Do Stock Prices in Ho Chi Minh City Trading Center Have Unit Roots? A Discussion on Power of ADF F test with Unexpected Initial Value

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Abstract

This paper attempts to apply most powerful unit root tests for stock prices in Ho Chi Minh City Trading Center (HoSTC) of Vietnam in the context extreme initial values are highly possible. Theoretically, we find in that case ADF F test is not only superior to the tests which are most powerful for small and moderate initial values, as shown by the recent researches such as Muller and Elliott (2003), but also has better performance against ADF t test given small and moderate sample sizes and, especially, autoregressive lag coefficient is close to unity. The procedure proposed by Holden and Perman (1994), which takes advantage of both t-type and F-type ADF tests is able to reject almost all of the series appearing to have extreme initial values in HoSTC. Although, surprisingly, unit root tests as a whole cannot decisively reject the null, we would maintain the view that the stock prices hardly follow random walk hypothesis implying the market is inefficient.

Do Stock Prices in Ho Chi Minh City Trading Center Have Unit Roots? A Discussion on Power of ADF F test with Unexpected Initial Value [i]

Key words: unit root test, power of test, ADF test, stock market, emerging market, efficient market hypothesis.

JEL: C12, C22, C32

1 Introduction

The Ho Chi Minh City-based Stock Trading Center of Vietnam (HoSTC) was officially inaugurated on July 20, 2000 with the first trading on July 28, 2000. After more than 5 years of development, it has recently received more attentions from international financial institutions and researchers as a newly emerging market. From the common belief that the market is hardly efficient, this paper would like to take a first analysis by using robust unit root tests to test the Efficient Market Hypothesis (in weak form) for stock prices in HoSTC.

Tests for the existence of unit root in univariate time series have been intensively discussed in the literature since the seminal research of Dickey and Fuller (1979). Among various methods, the tests of Dickey and Fuller (ADF test, 1979 and 1981) and Philips and Perron (PP test, 1988) together with their recently modified versions proposed by Elliot, Rothenberg, and Stock (GLS-DF test, 1996) and Perron and Ng (GLS-MZ test, 2001) have been widely applied for the empirical researches. While the original versions (DF, ADF, and PP tests) suffer significant size distortions and

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low power, the modified methods have shown much improvement especially when the series has an autoregressive root close to (but less than) unity or the moving average component with large negative root, as long as the selection of lag length is appropriate .

However, more recent researches (such as Elliott and Muller, 2003 and Muller and Elliot, 2006) have found that the nuisance parameter, initial value, does affect the power of these tests: If the initial value (IV) is considerably far from its unconditionally expected value, the performance of modified tests, e.g. GLS-DF and GLS-MZ tests become worse with the power approaching zero while t-type ADF test improves its power. The issue can also be partly observed through the simulation and evaluation of Dejong (1991) : the power of ADF t(1) increases when value of x_0^* increases. As there is no test uniformly most powerful for various values of IV deviation which is often difficult to verify, the selection of several tests at the same time or by using the tests that maximize power while achieving some degree of robustness to the impact of IV – see Muller and Elliott (2003) and Harvey and Leybourne (2006) – is unavoidable and need to be justified by the researcher. This paper, continuing from the current discussions on power of the tests, make an effort to show the usefulness of including ADF F test besides t test in testing for unit root of the series, which is very likely to have unexpected IVs. Although asymptotically, the power of both ADF t and F tests would be equivalently superior in the case of large IV deviation, for finite sample size ADF F test shows better performance than t test. We make a recommendation for applying Holden and Perman's procedure , thereafter called HP-ADF (Holden and Perman, 1994) – which proposes a strategy to use both ADF F and t tests – in compliment with others to construct robust tests for unit root. The recommended testing method is applied for the stock prices series in HoSTC, where the existences of extreme IVs are highly possible. The empirical results reveal F/HP-ADF test is indeed better than t test as well as the other used tests in detecting stationary series. However, it is surprising that the other unit root tests cannot reject null for almost all of the prices series of the stocks quoted in HoSTC. Given the high rejection rates of HP-ADF among the series with suspected extreme IVs and the low power of the other tests when the IV is close to the deterministic trend and the sample sizes are small/moderate, we would still support the view that the stock prices series in HoSTC behave like trend other than differences stationary processes.

The remaining of the paper is organized as follow: Section 2 shows that t-type and F-type ADF tests increase their power when the IV under alternative becomes further from its unconditionally expected value. In addition, we notes that F-type ADF test is even more powerful than t-type ADF test given the sample size is moderate. This discussion leads to our recommendation to apply Holden and Perman's procedure of using ADF tests (Holden and Perman, 1994). Section 3 presents simulations to illustrate the issues. In Section 4, we apply the tests recommended from the previous parts to test the random walk hypothesis for HoSTC. Comments which support the rejections of HP-ADF test are also given. The last section is the conclusion.

2 The power of F- and t-type ADF test

2.1 F test

This section aims at showing that the power of F test improves when the deviation of IV (in absolute value) from the deterministic component increases from some certain non-zero value. Suppose the series we want to test follows the DGP:

$$y_t = c + \alpha y_{t-1} + \beta t + \varepsilon_t, \qquad t = 1, 2, \ldots, T \qquad (1)$$

where $\varepsilon_t \sim IID(0,\sigma^2)$, c, α, and β are fixed parameters, with α <1. We assume that T, although being finite, but large enough to approximate $\sum_{t=1}^{T} \alpha^{t-1} \approx 1/(1-\alpha)$.

Let $\Delta y_0 = y_0 - w_0$, where w_0 is the unconditional expectation of y_0:

$$w_0 = c/(1-\alpha) - \beta\alpha/(1-\alpha)^2 \qquad (2)$$

By recursive transformation of (1) and replacement of (2), we get:

$$y_t = w_0 + \frac{\beta t}{1-\alpha} + \Delta y_0 \alpha^t + \sum_{i=0}^{t-1} \alpha^i \varepsilon_{t-i} \qquad (3)$$

We now consider the change of F statistic for (α, β) = (1,0) in (1), when the IV, y_0, moves out of the deterministic trend, given c, α, and β. F statistic is basically the ratio of sum of squared errors (SSE) restricted by (α, β) = (1, 0) and the unrestricted SSE. When Δy_0 changes, the regression (1) is adjusted in the way that $\Delta y_0 \alpha^t$ and $\Delta y_0 \alpha^{t-1}$ are added on y_t and y_{t-1}, respectively (see (3)). As the true parameters are fixed, given $\{\varepsilon_t\}$, we would expect the (relative) changes of the unrestricted SSE are ignorable, especially, when $|\Delta y_0|$ is big enough. Therefore, our focus is just on the changes of the restricted SSE.

