

Periodic Integration and Cointegration of U.S. Stock Prices, Dividends, and Interest Rates: A New Test of the Present Value Model

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Abstract

This paper presents a new test of the present value model of stock price determination, using some of the recent advances in the econometrics of seasonal time series. Unlike earlier studies which generally find stock prices, dividends, and interest rates to be characterized by standard nonseasonal unit roots, we find evidence of periodic seasonal integration in these variables. This means that the conventional cointegration tests may not be robust. Using a more appropriate periodic cointegration test, our results nevertheless fail to support the present value model, thus reinforcing the case against the efficient market hypothesis.

Keywords: time-series data, seasonal integration, equity valuation, market efficiency

JEL Classification codes: C22, G12, G14

In a series of seminal papers, Shiller (1981a, 1981b) and Leroy and Porter (1981) provide empirical evidence against the present value model of stock prices and, by implication, the efficient market hypothesis. In conducting their empirical analysis, however, these authors rely on the assumption that the underlying data, such as stock prices and dividends, are characterized by stationarity around deterministic trends. This assumption has been criticized by Kleidon (1986) and Marsh and Merton (1986), among others, on the grounds that it contradicts most existing evidence that such data are in fact difference stationary. In response to critics, and making use of the more recent advances in the econometrics of nonstationary processes, Campbell and Shiller (1989) present new evidence that, again, seems to be unfavorable to the present value model, thus reinforcing the earlier results. In particular, Campbell and Shiller show that stock prices and dividends, assumed to be difference stationary, fail to cointegrate in the sense defined by Engle and Granger (1987) and Johansen (1988). This finding, which effectively rules out the presence of a long-run relationship between stock prices and dividends, clearly bears negative implications for the present value model, in which dividends are supposed to be the major determinant of stock prices in the long run.

Despite its importance, the existing research on the present value model suffers from two major drawbacks. The first arises from an almost total abstraction from the issue of seasonality in the time series data. This is an important omission, since recent research has shown that seasonality is one of the most important components of most macroeconomic and financial time series, tending in many cases to dominate other non-trend components (Barsky & Miron, 1989; Miron, 1994).

On the one hand, seasonality has been shown to be an independent aspect of economic and financial behavior, thus deserving explanation in its own right (Birchenhall, Bladen-Hovell, Chui, Osborn, & Smith, 1989; Miron, 1986; Miron & Zeldes, 1988; Osborn, 1988;). On the other hand, evidence has been accumulated which questions the conventional treatment of seasonality as a constant feature of the data, to be adjusted away through deterministic dummies (Franses, 1996; Ghysels, 1994). Mirroring the parallel empirical debate about whether trend or difference stationarity best characterizes the trend component of most time series data, econometricians increasingly tend to model the seasonality component as a stochastic process, to be subjected to stationarity tests. Indeed, extending the econometrics of unit roots and cointegration to the study of seasonality, a number of researchers have developed similar seasonal integration and cointegration tests (Engle, Granger, Hylleberg, & Lee, 1993; Ghysels & Perron, 1993; Hylleberg, Engle, Granger, & Yoo, 1990).

Since inappropriate seasonal adjustment methods, such as using seasonal dummies to purge stochastic seasonality, can complicate standard unit root and cointegration results, pretesting the data for seasonal unit roots has now become standard practice among many researchers. Nevertheless, more recent studies have come to consider the seasonal unit roots approach, with its assumption of the constant autoregressive coefficients for all seasons, as too restrictive. By providing evidence to the contrary, the present study advocates a more general approach, the so-called periodic integration approach, in which the autoregressive coefficients are allowed to vary across seasons, while at the same time satisfying a newly defined condition for unit root behavior (Franses, 1996; Ghysels & Osborn, 2004; Ghysels, Osborn, & Rodrigues, 2006; Gil-Alana, Cunado, & de Garcia, 2008; Osborn, 1991). Clearly, for variables that display periodic as opposed to seasonal unit roots, one can simply replace the concept of seasonal with periodic cointegration.

