or the suitably normalised OLS estimator of the unit root has higher t-tests. In Dickey-Fuller augmented Dickey-Fuller or than the power particular, in models with a trend, an increase in the mean shift does not reduce the power of Bhargava's  $R_2$  test as much as it reduces the power of the Estimated response surfaces summarise the likely power loss due other tests. to any particular mean shift.

**KEYWORDS:** Testing; unit roots; structural break; mean shift; simulation.

## 1. Introduction

A mean shift can cause tests for a unit root to erroneously fail to reject the null hypothesis of the existence of a unit root. Perron (1990) and Hendry and Neale (1991) provide simulation evidence of this for (augmented) Dickey-Fuller tests in models without a time trend. This paper extends these analyses by considering a wider range of test statistics (including statistics proposed by Bhargava (1986)) applied to models (possibly including a time trend) subject to a shift in mean.

In the next section we outline various tests for a unit root, in models with and without a linear trend, and considers how a simple mean shift may be incorporated into the models. Section 3 outlines a Monte Carlo simulation study of the size and power properties of various tests for a unit root when applied to models subject to a mean shift. In Section 4 we show how estimated response surfaces can summarise the likely power loss due to any particular mean shift. Section 5 concludes.

#### 2. Unit Root Tests with Mean Shifts

A simple but common representation of a nonstationary time series is the random walk with drift model

$$y_t = \mu + y_{t-1} + \varepsilon_t$$
  $\varepsilon_t \sim IN(0,\sigma^2)$   $t = 1,...,T$ 

We can write

$$y_t = y_0 + \mu t + \sum_{i=1}^t \varepsilon_i$$

which is clearly nonstationary since  $E[y_t] = \mu t$  is time-dependent. The random walk with drift model is sometimes used to explain a variable that is believed to have a time trend. A common alternative to this is a model which is stationary about a deterministic trend, *i.e.* 

$$y_{t} - (m + \mu t) = \beta(y_{t-1} - (m + \mu(t-1))) + \varepsilon_{t}$$
  $|\beta| < 1$ 

where m is the mean of the stationary series  $(y_t - \mu t)$ . The problem we investigate here is that of a step change in m, such that  $m = m_1$  for  $t < t_0$ , and  $m = m_1 + m_2$  for  $t \ge t_0$ . Both Perron (1990) and Hendry and Neale (1991) argue that mean shifts may characterise many economic time series.

This paper seeks to examine (i) the extent to which the mean shift (or structural change) causes unit root tests to erroneously fail to reject the null hypothesis that a unit root exists, and (ii) the relative performance of a selection of different unit root tests under the influence of the mean shift. Recently, Hendry and Neale (1991) considered the impact of structural change in models without time trends on two Dickey-Fuller unit root tests. This study extends their analysis by considering models both with and without time trends and by examining the effect of mean shifts on unit root tests suggested by Bhargava (1986), in addition to Dickey-Fuller tests.

The Dickey-Fuller tests considered here are those commonly labelled  $\tau_{\mu}$  (used by Hendry and Neale),  $\tau_{\tau}$ ,  $\rho_{\mu}$ ,  $\rho_{\tau}$  and appropriate versions of the augmented Dickey-Fuller test of order one, labelled ADF(1) here. Note that there are two different ADF(1) tests, one when the augmented regression excludes a linear trend (as in Hendry and Neale's (1991) analysis), and another when the augmented regression includes a linear trend.

The first of the two Bhargava (1986) unit root test statistics considered here is

$$R_{1} = \frac{\sum_{t=2}^{T} (y_{t} - y_{t-1})^{2}}{\sum_{t=1}^{T} (y_{t} - \overline{y})^{2}} \quad \text{where } \overline{y} = T^{-1} \sum_{t=1}^{T} y_{t}$$

The  $R_1$  test is a uniformly most powerful invariant test of the null hypothesis that  $y_t$  follows a random walk, against the one-sided stationary alternative that

$$(y_t - m) = \beta(y_{t-1} - m) + \varepsilon_t \qquad \varepsilon_t \sim IN(0, \sigma^2) \qquad 0 \le \beta < 1$$

This test statistic (which is clearly equivalent to the Durbin-Watson test statistic) is invariant to the values of m and  $\sigma^2$ . 1% and 5% critical values are given in the first rows of table 1 of Sargan and Bhargava (1983).

The second of the Bhargava test statistics is

$$R_{2} = \frac{\sum_{t=2}^{T} (y_{t} - y_{t-1})^{2} - (T-1)^{-1} (y_{T} - y_{1})^{2}}{(T-1)^{-2} \sum_{t=1}^{T} (R_{t}^{*} - R_{t}^{**})^{2}}$$

 $R_t^* = (T-1)y_t - (t-1)y_T - (T-t)y_1$ 

where

and

$$R_t^{**} = (T-1)[\overline{y} - 0.5(y_1 + y_T)]$$
  
is a locally most powerful invariant test in the neighb

This is a locally most powerful invariant test in the neighbourhood of  $\beta = 1$  of the null hypothesis that y<sub>t</sub> follows a random walk with non-zero constant drift against one-sided stationary alternatives of the form

$$(\mathbf{y}_{t} - \mathbf{m} - \mu t) = \beta(\mathbf{y}_{t-1} - \mathbf{m} - \mu(t-1)) + \varepsilon_{t}$$
$$\varepsilon_{t} \sim \mathrm{IN}(0, \sigma^{2}) \qquad 0 \le \beta < 1$$

The R2 test statistic is invariant to the values of  $\mu$ , m and  $\sigma^2$ . 5% critical values are given in table 1 of Bhargava (1986). A 1% critical value for sample size T = 100 is estimated by Monte Carlo simulation; the estimated value based on 8101 replications is 0.47.