The restricted errors would be the residuals of the regression of $z_t = y_t - y_{t-1}$ on a constant. It turns out that the OLS estimated residual, e_t, will be $e_t = z_t - \bar{z}$ where $\bar{z}$ is the sample mean (by time) of z_t, From (3), we derive:

$$z_t = \frac{\beta}{1-\alpha} - \alpha^{t-1}(1-\alpha)\Delta y_0 + G_t(\varepsilon) \qquad (4)$$

where $G_t(\varepsilon) = \varepsilon_t - \sum_{i=1}^{t-1}(1-\alpha)\alpha^{i-1}\varepsilon_{t-i}$. We also get

$$\bar{z} = T^{-1}\sum_{t=1}^{T} z_t = \frac{\beta}{1-\alpha} - \frac{\Delta y_0}{T} + T^{-1}\sum_{t=1}^{T} G_t(\varepsilon)$$

therefore $$e_t = \Delta y_0 \left[1/T - (1-\alpha)\alpha^{t-1} \right] + H_t(\varepsilon) \qquad (5)$$

where $$H_t(\varepsilon) = G_t(\varepsilon) - T^{-1} \sum_{t=1}^{T} G_t(\varepsilon)$$

Let SSE_F is the restricted SSE we have:

$$SSE_F = \sum_{t=1}^{T} e_t^2 = \sum_{t=1}^{T} \left\{ \Delta y_0 \left[1/T - (1-\alpha)\alpha^{t-1} \right] + H_t(\varepsilon) \right\}^2$$

$$SSE_F = (\Delta y_0)^2 A + \sum_{t=1}^{T} \left[H_t(\varepsilon) \right]^2 + 2\Delta y_0 \left[1/T - (1-\alpha)\alpha^{t-1} \right] H_t(\varepsilon) \qquad (6)$$

where $A = \sum_{t=1}^{T} \left[1/T - (1-\alpha)\alpha^{t-1} \right]^2$. By some simple transformations, we can easily get

$$A = \frac{1-\alpha}{1+\alpha} - \frac{1}{T} = q - 1/T \qquad (7)$$

where $q = \frac{1-\alpha}{1+\alpha}$. But as $H_t(\varepsilon)$ is the residual of the regression with zero Δy_0, $\sum_{t=1}^{T} H_t(\varepsilon) = 0$. We also can derive that the third term of (6) is ignorable. Let us consider the absolute value of the ratio of the third term to the sum of the first two terms of (6), say P:

$$P = \frac{2\Delta y_0 (1-\alpha) Q}{(\Delta y_0)^2 A + S^2} = 2\Delta y_0 (1-\alpha) \frac{Q/T}{(\Delta y_0)^2 A/T + S^2/T}$$

where: $$Q = \left| \sum_{t=1}^{T} \alpha^{t-1} H_t(\varepsilon) \right| \text{ and } S^2 = \sum_{t=1}^{T} \left[H_t(\varepsilon) \right]^2, S \geq 0$$

As $\{H_t(\varepsilon)\}$ are zero-mean random variables, plim(Q/T) = 0 but plim(S/T) ≠ 0. As $\{H_t(\varepsilon)\}$ are zero-mean random variables with finite variances, plim(Q/T) = 0 but plim(S^2/T) ≠ 0. Therefore, with T big enough, P is close to zero implying the third term in (6) is ignorable. As our concerns are just for the case of large $|\Delta y_0|$, the ignorance of this term is just for purpose of simplicity that does not affect our final remarks. We are able to approximate $SSE_t \approx (\Delta y_0)^2 B + \sum_{t=1}^{T} [I_t(\varepsilon)]^2$, then:

$$F_{stat} \approx \frac{(\Delta y_0)^2 A + \sum_{t=1}^{T} [H_t(\varepsilon)]^2 - SSE_0}{SSE_0} \times \frac{(T-k)}{2} \quad (8)$$

where SSE_0 is the unrestricted SSE. Given the parameters of the DGP described in (1), from (8), it is clear that when $|\Delta y_0|$ increases (at least from certain positive value), y_0 more deviates from its unconditional expectation, the value of F statistic increases implying the power improvement of F-type ADF test.

2.2 t test

We will use the same approach by treating t test as a special F test with only one restriction. We have the restricted error at time t as the t^{th} residual of the following regression:

$$y_t - y_{t-1} = c + \beta t + e_t \quad (9)$$

Setting X as T x 2 matrix including columns of unities and time index, we have the restricted error at time t:

$$e_t = z_t - X(X'X)^{-1}X'z_t \quad (10)$$

Let $\begin{pmatrix} a & b \\ b & d \end{pmatrix} = (X'X)^{-1}$ (a symmetric matrix) and note that

$$X'X = \begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & 2 & \dots & T \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ \vdots & \vdots \\ 1 & T \end{pmatrix} = \begin{pmatrix} T & T(T+1)/2 \\ T(T+1)/2 & T(T+1)(2T+1)/6 \end{pmatrix}$$

We derive the value of a, b, and d as the functions of T:

$$a = \frac{2(2T+1)}{(T-1)T};\ b = -\frac{6}{T(T-1)};\ \text{and}\ d = \frac{12}{(T+1)(T-1)T} \tag{11}$$

We should also recognize that:

$$a + b(T+1)/2 = 1/T \tag{12}$$

$$b + d(T+1)/2 = 0 \tag{13}$$

Replace a, b, and d into (10), we have:

$$e_t = z_t - \left[a\sum_{i=1}^{T} z_i + b\sum_{i=1}^{T} iz_i + t\left(b\sum_{i=1}^{T} z_i + d\sum_{i=1}^{T} iz_i \right) \right] \tag{14}$$

For T big enough:

$$\sum_{i=1}^{T} iz_i = \frac{T(T+1)}{2(1-\alpha)}\beta - \frac{\Delta y_0}{1-\alpha} + \sum_{t=1}^{T} tG_t(\varepsilon) \tag{15}$$

Replace (4) and (15) into (14), gather the terms of Δy_0 and β in to separate groups, and pay attention to the equations (12) and (13), we will see that the group of terms with β become zero. Finally, we have:

$$e_t = \Delta y_0 \left[a + bt + \frac{1}{1-\alpha}(b + dt) - (1-\alpha)\alpha^{t-1} \right] + I_t(\varepsilon) \tag{16}$$

where $$I_t(\varepsilon) = G_t(\varepsilon) - (a + bt)\sum_{t=1}^{T} G_t(\varepsilon) - (b + dt)\sum_{t=1}^{T} tG_t(\varepsilon)$$

Let SSE_t is the restricted SSE, we have:

$$SSE_t = \sum_{t=1}^{T} e_t^2 = (\Delta y_0)^2 B + \sum_{t=1}^{T} [I_t(\varepsilon)]^2 + 2\Delta y_0 \sum_{t=1}^{T} \left[a + bt + \frac{1}{1-\alpha}(b+dt) - (1-\alpha)\alpha^{t-1} \right] I_t(\varepsilon)$$

where $B = \sum_{t=1}^{T} \left[a + bt + \frac{1}{1-\alpha}(b+dt) - (1-\alpha)\alpha^{t-1} \right]^2$.

Noting that $\sum_{t=1}^{T}(a+bt)^2 = a$, $\sum_{t=1}^{T}(b+dt)^2 = d$, and $\sum_{t=1}^{T}(a+bt)(b+dt) = b$, then:

$$B = \left[\frac{1-\alpha}{1+\alpha} - a - \frac{2b}{1-\alpha} - \frac{d}{(1-\alpha)^2} \right] = \left[q - a - \frac{2b}{1-\alpha} - \frac{d}{(1-\alpha)^2} \right] \qquad (17)$$

As $\{I_t(\varepsilon)\}$ are the regression residuals of (9), $\sum_{t=1}^{T} I_t(\varepsilon) = 0$ and $\sum_{t=1}^{T} tI_t(\varepsilon) = 0$. We are also able to approximate:

$$SSE_t \approx (\Delta y_0)^2 B + \sum_{t=1}^{T} [I_t(\varepsilon)]^2$$

then

$$t_{stat}^2 \approx \frac{(\Delta y_0)^2 B + \sum_{t=1}^{T} [I_t(\varepsilon)]^2 - SSE_0}{SSE_0} \times (T-k) \qquad (18)$$

Similar to the case of F test, given the fixed parameters, the value of t squared statistic increases when $|\Delta y_0|$ rises (at least from certain positive value) implying power improvement of ADF t test.