The second drawback of existing research on the present value model relates to the restrictive assumption that the required rate of return on the stock market is constant (i.e., controlled) over time. This assumption is evidenced by the absence of the rate of return from many of the cointegrating relationships used to test the present value model. There is, however, considerable empirical evidence that the rate of return is far from constant and that it is best modeled as an endogenous stochastic process, with the issue of its stationarity subject to empirical test. Accordingly, this paper allows the rate of return to vary over time and to appear as a separate variable in our cointegrating relationships. More specifically, following the work of Mankiw, Romer, and Shapiro (1991), we assume that the rate of return on the stock market is equal to the risk-free rate of interest plus a constant risk premium. This assumption, justified by Hansen and Singleton (1983), allows us to formulate the present value model in terms of the nominal values of stock prices and dividends and to avoid the measurement errors associated with the use of price indices as deflators.

The purpose of this paper is to advance the evidence on the empirical validity of the present value model of stock prices in two ways. First, we use some of the methodological advances in the econometrics of seasonal time series previously mentioned to explicitly model the seasonal behavior of the U.S. stock prices, dividends, and interest rates. We then examine the implications of such behavior for the tests of the present value model. Specifically, the paper shows evidence that the seasonal components of the U.S. stock prices, dividends, and interest rates are neither deterministic nor characterized by seasonal unit roots. Rather, they seem to be periodically integrated. In addition, we find no evidence of periodic cointegration among these variables, thus supporting the earlier findings against the present value model and the efficient market hypothesis.

The rest of the paper is organized as follows. In Section 2, we summarize the methodology used in the paper; in Section 3, we present the empirical results; and in Section IV, we offer some concluding remarks.

The Model

The present value model of stock prices can be written as follows:

$$P_t = E_t \left\{ \sum_{j=1}^{\infty} \frac{D_{t+j}}{(1 + R_{t+j})^j} \right\} \quad (1)$$

where P_t = the stock price at the beginning of period t , E_t = the expectations operator, conditional on all the information available at the beginning of period t , D_t = the dividend paid during period t , and R_t = the required rate of return on the stock for period t . As stated earlier, all variables are expressed in nominal terms. In addition, the required rate of return is assumed to be the sum of a risk-free rate of interest, r , and a constant risk premium, π , as shown below:

$$P_t = E_t \left\{ \sum_{j=1}^{\infty} \frac{D_{t+j}}{(1 + r_{t+j} + \pi)^j} \right\} \quad (2)$$

Under the assumption that the variables in Equation 2 are difference stationary, Campbell and Shiller (1989) show that the empirical validity of the present value model of stock prices can be assessed by a cointegration test of the log-linearized version of the above equation. More specifically, and adding the risk-free rate as an additional variable to their equation, they use the following cointegrating relationship, in which the lower case variables (except for the risk-free rate) are expressed in natural logarithms:

$$p_t = \alpha_0 + \alpha_1 d_t + \alpha_2 r_t + u_t \quad (3)$$

where u_t = a white noise process. Following Campbell and Shiller, we also use Equation 3 as our basic cointegrating relationship in our test of the present value model. However, as discussed more fully in the next section, our empirical methodology differs from theirs in that we pay explicit attention to both the seasonal behavior of our underlying data and the effect this behavior will have on our cointegration results.

Methodology

The first objective of this paper is to test the present value model of stock prices by explicitly addressing the seasonal properties of the underlying data. Since our data are quarterly, we use only four seasons per year. As a first step, we ascertain that there is indeed a seasonal pattern in our data. This is accomplished through a standard Wald test of joint significance of the seasonally dummied variables in the following autoregression equation:

$$y_t = a_0 + b_0 T + c_0 y_{t-1} + \sum_{i=1}^3 a_i D_i + \sum_{i=1}^3 b_i D_i T + \sum_{i=1}^3 c_i D_i y_{t-1} + \varepsilon_t \quad (4)$$

where y_t is the stock price in quarter t , T is a quarterly time trend, D_i is a seasonal dummy equal to one for the i th quarter and zero elsewhere, and ε_t is a white noise error term.