#### 3. Monte Carlo Simulation

The experimental design of our Monte Carlo simulation analysis sets three parameters as fixed, *i.e.* T = 100,  $\sigma^2 = 1$  and  $m_1 = 1$ . Other parameters vary as follows:

$$m_{2} = \{ 0 \ 0.5 \ 1 \ 2 \ 4 \}$$

$$\mu = \{ 0 \ 0.001 \ 0.01 \ 0.05 \ 0.1 \}$$

$$t_{0} = \{ 20 \ 40 \ 60 \ 80 \}$$

$$\beta = \{ 0.2 \ 0.4 \ 0.6 \ 0.8 \ 1 \}$$

The sample size is fixed at T = 100 for two reasons. First, critical values

for both the Dickey-Fuller and Bhargava tests seem to be available for only two sample sizes, T = 50 and 100. Second, much of the extensive literature on the finite sample performance of unit root tests suggests that for alternative hypotheses with  $\beta$  close to 1 these test all have very low power for small to moderate sample sizes. For example, DeJong *et al.* (1992, p. 431) recommend against using unit root tests when T < 100. Given that we fix both  $m_1 = 1$  and  $\sigma^2 = 1$ , our choice of values for  $m_2$  has the effect of defining the mean shift relative to the (standardised) value of  $\sigma^2$ , as is done by Hendry and Neale (1991). This experimental design defines a total of 500 experiments for the test statistics, which we evaluate at both 1% and 5% critical values. We set the number of replications of each experiment to 9604, so as to give a maximum 95% confidence interval for the test rejection frequency of 0.01.

For the experiments where  $|\beta| < 1$  the initial value  $y_0$  of the  $y_t$  series is given as

$$y_0 = \sigma m_1 + (1-\beta)^{-1/2} \varepsilon_0$$
 where  $\varepsilon_0 \sim IN(0,\sigma^2)$ 

so that  $y_0$  has the same distribution as the other values in the (detrended)  $y_t$  series for  $t < t_0$ . As all the test statistics can be shown to be invariant to the value of  $y_0$  when  $\beta = 1$ , we set  $y_0 = 0$  in these cases.

We begin the analysis of the simulation results by commenting on the cases where  $\beta = 1$ , that is, where the null hypothesis is true so that we are estimating the sizes of the tests (not that these are not reported here in any detail). Using 1% critical values, all the rejection frequencies for every test statistic fall within the approximate 95% confidence interval about 0.01. In fact, if we report the rejection frequencies to two decimal places we find only one case (for the R<sub>1</sub> test) where the rejection frequency is not equal to 0.01.

For 5% critical values, examining the results for  $\beta = 1$  we find for the Dickey-Fuller, R<sub>2</sub> and ADF(1) tests all the rejection frequencies fall between

0.04 and 0.06. Even to two decimal places there are only a couple of cases where the rejection frequency is not observed to be 0.05. The story for the  $R_1$  test is rather different. The  $R_1$  test is appropriate only when  $\mu = 0$ . As  $\mu$  increases, *ceteris paribus*, the value of the  $R_1$  test statistic falls, and hence so do rejection frequencies for the  $R_1$  test. As a result, in 27 out of 100 experiments (with  $\beta = 1$ ) the rejection frequency is not equal to 0.05 to two decimal places (in fact these are all *less* than 0.05) and in 21 of these cases the rejection frequency is less than 0.04. These cases all occur for relatively large values of  $\mu$  (0.05 or 0.1).

In general these results indicate that the existence of a mean shift (*i.e.* when  $m_2 \neq 0$ ) of which the econometrician is unaware does not prevent finding a unit root if one is present. Except for the problems with  $R_1$  noted above, we can use the tabulated critical values to estimate the powers of the tests.

We now consider the cases where  $m_2 = 0$  (and  $|\beta| < 1$ ), so that no mean Rejection frequencies will (see Tables 1 and 2). all shift occurs at therefore be estimates of the power of the tests for a unit root. As one would expect, for any given value of  $\mu$  rejection frequencies for each test decline as  $\beta$  increases towards one. For  $\mu = 0$ ,  $R_1$  seems to be the most considered, rejection frequencies only deviating the tests powerful of significantly from 1 when  $\beta = 0.8$ .  $R_1$  is followed by  $\rho_{\mu}$ ,  $\tau_{\mu}$ , ADF(1) and  $R_2$  in decreasing order of power. The  $R_2$  test performs relatively poorly because it is inappropriate in situations where the alternative model has no time trend.

For  $\mu$  non-zero (again with  $m_2 = 0$ ,  $|\beta| < 1$ ) the situation is slightly different. The  $\rho_{\tau}$ ,  $\tau_{\tau}$ , ADF(1) and  $R_2$  tests are all invariant to the value of  $\mu$  in the model. This is clearly illustrated by examining the rejection frequencies for these test statistics in Tables 1 and 2 for different non-zero values of  $\mu$  and any given value of  $\beta$  and noting how little they vary. The  $R_1$  test, however, is not invariant to  $\mu$  and rejection frequencies for this

test fall as  $\mu$  increases, making it the least powerful of the tests when  $\mu \neq 0$ . This is explained by the fact that the R<sub>1</sub> test is inappropriate if the alternative model has a time trend – in such a situation the econometrician should prefer the R<sub>2</sub> test (one might regard using the R<sub>1</sub> test in situations where  $\mu \neq 0$  as equivalent to wrongly performing a  $\tau_{\mu}$  test instead of a  $\tau_{\tau}$  test). For the other tests it is clear that in terms of decreasing power we have the order  $\rho_{\tau}$ ,  $\tau_{\tau}$ , and ADF(1) for all values of  $\beta$ . The relative power of the R<sub>2</sub> test changes with the value of  $\beta$ . For  $\beta < 0.8$  the power of R<sub>2</sub> is between that of  $\tau_{\tau}$  and ADF(1). However, when  $\beta = 0.8$  the R<sub>2</sub> test is the most powerful of the tests considered. This is because R<sub>2</sub> is locally most powerful in the neighbourhood of  $\beta = 1$ , and so we would expect it to out-perform the other tests (for  $\mu \neq 0$ ) as  $\beta$  approaches 1.

One general point to note is that the rejection frequencies do not differ very much from 1 until  $\beta$  reaches 0.8 (with the exception of the R<sub>1</sub> test for non-zero values of  $\mu$ ). For this reason, we concentrate on values of  $\beta \ge 0.6$ , and extend the analysis to include values of  $\beta = 0.85$ , 0.9, 0.95. Tables 3 to 6 show the remainder of the results. Since the R<sub>2</sub> test and appropriate versions of the  $\tau$ ,  $\rho$  and ADF(1) tests are invariant to the value of  $\mu$  we only show the effects of  $\mu = 0$  and  $\mu = 0.05$  on these tests.