2.3 F and t statistics sensitivity to Δy_0

From the previous parts, we know that both F and t statistics increase when $|\Delta y_0|$ goes up from certain values. We now prove that, at some finite T, F statistic increase at higher speed than t statistic when $|\Delta y_0|$ increases that indeed makes F test more powerful than t test.

We note that, when $\Delta y_0 = 0$, the distribution of F and t^2 statistics under alternative of stationary asymptotically follow noncentral F distributions, particular: $F \sim F(2, T\text{-}3, \delta_F)$ and $t^2 \sim F(1, T\text{-}3, \delta_t)$ where δ_F and δ_t are the noncentral parameters. If we set F_0 and t_0^2 are the F and t^2 statistics when $\Delta y_0 = 0$, from (8) and (18) we have:

$$F_0 = \frac{\sum_{t=1}^{T} \left[H_t(\varepsilon)\right]^2 - SSE_0}{SSE_0} \times \frac{(T-k)}{2} \tag{19}$$

$$t_0^2 = \frac{\sum_{t=1}^{T} \left[I_t(\varepsilon)\right]^2 - SSE_0}{SSE_0} \times (T-k) \tag{20}$$

With non-zero Δy_0, given $\{\varepsilon_t\}$ implying $H_t(\varepsilon)$ and $I_t(\varepsilon)$ are unchanged, replace (19) and (20) into (8) and (18) we get the statistics (again, we ignore the change of SSE_0)

$$F = F_0 + \frac{(\Delta y_0)^2 A}{SSE_0} \times \frac{(T-k)}{2} \tag{21}$$

$$t^2 = t_0^2 + \frac{(\Delta y_0)^2 B}{SSE_0} \times (T-k) \tag{22}$$

The equations (21) and (22) imply that when $\Delta y_0 \neq 0$ (and big enough), the distributions of F and t^2 statistics just move to the right or in other words, Δy_0 going up ‘moves’ the critical values to the left while holding the distributions unchanged, approximately. This means that the power of F and t^2 tests approaches 1 when $|\Delta y_0|$ increases. Set the ratio K

$$K = \frac{F - F_0}{t^2 - t_0^2} = \frac{A}{2B} \tag{23}$$

We see that, if K is big enough, the critical value of F test, F_{cv}, will ‘move’ to zero before that of t test, t_{cv} and vice versa. To numerically illustrate this issue, we consider a practical example: suppose $\alpha = 0.98$; T = 1,000 and we test at 5% of significance, which leads to F_{crit} = 6.25 and t_{crit} = -3.41 (for one-side test) or t_{crit}^2 = 11.63. We get q = 0.02/1.98 = 0.0101, A = q – 1/T = 0.0091, and B = q – a – 2b/(1-α) – d/(1-α)^2 = 0.0067, then

$$K = \frac{0.0091}{2 * 0.0067} = 0.6827$$

When F_{crit} 'moves' to zero, t^2_{crit} moves to t^{*2}, which is:

$$t_{crit}^2 - t^{*2} = F_{crit} / K = 6.25 / 0.6827 = 9.16$$

or $$t^{*2} = 11.63 - 9.16 = 2.47 > 0$$

The positive t* indicates that for a sample of $\{y_t\}$ with above specifications, there will be some value of Δy_0 that make the power of F test reach 1 while that of t test is still at some rate which is less than 1. In other words, F test will be superior to t test if $|\Delta y_0|$ becomes bigger than a certain value. We can also derive, given α = 0.98, only with very large sample sizes, T > 4,300, would make F test never superior to t test that implies the practicality of the use of F test. This critical size will reduce if α is smaller (e.g. if α = 0.95, the critical sample size, T > 1,800). However, these sample sizes are so large that both F and t test have power very close to 1.

Remarks:

We are now ready to make some remarks about the power of F and t test against the alternative described in (1). From (6) and (15), we realize that both t-typed and F-typed ADF tests are not affected by the nuisance parameter β, the time trend coefficient, c, the intercept, but depend on $|\Delta y_0|$, the deviation of IV from its unconditional expectation under alternative hypothesis, T, the sample size, and α, the autoregressive lag coefficient.

Regarding to Δy_0, both t-type and F-type ADF tests may have small power at near-zero Δy_0, when the IV lies at the unconditional expectation under alternative hypothesis. As t-typed ADF test is one-side test, its power is higher than that of F test when $|\Delta y_0|$ is small and zero. When $|\Delta y_0|$ increases from a certain big value, the power of the tests both increase. However, with moderate (practical) sample size T, F-type ADF test raises its power more quickly than the t test and to a certain big value of $|\Delta y_0|$, F test even dominates t test. The more powerful of F test when the IV is far from its unconditional expectation is not derived from joint hypothesis test (as mentioned in the first point, the power does not depend on β) but from the higher sensitivity of F statistic to Δy_0 than that of t statistic.

Regarding to sample size, both tests improve their statistic value with the increase of T. Referring to (7) and (17), when T goes to infinitive, A and B approach q and the power of the tests become closer to the bounds. At very large T, A and B are no longer significantly different, the ratio K in (23) reduces and approach 0.5. Therefore, at substantially large T, F-type ADF test maybe no longer superior to ADF-t test for all Δy_0. However, it is very likely that both tests achieve power of 1 for all Δy_0.

Regarding to α, the first lag coefficient, from (23), we see that the ratio K will increase when α approaches unity implying F test is more distinguishable from t test, given moderate sample size and substantial $|\Delta y_0|$.

2.4 Holden and Perman's approach

The power superiority of F test when unexpected IV appears, especially when α is close to unity, is worth to consider including it in the unit root test procedure. The approach proposed by Holden and Perman (1994), which uses both F and t tests in their sequential procedures would be recommended. We limit the discussion on the tests concerning only with lag and time trend coefficients (ADF t and φ_3 tests). There are advantages in this approach over applying pure t-typed or F-typed ADF test. HP-

ADF basically has similar size to t and F tests in relevant cases[ii]. Any improvement in power of HP-ADF would be an advantage. HP-ADF indeed overcomes ADF t test when $|\Delta y_0| \neq 0$ (and large enough). In critical situation, as F test becomes more powerful, it may reject null while t test cannot. The normality test based on null of ($\alpha = 1|\beta \neq 0$) at the subsequent step of HP-ADF procedure would be more likely to lead to rejection by HP-ADF test[iii]. For the case of zero Δy_0, as (one-side) t test has higher power than F test, it is possible that F test accepts the null while t test does not. Therefore, in this case, it is recommended to follow the rejection of t test. If following this rule, HP-ADF is more powerful than F test when IV lies in/near the deterministic trend. In summary, HP-ADF test is superior to both pure t and F tests; especially HP-ADF is more powerful than ADF t test when the IV is far from the deterministic trend under the alternative.

Since it is difficult to justify if the series have extreme IV or not, an appropriate strategy is to select the asymptotically efficient unit root tests for different ranges of IV. We recommend, in such situation, HP-ADF test should be used in compliment with GLS-DF (Elliott et al, 1996) or other tests, which are powerful against the alternative of small or moderate $|\Delta y_0|$ (such as the tests analyzed in Muller and Elliott, 2003).

[ii] If the series follows a process with unit root and time trend, t test is likely to reject too few while the rejection of HP-ADF is more appropriate, at the rate close to nominal size. This is because, when the time trend coefficient is non-zero, the distribution of t statistic follows standard normal distribution (or t distribution) other than the non-standard distribution discovered by Dickey and Fuller (see Holden and Perman, 1994). The over-rejection of F test is clear due to joint test nature.

[iii] Similar to Elder et. al's (2001) discussion for φ_1 test, φ_3 test cannot improve the power given expected IV. The more powerful of φ_3 is just derived from more sensitive of the statistic to Δy_0, not from the nature of joint test by itself.