Since the results we present later in the paper do indicate the presence of a seasonal pattern in our data, we need to find an appropriate approach for modeling such seasonal behavior. There is substantial evidence that much of the seasonal variation over time is not constant (Hylleberg, 1994; Canova & Hansen, 1995). Thus, it is of considerable interest to determine whether the seasonal pattern in our data follows a stationary stochastic process, and if not, how one could render it stationary. At the same time, it is well known that any quarterly time series can be purged of its seasonal effects through the use of the fourth differencing filter, Δ_4 . If this filter renders a seasonal series stationary, then the series is said to be seasonally integrated, or to have seasonal unit roots. Hylleberg et al. (1990; henceforth HEGY) provide a methodology to test for the presence of seasonal unit roots in quarterly time series data. As HEGY show, underlying the fourth differencing filter

is the assumption that there are four nonseasonal and seasonal unit roots in the underlying data. Specifically, with B denoting the lag operator, we can solve the fourth differencing equation to obtain $\Delta_4 = 0 = (1 - B^4) = (1 - B)(1 + B)(1 + B^2)$, with four unit roots of 1, -1, i , and $-i$, with i representing the imaginary number. The unit root 1 is the nonseasonal unit root, while the other three roots are seasonal unit roots. Clearly, should any of these unit roots be absent, the fourth differencing filter may result in overdifferencing of the data.

To determine the number of unit roots, we can perform the HEGY test, which is based on the following auxiliary regression:

$$\Phi(B) y_{4,t} = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t \quad (5)$$

where $\Phi(B)$ is an autoregressive polynomial in B with order r chosen to render the error term in the above equation white noise, μ_t is a combination of seasonal dummies and a time trend, and the y variables are defined as follows:

$$\begin{aligned} y_{4,t} &= (1 - B^4) y_t \\ y_{1,t} &= (1 + B + B^2 + B^3) y_t \\ y_{2,t} &= -(1 - B)(1 + B^2) y_t \\ y_{3,t} &= -(1 - B^2) y_t \end{aligned}$$

HEGY show that the test for the presence of nonseasonal and seasonal unit roots amounts to testing for the significance of the π terms in the above auxiliary equation. If π_1 equals zero, then the null hypothesis of a nonseasonal unit root 1 cannot be rejected. If π_2 equals 0, the null of a seasonal unit root -1 cannot be rejected. Finally, if $\pi_3 = \pi_4 = 0$ then the null of two seasonal unit roots of $+i$ and $-i$ cannot be rejected. To test the above hypotheses, HEGY show that we can use t tests for π_1 and π_2 and a joint F -test for π_3 and π_4 , using the nonstandard critical values they provide.

One drawback of the HEGY test is the restriction that the coefficients of the auxiliary regression (2) are constant over the seasons. Franses (1993) proposes an alternative periodic approach that relaxes this restriction by allowing the coefficients to vary across seasons. In addition, by stacking quarterly data into a 4×1 vector of annual series, Franses (1994) offers an alternative multivariate approach to testing for nonseasonal and seasonal unit roots, using the Johansen (1988) cointegration method. Under this alternative approach, the hypotheses concerning the presence of nonseasonal and seasonal unit roots can be replaced by testable hypotheses on the coefficient values of the Johansen cointegration vectors. Indeed, as we will show later in the paper, an application of the HEGY approach to our data indicates only nonseasonal unit roots, with no evidence of seasonal unit roots. Given these results, we decided to also perform the multivariate Franses (1994) test and, based on this test, we reject even nonseasonal unit roots. In light of these negative findings, we test for periodic unit roots and find that they characterize all our stock prices. As part of our periodic unit root tests, we find a first-order periodic autoregression to be appropriate for our data. Hence, in the remainder of this section, we briefly describe the periodic integration approach only in the context of a simple first-order periodic process, given by following expression:

$$y_t = \phi_{1,s} y_{t-1} + \varepsilon_t \quad (6)$$

where $\phi_{1,s} \neq \phi_1$ for $s = 1$ to 4. In addition, we can stack the quarterly series y_t into a 4×1 vector Y_T of annual series, where $Y_T = (Y_{1T}, Y_{2T}, Y_{3T}, Y_{4T})'$, and Y_{sT} is the season s observation in the year T . Thus, Equation 3 can be expressed in vector notation as follows:

$$A_0 Y_T = A_1 Y_{T-1} + \varepsilon_T \quad (7)$$

with

$$A_0 = \begin{Bmatrix} 1 & 0 & 0 & 0 \\ -\phi_{12} & 1 & 0 & 0 \\ 0 & -\phi_{13} & 1 & 0 \\ 0 & 0 & -\phi_{14} & 1 \end{Bmatrix}$$

$$A_1 = \begin{Bmatrix} 0 & 0 & 0 & \phi_{11} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{Bmatrix}$$