Consider the cases where  $\mu = 0$  ( $|\beta| < 1$ ) and tests are performed using 1% critical values (Table 3; note that the results at 5% in Table 5 follow very similar patterns). For a small mean shift ( $m_2 = 0.5$  or 1) we find that the rejection frequencies are not very much smaller than for the situation where  $m_2 = 0$ . However as  $m_2$  increases the rejection frequencies tend to fall. This is most noticable when  $m_2 = 4$  and the rejection frequencies fall very close to zero for every test statistic when  $\beta = 0.8$ . In fact, when  $\beta = 0.8$  a mean shift of  $m_2 = 2$  is sufficient to approximately halve the power of all the tests (except  $R_2$ ) from the level experienced for  $m_2 = 0$ .

Indeed, we may identify some cases where the tests are biased, in the

sense that there seems to be a lower probability of rejecting the null hypothesis that  $\beta = 1$  when it is false than when it is true (indicated in Table 3 by rejection frequencies of less than 0.01). For example, see the rejection frequencies for the  $\tau_{\mu}$  test when  $m_2 = 4$ ,  $\beta = 0.6$  and  $t_0 = 60$ , and for the ADF(1) test when  $m_2 = 4$ ,  $\beta = 0.6$  or 0.8, and  $t_0 = 40$  or 60. Values less than 0.008 are significantly biased in 9604 replications using a 5% test.

The position of the mean shift  $(t_0)$  does seem to have some effect on the rejection frequencies. Examination of Table 3 indicates that we have similar results, in general, for  $t_0 = 20$  and 80, and similar results for  $t_0 = 40$  or 60, with higher rejection frequencies in the former case.

The comparative performance of the tests for  $\mu = 0$  and  $m_2$  non-zero is very similar to the  $\mu = m_2 = 0$  case. Thus the order in terms of decreasing power seems to be  $R_1$ ,  $\rho_{\mu}$ ,  $\tau_{\mu}$  and ADF(1). The  $R_2$  test is inappropriate here (as  $\mu = 0$ ), so we might expect it to be the least powerful of the tests in this case. This is true for  $m_2 = 0.5$ , but as  $m_2$  increases the relative performance of the  $R_2$  test improves (although its absolute power declines), so that when  $m_2 = 4$  it is the most powerful of the tests considered. Thus the mean shift does not reduce the power of the  $R_2$  test as much as it reduces the power of the other tests.

We now turn to the cases where  $\mu = 0.05$  ( $|\beta| < 1$ ) and tests are performed using 1% critical values (Table 4; again the results for 5% follow similar patterns: see Table 6). In general we observe that as either  $m_2$  or  $\beta$  increase the rejection frequencies for each test fall. It is fair to say therefore that the results in Table 4 follow a similar pattern to those in Table 3, with the notable exception of the  $R_1$  test. Not being invariant to the value of  $\mu$ , the power of the  $R_1$  test falls towards zero as  $\mu$  increases, and so the  $R_1$  test is the least powerful test for  $\mu$  non-zero.

One important difference between the results of Tables 3 and 4 is the effect of the position of the mean shift  $(t_0)$ . It is true that for some cases

where  $\mu = 0.05$  the effect of the value of  $t_0$  on rejection frequencies is the same as for the  $\mu = 0$  cases. However, this seems to be the exception rather than the rule, and the precise effect of the value of  $t_0$  seems unclear when  $\mu$  is non-zero.

Comparing the performance of the tests from Table 4 leads us to exactly the same conclusions as we reached from Table 1 with  $R_2$  being the most powerful test for  $\beta$  close to 1, and  $\rho_{\tau}$  being the most powerful elsewhere. Note that these results hold for all other non-zero values of  $\mu$  not reported here. The  $R_1$  test is not invariant to the value of  $\mu$ . This causes the  $R_1$ test to be biased for many large values of  $\mu$  (for example  $\mu = 0.1$ ). In fact, as the value of  $\mu$  increases, the power of the  $R_1$  test falls to zero for any given value of  $m_2$  and  $\beta$ , since the calculated value of the  $R_1$  test statistic will fall as  $\mu$  increases.

To summarise, we find that the introduction of a simple mean shift reduces the power of all of the tests for a unit root considered here. This reduction is more pronounced when the trend parameter  $\mu$  is non-zero. However, the power advantage of the  $\rho_{\mu}$  and  $R_1$  tests over the more commonly used  $\tau_{\mu}$  and ADF(1) tests (when  $\mu = 0$ ), and of the  $\rho_{\tau}$  and  $R_2$  tests over the  $\tau_{\tau}$  and ADF(1) tests (when  $\mu \neq 0$ ), is maintained when  $m_2 \neq 0$ . It also seems to be the case that the larger is the mean shift  $m_2$ , the greater is the advantage of the  $R_1$ and  $R_2$  tests (when  $\mu = 0$  and  $\mu \neq 0$  respectively) over the Dickey-Fuller and augmented Dickey-Fuller tests. As an illustration of this, Figure 1 indicates the power curves (generated for  $\beta = 0.6$  (0.05) 1) of the tests when  $m_2 = 0$ (the top four curves) and for  $m_2 = 4$  (the bottom four curves), in both cases when  $\mu = 0.05$ . Notice how the power of the  $R_2$  test dominates that of the other tests for  $0.6 \leq \beta \leq 1$  when  $m_2 = 4$ .

#### 4. Response Surfaces

We fit a response surface for the rejection frequencies for each of the

test statistics. Response surfaces summarise the relationship between rejection frequency and the parameters of the simulation (here,  $m_2$ ,  $\mu$ ,  $\beta$  and  $t_0$ ). These estimated response surfaces should give us some idea of the probable power loss due to any particular mean shift. Since we are concerned with power we can exclude all experiments where  $\beta = 1$ .

It has already been indicated that the  $R_1$  test is inappropriate in situations where  $\mu$  is non-zero, and so as we are interested in examining the effect of a mean-shift on unit root tests, it is sensible to fit the response surface for  $R_1$  only for those experiments where  $\mu = 0$ . Similarly, the response surface for the  $R_2$  test is estimated only for those experiments with non-zero values of  $\mu$ .