3 Simulations

In this section, simulations are carried out to illustrate some issues remarked at the end of 2.3 and 2.4, which are concerned with the behavior of the tests power regarding to the changes of Δy_0 and T. We limit the simulations for the case of white noise errors. Further details about the behavior when the errors are serial correlated and the size of the tests are presented in the Appendix. Since the increase in power of ADF t test when IV is far from the expected value has been confirmed in several recent researches, in this part, we just consider the superiority of F/HP-ADF test over t test. In addition, the results by using GLS-DF are also included for comparative analysis. The DGP is:

$$y_t = \alpha y_{t-1} + \beta t + \varepsilon_t, \qquad (24)$$

where $\varepsilon_t \sim IIN(0, 0.01^2)$, t = 1, 2, …, T. The IV is determined by

$$y_0 = w_o + \Delta y_0$$

where $w_0 = -\beta\alpha/(1-\alpha)^2$

and $|\Delta y_0| = (0, 10, 20, \dots, 50)\sigma$

Two sample sizes of T = 500 and T = 1,000 are selected to see the effect of size on the power of the tests and statistic. For simplicity, we do not include the nuisance parameter c, the intercept that does not affect the essentials of the simulation and its result. We arbitrarily set $\beta = 0.00005$ and $\alpha = 0.98$. The output of the simulation is based on 5,000 replications for each value of Δy_0. The results are shown in Table 1, which support the remarks in the previous part (note that the power of HP-ADF and F tests in the simulations are identical).

[Table 1 is about here]

We first compare the power of F/HP-ADF to ADF t test. The power of both tests is minimum at zero Δy_0 (y_0 = -0.1225) of which, the power of pure t test is higher for both sample sizes of 500 and 1,000. Actually, the power of HP-ADF should equal ADF t test if we follow the recommended rule that when F test cannot reject the null while t test can, HP-ADF reject the null. We keep not following this rule to show the superiority of t test over F test when $\Delta y_0 = 0$. The minimum power of F/HP-ADF test is 13% and 49% while those of pure t test are 16% and 56% for the sizes of 500 and 1,000, respectively. However, when $|\Delta y_0|$ becomes bigger, t test is dominated by F/HP-ADF test. For the sample size of 500, when y_0 deviates to -20σ and +20σ, the power of F/HP-ADF increases to 35% and 34% while t test just reject at rates of 28% and 27%, respectively. The same phenomenon is observed for the sample size of 1,000.

Comparing the cases of different sample sizes, T, of 500 and 1,000, we also recognize the trends of convergences of F/HP-ADF and t tests when sample sizes go to infinitive, implying the reductions in the differences among the tests when T becomes very large. It is visualized in Figure 1 and Figure 2, of which, the differences among the power curves are less clear in the second than that in the first.

The power of GLS-DF test, as predicted, dominates F/HP-ADF and ADF t tests at zero Δy_0, which reaches 24% and 78% for the sample sizes of 500 and 1,000, respectively. However, its power falls too fast when $|\Delta y_0|$ increases: even at $\Delta y_0 = \pm 10\sigma$, GLS-DF is no longer more powerful than the remaining tests: for the sample size of 500, GLS-DF rejects only at rates of 6.4% and 7.4%, while those of F/HP-ADF and ADF t test are more than 15%; for the sample sizes of 1,000, GLS=DF rejects at rate of 19.4% while those of F/HP-ADF and ADF t tests are more than 50%.

[Figure 1 and Figure 2 are about here]

4 Tests for Unit Root for Stock Prices in Ho Chi Minh City Stock Trading Center

In this part, we apply the robust unit root tests recommended in the previous parts to examine the random walk hypothesis (RWH) for the stock prices in HoSTC. There have been various researches applying unit root tests as a step to exam RWH for the emerging as well as the developed markets. The results are mixing. Supporting evidences for null hypothesis include the three indices of Athens Stock Exchange (Panagiotidis, 2004) and monthly price indices of eighteen developed countries (Chan et al., 1997). For the rejections of null we may mention the cases of Sri Lanka's indices, SSI and FSI (Abeysekera, 2001) and New Zealand's indices, NZSE's (Li and Xu, 2002). The so-young market of Vietnam would be widely believed not being efficient even in weak form. In addition, the observations on price behavior of the stocks quoted in HoSTC reveal the patterns which seem to be relevant to the issue of unexpected IV discussed above: (1) the composite index called Vietnam Index (VNINDEX) went to its first peak right after the open of the market, reaching 571 points from the starting value of 100 points, then followed by a dramatically adjusted period. (2) There were the opening prices which seemed to distinctively high (may derived from IPO overpricing) leading to the adjustments of the market in the subsequent trading sessions. Hence the prices series often had big IV followed by an adjustment period then a time trend later. These behaviors are likely to reflect the inefficiency of the market. However, the samples selected in the way that excludes such IVs may make unit root tests have low power, especially, when the sample sizes are small. We recall from Table 1 that the power of HP-ADF and GLD-DF tests are just about 20% or less for the case of expected IV when sample size is 500 with $\alpha = 0.98$. We will take this point into account when selecting the sample period. Another note is that while the rejection of unit root hypothesis can be strong evidence against RWH, assuming constant expected returns, the acceptance of null is not enough to prove RWH. Despite the fact that the RWH are contained in the unit root null hypothesis, it is the permanent/temporary nature of shocks to price that concerns such tests (Campbell and McKinlay, 1997).

4.1 Data and the selected tests

In order to have the samples which contain as many as possible series with extreme IVs, we deliberately select the starting point of the sample period at the first peak of the market. The data includes all available stock prices series of HoSTC during the period from June 25 of 2001 (the peaked date of VNINDEX) to November 14 of 2005. The samples consist of 31 series (including VNINDEX) with the sizes vary from 83 to 899. The prices series are adjusted for dividend payments and splits and then transformed into natural logarithm form.

As discussed in the previous parts, for the robustness, GLS-DF test of Elliott et al. (1996), KPSS of Kwiatkowski et al. (1992) are used together with t-type ADF test and HP-ADF test. We expect that GLS-DF improves size and power of the test for the case of expected IV while t-type ADF test and, especially, HP-ADF will be a good test in the case of unexpected IV. KPSS, which, oppositely to the others, set the null hypothesis of stationarity, would provide a good complimentary view

4.2 Results and discussions

[Table 2 is about here]

Table 2 shows the results of unit root tests. For the following comments, we apply 5% significance for all the tests. GLS-DF and KPSS strongly support the hypothesis that unit roots exist: GLS-DF cannot reject any series while KPSS cannot reject the null of stationarity of only one series, MHC. Contrarily, HP-ADF is able to reject 10 out of 31 series, including VNINDEX. An interesting point is all of the series which seem to have extreme IVs (Figure 3) are rejected by HP-ADF except the cases of HAP, LAF, and REE. However, F statistic of HAP is just almost at the critical value (6.24 versus 6.25) while those for LAF and REE are relatively high (5.35 and 5.40, respectively). The presences of extreme IVs are either due to the peak of the market (as for the case of VNINDEX and SAM) or due to first opening pricing (such as DHA and DPC).

Since ADF tests may suffer size distortions if the series have negative MA root in error terms and/or the sample sizes are small, the rejections of HP-ADF are more convincing with several rejected series seem not to have negative MA roots and have moderate sample sizes, such as VNINDEX, DPC, and SAM (see Table 3). Note that these three series cannot be rejected by ADF t test. Furthermore, we also realize the domination of HP-ADF test over the pure ADF t test: HP-ADF rejects 10 series, nearly as double number of the rejections as by ADF t test, 6 series. All of the series rejected by t test are also rejected by HP-ADF. In general, surprisingly, robust tests for unit root still cannot decisively reject null of unit root for stock prices series in HoSTC, although we would be impressed by the rejections of HP-ADF test for a considerable number of the series, including VNINDEX.