We now define the parameter vector $\phi = (\phi_{11}, \phi_{12}, \phi_{13}, \phi_{14})$. The vector process Y_T is stationary provided that the root of the characteristic equation

$$|A_0 - A_1 z| = (1 - (\phi_{11} \phi_{12} \phi_{13} \phi_{14}) z) = 0 \quad (8)$$

lies outside the unit circle, i.e. if $\phi_{11} \phi_{12} \phi_{13} \phi_{14} < 1$. On the other hand, the process Y_T can be said to be integrated if Equation 8 has a unit root, i.e., if it is the case that

$$\phi_{11} \phi_{12} \phi_{13} \phi_{14} = 1 \quad (9)$$

To test the above restriction, we first estimate the following unrestricted equation

$$y_t = \sum_{s=1}^4 \phi_{1s} D_{st} y_{t-1} + \varepsilon_t \quad (10)$$

Next, by imposing the above restriction, we have the following restricted equation:

$$y_t = \phi_{11} D_{1t} y_{t-1} + \phi_{12} D_{2t} y_{t-1} + \phi_{13} D_{3t} y_{t-1} + (\phi_{11} \phi_{12} \phi_{13})^{-1} D_{4t} y_{t-1} + \varepsilon_t \quad (11)$$

which can be estimated by non-linear squares (NLS). A likelihood ratio test can then be expressed in the following form:

$$LR = n \bullet \ln(RSS_0 / RSS_1) \quad (12)$$

where RSS_0 and RSS_1 denote the residual sums of squares from (7) and (8), respectively. The above likelihood ratio can then be used to construct the following one-sided test, which follows a Dickey-Fuller (1979) t distribution:

$$LR_\tau = \left[\text{sign}(\phi_{11} \phi_{12} \phi_{13} \phi_{14} - 1) \cdot LR^{1/2} \right] \quad (13)$$

Having established periodic integration for our underlying variables data, it is of interest to also test for the presence of periodic cointegration among them. Boswijk and Franses (1995) extend the standard cointegration definition to periodically integrated series and formulate the periodic cointegration test as a Wald test of joint significance of the 4-quarter lagged variables in the following vector autoregression:

$$\Delta_4 y_t = \sum_{s=1}^4 (\mu_{0s} D_{st} + t_s D_{st} T) + \sum_{s=1}^4 \delta'_s D_{st} x_{t-4} + \pi' \omega_t + \varepsilon_t \tag{14}$$

where y_t is the variable chosen to serve as the dependent variable, x_t represents all the other variables, and ω_t stands for the lagged values of the fourth-differenced variables in the system, needed to render the error term a white noise process. Under the Boswijk-Franses cointegration test, the null of no cointegration can thus be rejected if the δ'_s coefficients in the above regression are found to be jointly and significantly different from zero, using the nonstandard critical values tabulated by these authors. Since this test, an extension of the Engle-Granger (1987) two-stage cointegration test, fails to reveal the number of cointegrating vectors, and its results may depend on the choice of the variable for the left-hand side of the equation, we address these concerns by substantiating the results using the Johansen cointegration test.

Empirical Results

Before offering our quantitative results concerning the seasonal characteristics of the U.S. stock prices, dividends, and interest rates, we present a visual impression of these characteristics in Figures 1 to 3. Each graph contains four curves corresponding to each of the underlying variables for the four quarters of the year, where all variables are nominal, logarithmic, and cover the period 1950:1 to 2007:1. The stock prices are measured by the S&P 500 index, dividends are those of the S&P 500 companies, and interest rates are represented by long-term Treasury yields. All the data are taken from the Shiller website (<http://www.econ.yale.edu/~shiller/>).