In addition, since the  $\tau_{\tau}$ ,  $\rho_{\tau}$ ,  $R_2$  tests and appropriate versions of the ADF(1) test are invariant to the value of  $\mu$  we need only consider one value of  $\mu$ , and so we fit response surfaces for the above tests only for experiments where  $\mu = 0.05$ . We thus estimate eight response surfaces, each with a maximum of 80 experiments.

For the rejection frequency  $\pi$  of each test statistic we use the logistic transformation  $\ln(\pi/(1-\pi))$ ; note that this means that experiments with  $\pi = 0$  or 1 will be omitted from the response surface. All variables in the response surfaces are multiplied by  $(N\pi(1-\pi))^{1/2}$  (where N is the number of replications of each experiment; here this is 9604) so that each transformed rejection frequency will have unit variance. This heteroscedasticity transformation is also used by Hendry and Neale (1991).

When  $m_2 = 0$  we need to explain the power of each test by  $\beta$  alone. In fact, preliminary investigation showed that using  $\beta^3$  provided a better fit in each response surface regression than did  $\beta$ . Since the simulation results indicated similar patterns for  $t_0 = 20$  or 80, and for  $t_0 = 40$  or 60 (as indicated by Perron (1990), we also use  $km_2$  as well as  $m_2$ , where  $k = \min[t_0/100, (1-t_0/100)]$ . As an illustration, we report below response

surfaces of the rejection frequencies of tests using 1% critical values.  $HL(\tau_{\mu}) = \begin{array}{c} 4.5075 \text{H} - 7.3890 \text{H}\beta^{3} - 0.6706 \text{Hm}_{2} - 1.6268 \text{Hkm}_{2} \\ (7.66) & (-7.42) & (-3.64) \end{array}$ 53 observations  $v_{\rm W} = 0./912$ Norm(2) = 5.05  $R^2 = 0.6019$  $R^2 = 0.6019$ AR(1) = 22.96 Hetero(1) = 1.05 $HL(\tau_{\tau}) = 5.0193H - 10.3565H\beta^{3} - 0.9598Hm_{2} + 0.7921Hkm_{2} + (14.31) + (-16.48) + (-7.66) + (2.40)$ DW = 0.8370 52 observations Norm(2) = 10.27 Hetero(1) = 1.30  $R^2 = 0.8494$ AR(1) = 17.54 $\text{HL}(\rho_{\mu}) = \underbrace{ 4.5473 \text{H}}_{(8.39)} \underbrace{ -6.2906 \text{H}\beta^3 - 0.5343 \text{Hm}}_{(-3.57)} \underbrace{ -1.8739 \text{H}km}_{(-4.31)}$  $R^2 = 0.6824$  DW = 0.5817 AR(1) = 24.16 DW = 2.31 DW = 0.5817 46 observations Norm(2) = 2.31 Hetero(1) = 0.94  $\text{HL}(\rho_{\tau}) = 4.9982\text{H} - 9.9118\text{H}\beta^{3} - 0.8623\text{Hm}_{2} + 0.7355\text{Hkm}_{2} \\ (13.13) \quad (-14.82) \quad (-6.90) \quad (2.23)$  $R^2 = 0.8185$  DW = 0.8325 51 observations AR(1) = 17.51 Norm(2) = 10.51 Hetero(1) = 0.11  $HL(R_{1}) = \begin{array}{c} 4.7176H - 6.2900H\beta^{3} - 0.5315Hm_{2} - 1.9070Hkm_{2} \\ (8.77) & (-7.19) \end{array}$  $R^2 = 0.7136$  DW = 0.6039 43 observations AR(1) = 20.63 Norm(2) = 1.58 Hetero(1) = 1.13  $HL(R_{2}) = 4.9170H - 9.7021H\beta^{3} - 0.6330Hm_{2} + 0.0719Hkm_{2}$ (23.92) (-25.45) (-7.81) (0.32)  $R^2 = 0.8849$ - 32.49 DW = 0.6345 70 observations Norm(2) = 15.15 Hetero(1) = 0.003  $HL(ADF(1)) = 3.8714H - 6.7325H\beta^{3} - 0.7642Hm_{2} - 1.7074Hkm_{2}$ [" = 01 (12.98) (-12.69) (-4.43) (-3.04)  $[\hat{\mu} = \hat{0}]$  (12.98) (-12.69) (-4.43)  $R^2 = 0.7481$  DW = 0.8737 65 observations AR(1) = 21.88 Norm(2) = 8.49 Hetero(1) = 0.03  $\begin{array}{rl} \mathrm{HL(ADF(1))} &=& 3.6990\mathrm{H} - 7.7630\mathrm{H}\beta^3 - 1.1693\mathrm{Hm}_2 + 0.6086\mathrm{Hkm}_2 \\ [\mu &=& 0.05] & (14.56) & (-14.45) & (-7.69) \end{array}$  $R^2 = 0.8000$  DW = 0.3749 AR(1) = 47.89 Norm(2) = 9.09 72 observations Hetero(1) = 0.86

Numbers in parentheses below estimated coefficients are asymptotic *t*-ratios;

the serial correlation (denoted AR), normality, and heteroscedasticity tests are all asymptotically distributed as  $\chi^2$ , with degrees of freedom given in parentheses.

As might be expected, the regressors  $\beta^3$  and  $m_2$  have negative coefficients in every response surface, indicating that power falls as  $\beta$  approaches 1, or as  $m_2$  increases. However, the  $R^2$  for each response surface is not particularly high. This may be because this Monte Carlo study uses a wide range of values of  $\beta$ , whereas other similar studies (for example, Hendry and Neale (1991)) have considered a smaller range of values of  $\beta$  so that any power function may be approximately linear.

The heteroscedasticity transformation seems to perform well, as we are unable to reject the null hypothesis of homoscedastic errors for any of the response surfaces, even at a 10% significance level. However, there is clear evidence of serial correlation in the residuals of each response surface regression. As our regression data have no specific order, it may be possible to reorder the data in such a way so as to remove this serial correlation. However, taken together with the relatively low  $R^2$  values this evidence of serial correlation suggests that the relationships are misspecified, so that it is likely that the response surfaces could be improved upon.