[Table 3 is about here]

[Figure 3 is about here]

A possible interpretation is the stock prices in HoSTC are stationary with the autoregressive coefficient very close to unity. Given the actual sample sizes of the series are around 100 to 900, referring to the simulation in the previous section, it is understandable that the unit root tests which are superior when IVs near the deterministic trend (e.g. GLD-DF) may not be powerful enough to reject the null. On the other hand, the rejections of HP-ADF for majority of the series with suspected extreme IVs are reasonable. To see if the IVs are large enough to raise the power of HP-ADF, we make a small simulation of DHA series, which is not rejected by ADF t, DF-GLS, and KPSS tests but HP-ADF test. Based on the ARMA estimate and tests results of DHA, we can derive a simple model for DHA:

$$y_t = 0.0624 + 0.00005t + 0.98y_{t-1} + u_t$$

$$u_t = -0.33u_{t-1} + \varepsilon_t + 0.36\varepsilon_{t-1}$$

where $\varepsilon_t \sim IIN(0,0.01)$, t = 1, 2,…, 401. The initial value is $y_0 = 3.4$ (real value of 3.46). A sample of 250 series from this DGP shows that: HP-ADF rejects 86.4%, ADF t test rejects 43.2% while DF-GLS rejects 0% (KPSS with trend accept null of stationarity at rate of 2/250 = 0.8%). Figure 4 showed the first series in the simulated sample and the real series of DHA, which appear to be quite close to each other. The simulation results well support our interpretation.

[Figure 4 is about here]

We may come up with a description of the prices behavior in HoSTC. The price could follows but considerably swings around a certain deterministic trend that as a whole is very close to the random walk process. However, whenever there is a peak (the price goes extremely far from the trend), it will have prone to reverse to the deterministic trend. The peak-adjusted or mean-reversion behavior is clearly a property of a stationary process. For HoSTC, we may interpret this behavior as the consequences of over-reaction of the market and/or the effect of price limit regulation. On one hand, because the market lack of information, the investors often react in a massive way mainly based on the psychological factors. On the other hand, price limit may also prevent immediate price adjustment when new information arrives. Even the unit root tests in general cannot decisively reject the null for the stock prices in HoSTC, the rejections of HP-ADF are important to support our view that the market is inefficient with prices having mean reversion behavior, especially, after a peak.

We also have a look at the previous researches which used standard ADF t test for different stock indices. The non-rejection by ADF t test for the case of HoSTC (represented by VNINDEX), is remarkable if we compare with the tests results for Sri Lanka (Abeysekera, 2001) and New Zealand markets (Li and Xu, 2002). Both of these researches are able to reject null of unit root of the indices series, especially, the former can reject for the cases of small sample sizes of weekly and monthly FSI and SSI (the indices for Sri Lanka stock market). The differences suggest VNINDEX may behave more like random walk process than the indices of Sri Lanka and New Zealand, although rejected by HP-ADF test. A final notice is that the inclusion of HP-ADF test may be appropriate for several researches which could not reject the null based on moderate/small sample sizes such as Chan et al. (1997) and Panagioditis (2004) as long as the samples could catch the large IVs.

5 Conclusion

This paper is a first analysis of the stock prices behavior in Ho Chi Minh City Stock Trading Center of Vietnam to examine the informational efficiency of the market. The robust unit root tests surprisingly cannot decisively reject the random walk hypothesis. However, in the case of high possibility of extreme initial value in stock prices observed during the sampling period the rejections based on HP-ADF test is remarkable. The large initial values may start from the peaks or high opening prices reflecting the inefficiency of the market. We have proved with simulations that this price behavior would be caught by HP-ADF test while the other tests including ADF t test have low power against such alternative given small and moderate sample size and, especially, when the autoregressive coefficients are close to unity. Therefore the rejections of HP-ADF test for almost all of the series with suspected large initial values would be persuasive evidence against random walk hypothesis in HoSTC. On the other hand we also realize that stock prices series of HoSTC seem to be more close to random walk process than those of several emerging markets tested in the previous researches, at least during the non-peak period. For further concerns about testing RWH of HoSTC, more methods such as autocorrelation, runs, and variances ratios tests might be employed to clarify the issues.

Since no test is superior for all possible values of the initial value, the choice to use several tests for the robustness is often necessary. In general, we recommend including HP-ADF test in the case that researcher suspects about the possibility of extreme initial value, e.g. the case of stock prices in emerging market. The other powerful tests assuming fixed or unconditionally distributed initial value, like DF-GLS, GLS-MZ and the tested proposed by Elliott et al. (1999) should be used in combination to produce robust results.

Appendix: Simulation for the model with serial correlated errors

Power

We extend the simulation to the models with serial correlated errors. In this part, we just focus on examining how the error structures affect the performance of HP-ADF and ADF t tests at various small to moderate sample sizes. The model is the same as (24) except:

- The error terms now is either AR(1), which is:

  $\varepsilon_t = \rho\varepsilon_t + \eta_t$, where $\eta_t \sim IIN(0,0.01)$

  or MA(1): $\varepsilon_t = \eta_t + \theta_t\varepsilon_{t-1}$, where $\eta_t \sim IIN(0,0.01)$

- We fix IV at $\Delta y_0 = 40\sigma$, and expand the investigated sample sizes to include T = 100, 250, 500, and 1000 to focus more on small sample size performance of the tests.

The results, which are based on 5,000 replications, are shown in Table 4. For different error structures, we also observe the overall superiority of HP-ADF test over the t test and the improvements of the both tests when the sample size increases. However, the influences of error structures are considerable: both tests reduce their power when θ/ρ increases. For example, for the sample size of 250, when θ increases from -0.8 to 0.8, the rejection rates of F/HP-ADF and ADF t tests reduce from 100% and 94% to 15% and 9%, respectively. Based on the output of the simulation, Figure 5 and Figure 6 show the patterns of the superiority of F/HP-ADF over t test for different sizes and error structures, which are MA(1) and AR(1). For both types of error structures, we would recognize that the superiority of F/HP-ADF test over t test is eroded as the lag coefficient increase. For MA(1) errors, the maximum differences in power across sample sizes are more than 30% when $\theta \leq 0$ while those for positive θ are about 20% or smaller. Similarly for AR(1) errors, the maximum power differences when $\rho \leq 0$ are more than 40% while they are less than 10% when $\rho > 0$. Even when $\rho = 0.8$, the power of the F/HP-ADF is lower than t test for the sample sizes of 250, 500, and 1,000. In summary, from the simulation, F/HP-ADF test is still generally better than pure t test, especially, for small sample sizes although we should also be alerted about the effects of different error structures, especially when ρ or θ is positive and large that may diminish the superiority of F/HP-ADF test over the t test.

[Figure 5 and Figure 6 are about here]

Size

Table 5 shows the simulation results for actual size of HP-ADF and t tests at nominal size of 5% with sample sizes of 100, 200, and 500 for different error structures. As the size of ADF t test has been studied in the past researches (moreover, Muller and Elliott (2003) showed that IV does not affect size of the tests), in this part we try to point out that the size of HP-ADF and t tests are basically the same. As expected, from the results, we see that the rejection rates of HP-ADF and t tests are close to each other for all different error structures and sample sizes. Consistent with the previous research, both tests suffer serious size distortions when the MA roots are negative, even for large sample sizes. For example, for the size of 500 and $\theta = -0.8$, HP-ADF and t tests reject null at the rates of about 30%. However, the distortions are acceptable for the all the cases of non-negative θ although we should be alerted about slight size distortions when the sample size is small, e.g. of 100: the actual sizes of the both tests are about 8.5% and 12% when $\theta = 0.5$ and $\rho = -0.5$, respectively.