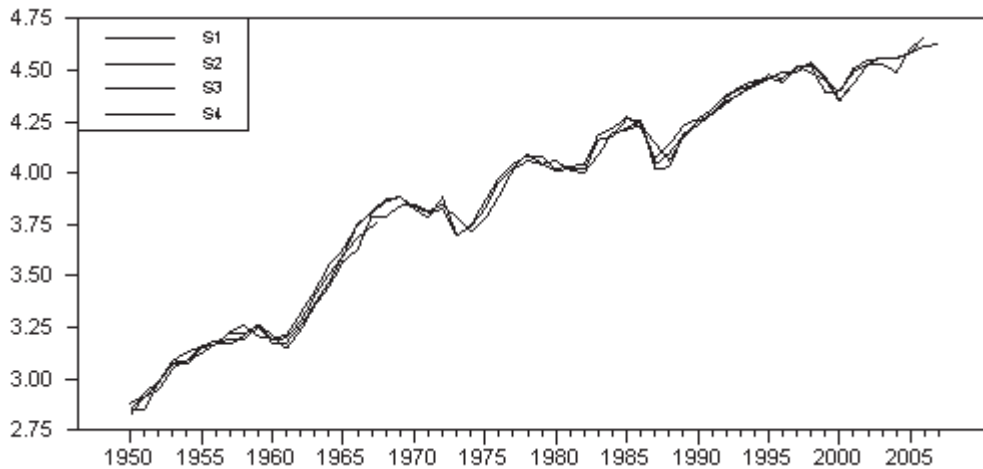


Figure 1. Stock Prices by the Quarter of the Year.

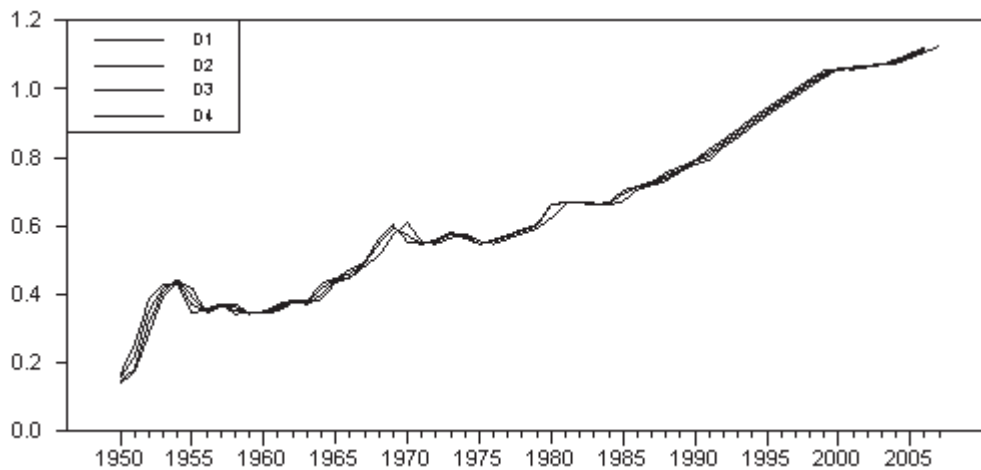


Figure 2. Dividends by the Quarter of the Year

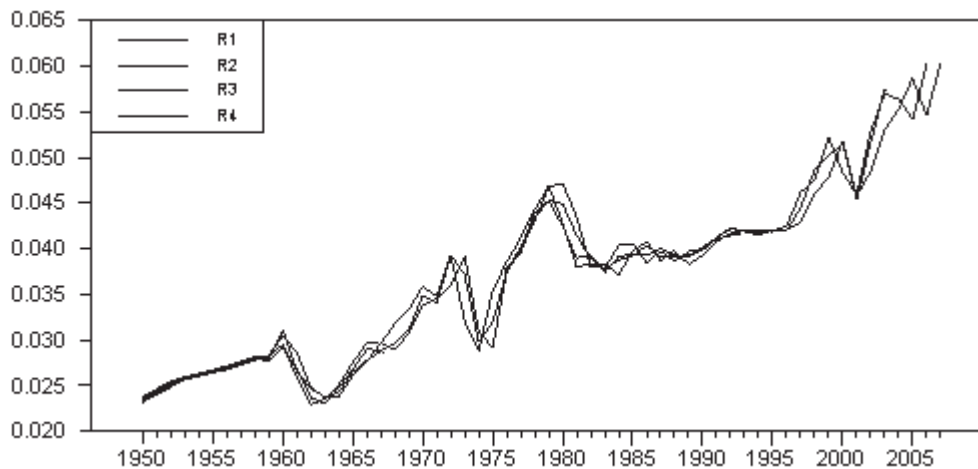


Figure 3. Interest Rates by the Quarter of the Year

Figures 1 to 3 show clearly that there is considerable seasonal variation for each of the variables in the sample, as evidenced by the frequent crossings of the quarterly curves in the figures. To bolster this visual impression, we conduct the Wald test of joint significance of the dummied seasonal variables in Equation 4, presented earlier. The F values of the Wald test, which range from 3.96 to 22.87, are all significant at the 5 % level, indicating the presence of seasonal changes for all the sample variables.