We may use the response surfaces to predict the power loss for each test due to a particular mean shift. If a test (labelled Z) has an estimated response surface given by

 $\hat{\mathrm{HL}}(Z) = \hat{\alpha}_0 H + \hat{\alpha}_1 H \beta^3 + \hat{\alpha}_2 H m_2 + \hat{\alpha}_3 H k m_2 ,$ then the power of the test will be given by  $\exp(\gamma) [1 + \exp(\gamma)]^{-1}$ , where

 $\gamma = \hat{\alpha}_0 + \hat{\alpha}_1 \beta^3 + \hat{\alpha}_2 m_2 + \hat{\alpha}_3 k m_2 .$ 

#### 5. Conclusions

Our simulation results show that, at least for alternatives close to the unit root, either an appropriate Bhargava test statistic or the suitably normalised OLS estimator of the unit root (*i.e.*  $\rho_{\mu}$  or  $\rho_{\tau}$ ) has higher power than the Dickey-Fuller or augmented Dickey-Fuller *t*-tests. In particular, in models with a trend, an increase in the mean shift does not reduce the power of Bhargava's  $R_2$  test as much as it reduces the power of the other tests. Estimated response surfaces illustrate how we may summarise the likely power loss due to any particular mean shift.

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Rejection Frequencies Without a Mean Shift  $(m_2 = 0)$ 1% critical values

μ	β	$\tau_{\mu}/ au_{ au}$	$\rho_{\mu}^{}/\rho_{ au}$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)
0	0.2 0.4 0.6 0.8 1	1.000 1.000 0.998 0.517 0.010	$   \begin{array}{r}     1.000 \\     1.000 \\     1.000 \\     0.683 \\     0.010 \\   \end{array} $	1.000 1.000 1.000 0.719 0.010	1.000 0.998 0.952 0.379 0.010	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.969 \\ 0.414 \\ 0.009 \end{array}$
0.001	0.2 0.4 0.6 0.8 1	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.975 \\ 0.296 \\ 0.011 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.989 \\ 0.364 \\ 0.010 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.719 \\ 0.009 \end{array}$	$\begin{array}{c} 1.000 \\ 0.997 \\ 0.952 \\ 0.380 \\ 0.012 \end{array}$	$\begin{array}{c} 1.000 \\ 0.994 \\ 0.857 \\ 0.235 \\ 0.011 \end{array}$
0.01	0.2 0.4 0.6 0.8 1	1.000 1.000 0.976 0.301 0.011	1.000 1.000 0.989 0.375 0.010	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.999 \\ 0.682 \\ 0.010 \end{array}$	$\begin{array}{c} 1.000 \\ 0.996 \\ 0.955 \\ 0.375 \\ 0.011 \end{array}$	1.000 0.994 0.861 0.237 0.010
0.05	0.2 0.4 0.6 0.8 1	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.978 \\ 0.300 \\ 0.010 \end{array}$	1.000 1.000 0.991 0.371 0.011	0.963 0.762 0.363 0.125 0.010	1.000 0.996 0.952 0.383 0.011	$\begin{array}{c} 1.000 \\ 0.995 \\ 0.865 \\ 0.230 \\ 0.011 \end{array}$
0.1	0.2 0.4 0.6 0.8 1	1.000 1.000 0.978 0.295 0.010	1.000 1.000 0.988 0.367 0.010	0.000 0.000 0.000 0.000 0.007	1.000 0.996 0.947 0.382 0.010	$\begin{array}{c} 1.000 \\ 0.995 \\ 0.860 \\ 0.227 \\ 0.010 \end{array}$

Rejection Frequencies Without a Mean Shift  $(m_2 = 0)$ 

5% critical values

μ	β	$\tau_{\mu}/\tau_{\tau}$	${^{\rho}\mu}^{/ ho} au$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)
0	0.2 0.4 0.6 0.8 1	1.000 1.000 1.000 0.879 0.052	1.000 1.000 1.000 0.955 0.050	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.969 \\ 0.053 \end{array}$	1.000 1.000 0.993 0.722 0.048	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.999 \\ 0.798 \\ 0.052 \end{array}$
0.001	0.2 0.4 0.6 0.8 1	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.999 \\ 0.662 \\ 0.051 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.739 \\ 0.050 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.969 \\ 0.051 \end{array}$	1.000 1.000 0.992 0.719 0.050	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.981 \\ 0.568 \\ 0.051 \end{array}$
0.01	0.2 0.4 0.6 0.8 1	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.999 \\ 0.661 \\ 0.051 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.735 \\ 0.050 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.956 \\ 0.053 \end{array}$	1.000 1.000 0.992 0.718 0.049	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.984 \\ 0.564 \\ 0.052 \end{array}$
0.05	0.2 0.4 0.6 0.8 1	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.999 \\ 0.664 \\ 0.053 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.741 \\ 0.051 \end{array}$	$\begin{array}{c} 1.000 \\ 0.996 \\ 0.891 \\ 0.454 \\ 0.048 \end{array}$	1.000 1.000 0.991 0.726 0.051	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.982 \\ 0.562 \\ 0.054 \end{array}$
0.1	0.2 0.4 0.6 0.8 1	1.000 1.000 0.999 0.666 0.050	$\begin{array}{c} 1.000 \\ 1.000 \\ 1.000 \\ 0.745 \\ 0.049 \end{array}$	0.008 0.000 0.000 0.002 0.035	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.992 \\ 0.720 \\ 0.048 \end{array}$	$\begin{array}{c} 1.000 \\ 1.000 \\ 0.981 \\ 0.562 \\ 0.051 \end{array}$