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Table 1 – Power of HP-ADF, t, and GLS-DF tests with different IV[b]

y0	T = 500			T = 1,000		
	HP-ADF	ADF t	GLS-DF	HP-ADF	ADF t	GLS-DF
-0.6225	0.979	0.853	0.000	0.999	0.997	0.000
-0.5225	0.929	0.667	0.000	0.995	0.986	0.000
-0.4225	0.682	0.449	0.000	0.955	0.921	0.000
-0.3225	0.349	0.282	0.001	0.784	0.769	0.000
-0.2225	0.162	0.181	0.074	0.571	0.624	0.194
-0.1225[a]	0.129	0.163	0.244	0.489	0.563	0.778
-0.0225	0.177	0.189	0.064	0.575	0.632	0.194
0.0775	0.337	0.273	0.002	0.790	0.782	0.001
0.1775	0.680	0.444	0.000	0.959	0.934	0.000
0.2775	0.925	0.662	0.000	0.992	0.983	0.000
0.3775	0.976	0.848	0.000	0.998	0.996	0.000

[a] The unconditional expectation of IV

[b] GLS-DF is used with MAIC for lag selection while GTS approach is used for HP-ADF and t tests.

Table 2 – Unit root tests for HoSTC

Stock	Size	DF-GLS (MAIC)		KPSS	HP-ADF				
		$t_{stat.}$	$T_{crit.}$ 5%		$t_{stat.}$	$t_{crit.}$ 5%	$t_{crit.}$ 1%	$F_{stat.}$	$F_{crit.}$ 5%
AGF	887	-1.35	-2.89	0.30**	-2.07	-3.41	-3.96	2.78	6.25
BBC	583	-0.56	-2.89	0.61**	-2.11	-3.41	-3.96	3.75	6.25
BBT	423	-0.43	-2.92	0.59**	-2.32	-3.42	-3.98	6.39*	6.31
BPC	899	-1.42	-2.89	0.30**	-2.21	-3.41	-3.96	2.82	6.25
BT6	894	-0.96	-2.89	0.35**	-2.48	-3.41	-3.96	3.55	6.25
BTC	569	-1.59	-2.89	0.37**	-2.11	-3.41	-3.97	2.85	6.27
CAN	608	-1.29	-2.89	0.58**	-0.98	-3.41	-3.96	1.66	6.25
DHA	401	-0.31	-2.89	0.46**	-1.93	-3.42	-3.98	8.24*	6.32
DPC	592	0.13	-2.89	0.55**	-1.90	-3.41	-3.96	7.64*	6.25
GIL	577	-1.42	-2.89	0.26**	-1.13	-3.41	-3.96	1.10	6.26
GMD	892	-0.77	-2.89	0.38**	-1.63	-3.41	-3.96	2.66	6.25
HAP	658	-0.62	-2.89	0.61**	-2.80	-3.41	-3.96	6.24	6.25
HAS	723	-1.56	-2.89	0.39**	-1.74	-3.41	-3.96	1.67	6.25
KHA	810	-1.45	-2.89	0.44**	-2.27	-3.41	-3.96	2.74	6.25
LAF	658	-0.50	-2.89	0.64**	-2.45	-3.41	-3.96	5.35	6.25
MHC	168	-1.78	-2.96	0.09	-4.83**	-3.44	-4.02	12.05*	6.42
NKD	230	-0.98	-2.93	0.41**	-0.10	-3.43	-4.00	4.45	6.37
PMS	509	-1.47	-2.89	0.17*	-3.44*	-3.42	-3.98	6.64*	6.30
PNC	90	-2.63	-3.07	0.23**	-3.12	-3.46	-4.06	4.94	6.54
REE	658	-0.47	-2.89	0.53**	-2.72	-3.41	-3.96	5.40	6.25
SAM	658	-0.78	-2.89	0.46**	-3.67*	-3.41	-3.96	8.23*	6.25
SAV	882	-1.17	-2.89	0.32**	-2.35	-3.41	-3.96	3.29	6.25

Table 2 – Unit root tests for HoSTC (continued)

Stock	Size	DF-GLS (MAIC)		KPSS	HP-ADF				
		$t_{stat.}$	$T_{crit.}$ 5%		$t_{stat.}$	$t_{crit.}$ 5%	$t_{crit.}$ 1%	$F_{stat.}$	$F_{crit.}$ 5%
SFC	291	-0.74	-2.91	0.35**	-4.69**	-3.43	-3.99	13.02*	6.33
SGH	649	-2.12	-2.89	0.62**	-1.90	-3.41	-3.96	4.70	6.25
SSC	182	-1.67	-2.95	0.36**	-1.96	-3.44	-4.01	1.92	6.41
TMS	658	-0.71	-2.89	0.56**	-3.64*	-3.41	-3.96	9.43*	6.25
TNA	83	-1.02	-3.11	0.30**	-5.17**	-3.47	-4.08	27.28*	6.58
TRI	579	-0.93	-2.89	0.38**	-1.27	-3.41	-3.96	2.08	6.26
TS4	817	-0.97	-2.89	0.30**	-3.08	-3.41	-3.96	5.74	6.25
VNI[a]	658	-0.61	-2.89	0.55**	-3.27	-3.41	-3.96	7.84*	6.25
VTC	693	-1.31	-2.89	0.51**	-1.09	-3.41	-3.96	0.91	6.25

Note:

- *For KPSS tests, critical values are 0.216 (1%), 0.146 (5%), and 0.119 (10%).*
- *All the tests are specified with time trend. GLS-DF is used with MAIC for lag selection. KPSS is used with Newey-West using Bartlett kernel method for selection of bandwidth. HP-ADF is used with OLS F-test and t-test for lag selections (GTS approach)*
- *(*) or (**) mean the tests reject null at 5% or 1% respectively.*
- *t critical values for HP-ADF tests shown in this table based on non-standard distribution assuming that β (time trend coefficient) is zero. If β is non-zero, t statistic would follow standard normal distribution (-1.65 at 5%, one-side).*
- *[a]: Stands for VNINDEX*

Table 3 – ARMA(1,1) estimates of difference series rejected by ADF t and HP-ADF tests

Stock	Const	AR(1)	MA(1)
BBT	0.0010	0.98	-0.99
DPC	-0.0014	-0.34	0.42
DHA	0.0018	0.58	-0.63
MHC	0.0040	0.47	-0.62
PMS	0.0012	0.03	-0.23
SAM	0.0005	0.20	0.06
SFC	0.0037	0.89	-1.00
TMS	0.0016	0.97	-0.96
TNA	0.0021	0.20	0.47
VNINDEX	-0.0008	0.10	0.23

Table 4 – Power of F/HP-ADF and t-type ADF tests with serial correlated errors[a]

Size (T)	θ	HP-ADF	ADF	ρ	HP-ADF	ADF
100	-0.8	0.369	0.011	-0.8	0.390	0.042
	-0.5	0.235	0.060	-0.5	0.271	0.052
	0	0.147	0.048	0	0.147	0.048
	0.5	0.108	0.079	0.5	0.075	0.054
	0.8	0.096	0.079	0.8	0.066	0.062
250	-0.8	1.000	0.937	-0.8	0.928	0.476
	-0.5	0.946	0.394	-0.5	0.896	0.347
	0	0.632	0.176	0	0.632	0.176
	0.5	0.236	0.114	0.5	0.141	0.092
	0.8	0.153	0.091	0.8	0.068	0.074
500	-0.8	1.000	1.000	-0.8	0.994	0.972
	-0.5	0.998	0.981	-0.5	0.989	0.939
	0	0.925	0.662	0	0.925	0.662
	0.5	0.526	0.348	0.5	0.327	0.267
	0.8	0.334	0.264	0.8	0.146	0.169
1,000	-0.8	1.000	1.000	-0.8	1.000	1.000
	-0.5	1.000	1.000	-0.5	1.000	0.999
	0	0.992	0.983	0	0.992	0.983
	0.5	0.897	0.858	0.5	0.769	0.759
	0.8	0.749	0.729	0.8	0.472	0.531

[a]: Both HP-ADF and ADF t tests use GTS approach to select the lag lengths.