Given the presence of seasonal variations in the data, we need to model them. To this end, we employ the HEGY seasonal unit root tests discussed earlier, where a lag of eight quarters is chosen for each country through a process of testing down for significant lags. Table 1 presents the results of these tests. As the table shows, the U.S. stock prices, dividends, and interest rates are all characterized by only one nonseasonal (standard) unit root and no seasonal unit roots. This result means that, according to HEGY, a simple first differencing filter is all that is needed to render these variables stationary. In addition, given that our variables contain only nonseasonal unit roots, we can test for the presence of common stochastic trends among them through the standard Johansen cointegration procedure.

Table 1
HEGY Seasonal Unit Roots Test

Statistic	Unit root: +1 t-value for $\pi_1 = 0$	Unit root: -1 t-value for $\pi_2 = 0$	Unit roots: $\pm i$ F-value for $\pi_1 = \pi_2 = 0$
Stock prices	-2.55	-5.67*	16.01*
Dividends	-2.56	-3.93*	16.54*
Interest rates	-2.36	-5.91*	12.32*

* indicates significant at the 5 % and 10 % levels, respectively.

Before proceeding further, however, it is important to obtain independent verification of the HEGY test results through the multivariate Franses (1994) test of seasonal unit roots. As mentioned earlier, this test consists in stacking quarterly data into four separate vectors of quarters (VQs), with each vector corresponding to a particular season of the year. Under these conditions, the number of cointegrating vectors for these VQs provides information concerning the stochastic seasonal properties of the underlying data. In particular, to provide independent support for the above HEGY test results of only one nonseasonal unit root for our data, it is necessary (though not sufficient) to find three cointegrating vectors for our VQs. To render the finding of three cointegrating vectors also sufficient for a nonseasonal unit root, we must test the restriction that first-differencing the data renders them stationary. This means that the three cointegrating vectors, after appropriate normalizations, must be presentable as (-1,1,0,0), (0,-1,1,0), and (0,0,-1,1). Clearly, these vector forms can be tested as imposed restrictions on the cointegrating vectors by using the Johansen methods. At the same time, a finding of three cointegrating vectors could also indicate the presence of only one seasonal unit root, specifically the -1 root. Since under this seasonal unit root the data can be rendered stationary by adding successive observations, it is clear that we can also test for the -1 root by testing whether the cointegrating vectors can be presented as (1,1,0,0), (0,1,1,0), and (0,0,1,1).

The results of the Franses (1994) test are presented in Panels A and B of Table 2. Panel A gives the number of cointegrating vectors for each of the variables, using the Johansen cointegration test with one lag for all the variables, as selected by the Hannan-Quinn (1979) method. For each variable in the sample, there are three cointegrating vectors among the VQs, indicating that each of the underlying variables is nonstationary and driven by a common stochastic seasonal factor. In addition, this common factor can be either the nonseasonal unit root 1 or the seasonal unit root -1. Thus, as mentioned earlier, we need to perform an additional likelihood ratio test on the values of the cointegrating coefficients to determine whether the root is 1 or -1. This likelihood ratio test has a chi-squared distribution with $k-r(r-1)$ degrees of freedom, with k denoting the number of restrictions imposed on cointegrating vectors and r the number of cointegrating vectors. The results of these tests are presented in Panel B of Table 2. As the panel indicates, based on the Franses test results, we can reject both the nonseasonal and seasonal unit roots hypotheses for our sample data.