Rejection Frequencies at 1% critical values when $\mu = 0$									
m <sub>2</sub>	β	t <sub>o</sub>	$\tau_{\mu}$	$ ho_{\mu}$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)		
0	0.6 0.8 0.85 0.9 0.95		0.998 0.517 0.255 0.095 0.027	1.000 0.683 0.383 0.146 0.040	1.000 0.719 0.418 0.160 0.042	0.952 0.379 0.181 0.069 0.023	0.969 0.414 0.218 0.090 0.027		
0.5	0.6	20 40 60 80	0.998 0.994 0.995 0.996	1.000 0.999 0.999 0.999	1.000 0.999 1.000 1.000	0.942 0.943 0.947 0.947	0.951 0.941 0.942 0.950		
	0.8	20 40 60 80	0.485 0.486 0.486 0.491	0.662 0.658 0.658 0.666	0.700 0.696 0.694 0.701	0.358 0.372 0.373 0.373	0.390 0.391 0.396 0.397		
	0.85	20 40 60 80	0.252 0.249 0.253 0.242	0.368 0.369 0.377 0.376	0.402 0.406 0.412 0.410	0.181 0.177 0.179 0.176	0.213 0.203 0.211 0.205		
	0.9	20 40 60 80	0.088 0.085 0.089 0.088	0.140 0.144 0.143 0.142	0.155 0.159 0.157 0.156	0.064 0.065 0.066 0.067	0.082 0.082 0.086 0.081		
	0.95	20 40 60 80	0.029 0.026 0.025 0.028	0.043 0.038 0.039 0.040	0.046 0.042 0.041 0.043	0.022 0.021 0.023 0.026	0.029 0.025 0.026 0.026		
1.0	0.6	20 40 60 80	0.991 0.982 0.980 0.988	0.999 0.996 0.996 0.998	0.999 0.997 0.998 0.999	0.936 0.940 0.935 0.938	0.906 0.854 0.848 0.891		
	0.8	20 40 60 80	0.451 0.421 0.420 0.448	0.608 0.574 0.588 0.617	0.644 0.613 0.630 0.660	0.353 0.354 0.354 0.351	0.352 0.328 0.332 0.357		
	0.85	20 40 60 80	0.226 0.208 0.211 0.221	0.343 0.325 0.324 0.343	0.372 0.352 0.358 0.380	0.169 0.173 0.179 0.174	0.193 0.172 0.178 0.187		
	0.9	20 40 60 80	0.087 0.081 0.079 0.084	0.138 0.127 0.130 0.139	0.153 0.142 0.145 0.154	0.068 0.065 0.065 0.064	0.082 0.072 0.075 0.076		
	0.95	20 40 60 80	0.026 0.026 0.023 0.026	0.040 0.041 0.036 0.038	0.043 0.044 0.040 0.040	0.022 0.024 0.019 0.021	0.026 0.023 0.024 0.025		

Rejection Frequencies at 1% critical values when  $\mu = 0$ 

2		Δ	
∠	•	υ	

2.0	0.6	20 40 60 80	0.917 0.751 0.720 0.849	0.969 0.880 0.870 0.955	0.971 0.899 0.900 0.972	0.877 0.872 0.868 0.878	0.664 0.400 0.364 0.551
	0.8	20 40 60 80	0.318 0.226 0.219 0.296	0.439 0.337 0.341 0.448	0.453 0.365 0.381 0.495	0.283 0.302 0.295 0.286	0.236 0.163 0.163 0.220
	0.85	20 40 60 80	0.166 0.130 0.130 0.167	0.244 0.199 0.212 0.266	0.258 0.218 0.239 0.299	0.146 0.147 0.149 0.147	0.138 0.106 0.107 0.135
	0.9	20 40 60 80	0.066 0.061 0.060 0.074	0.104 0.100 0.098 0.119	0.115 0.110 0.111 0.135	0.061 0.062 0.062 0.064	0.059 0.058 0.055 0.068
	0.95	20 40 60 80	0.025 0.023 0.023 0.023	0.039 0.035 0.036 0.034	0.041 0.038 0.038 0.036	0.024 0.024 0.020 0.022	$\begin{array}{c} 0.026 \\ 0.023 \\ 0.024 \\ 0.022 \end{array}$
4.0	0.6	20 40 60 80	0.225 0.011 0.005 0.069	0.290 0.027 0.021 0.198	0.246 0.030 0.032 0.289	0.431 0.492 0.487 0.431	0.063 0.001 0.001 0.013
	0.8	20 40 60 80	0.066 0.014 0.012 0.045	0.085 0.023 0.026 0.103	0.075 0.024 0.033 0.135	0.118 0.146 0.140 0.116	0.044 0.009 0.008 0.035
·	0.85	20 40 60 80	0.049 0.016 0.017 0.047	0.063 0.025 0.026 0.088	0.060 0.028 0.031 0.110	0.075 0.088 0.085 0.077	0.037 0.012 0.012 0.040
	0.9	20 40 60 80	0.031 0.020 0.017 0.037	0.041 0.029 0.030 0.061	0.042 0.030 0.035 0.068	0.044 0.048 0.042 0.043	0.028 0.018 0.016 0.031
	0.95	20 40 60 80	0.017 0.017 0.016 0.020	0.024 0.024 0.026 0.030	0.025 0.026 0.028 0.034	0.020 0.022 0.021 0.019	0.018 0.016 0.015 0.019
					-		

Table 4	
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Rejection Frequencies at 1% critical values when  $\mu = 0.05$ 

m <sub>2</sub>	β	t <sub>o</sub>	ττ	$ ho_{ au}$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)
0	0.6 0.8 0.85 0.9 0.95		0.978 0.300 0.131 0.052 0.018	0.991 0.371 0.171 0.063 0.020	0.363 0.125 0.085 0.057 0.030	0.952 0.383 0.180 0.070 0.022	0.865 0.230 0.112 0.047 0.017
0.5	0.6	20 40 60 80	0.971 0.972 0.973 0.966	0.985 0.988 0.988 0.984	0.199 0.145 0.148 0.203	0.951 0.947 0.949 0.951	0.846 0.840 0.848 0.835
	0.8	20 40 60 80	0.287 0.298 0.291 0.286	0.357 0.367 0.357 0.355	0.071 0.060 0.061 0.079	0.368 0.373 0.370 0.367	0.221 0.230 0.219 0.221
	0.85	20 40 60 80	0.127 0.134 0.127 0.137	0.163 0.168 0.161 0.176	0.056 0.053 0.053 0.066	0.179 0.178 0.177 0.184	0.110 0.114 0.108 0.112
	0.9	20 40 60 80	0.050 0.053 0.048 0.051	0.062 0.063 0.060 0.061	0.043 0.041 0.042 0.047	0.070 0.067 0.062 0.071	0.046 0.048 0.043 0.045
	0.95	20 40 60 80	0.018 0.018 0.020 0.021	0.020 0.021 0.022 0.021	0.023 0.025 0.027 0.028	0.025 0.021 0.022 0.023	0.017 0.019 0.017 0.020
1.0	0.6	20 40 60 80	0.950 0.958 0.957 0.953	0.973 0.978 0.978 0.976	0.081 0.031 0.034 0.091	0.937 0.931 0.931 0.939	0.790 0.806 0.801 0.786
	0.8	20 40 60 80	0.272 0.278 0.276 0.274	0.333 0.342 0.345 0.334	0.040 0.025 0.026 0.048	0.344 0.354 0.352 0.355	0.207 0.213 0.216 0.215
	0.85	20 40 60 80	0.127 0.124 0.127 0.126	0.162 0.159 0.158 0.160	0.037 0.028 0.030 0.049	0.172 0.175 0.172 0.167	0.105 0.105 0.108 0.102
	0.9	20 40 60 80	0.050 0.047 0.048 0.050	0.063 0.056 0.059 0.061	0.034 0.027 0.030 0.039	0.071 0.061 0.066 0.068	0.044 0.044 0.048 0.045
	0.95	20 40 60 80	0.019 0.018 0.019 0.020	0.021 0.021 0.021 0.024	0.024 0.025 0.025 0.026	0.023 0.023 0.021 0.022	0.018 0.017 0.018 0.020