Table 5 – Size comparison between HP-ADF and pure ADF t test[a]

Size (T)	θ	HP-ADF	ADF t	ρ	HP-ADF	ADF t
	-0.8	0.792	0.805	-0.8	0.051	0.049
	-0.5	0.426	0.452	-0.5	0.122	0.123
100	0	0.051	0.047	0	0.051	0.047
	0.5	0.084	0.086	0.5	0.053	0.045
	0.8	0.069	0.066	0.8	0.062	0.053
	-0.8	0.571	0.595	-0.8	0.047	0.046
	-0.5	0.215	0.238	-0.5	0.049	0.047
200	0	0.051	0.052	0	0.051	0.052
	0.5	0.072	0.075	0.5	0.049	0.050
	0.8	0.051	0.056	0.8	0.052	0.052
	-0.8	0.303	0.328	-0.8	0.049	0.052
	-0.5	0.133	0.145	-0.5	0.051	0.053
500	0	0.054	0.055	0	0.054	0.055
	0.5	0.050	0.049	0.5	0.051	0.054
	0.8	0.054	0.054	0.8	0.052	0.053

[a]**:** The specifications of the model is the same as in the previous simulation except α = 1 and β = 0. Both HP-ADF and ADF t tests use GTS approach to select the lag lengths.

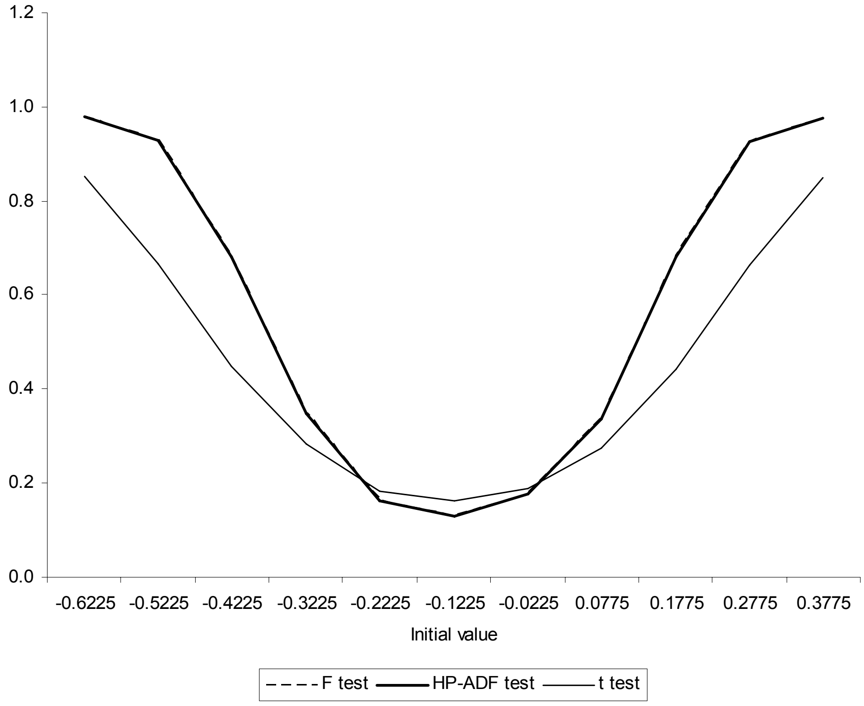


Figure 1 – Power of F test, HP-ADF test, and t test with varying IV (T = 500)

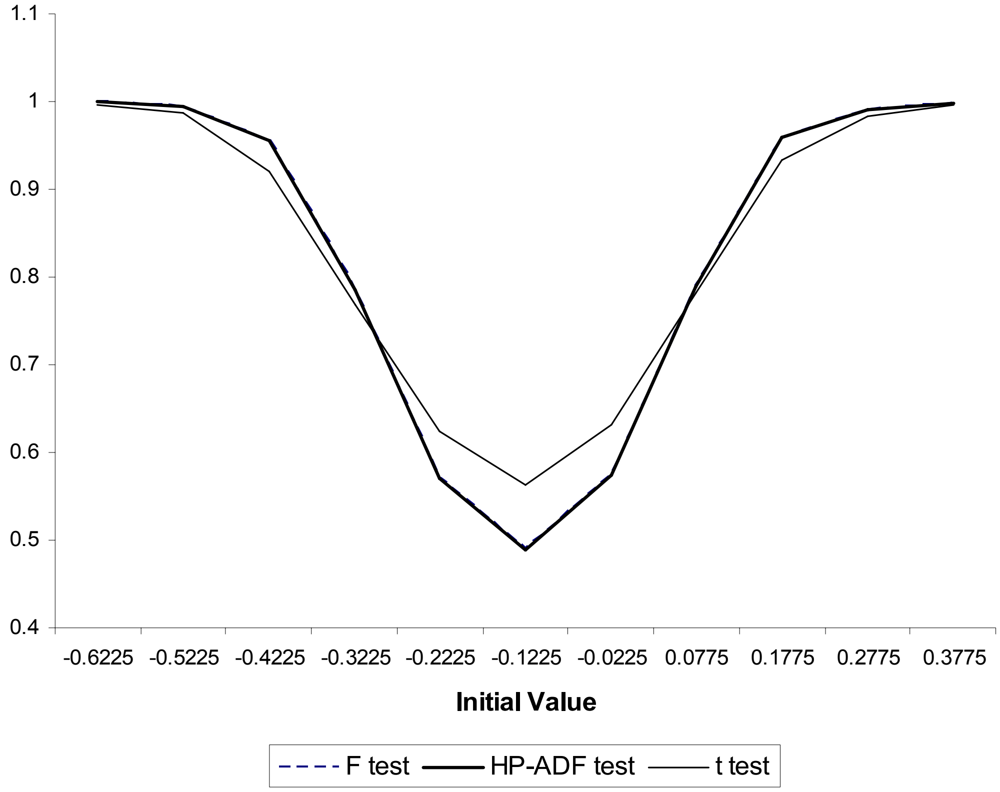
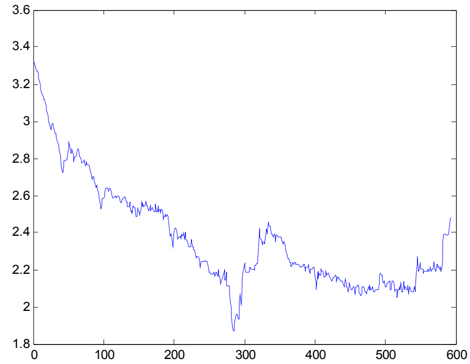
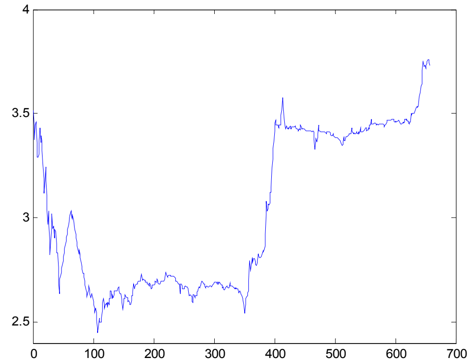