Table 2
Franses Seasonal Unit Roots Test (Number of Cointegrating Vectors and Restrictions on Cointegrating Vectors)

	Stock prices	Dividends	Interest rates
Panel A			
Null hypothesis	Trace Test		
$r = 0$	219.33*	396.58*	233.04*
$r \leq 1$	101.94*	132.12*	82.47*
$r \leq 2$	45.52*	54.47*	37.66*
$r \leq 3$	7.23	8.72	6.86
Panel B			
Unit roots	Likelihood ratio test (chi-squared with 6 degrees of freedom)		
1	14.80*	15.41*	11.69**
-1	79.63*	71.46*	94.49*

* and ** indicate significant at the 5 and 10 percent levels, respectively.

Having established the absence of standard nonseasonal and seasonal unit roots in the underlying variables, we turn to the issue of whether the nonstationarity of these variables can be captured by periodic unit roots. To this end, we simply employ the methodology outlined earlier in the paper. In particular, and as part of our periodic unit roots test, we use a first order periodic autoregression, a lag already selected by the Hannan-Quinn (1979) method. Next, we estimate Equation 9 as our unrestricted version of the periodic model for the sample (a Wald test of the constancy of the autoregressive coefficients in Equation 9 is rejected, with the F ratios ranging from 2.77 to 9.30, each significant at the 5 % level). Finally, under the null hypothesis according to which the underlying data are characterized by periodic unit roots, we also use the nonlinear least squares (NLS) method to estimate Equation 10 for our data. Based on our estimation results for Equations 9 and 10, we then compute the likelihood ratio statistic defined by Equation 12, which, as stated before, has a Dickey-Fuller (1979) nonstandard t-distribution. A nonsignificant value for this statistic is indicative that the null hypothesis of the periodic unit root cannot be rejected. The test results are presented in Panel A of Table 3 which shows clearly that none of the likelihood ratio statistics are significant at the standard levels. Thus, we cannot reject the null hypothesis of a periodic unit root for our variables.

Given our finding that the U.S. stock prices, dividends, and interest rates are all periodically integrated, it is of considerable interest to determine whether these variables are also periodically cointegrated, that is, whether there are linear combinations of these variables which lack periodic unit roots. As stated earlier, such a cointegration test is needed to assess the empirical validity of the present value model of stock prices. For the reasons mentioned above, our cointegration tests are based on the Boswijk-Franses (1995) test (Equation 13), with substantiation provided by using an auxiliary test employing the Johansen method, where in the latter method we test for the presence of cointegrating relationships among the VQs of the stock prices, dividends, and interest rates. The Boswijk-Franses test results appear in Panel B of Table 3 (the results of the Johansen tests, not reported here but available from the authors, are essentially the same). As the panel shows, none of the F-statistics is significant at the standard levels, indicating no periodic cointegration for the variables in our sample. The lack of periodic cointegration among the U.S. stock prices, dividends, and interest rates, in turn, raises questions concerning the validity of the present value model of U.S. stock prices. This finding also tends to refute the efficient market hypothesis as the correct paradigm for the working of the US stock market.

Table 3
Periodic Unit Root Test and Periodic Cointegration Test

	Stock prices	Dividends	Interest rates
Panel A			
Statistic	-1.95	-1.36	-1.66
Panel B			
Variable used as the dependent variable			
Statistic	2.08	3.91	2.05

Concluding Remarks

In this paper, using recent advances in the econometric analysis of seasonal and periodic time series, we offer a new test of the empirical validity of the present value model of U.S. stock prices. While this test follows the earlier research studies in interpreting the present value model as the presence of a cointegrating relationship among U.S. stock prices, dividends, and interest rates, it deviates from other research in its explicit attention to the seasonal and periodic time series properties of the underlying data. Given the presence of seasonal variations in the data, we employ a number of standard and seasonal unit root tests and find no evidence of such unit roots in the data. However, the paper does show evidence of periodic unit roots, which renders the standard cointegration tests of the present value model unreliable. To obtain more robust results, we test for periodic cointegration among the relevant variables, using some recently developed techniques, but we find no evidence for it. This negative finding raises doubts about the empirical validity of the present value model and, by implication, the efficient market hypothesis, at least in the U.S. context. Thus, our results tend to reinforce the earlier negative findings of Campbell and Shiller (1989) for the efficient market hypothesis by extending their results to the situations in which the underlying data may be characterized by the presence of periodic seasonal unit roots.

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