$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccc} 72 & 0.630 \\ 74 & 0.649 \\ 82 & 0.565 \\ 95 & 0.162 \\ 11 & 0.182 \\ 99 & 0.175 \\ \end{array}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11 0.182 99 0.175
80 0.216 0.269 0.015 0.29	94 0.163
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	46 0.092 44 0.095
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	60 0.043 59 0.042
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	220.020240.018
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	.840.170.800.187.410.084
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	420.077320.082200.059
60 0.064 0.077 0.000 0.0	0.0820.0430.0860.0530.0800.0540.0800.043
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0430.0280460.0300410.0290420.029
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0210.0170180.0170190.0170190.015

Table	5
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Rejection Frequencies at 5% critical values when  $\mu = 0$ 

m <sub>2</sub>	β	t <sub>o</sub>	$ au_{\mu}$	$\rho_{\mu}$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)
0	0.6 0.8 0.85 0.9 0.95		1.000 0.879 0.639 0.337 0.123	1.000 0.955 0.780 0.460 0.169	1.000 0.969 0.821 0.502 0.182	0.993 0.722 0.475 0.240 0.095	0.999 0.798 0.575 0.314 0.120
0.5	0.6	20 40 60 80	1.000 1.000 1.000 1.000	1.000 1.000 1.000 1.000	1.000 1.000 1.000 1.000	0.991 0.991 0.991 0.992	0.998 0.998 0.996 0.997
	0.8	20 40 60 80	0.864 0.868 0.861 0.868	0.946 0.951 0.944 0.949	0.961 0.962 0.944 0.965	0.706 0.717 0.713 0.720	0.779 0.775 0.779 0.783
	0.85	20 40 60 80	0.630 0.626 0.632 0.630	0.770 0.765 0.770 0.769	0.808 0.804 0.810 0.814	0.472 0.464 0.474 0.467	0.561 0.563 0.565 0.562
	0.9	20 40 60 80	0.318 0.321 0.329 0.329	0.437 0.450 0.455 0.456	0.477 0.488 0.494 0.493	0.229 0.232 0.231 0.232	0.296 0.300 0.315 0.303
	0.95	20 40 60 80	0.130 0.125 0.126 0.128	0.175 0.172 0.172 0.174	0.192 0.185 0.190 0.187	0.095 0.096 0.097 0.098	0.131 0.117 0.122 0.128
1.0	0.6	20 40 60 80	1.000 1.000 1.000 1.000	1.000 1.000 1.000 1.000	$1.000 \\ 1.000 \\ 1.000 \\ 1.000 $	0.989 0.988 0.989 0.990	0.993 0.988 0.984 0.989
• •	0.8	20 40 60 80	0.841 0.804 0.809 0.830	0.930 0.906 0.912 0.928	0.945 0.928 0.933 0.952	0.694 0.692 0.708 0.688	0.752 0.708 0.717 0.742
	0.85	20 40 60 80	0.600 0.574 0.569 0.591	0.740 0.720 0.710 0.746	0.775 0.762 0.755 0.794	0.454 0.462 0.461 0.460	0.528 0.507 0.501 0.529
	0.9	20 40 60 80	0.313 0.297 0.309 0.322	0.433 0.416 0.426 0.445	0.470 0.453 0.466 0.488	0.235 0.229 0.228 0.229	0.297 0.279 0.285 0.301
	0.95	20 40 60 80	0.123 0.123 0.118 0.121	0.171 0.167 0.164 0.167	0.183 0.182 0.180 0.181	0.094 0.099 0.090 0.090	0.122 0.121 0.119 0.119

2.0	0.6	20 40 60 80	0.998 0.978 0.967 0.987	0.999 0.995 0.994 0.999	1.000 0.997 0.997 1.000	0.980 0.975 0.974 0.983	0.946 0.811 0.782 0.883
,	0.8	20 40 60 80	0.712 0.592 0.582 0.668	0.831 0.738 0.736 0.830	0.848 0.774 0.784 0.883	0.621 0.632 0.633 0.623	0.608 0.485 0.467 0.569
	0.85	20 40 60 80	0.486 0.412 0.410 0.475	0.625 0.544 0.554 0.639	0.650 0.582 0.607 0.705	0.409 0.412 0.420 0.409	0.427 0.355 0.355 0.419
	0.9	20 40 60 80	0.273 0.245 0.244 0.271	0.368 0.339 0.341 0.388	0.394 0.365 0.371 0.435	0.221 0.217 0.213 0.218	0.246 0.228 0.221 0.253
	0.95	-20 40 60 80	0.119 0.117 0.112 0.116	0.160 0.153 0.154 0.160	0.172 0.164 0.170 0.176	0.097 0.092 0.091 0.093	0.114 0.110 0.110 0.112
4.0	0.6	20 40 60 80	0.773 0.208 0.144 0.402	0.865 0.371 0.321 0.715	0.832 0.411 0.424 0.857	0.839 0.821 0.823 0.834	0.421 0.045 0.025 0.138
	0.8	20 40 60 80	0.314 0.107 0.092 0.219	0.382 0.165 0.168 0.384	0.356 0.181 0.206 0.501	0.365 0.404 0.393 0.374	0.233 0.073 0.061 0.165
	0.85	20 40 60 80	0.224 0.093 0.086 0.195	0.273 0.139 0.144 0.326	0.263 0.151 0.175 0.411	0.252 0.285 0.275 0.259	0.186 0.078 0.068 0.165
	0.9	20 40 60 80	0.147 0.092 0.087 0.152	0.181 0.127 0.142 0.239	0.180 0.140 0.165 0.287	0.161 0.175 0.163 0.160	0.135 0.086 0.082 0.142
	0.95	20 40 60 80	0.085 0.076 0.082 0.097	0.107 0.105 0.110 0.137	0.113 0.116 0.122 0.155	0.085 0.087 0.082 0.081	0.084 0.076 0.080 0.096