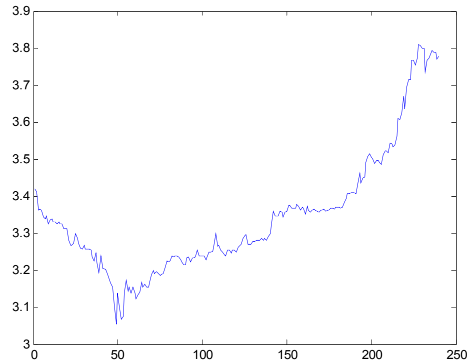
Figure 2 - Power of F test, HP-ADF test, and t test with varying IV (T = 1,000)



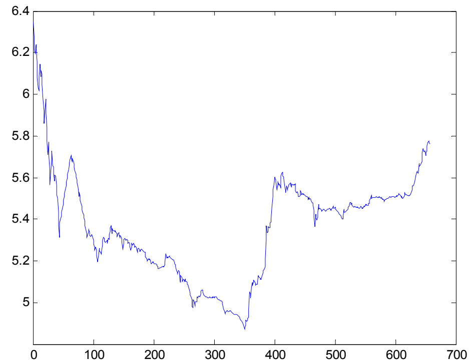
DPC



SAM



DHA



VNINDEX

Figure 3 – Four (of ten) series which are rejected by HP-ADF test

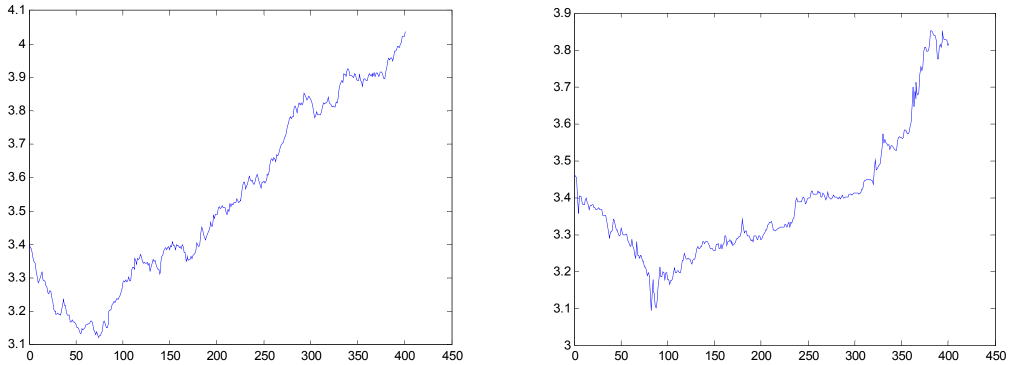


Figure 4 - Simulated DHA and the real series (in log form)

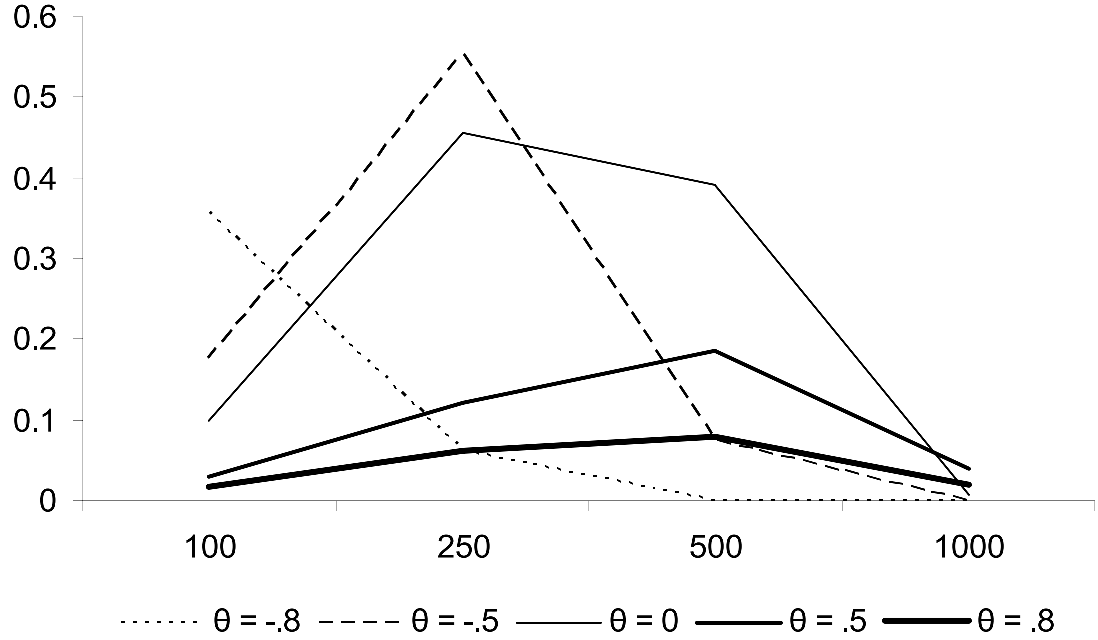


Figure 5 – The superiority (differences) of F/HP-ADF over t test for different sample sizes when errors follow MA(1) with coefficient θ.

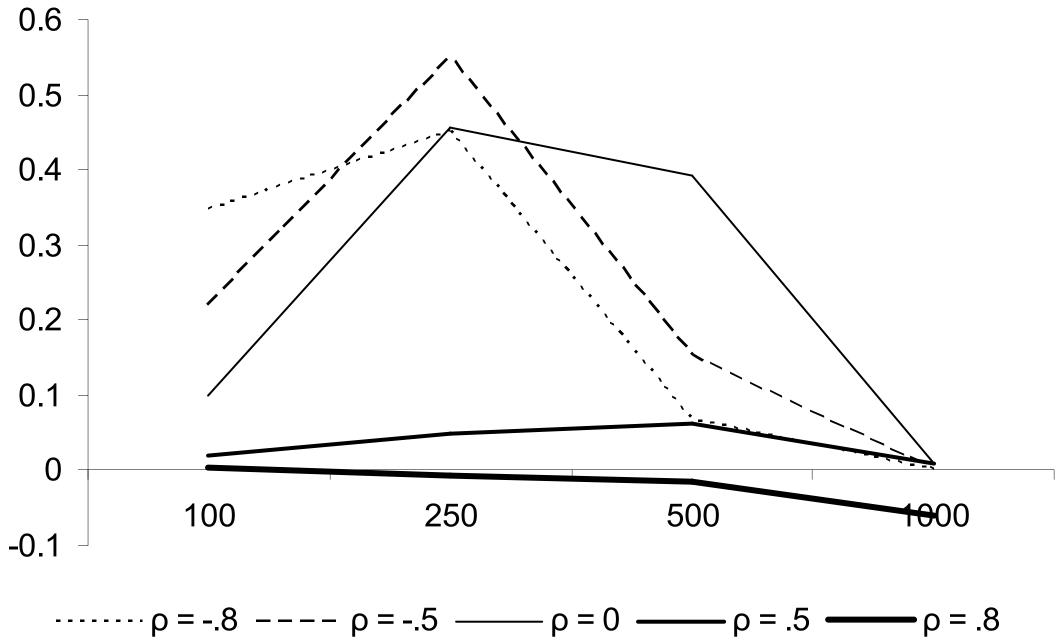


Figure 6 – The superiority (differences) of F/HP-ADF over t test for different sample sizes when errors follow AR(1) with coefficient ρ.