	Rejection	n Frequenc	ies at 5%	critical valu	les when $\mu$	= 0.05	
m <sub>2</sub>	β	t <sub>0</sub>	ττ	$^{ ho} au$	R <sub>1</sub>	R <sub>2</sub>	ADF(1)
0	0.6 0.8 0.85 0.9 0.95		0.999 0.664 0.403 0.190 0.087	$\begin{array}{c} 1.000 \\ 0.741 \\ 0.474 \\ 0.225 \\ 0.095 \end{array}$	0.891 0.454 0.333 0.232 0.130	0.991 0.726 0.474 0.233 0.092	0.982 0.562 0.348 0.178 0.085
0.5	0.6	20 40 60 80	0.999 0.999 0.999 0.999	1.000 1.000 1.000 1.000	0.778 0.713 0.718 0.783	0.993 0.991 0.991 0.992	0.979 0.978 0.980 0.976
	0.8	20 40 60 80	0.646 0.653 0.656 0.647	0.724 0.729 0.734 0.718	0.336 0.302 0.311 0.362	0.716 0.707 0.707 0.703	0.548 0.559 0.555 0.546
	0.85	20 40 60 80	0.392 0.398 0.387 0.398	0.459 0.463 0.455 0.472	0.259 0.238 0.232 0.275	0.473 0.469 0.462 0.477	0.342 0.343 0.338 0.353
	0.9	20 40 60 80	0.196 0.201 0.186 0.193	0.233 0.239 0.220 0.229	0.190 0.183 0.182 0.197	0.233 0.239 0.229 0.231	0.180 0.188 0.177 0.179
	0.95	20 40 60 80	0.082 0.082 0.087 0.087	0.091 0.090 0.094 0.098	0.116 0.115 0.120 0.124	0.094 0.094 0.091 0.096	0.080 0.085 0.084 0.089
1.0	0.6	20 40 60 80	0.998 0.998 0.997 0.997	0.999 1.000 0.999 0.999	0.592 0.428 0.426 0.612	0.991 0.988 0.988 0.989	0.963 0.969 0.970 0.962
	0.8	20 40 60 80	0.618 0.633 0.632 0.628	0.695 0.716 0.708 0.704	0.236 0.185 0.190 0.273	0.684 0.700 0.689 0.693	0.524 0.533 0.539 0.534
	0.85	20 40 60 80	0.393 0.386 0.392 0.384	0.460 0.453 0.461 0.446	0.192 0.152 0.160 0.225	0.460 0.459 0.461 0.460	0.338 0.342 0.344 0.334
	0.9	20 40 60 80	0.193 0.188 0.187 0.189	0.233 0.221 0.218 0.218	0.151 0.133 0.143 0.170	0.236 0.229 0.227 0.231	0.180 0.175 0.177 0.176
	0.95	20 40 60 80	0.085 0.084 0.085 0.086	0.091 0.093 0.092 0.096	0.110 0.105 0.110 0.126	0.094 0.094 0.091 0.098	0.081 0.081 0.084 0.085

2.0	0.6	20 40 60 80	0.983 0.988 0.990 0.980	0.994 0.996 0.995 0.993	0.208 0.049 0.051 0.221	0.982 0.973 0.975 0.981	0.880 0.906 0.912 0.871
	0.8	20 40 60 80	0.543 0.572 0.565 0.532	0.616 0.652 0.638 0.610	0.085 0.038 0.046 0.126	0.636 0.635 0.628 0.623	0.447 0.490 0.470 0.439
	0.85	20 40 60 80	0.334 0.343 0.346 0.337	0.397 0.411 0.407 0.398	0.081 0.047 0.053 0.127	0.412 0.409 0.409 0.417	0.300 0.302 0.306 0.297
	0.9	20 40 60 80	0.175 0.183 0.178 0.175	0.208 0.209 0.207 0.211	0.083 0.064 0.075 0.126	0.211 0.214 0.213 0.217	0.165 0.169 0.165 0.162
	0.95	20 40 60 80	0.084 0.080 0.085 0.074	0.092 0.090 0.091 0.085	0.078 0.079 0.079 0.100	0.094 0.089 0.091 0.088	0.085 0.083 0.082 0.073
4.0	0.6	20 40 60 80	0.701 0.796 0.840 0.674	0.782 0.873 0.890 0.772	0.001 0.000 0.000 0.002	0.844 0.820 0.815 0.842	0.362 0.498 0.545 0.340
	0.8	20 40 60 80	0.270 0.330 0.345 0.272	0.330 0.399 0.391 0.328	0.003 0.001 0.000 0.009	0.377 0.393 0.387 0.375	0.208 0.269 0.277 0.211
	0.85	20 40 60 80	0.200 0.239 0.226 0.197	0.241 0.288 0.261 0.238	0.007 0.002 0.002 0.021	0.266 0.285 0.257 0.261	0.171 0.210 0.205 0.169
	0.9	20 40 60 80	0.123 0.147 0.138 0.125	0.149 0.172 0.155 0.148	0.015 0.008 0.013 0.049	0.161 0.169 0.157 0.156	$\begin{array}{c} 0.117 \\ 0.137 \\ 0.130 \\ 0.117 \end{array}$
	0.95	20 40 60 80	0.080 0.083 0.077 0.070	0.087 0.087 0.081 0.078	0.042 0.039 0.047 0.077	0.088 0.086 0.079 0.083	0.079 0.081 0.073 0.072

